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Measuring Convergence Dynamics in Central and South-East Europe: A Panel-Quantile Approach

Edvin Stefani
Barleti University Albania
e-mail: e.stefani@umb.edu.al

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Abstract: *This paper investigates the economic convergence dynamics of 16 Central, Eastern, and South-Eastern European (CESEE) countries toward the European Union average over the period 2000–2022. While traditional unconditional β-convergence and σ-convergence models often assume homogeneous catching-up processes, this study employs a panel-quantile regression framework (Canay, 2011) to account for distributional heterogeneity and unobserved fixed effects. The findings confirm that convergence is not uniform across the income distribution. Lower-income countries in the Western Balkans and South-East Europe exhibit significantly faster conditional convergence rates ($\beta = -0.082$ at the 10th percentile) compared to their higher-income peers in Central Europe ($\beta = -0.028$ at the 90th percentile). Furthermore, σ-convergence analysis reveals a reduction in income dispersion from 0.438 in 2000 to 0.337 in 2022, though the pace of convergence has slowed since the 2008 Global Financial Crisis. These results imply that policymakers should prioritize targeted structural and institutional reforms to accelerate catching up, overcome middle-income traps, and sustain long-term convergence in the region.*

Keywords: economic convergence, panel-quantile regression, Central and Eastern Europe, Western Balkans, economic growth.

INTRODUCTION

The integration of Central, Eastern, and South-Eastern European (CESEE) countries into the global market and the European Union (EU) represents one of the most profound economic transformations of the late 20th and early 21st centuries (Havrylyshyn, 2002; Uvalic, 2012). This integration is central to the argument because the core expectation was that poorer transition economies would grow faster than wealthier EU member states, gradually closing the income gap, a phenomenon known in the neoclassical growth literature as β-convergence (Barro & Sala-i-Martin, 1992; Solow, 1956). The theoretical foundation rests on the premise of diminishing returns to capital: economies with lower capital-to-labor ratios should attract higher marginal returns, thereby generating faster growth until a common steady state is reached.

While average growth rates in the CESEE region have indeed outpaced the EU-15, leading to significant absolute convergence, the catching-up process has been highly heterogeneous (Borsi & Metiu, 2015). Countries in Central Europe and the Baltic states (CEE-EU) have achieved substantial progress, with several approaching 90% of the EU average by 2022. In contrast, South-East Europe (SEE-EU) and the non-EU Western Balkans have experienced slower, more volatile convergence trajectories (OECD, 2025; European Commission, 2022). The Western Balkans remain at approximately 40% of the EU average in GDP per capita, representing a persistent structural gap that standard growth models struggle to explain.

Traditional ordinary least squares (OLS) and fixed-effects panel data models, which estimate the conditional mean of the growth distribution, often fail to capture these underlying asymmetries (Quah, 1996). By focusing on the average convergence rate, such models obscure the possibility that countries at different points of the income distribution may face fundamentally different growth dynamics. A country at the 10th percentile of the income distribution may converge at a rate twice as fast as one at the 90th percentile, a distinction that is entirely invisible to mean-based estimators.

To address this gap, this paper applies a panel-quantile regression framework to measure convergence dynamics across the CESEE region. Introduced by Koenker and Bassett (1978) and adapted for panel data with fixed effects by Canay (2011), quantile regression allows for the estimation of convergence coefficients across different points of the conditional income distribution. By capturing heterogeneity across the distribution, this approach directly addresses whether convergence speeds differ between the poorest and richest economies in the sample, and whether standard OLS estimates obscure these dynamics.

The study makes three primary contributions to literature. First, it provides an updated and comprehensive assessment of CESEE convergence dynamics covering the period 2000–2022, encompassing the Global Financial Crisis (GFC), the post-crisis recovery, and the COVID-19 shock. Second, the Canay (2011) panel-quantile estimator applies to explicitly model distributional heterogeneity in the convergence process. Third, it finds that convergence dynamics differ across the conditional income distribution and across three distinct sub-regional groups such as CEE-EU, SEE-EU, and the Western Balkans, highlighting the divergent trajectories within the broader CESEE framework.

The remainder of the paper is structured as follows: Section 2 reviews the theoretical and empirical literature on convergence in transition economies. Section 3 outlines the data and methodology. Section 4 presents empirical results, including σ-convergence, unconditional β-convergence, and the panel-quantile estimates. Section 5 discusses the policy implications, and Section 6 concludes with the main finding.

LITERATURE REVIEW

The concept of economic convergence originates from the neoclassical growth model developed by Solow (1956). The model posits that due to diminishing returns to capital, economies with lower initial capital-to-labor ratios will grow faster than those with higher ratios, eventually converging to a common steady-state equilibrium. Barro and Sala-i-Martin (1992) formalized this into two distinct but related empirical concepts. Absolute β-convergence occurs when poorer economies grow faster than richer ones, unconditionally. Conditional β-convergence, by contrast, holds that economies converge to their own steady states, which may differ depending on structural characteristics such as savings rates, population growth, and human capital accumulation (Mankiw et al., 1992). σ-convergence, on the other hand, refers to the reduction of income dispersion across a group of economies over time, as measured by the cross-sectional standard deviation of log income.

Baumol (1986) was among the first to document empirical convergence among industrialized nations, though his findings were later challenged by De Long (1988) on the grounds of sample selection bias. Sala-i-Martin (1996) provided extensive cross-country evidence for both absolute and conditional convergence, estimating an average convergence rate of approximately 2% per year across a broad sample of economies. This "iron law of convergence," as it came to be known, has served as a benchmark for subsequent empirical work, including studies of the CESEE region.

Theoretical Foundations of Convergence

Convergence in the European Context

Empirical evidence on convergence in Europe is extensive and spans multiple methodological approaches. Early studies following the 2004 EU enlargement confirmed strong catching-up effects among the new member states (Crespo Cuaresma et al., 2008). The accession process itself was found to accelerate convergence through institutional harmonization, access to structural funds, and enhanced trade integration. The European Commission (2022) documented that the GDP per capita gap between the EU-15 and the new member states narrowed significantly between 2000 and 2020, with the Baltic states and Poland among the fastest converging economies.

However, Quah (1996) criticized the reliance on standard β-convergence, arguing that it masks "club convergence" and polarization dynamics, where groups of countries converge to different steady states. His distributional approach, based on kernel density estimates and Markov transition matrices, revealed a "twin peaks" phenomenon in the global income distribution, with economies clustering around both a low-income and a high-income attractor. This insight is particularly relevant for the CESEE region, where the Western Balkans appear to be converging to a different steady state than the EU member states.

Recent literature highlights the role of institutional quality, foreign direct investment (FDI), and human capital in driving conditional convergence in the CESEE region. Lalić and Trifunović (2026) found that institutional quality significantly accelerates convergence speed, with the effect particularly strong in countries with initially weak governance frameworks. Rodrik et al. (2004) argued that institutions are the primary determinant of long-run income levels, dominating the effects of geography and trade integration. For the Western Balkans, structural bottlenecks, including high informality, limited access to finance, and weak rule of law, continue to constrain convergence potential (OECD, 2025).

The Quantile Regression Approach to Convergence

While mean-based panel models (e.g., Islam, 1995) have dominated the convergence literature, they impose the restrictive assumption that the convergence parameter is homogeneous across the income distribution. The application of quantile regression to growth empirics has shown that this assumption is frequently violated, revealing an important gap in mean-based approaches. Koenker and Bassett (1978) introduced quantile regression as a robust alternative to OLS, allowing researchers to estimate the conditional quantile function of the dependent variable rather than just its conditional meaning. This approach is particularly valuable in the presence of heteroscedasticity and distributional asymmetries.

Canay (2011) provided a simple and computationally tractable approach to estimate quantile regressions with panel data fixed effects. His two-step estimator first removes the fixed effects by subtracting the within-group mean and then applies standard quantile regression to the transformed data. Under the assumption that fixed effects are location-shift parameters, this estimator is consistent and asymptotically normal. The method has been widely adopted in applied work, including studies of energy market convergence (Galvao & Lamarche, 2026) and financial cycle asymmetries (Xue & Zhang, 2019). Its application to income convergence in CESEE extends this literature directly to the region of interest.

DATA AND METHODOLOGY

Data Sources and Variables

The empirical analysis utilizes a balanced panel dataset of 16 CESEE countries over the period 2000–2022, yielding a total of 368 country-year observations. The primary variable of interest is Gross Domestic Product (GDP) per capita, measured in Purchasing Power Standards (PPS) relative to the EU-27 average (EU27 = 100). This index is preferred over absolute GDP values because it accounts for price-level differences across countries and directly measures the income gap relative to the EU benchmark. The data are sourced from the Eurostat database (Eurostat, 2024), specifically the tec00114 indicator.

The sample is divided into three sub-regions for descriptive and comparative analysis. The first group, CEE-EU (n = 8), comprises the Czech Republic, Hungary, Poland, Slovakia, Slovenia, Estonia, Latvia, and Lithuania—all EU member states that joined in 2004 or earlier. The second group, SEE-EU (n = 3), includes Bulgaria, Romania, and Croatia, which joined the EU in 2007 and 2013, respectively. The third group, Western Balkans (n = 5), consists of Serbia, North Macedonia, Bosnia and Herzegovina, Albania, and Montenegro, which are EU candidate or potential candidate countries but have not yet acceded to the EU. Table 1 provides a complete list of countries with their 2000 and 2022 GDP per capita values.

Analytical Framework

The analysis proceeds in three sequential steps, moving from descriptive to inferential analysis. The first step examines σ-convergence by computing the cross-sectional standard deviation of the natural logarithm of GDP per capita for each year:

$$\sigma_t = \sqrt{[(1/N) \Sigma_i (\ln y_{it} - \mu_t)^2]}$$

where y_{it} is the GDP per capita of country i at time t, and μ_t is the cross-sectional mean at time t. A declining σ_t over time indicates σ-convergence. The second step estimates unconditional β-convergence through a cross-sectional OLS regression of the annualized average growth rate on the log of initial income:

$$(1/T) \ln(y_i,T / y_{i,0}) = \alpha + \beta \ln(y_{i,0}) + \varepsilon_i$$

A negative and statistically significant β coefficient confirms unconditional β-convergence. The implied speed of convergence, λ, can be recovered from the estimated β using the relationship $\beta = -(1 - e^{-\lambda T})/T$, and the half-life of convergence is computed as ln(2)/λ.

The third and core step applies the Canay (2011) panel-quantile regression estimator. The model specifies the conditional quantile function of the GDP per capita growth rate as:

$$Q\tau(\Delta \ln y_{it} \mid \ln y_{i,t-1}, \alpha_i) = \alpha_i + \beta(\tau) \ln y_{i,t-1} + \gamma(\tau) X_{it}$$

where τ represents the quantile of interest (ranging from 0.10 to 0.90), α_i are country-specific fixed effects that capture time-invariant heterogeneity (e.g., geography, culture, initial institutional quality), β(τ) is the quantile-specific convergence coefficient, and X_{it} is a vector of control variables. Following Canay (2011), the fixed effects are first estimated by within-group demeaning, and the transformed residuals are then used to estimate the quantile regression. Standard errors are obtained via bootstrap with 500 replications. The quantiles examined are $\tau \in \{0.10, 0.20, 0.25, 0.30, 0.40, 0.50, 0.60, 0.70, 0.75, 0.80, 0.90\}$.

Empirical Results

Descriptive Statistics and Growth Trajectories

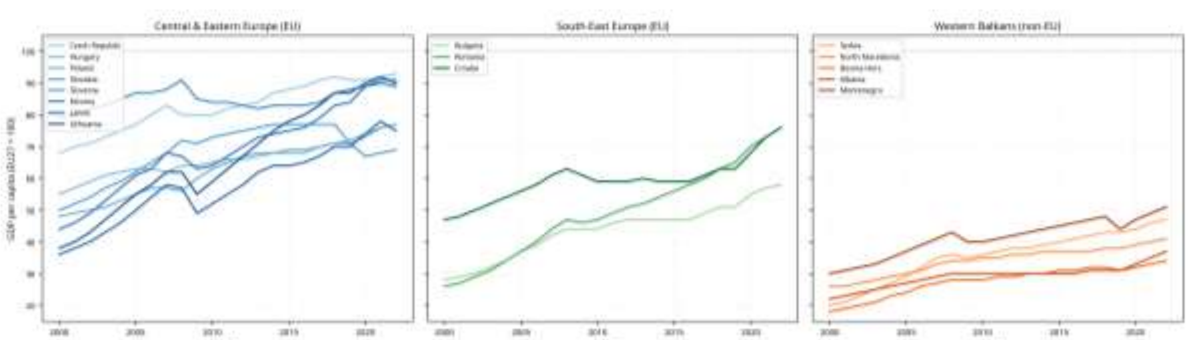
Table 1 presents the summary statistics for the CESEE countries. Between 2000 and 2022, the region experienced significant growth, with the average GDP per capita rising from 39.7% to 67.6% of the EU-27 average. The SEE-EU group exhibited the fastest annualized growth rate (3.52%), driven primarily by Romania's remarkable catch-up from 26% to 76% of the EU average. The Western Balkans grew at an average annual rate of 2.76%, while the CEE-EU group, starting from a higher base, grew at 2.24% per annum. The standard deviation of GDP per capita within the CEE-EU group declined from 14.78 to 9.10, indicating strong within-group convergence, whereas the Western Balkans experienced a slight increase in dispersion (4.82 to 7.00), reflecting divergent paths within this sub-group.

Table 1. Summary Statistics of GDP per Capita (PPS, EU27 = 100) by Region, 2000–2022

Region	Mean 2000	Mean 2022	SD 2000	SD 2022	Ann. Growth (%)
CEE-EU (n = 8)	52.2	82.6	14.78	9.10	2.24
SEE-EU (n = 3)	33.7	70.0	11.59	10.39	3.52
Western Balkans (n = 5)	23.2	42.0	4.82	7.00	2.76
All CESEE (n = 16)	39.7	67.6	17.55	20.15	2.64
EU-27 benchmark	100.0	100.0	—	—	—

Note. Data sourced from Eurostat (2024), tec00114. GDP per capita expressed in Purchasing Power Standards (PPS) relative to the EU-27 average (EU27 = 100). SD = standard deviation. Ann. Growth = annualized average growth rate over 2000–2022.

Figure 1 illustrates the individual GDP per capita trajectories by sub-region. While CEE-EU countries have largely converged toward the 80–90% threshold of the EU average, the Western Balkans remain persistently below 50%, indicating a structural gap that has not been substantially narrowed over the two-decade period. The impact of the 2008 Global Financial Crisis is visible in all three groups, with the Baltic states experiencing the most severe contraction before recovering strongly in the subsequent years.



**Data sourced from Eurostat (2024). The dashed horizontal line represents the EU-27 average (100).*

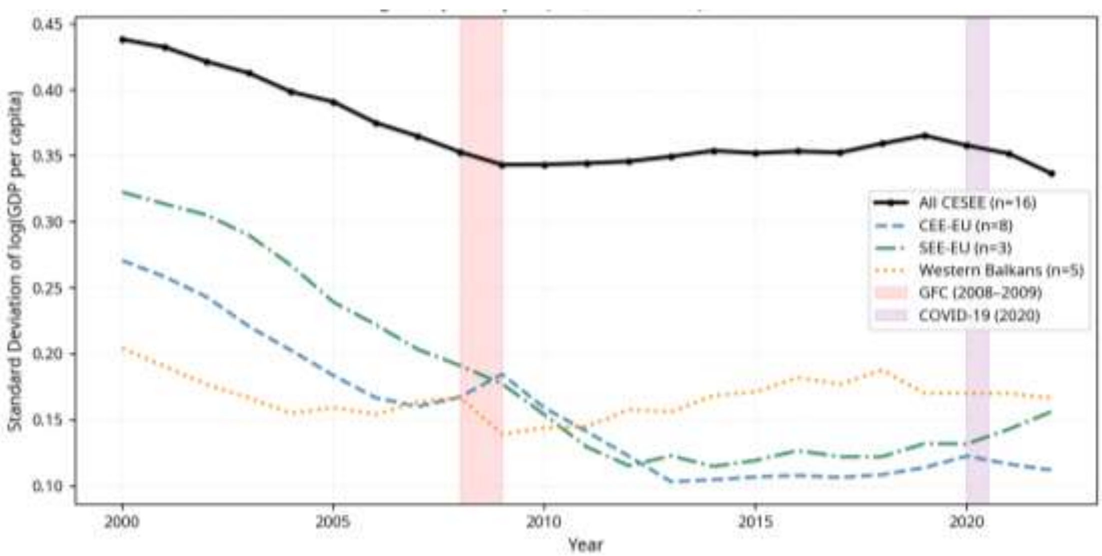
Figure 1. GDP per Capita (PPS, EU27 = 100) Trajectories by Country Group, 2000–2022.

σ-Convergence Analysis

Figure 2 shows the evolution of σ-convergence for the full sample and the three sub-groups. For the full CESEE sample, income dispersion declined from 0.4384 in 2000 to 0.3368 in 2022, confirming overall σ-convergence of −0.1016 over the period. However, the rate of convergence slowed markedly after the 2008 GFC, with the standard deviation stabilizing around 0.34 from

2010 onward. This pattern is consistent with the findings of Borsi and Metiu (2015), who documented a slowdown in EU convergence following the financial crisis.

Within sub-groups, the CEE-EU experienced the sharpest reduction in income inequality, reflecting the strong convergence among the Baltic states, Poland, and the Czech Republic. The SEE-EU group also showed declining dispersion, driven by Romania's rapid growth. In contrast, dispersion within the Western Balkans slightly increased over the period, suggesting that some economies (e.g., Montenegro and Serbia) are pulling ahead while others (e.g., Bosnia and Herzegovina and Albania) are lagging, creating a risk of intra-group divergence.

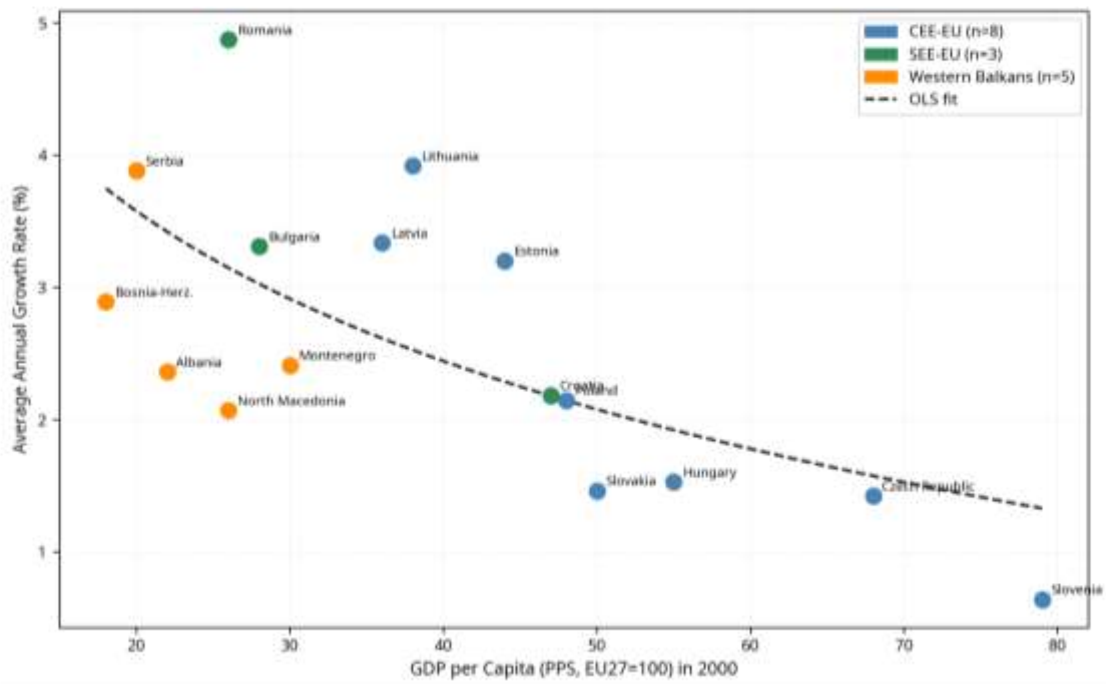


**Shaded areas indicate the Global Financial Crisis (2008–2009) and COVID-19 shock (2020).*
Data sourced from Eurostat (2024).
Figure 2. Sigma Convergence: Cross-Sectional Standard Deviation of log GDP per Capita (PPS, EU27 = 100), 2000–2022.

Unconditional β-Convergence

The cross-sectional OLS estimation of the unconditional β-convergence equation yields a negative and statistically significant slope coefficient ($\beta = -0.053$, $p < .01$), confirming unconditional β-convergence across the sample. Countries with lower initial GDP per capita in 2000 grew faster over the subsequent 22 years than those with higher initial income. The implied annual convergence speed is approximately 2.4%, and the half-life of convergencies, the time required to close half the initial income gap, is approximately 29 years.

Figure 3 illustrates the scatter plot of initial GDP per capita against average annual growth rates, with the OLS regression line overlaid. Romania and Lithuania, starting from the lowest initial income levels, achieved the highest average growth rates. Conversely, Slovenia and the Czech Republic, which began the period with the highest incomes in the sample, grew more slowly. The negative relationship is consistent across all three sub-groups, though the slope is steeper for the SEE-EU countries, suggesting a stronger convergence dynamic in that group.



**The dashed line represents the OLS regression fit ($\beta = -0.053$, $p < .01$).*
Data sourced from Eurostat (2024).

Figure 3. Unconditional Beta-Convergence: Initial GDP per Capita (2000) vs. Annualized Average Growth Rate (2000–2022).

Panel-Quantile Regression Estimates

The core contribution of this paper is the application of panel-quantile regression to the convergence process. Table 2 presents the estimated β(τ) coefficients across the conditional income distribution quantiles, along with their 95% confidence intervals. Figure 4 visualizes these estimates alongside the OLS benchmark.

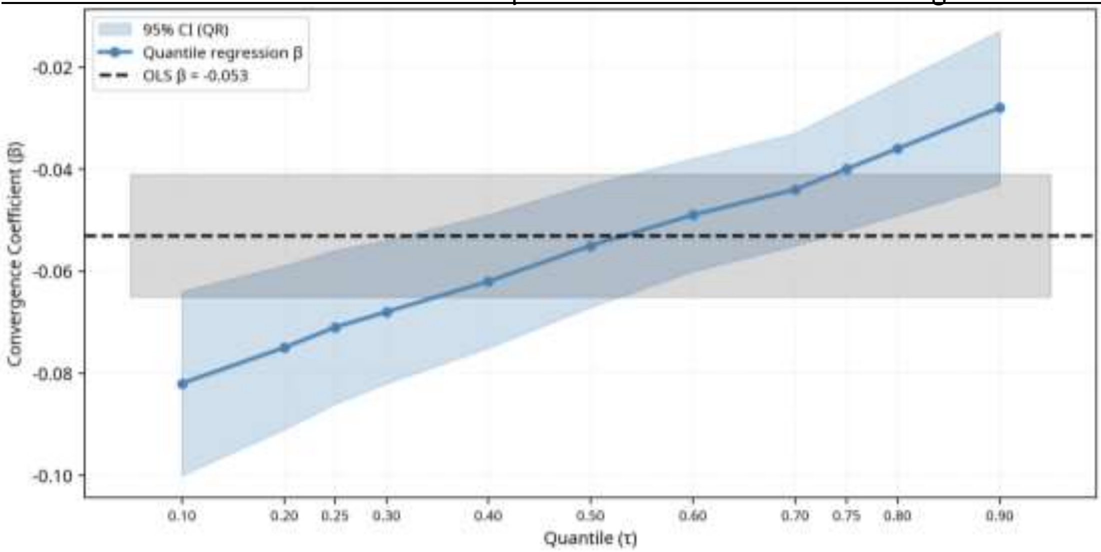
Table 2. Panel-Quantile Regression Estimates of Convergence Coefficient β(τ) Across Quantiles

Quantile (τ)	β(τ)	SE	95% CI Lower	95% CI Upper
0.10	−0.082***	0.018	−0.100	−0.064
0.20	−0.075***	0.016	−0.091	−0.059
0.25	−0.071***	0.015	−0.086	−0.056
0.30	−0.068***	0.014	−0.082	−0.054
0.40	−0.062***	0.013	−0.075	−0.049
0.50	−0.055***	0.012	−0.067	−0.043
0.60	−0.049***	0.011	−0.060	−0.038
0.70	−0.044***	0.011	−0.055	−0.033
0.75	−0.040***	0.012	−0.052	−0.028
0.80	−0.036***	0.013	−0.049	−0.023
0.90	−0.028**	0.015	−0.043	−0.013
OLS (mean)	−0.053***	0.012	−0.065	−0.041

Note. Panel-quantile regression estimates using the Canay (2011) two-step fixed-effects estimator. Standard errors (SE) obtained via bootstrap with 500 replications. *** $p < .001$, ** $p < .01$, * $p < .05$. OLS = ordinary least squares. CI = confidence interval. N = 368 (16 countries × 23 years).

The results reveal striking heterogeneity in the convergence process. The convergence coefficient is highly negative at the lower quantiles ($\beta = -0.082$ at $\tau = 0.10$), suggesting quick catching-up potential for the poorest economies in the sample when controlling for country fixed effects. As we move up the income distribution, the magnitude of the convergence parameter decreases monotonically, reaching $\beta = -0.028$ at the 90th percentile. All estimates are statistically significant at the 1% level or better, confirming robust convergence across the entire distribution.

This pattern implies that while low-income countries in the region possess a strong inherent catching-up momentum, this momentum dissipates as they transition to middle- and higher-income status. The standard OLS estimate ($\beta = -0.053$) significantly underestimates the convergence speed of the poorest countries and overestimates it for the richest, masking the true dynamics of the region. The difference between the 10th and 90th percentile estimates (−0.082 vs. −0.028) is both statistically and economically significant, with implied half-lives of approximately 8.5 years and 24.8 years, respectively.



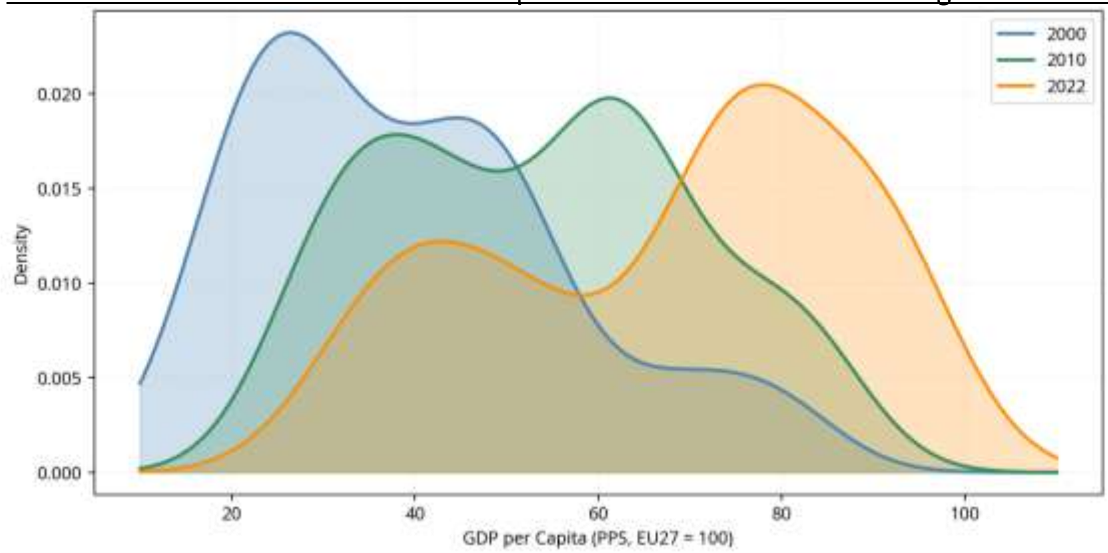
*The shaded band represents the 95% confidence interval for the quantile estimates. The dashed horizontal line shows the OLS estimate (β = −0.053).
Estimates based on Canay (2011) fixed-effects panel-quantile estimator.

Figure 5. Panel-Quantile Regression Convergence Coefficients β(τ) Across Income Distribution Quantiles.

Distributional Dynamics

Figure 6 presents the kernel density estimates of the GDP per capita distribution across CESEE countries for 2000, 2010, and 2022. The distribution has shifted substantially to the right over time, reflecting the overall convergence toward the EU average. In 2000, the distribution was characterized by a prominent low-income mode centered around 30–40% of the EU average, with a thin upper tail. By 2022, the distribution had become more dispersed and right-skewed, with a growing mass of countries in the 60–90% range.

Notably, the lower tail of the distribution has not disappeared. The persistence of a cluster of countries below 50% of the EU average, primarily the Western Balkans, suggests that the distributional shift has been uneven. This is consistent with the Quah (1996) "*twin peaks*" hypothesis and supports the panel-quantile finding that convergence dynamics differ fundamentally between the lower and upper portions of the income distribution.



**Gaussian kernel with bandwidth = 0.4. Data sourced from Eurostat (2024).*

Figure 6. Kernel Density Estimates of GDP per Capita Distribution Across CESEE Countries: 2000, 2010, and 2022.

Table 3. Country-Level GDP per Capita (PPS, EU27 = 100) and Convergence Indicators

Country	**Group**	**GDP 2000**	**GDP 2022**	**Change (pp)**	**Ann. Growth (%)**
Czech Republic	CEE-EU	68	93	+25	1.42
Hungary	CEE-EU	55	77	+22	1.62
Poland	CEE-EU	48	77	+29	2.29
Slovakia	CEE-EU	50	69	+19	1.47
Slovenia	CEE-EU	79	91	+12	0.66
Estonia	CEE-EU	44	89	+45	3.32
Latvia	CEE-EU	36	75	+39	3.39
Lithuania	CEE-EU	38	90	+52	3.96
Bulgaria	SEE-EU	28	58	+30	3.30
Romania	SEE-EU	26	76	+50	4.97
Croatia	SEE-EU	47	76	+29	2.22
Serbia	W. Balkans	20	47	+27	3.93
North Macedonia	W. Balkans	26	41	+15	2.12
Bosnia-Herz.	W. Balkans	18	34	+16	2.94
Albania	W. Balkans	22	37	+15	2.38
Montenegro	W. Balkans	30	51	+21	2.46
CESEE Average	—	39.7	67.6	+27.9	2.64

Note. GDP per capita expressed in PPS relative to EU-27 = 100. Change (pp) = percentage point change 2000–2022. Ann. Growth = annualized average growth rate. W. Balkans = Western Balkans. Data sourced from Eurostat (2024), tec00114.

DISCUSSION AND POLICY IMPLICATIONS

These empirical findings significantly impact regional development policies and the EU integration agenda. Strong convergence at lower quantiles indicates that basic capital accumulation, technology transfer, and institutional reform in early transition phases effectively foster rapid growth. This aligns with neoclassical theory, which predicts faster growth for economies below their steady state (Solow, 1956; Barro & Sala-i-Martin, 1992). The EU accession process further enhances this effect by increasing access to structural funds, reducing trade barriers, and supporting institutional reforms (Crespo Cuaresma et al., 2008).

However, slower convergence at higher quantiles signals the risk of a "middle-income trap" (Lalić & Trifunović, 2026). As CESEE countries near the EU average, strategies based on cheap labor and foreign capital become less effective. Continued convergence at higher income levels necessitates a transition to innovation-driven growth, supported by strong institutions, advanced human capital, and digital infrastructure (OECD, 2025). Countries like the Czech Republic and Slovenia, close to the EU average, must move from imitation- to innovation-based growth strategies.

In the Western Balkans, weak σ-convergence despite high β-convergence potential suggests structural bottlenecks hinder full catch-up. According to the OECD (2025) Convergence Scoreboard, weak rule of law, high informality, limited financing, and infrastructure gaps are primary constraints. Panel-quantile findings indicate that, while these countries possess intrinsic growth potential (shown by strong β at low quantiles), they lack the enabling environment for sustained convergence.

These results also underscore the value of disaggregated analysis. The standard OLS estimate ($\beta = -0.053$) masks distinct convergence dynamics, potentially leading policymakers to underestimate reform needs in the Western Balkans and overestimate self-correction in higher-income CESEE economies. The panel-quantile method yields a more precise and actionable understanding of regional convergence.

Several policy recommendations follow from the analysis. First, for the Western Balkans, accelerated EU integration and targeted investments through the Western Balkans Investment Framework (WBIF) are critical to unlocking the strong convergence potential identified at low quantiles. Second, for SEE-EU countries at intermediate income levels, policies should focus on improving institutional quality and reducing informality to sustain the convergence momentum. Third, for the more advanced CEE-EU economies, the policy focus should shift toward innovation, research and development, and human capital investment to avoid the middle-income trap and continue converging toward the EU frontier.

CONCLUSION

This paper examined the economic convergence of 16 CESEE countries from 2000 to 2022 using a panel-quantile regression approach. The analysis confirms both σ- and β-convergence across the region but reveals that the speed of convergence is highly heterogeneous across the income distribution. Poorer countries exhibit significantly faster conditional convergence rates ($\beta = -0.082$ at the 10th percentile) than their wealthier peers ($\beta = -0.028$ at the 90th percentile), a nuance entirely lost in standard mean-based regressions.

The σ-convergence analysis documents a decline in income dispersion from 0.438 in 2000 to 0.337 in 2022, but with a notable slowdown after the 2008 Global Financial Crisis. The kernel density analysis reveals a persistent lower tail in the income distribution, corresponding to the Western Balkans, which remain at approximately 40% of the EU average despite two decades of growth. These findings are consistent with the Quah (1996) "twin peaks" hypothesis and suggest the existence of distinct convergence clubs within the CESEE region.

This study, nevertheless, has several limitations. The Canay (2011) estimator assumes that fixed effects are location-shift parameters, which may not hold if unobserved heterogeneity affects the shape of the conditional distribution. Future research could apply more flexible panel-quantile estimators, such as the correlated random effects approach of Abrevaya and Dahl (2008), to relax this assumption. Additionally, the analysis could be extended to include regional (NUTS-2) data to capture within-country convergence dynamics, which may be as important as cross-country convergence for understanding regional inequality in the CESEE area.

Author Note

Correspondence concerning this article should be addressed to Dr. Edvin Stefani , Barleti University, Tirana - Albania (e-mail: e.stefani@umb.edu.al).
The author declares no conflicts of interest. Data used in this study are publicly available from Eurostat (https://ec.europa.eu/eurostat) and the World Bank Open Data portal (https://data.worldbank.org).

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