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Beyond Rising Prices: Inflation and Income Inequality in the European Union

Abstract. *This research aims to identify the potential impact of inflation on income inequality. For this purpose, a panel database with indicators for the European Union Member States was used during the period 2017-2023. Following the literature review, indicators such as inflation index, tax rate, gross domestic product per capita and average annual wage, as well as the dependent variable - income instability - were selected. The research consists of two parts, the first of which is based on the grouping of indicators into three clusters according to the economic development of the countries. The results of this first part confirm the uncertainty present in the literature on the influence of inflation on income instability, as inflation affects differently, as do the other independent variables, depending on the development of the respective countries. In the second part of the research, considering some issues of collinearity of results, an all-embracing analysis is used, considering all Member States. The model shows that inflation contributes significantly to the amplification of income inequality, suggesting the need for social protection-oriented economic policies to counter the regressive impact of price increases.*

Keywords: *income inequality, inflation, clustering, economic development, European Union.*

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1. Introduction

Inflation, often defined as a persistent increase in the general price level, remains one of the most debated macroeconomic phenomena (Sanga et al., 2023).

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Policymakers and economists frequently discuss its effects on economic stability, growth, and income distribution. Although some authors argue that inflation disproportionately affects low-income groups, others suggest that it can reduce inequality by reducing the real debt burden (Amassoma et al., 2018).

Despite numerous empirical studies, the literature remains inconclusive on whether inflation worsens or reduces income inequality. Some studies indicate a positive correlation between inflation and inequality (Afonso & Sequeira, 2022), while others find the opposite (El Herradi et al., 2022). Given this discrepancy, a meta-analysis provides a systematic approach to synthesising evidence and identifying potential publication biases and heterogeneous effects.

Inflation affects income groups differently and has the potential to increase economic inequality. People with low incomes are more vulnerable to rising prices, while those with financial assets can benefit from inflation. The study aims to analyse whether and to what extent inflation contributes to the increase in income inequality in Romania and compare it to other EU countries (Zapodeanu et al., 2014).

This paper aims to determine whether there is a statistically significant relationship between the inflation rate and income inequality in the EU Member States by considering indicators that can measure income inequality as well as indicators that can be considered as influencing factors, such as the inflation rate, Gross Domestic Product per capita, average annual wage, and tax rates.

For the above structured research question, we consider the hypothesis that the level of inflation significantly affects income inequality, but at the same time, there are different approaches to these interdependencies, depending on the level of economic development of the Member States.

2. Literature review

The relationship between inflation and income inequality has long been debated by economists and policymakers (Ali & Asfaw, 2023). Although inflation is a macroeconomic phenomenon that affects all segments of society, its impact on income distribution remains uncertain. Some researchers argue that inflation disproportionately harms lower-income groups, while others argue that it can reduce inequality through various redistributive effects (Berisha et al., 2022).

In recent decades, increasing income inequality has become a major challenge for developed and emerging economies, with serious implications for economic growth and social stability (Colciago et al., 2019). Although fiscal policies, such as taxes and transfers, are often used to tackle inequality, they can generate corruption and economic distortions. In contrast, monetary policy and hence inflation have often been considered neutral in terms of income distribution, but recent research suggests that they have significant effects on wealth distribution (Siami-Namini & Hudson, 2019).

Inflation affects income inequality through several mechanisms. One of them is the inflation tax effect, as inflation acts as a regressive tax on cash holdings, affecting especially low-income households that lack access to high-yielding financial assets (Law & Soon, 2020).

In Sintos' (2023) study, the results suggest that inflation has a small to moderate inequality-increasing effect. In general, higher inflation tends to worsen the income distribution, as lower-income households are more vulnerable to price increases, especially when wages and benefits are not fully indexed to inflation.

However, the magnitude of this effect varies depending on methodological specificities, data characteristics, and regional differences (Sieroń, 2017).

Regional differences further highlight the complexity of the relationship. The effect of inflation on inequality appears to be stronger in developing countries than in developed economies. This may be due to weaker financial systems, less efficient monetary policies, and higher economic volatility in emerging markets (Ndou, 2024). Countries with higher government spending and stronger democratic institutions tend to experience a weaker link between inflation and income inequality. This suggests that policy interventions such as social safety nets and progressive taxation can mitigate the regressive effects of inflation. Moreover, financial development and access to inflation-hedging assets play a crucial role in determining how inflation affects different income groups (Law & Soon, 2020).

While inflation tends to increase inequality, the magnitude of this effect depends on a variety of factors, including data selection, methodological approaches, and the policy environment. Studies using the consumer price index (CPI) as a measure of inflation tend to report stronger inequality effects compared to those using the GDP deflator (Balcılar et al., 2016). Similarly, studies using cross-sectional data often overestimate the impact of inflation compared to studies using panel data, which take into account longer-term trends (Jaravel, 2021).

The study by Kim and Lin (2023) shows that, in general, inflation worsens income inequality, but financial development can mitigate this negative effect by facilitating people's access to financial services that protect against inflation risk. The analysis also shows that financial development can have both positive and negative effects on income inequality. On the one hand, facilitating access to credit and diversifying financial instruments may reduce inequality, but on the other hand, financial development may disproportionately favour high-income individuals who have the capacity to invest and take advantage of the opportunities offered by financial markets.

Studying this influential relationship from a different perspective, there are studies suggesting that inflation reduces innovation and growth, but its effect on income inequality can be positive, negative, or U-shaped, depending on the wealth-skill ratio and how interest and labour income respond to inflation (Hu et al., 2024).

Some approaches argue that the benefits of economic growth are not equally distributed across individuals. In this context, public policies, including monetary policy, can have a significant impact on income inequality (Heshmati et al., 2019).

The paper by Zheng et al. (2023) presents a model built on Schumpeterian innovation theory and introduces heterogeneous households, innovative firms, and a liquidity constraint mechanism for R&D investment. In this context, the authors show that inflation affects income inequality through two main channels. In small economies, which have a negligible impact on aggregate interest rates, inflation worsens income inequality because the higher costs of investing in innovation reduce opportunities for emerging firms, strengthening the position of existing firms and favouring financial asset holders. On the other hand, in large economies, which influence the overall interest rate, the relationship between inflation and inequality may follow a U-shaped curve.

The paper by Aprea and Raitano (2025) emphasises that traditional inequality studies rely on nominal income adjusted by a unit price index, which does not fully capture the differential effects of inflation on living standards. To overcome this limitation, the paper proposes the use of disposable income net of expenditure on basic goods as a more accurate indicator of economic well-being. The study is applied to five countries in the European Union (France, Italy, Poland, Spain, and Sweden), using data from 2020 and applying inflation rates between 2020 and 2023. The results show that inequality increases significantly when income is net of food expenditure, as lower-income households allocate a higher proportion of their income to these essential goods.

Income inequality has increased significantly in major economies and has attracted the attention of central banks, especially in the context of high inflation in recent years. Previous empirical studies have provided mixed results on the relationship between inflation and inequality, with some suggesting a positive correlation and others suggesting a negative or even a non-linear, U-shaped effect.

3. Model specification

The research aimed to determine the possible influence of inflation on income inequality. The literature review revealed several variables that can influence income inequality; thus, in addition to inflation, it was deemed necessary to include in our analysis data on GDP per capita, average annual wage, and tax rate.

Data were extracted from the European Eurostat database and refer to the 27 Member States during the period 2017-2023. A panel database was therefore constructed to model them econometrically. In the panel data formation, it was noted that for the Netherlands, there was no data for one of the variables (average annual wage); therefore, this country was excluded, resulting in the analysis of the 26 Member States over the 7 years analysed, leading to a total number of observations of 182.

To enhance the transparency and replicability of the empirical analysis, additional details about the panel database are provided. The constructed panel dataset has a country–year structure, where each cross-sectional unit corresponds to an EU Member State, and each time unit represents an annual observation from 2017 to 2023. The database integrates harmonised Eurostat indicators collected through the same reporting methodology, ensuring comparability across countries and over time. Data access and queries were performed exclusively using the Eurostat API and the structured extraction tools, allowing automated retrieval of time-series indicators and minimising transcription errors. Each variable was stored in long format, indexed by country code and year, which facilitates econometric modelling, lag creation, and panel-specific diagnostics. Before estimation, consistency checks were applied to detect missing values, outliers, and coding inconsistencies.

In Table 1, the variable names, their abbreviations, and their details have been centralised.

Table 1. Centralisation and coding of variables

Indicator	Coding	Description	Unit of measurement
Income inequality	GINI_income	The indicator measures income inequality through the GINI coefficient (Eurostat): a value close to 0 indicates a fair distribution of income, while a value close to 100% indicates a concentration of income in the hands of a small number of people.	Precent
Gross domestic product per inhabitant	GDP_cap (GDP_capita)	The indicator measures the amount of Gross Domestic Product in country i in year t, per person.	Euro/person
Average annual salary	Avg_annual_salary Salary	The indicator measures the average annual wage that the average person in country i receives (in year t)	Euro
Inflation rate	Inflation_index INFLIX	The indicator measures the inflation rate in country i in year t, based on the CPI as measured by Eurostat. The indicator has been transformed into an inflation index to make it easier to work with periods of deflation.	Precent
Tax rate	Tax_Rate TaxR	The indicator measures the share of annual taxes paid by the population.	Precent

In some of the models, statistical processing was necessary; thus, the data representing these variables were logarithmized. For this, the abbreviation Log was used in front of the variable code.

Source: Authors' processing.

The methodological combination used in this study follows a structured logic. Granger causality tests are used to explore temporal precedence among variables, complementing the cross-sectional typologies produced through clustering. Cluster analysis is applied first to identify economically homogeneous groups of Member States, which allows the estimation of relationships within relatively comparable structural contexts. Regression models estimated separately for each cluster capture structural heterogeneity in the determinants of inequality. Finally, PCA and GLS are incorporated in the holistic model to address multicollinearity and serial correlation inherent in the panel dataset. This multi-stage approach ensures both internal consistency and methodological robustness in analysing inequality dynamics.

The dataset exhibits a short-panel structure (T = 7, N = 26), which imposes methodological constraints. Classical Granger causality tests are maintained for exploratory purposes, but their interpretation is cautious. Alternatives such as the Dumitrescu–Hurlin panel causality test require longer time dimensions for reliable inference and are unsuitable for the 2017–2023 interval. The subsequent GLS-REML estimation accounts for the unbalanced autocorrelation structure of short panels through the AR(1) correction, providing more reliable coefficient estimates. Thus, each method was selected in accordance with the empirical characteristics of the panel.

Considering the information and observations found in the literature review, it was proposed to develop the research from two perspectives. In the first part, it was desired to realise the classification /grouping of variables, given the quite large variations between certain states and certain years, compared to other states in other years. Therefore, it was proposed to realise the grouping using the k-means clustering method, and following the grouping of the variables, it was resorted to the study of their interdependence, Granger causality analysis, and the realisation of linear regression models, applied on three clusters.

The second part of the paper aimed at a unitary approach, including all 182 observations, and this was achieved by studying the variance factor of inflation. The estimated model uses the generalised least squares (GLS) method with Restricted Maximum Likelihood (REML) to analyse the impact of inflation, taxes and a principal component on the change in income inequality. The use of GLS with REML and an AR(1) structure allows controlling for serial autocorrelation and heteroscedasticity of the panel data.

K-Means clustering is a multivariate statistical technique used to group objects based on their characteristics, ensuring high internal homogeneity within clusters and high external heterogeneity between clusters. Unlike other multivariate techniques, it does not empirically estimate variables but relies on a predefined set chosen by the researcher. The reference to “other multivariate techniques” includes procedures such as factor analysis, principal component analysis (PCA), discriminant analysis, or hierarchical clustering, which rely on internal data-driven estimation of latent structures or distance hierarchies. In contrast, K-Means clustering requires the researcher to explicitly select the variables included in the clustering space. The selection was based on established economic criteria, particularly indicators reflecting income distribution, price dynamics and economic development (GDP per capita, inflation, average wage and GINI). This approach ensures that the resulting clusters reflect meaningful economic typologies rather than statistical artefacts. This method is widely used due to its efficiency and scalability, making it particularly suitable for classifying large datasets based on similarity measures (Gupta & Aggarwal, 2023).

The algorithm partitions a dataset X into k clusters, each represented by a centroid. The process begins by determining the number of clusters and initialising k centroids randomly. Each object is then assigned to the nearest centroid based on a distance metric. The centroid of each cluster is recalculated as the mean of all objects assigned to it. The process iterates until the centroids stabilise, meaning that objects no longer switch clusters, or the change in centroid values falls below a predefined threshold (Li & Wu, 2012).

The centroid vj for each cluster Cj is calculated as (Ediyanto & Satyahadewi, 2013):

$$v_j = \frac{1}{|C_j|}\sum_{x_i \in C_j} x_i$$

Where:

- vj is the centroid of cluster j,
- xi represents the objects assigned to cluster j,
- |Cj| is the number of objects in cluster j.

The assignment of objects to clusters is determined using the Euclidean distance formula (Ediyanto & Satyahadewi, 2013):

$$d(x_i, v_j) = \sqrt{\sum_{m=1}^{n} (x_{im} - v_{jm})^2}$$

Where xim and vjm correspond to the m-th attribute of object i and the centroid vj, respectively, while n represents the number of attributes.

The algorithm iterates until the centroids remain unchanged or the total within-cluster variance, expressed as:

$$\sum_{i=1}^{N} \cdot \sum_{j=1}^{k} d(x_i, v_j)^2 (total\, within - cluster\ variance)\ is\ minimized$$

In this context, the distance metric used is the Euclidean distance, which quantifies the similarity between observations by measuring the straight-line distance in the multidimensional space defined by the selected indicators. This metric is appropriate because all variables were standardised before clustering, ensuring that differences are comparable across dimensions.

In the K-Means algorithm, an “object” refers to a country-year observation, i.e., a unique combination of a Member State and a specific year in the panel (e.g., Germany-2019). Each object is thus represented by its standardised values of GDP per capita, inflation index, average annual salary, and GINI coefficient.

K-Means clustering is widely applied in fields such as market segmentation, image processing, anomaly detection, and bioinformatics. Its advantages include high computational efficiency, simple implementation, and clear interpretability (Agusta, 2007).

Although there are specialised clustering techniques for panel data (e.g., longitudinal k-means or model-based time-evolving clustering), they require longer temporal horizons or repeated within-unit variability. Given the short time span of only seven years, the variation within each country is limited, making classical K-Means more appropriate for distinguishing economic structures based on level differences rather than dynamic trajectories. Therefore, clustering is applied to the standardised level indicators, which are stable enough across time to enable meaningful segmentation.

Granger causality is a statistical hypothesis test used to determine whether one time series can predict another. It is particularly useful in econometrics, finance, and other fields dealing with time series data, where understanding the direction of influence between variables is crucial (Siggiridou et al., 2019; Siew et al., 2023).

The model is typically estimated using a vector autoregression (VAR) framework, where both variables are regressed on their own lagged values as well as the lagged values of the other variable (Siggiridou & Kugiumtzis, 2015).

In the second part of the work, the holistic approach was desired; therefore, a model was envisaged to include the whole dataset, without realising a cluster classification.

The model used for this analysis is Generalised Least Squares (GLS), estimated by Restricted Maximum Likelihood (REML). This method was chosen to ensure robust estimates, considering the panel data structure. In order to control for serial autocorrelation, a first-order autoregressive (AR(1)) structure was included, which allowed a more accurate adjustment of the time-correlated errors.

The regression model can be expressed as:

$$\Delta GINI_{income} = \beta_0 + \beta_1 \log(Inflation_{index}) + \beta_2 \log(Tax_{rate}) + \beta_3 PCA + \varepsilon$$

Where the dependent variable, $\Delta GINIincome$, is the log difference of the GINI_income calculated at the country level. Independent variables include log(Inflation_Index), which reflects inflation expressed logarithmically, and log(Tax_rate), which expresses the tax rate in the same form. The principal component (PCA) was used to reduce collinearity problems between GDP per inhabitant and annual average wages by aggregating their information into a single synthetic variable. The term ε represents the model error.

4. Results and discussion

The empirical section begins with the Granger causality analysis (Table 2), which provides a preliminary understanding of the temporal relationships among the variables included in the study. This initial step is followed by the clustering procedure, which groups the Member States into economically comparable categories based on structural characteristics. After the segmentation is established, the econometric modelling is developed separately for each cluster and subsequently for the full dataset. This sequence ensures a coherent analytical flow, progressing from temporal dynamics to structural differentiation and, finally, to regression-based quantification.

Table 2. Granger causality test between the variables analysed

Null Hypothesis	Obs	F-Statistic	Prob.
LOG_GINI does not Granger Cause LOG_GDPCAP	180	0.92351	0.3991
LOG_GDPCAP does not Granger Cause LOG_GINI	180	5.02438	0.0076
LOG_INFLIX does not Granger Cause LOG_GDPCAP	180	18.3616	$6*10^{-8}$
LOG_GDPCAP does not Granger Cause LOG_INFLIX	180	11.0394	$3*10^{-5}$
LOG_SALARY does not Granger Cause LOG_GDPCAP	180	2.08529	0.1273

Null Hypothesis	Obs	F-Statistic	Prob.
LOG_GDPCAP does not Granger Cause LOG_SALARY	180	3.66683	0.0275
LOG_INFLIX does not Granger Cause LOG_GINI	180	3.09832	0.0476
LOG_GINI does not Granger Cause LOG_INFLIX	180	5.96276	0.0031
LOG_SALARY does not Granger Cause LOG_GINI	180	7.33982	0.0009
LOG_GINI does not Granger Cause LOG_SALARY	180	1.31432	0.2713
LOG_SALARY does not Granger Cause LOG_INFLIX	180	9.52674	0.0001
LOG_INFLIX does not Granger Cause LOG_SALARY	180	12.8964	$6*10^{-6}$

Source: Authors' processing using Eviews.

According to the causality test, it can be observed that the F-Statistic level and the probability below 5% are first recorded for the second null hypothesis, the one stating that GDP per capita does not influence income inequality. As the significance level rejects the null hypothesis, we can say that income inequality, i.e., the GINI coefficient of income inequality, is influenced by the value of GDP per capita.

The second set of null hypotheses concerns the interdependence between inflation and GDP per capita; both null hypotheses are rejected, and hence there is a mutual influence between these variables.

Another significant relationship identified in the Granger framework is the link between GDP per capita and the average annual wage. The null hypothesis stating that GDP per capita does not Granger-cause wages is rejected (p = 0.0275). This result indicates that changes in GDP per capita systematically precede and help predict subsequent variations in wage levels. This finding is consistent with the standard economic mechanism through which increases in output are associated with productivity gains, higher labour demand and, consequently, wage adjustments.

By contrast, the reverse null hypothesis – wages do not Granger-cause GDP – is not rejected (p = 0.1273). This implies that wage fluctuations do not significantly improve the prediction of GDP in the short run. This asymmetry is theoretically plausible: in most EU economies, wages exhibit downward and upward rigidity, institutional constraints, and collective bargaining structures that make wage changes slower than output changes. Therefore, GDP tends to lead wage adjustments, while wage movements do not exert immediate or predictive effects on aggregate output. In other words, wages respond to economic conditions rather than determining them within the short time horizon of the dataset.

Also, given the general model presented at the beginning of the paper, it is of interest to study the hypothesis that the level of inflation influences income inequality, and this alternative hypothesis is also accepted, given the low significance level of the null hypothesis.

We also observe an influence on income inequality in the case of the level of the average annual wage, so that all the variables considered as independent have a statistically significant influence on the dependent variable, income inequality, measured by the GINI coefficient, according to Eurostat.

This paper aims to analyse the perceived influence of inflation on income inequality. In the first part of the research, a structured approach was intended, realised on the grouping of variables using the k-means cluster method. In view of certain discrepancies between certain states or important differences between the time periods analysed, this method was used in order to determine more precisely the interrelations between variables.

4.1 Segmenting EU economies through cluster analysis

Analysing the centralised data, from a descriptive statistical point of view, quite large variations were observed among the observations (Table 3), which is natural, given the differences between the EU economies, with developed states, as well as emerging or developing states. In order for this phenomenon to affect the research as little as possible, the variables were segmented and structured into clusters according to the k-means method.

Table 3. Descriptive analysis of initial data
Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
GINI	182	20,90	40,80	29,6313	4,00989
INFLAT_INDEX	182	98,70	119,40	103,7912	3,99663
GDP_CAP	182	7665,04	120126,07	33063,6565	22482,45846
ANNUAL_SAL	182	7418,00	81064,00	30242,1978	16756,21643
Valid N (listwise)	182				

Source: Authors' processing.

Analysing the entire dataset, from a descriptive statistics point of view, certain situations can be observed, especially quite large variations in terms of GDP per capita and average annual income. At the level of the 26 Member States analysed for the period 2017-2023, income inequalities measured using the GINI coefficient were recorded between 20.9% and 40.8%, the average being 29.6%, and the variation from this being ±14%.

Measurement of the Inflation Rate Index, to better study deflation situations, an inflation rate ranging between -1.3% and 19.4% is observed, with an average of 3.8% with a variation of ±4%.

As previously mentioned, large variations are recorded for the variables GDP per capita and Average annual income, the minimum being 7.66 thousand euros, and 7.42 thousand euros respectively, and the maximum being much higher, 120 thousand euros and 81 thousand euros, respectively. The coefficient of variation for these variables is ±68% for GDP and ±55% for average annual income.

Following this situation, the variables were standardised, using the mean and standard deviation, and subsequently both Initial Cluster Centres and Final Cluster Centers were identified. In Table 4, the distribution of the number of cases for each cluster was determined, using the method presented.

Table 4. Number of Cases in each Cluster

Cluster	1	81,000
	2	58,000
	3	43,000
Valid		182,000

Source: Authors' processing.

Table 5. Country membership in clusters by frequency

Cluster	Countries included	Maximum no. of cases
Cluster 1	Slovakia, Spain, Cyprus, Greece, Greece, Croatia, Czech Republic, Estonia, Estonia, France, Hungary, Italy, Malta, Poland, Portugal, Romania, Lithuania, Romania	7 (Slovakia)
Cluster 2	Austria, Belgium, Denmark, Finland, Germany, Ireland, Luxembourg, Sweden, France	7 (most countries)
Cluster 3	Bulgaria, Latvia, Lithuania, Romania, Croatia, Czech Republic, Estonia, Hungary, Italy, Malta, Poland, Portugal, Cyprus, Greece, Spain, Portugal, Cyprus, Greece	7 (Bulgaria)

Source: Authors' own creation.

From the total of seven possibilities, for each country, the distributions on each cluster can be observed. Thus, cluster 1 comprises 81 observations, consists of states with moderate levels of income inequality, relatively low inflation, and below-average incomes, both in terms of GDP per capita and annual salary. The second cluster contains 58 observations, it includes countries with significantly higher GDP and wages than the sample average, but which are characterised by lower inequality and inflation. This group most likely corresponds to the strong economies of the European Union. The last cluster contains 43 observations, it includes countries with the highest levels of inequality and inflation, but with lower GDP and wages, suggesting economies vulnerable to macroeconomic fluctuations.

The results of this analysis suggest that the economic structure of EU states presents significant differences in terms of income distribution, inflation, and living standards. These conclusions may be relevant for the economic and social policies of the European Union, providing insight into the relationship between economic development and income inequality.

To analyse the relationship between the GINI Coefficient and selected economic variables (GDP per capita, inflation, annual salary, and tax rate), individual regressions were performed for each previously identified cluster. The models obtained provide insight into the factors that influence income inequality in each economic group.

Using the same set of variables for clustering and subsequent regressions is intentional and methodologically justified. The clustering step establishes groups of countries with similar structural levels of inequality, inflation, and economic development. The subsequent regressions examine whether the determinants of inequality differ across these structurally homogeneous groups. This design is consistent with standard segmentation-then-estimation approaches in applied econometrics and avoids omitted-variable bias by ensuring comparability across analytical stages.

Table 6. The result of the regression models for each cluster

Variable	Cluster 1	Cluster 2	Cluster 3
GDP Coefficient (LOG_GDP)	-0,148	0,122	-0,393
Sig.	(0,3314)	(0,0443)	(0,0470)
Inflation Coefficient (LOG_INFLIX)	-2,782	-0,088	-0,984
Sig.	(0,0001)	(0,7864)	(0,0105)
Salary Coefficient (LOG_SALARY)	0,156	-0,088	0,283
Sig.	(0,2504)	(0,4334)	(0,1633)
Tax Coefficient (LOG_TAXR)	-0,063	0,011	-0,058
Sig.	(0,2194)	(0,8756)	(0,4685)
Intercept	7,1	1,439	4,081
Sig.	(0,0000)	(0,0365)	(0,0000)
R-Square	0,2587	0,1812	0,5098
Sig. (p-value)	0,0001	0,0289	0,000014
Durbin-Watson	1,7902	2,5492	2,2132
N	81	58	43

Source: Authors' processing.

The model explains about 25.87% of the variation in GINI. GDP per capita and the tax rate show negative but statistically insignificant effects. In contrast, inflation has a significant negative impact, indicating that higher inflation is associated with lower inequality, possibly through wage adjustments or social protection mechanisms. The Durbin–Watson statistic suggests potential autocorrelation, indicating that the model may not fully capture all relevant relationships.

The explanatory power is weaker ($R^2 = 0.1812$). GDP has a positive and significant effect, implying that economic growth increases income inequality, likely due to concentrated gains. Inflation, wages, and taxes have insignificant effects, suggesting a limited influence on income distribution. The Durbin–Watson result indicates no autocorrelation, supporting the model's robustness.

This model performs best ($R^2 = 0.5098$). GDP shows a negative and significant effect, suggesting that economic growth reduces inequality, consistent with the idea of more inclusive development in less advanced economies. Inflation also has a significant negative effect, indicating that rising prices may reduce inequality through adjustment mechanisms. Wages and taxes remain insignificant. The Durbin–Watson statistic indicates only mild, acceptable autocorrelation.

The regression results highlight clear differences between the three clusters in terms of the relationship between income inequality and the economic variables analysed. In Cluster 1, inflation plays a significant role in reducing inequality, while other variables have no clear impact. In Cluster 2, GDP is the only significant variable, indicating a possible increase in inequality with economic development. In Cluster 3, both GDP and inflation have significant effects on inequality, suggesting that these economies are more sensitive to economic and financial changes.

The analysis of Cluster 1, which comprises economies with values slightly below the sample average, indicates that inflation plays a meaningful role in reducing income inequality. This finding aligns with Eurofound (2017), which argues that inflation may facilitate income redistribution in contexts where wages are frequently adjusted in response to price increases. The report further notes that, during periods of economic crisis, inflation had a weaker effect on inequality in economies with more balanced wage structures. Accordingly, in the countries within this cluster, inflation appears to function as an adjustment mechanism that supports social stability and contributes to narrowing income disparities.

Cluster 2, which includes the EU's most developed economies, shows a pattern in which rising GDP is associated with widening inequality, suggesting that the gains from economic expansion are not evenly shared. This outcome is consistent with the International Labour Organisation (2017), which documents that wage growth in advanced economies has lagged behind productivity increases, thereby intensifying income polarisation. The report emphasises that growth-oriented economic strategies alone do not guarantee reductions in inequality and highlights the need for effective redistributive policies to mitigate social imbalances.

In Cluster 3, characterised by high levels of inequality and inflation alongside comparatively low GDP and wages, the results suggest that economic growth helps reduce income disparities. This conclusion corresponds with Șoldan (2023), who finds that in emerging or transition economies, sustained economic growth fosters income convergence by improving employment prospects and raising wage levels. The study also notes that moderate inflation can facilitate economic adjustment by increasing real wages, thereby supporting a more equitable distribution of income.

The results suggest that the relationship between economic development, inflation, and inequality differs depending on the level of prosperity of each country. In more developed economies, economic growth can amplify inequality, which requires measures to redistribute income. In less developed economies, stimulating GDP growth seems to be an effective solution to reduce inequality, and inflation plays an important role in adjusting income distribution. These findings highlight the need for economic policies adapted to each national context to ensure equitable and sustainable economic growth.

Considering certain aspects of the previous analysis regarding the unfavourable influence on the robustness of the model, due to autocorrelation elements, we consider it appropriate to take a holistic approach and apply principal components analysis.

4.2 The interdependence between inflation and income inequality: a holistic analysis

For completeness and methodological transparency, a supplementary table has been included in the appendix, presenting the eigenvalues and loadings of the principal component analysis, together with the estimated AR(1) autocorrelation parameter from the GLS-REML model. The first principal component accounts for 96% of the combined variance of GDP per capita and average annual wages, confirming that it captures nearly all relevant information from the original variables.

In addition, the statistically significant AR(1) parameter validates the choice of incorporating serial correlation adjustments within the GLS framework.

The variance inflation factor (VIF) is a measure used to detect collinearity between independent variables in a regression model. Collinearity occurs when two or more explanatory variables are highly correlated, which can lead to instability in the estimation of coefficients and difficulty in interpreting the effect of each variable on the dependent variable.

Initially, the variables GDP per capita and average annual salary had VIF values of around 8, indicating strong collinearity between them. This suggested that the two variables contained redundant information, and the model could be improved by reducing this effect.

To solve this problem, a principal component analysis (PCA) was applied, which transformed GDP per capita and average annual salary into a new variable – PCA. The first principal component obtained explains 96% of the variability of these two variables, which means that it retains almost all of the essential information from the original data.

The result of using PCA was reflected in a significant decrease in collinearity, and the new variable recorded a VIF of only 1.1.

By replacing the variables originally correlated with PCA, the multicollinearity problem was eliminated without losing essential information. The VIF values for all the variables in the model are now close to 1, confirming that the predictors are independent of each other, ensuring more stable estimates and more precise interpretations of the relationships in the model.

This example demonstrates the effectiveness of PCA as a method for reducing multicollinearity while maintaining essential information. By explaining 96% of the original variability, the principal component provides an optimal balance between reducing redundancy and maintaining the econometric relevance of the model.

This section presents the results obtained from the estimated model and their economic implications. The Generalised Least Squares (GLS) model, estimated by Restricted Maximum Likelihood (REML), was used to analyse the impact of inflation, taxes and the principal component (PCA) on changes in income inequality, as measured by the logarithmic difference of GINI_income.

The model has an AIC of -600.15 and a BIC of -509.24, values that suggest a good fit, especially compared to alternative models. The high Log-Likelihood of 330.07 indicates an optimal fit to the data.

$$\Delta GINI_{income} = 0{,}1262 \log(Inflation_{index}) + 0{,}0049 \log(Tax_{rate}) + 0{,}0027\ PCA$$

The results show that inflation and the tax rate significantly influence changes in income distribution. Inflation has a positive and statistically significant effect (0.1262, $p = 0.002$), indicating that higher inflation is associated with rising income inequality. The tax rate also shows a smaller but significant positive impact (0.0049, $p = 0.0034$). The PCA component replacing GDP per capita and average annual wage remains significant (0.0027, $p = 0.0305$), confirming its ability to capture their combined effect.

Correlations among predictors are generally low, with only a moderate link between inflation and taxation, suggesting that collinearity is not a major concern. Residuals follow an approximately normal distribution, with no problematic outliers and a residual standard error of 0.0236. The model's sample size and degrees of freedom ensure reliable estimates.

The GLS model offers a solid explanation of inequality dynamics, effectively addressing serial autocorrelation and heteroscedasticity. The significant coefficients confirm that inflation, taxation, and the PCA-derived economic factor directly shape variations in income inequality.

Because Delta_GINI_income is expressed as a logarithmic difference and several predictors are also in logarithmic form, the estimated coefficients can be interpreted as elasticities. Thus, for the logarithm of the inflation index, the coefficient of 0.1262 indicates that a 1% increase in inflation is associated with an average rise of about 0.1262% in income inequality. This positive relationship aligns with existing research showing that inflation can disproportionately affect lower-income groups by eroding purchasing power (Chang et al., 2020).

The coefficient for the logarithm of the tax rate is 0.0049, implying a much smaller effect: a 1% increase in taxation leads to a 0.0049% rise in inequality. Although positive, this impact is limited, reflecting findings in the literature that the distributive effect of taxation depends largely on its structure and progressivity (Sologon et al., 2020).

The PCA-derived variable, which captures the combined variation of GDP per capita and average annual wage, has a smaller but significant coefficient of 0.0027. Its positive sign suggests that increases in these underlying economic variables are associated with a modest rise in inequality, consistent with studies arguing that economic growth in developed economies does not automatically translate into an equitable income distribution (Tsapko-Piddubna, 2021).

The model shows that inflation has the strongest impact on income inequality, followed by taxation, while the PCA component exerts a smaller, but meaningful effect.

To validate the robustness of the Generalised Least Squares (GLS) model estimated by REML, several statistical tests were performed to detect autocorrelation, heteroscedasticity, influence of observations, and normality of residuals. These analyses are essential to verify that the model respects the assumptions necessary for a correct and interpretable estimation.

The Durbin–Watson statistic (DW = 2.5619, p = 0.9998) indicates no positive autocorrelation in the residuals, with only a minor, non-significant tendency toward negative autocorrelation. This confirms that the GLS model, through its AR(1) structure, effectively addressed serial dependence. The Breusch–Pagan test (BP = 0.6494, p = 0.7227) provides no evidence of heteroscedasticity, supporting the assumption of constant residual variance.

Cook's Distance identified several influential observations (25, 26, 27, 47, 65, 78, 95, 103, 106, 108, 127, 131, 133), which warrant further inspection to determine whether they reflect meaningful structural characteristics or potential data irregularities. Tests of residual normality showed mixed results: while the Kolmogorov–Smirnov test indicates no significant deviation from normality, the Shapiro–Wilk test suggests a slight departure. Given the robustness of GLS and the absence of strong variance or autocorrelation issues, this deviation is unlikely to undermine model validity.

The Box–Ljung test ($p = 0.1016$) confirms the absence of serial correlation in residuals, and the Ramsey RESET test ($p = 0.826$) provides no evidence of model misspecification, indicating that the linear functional form is appropriate. Overall, the diagnostic assessment shows that the GLS model with REML offers a stable and well-specified framework for analysing changes in income inequality. Although some influential observations merit closer examination, the model remains reliable for evaluating the effects of inflation, taxation, and the PCA-derived economic component on inequality dynamics.

The analysis shows that inflation is the main factor driving income inequality, with a significant impact and of considerable magnitude. Taxes, although influencing income distribution, fail to mitigate the effects of inflation on inequality. In addition, the economic dynamics reflected by the PCA play an important role, indicating that economic development does not automatically ensure a fair distribution of income.

These findings suggest that, to reduce income inequality, economic policies that control the effects of inflation on vulnerable groups are needed. It is also important that fiscal policies are better targeted to have a stronger redistributive effect. Finally, economic growth should be supported by complementary measures that ensure a fair distribution of the benefits generated by it.

5. Conclusions

Cluster analysis of EU Member States' economies highlights strong differences in GDP per capita, wages, inflation, and income inequality (GINI), justifying the segmentation of countries into groups. Cluster 1 consists of economies with moderate inequality, low inflation, and below-average incomes, showing stability but limited growth. Cluster 2 includes developed economies with high GDP, higher wages, and low inequality, confirming the link between growth and more equitable resource distribution. Cluster 3 groups more fragile economies, marked by high inequality, inflation, and below-average income, making them vulnerable to macroeconomic shocks.

The regression results show that the drivers of inequality vary by cluster. In Cluster 1, inflation reduces inequality, suggesting that adjustment mechanisms can foster a fairer income distribution, while GDP and wages are not significant. In Cluster 2, GDP growth increases inequality, indicating that prosperity benefits certain groups disproportionately. In Cluster 3, both GDP and inflation significantly affect inequality, reflecting the higher sensitivity of vulnerable economies to macroeconomic shifts.

The policy implications differ by development level. Advanced economies should complement growth with redistribution to avoid rising inequality, while emerging economies may benefit from growth and inflationary adjustments to ease disparities. Vulnerable countries require targeted measures to curb inflation and promote inclusive growth, reducing risks of polarisation.

The analysis accounts for statistical variations and autocorrelation through principal component analysis (PCA). The results highlight inflation as a major driver of inequality: a 1% rise increases inequality by about 0.126%. Inflation hits low-income households hardest, as they spend more on essential goods, while wealthier groups can shield themselves through assets, widening inequality.

Taxation has a smaller but significant effect (coefficient 0.0049), indicating current systems do not sufficiently counter inflation's regressive impact. The PCA component combining GDP per capita and wages also shows a positive but modest effect on inequality, confirming that economic and income growth alone do not ensure fairness. Expansion often benefits specific sectors and groups, perpetuating disparities.

Inflation emerges as the key determinant of inequality, calling for policies that protect vulnerable households. Although taxation can help redistribute income, its effect remains limited. Economic growth alone cannot reduce inequality; it must be supported by targeted fiscal and social measures to ensure inclusive and equitable development.

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Appendix

A1 – GLS Model Summary for Delta_GINI_income with Explanatory Variables: log(Inflation_Index), log(Tax_rate) and PCA

Variable	Value	Std.Error	t-value	p-value
log(Inflation_Index)	0.12620895	0.04020615	3.139046	0.002
log(Tax_rate)	0.0049337	0.00165739	2.97678	0.0034
PCA	0.00265913	0.00121802	2.183168	0.0305

Country	Variance Estimate	Country	Variance Estimate	Country	Variance Estimate
Austria	1	France	0.63	Malta	2.16
Belgium	1.2	Germany	1.97	Poland	1.21
Bulgaria	1.24	Greece	1.31	Portugal	1.52
Croatia	0.98	Hungary	0.99	Romania	2.06
Cyprus	1.5	Ireland	1.64	Slovakia	2.33
Czechia	0.86	Italy	0.95	Slovenia	0.62
Denmark	0.56	Latvia	1.3	Spain	0.91
Estonia	0.8	Lithuania	0.89	Sweden	1.52
Finland	0.91	Luxembourg	2.29		

A2 – Statistical Test Results for GLS Model Validation

Test Name	Statistic	Value	p-value
Durbin-Watson Test	DW	2.5619	0.9998
Breusch-Pagan Test	BP	0.6494	0.7227
Kolmogorov-Smirnov Test	D	0.067362	0.4786
Shapiro-Wilk Test	W	0.97476	0.005811
Box-Ljung Test	X-squared	15.931	0.1016
RESET Test	RESET	0.29917	0.826