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DETERMINANTS OF INCOME INEQUALITY IN THE SELECTED GROUP OF EUROPEAN COUNTRIES: A PANEL DATA ANALYSIS

ДЕТЕРМИНАНТЕ ДОХОДНЕ НЕЈЕДНАКОСТИ У ОДАБРАНОЈ ГРУПИ ЕВРОПСКИХ ЗЕМАЉА - ПАНЕЛ АНАЛИЗА

Summary: *The paper focuses on providing basic characteristics of income inequality in a group of selected European countries in the period from 2000 to 2019. After presenting stylized facts and brief literature review, the paper proceeds to empirical analysis of income inequality in the observed countries by panel data techniques. Fixed and random effects models are estimated. After Hausman test approved the usage of fixed effects model, it was tested for serial correlation and robust standard errors were calculated. The empirical analysis of the determinants of income inequality shows that GDP growth, share of population in upper 10% of income percentile, Human Development Index and unemployment rate increase income inequality measured by Gini index, while share of workforce and share of population with tertiary education decrease income inequality. The results of the empirical analysis provide insight into determinants of income inequality, which may be useful for economic policy decision makers in their efforts to decrease the income inequality.*

Keywords: *Income inequality, Gini index, economic growth, panel analysis, fixed effects model*

JEL Classification: D31, E24, E64

Резиме: *Рад се фокусира на пружање основних карактеристика доходовне неједнакости у групи одабраних европских земаља у периоду од 2000. до 2019. године. Након изношења стилизованих чињеница и кратког прегледа литературе, прелази се на емпиријску анализу доходне неједнакости у посматраним земљама примјеном панел технике. Оцијењени су модели фиксних и случајних ефеката. Након што је Хаусманов тест упутио на употребу модела фиксних ефеката, модел је тестиран је на серијску корелацију и израчунате су робусне стандардне грешке. Емпиријска анализа детерминанти доходовне неједнакости показује да раст БДП-а, учешће становништва у горњих 10% дохотног перцентила, индекс хуманог развоја и стопа незапослености повећавају доходовну неједнакост мјерену Џинијевим индексом, док је удио радне снаге и становништва са терцијарним образовањем смањује. Резултати емпиријске анализе пружају увид у детерминанте доходовне неједнакости, што може бити од користи доносиоцима одлука о економској политици у њиховим настојањима да смање неједнакост дохотка.*

Кључне ријечи: *доходна неједнакост, Џини индекс, економски раст, панел анализа, модел фиксних ефеката*

ЈЕЛ касификација: *D31, E24, E64*

1. INTRODUCTION

Rising income inequality is the key challenge of our time. In advanced economies, the gap between rich and poor is at its highest level in decades. Inequality trends are more mixed in emerging and developing countries, with inequality declining in some countries, but inequalities in access to education, healthcare and finance are still widespread. It is therefore not surprising that the extent of inequality, its determinants and measures to address it have become some of the most pressing issues debated by both economic policymakers and researchers (Dabla-Norris et al. 2015).

One of the objectives of macroeconomic policy is equitable and sustainable economic and social well-being. In relation to this goal, the main objective of macroeconomic stabilisation policies is to achieve stable economic growth, especially as this is also a key factor in reducing global poverty (Mijiyawa 2008). Policies aimed at reducing income inequality are considered to be effective in promoting long-term sustainable growth (Berg and Ostry 2011). The theoretical inferences between these variables are relevant for policy recommendations, as promoting economic growth and ensuring equitable income distribution is at the heart of the trade-off between efficiency and equality that shapes policy debates in many countries (De Dominicis et al. 2008).

It is well known that income and wealth inequality in most rich countries, especially in the United States, have risen sharply in recent decades and have worsened since the Great Recession (Striglitz 2013). In most countries, disparities between countries are widening rather than narrowing. Rising economic forces have not lifted millions out of poverty, but have contributed to an even greater concentration of wealth among the elite. Inequality within poor and middle-income countries is worsening. According to Stiglitz (2013) instead of moving towards a more just world, we are moving towards a more unjust society.

Kuznets (1955) laid the foundations for a number of subsequent inequality studies. Based on the very limited data, he found that inequality follows a pattern that inequality first increases with rising average incomes, along with economic growth, then peaks and begins to decline as average incomes continue to rise. This phenomenon is known as the Kuznets curve. The logic of this hypothesis is that as countries industrialise, inequality increases until the country reaches a level of income that allows it to establish a social safety net and universal education, which tend to reduce inequality.

Income inequality reflects the unfair distribution of wealth and opportunities in society. High levels of income inequality lead to social instability. People who feel financially disadvantaged are more prone to discontent, protest and even social unrest. This can threaten the stability of society and the economy. Income inequality also affects economic efficiency. Too much inequality can limit access to education, health care and other resources, reducing human capital and labour productivity. In the long term, this hinders economic growth. Research on income inequality is important because it allows us to better understand the challenges facing societies and to design policies and measures to reduce inequality and improve well-being.

The paper continues with a brief literature review regarding the main determinants of income inequality in developed countries in chapter 2, review of main inequality indicators in chapter 3, while chapter 4 presents stylized facts about income inequality in selected European economies. Chapter 5 is devoted to panel data analysis with dataset and methodology presentation, displaying results and discussion. The paper concludes with an overview of the main findings and applications.

2. DETERMINANTS OF INCOME INEQUALITY IN DEVELOPED COUNTRIES: A LITERATURE REVIEW

According to Heimberger (2020) differences in the level of income inequality between countries are driven by differences in labour market outcomes, household composition, capital income concentration and differences in the progressivity of tax and transfer systems. The OECD project (2012) classifies countries into five groups according to the origin of inequality and finds large differences between EU countries.

In the Scandinavian countries and Switzerland, labour income dispersion is low, money transfers tend to be universal and taxes are not very progressive. In Belgium, the Czech Republic, Estonia, Finland, France, Italy, Slovakia, Slovenia and the Czech Republic, wage dispersion is generally low and employment rates are also low, while part-time employment is high. Taxes and transfers are not very progressive. Austria, Germany, Greece, Hungary, Luxembourg, Poland and Spain are characterised by a significant concentration of labour income, but much redistribution occurs at the family level. In the UK, Ireland and the Netherlands, part-time employment is high, leading to inequality in labour market outcomes. Taxes and transfers have a large redistributive effect. Portugal is the only European country in the latter group with a high concentration of income from labour, capital and self-employment and a high poverty rate. Transfers have a low redistributive impact (Castells-Quintana et al. 2015).

Looking at the evolution of inequality over time, the pattern is more common across European countries (Fredriksen 2012). The top decile seems to be gaining an increasing share of total income. The same is true for almost all OECD countries, which have seen an increase in income dispersion since 2000. Compared to some Anglo-Saxon countries and the US in particular, the increase in top incomes in continental Europe is rather modest, especially when looking at the top 1% of the distribution. There is no consensus on the causes of this development. In the literature, changes in taxation, labour market institutions and globalisation and technological change are among the most important explanations.

In many OECD countries, the progressivity of the tax scale at the top of the income distribution has been reduced since 2005, due to the lowering of top marginal tax rates and the raising of the income threshold. In Europe, the picture is mixed, with tax progressivity at the highest income levels declining significantly in Denmark and Ireland and to a lesser extent in France, while it has increased in the Czech Republic, Hungary, Greece and the Netherlands. In other countries, there have been only minor changes. In addition to changes in the income tax scale, the wealth tax was abolished in Austria (1997), Denmark (1997), Germany (1997), Finland (2006), Luxembourg (2006), Sweden (2007) and Spain (2008) (Dauderstädt and Kelmtek 2011).

Piketty et al. (2011), who restrict their analysis to the top 1% of the distribution, find a strong negative correlation between top income shares and top income tax rates over the period 1975-2008. In no country has there been an increase in top income shares without a significant decrease in top tax rates. The link appears to be stronger in Anglo-Saxon countries than in some European countries. It has been found that a reduction in top tax rates increases the incomes of the richest mainly because it encourages the highest earners to bargain more for higher wages, rather than because they work more or avoid less tax.

In general, income inequality may increase due to changes affecting labour supply (immigration, part-time work, institutional changes related to minimum wages, trade unions, etc.) and changes affecting labour demand, such as capital market liberalisation, outsourcing, technological change and many others (Alderson et al. 2005).

Globalisation and technological change may also have led to a higher return on skills and thus incomes in the top decile compared to the rest of the population. At the extreme end of the distribution, higher returns to certain types of talent, particularly in the sports and entertainment industries and for financial traders, have probably contributed to the increase in the relative income of the top 1% (Gordon and Dew-Becker 2008). The rewarding of managerial skills is also likely to have been positively affected by globalisation, not least because of the better alternative transport options available and the internationalised competition for managers, which has strengthened their bargaining power. These explanations are further reinforced by the increasing use of performance-related pay, especially for CEOs and finance professionals.

The study by Pervukhin and Tosov (2023) examines the relationship between globalisation and income inequality in the context of the European Union (EU). Using the World Bank database, the study looks in detail at how globalisation factors affect the distribution of income in EU countries. Covering the period from 2011 to 2020, the study focuses on a group of 27 EU Member States to shed light on the dynamics of income inequality amidst globalisation forces.

At the other end of the distribution, income growth in the bottom decile in Europe has been lower on average than for the rest of the population since 2000. Some aspects of globalisation may shed light on these developments. Increased international trade may have reduced employment or relative earnings of low-income workers, as high-income workers are disproportionately employed in (high-productivity) exporting firms. Changes in the labour market may also have played a role. The strength of labour market institutions and policies has declined on average in many OECD countries since 2000. This may have had a negative impact on low-income earners in the countries concerned. However, many such policies, such as employment protection legislation and minimum wages, have had counterproductive effects on employment and wage dispersion (Fredriksen 2012).

Rising income inequality in most countries is a fact of great concern to economists and policy makers in both developed and developing countries. Despite technological improvements, liberal market-oriented reforms and integration of countries, the benefits of rising incomes and output growth have not been shared equally among all population groups (Asteriou et al. 2014).

The study by Asteriou et al. (2014) investigates the relationship between income inequality and macroeconomic variables in European Union (EU) countries over the period 1995-2009. Using panel regression models, the analysis aims to disentangle the impact of globalisation, including trade openness and financial sophistication, on income distribution. This comprehensive approach provides a detailed understanding of the dynamics between globalisation and inequality in the EU-27.

Bucevska (2019) examines the determinants of income inequality in three EU candidate countries - North Macedonia, Serbia and Turkey - over the period 2005-2017. Using panel data analysis, the researchers aim to identify the macroeconomic and demographic factors affecting income distribution in these countries. To achieve this objective, the study uses a fixed effects model. The study highlights the negative impact of unemployment on income distribution, in addition to the positive correlation between GDP per capita and income inequality. It also highlights the mitigating effect of gross fixed capital formation on income inequality, suggesting that infrastructure investment plays a key role in reducing income inequality. In addition to macroeconomic factors, demographic factors such as population growth and educational attainment have also been found to have an important impact on income distribution.

3. INCOME INEQUALITY MEASUREMENT

The Gini index is by far the most commonly used measure of income inequality. It ranges from 0 to 100, with 0 representing perfect equality and 100 representing the greatest inequality, with one individual having all the income and the rest having none. The Gini index can be easily represented in a Lorenz (1905) graph for a more intuitive description, as it represents the ratio of the difference between the line of absolute equality and the Lorenz curve, which represents the distribution of income between quintiles of the population (Charles-Coll 2011).

A low Gini index usually indicates a relatively low degree of inequality in income distribution. In general, Gini index values can be divided into four groups. Values between 0 and 20 indicate a very low degree of inequality. The distribution of income is relatively even among the population. This may be typical of societies with strong social programmes that promote equality. Values between 20 and 30 indicate a low level of inequality. There are minor differences in income distribution among the population, but some inequality is still evident. Of our selected countries, 13 had a Gini index value between 20 and 30 in 2019. Values between 30 and 40 tell us that the index is still relatively low. Such Gini values may indicate a moderate degree of inequality. Differences between populations are slightly higher, but there are still no signs of serious social or economic stratification. Among our selected countries, 16 had a Gini index value between 30 and 40 in 2019. When the Gini index value is above 40, significant disparities in the distribution of wealth or income among the population are visible. These values are worrying, especially if inequality is increasing. Among our selected countries, only Bulgaria had a Gini index value above 40 in 2019. It should be noted, however, that these limits are quite relative and may vary depending on the context and socio-economic conditions. What may be considered a low level of inequality in one society may not apply to another (Sitthiyot and Holasut, 2020).

The Gini index is used by almost all government and international agencies to measure inequality of income or wealth in a country or the world. Although originally developed as a standardised measure of statistical dispersion to understand income distribution, the Gini index has evolved to measure inequality in all types of income distribution, wealth, gender equality, access to education and health services, and environmental policies, among others (Charles et al. 2022).

The most important advantage of the Gini index is that it satisfies the four main principles that any measure of inequality must satisfy in order to be considered a reliable measure, namely, the transfer principle (1), also known as the Pigou-Dalton principle of Dalton (1920) and Pigou (1912), according to which a transfer from a poorer to a richer individual should be reflected in an increase in the measure of inequality, regardless of the magnitude of the transfer or the relative position of the poor compared to the rich. Scale-independence (2), which states that if the overall level of income increases by a certain amount, then the overall value of the measure of inequality should not change at all. The principle of anonymity (3), according to which the identity of income recipients is irrelevant for determining the value of the inequality measure. Population independence (4), which means that the inequality measure should not be affected by the size of the population (Schwarze and Härpfer, 2007).

The main disadvantage of the Gini index as a measure of inequality calculated from the Lorenz curve is that the value of the Gini index can be the same for different sets of distributions. The Lorenz curve can have different shapes that capture the same area under the curve and thus reflect the same Gini index, which can be a serious drawback for someone interested in analysing and perhaps comparing the structure of income distribution in different quintiles of the population (Todaro and Smith, 2014).

A traditionally less well-known measure of inequality is the quintile share ratio, but in recent years it has become more well-known and popular, especially following the European Union's decision in 2001 to include it in its Laeken indicators as one of two indicators of inequality, the other being the Gini index (Brazauskas and Ghorai 2007). The quintile ratio, presented by Eurostat, is the ratio of the total income received by the 20% of the population with the highest income (highest quintile) to the 20% of the population with the lowest income (lowest quintile) (Drezner et al. 2014), It is commonly referred to as the S80/S20 quintile ratio.

The Palma ratio is a special feature in the family of inequality measures that divide the population by income inequality into deciles. The Palma ratio compares the income ratio of the top 10% of households and the bottom 40%. The basis for the Palma ratio is an empirical observation by Palma (2014) on the stability of the median income share, where it is found that the distribution is mostly a matter of the extreme tails of the distribution. Palma has been published in all major databases on income inequality in recent years.

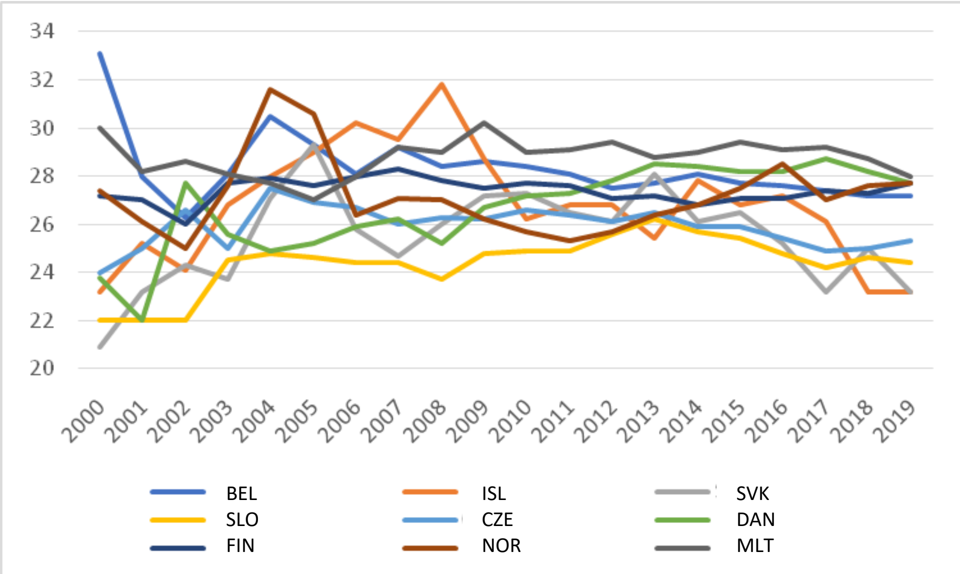
Due to space constraints, we will present the income distribution in the selected European countries using only the Gini index, which is also the independent variable in the empirical part of the paper.

4. INCOME INEQUALITY IN OBSERVED EUROPEAN COUNTRIES

Below, we present the size distribution of income in selected European countries, using the Gini index. In our work we have selected for study; Belgium, Bulgaria, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, the Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland and the United Kingdom.

For the sake of clarity, we have grouped the countries into three groups. We first show the countries with the lowest values in the most recent year of observation, i.e. 2019. We then show the countries with medium values in and then the countries with the highest values of Gini index in 2019.

Figure 1 Observed European countries with the lowest Gini index in year 2019

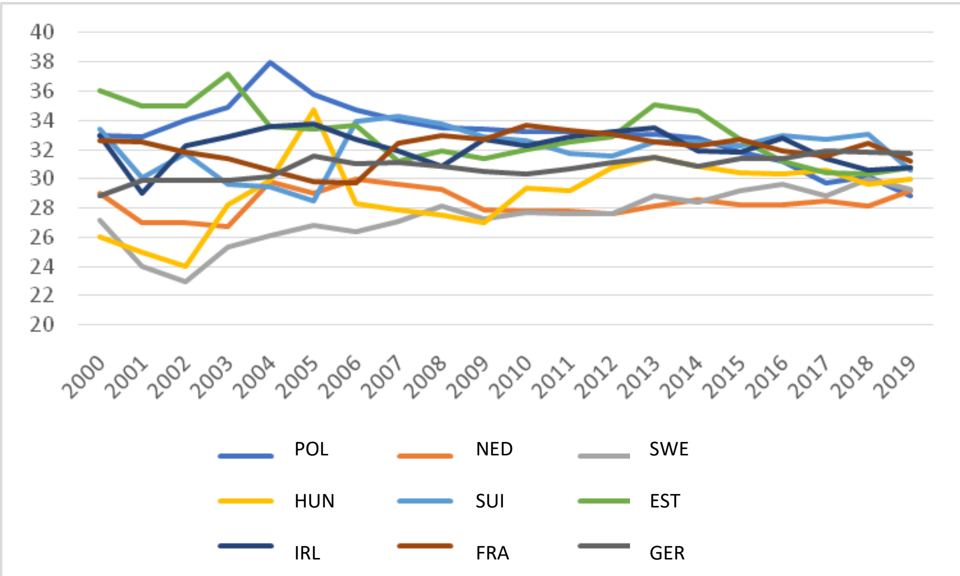


Source of data: World Bank 2023a

Figure 1 shows the Gini index of the observed European countries with the lowest values in 2019. Overall, it can be observed that income inequality has increased slightly in most countries over the period. In 2000, the lowest Gini index value was 20.9, while the highest was 33.1. In 2000, Slovakia had the lowest Gini index, while Belgium had the highest. In 2019, Slovakia still had the lowest Gini index value (23.2), while Malta had the highest (28). This could be due to a variety of factors, including economic changes, policy measures and global trends. However, it should be noted that there were differences between countries. Some countries experienced a sharp increase in inequality, while others maintained stability or even reduced inequality. It can also be observed that in most countries income inequality increased until the onset of the financial crisis and then, in the years following the end of the crisis, income inequality gradually declined in all countries except Norway and Finland. It can be seen that income inequality decreased the most in Belgium and increased the most in Denmark during the period under review. Of all the countries monitored in Figure 1, only Belgium and Malta saw a decrease in income inequality over the period.

The dynamics of the Gini index for the group of European countries with median values in 2019 are shown in Figure 2. First, we observe that income inequality has increased in most countries, although these changes have differed between countries. Some countries have seen a marked increase in inequality, while others have maintained a stable level or even reduced inequality. In 2000, Hungary had the lowest Gini index (26), while Estonia had the highest (36). In 2019, Poland had the lowest Gini index (28.8), while Germany had the highest (31.7). An important pattern is also related to the financial crisis period, as changes in the Gini index were much more dynamic in the pre-crisis period than in the post-crisis period. It can be observed that over the period under review, income inequality decreased in five countries, namely France, Ireland, Estonia, Switzerland and Poland. It increased in the Netherlands, Sweden, Hungary and Germany. Income inequality increased the most in Hungary and decreased the most in Estonia. We can see that income inequality has decreased over the observation period, in more of the observation countries with the middle Gini index in 2019 (5) than in the observation countries with the lowest Gini index in 2019 (2).

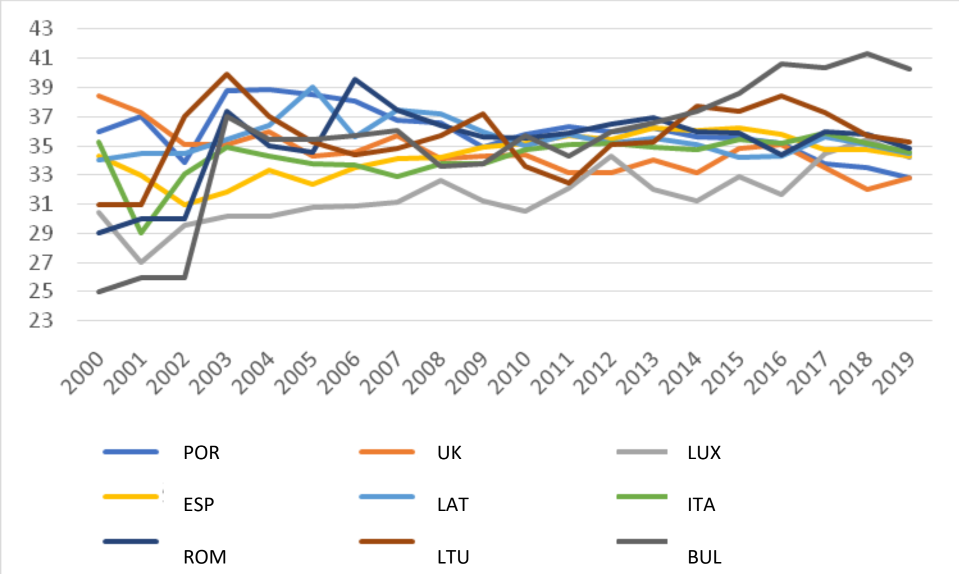
Figure 2 Observed European countries with the mid-size Gini index in year 2019



Source of data: World Bank, 2023a

An in-depth analysis of the Gini index in the observed European countries with the highest Gini index in 2019 is presented in Figure 3. It can be observed that some European countries stand out due to their high Gini index, which indicates a high degree of income inequality. This could have important implications for social stability and economic growth in these countries. It is important to stress that high income inequality can have a negative impact on social cohesion and create economic and social challenges. We should therefore consider measures to reduce income inequality in order to make these countries more sustainable and inclusive societies. Figure 3 also reveals that income inequality has decreased in three countries, namely Italy, the United Kingdom and Portugal. In the remaining countries, income inequality has increased or remained the same as at the beginning of the period. In 2000, Bulgaria had the lowest Gini index (25), while the UK had the highest (38.4). In 2019, Portugal and the UK had the lowest Gini index (32.8), while Bulgaria had the highest (40.3).

Figure 3 Observed European countries with the highest Gini index in year 2019



Source of data: World Bank, 2023a

5. DETERMINANTS OF INCOME INEQUALITY: AN EMPIRICAL ANALYSIS

5.1 Description of dataset and methodology

The basic characteristics of the data used in this empirical analysis are reported in Table 1, including abbreviations, units of measurement and data sources. The annual data covers a panel of 27 European countries (Belgium, Bulgaria, Czech Republic, Denmark, Estonia, Finland, France, Germany, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, the Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland and the United Kingdom) in the period from 2000 to 2019, resulting in 27 cross sections (i), 20 periods (t), and 540 total observations. The panel data estimation was conducted using EViews 13.

Table 1 List of variables and their basic characteristics

Variable	Abreviation	Unit of measurement	Source
Gini index	GINI	Among 0 and 100	World Bank (2023a)
GDP growth	GDPG	%	World Bank (2023b)
Labour force participation rate	LF	Share in %	World Bank (2023c)
Top 10 % of population	U10	Share in %	WIID (2023)
Human Development Index	HDI	Among 0 and 1	UNDP (2023)
Tertiary education	EDUC	Share in v %	Eurostat (2023)
Rate of unemployment	UNEMPL	Share in %	World Bank (2023d)

Source: Authors' compilation

First, we employed the one way fixed effect model, which takes into account the heterogeneity among cross sections and allows the constant to vary for each cross section, represented by β_{1i} in Equation 1 (Wooldridge 2002):

$$GINI_{it} = \beta_{1i} + \beta_2 GDPG_{i,t-1} + \beta_3 LF_{i,t-2} + \beta_4 U10_{it} + \beta_5 HDI_{it} + \beta_6 EDUC_{it} + \beta_5 UNEMPL_{it} + u_{it} \quad (1)$$

Furthermore, the one way random effects in the panel model was estimated, which assume that the β_{1i} is a random variable with mean value of β_1 and random term ε_i for each individual cross-section observation:

$$GINI_{it} = \beta_1 + \beta_2 GDPG_{i,t-1} + \beta_3 LF_{i,t-2} + \beta_4 U10_{it} + \beta_5 HDI_{it} + \beta_6 EDUC_{it} + \beta_5 UNEMPL_{it} + w_{it} \quad (2)$$

In random effects model the error term (w_{it}) has two components: $w_{it} = \varepsilon_i + u_{it}$, where ε_i is the cross section specific error term, while u_{it} represents idiosyncratic term varying over cross sections and over time (Gujarati, 2015).

Since random effects model results in inconsistent estimates of regression coefficients if the composite error term (w_{it}) is correlated with regressors, we have applied Hausman test, which searches for the correlation among the cross section specific error component and regressors. If the error term and regressors are correlated, fixed effects model is appropriate (Gujarati 2015). The results are presented below. It turned out that the fixed effect model is more appropriate than random effects model. Thus, the serial correlation test was performed for fixed effects models. Finally, the robust standard errors and covariances were estimated for the fixed effects model by applying the White cross-section and White period approach (Arellano 1987; and White 1980).

5.2 Results

Table 2 exhibits the results of panel data estimation using fixed effects and random effects models.

Table 2 Panel data estimation of income inequality determinants (dependent variable: GINI)

Independent variable	Fixed effects	Random effects
Constant	9.51493* (5.065055)	7.623604 (4.819907)
$GDPG_{i,\ t-1}$	0,058754** (0.025743)	0.050019* (0.025498)
$LF_{i,\ t-2}$	-0.100603** (0.046829)	-0.064691* (0.225693)
$U10_{i,\ t}$	25.13044*** (4.423967)	36.49158*** (4.031036)
$HDI_{i,\ t}$	20.10134*** (5.756617)	15.06003*** (5.335095)
$EDUC_{i,\ t}$	-0.055869** (0.027612)	-0.036945 (0.025799)
$UNEMPL_{i,\ t}$	0.180978*** (0.030708)	0.195218*** (0.030168)
R^2	0.868304	0.468038
DW statistic	0.937762	0.23063
F-statistic	93.33566***	21.19475***
Periods included	18	
Cross sections included	27	
Total panel observations	486	
Hausman test (χ^2)	43.157777***	

*Notes: ***Statistically significant at 1% significance level. ** Statistically significant at 5% significance level. *Statistically significant at 10% significance level. Standard errors in parenthesis.*
Source: Authors' calculation

The estimated coefficients tell a similar story in both cases. GDP growth, the top 10% of the population with the highest income, the HDI and the unemployment rate increase the level of income inequality in the group of selected European countries. On the other hand, the labour force participation rate and the level of tertiary education have a negative impact on income inequality. All estimated coefficients are statistically significantly different from zero at a significance level of at least 10%. The coefficient of determination (R2) is significantly higher in the case of the fixed effects model, while the F-statistics confirm the overall validity of the model. However, the Hausman test statistic is highly statistically significant, supporting the fixed effects model. Therefore, only the fixed effects model is analysed further.

The Wooldridge panel data autocorrelation test (Wooldridge 2002) in Table 3 displays the fact that the estimation of fixed effects model fails to fulfil the requirement of the absence of autocorrelation. Under the null hypothesis that the original idiosyncratic errors are uncorrelated, the residuals should have an autocorrelation coefficient of -0.5. As stated in Table 3, we obtained an estimate of ρ=0.441. The statistical significance of the obtained value is checked using the Wald F-test, which did not confirm the null about the autocorrelation coefficient. Thus, proving evidence that in the fixed effects model residuals are serially correlated. Since there is evidence of positive autocorrelation, the standard errors of the coefficients might be underestimated and consequently their statistical significance overrated.

Table 3 Serial Correlation Test for Fixed Effects Model

	Coefficient/Statistic	p-value
Autocorrelation coefficient (ρ)	0.441148	0.0000
Wald F test (ρ=-0.5)	624.6604	0.0000

Source**:** Authors' calculation

Finally, the robust standard errors by White cross-section and by White period method were assessed and are exhibited in Table 4. Considering the cross-section correlation and heteroscedasticity the White cross-section standard errors result in statistically insignificant coefficient for HDI and tertiary education (EDUC), while all other coefficients remain statistically significant. Nevertheless, when serial correlation is acknowledged by White period standard errors estimates, the results are similar. The estimated coefficients for HDI and tertiary education become statistically insignificant, and the statistical significance for the estimated coefficient for GDP growth (GDPG) worsens but remains statistically significant at 10% significance level.

Table 4 Fixed Effects Model with Robust Standard Errors and Covariances

	Estimated coefficients	Standard errors (p-value)		
		OLS	White cross section	White period
Constant	9.51493	5.065055 (0.0609)	12.98973 (0.4642)	11.29937 (0.4002)
$GDPG_{i, t-1}$	0.058754	0.025743 (0.0229)	0.024076 (0.0151)	0.033861 (0.0834)
$LF_{i, t-2}$	-0.100603	0.046829 (0.0322)	0.046552 (0.0312)	0.039204 (0.0106)
$U10_{i, t}$	25.13044	4.423967 (0.0000)	4.234713 (0.0000)	6.908300 (0.0003)
$HDI_{i, t}$	20.10134	5.756617 (0.0005)	14.35845 (0.1622)	13.12159 (0.1262)
$EDUC_{i, t}$	-0.055869	0.027612 (0.0436)	0.042909 (0.1936)	0.069413 (0.4213)
$UNEMPL_{i, t}$	0.180978	0.030708 (0.0000)	0.029673 (0.0000)	0.057476 (0.0017)

Source**:** Authors' calculation

5.3 Discussion

The results of our econometric analysis provided us with answers on the impact of the selected factors on the Gini index and, consequently, on income inequality. We found that when economic growth increases, income inequality also increases. This is consistent with the findings of Rubin and Segal (2015), where the authors showed that there is a positive relationship between economic growth and income inequality.

The empirical literature has not fully explored the link between growth drivers, such as productivity and technological progress, and income inequality. Technological progress has traditionally been identified as a driver of overall productivity and wage growth for workers, which consequently lowers the income inequality. However, the literature has shown that technological change can be biased, which can lead to greater income inequality between workers (Acemoglu and Autor 2011; Chusseau et al. 2008). For example, skills-based technological change has led to an increase in income inequality between workers (Goldin and Katz 2008; Goos et al. 2014). In addition, globalisation, fuelled by technological progress, can reinforce inequality, especially in favour of highly skilled workers (Keller and Olney 2018) and superstar firms (Manyika et al. 2018, Autor et al. 2020). Meanwhile, the automation of jobs, in particular through industrial robots, can have a negative impact on the employment of low-skilled workers, further increasing income inequality (Dauth et al. 2017, and Acemoglu and Restrepo 2017).

Our result on the impact of labour force on income inequality tells us that when the labour force increases, income inequality decreases. This was also found by (Abraham and Kearney 2020) and (Hoynes and Schanzenbach 2012), who concluded that the additional household income resulting from women's increased labour force participation reduced income inequality.

Our result on the income share of the richest 10% of the population revealed that if this share increases, income inequality will increase. Dabla-Norris et al. (2015) show that the rise in income inequality in most developed and emerging economies is mainly driven by the rising income share of the top 10%. In their study, they argue that the income share of the top 10% is now almost nine times higher than that of the bottom 10%. However, the financial crisis of 2008 has further widened this gap.

Alvan (2009) notes that as human development (HDI growth) increases, the distribution of income becomes more equal. He also argues that human development improves when income distribution is more equal. On the other hand, medium and low levels of human development increase income inequality. This finding contradicts our result for the HDI index. Our result suggests that when the HDI index increases, income inequality also increases. However, we should point out that our estimates of robust standard errors, White cross-section and White period methods, show that our regression coefficient of the HDI index is not statistically significant. Therefore, we cannot rely on our result for this regression coefficient.

In their work, Abdullah et al. (2015) conclude that education reduces the income share of those with the highest incomes and increases that of those with the lowest incomes. This is confirmed by our study, as our regression coefficient on the level of tertiary education attained tells us that when the level of tertiary education increases, income inequality decreases. However, also this result should be treated with caution since it turned out that the estimated coefficient is not statistically significant.

In their works, Mocan (1999), Jäntti (1994) and Cardoso (1993) find that an increase in structural unemployment significantly worsens income inequality. Nolan (1986) has shown that unemployment causes a change in the income distribution, with the highest decile increasing, and the effect of unemployment on the worsening of the income distribution is highly significant. This is consistent with our finding that when unemployment increases, income inequality also increases.

6. CONCLUSION

Our econometric analysis, using the Gini index as the dependent variable, and our analysis of the dynamics of income inequality indicators, analysing changes in the Gini index over the period from 2000 to 2019, have provided important information on the characteristics of income inequality in selected European countries. We found out that income inequality remains high and has even increased in many countries. This finding is important as it raises questions about the effectiveness of existing policies and highlights the need for further approaches to reduce inequality in society.

We found out that increasing the labour force and raising the share of tertiary education have a positive impact on reducing income inequality, as our econometric analysis showed that increasing the labour force and raising the share of tertiary education reduces income inequality. Our empirical analysis also found that GDP growth, an increase in the share of the top 10% of the population with the highest income, an increase in the HDI index and an increase in the unemployment rate have a negative impact on reducing income inequality between countries, as GDP growth, an increase in the share of the income of the richest 10% of the population, an increase in the level of human development (HDI index) and an increase in the unemployment rate increase income inequality.

All our results, with the exception of the increase in human development, are consistent with the findings of other authors. This tells us that our research has been robust and, together with the existing literature, contributes to a better understanding of the complex causes and consequences of income inequality and supports the need for comprehensive approaches to address this important societal problem. The results of the empirical analysis provide insight into determinants of income inequality, which may be useful for economic policy decision makers in their efforts to decrease the income inequality.

Recommendations for future research include broadening the range of variables, extending the timeframe and extending the scope of economies to other developed countries. Regarding methodological issue, future improvement could include also dynamic panel estimation.

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