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A NEW COMPOSITE INDEX OF SOCIAL INEQUALITIES IN ROMANIA

Mihai Antonia[a], Zizi Goschin[b]*

[a] Bucharest University of Economic Studies, Romania

[b] Institute of National Economy, Romania

* Corresponding author

Address: 13 Calea 13 Septembrie, Bucharest, Romania

E-mail: zizigoschin@gmail.com

Biographical Notes

Mihai Antonia is PhD candidate at the Bucharest University of Economic Studies. His research interests include economic statistics and spatial analysis, with a focus on regional socio-economic inequalities. ORCID ID: 0000-0001-5856-9775

Zizi Goschin, PhD is Senior Researcher at the Institute of National Economy. Her main research interests are focused on spatial statistics and spatial econometrics. ORCID ID: 0000-0002-9030-7772

Abstract

Regional inequalities in Romania are not only among the highest in the European Union, but they are also perpetuated by inefficient public policies and an inequitable distribution of resources. Given that inequalities in access to education, healthcare and general services are closely linked to the standard of living and development opportunities, a vicious circle of poverty and social exclusion is created in the lagging regions. Social, economic and political inequalities are closely linked, and research should consider unequal access to essential resources and services, such as education, health services, housing or job opportunities, as essential factors that exacerbate disparities between social groups or regions. Aiming to provide a more comprehensive and clearer image of regional socio-economic inequalities in Romania, we built a new composite index of regional inequalities and examined its long-term convergence trend, as well as its relationship with economic growth. Our research contributes to the identification of areas where interventions can most effectively address social and economic imbalances.

Keywords: socio-economic inequalities, composite index, economic growth, counties
JEL Classification: R12, R15

1. Introduction

Socioeconomic inequality is a major challenge in contemporary society, with profound effects on social cohesion, political stability and individual well-being. Although the fundamental principles of democracy, such as freedom and equality, are essential for the development of a just society, the reality shows that access to opportunities and resources is not evenly distributed. In Romania, inequalities manifest themselves in multiple forms, reflecting deep divisions between urban and rural areas, as well as between developed and lagging regions. For instance, the western counties, such as Timiș or Cluj, attract larger flows of foreign direct investment and benefit from modern economic infrastructure, while northeastern regions lag both economically and socially. Such regional disparities are worsened by inequal access to education and health, as well as by the migration of young people to more developed areas or abroad, leaving poor communities in a situation of chronic underdevelopment.

According to a World Bank report (World Bank, 2018), regional inequalities in Romania are some of the highest in the European Union and tend to be perpetuated by inefficient public policies and an inequitable distribution of resources. Successive economic crises have contributed to the persistence of the inequalities, the recent pandemic being the latest major disruptive factor of economic growth (Ionescu et al, 2020; Patache et al., 2021). In addition, research shows that inequalities in access to education and healthcare are closely linked to disparities in standard of living and development opportunities of individuals, creating a vicious circle of poverty and social exclusion (Zamfir, 2023). Likewise, several studies (e.g., Sandu, 2020) emphasize the impact of internal and external migration on inequalities, highlighting how it contributes to demographic and economic imbalances between regions.

Inequalities are not only economic. Social, economic and even political inequalities are closely linked, making spatial disparities a complex and difficult to alleviate phenomenon. Unequal access to essential resources and services, such as quality education, health services, housing or job opportunities, can exacerbate disparities between social groups or regions. Different forms of inequality overlap and enhance each other, creating a cycle that is difficult to break. Therefore, in-depth analyses of spatial inequality should include, alongside traditional economic factors, differences in regional access to healthcare, education, and general services, connecting it with the concept of "spatial justice" (Plotnikova and Vinuela, 2020).

Starting from these considerations, we have undertaken an investigation into long-term regional socio-economic inequalities in Romania. To this end, we built a new composite index of inequalities and examined its convergence/divergence trend, as well as its relationship with economic growth. Our research offers useful results for decision makers, contributing to the identification of areas where interventions can most effectively address social and economic imbalances.

2. Theoretical background

The literature is abundant with studies that aim to show the importance of inequalities in society and their multiple negative effects (e.g., Chakravorty, 1996; Țâra, 2013). Inequality, in all its forms, is widely considered morally unacceptable, with profound consequences for society, economy and political system. In his work "Why Does Inequality Matter?" (Scanlon, 2018), the author identifies six main reasons why inequality is morally problematic: it is humiliating, it gives disproportionate power to the wealthy, it undermines equal opportunities, it distorts the fairness of political institutions, it violates the principle of equality before the law, and it is often rooted in unfair economic systems. These arguments highlight both the intrinsic and instrumental harms of inequality, underscoring its corrosive effects on individual dignity and societal well-being.

To address these challenges and to address inequalities that go beyond the economic dimension, the Human Development Index (HDI) was created. It considers not only income but also other essential dimensions, such as health and education, providing a broader perspective on human progress.

The index of economic and social well-being has evolved considerably in recent decades, reflecting not only aspects related to economic growth, but also broader dimensions of inequality and sustainability. Recent studies have highlighted that measuring inequality cannot be limited to income distribution alone, but must also consider access to essential resources, economic and social opportunities, and quality of life (Osberg & Sharpe, 2001; Van de Kerk & Manuel, 2008).

Most well-being indices that take inequality into account focus on economic inequality (Peterson, 2013) and use either the Gini coefficient or the Atkinson measure of inequality to reflect gaps between social segments (Rawls, 1971). John Rawls, in his seminal work "A Theory of Justice" (1971), introduces the concept of “justice as fairness”, based on two fundamental principles: the liberty principle, which guarantees each individual the most extensive system of basic freedoms, and the difference principle, which allows social and economic inequalities only if they benefit the least advantaged and are linked to positions open to all under conditions of fair equality of opportunity. For example, the Sustainable Society Index (SSI) measures inequality by comparing the income of the richest 10% with that of the poorest 10%, thus providing a clear perspective on the extremes of the income distribution (Van de Kerk & Manuel, 2008).

Osberg and Sharpe created an instrument intended to provide a more comprehensive measure of economic well-being than traditional indicators such as GDP (Osberg & Sharpe, 2001). Their index, called the Index of Economic Well-being (IEWB), assesses economic well-being through four main dimensions: actual consumption, wealth accumulation, income equality, and economic security. The methodology combines these factors into a single index, using weights that reflect the relative importance of each dimension. Applications of the IEWB in various countries have shown that while GDP may indicate economic growth, real well-being can stagnate or even decline as inequality and economic insecurity increase. The IEWB thus emphasizes the need for policies that promote a fair distribution of resources and provide adequate social protection. The authors have given greater weight to poverty than to income distribution, considering that poverty reduction is a higher priority than reducing income inequality (Osberg & Sharpe, 2001). This approach reflects the principles of social justice earlier promoted by Rawls, who argues that any increase in welfare must primarily benefit the most disadvantaged people (Rawls, 1971).

Alternative methodologies include the Indices of Sustainable Well-being ISEW (Thiry, 2011) and the Genuine Progress Indicator GPI (Talberth, 2012), which adjust personal consumption expenditures by weighting them with the Gini coefficient. This method provides a clearer picture of the social costs generated by inequality, showing how income distribution influences quality of life and economic stability in the long term (Talberth, 2012).

One of the most relevant indices constructed in this context is the Inequality-Adjusted Human Development Index (IHDI), developed by the United Nations Development Programme (UNDP, 2011). Unlike the traditional Human Development Index (HDI), which measures only the average of key indicators such as life expectancy, education and income, the IHDI adjusts these values according to the level of inequality. This approach allows for a more realistic assessment of human development, highlighting disparities that may hide structural deficiencies in the distribution of opportunities and resources.

Continuing its efforts to address inequalities, UNDP has published reports which examine the changing nature of inequalities and their impact on human development. The 2019 Human Development Report highlights that traditional measures of inequality, such as income differences, do not fully capture the deep and persistent disparities that shape contemporary societies. A central concept of the report is “beyond income, beyond averages, beyond today”, highlighting that inequalities are not only economic, but are also influenced by factors such as access to education, health, technology and political representation. The report also examines how power dynamics, discrimination and structural barriers contribute to the maintenance of inequalities, especially among marginalized groups. In addition, it highlights the risks associated with climate change, automation and globalization, which may exacerbate disparities if inclusive policies are not implemented.

Inequalities are multifaceted and complex. Social, economic and political inequalities are closely linked, and unequal access to essential resources and services, such as quality education, health services, housing or job opportunities, can worsen regional disparities. Therefore, it is essential to extend the analysis beyond traditional indicators such as income, education and life expectancy in the analysis of socio-economic inequalities. In this way, we can highlight other additional dimensions that deeply influence social mobility and regional cohesion.

Access to justice and public safety. Integrating access to justice as a measure of inequality allows for a more accurate assessment of social and economic exclusion. Although inequality has traditionally been measured through indicators such as income, education and life expectancy, these dimensions do not always reflect the systemic barriers that hinder social mobility. Legal inequality and lack of access to justice are determinant factors in the perpetuation of social and economic disparities, and the existence of high costs for legal services, corruption or institutional discrimination limit citizens' chances of defending their rights and benefiting from the protection of the law.

Quality of public services and inequality in access to essential goods. Traditional indicators of the Human Development Index (HDI) do not capture the existing disparities in the provision of public services, such as education, health and access to public utilities. A measurement system that includes differences in the quality and accessibility of these services should be analysed, given that a deficient education system or an inefficient health sector can accentuate intergenerational inequalities. In the case of a child attending an underfunded school in a rural area, he or she has much less chance of competing in the labour market with a child from an urban environment, even if formally both have access to education. Similarly, differences in access to medical services, electricity, natural gas, and transportation infrastructure are critical factors that can influence the level of attractiveness of a county.

Cultural participation. In addition to material goods and essential services, participation in cultural or sporting events is also important as a determinant of well-being and social inclusion. Limited access to culture and artistic expression can create social exclusion, affecting marginalized groups or ethnic and linguistic minorities.

In this context, to better understand the size and complexity of the regional inequalities in Romania, we have developed an index of social inequalities. This index considers factors such as education, health, access to infrastructure and public services, and other elements that can influence the standard of living in each region, providing a more comprehensive picture of inequalities in

Romanian society, contributing to the identification of areas where interventions can most effectively address social and economic imbalances.

3. Methodological framework

The empirical analysis of social inequalities in the period 2000–2023 aims to assess and compare the level of socio-economic development between Romanian counties, measuring existing disparities and identifying trends over time. The main objective is to build a multifaceted index, including various indicators and calculated using multiple methods, such as the arithmetic mean, the geometric mean and the Principal Component Analysis method, to ensure the comparability and robustness of the results, while also reflecting the complexity of the phenomenon of social inequality and allowing for rigorous comparative analysis between counties.

In the first stage, the indicators were selected and organized into groups, resulting seven major categories, as follows.

Income and standard of living

• Average monthly net wage - reflects the purchasing power of the population and the general standard of living, being an essential indicator for measuring economic disparities between regions.

• Average monthly state social insurance pension - an indicator of social protection for the elderly population, this indicator helps to assess the equity in the distribution of post-work income.

• Living space (m2/inhabitant) - provides information on housing conditions and access to an adequate living environment, a crucial aspect of social well-being.

Education

• Higher education graduates (number/1000 inhabitants) - an essential factor for social development and sustainable economic growth.

• PCs and IT equipment in educational institutions (number/100 pupils and students) - reflects the digitalization of the educational system and students' access to modern learning resources.

• Teaching staff (number/100 pupils and students) - directly influences the quality of education.

• Classrooms and amphitheatres (number/1000 pupils and students) - reflects access to educational infrastructure.

Health

• Average life expectancy (years) - indicator of the general health status of the population and the quality of medical services.

• Beds in healthcare facilities (number/1000 inhabitants) - reflects the capacity of the healthcare system to meet the needs of the population.

• Medical and health personnel (number/1000 inhabitants) - a determining factor for access to quality medical services.

Utilities and infrastructure

• Number of localities benefiting from natural gas distribution (percentage of total localities) - indicator of the quality of life and regional development.

• Number of localities with water distribution network (percentage of total localities) - represents access to basic infrastructure, essential for the health of the population.

• Length of modernized public roads (percentage of total roads) - availability and quality of road infrastructure influences access to economic and social opportunities.

• Green spaces (hectares/1000 inhabitants in urban areas) - the quality of the urban environment is an important factor in the well-being of the population.

Sports and tourism

• Number of sports clubs (number/1000 inhabitants) - access to sports activities contributes to physical health and social integration.

• Tourist accommodation capacity (number of rooms/1000 inhabitants) - represents the tourist attractiveness and economic potential of the county.

Justice and public safety

• Persons convicted (number/1000 inhabitants) - signals social problems or lack of economic opportunities.

• Solved crimes (number/1000 inhabitants) - reflects the capacity of the justice system to ensure respect for the law and public safety.

Culture and access to public events

• Performance/concert institutions and companies (number/1000 inhabitants) - access to cultural events is an indicator of quality of life and social development.

• Museums and public collections (number/1000 inhabitants) - culture and heritage contribute to local identity and tourist attractiveness.

• Cinematographic performances (number/1000 inhabitants) - capture the population's access to various forms of entertainment and cultural education.

The main source for all indicators was the National Institute of Statistics and own calculations were also necessary. To ensure comparability between regions, primary indicators were divided either by the population or by the total number of localities. For example, the number of higher education graduates per 1000 inhabitants, hospital beds per 1000 inhabitants, the percentage of localities connected to running water out of the total number of localities in a county and the number of sport clubs per 1000 inhabitants. The average annual net salary per inhabitant was estimated at 2023 prices by adjusting for the inflation rate.

These groups of macroeconomic indicators cover a wide range of areas essential for assessing the level of development and social well-being.

The next step consisted in applying the process of normalizing the values of the selected indicators using the minimum-maximum method, so that they are expressed in a standardized range of values (between 0 and 1), regardless of the type of indicator or its initial variation margins. Thus, the normalized value of 0 represents the most unfavourable case, and the value of 1 corresponds to the most favourable case. This transformation is ensuring greater comparability between the indicators and is facilitating their analysis in a standardized context. The normalization transformations of the data using the minimum-maximum method is applied as follows:

• for indicators with positive significance (e.g., income) the normalized values are calculated with the relationship:

$$I_j^i = \frac{X_i^j - X_{min}^j}{X_{max}^j - X_{min}^j} \qquad (1)$$

where:

X_i^j - the level of indicator j for county i;

X_{min}^j si X_{max}^j - the minimum and maximum value of the indicator j.

• for indicators with negative significance (e.g. school dropout, number of convicted persons), the formula is modified so that the maximum value of the indicator, which now indicates the most unfavourable situation, receives the normalized level 0, and the minimum value (best case) corresponds to the normalized level 1, becoming similar to indicators with positive significance:

$$I_j^i = \frac{X_{max}^j - X_i^j}{X_{max}^j - X_{min}^j} \qquad (2)$$

Following the application of the normalization procedure, all primary indicators are standardized (they have same margin of variation, between 0 and 1, and the same unit of measurement), allowing subsequent aggregation.

Partial indices for each group of variables are further obtained by calculating the simple arithmetic mean of the group's indicators:

$$I_i = \frac{\sum_{j=1}^{m} I_i^j}{m}, \qquad (3)$$

where $I_i$is the partial index of group i, and m represents the number of indicators in the group.

Finally, to obtain a global composite index, three distinct methods were applied: arithmetic mean, geometric mean and principal component analysis.

Arithmetic mean - the method involves calculating the simple arithmetic mean of the standardized indicators as follows:

$$I_{MA} = \frac{1}{n}\sum_{i=1}^{n} x_i \quad (4)$$

where I_{MA} represents the composite index obtained by arithmetic mean, n is the number of indicators, and x_i are the standardized values of the indicators.

Weighted geometric mean - this approach involves calculating the geometric mean of the standardized indicators, providing a different weighting of the values:

$$I_{MG}^{i} = \left(\prod_{i=1}^{n} x_i^{w_i}\right)^{\frac{1}{\sum w_i}} \quad (5)$$

where I_{MG}^{i} is the composite index obtained by weighted geometric mean, n represents the number of indicators, x_i is the partial index of each group, and w_i represents the importance of each group's index in the composition of the final indicator.

The Principal Component Analysis (PCA) reduces the size of the data set by identifying the principal components that explain most of the variation in the data. The composite index I_{PCA} is calculated as:

$$I_{PCA} = \sum_{i=1}^{k} w_i \cdot PC_i \quad (6)$$

where k represents the number of selected principal components, w_i are the weighting coefficients (corresponding to the variance explained by each component), and PC_i are the principal component scores.

The variation of the composite index of social inequalities and some of the component indicators will be further analysed with the standard method proposed by Barro and Sala-i-Martin (Barro & Sala-i-Martin,1992), namely **σ-convergence**, which evaluates the decrease or increase in disparities between regions over time. Sigma convergence represents the decrease in disparities, meaning lower dispersion of the individual values from the mean or the gradual decrease in differences between two or more time series.

The computation of the σ-convergence indicator is as follows:

$$\sigma = \frac{\sqrt{\frac{\sum_{i=1}^{n}(y_i-\bar{y})^2}{n}}}{\bar{y}} \quad (7)$$

where $\sqrt{\frac{\sum_{i=1}^{n}(y_i-\bar{y})^2}{n}}$ represents the standard deviation (a measure of dispersion), n is the number of observations (counties) in the sample, and ($\bar{y}$) is the national average.

If σ declines over the time ($\sigma_{t_0+T} < \sigma_{t_0}$), it indicates a process of economic convergence, when regional disparities are reducing. Conversely, if σ increases ($\sigma_{t_0+T} > \sigma_{t_0}$) , there is economic divergence, which means that regional disparities are widening.

To analyse the trend of σ over time, the following linear regression equation is used:

$$\sigma_t = a + bt + \varepsilon_t, \tag{8}$$

where σ_t is the time series of annual sigma values, bt is the corresponding trend line, a and b are the coefficients of the regression function, and ε_t is the error term.

A negative and statistically significant b-coefficient indicates a convergence process (a decrease in disparities over time), while a positive b-coefficient suggests a divergence process (increasing disparities).

For the analysis of the composite index of social inequalities, an autoregressive process AR(1) can be introduced into the above regression equation, resulting the following specification:

$$\sigma_t = a + bt + \rho\sigma_{t-1} + \varepsilon_t \tag{9}$$

The AR(1) process can be used to test for non-stationarity (an autoregressive AR(1) process with ρ =1 indicating a unit root) of the time series σ based on the Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1981). A more powerful variant of the ADF test is the Dickey-Fuller Generalized Least Squares (DF-GLS) test (Elliott et al., 1996), which will be used to consolidate the results. The ADF test involves estimating the following equation, obtained by subtracting σ_{t-1} from both sides of the previous relationship:

$$\Delta\sigma_t = a + bt + c\sigma_{t-1} + \varepsilon_t \tag{10}$$

where $\Delta\,\sigma_t$ is the first-order difference in the sigma time series; bt represents the corresponding trend line, and c = ρ -1 represents the unit root.

The null hypothesis of the ADF test is the presence of a unit root (c = 0), which indicates a non-stationary time series, implying that the variance is not decreasing over time, but rather tends to go up and down, therefore contradicting sigma convergence. If c is negative and significant, the null hypothesis of unit root is rejected, suggesting the stationarity of the series and a process of sigma convergence. This methodology is employed for the rigorous assessment of the convergence / divergence of the analysed indices, providing a clear perspective on the evolution of regional disparities over time.

To further analyse the relationship between the composite index of social inequalities, calculated by the three methods specified above, and the gross domestic product (GDP) per capita, a linear regression model will be applied to a panel data set covering the period 2000-2023. This approach allows to capture both time and space variations, providing a more detailed perspective on the dynamics of the relationship.

The linear regression model for panel data is as follows:

$$Y_{it} = \alpha + \beta X_{it} + u_{it} \qquad (11)$$

where Y_{it} represents the value of the composite index of social inequalities for county i in the year t; X_{it} is the value of GDP per capita for county i in year t; α is the intercept; β is the coefficient measuring the impact of X_{it} on Y_{it}; u_{it} is the error term.

The estimation of the parameters of this model will be done using the ordinary least squares (OLS) method, adapted for panel data. This involves checking and, if necessary, controlling for fixed or random effects, as well as for possible heteroscedasticity or autocorrelation of errors. The use of a panel data model offers the advantage of controlling for unobserved variables that may influence the relationship between inequality and GDP per capita, thus ensuring more robust and precise estimates.

4. Results and discussion of the composite index of social inequalities and sigma convergence

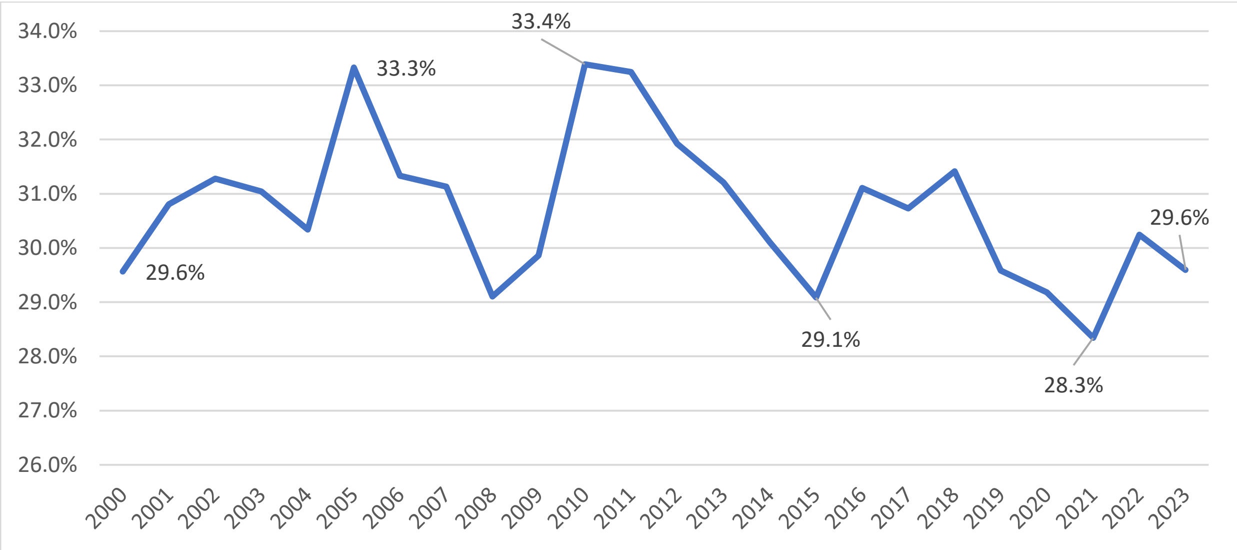
Aiming an empirical analysis of socio-economic inequalities at regional level, we constructed a composite index that allows for the comparative assessment of counties from a multidimensional perspective, integrating the various facets of social, economic and institutional inequalities. The composite index was calculated by aggregating the seven partial indices previously presented, using the following aggregation methods: arithmetic mean, geometric mean and principal components analysis (PCA).

Arithmetic mean

The use of the arithmetic mean in the case of well-being indices is justified by its simplicity and ease of use and understanding, as well as its broad applicability. We constructed an index of social inequalities by calculating the arithmetic mean of several partial indices of inequality (income, education, health, access to utilities, etc.), implicitly assuming that all indices contribute equally to the overall phenomenon. The major advantage of the arithmetic mean is its transparency and simplicity – it is easy to interpret and communicate (Booysen, 2002). However, a composite index calculated as an arithmetic mean may suffer from the effect of complete compensation between components: a very high value on one indicator may compensate for a very low one on another (Mazziotta & Pareto, 2013). In the context of inequalities, this means that strong improvement in one dimension (e.g., a decrease in crime) could mask stagnation or worsening in another dimension (e.g., access to education), keeping the average relatively stable.

The arithmetic mean treats all dimensions as perfectly substitutable, which has been criticized internationally – for example, the old formula of the Human Development Index (until 2009) used the arithmetic mean of indicators and was accused of allowing unrealistic compensations between dimensions of development (Mazziotta & Pareto, 2013). In the given case, if we use a simple index (e.g. the arithmetic mean from some partial indices), it is possible that the downward trend of inequalities is similar in direction (if most inequality indicators have improved over time), but the average depends on how synchronized the improvements were across all dimensions. If some partial indices of inequality have decreased sharply, while others have declined more slowly, the arithmetic mean would show a more attenuated overall decrease (because they compensate each other), which is the main limitation of the method.

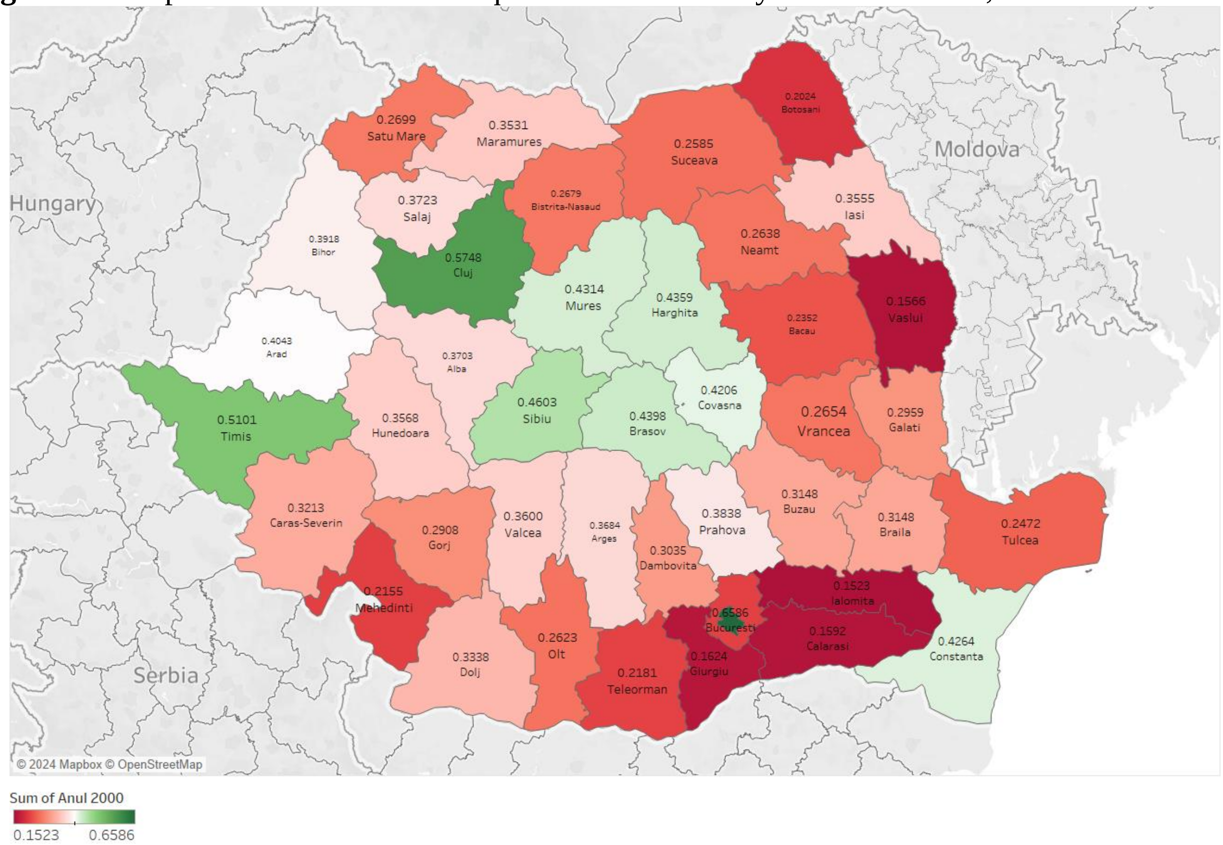
Figure 1. Sigma convergence of the composite index of social inequalities calculated using the arithmetic mean



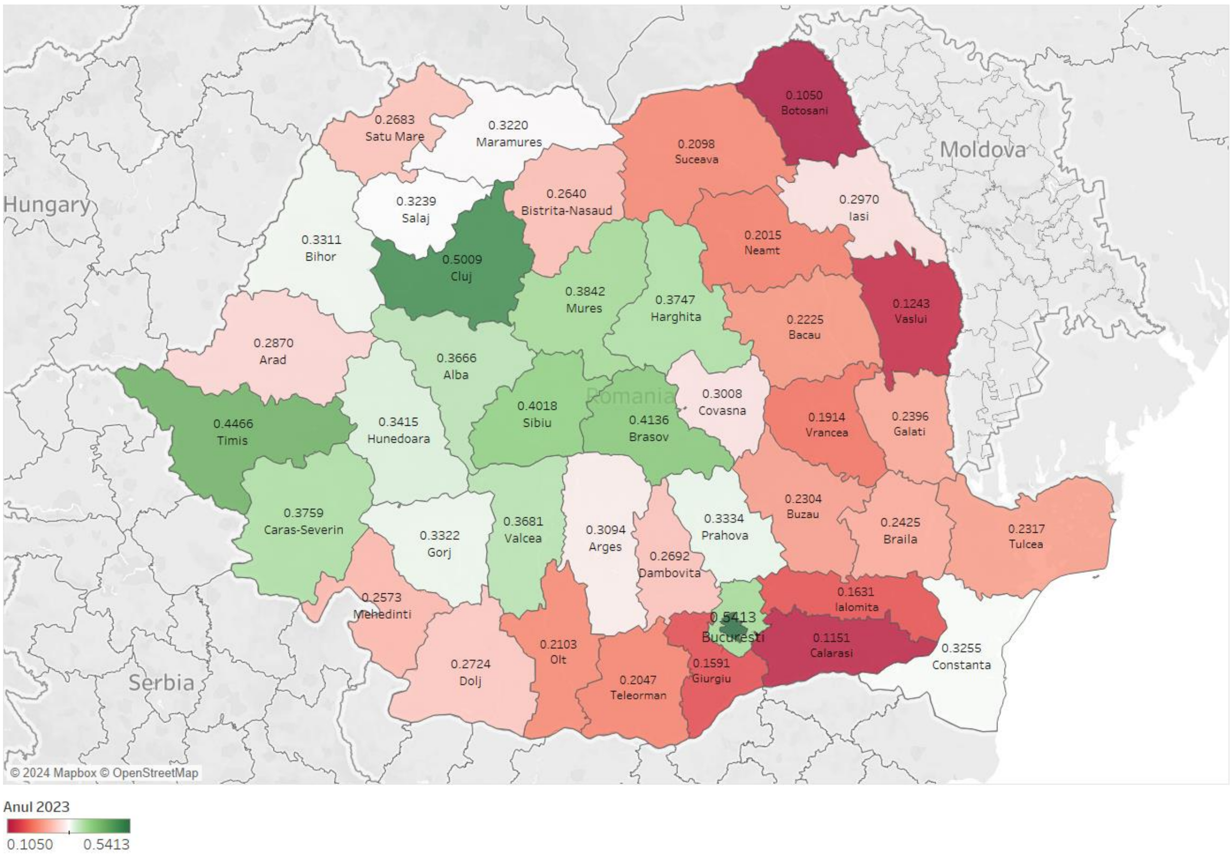
Source: developed by the authors based on data from the INS and own calculations

Figure 1 shows the evolution of the composite index of social inequalities in the period 2000-2023, calculated using the arithmetic mean. In the period 2000-2010, inequalities fluctuated, reaching a maximum of 33.4% in 2010, which suggests an increase in social disparities during the economic crisis. After 2010, the composite index shows a gradual reduction in inequalities, with a minimum of 28.3% in 2021, the year in which the measures taken during the pandemic were felt. In recent years, a slight rebound in inequalities has been noted, reaching 29.6% in 2023. This trend confirms that, although social inequalities tend to reduce over time, the process has not been linear, being moved in opposite directions by various economic and political factors.

Figure 2. Composite index of social inequalities calculated by arithmetic mean, 2000 and 2023



2000



2023

Source: developed by the authors using Tableau 2024.2

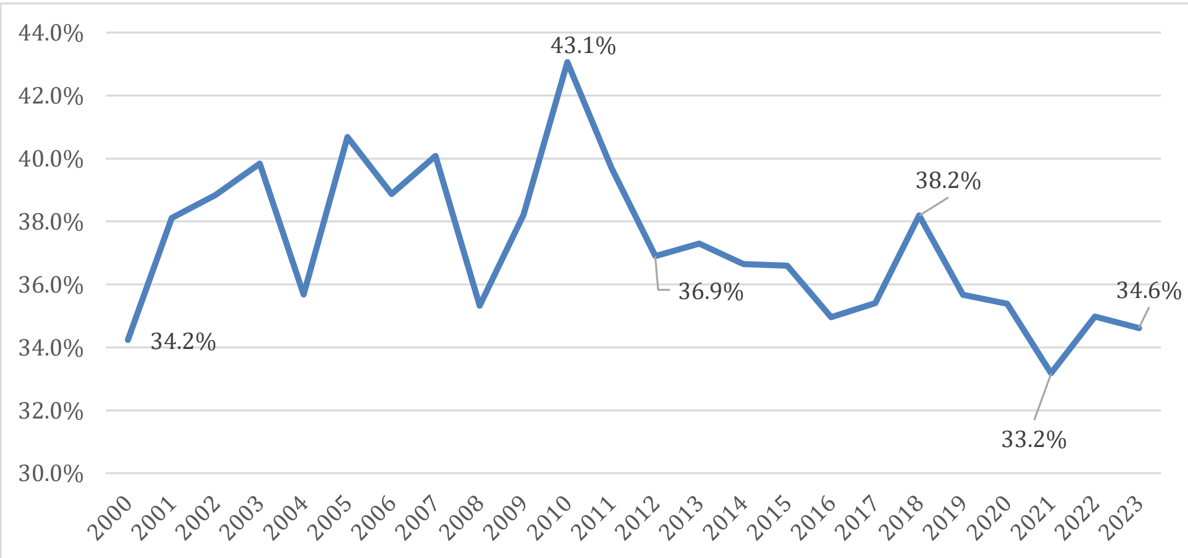
The comparison of the territorial distribution of the Composite index of social inequalities from 2000 and 2023 (Figure 2) highlights a significant change in the regional distribution of social inequalities. In 2000, the counties with the highest levels of inequality were in the southeast and northeast of the country (e.g. Vaslui, Ialomița, Călărași), and the most developed areas were concentrated around large urban centers, such as Bucharest, Cluj and Timiş. In 2023, a general reduction in inequalities is observed, but significant differences persist between developed regions (Cluj, Braşov, Sibiu, Timiș) and the most vulnerable ones (Vaslui, Teleorman, Ialomița, Călărași).

Regional disparities show that counties with solid economic infrastructure have benefited the most from the reduction of social inequalities, while less developed areas continue to experience significant deficits.

Geometric mean

Calculating a composite index of social inequalities using the geometric mean provides a more robust and realistic approach, reducing distortions caused by overcompensation and more accurately reflecting inequalities across dimensions. This method is particularly suitable for aggregating non-substitutable indicators, ensuring that each aspect of inequality is considered fairly (Hajdu, 2021; Chakrabartty, 2024). Unlike the arithmetic mean, which allows a very high value of one indicator to compensate for a very low value of another, the geometric mean attenuates this effect, being more sensitive to low values (Schlossarek, et al., 2019). This is essential in the case of the social inequality index, where a high level of one indicator, such as income, should not mask a low level of another, such as health or education.

Figure 3. Sigma convergence of the composite index of social inequalities calculated using the geometric mean



Source: developed by the authors based on data from the INS and own calculations

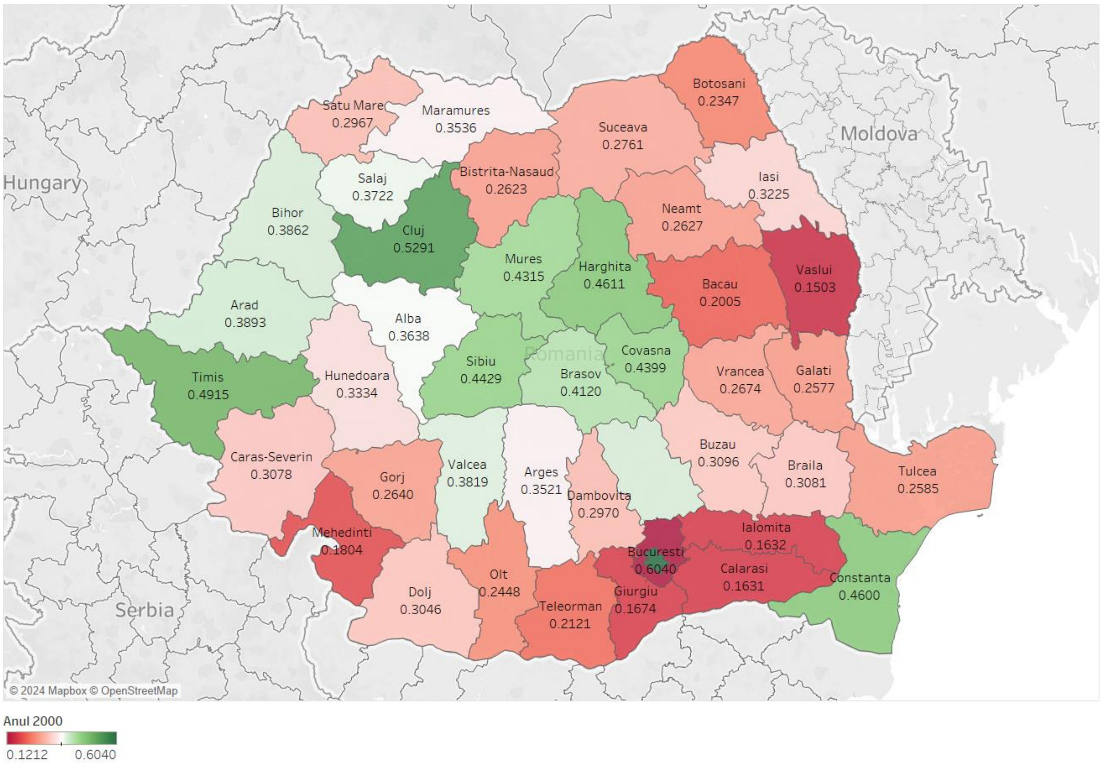
In the context of well-being indices, where certain dimensions are essential and cannot be compensated by others, the geometric mean ensures that each indicator contributes equitably to the final value of the index (Hadad, et al., 2022). A conclusive example is the Human Development Index (HDI), where the shift from arithmetic to geometric mean was made precisely to avoid excessive compensation and to ensure that each dimension (life expectancy, education and GDP) is adequately represented (Booysen, 2002).

The geometric mean is also particularly useful when indicators are non-substitutable, that is, when a deficit in one indicator cannot be compensated by a surplus in another. In the case of well-being, dimensions such as health, education and income are often considered non-substitutable, since each has an intrinsic importance. The geometric mean, being a partially compensatory method, ensures that all indicators contribute in a balanced way, without allowing for extreme compensations. This method is essential in the development of composite indices of social inequalities, providing a more balanced and reliable representation of socio-economic realities.

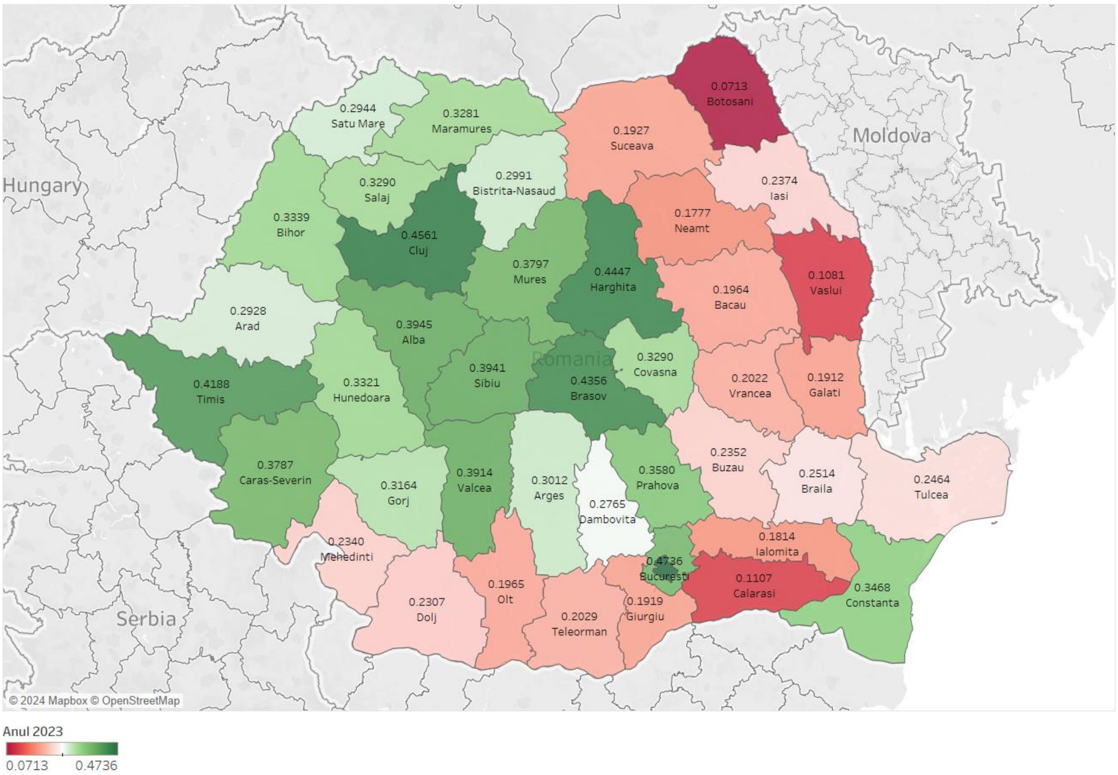
Figure 3 shows the dynamics of social inequalities, calculated by the geometric mean, highlighting the amplitude of inequalities' dispersion between counties. There has been a general trend of reducing social inequalities between 2010 and 2023, indicating sigma convergence of Romanian counties. In the period 2000 to 2010, inequalities fluctuated, reaching a peak of 43.1% in 2010, probably due to the global economic crisis of 2008-2009, which hit harder the more vulnerable regions. After 2010, a gradual decrease is observed, with a minimum of 33.2% in 2021, associated with the support measures during the COVID-19 pandemic. In 2023, the index returns to 34.6%, indicating an increase in social inequalities, possibly caused by inflation and recent macroeconomic problems.

In 2000, regional disparities were sizeable, with the largest social inequalities concentrated in Moldova and southern Romania, where counties such as Vaslui (0.1503), Bacău (0.2005), Teleorman (0.2121), Giurgiu (0.1674) and Ialomița (0.1632) recorded high levels. On the other hand, counties in the west and center of the country, such as Timiș (0.4915), Cluj (0.5291), Brașov (0.4120), Sibiu (0.4429) and Hunedoara (0.3334), were at the top of the ranking, with a well-being index above the national average (Figure 4).

Figure 4. Composite index of social inequalities calculated by geometric mean, 2000 and 2023



2000



2023

Source: developed by the authors using Tableau 2024.2

By 2023, social inequalities had been reduced in most counties, yet significant disparities persist at the regional level. In the western and central counties, such as Cluj (0.4651), Timiș (0.4188), Sibiu (0.4356), Alba (0.3945) and Arad (0.2928), major improvements were recorded, these countries exhibiting the lowest social inequality (Figure 4). On the other hand, in the poorer counties, such as Vaslui (0.1081), Botoșani (0.0713), Călărași (0.1107), Ialomița (0.1814), Giurgiu (0.1919) and Teleorman (0.2029), social inequalities persist, although smaller compared to the previous period.

The comparative analysis between the values of 2000 and 2023 inequality indices highlights an overall reduction in social inequalities, confirmed by a more uniform distribution of the index in 2023, reflecting the sigma convergence trend. The west and center of the country remain the most developed regions, maintaining a low level of inequalities, while Moldova and the south of the country continue to record the highest social inequalities, although some counties have experienced significant improvements. Economic crises and government measures have had a major impact on the evolution of the index, with post-crisis improvements and slight increases in inequalities during periods of economic instability.

The principal components method

The composite index of social inequalities was also calculated using the Principal Components Analysis (PCA) method, a statistical approach that combines multiple indicators into a synthetic measure, based on the statistical variance of the data. PCA assigns objective weights to indicators, automatically determining which variables contribute the most to the total variation, with the first principal component maximizing the explained variance. This method differs from other approaches, such as the arithmetic mean (which uses a simple or weighted sum of indicators) or the geometric mean (which reduces the effect of compensation between indicators through multiplicative aggregation).

The PCA method (Jolliffe, 2002; Yeturu, 2020) was used to create a composite index of social inequalities, as it allows the reduction of complex multidimensional data to a few principal components that capture most of the variation, eliminating the redundancy of correlated variables. This method provides an objective synthesis of social and economic indicators, such as average income, health, education, culture, justice, utilities, sports and tourism, accurately reflecting socio-economic trends and differences between counties. PCA is particularly useful for identifying key factors influencing social inequalities and for providing a clearer picture of their distribution across counties.

The method was applied to a data set comprising 1,008 observations, representing 42 counties over a period of 24 years and generated seven principal components, each with a distinct weight in explaining the total variation.

Table 1. Components

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	3.36909	2.31068	0.4813	0.4813
Comp2	1.05841	0.24015	0.1512	0.6325
Comp3	0.818258	0.229877	0.1169	0.7494
Comp4	0.588382	0.0555005	0.0841	0.8334
Comp5	0.532881	0.119406	0.0761	0.9096
Comp6	0.413475	0.193965	0.0591	0.9686
Comp7	0.21951		0.0314	1.0000

Source: own calculations based on data from INS, using Stata 18.5

The first two principal components (Comp1 and Comp2) together explain 63.25% of the total variation, which means that they capture most of the essential information in the data. Comp1, which explains 48.13% of the variation, is strongly influenced by income, health, education and culture, suggesting that these are key determinants of social inequalities. Comp2, which explains 15.12% of the variation, is dominated by crime, indicating that this factor has a distinct impact on the distribution of inequalities. The first three components explain 74.94% of the total variation, which is a high level of representation of the data. The subsequent components provide additional information about the relationships between the variables. Comp3, which explains 11.69% of the variation, highlights a link between tourism and utilities. Comp4, with 8.41% of the variation, shows an inverse relationship between tourism and utilities. Comp5, which explains 7.61% of the variation, is associated with culture but is inversely related to education. Comp6, which accounts for 5.91% of the variation, is influenced by income and is also inversely related to education. Comp7, which explains 3.14% of the variation, is dominated by education but is inversely related to health. These components provide additional insights into how variables interact and contribute to the structure of social inequalities.

Table. 2 Contribution of Variables to Principal Components (Eigenvectors)

Variable	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Comp7	Unexplained
Income	0.4388	-0.1910	-0.0964	0.0953	-0.0380	0.8313	0.2452	0
Health	0.4637	0.1116	-0.3300	0.0560	-0.2879	-0.0533	-0.7582	0
Culture	0.3923	0.1239	-0.2765	-0.3038	0.7953	-0.1587	0.0652	0
Tourism	0.3443	-0.0098	0.6086	-0.6780	-0.2222	-0.0403	-0.0186	0

Education	0.4488	0.1473	-0.2275	0.1619	-0.3977	-0.4400	0.5891	0
Crime	-0.0064	0.9320	0.2302	0.1621	0.0435	0.2238	0.0127	0
Utilities	0.3443	-0.2131	0.5746	0.6191	0.2715	-0.1887	-0.1150	0

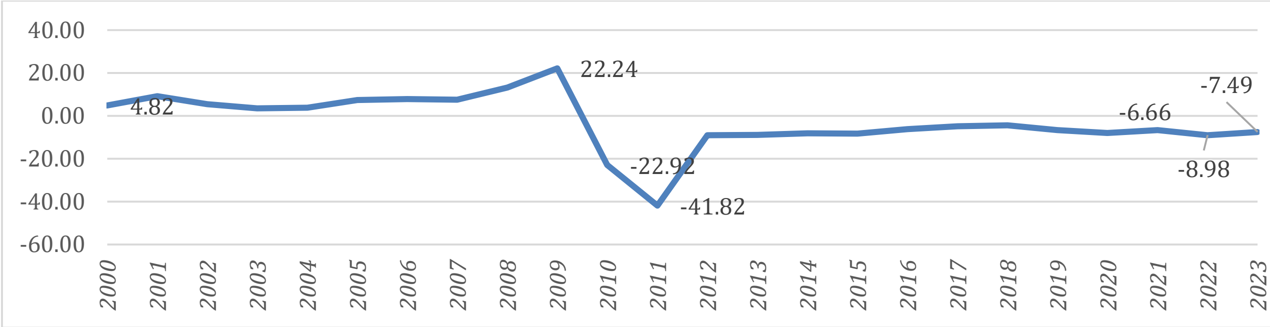
Source: own calculations, using Stata 18.5

PCA indicates that income, health and education contribute significantly to Comp1, highlighting their essential role in determining social inequalities, while crime dominates Comp2, confirming its status as an independent variable in this analysis; at the same time, the close relationship between tourism and utilities is reflected in their impact on Comp3 and Comp4, and culture and education strongly influence Comp5 and Comp6, but in opposite directions.

The PCA analysis generated a new variant of the composite index of social inequalities, offering an alternative to previous methods based on the arithmetic mean or weighted geometric mean. The results highlighted that social inequalities are determined by a complex combination of economic, social and cultural factors, and the first two principal components, dominated by income, health, education and crime, capture most of the variation.

As some authors point out, when composite indicators are used to measure a concept such as social inequality or well-being, there is a risk that PCA will generate an index that does not exactly correspond to the theoretical concept if applied mechanically (Pareto, 2015; Mazziotta & Pareto, 2018). In the case of social inequalities, which are a construct formulated by public policies and socio-economic theory, we could have a clear definition of what it means to reduce inequality. If the PCA decides that, say, the partial index of income receives a high weight and health a very low weight (due to different variances), then the PCA index will reflect almost entirely the convergence of income and less the convergence of other social aspects. Thus, the limitation is that the PCA index can provide a partial view, oriented by the variance statistics, of social inequality, while a holistic view should ensure that aspects with lower variance, but social importance are also adequately taken into account. In our case, the construction of the composite index faithfully reflected the theoretical concepts. Thus, Comp1, which explains 48.13% of the variation, is strongly influenced by income, health, education and culture, suggesting that these are key determinants of social inequalities.

Figure 5. Sigma convergence of the composite index of social inequalities calculated using PCA

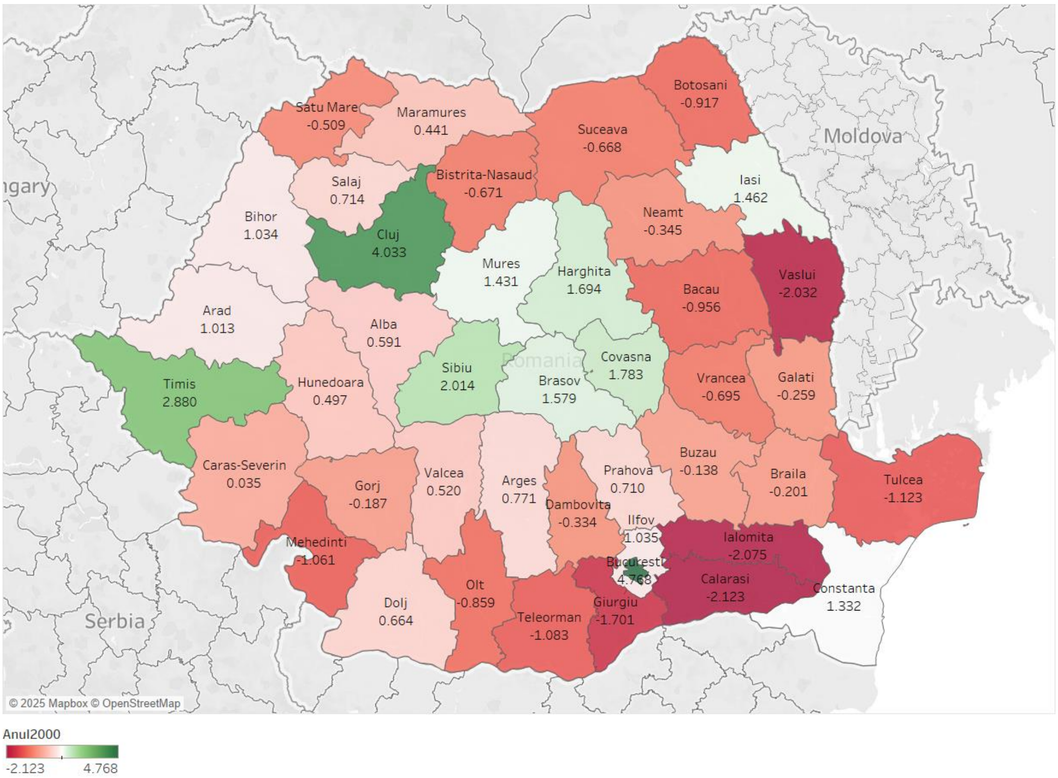


Source: developed by the authors based on data from the INS and own calculations

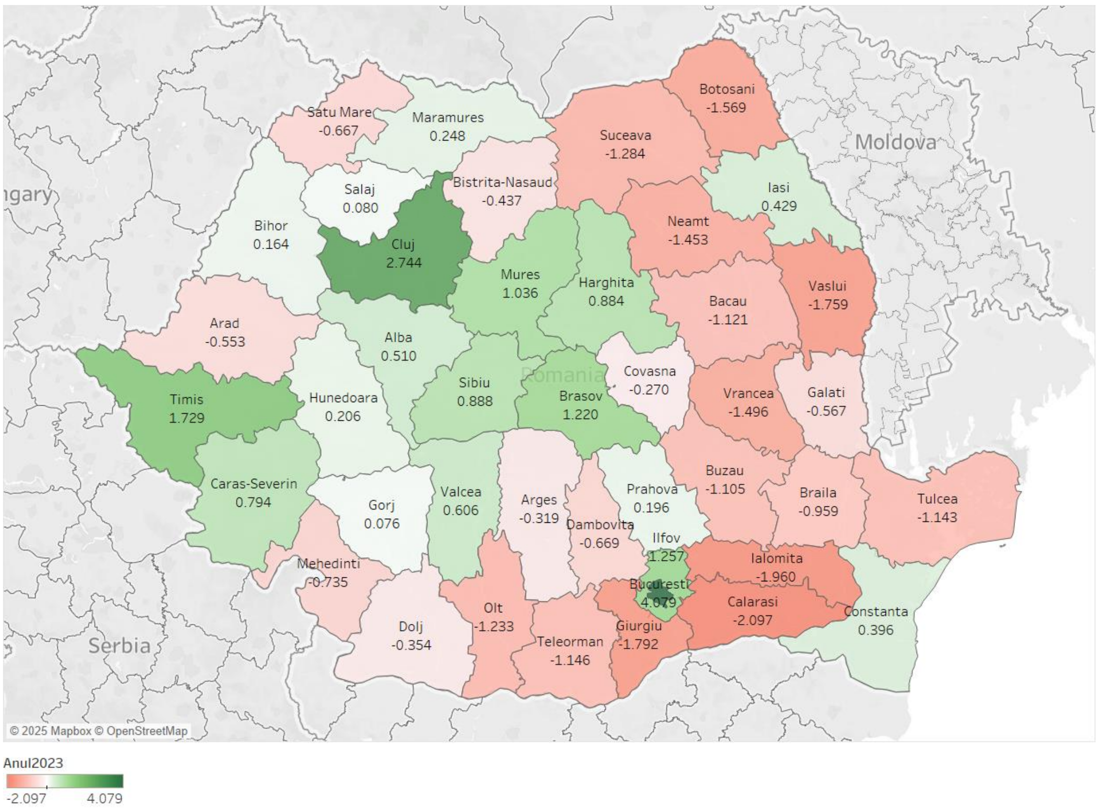
The graph on the sigma convergence of the composite index of social inequalities calculated using the principal components method (Figure 5) highlights the variations in social inequalities between 2000 and 2023, providing an insight into the evolution of regional disparities. During the period 2000-2008, the index shows a trend of increasing divergence between counties, reaching a maximum of 22.24 in 2009, coinciding with the effects of the global economic crisis that accentuated regional inequalities. After 2010, a sharp decrease in the index was observed (-41.82 in 2011), reflecting a significant reduction in inequalities, probably because more developed counties were more strongly affected by the crisis and due to the economic and social supporting measures implemented at national and European level. During the period 2013-2023, the index remained relatively stable, oscillating around the value of -10, which suggests a process of convergence of social inequalities. In 2023, the index is -7.49, indicating that although social inequalities have significantly reduced since 2010, the process has slowed down and regional disparities persist. In conclusion, while social inequalities have decreased since 2010, the convergence process is not complete and differences between regions remain visible, highlighting the need for continued policies to ensure a sustainable reduction in disparities.

Thematic maps in Figure 6 illustrate the distribution of the PCA composite index across Romanian counties in 2000 and 2023, reflecting the evolution of social inequalities at the regional level. In 2000, social disparities were larger, with the highest inequalities (negative values of the index) concentrated in the south and east counties: Vaslui (-2.032), Ialomița (-2.075), Călărași (-2.123), Tulcea (-1.123) and Teleorman (-1.083). These counties were affected by low incomes, poor infrastructure and limited access to education and social services. On the other hand, the counties in the west and center of the country, such as Cluj (4,033), Timiș (2,880), Sibiu (2,014), Mureș (1,431) and Brașov (1,579), had the best social positions, benefiting from developed economies, substantial investments and better access to education and health services. This distribution highlights the significant regional disparities that existed at the beginning of the period.

Figure 6. Composite index of social inequalities calculated using PCA, 2000 and 2023



2000



2023

Source: developed by the authors using Tableau 2024.2

For the year 2023, the map in Figure 6 shows a reduction in social inequalities in many counties, reflecting a more uniform distribution of the PCA index, which confirms the sigma convergence trend. Counties such as Timiș (1.729), Cluj (2.744), Sibiu (0.888), Alba (0.510) and Brașov (1.220) continue to have high values of the index, consolidating their status as developed regional centers, while counties such as Bihor (0.164), Arad (-0.553), Hunedoara (0.206) and Maramureș (0.248) experienced significant improvements compared to 2000. However, social inequalities persist in the southeast and east of the country, where counties such as Vaslui (-1.759), Ialomița (-1.960), Călărași (-2.097) and Teleorman (-1.792) continue to have negative values, reflecting significant economic and social disparities, such as poorly developed infrastructure, low incomes and limited access to essential services. In conclusion, although social disparities have reduced between 2000 and 2023, regional gaps persist, with the western and central regions maintaining their advantage over the eastern and southern parts of the country, highlighting the need for continued policies to address these imbalances.

Table 3. Results of estimating the trend equation for the Composite Index of Social Inequality calculated by different methods

	Coefficient	**Std. err.**	**t**	**P>|t|**	**[95% conf. interval]**	
Variant 1. Arithmetic mean						
t	-.0006461	.0000581	-11.12	0.000	-.0007601	-.0005321
_cons	1.606687	.1168812	13.75	0.000	1.377316	1.836058
R^2	0.1136					
F statistic	0.000					
Variant 2. Geometric mean						
t	-.0016366	.0000961	-17.03	0.000	-.0018253	-.001448
_cons	3.663939	.1933501	18.95	0.000	3.284504	4.043374
R^2	0.2130					
F statistic	0.000					
Variant 3. PCA						
t	-.8213093	.0517839	-15.86	0.000	-.9229313	-.7196873
_cons	1649.26	104.1639	15.83	0.000	1444.846	1853.674
R^2	0.2068					
F statistic	0.000					

Source: own calculations using Stata 18.5

The regression results in Table 3 show a decreasing trend in social inequalities, indicated by the negative coefficient of the trend variable (-0.0006461). This coefficient is statistically significant at a very high level of confidence ($p < 0.001$), which suggests that, in the long term, social disparities, in the case of the composite index of social inequalities calculated with the arithmetic mean, have had a decreasing trend. The relatively small value of the coefficient suggests a slow convergence process, which indicates that, although social inequalities are reducing, the pace of this process is not fast enough to eliminate the differences between counties. The intercept coefficient (cons = 1.606687) is positive and significant, indicating that the initial level of social inequalities measured by this index was high. Also, the value of the R^2 coefficient (0.1136) suggests that the trend variable explains only a small part of the variation in social inequalities, which indicates the presence of additional factors that influence this evolution and that are not captured by the trend equation.

Similarly, in the case of estimating the trend equation for the composite index of social inequalities calculated by the geometric mean method (Table 3) we observe a decreasing trend in social inequalities over time. The coefficient of the trend variable (-0.0016366) is negative and highly statistically significant ($p < 0.0001$), which confirms the existence of the convergence process. Compared to the arithmetic mean method, the value of this coefficient is higher, which suggests a faster reduction in social inequalities according to this model. The R^2 coefficient (0.2130) suggests that approximately 21.3% of the variation in social inequalities can be explained by the trend equation, a better explanatory capacity compared to the model based on the arithmetic mean (R^2 = 0.1136).

The results presented in Table 3 for the PCA method indicate a significant downward trend in social inequalities over time, confirming the existence of a convergence process. The estimated coefficient for the t variable is -0.8213, being negative and statistically significant at a 99% confidence level (p-value = 0.000). This means that the probability that this downward effect is due to chance is extremely low, reinforcing the conclusion that social inequalities have been systematically reduced over the analysed period.

Of the three methods, the principal components method indicates the most pronounced downward trend in social inequalities (-0.8213), also confirmed by the graph of the evolution of the sigma convergence. The R^2 value of 0.2068 shows that only 20.68% of the variation is explained by the trend equation. This result suggests a process of "social convergence": the differences (disparities) between counties in terms of the social indicators included in the composite index tend to decrease with the passage of time.

The Augmented Dickey-Fuller (ADF) test was further used to verify whether the composite index of social inequalities is stationary or whether there is a sigma convergence trend. The results are presented for three different methods of calculating the index: arithmetic mean (AM), geometric mean (GM) and principal component analysis (PCA).

Table 4. ADF test (dependent variable Δσ)

	Coefficient	Std. err.	t	P>|t|
Variant 1. Arithmetic mean				
t	-.0006969	.0000596	-11.69	0.000
$\Delta \boldsymbol{I_{AM}}$	.2861744	.0296364	9.66	0.000
_cons	1.621685	.1230294	13.18	0.000
$\mathbf{R^2}$	0.2616			
F statistic	0.000			
Variant 2. Geometric mean				
t	-.0006942	.0000652	-10.65	0.000
$\Delta \boldsymbol{I_{GM}}$	.1126008	.0184411	6.11	0.000
_cons	1.662206	.1343279	12.37	0.000
$\mathbf{R^2}$	0.2185			
F statistic	0.000			
Variant 3. PCA				
t	-.0010745	.0000655	-16.40	0.000
$\Delta \mathbf{I_{PCA}}$	-.0002337	.0000341	-6.85	0.000
_cons	2.468749	.1317396	18.74	0.000
$\mathbf{R^2}$	0.2263			
F statistic	0.000			

Source: own calculations using Stata 18.5

For all three methods of calculating the Composite Index of Social Inequality (arithmetic mean, geometric mean and principal component analysis), the coefficients of the t variable are negative and statistically significant (Table 4). This suggests a tendency for social inequalities to decrease over time, indicating a sigma convergence process. In the case of the Augmented Dickey-Fuller (ADF) test, the coefficient associated with the variable Δσ is negative and statistically significant in all variants of calculating the inequality index, which means that we can reject the null hypothesis of unit root. Consequently, the Δσ series is stationary, which suggests the existence of sigma convergence.

Summarizing, all results indicate the existence of convergence: the social inequality index tends to decrease over time, regardless of the method of calculating the composite index of social inequalities. The differences between the trend coefficients suggest that the PCA index, calculated by the method of principal components, captures this process most strongly. However, the relatively low R^2 values for all models indicate that additional factors, such as economic shocks, public policies or regional characteristics, play an important role in the evolution of social inequalities. Thus, although the convergence trend is clear and significant, short-term fluctuations are not fully explained by the trend equations.

To clarify these aspects (at least partially), we are going to analyse the impact of the 2009 economic crisis, as well as the COVID-19 pandemic, on the progression of the convergence process, investigating to what extent these events influenced the dynamics of social inequalities and whether they generated episodes of temporary divergence.

Table 5. The influence of economic crises on the convergence of the Social Inequality Index

	Coefficient	**Std. err.**	**t**	**P>|t|**	**[95% conf. interval]**	
Variant 1. Arithmetic mean						
t	-.0003519	.0000581	-6.05	0.000	-.000466	-.0002378
criza_2009	.007677	.0013454	5.71	0.000	.0050368	.0103172
criza_2020	-.0170893	.0014569	-11.73	0.000	-.0199483	-.0142303
_cons	1.015715	.1169276	8.69	0.000	.7862527	1.245177
Variant 2. Geometric mean						
t	-.0012669	.0000908	-13.95	0.000	-.0014451	-.0010887
criza_2009	.0333718	.0021014	15.88	0.000	.029248	.0374956
criza_2020	-.0162061	.0022755	-7.12	0.000	-.0206716	-.0117406
_cons	2.918784	.1826306	15.98	0.000	2.560384	3.277184
Variant 3. PCA						
t	-.8766805	.0562122	-15.60	0.000	-.9869931	-.766368
criza_2009	-5.792677	1.079709	5.37	0.000	3.673823	7.911532
criza_2020	-3.786817	1.408337	2.69	0.007	1.023054	6.55058
_cons	1760.23	113.0321	15.57	0.000	1538.412	1982.048

Source: own calculations using Stata 18.5

The results in Table 4 indicate a general trend of reducing social inequalities, confirmed by the coefficient of the time variable (t=-0.0003519), which is negative and statistically significant ($p < 0.001$). This finding supports the existence of a sigma convergence process, suggesting that differences in social inequality across counties have decreased between 2000 and 2023. However, the analysis of the influence of economic crises on this process (Table 5) reveals contrasting effects: the 2009 economic crisis had a significant positive impact (coefficient = 0.007677), suggesting that this recession led to an increase in social inequalities. This result indicates that the effects of the crisis were very unevenly distributed across counties, accentuating pre-existent disparities. On the contrary, the COVID-19 crisis had a significant negative impact (coefficient = -0.0170893), suggesting a decrease in inequalities during that period. This effect could be explained by the economic support measures implemented by the government, such as technical unemployment and investments in health infrastructure, which had a compensating effect on the lagging counties. These results highlight the sensitivity of the convergence process to major economic shocks and suggest that government interventions can play an essential role in mitigating their negative effects on social inequalities.

Similar to previous results, periods of crisis had a significant impact on the convergence of the social inequality index, calculated using the geometric mean method. The 2009 crisis led to an increase in social inequalities (coefficient = 0.0334), confirming their sensitivity to economic recessions. In contrast, the 2020 COVID-19 crisis had the opposite effect, contributing to the reduction of inequalities (coefficient = -0.0162). In conclusion, although long-term social inequalities have experienced a decline, periods of crisis have temporarily distorted this evolution. The 2009 economic crisis amplified disparities, affecting vulnerable regions more strongly, while the COVID-19 crisis had a compensating effect, thanks to economic and social interventions. To maintain the trend of reducing inequalities, it is essential to adopt a flexible economic strategy, capable of responding effectively to the challenges generated by external shocks and supporting the most affected counties.

The influence of crisis periods on the convergence process is stronger when using PCA as calculation method for the composite index of social inequalities (Table 5). Both the 2009 financial crisis (coefficient = -5.7927) and the 2020 COVID-19 crisis (coefficient = -3.7868) had a significant and steep impact on reducing social inequalities, contrary to the results for arithmetic and geometric means, where the 2009 crisis had the opposite effect. This discrepancy suggests that the PCA method is more sensitive to economic variations, capturing more precisely how economic shocks influence social inequalities. The differences between the calculation methods highlight the complexity of the phenomenon of social inequalities and the need for a multidimensional approach to better understand their dynamics.

5. Social inequalities and economic growth

Gross Domestic Product (GDP) is one of the most important macroeconomic indicators, used to measure the level of economic development of a country. It reflects the total value of goods and services produced during a given period and is frequently used to compare the level of prosperity between countries. However, GDP has significant limitations, as it does not effectively capture the level of well-being of the population. An economy can exhibit a significant increase in GDP, while affected by inequitable distribution of resources, limited access to education and health services, and therefore a high level of social inequalities.

GDP is not always correlated with a fair distribution of income and an increase in the quality of life for all citizens, although a high GDP is often associated with economic prosperity. GDP can be used as an indicator of well-being only if it is adjusted to include income distribution and quality of life (Clarke & Islam, 2002). Otherwise, this indicator risks overestimating the real development of a country, masking structural problems such as social exclusion and unequal access to economic opportunities. Furthermore, (Grigoryev & Pavlyushina, 2019) demonstrate that in many countries, even in periods of economic growth, social inequalities remain high. They analyse the evolution of inequality indicators at the global level and conclude that an economic policy based only on GDP growth does not automatically guarantee poverty reduction or improvement of living conditions for all citizens. While an economy may experience steady GDP growth, this progress does not automatically entail an improvement in the quality of life for the entire population, especially if income is distributed inequitably (Singh & Singh, 2020). In many countries, rapid economic development has led to widening social gaps, as additional resources have been concentrated in narrow segments of society, while access to essential services, such as education and health, has remained limited for vulnerable groups. In this context, the HDI offers a more balanced approach to assessing real development by considering not only economic output, but also essential factors of human well-being. Therefore, Singh & Singh (2020) argue that GDP, in the absence of effective resource redistribution policies, can be a misleading indicator of progress, highlighting the importance of using multidimensional measures to more accurately reflect the social and economic reality of a country.

To analyse the relationship between GDP and the composite index of social inequalities, calculated using the three methods (arithmetic mean, geometric mean and principal components method), we applied a statistical regression model. This model allowed us to investigate the impact of economic growth, measured by GDP, on the level of social inequalities, considering the different approaches to aggregating the indicators.

Table 6. Evolution of social inequality indices in relation to GDP

	I_{PCA}		I_{MG}		I_{MA}	
Variable	**Coefficient**	**P>|t|**	**Coefficient**	**P>|t|**	**Coefficient**	**P>|t|**
GDPcap	.0001361	0.000	9.23e-06	0.000	.0000119	0.000
_cons	-1.870514	0.000	.1647209	0.000	.2249988	0.000
Prob > F	0.0000		0.0000		0.0000	
R^2	0.4065		0.3140		0.4374	
Adj R^2	0.4059		0.3133		0.4368	

Source: own calculations using Stata 18.5

The analysis of the relationship between GDP per capita and social inequality indices calculated by the three methods confirms the existence of a significant link between these variables. All methods used indicate a positive correlation, which suggests that as GDP per capita increases, the well-being index increases.

The index calculated by PCA (I_{PCA}) presents the highest coefficient (0.0001361), which indicates that this method more strongly reflects the relationship between GDP and well-being/inequalities. However, the index calculated by Arithmetic Mean (I_{MA}) has the highest R^2 (0.4374), which means that this method provides the best statistical explanation of the variation in social inequalities depending on GDP per capita. In contrast, the index based on Geometric Mean (I_{MG}) presents the weakest correlation, with an R^2 of 0.3140, indicating a weaker (although still significant) relationship between these variables.

The results of the analysis confirm that GDP is a fundamental economic indicator, but insufficient to assess the real level of welfare and social inequality. Although there is a positive correlation between GDP and the composite index of social inequalities, the way in which this relationship manifests itself depends on the calculation method used. An essential aspect that emerges from these results is that, although GDP increases, this does not automatically guarantee a reduction in social inequalities or a uniform improvement in the quality of life. Studies in the literature (Clarke & Islam, 2002) have demonstrated that economic policies based exclusively on GDP growth are not sufficient to ensure a fair distribution of resources, and complementary measures are needed that target social inclusion and equal access to education, healthcare and economic opportunities.

6. Conclusion

The study highlights the complexity of the phenomenon of social and economic inequalities and the need to use a multidimensional approach to better understand and manage this process. Social inequalities cannot be reduced through economic growth alone, but require integrated policies, based on fair redistribution, social investments and targeted interventions for vulnerable groups**.**

The choice of the method for calculating our new composite inequality index influences the measure and interpretation of this phenomenon, each one of the three methods employed having both advantages and limitations. The PCA method best captures the dynamic variations of inequalities, the geometric mean offers a balanced approach, and the arithmetic mean is the most accessible and intuitive.

In the long term, the analysis indicates a general trend of reducing social inequalities, but this process has not been uniform or linear, and the overall decline in regional inequalities is feeble.

Our results indicate that the long-term evolution of regional inequalities has been influenced by economic factors, such as the pace of GDP growth, and also by external shocks such as economic crises or pandemics. The global financial crisis of 2009 led to a sharp increase in social disparities, particularly affecting more vulnerable regions, while the support measures implemented during the COVID-19 pandemic contributed to a temporary reduction in inequalities. These fluctuations demonstrate that social inequalities are not a static phenomenon but depend on economic dynamics and the effectiveness of government interventions.

Reducing social inequalities requires a long-term strategy, based on adaptable public policies, robust measurements and a holistic view of economic and social development. The success of this process hinges on the capacity of governments to implement effective policies to reduce social disparities and to adapt to the new global economic realities.

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