Investigating the Link Between Income Distribution and Growth Volatility: Panel Analysis of Selected Countries

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This paper investigates the dynamic relationship between economic growth and income inequality, with a particular focus on how inequality levels shape countries' resilience to crises. The central question is whether more equitable income distribution contributes to greater growth stability, especially during periods of financial turbulence. To address this, we estimate panel VECM models for 26 European and Asian countries over the period 1995–2022. The results indicate that countries with more equal income distributions did not experience more stable growth rates during crises, as confirmed by dynamic modeling and the Chow breakpoint test. Furthermore, the financial crisis shock was not observed in high-inequality countries, whereas it was present in lower-inequality countries. This outcome is linked to structural features, particularly the strength of the industrial base and domestic demand, which act as buffers against external shocks.

Keywords: Economic growth, income inequality, panel data, 2008 financial crisis.

JEL Classification: C33, O15

INTRODUCTION

Concerns regarding income distribution have long been central to economic and policy debates. With the evolution of governance and market institutions, perceptions of inequality have also changed, yet income disparities remain a persistent global issue. Present trends seem to defy the logic behind the Kuznets hypothesis, which suggested that greater economic development and rising per capita income would be associated with declining inequality (see, e.g., Barro, 2000; Piketty, 2014). While moderate inequality can, under certain conditions, stimulate economic progress by incentivizing individuals to invest in education, accumulate skills and pursue entrepreneurial activities, excessive inequality un-

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dermines growth. In particular, when disparities surpass a critical threshold, they erode the purchasing power of the working and middle classes, weaken aggregate demand, and ultimately depress productivity, innovation and long-term growth.

This paper is structured into three main chapters and a conclusion. It begins by outlining key trends in income inequality, followed by the conceptual framework, methodology and description of the time series data. The fourth chapter, Empirical Evidence, presents the econometric analysis and hypothesis testing, along with a discussion of the results. This structure supports the main goal of the research, exploring the relationship between economic growth and income distribution, with a focus on how shocks affect countries with varying levels of inequality. Before that, we will say something about the motivation for this research and give a review of the literature.

Motivation and research question

Despite decades of research on the inequality-growth nexus, important questions remain about how income distribution affects the stability of growth during large macroeconomic shocks. In particular, the 2008 global financial crisis offers a natural experiment to test whether countries with different levels of pre-crisis inequality experienced different growth volatility and recovery patterns. Existing cross-country panel work has produced mixed results because

i. samples and measures of inequality differ widely, and
ii. many studies focus on long-term levels of growth rather than on growth volatility and structural breaks around crises.

This paper therefore asks: "Do countries with more equal income distributions exhibit more stable growth paths and milder responses to the 2008 shock?" To answer this, we used a panel VECM framework on an unbalanced panel of 26 European and Asian economies (1995–2022), combined impulse response and variance-decomposition analysis with a Chow breakpoint test, and performed subsample comparisons by pre-crisis inequality levels. Our contribution is threefold:

1. we focus on growth stability/volatility (not only long-term levels),
2. we apply a bivariate panel VECM that permits cointegration and dynamic feedback while keeping the analysis transparent and robust, and,
3. we compare heterogeneous country groups to reveal how structural characteristics (industry strength, domestic demand) shape crisis transmission.

Keeping that in mind, we can say that this study contributes by examining the relationship between income distribution and growth volatility in the context of the 2008 financial crisis, focusing on economic resilience relative to inequality levels. Its value also lies in targeting underrepresented regions, the Balkans and Eastern Europe, alongside the HPAEs, China and India, forming a diverse sample of 26 countries.

The sample of 26 countries combines European transition economies and rapidly growing Asian economies (the High-performing Asian economies (HPAEs), China, India). Transition economies in Europe have undergone profound structural changes since the 1990s, moving from centrally planned to market systems, with reforms in trade, institutions and EU integration. In contrast, Asian economies experienced rapid, export-driven growth and industrialization. Bringing these groups together allows us to meaningfully contrast how inequality interacts with growth under different structural and institutional settings. This approach follows the practices of

global institutions such as the World Bank and the IMF, which often compare regions like Europe & Central Asia with East Asia & Pacific in their economic updates (World Bank, 2018; World Bank, 2024). Thus, the mixed sample strengthens the generalizability of results and highlights whether growth–inequality dynamics are region-specific or more universal.

LITERATURE REVIEW

Kuznets (1955) speculated that the relationship between income inequality and national income follows an inverted U-shape, later termed the Kuznets Curve. His conclusion was that inequality tends to rise in the early stages of economic growth but declines at higher stages of development due to structural changes in the economy, such as labor moving from low-productivity sectors (e.g., agriculture) to high-productivity sectors (e.g., industry). However, more recent research has challenged these conclusions. Piketty (2014), for instance, argued that the patterns described by Kuznets were not necessarily driven by fundamental forces such as technological progress and sectoral shifts, but rather by exogenous factors, including taxation and asset depreciation. Similarly, Lyubimov (2017) posited that growth in economic output alone is insufficient to address poverty and inequality without redistributive policies that enhance equity. Building on this line of critique, Milanović (2016) extended Kuznets' hypothesis by proposing the concept of "Kuznets waves," suggesting that inequality follows recurrent wave-like patterns over time.

Some other empirical works cast additional light on the relationship between inequality and growth by using more quantitative approaches. Castelló-Climent (2010) conducted panel data estimation across various world regions, finding a negative connection between inequality and economic growth in low and middle-income countries, whereas the relation in high-income countries was null or positive. Even in the developed world, however, inequality's effects on growth change over time. Atems and Jones (2014) employed a vector autoregression (VAR) model to demonstrate that shocks to the Gini coefficient reduce per capita income levels by a considerable amount, corroborating the thesis that rising inequality can have negative impacts on economic growth. Furthermore, Amri (2018) examined Indonesian provinces from 2005 to 2015 using cointegration and causality tests to demonstrate a lastingly significant negative correlation between economic growth and income inequality, while Popović et al. (2023) did so by examining the effects of the labor market on income inequality using VAR models in Montenegro.

While many studies analyze inequality and growth in multi-variable panels, a growing strand of literature demonstrates that focused bivariate VAR/VECM specifications can provide transparent identification of dynamic feedbacks and useful impulse-response evidence, particularly when combined with robustness checks and subsample analyses (Atems & Jones, 2014). Our paper follows this approach and adds the crisis-era volatility perspective for a mixed sample of European and Asian economies.

Empirical findings vary by region and model specification. Wolde et al. (2022) showed that inequality hinders long-run but supports short-run growth in Ethiopia. Ifeakachukwu (2020) found that inequality and globalization drive growth in Nigeria, while growth and globalization influence inequality.

These studies highlight the complex nature of the relationship between inequality and growth and emphasize the need for further research to inform effective policy.

ECONOMIC INEQUALITY DYNAMICS

When it comes to the countries that are the focus of this research, the following table clearly illustrates the trend of inequality, specifically the share of the poorest 50% in income distributions within each country.

Table 1
Share of the poorest 50% in total income

	1995	2001	2011	2021	Change in 2021 compared to 1995
Albania	0.188	0.182	0.190	0.184	-2.13%
Bosnia and Hercegovina	0.207	0.189	0.178	0.184	-11.11%
Bulgaria	0.178	0.197	0.195	0.167	-6.18%
Greece	0.171	0.154	0.196	0.215	25.73%
Romania	0.196	0.196	0.164	0.154	-21.43%
Slovenia	0.233	0.233	0.229	0.229	-1.72%
Serbia	0.201	0.190	0.150	0.169	-15.92%
North Macedonia	0.178	0.174	0.172	0.208	16.85%
Croatia	0.196	0.191	0.189	0.191	-2.55%
Montenegro	0.211	0.210	0.162	0.159	-24.64%
Balkan countries average	0.196	0.192	0.182	0.186	-5.10%
Belarus	0.207	0.199	0.193	0.252	21.74%
Estonia	0.148	0.155	0.174	0.168	13.51%
Latvia	0.196	0.175	0.185	0.186	-5.10%
Lithuania	0.185	0.192	0.196	0.181	-2.16%
Moldova	0.165	0.161	0.168	0.179	8.48%
Russia	0.142	0.133	0.160	0.157	10.56%
EE countries average	0.174	0.169	0.179	0.170	-2.30%
Indonesia	0.132	0.175	0.143	0.165	25.00%
Japan	0.184	0.165	0.169	0.168	-8.70%
Republic of Korea	0.208	0.208	0.202	0.211	1.44%
Malaysia	0.137	0.144	0.152	0.138	0.73%
Singapore	0.221	0.164	0.171	0.226	2.26%
Taiwan	0.152	0.118	0.105	0.118	-22.37%
Thailand	0.102	0.086	0.118	0.097	-4.90%
Hong Kong, China	0.167	0.153	0.127	0.136	-18.56%
HPAEs average	0.163	0.151	0.148	0.157	-3.68%
India	0.189	0.181	0.137	0.131	-30.69%
People's Republic of China	0.185	0.168	0.141	0.137	-25.95%
Worldwide and regional data					
Year	**1995**	**2001**	**2011**	**2021**	**Change in 2021 compared to 1980**
World	0.0650	0.0695	0.0782	0.0786	20.92%
Europe	0.1666	0.1659	0.1731	0.1826	9.6%
Eastern Europe	0.1836	0.1831	0.1547	0.1794	-2.28%
East Asia	0.1021	0.1110	0.1200	0.1261	23.5%
Asia	0.0999	0.1052	0.0989	0.0983	-1.6%

Source: Data retrieved from the WID website, https://wid.world/ (accessed 6 August 2024).

In 16 out of the 26 economies included in this study, the share of the poorest 50% of the population in total income was lower in 2021 than in 1995. Among the countries in the sample, across all three analyzed regions, the change has been negative. The share of the poorest 50% has decreased the most, by more than 20%, in Romania, Montenegro, Taiwan, India and the People's Republic of China. These findings support the claim that inequality within countries has increased, despite globalization bringing continents and economic systems closer together and thereby reducing inequality on a global scale (Milanović, 2016). Of course, given that this study examines only 26 countries, broad generalizations should be made with caution, but the findings are still highly significant. Global data shows that the share of the poorest 50% in total income is higher, but for the most economies in our sample that was not the case.

Inequality within countries is rising and global stratification is evident, meaning that addressing inequality must be approached at the national level, with governments actively working on this issue, and it can be said that such efforts would ultimately contribute to reducing both global and national inequality.

CONCEPTUAL FRAMEWORK

The main hypotheses that underpin the focus of this research are given below:

$H_{1.}$ The Kuznets Curve can explain the relationship between economic inequality and economic growth rates in the analyzed economies over the observed period.

$H_{2.}$ Countries with more equal income distributions experience more stable economic growth rates over time.

$H_{2.1.}$ In economies with lower income inequalities, the shocks caused by the 2008 global financial crisis had a milder impact and were shorter in duration.

When formulating the hypotheses in this paper, Piketty's (2014) research provided significant theoretical support, as it was the first to systematically create and analyze data series on economic inequality, covering the period from the early 20th century. These data series encompassed major economic fluctuations and crises, offering a long-term perspective on inequality trends. Building on this foundation, Blanchet et al. (2021) analyzed global changes in long-term economic inequality and economic growth, with a particular focus on intra-economy trends and an examination of the principles Kuznets outlined in the mid-20th century. Inequality and the financial sector have been especially interesting in recent studies. Isojaervi & Jerow (2024) were the first to take steps toward a broader understanding of the potential channels through which inequality may affect financial stability. This is why we examined ($H_{2.1}$), namely whether economies with lower income inequality experienced milder and shorter-lived effects of the 2008 global financial crisis compared to economies with higher levels of inequality.

The analysis will use panel data from a sample of 26 countries, including 10 Balkan countries: Albania, Bosnia and Herzegovina, Bulgaria, Greece, North Macedonia, Romania, Slovenia, Serbia, Croatia and Montenegro; 6 Eastern European countries: Belarus, Estonia, Latvia, Lithuania, Moldova and Russia; 8 rapidly growing Asian economies, referred to as the High-performing Asian economies (HPAEs): Indonesia, Japan, Malaysia, Republic of Korea, Singapore, Taiwan, Thailand and Hong Kong; the People's Republic of China and India, due to their rapid and specific development during the analyzed period from 1995 to 2022. The selected period was determined by data availability, comparability and quality.

Methodology

The empirical analysis was conducted within the framework of statistical and econometric panel analysis. The type of panel regression analysis to be applied was determined by applying econometric tests to check the stationarity of the analyzed panel data: Panel Vector Autoregressive Model (VAR – Fixed effect or Random effect model), Panel Vector Error Correction Model (VECM) or Panel Autoregressive Distributed Lag (ARDL) model.

According to Granger's theorem, the cointegration relationship can be represented as an error correction model, and conversely, the existence of cointegration can be tested through the error correction model. The basic bivariate specification of the VECM model is given below (Johansen, 1995):

$$\begin{aligned} \Delta Y_t &= a_1 + \Sigma_{i=1}^{p-1} \beta_{1i} \Delta Y_{t-i} + \\ &+ \Sigma_{i=1}^{p-1} y_{1i} \Delta X_{t-i} + \lambda_1 ECT_{t-1} + \varepsilon_{1t} \\ \Delta X_t &= a_2 + \Sigma_{i=1}^{p-1} \beta_{2i} \Delta Y_{t-i} + \\ &+ \Sigma_{i=1}^{p-1} y_{2i} \Delta X_{t-i} + \lambda_2 ECT_{t-1} + \varepsilon_{2t} \end{aligned} \quad (1)$$

where:

- Δ – first difference operator;
- $a_1 a_2$ – constants;
- $\beta_1 \beta_2$ – coefficients for lagged values of the first difference of the dependent variable Y_t;
- $y_{1i} y_{2i}$ – coefficients for lagged values of the first difference of the independent variable;
- $\lambda_1 \lambda_2$ – adjustment error coefficients;
- ECT_{t-1} – error from the cointegration vector, representing the long-term relationship between variables, $ECT_{t-1} = Y_{t-1} - \phi X_{t-1}$, where ϕ is the cointegration vector coefficient;
- $\varepsilon_{1t} \varepsilon_{2t}$ – error terms.

This model essentially represents a special case of the VAR model, a VAR model with restrictions, known as a vector error correction model (VECM model).

In this research, VECM models were used to examine the relationship between GDP per capita and the Gini coefficient. In all econometric tests, the significance level was set at 5%, and the EViews software tool was used for analysis. Pedroni's cointegration test was applied to determine whether there is a long-term equilibrium relationship between variables in the panel data context. This test extends the concept of cointegration from time-series data to panel data, allowing for more complex and heterogeneous relationships (Jovičić & Dragutinović-Mitrović, 2011). Pedroni's test accounts for heterogeneity in panel data, meaning it allows for individual-specific effects and dynamics, recognizing that each cross-sectional unit may have different characteristics and relationships among variables.

We used a bivariate panel VECM (Gini; GDP per capita) for three reasons. First, a focused two-variable specification gives a transparent representation of the dynamic feedback between income distribution and aggregate income, which facilitates interpretation of impulse responses and variance decompositions (Atems & Jones, 2014; Sbaouelgi & Boulila, 2013). Second, the long timespan (1995–2022) and panel cointegration framework mitigate spurious inference in simple bivariate relations and permit testing of both short-run and long-run causality. Third, to address concerns about omitted variables we (i) conducted subsample (low vs. high inequality) analyses, (ii) reported impulse responses and variance decompositions, and (iii) tested for structural breaks (Chow), thereby providing triangulated evidence. While multivariate approaches are widely used in the literature, our analysis begins with a bivar-

iate baseline in order to provide transparent and interpretable evidence on the core dynamics.

We tested for panel cointegration using Pedroni's residual-based tests, which allow for heterogeneous long-run and short-run dynamics across cross-section units (Pedroni, 1999; Pedroni, 2004). This feature is important given the mixed composition of our sample (the Balkans, Eastern Europe, the HPAEs, China, India). To further account for heterogeneity we estimated the panel VECM on two subsamples (countries with Gini above/below the sample mean) and reported the results separately (Section 3.1. and Appendices). These steps reduce the concern that a single homogeneous long-run relationship is forced on fundamentally different economies.

Methodology for Detecting Structural Breaks: The Chow Test Approach

The Chow test, introduced by Gregory Chow in 1960, is a statistical method for identifying structural breaks in time series or panel data by comparing coefficients in two linear regressions. Green and William (2018) emphasize its intuitive application and effectiveness in detecting shifts in regression relationships at specific points in time. They also note its flexibility across various models and its usefulness in analyzing financial crises.

However, Cheng (2014) highlights some limitations, such as the assumption that the break point is known beforehand, which can be unrealistic. The test also assumes uniform structural breaks across all units in the panel, though different countries may be affected at different times or not at all.

To apply the test, a model is estimated for the full dataset to calculate the sum of squared residuals (SSR), then the data is split at the suspected break point. Separate regressions for each subperiod are estimated, and the Chow statistic is calculated using the F-distribution to test if the coefficients differ significantly (Green & William, 2018).

The formula for computing the **F**-statistic in the Chow test is as follows:

$$F = \frac{\left(SSR_{total} - \left(SSR_{pre} + SSR_{post}\right)\right)/k}{\left(SSR_{pre} + SSR_{post}\right)/\left(N_{pre} + N_{post} - 2k\right)} \quad (2) Chow test formula$$

where:

k is the number of parameters,

N-pre is the number of observations before the break point, and

N-post is the number of observations after the break point.

Data and limitations

This research is based on data from 26 countries, with the sample consisting of economies from Europe and Asia. The hypotheses were tested using data from the World Inequality Database and the World Bank. The reason for this choice is the availability and length of time series, which in this case spans 28 years, covering the period from 1995 to 2022. Table 2 provides an overview and description of the indicators of economic inequality and economic growth used for the sample of the 26 aforementioned countries.

Table 2
Macroeconomic research framework

Variable	Description	Source	Note
Gini coefficient	Gini index of Pretax income	World Inequality Database – Wid. world	Market income includes social security benefits (and removes the corresponding contributions), but excludes other forms of redistribution (income taxes, social assistance benefits, etc.)
GDP per capita	Gross domestic product per capita in current US dollars	World bank	Data for Taiwan, as well as for Montenegro from 1995 to 1999, are not available in the World Bank database. Data for Taiwan have been supplemented with data from the IMF database.
National income	National Income (NI)	World Inequality Database – Wid. world	NI measures the value created by the residents of a country.
GDP per capita PPP	GDP per capita in purchasing power parity	World bank	Data for Taiwan is not available.

Source: Authors' creation.

The data is organized as an unbalanced sample in most models. However, the long timespan allows for more reliable econometric modeling and credible results. Not all the variables presented became part of the best-performing model.

The sample was designed with two goals in mind: to analyze inequality and growth in less-developed economies that have undergone stabilization and restructuring over the past 30 years, and to compare experiences across two continents using a homogeneous sample suitable for panel analysis. Countries were split into two subsamples based on whether their Gini coefficients were above or below the sample average.

While this division allows for meaningful comparison, it introduces heterogeneity concerns, as similar Gini levels may mask differences in institutional structures, policies and crisis responses (Berg et al., 2018; Milanović, 2016). Additionally, inequality may influence resilience in non-linear ways, raising endogeneity concerns (Galor, 2011). Though the dynamic panel model's high dimensionality ensures robustness across time and countries, it adds complexity to specification and interpretation. These were addressed through guidance from existing literature, use of bivariate panel VAR models, and adherence to modeling requirements.

In VECM estimation, heterogeneity in cointegration dynamics poses another challenge. This was mitigated by standardizing data sources and focusing on two key time series. GDP per capita and the Gini coefficient, ensuring consistency and clarity in analyzing the inequality-growth nexus.

EMPIRICAL EVIDENCE – PANEL DATA APPROACH IN EXAMINATION OF THE LINK BETWEEN INCOME INEQUALITY AND ECONOMIC GROWTH

Economic inequality is represented by the pre-tax Gini coefficient, while economic growth is measured by GDP per capita. This choice was made due to the better characteristics of the bivariate model compared to models incorporating the

Gini coefficient and national income, as well as the fact that Kuznets used GDP per capita in his research. Table 3 presents descriptive statistics for the Gini coefficient and GDP per capita for the entire sample, and for the groups of countries.

Before defining the quantitative research model, it is necessary to test the stationarity of the time series used. The time series tested for stationarity were the Gini coefficient and GDP per capita, with the test results presented in Table 4. The applied stationarity tests include the suite of tests available in EViews software (LLC, IPS, ADF-Fisher, PP-Fisher, and Hadri).

Table 3
Descriptive statistics for the Gini coefficient and GDP per capita

Variable	**Observation**	**Average**	**Max.**	**Min.**	**Std. Deviation**
Gini coeff.	728 (26*28)	0.512	0.681	0.346	0.062
GDP per capita	723 (25*28+23)	12 201	82 807	373.63	12 816
Statistics for the Balkan countries in the sample					
Variable	Observation	Average	Max.	Min.	Std. Deviation
Gini coeff.	280 (10*28)	0.474	0.584	0.367	0.039
GDP per capita	275 (9*28+23)	8 550	32 128	497.68	7 128
Eastern European countries statistics					
Variable	**Observation**	**Average**	**Max.**	**Min.**	**Std. Deviation**
Gini coeff.	168 (6*28)	0.505	0.634	0.389	0.049
GDP per capita	168 (6*28)	8 530	28 247	399.50	6 845
HPAEs statistics					
Variable	**Observation**	**Average**	**Max.**	**Min.**	**Std. Deviation**
Gini coeff.	224 (8*28)	0.551	0.681	0.346	0.067
GDP per capita	224 (8*28)	21 576	82 807	459.20	17 217
Statistics for the People's Republic of China and India					
Variable	Observation	Average	Max.	Min.	Std. Deviation
Gini coeff.	56 (2*28)	0.559	0.634	0.471	0.049
GDP per capita	56 (2*28)	2 995	12 720	373.63	3 399

Source: Authors' calculations.

Table 4
Stationarity and Cointegration Test for the Gini Coefficient and GDP per Capita for the Entire Sample

Series	Level	First difference	Stationarity	Cointegration
Gini coefficient	Unit root	No unit root	I(1)	Exists
GDP per capita	Unit root	No unit root	I(1)	

Source: Authors' calculations. p<0.05

Both series are stationary at the first difference, after which the Pedroni panel cointegration test was conducted, confirming the existence of cointegration between the variables in the sample, meaning there is a long-term relationship between them. The next step is the selection of the optimal lag, where it was determined that the optimal model is a two-lag model (Appendix 1). Since cointegration between the series was confirmed and both are stationary at the first level, a VECM model with two lags was formed. Table 5 presents the selected panel VECM model for the Gini coefficient and GDP per capita for the entire sample.

Table 5
Panel VECM Model of the Gini Coefficient and GDP per Capita for the Entire Sample

Error Correction	D(Gini)	D(GDP_per_capita)
CointEq1	-0.012 (0.00541)	1750.747 (515.416)
D(GINI_INDEX(-1))	-0.043 (0.03832)	-11598.09 (3649.34)
D(GINI_INDEX(-2))	-0.008 (0.03885)	-5539.172 (3700.18)
D(GDP_PER_CAPITA(-1))	7.26E-07 (4.2E-07)	0.173 (0.040)
D(GDP_PER_CAPITA(-2))	-9.87E-07 (4.6E-07)	-0.238 (0.044)
C	0.001 (0.001)	533.243 (66.280)
R-squared	0.021	0.097
Log likelihood	-3910.536	
Akaike info criter	12.169	
Schwarz	12.266	

Source: Authors' calculations. p<0.05

Through the model specification, we can observe the parameters: Log likelihood, Akaike, and Schwarz info criterion, which indicate the strength of the model. The selected lag structure minimizes the information criteria and supports the choice of the preferred specification. The analysis continues by testing the statistical significance of the coefficients, as shown in Table 6.

Table 6
Statistical Significance of Coefficients

	Coefficient	Prob.
C(1)	-0.012	0.023
C(2)	-0.043	0.256
C(3)	-0.009	0.820
C(4)	7.26E-07	0.086
C(5)	-9.87E-07	0.033
C(6)	-0.012	0.023
Determinant residual covariance	632.663	
Equation: D(GINI_INDEX) = C(1)*(GINI_INDEX(-1) + 8.34070390608E-06*GDP_PER_CAPITA(-1) – 0.616211622425) + C(2)*D(GINI_INDEX(-1)) + C(3)*D(GINI_INDEX(-2)) + C(4)*D(GDP_PER_CAPITA(-1)) + C(5)*D(GDP_PER_CAPITA(-2)) +C(6)		

Source: Authors' calculations. p<0.05

The estimated model and the statistical significance of the coefficients show that GDP per capita has a long-term impact, which is statistically significant. The long-term relationship coefficient C(1) is statistically significant (the probability is less than 0.05), and the coefficient value is negative. It can be concluded that 1.2% of the variation in the Gini coefficient has been corrected during each period, implying that GDP per capita Granger-causes the Gini coefficient in

the long run. Regarding the short-term impact, it is necessary to determine whether the coefficients C(4) and C(5) have a significant impact on the Gini coefficient by using the Wald test, as shown in Table 7.

Table 7
Wald Test for Significance of Coefficient Effects

	Value	df	Prob.
Chi-square	6.652	2	0.036
Null hypothesis: C(4)=C(5)=0			

Source: Authors' calculations. p<0.05

Since the probability is less than 0.05, the null hypothesis that there is no short-term relationship can be rejected, meaning that both short-term and long-term effects of GDP per capita on the Gini coefficient exist. The stability test confirms that the VECM is stable, while the LM test indicates no evidence of residual autocorrelation when the model is specified with two lags, see Appendix 3. To complete the analysis, it was necessary to determine the feedback effect, that is, to what extent and in what way the Gini coefficient affects GDP per capita. Examining the feedback relationship involves switching the places of the Gini coefficient and GDP per capita in the model, as shown in Table 8.

Although the coefficients are the same as in the previous case, the speed of long-term adjustment has not been found to be negative, suggesting that a meaningful long-term relationship is unlikely. Nevertheless, it was necessary to test the statistical significance of the coefficient C(1), as shown in Table 9.

Table 9
Statistical Significance of Coefficients

	Coefficient	Prob.
C(1)	0.015	0.001
C(2)	0.173	0.000
C(3)	-0.238	0.000
C(4)	-11598.09	0.001
C(5)	-5539.172	0.135
C(6)	533.243	0.000
Determinant residual covariance		632.6638
Equation: D(GDP_PER_CAPITA) = C(1)*(GDP_PER_CAPITA(-1) + 119893.957*GINI_INDEX(-1) – 73880.050) + C(2) *D(GDP_PER_CAPITA(-1)) + C(3)*D(GDP_PER_CAPITA(-2)) + C(4)*D(GINI_INDEX(-1)) + C(5)*D(GINI_INDEX(-2)) + C(6)		

Source: Authors' calculations. p<0.05

Table 9 shows that the coefficient C(1) is not negative, even though it is statistically significant, indicating that there is no long-

Table 8
Panel VECM Model of GDP per Capita and the Gini Coefficient for the Entire Sample

Error Correction	D(GDP_per_capita)	D(Gini)
CointEq1	0.015 (0.004)	-1.03E-07 (4.5E-08)
D(GDP_per_capita(-1))	0.173 (0.040)	7.26E-07 (4.2E-07)
D(GDP_per_capita(-2))	-0.238 (0.044)	-9.87E-07 (4.6E-07)
D(Gini_Index(-1))	-11598.09 (3649.34)	-0.043 (0.038)
D(Gini_Index(-2))	-5539.172 (3700.18)	-0.009 (0.039)
C	533.243 (66.280)	0.001 (0.001)
R-squared	0.097	0.022
Log likelihood	-3910.536	
Akaike info criter	12.169	
Schwarz	12.266	

Source: Authors' calculations. p<0.05

term equilibrium and that the Gini coefficient does not significantly affect GDP per capita in the long run. The short-term relationship is different, as observed through the Wald test of the impact of coefficients C(4) and C(5), presented in Table 10.

Table 10
Wald Test for Significance of Coefficient Effects

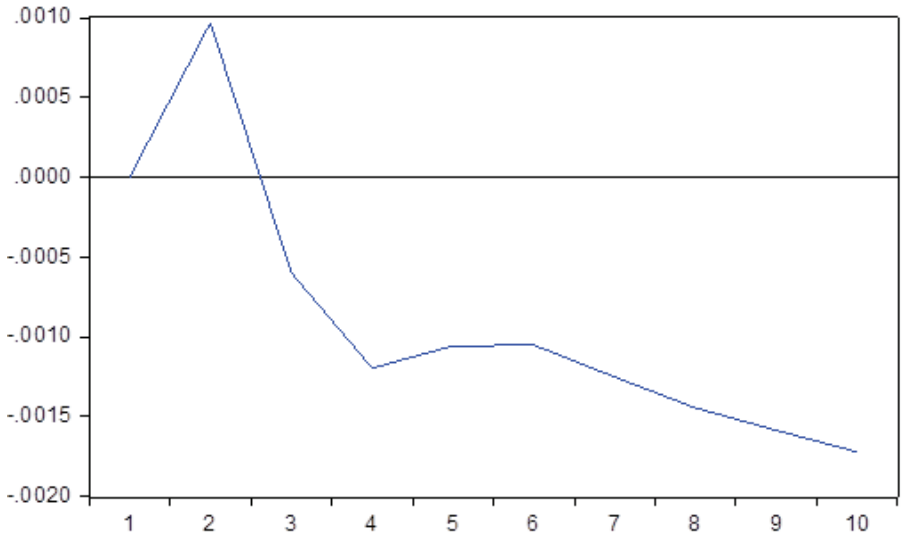
	Value	df	Prob.
Chi-square	11.615	2	0.003
Null hypothesis: C(4)=C(5)=0			

Source: Authors' calculations. p<0.05

Based on the results of the Wald test we conducted, we can conclude that the null hypothesis should be rejected and that the Gini coefficient significantly affects GDP per capita in the short term. The relationship between the two variables is further explained through the impulse response function figures in both cases, shown in Figures 2 and 3.

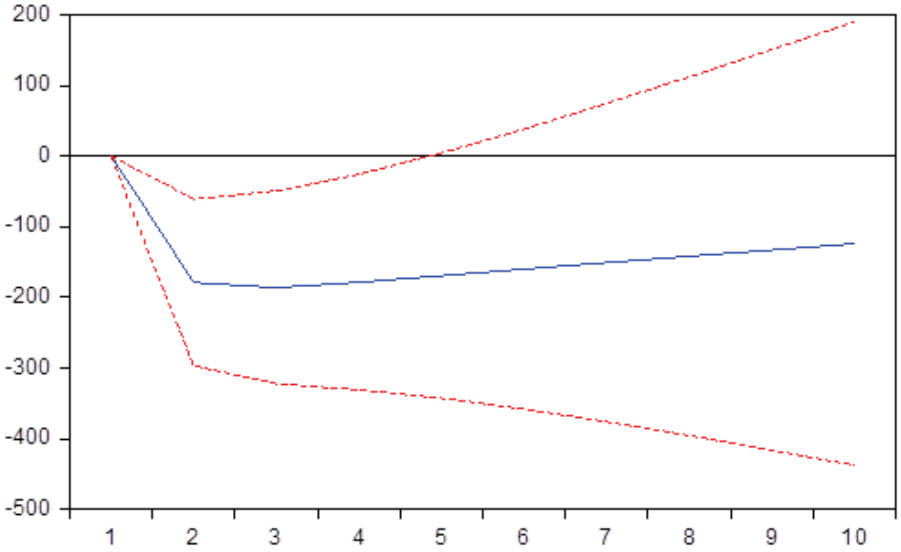
The movement of the Gini coefficient following a shock in the GDP per capita series shows that the Gini coefficient will initially increase, meaning that the impact of GDP growth will lag, and that after the second period, an increase in GDP per capita will lead to a continuous decline in the Gini coefficient. Variance decomposition, detailed in the Appendix, shows that from the second period onward, 0.18% of the Gini coefficient variations are explained by impulses in the GDP per capita series, and this relationship gradually increases. Regarding the reverse effect, that is, the impact of the Gini coefficient on GDP per capita, the impulse response function is presented below.

Figure 2
Impulse Response of the Gini Coefficient to Shocks in GDP per Capita



Source: Authors' calculations. p<0.05

Figure 3
Impulse Response of GDP per Capita to Shocks in the Gini Coefficient Series



Source: Authors' calculations. p<0.05

Figure 3 shows that an increase in the Gini coefficient series negatively affects the GDP per capita series, meaning its value will decrease. The initial shock has the strongest effect, lasting until the third period, after which it gradually diminishes.

The impulse response functions suggest a nuanced dynamic between inequality and growth. A positive shock to GDP per capita is associated with a short-run increase in the Gini coefficient, followed by a gradual long-run decline, implying that sustained growth ultimately supports a more equitable distribution of income. This pattern resonates with the logic of the Kuznets hypothesis, whereby early stages of growth may exacerbate inequality, but prolonged growth tends to reduce it. Conversely, a positive shock to inequality (Gini) has a persistently negative effect on GDP per capita, indicating that rising inequality undermines growth prospects. These dynamics highlight the fact that while growth fosters equality over the long term, higher inequality consistently weakens economic performance. It should be emphasized, however, that the impulse responses capture dynamic correlations rather than definitive causal directions. Based on the Dumitrescu & Hurlin panel Granger causality test (see Appendix 5), we have found evidence of a unidirectional long-run causality from GDP per capita to inequality, while acknowledging possible heterogeneity across countries.

It can be said that these conclusions are logical and economically meaningful because GDP per capita is one of the fundamental indicators of the standard of living in a country and will directly affect inequality. On the other hand, inequality exerts a significant negative effect on GDP per capita in the short run, but this effect does not persist in the long run once other structural factors are accounted for, which is in accordance with a 2017 IMF study (IMF, 2017).

Our results do not categorically validate Kuznets' inverted U as a universal law. Instead, the dynamic responses we estimated show an initial rise in inequality following growth shocks, followed by a longer-run decline in the Gini index, a pattern that is partly consistent with Kuznets-style transitional dynamics but is not a blanket confirmation of the hypothesis across all sample economies. This is in compliance with findings from Fields (1980) that there is no tendency for income inequality in poor countries to increase (rather than decrease) and no tendency for income inequality in rich countries to decrease (rather than increase), and Piketty (2014), who argued that the decline in inequality observed in the early to mid-20th century was not an inevitable outcome of economic development. Nonetheless, the impulse response analysis suggests that certain transitional dynamics remain consistent with the Kuznets framework, which implies that the hypothesis cannot be entirely disregarded in explaining short-run inequality–growth interactions.

Examining economic growth volatility during crises in countries with higher and lower income inequality

To test the following hypotheses: $H_{2.}$ "Countries with more equal income distributions experience more stable economic growth rates over time" and $H_{2.1.}$ "In economies with lower income inequality, shocks resulting from 2008 financial crises had a milder effect and were shorter in duration", two subsamples were created from the main sample of 26 countries.

Countries were divided based on their Gini coefficients as follows: The average Gini coefficient in the sample was 0.5115. Countries with Gini coefficients above the average (10 in total) formed the first subsample. The second subsample consisted of 16 countries with Gini coefficients below the average. The rationale for this division was to examine the relationship between inequality (measured by the Gini coefficient) and economic growth (measured by GDP per capita) among countries with lower and higher levels of inequality. Additionally, this section tests the effects of shocks caused by economic crises, specifically the global financial crisis. Table 11 shows descriptive statistics for both subsamples.

Table 11
Descriptive Statistics for the First and Second Subsample

Sample of countries with Gini coefficient values below average – first subsample					
Variable	**Observation**	**Average**	**Max.**	**Min.**	**Std. Deviation**
Gini coeff.	448 (16*28)	0.476	0.617	0.346	0.042
GDP per capita	443 (15*28+23)	11 376	82 807	399.5	12 211

Sample of countries with Gini coefficient values above average – second subsample					
Variable	**Observation**	**Average**	**Max.**	**Min.**	**Std. Deviation**
Gini coeff.	280 (10*28)	0.568	0.681	0.471	0.045
GDP per capita	280 (10*28)	13 507	49 764	373.63	13 640

Source: Authors' calculations.

The descriptive statistics show that the average Gini coefficient in the first subsample is 0.48, whereas in the second subsample, it is 0.57. In contrast, GDP per capita has a higher average value in the second subsample (13 507) compared to the first (11 376).

Given the methodology and steps required for conducting the Chow test, selecting an appropriate model is crucial. Therefore, stationarity and cointegration tests were conducted first, as shown in Table 12.

The test results indicate that both subsamples exhibit cointegration and that the series are stationary at the first difference. This suggests that a panel VECM model is appropriate. The detailed model results are provided in the Appendix, while Table 13 presents a summary of the relationships between the two variables in both models, along with the models' characteristics.

Table 12
Stationarity and Cointegration Tests for Both Subsamples

Sample of countries with Gini coefficient values below average				
Series	**Level**	**First difference**	**Stationarity**	**Cointegration**
Gini coeff.	Has Unit root	No unit root	I(1)	Exist
GDP per capita	Has Unit root	No unit root	I(1)	
Sample of countries with Gini coefficient values above average				
Series	**Level**	**First difference**	**Stationarity**	**Cointegration**
Gini coeff.	Has Unit root	No unit root	I(1)	Exist
GDP per capita	Has Unit root	No unit root	I(1)	

Source: Authors' calculations.

Table 13
Panel VECM Model Results for Both Subsamples

Sample of countries with Gini coefficient values below average – first subsample				
Model	**Long-run relationship**	**Short-run relationship**	**Model stability**	**Autocorrelation**
VECM – Gini coeff. and GDP per capita	Exists	Exists	Achieved	None for two lags
Inverse effect	Does not exist	Exists		

Sample of countries with Gini coefficient values above average – second subsample				
Model	**Long-run relationship**	**Short-run relationship**	**Model stability**	**Autocorrelation**
VECM – Gini coeff. and GDP per capita	Exists	Exists	Achieved	None for two lags
Inverse effect	Does not exist	Exists		

Source: Authors' calculations.

It is interesting to observe that, as in the main sample from the earlier analysis, the analysis for countries with more equal income distributions (first subsample) has yielded identical results. Namely, there is a unidirectional long-run Granger causality from GDP per capita to inequality, where GDP (Granger-)causes the Gini coefficient. Additionally, a bidirectional short-term relationship is also present.

On the other hand, in countries with higher inequality (second subsample), the results differ somewhat. There is no singular impact of GDP per capita on the Gini coefficient, that is, more precisely, only a long-run relationship is present, not a short-run one. Furthermore, in the case of the inverse relationship, there is no statistically significant effect in either the short or long run.

To conduct the Chow breakpoint test, both subsamples were divided into two subperiods: one covering the period from 1995 to 2009, and the other from 2010 to 2021. The assumed breakpoint is 2010, the year when the global financial crisis had the greatest impact on the observed regions. The Asian Development Bank reports that East Asian economies experienced a significant slowdown in 2010 due to reduced global demand, which particularly affected export-driven countries. Additionally, the analysis highlights that, although some countries initially showed resilience, the prolonged global economic downturn eventually impacted their growth rates and trade volumes (Ruiz-Brunschwig, 2011).

In the case of Central and Eastern Europe, the European Central Bank emphasized in its reports that these regions experienced significant economic disruptions in 2010. Countries such as Bulgaria and the Baltic states faced substantial GDP declines and financial instability (ECB, 2010).

The reason for forming additional subsamples was to calculate the sum of squared residuals, which serve as inputs for computing the F-statistic of the Chow breakpoint test, following the previously presented formula.

$$F = \frac{\left(SSR_{total} - (SSR_{pre} + SSR_{post})\right)/k}{(SSR_{pre} + SSR_{post})/(N_{pre} + N_{post} - 2k)} = 8.06$$

(3) *Chow Breakpoint Test for Subsample 1*

The computed F-statistic value is 8.06, which is greater than the tabulated F-statistic of 2.214 for a numerator of 5 and a denominator of 385. The numerator represents the number of parameters (k) in the model. Since our model includes two variables with two lags and a constant, the total sum is 5. The denominator represents the difference between the number of observations in subsample 1 and the product of k multiplied by two. A higher computed F-statistic value indicates that the null hypothesis, which states that there is no structural break at the given point, should be rejected. This means that a structural break occurred in this subsample (countries with lower inequality).

Now, let us examine the Chow test results for subsample 2, which includes countries with greater income disparities.

$$F = \frac{\left(SSR_{total} - (SSR_{pre} + SSR_{post})\right)/k}{(SSR_{pre} + SSR_{post})/(N_{pre} + N_{post} - 2k)} = 1.86$$

(4) *Chow Breakpoint Test for Subsample 2*

The results become particularly interesting here, as the computed F-statistic of 1.86 is lower than the tabulated F-statistic of 2.21. This means that the null hypothesis, which states that there is no structural break at the given time, cannot be rejected. In other words, no structural break occurred in subsample 2 in 2010.

Using economic terminology, these results suggest the Chow test does not provide evidence of a structural break in the

growth–inequality relationship for the high-inequality subsample. That may be because developed economies (which usually have lower inequality) are more exposed to financial markets. Although this might seem counterintuitive at first glance, such results are not surprising from an economic theory perspective. The literature provides examples where strong, developed economies with substantial domestic demand are not highly dependent on global economic trends, especially financial ones, if they possess strong industrial sectors.

For instance, the Chinese economy, as noted by Xie and Zhou (2014), remained resilient due to its large domestic demand, strong exports and industrialization. India is another example of such an economy, as Rathin, Suraj and Shoaib (2021) highlight, owing to technological advancements, a robust service sector and a large domestic market.

A closer look at the composition of subsample 2, countries with higher inequality, reveals the following economies: the People's Republic of China, Estonia, Hong Kong, China, India, Indonesia, Japan, Malaysia, Russia, Taiwan and Thailand. Clearly, these are economies where domestic demand and industry are exceptionally strong, particularly in the cases of Russia, the People's Republic of China, India, Japan, Malaysia, Thailand and Indonesia. For example, in 2010, compared to 2009, their average GDP per capita growth was 17.7%. Of the ten countries in subsample 2, only Estonia recorded negative growth. And, according to a study by the International Monetary Fund (Cocozza et al., 2011), this was the peak of the crisis for the regions these countries belong to.

On the other hand, the below-average inequality subsample consists of 16 economies: Albania, Belarus, Croatia, Greece, Republic of Korea, Lithuania, Montenegro, Latvia, North Macedonia, Romania, Serbia, Singapore, Slovenia, Moldova and Bulgaria. These economies are undoubtedly smaller and more vulnerable to financial shocks, such as the global financial crisis. Their average GDP per capita growth in 2010 compared to 2009 was 2.7%. This positive value is primarily due to Moldova and Singapore, which achieved growth rates of 28% and 21%, respectively. Of the others, only Belarus, Republic of Korea and Lithuania had positive growth rates, while the remaining 11 economies recorded negative GDP per capita growth. Overall, these results imply that hypotheses H_2 and $H_{2.1}$, as set in this research, should be rejected.

DISCUSSION OF FINDINGS

When testing hypothesis H_1, panel data analysis was conducted on the full sample. The conclusion of this part of the econometric analysis is that, in the long run, GDP per capita Granger-causes the Gini coefficient, whereas the reverse effect is not supported by the evidence. Moreover, in the long run, an increase in GDP per capita leads to a reduction in the Gini coefficient. In the short run, the relationship between the two variables is also significant, but a decrease in the Gini coefficient occurs only after the second period following an increase in GDP per capita.

The results of this research further support the argument that Kuznets' hypothesis cannot be universally applied, particularly in its early stages, where it suggests a direct link between economic growth and rising inequality at lower levels of development. Similar conclusions were drawn by Palma (2016), who observed that many low and low-middle-income countries now exhibit income distributions similar to those of middle-income countries, contradicting the expected inverted U-shaped relationship between income inequality and economic development proposed by Kuznets. Fields (1991) and Piketty (2014) also support these findings.

Robustness checks using PMG and CCEMG estimators broadly confirm the baseline results, but also show that the effect weakens once heterogeneity and cross-sectional dependence are fully accounted for. This suggests that the growth–inequality relationship is context-specific rather than universal (Appendix 6). Taken together, these findings suggest that H1 receives partial support.

Overall, the findings indicate that GDP per capita growth supports a more equitable income distribution in the long run, despite short-run distributional pressures, while higher inequality exerts a significant negative influence on GDP per capita in the short run. These results align with the broader logic of the Kuznets hypothesis and underscore the view that equality is ultimately conducive to sustainable growth.

When testing the hypotheses (H_2 and $H_{2.1}$), which examine whether more equitable income distribution contributes to greater economic stability and resilience to shocks such as the 2008 global financial crisis, the results showed that economies with higher inequality did not experience a significant shock from the global financial crisis, whereas economies with lower inequality did. Given these findings, hypotheses H_2 and $H_{2.1}$ were rejected, as the results demonstrated that, in the case of the global 2008 financial crisis, countries with more equal income distributions suffered a greater shock and a longer-lasting crisis impact. Consequently, economies with higher inequality exhibited greater stability. This implies that their sources of growth are concentrated elsewhere. These findings align with the 2017 IMF study on the relationship between economic inequality and economic development (Grigoli, 2017), and the cases of Ecuador, Jordan, Nigeria and Panama.

It can be concluded that these findings are both logical and economically meaningful, as GDP per capita is one of the fundamental indicators of a country's standard of living and directly affects inequality. On the other hand, the lack of a long-term effect of the Gini coefficient on GDP per capita suggests that, in the long run, GDP trends depend on other economic and non-economic factors. However, in the short run, inequality significantly influences GDP dynamics, confirming the hypothesis of their interdependence. Future research could make significant contributions to this topic by expanding the current analysis to individual country case studies within the sample. Such an approach would add valuable insights to this type of analysis.

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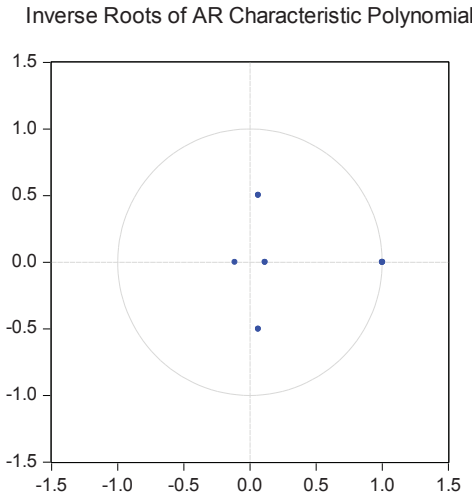
APPENDICES

Appendix 1
Criteria for Optimal Lag Selection in the Panel VECM Model

Lag	LogL	SC	HQ
0	-4921.988	19.139	19.129
1	-3188.076	12.454	12.407
2	-3176.524	12.453*	12.383*
3	-3163.075	12.457	12.387
4	-3156.779	12.478	12.424

Appendix 2
Stability of the Panel VECM Model of the Gini Coefficient and GDP per Capita for the Entire Sample – Figure and Table



Roots of Characteristic Polynomial	
Endogenous variables: GINI_INDEX GDP_PER_CAPITA	
Exogenous variables:	
Lag specification: 1 2	
Date: 05/14/24 Time: 15:10	
Root	Modulus
1.000212	1.000212
1.000000	1.000000
0.063723 - 0.501537i	0.505569
0.063723 + 0.501537i	0.505569
0.115063	0.115063
-0.113958	0.113958
VEC specification imposes 1 unit root(s).	

Appendix 3
Autocorrelation Test in the Panel VECM Model of the Gini Coefficient and GDP per Capita for the Entire Sample

VEC Residual Serial Correlation LM Tests		
Null Hypothesis: no serial correlation at lag order h		
Date: 05/14/24 Time: 15:12		
Sample: 1995 2022		
Included observations: 645		
Lags	LM-Stat	Prob
1	11.97095	0.0176
2	7.381959	0.1170
3	26.65046	0.0000
Probs from chi-square with 4 df.		

Appendix 4
Variance Decomposition for the VECM Model of the Gini Coefficient and GDP per Capita – Cholesky Ordering: Gini Coefficient, GDP per Capita

Variance Decomposition of GINI_INDEX:			
Period	**S.E.**	**GINI_INDEX**	**GDP_PER_CAPITA**
1	0.016329	100.0000	0.000000
2	0.022489	99.81435	0.185651
3	0.027046	99.82284	0.177165
4	0.030934	99.71513	0.284869
5	0.034365	99.67468	0.325315
6	0.037411	99.64661	0.353390
7	0.040158	99.59615	0.403853
8	0.042677	99.52776	0.472238
9	0.045008	99.45139	0.548614
10	0.047179	99.36765	0.632351
Variance Decomposition of GDP_PER_CAPITA:			
Period	**S.E.**	**GINI_INDEX**	**GDP_PER_CAPITA**
1	1555.071	0.028084	99.97192
2	2417.596	0.300088	99.69991
3	2877.356	0.785603	99.21440
4	3229.706	0.878882	99.12112
5	3583.610	0.801539	99.19846
6	3928.811	0.712577	99.28742
7	4249.265	0.633877	99.36612
8	4550.925	0.560833	99.43917
9	4841.902	0.496195	99.50381
10	5124.681	0.443597	99.55640
Cholesky Ordering: GINI_INDEX GDP_PER_CAPITA			

Appendix 5
Dumitrescu–Hurlin panel Granger causality test

Dumitrescu & Hurlin (2012) Granger non-causality test results:	
Lag order: 2	
W-bar =	4.4845
Z-bar =	6.3342 (p-value = 0.0000)
Z-bar tilde =	4.7194 (p-value = 0.0000)
H0: GDPpc does not Granger-cause Gini.	
H1: GDPpc does Granger-cause Gini for at least one panel (Country_id).	

Appendix 6
Robustness of long-run GDPpc → Gini relationship across estimators

Estimator	**Coefficient**	**Std. error**	**P-value**
PMG	5.33e-06	8.31e-07	0.000
CCEMG	1.81e-06	3.27e-06	0.579

Appendix 7
Original Panel VECM Model Output in the First Subsample for Testing Hypotheses H_2 and $H_{2.1}$

Vector Error Correction Estimates	
Date: 05/16/24 Time: 09:29	
Sample (adjusted): 1998 2022	
Included observations: 395 after adjustments	
Standard errors in ( ) & t-statistics in [ ]	
Cointegrating Eq:	CointEq1
GINI_INDEX(-1)	1.000000
GDP_PER_ CAPITA(-1)	4.13E-06
	(8.6E-07)
	[4.78498]
C	-0.525795

Error Correction:	D(GINI_ INDEX)	D(GDP_ PER_ CAPITA)
CointEq1	-0.052164	6705.382
	(0.01460)	(1308.34)
	[-3.57379]	[5.12512]
D(GINI_INDEX(-1))	-0.065043	-18280.05
	(0.04906)	(4397.30)
	[-1.32584]	[-4.15711]
D(GINI_INDEX(-2))	0.024803	-9032.567
	(0.04930)	(4419.05)
	[0.50310]	[-2.04401]
D(GDP_PER_ CAPITA(-1))	1.64E-06	0.113166
	(5.7E-07)	(0.05083)
	[2.88918]	[2.22636]
D(GDP_PER_ CAPITA(-2))	-6.86E-07	-0.282487
	(6.5E-07)	(0.05827)
	[-1.05487]	[-4.84776]
C	-0.000294	645.5807
	(0.00097)	(86.9449)
	[-0.30314]	[7.42517]
R-squared	0.055258	0.155529
Adj. R-squared	0.043115	0.144674
Sum sq. resids	0.118682	9.54E+08
S.E. equation	0.017467	1565.645
F-statistic	4.550508	14.32864
Log likelihood	1041.283	-3463.099
Akaike AIC	-5.241937	17.56506
Schwarz SC	-5.181499	17.62550
Mean dependent	0.000302	573.0443
S.D. dependent	0.017856	1692.885
Determinant resid covariance (dof adj.)		745.4218
Determinant resid covariance		722.9481
Log likelihood		-2421.171
Akaike information criterion		12.32998
Schwarz criterion		12.47100

Appendix 8

Original Panel VECM Model Output in the Second Subsample for Testing Hypotheses H_2 and $H_{2.1}$

Vector Error Correction Estimates		
Date: 05/16/24 Time: 14:57		
Sample (adjusted): 1998 2022		
Included observations: 250 after adjustments		
Standard errors in ( ) & t-statistics in [ ]		
Cointegrating Eq:	CointEq1	
GINI_INDEX(-1)	1.000000	
GDP_PER_CAPITA(-1)	6.59E-07	
	(1.0E-06)	
	[0.65928]	
C	-0.578040	
Error Correction:	D(GINI_INDEX)	D(GDP_PER_CAPITA)
CointEq1	-0.060628	2679.689
	(0.02001)	(2165.42)
	[-3.02920]	[1.23749]
D(GINI_INDEX(-1))	0.064415	98.73556
	(0.06042)	(6536.51)
	[1.06621]	[0.01511]
D(GINI_INDEX(-2))	-0.027325	-3552.346
	(0.06332)	(6850.36)
	[-0.43157]	[-0.51856]
D(GDP_PER_CAPITA(-1))	-3.03E-07	0.216380
	(6.0E-07)	(0.06517)
	[-0.50251]	[3.32018]
D(GDP_PER_CAPITA(-2))	-6.55E-07	-0.211571
	(6.2E-07)	(0.06656)
	[-1.06464]	[-3.17873]
C	0.001504	405.3236
	(0.00092)	(99.7560)
	[1.63133]	[4.06315]
R-squared	0.051942	0.072909
Adj. R-squared	0.032514	0.053912
Sum sq. resids	0.045905	5.37E+08
S.E. equation	0.013716	1484.006
F-statistic	2.673636	3.837790
Log likelihood	720.5945	-2177.323
Akaike AIC	-5.716756	17.46659
Schwarz SC	-5.632241	17.55110
Mean dependent	0.001171	421.0841
S.D. dependent	0.013945	1525.702
Determinant resid covariance (dof adj.)		414.3283
Determinant resid covariance		394.6792
Log likelihood		-1456.728
Akaike information criterion		11.76583
Schwarz criterion		11.96303

Sažetak

ISTRAŽIVANJE POVEZANOSTI IZMEĐU DISTRIBUCIJE DOHODAKA I VOLATILNOSTI RASTA: PANEL-ANALIZA ODABRANIH ZEMALJA

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Ovaj rad istražuje dinamičan odnos između gospodarskog rasta i dohodovne nejednakosti, s posebnim naglaskom na to kako razina nejednakosti oblikuje otpornost zemalja na krize. Središnje istraživačko pitanje glasi: doprinosi li ravnomjernija raspodjela dohotka većoj stabilnosti rasta, osobito tijekom razdoblja financijskih potresa? Kako bismo odgovorili na to pitanje, procijenili smo modele panel VECM za 26 europskih i azijskih zemalja u razdoblju od 1995. do 2022. godine. Rezultati pokazuju da zemlje s ravnomjernijom raspodjelom dohotka nisu imale stabilnije stope rasta tijekom kriza, što je potvrđeno dinamičkim modelima i Chowovim testom strukturnog prijeloma. Nadalje, financijski šok nije se pojavio u zemljama s višom nejednakošću, dok je bio prisutan u zemljama s nižom nejednakošću. Ovakav ishod povezan je sa strukturnim obilježjima, ponajprije snagom industrijske baze i domaće potražnje, koji djeluju kao zaštitni čimbenici od vanjskih šokova.

Ključne riječi: ekonomski rast, nejednakost dohotka, panel podaci, financijska kriza 2008.