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Exploring variation in data on income inequality across databases and measures in post-socialist countries

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Abstract

Despite the growing interest in income inequality, cross-country evidence often shows variation between measures and databases, which complicates research and policy evaluation. The objective of the article is to compere the consistency of data on income inequality in post-socialist countries from Central and Eastern Europe and Central Asia for the commonly used measures on the basis of leading databases in this area. Other such analyses typically focus on individual measures, databases or specific countries, which prompted the idea to fill the research gap for a targeted country group. The formulated hypotheses were to test the consistency of the following: development trends, the rankings of countries from the most to the least equal in terms of income, and the values for different measures indicated by databases.
The study reveals high correlations in income inequality trends over the long term, particularly among the EU subgroups. Certain consistency was observed in the context of identifying countries with extreme income equality or inequality, and in the rankings between different measures from the same database. However, there was no full consistency, especially in non-EU countries, which highlights the impact of the methodological differences.
This article contributes to the existing body of research on income inequality by providing a broad analysis of the consistency and variability of the related data across different measures and databases, with a particular focus on post-socialist countries. It points to the importance of careful data selection when analyzing income inequality in the indicated group of countries, as individual differences between measures, databases and countries tend to affect the final results of the research.

Key words: income inequality, post-socialist countries, statistical analysis.

1. Introduction

Measuring income inequality is a comprehensive task that involves complex and multifaceted decisions. The process begins with selecting data collection methods and defining how to process and interpret the values. Key decisions also include aspects such as replacing missing responses, choosing the right measure, or interpreting

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findings in a social and economic context. In addition, inequality is measured at specific points in time, not providing a complete picture of its evolution. Even the most precise measures capture inequality only within a population at a given time, without reflecting changes in individual income or wealth over time (Pascola, Rucha, 2017).

The aim of the article is to examine the variation and consistency in changes in income inequality over time in post-socialist countries of Central and Eastern Europe and Central Asia, using leading databases and common measures that differ in their data collection methods, directly affecting the obtained results. Since the transformation from the socialist system in 1989, there were significant changes affecting income distribution in all studied countries, but with varying intensity among them (Milanovic, 1998; Brzezinski, Salach, 2022). A group of post-socialist countries began their economic transition with low levels of inequality and relatively small disparities between them. Today, however, the variation in income inequality within this group is substantial, ranging from low to high polarization.

The transformations of the past three decades pose greater challenges for measuring income polarization than in countries without such systemic shifts. However, studies on variation and homogeneity of income inequality mostly focus on Western European countries rather than on the post-socialist group. The study presented in this article focuses on a broad comparison of development trends, levels and rankings of income inequality using data for the Gini coefficient, income shares of individual deciles, Atkinson index, and Palma ratio from eight databases such as World Inequality Database, Standardized World Income Inequality Database, Luxembourg Income Study, OECD, World Income Inequality Database, World Development Indicators, Eurostat, and Global Consumption and Income Project The results may contribute to international analyses of income polarization within this group.

Section 2 discusses methodological issues related to inequality measurement and differences between databases and measures, followed by an analysis of inequality evolution since the 1990s. Section 5 examines trend stability, ranking consistency, and value variation, while the final section presents conclusions.

2. Methodological issues of measuring inequality

To provide a detailed introduction to the problem under study, this section presents the differences between the measures, databases, and data collection methods, as well as an overview of empirical studies focused on these three dimensions. Each of these components can affect the final values of income distribution equality differently, leading to a more or less accurate representation of reality. The literature reports cross-country variation in inequality levels, differences in data smoothing across sources, and partial consistency in long-term trends or country rankings.

2.1. Differences depending on methods of data collection

The choice of data collection method significantly affects inequality estimates and their reflection of reality. Unfortunately, various methodological problems are associated with different methods. The literature distinguishes three main approaches: survey-based, fiscal, and mixed methods.

Standardized questionnaires are a common quantitative research method, valued for structure and cross-respondent comparability. However, this method faces challenges of nonresponse and underreporting, which may distort estimates, particularly for high-income households (Vermeulen, 2016). Refusals to participate in surveys can further skew the representation of the surveyed population, although this approach ensures frequent data collection. Despite these limitations, surveys excel in representing the incomes of lower-income individuals or households but may not fully capture the impact of high earners on overall income inequality dynamics (Larrimore, Burkhauser, Armour, 2018). Moreover, respondent errors in reporting income introduce inaccuracies, potentially blurring the true income distribution, especially if not uniformly distributed across respondents. Therefore, while survey-based methods offer valuable insights, their integration with other data sources and rigorous statistical techniques is essential for a comprehensive understanding of income inequality dynamics.

Top incomes, although representing a small part of the population, contribute significantly to total income and tax revenues, making them crucial for inequality indicators (Alvaredo, 2011; Atkinson, Piketty, Saez, 2011; Blanchet et al., 2018). Tax data serve as the primary source for capturing this income level, free from survey participation biases. However, this method faces drawbacks, such as limited comparability over time due to legislative changes and across countries due to tax-system differences (Atkinson, Piketty, Saez, 2011). Additional challenges include tax evasion, underreporting, and omission of income sources such as transfers, informal earnings, or agriculture (Bukowski, Novokmet, 2017). These factors risk overestimating income inequality and underrepresenting lower earners in the analysis.

The strengths and weaknesses of survey-based and tax-based approaches complement each other. Surveys capture poorer households well but tend to underestimate inequality. Conversely, tax data accurately depict top incomes but may exaggerate inequality levels. Mixed methods, such as the UK’s 'SPI adjustment' (Larrimore, Burkhauser, Armour, 2018) and the WID approach combining survey data for lower incomes (below the 0.90th percentile) with tax data for the top ones (above the 0.99th percentile) (Alvaredo et al., 2016), aim to reconcile these disparities. These methods reduce under- and overestimation, resulting in a more accurate picture of reality. Such approaches contribute to providing comprehensive insights into income distribution dynamics across different income percentiles.

In summary, the selection of data collection methods strongly impacts measurements of inequality and introduces methodological hurdles. Surveys provide structured data but suffer from downward bias, particularly for higher incomes. Fiscal data captures high earners but overlooks certain sources and lacks international uniformity. Mixed methods aim to counter these shortcomings by merging survey and tax data. Implementation challenges include limited access to fiscal data and methodological complexity. Collaborative endeavors are vital to refining methodologies and maximizing data utility for a comprehensive analysis of inequality. All this can lead to differences of several p.p. between data based on various data collection methods at specific points in time and even show different development trends over time.

2.2. Differences depending on selected measures of income inequality

The perception of income inequality depends not only on data collection methods but also on the choice of inequality measures. The choice of a particular measure of income inequality can significantly change the perceived level of it, and even, through methodological differences, indicate differential development trends, even though they are often really similar between measures (The Equality Trust, 2011). One of the reasons for the varying empirical results is being sensitive to different parts of the income distribution (De Maio, 2007).

The Gini coefficient (Farris, 2010) is a widely used measure of income inequality, calculated as the average income difference between all pairs in a population divided by twice the mean income. It ranges from 0 (perfect equality) to 1 (perfect inequality). While intuitive and easy to visualize, it is most sensitive to changes in the middle of the distribution and cannot be decomposed analytically (Solt, 2020). Moreover, identical Gini values may correspond to different income distributions, and the measure ignores demographic shifts or income mobility, which has raised methodological concerns (Piketty, 2014; Corak, 2013).

The Atkinson index (Atkinson, 1970) provides a broader perspective by incorporating social preferences for equality through a welfare function. Its value depends on the inequality-aversion parameter ε (Dubois, 2016; Latty, 2015), which weights disparities at different income levels. Unlike the Gini coefficient, it is sensitive to changes across the entire income distribution (De Maio, 2007). However, the index's subjectivity complicates cross-study comparisons when different ε parameters are applied. Despite being decomposable (Bellu and Liberati, 2006), it remains less commonly used than the Gini coefficient.

Income shares across quartiles, deciles, or percentiles provide valuable insights into distributional dynamics (Jędrzejczak, Pekasiewicz, 2018). While aggregate measures offer a general picture, examining individual distribution segments, especially pre- and post-transfer data, allows deeper analysis of who benefits from policy or economic change (Eurostat, 2020; Voitchovsky, 2005; Sitthiyot, Holasut, 2020). On this basis, positional indicators such as the Palma ratio compare the income share of the richest decile with that of the poorest 40% (Cobham, Schlögl, Sumner, 2016), focusing on the distribution tails, assuming stability in middle deciles (Cobham, Summer, 2013).

Income inequality analysis involves various measures that present slightly different calculations of the level of inequality in the income distribution, with individual sets of both the advantages and disadvantages. While the Gini index is popular and simple to interpret, it can take exactly the same values with widely varying income distributions skewing the final picture of inequality. The Atkinson Index provides a unique perspective based on social preferences, but this can be a problem when drawing conclusions. Data on average income and social group shares help to understand the dynamics of specific segments of society, but do not provide a clear, straightforward answer about the level of inequality in society as a whole. In contrast, using the Palma ratio, targeting the extremes of the distribution can better respond to changes in key areas of inequality, but it ignores 50% of income distribution. Therefore, a full understanding of income inequality can require a combination of different measures to capture the multifaceted nature of this complex phenomenon.

2.3. Differences between databases

The third factor affecting inequality estimates is the choice of database and its underlying methodology. Many databases are secondary sources but differ in interpolation, data types, and the treatment of missing observations or zero incomes. All these aspects can affect the outcomes, even if the original, primary-source dataset was identical among few databases. The most important databases include Luxembourg Income Study, Eurostat, Global Consumption and Income Project, Standardized World Income Inequality Database, World Income Inequality Database, OECD – Income Distribution Database, World Development Indicators, and World Inequality Database.

Luxembourg Income Study (LIS) provides harmonised, survey-based microdata collected by national statistical agencies under common protocols. These data are fully based on surveys and are kept only for individual years without interpolation, unlike most of the databases, where the coverage covers even several dozen years for individual countries. Its great advantage is the full methodological consistency between the countries surveyed, from the level of the questionnaire, which is compiled to make it easy to understand for the recipients, to the way it is harmonized. However, LIS remains vulnerable to top-income undercoverage and non-response (Ravallion, 2015).

Eurostat provides primary survey data from the European Union Statistics on Income and Living Conditions (EU-SILC) survey, which collects data on income, poverty, social exclusion, and living conditions of households and individuals across the EU. Data collection is outsourced to statistical offices in individual member states, which tune into the methodology adopted by Eurostat. EU-SILC is not inequality-specific; it primarily reports income (including quintiles) and poverty indicators. Eurostat also provides the so-called "experimental" data calculated as part of the Income, Consumption and Wealth (ICW) statistics, which are computed through the statistical matching of three data sources: the EU Statistics on Income and Living Conditions (EU-SILC), the Household Budget Survey (HBS) and the Household Finance and Consumption Survey (HFCS). Another database based on primary household survey data obtained from government statistical agencies and World Bank country departments is World Development Indicator (WDI), but for high-income economies data are incorporated mostly from the LIS database. Regardless of the source, the data used are subject to a uniform estimation method.

In terms of secondary source databases, the dataset by Lahoti et al. (2016) - the Global Consumption and Income Project (GCIP) - is another example based mostly on survey data, though not exclusively. Its survey component compiles data from multiple sources, mainly other databases focused on international comparisons, but also from national statistical offices and academic studies on individual countries, creating a large and diverse dataset built on a homogeneous methodology. The aim is comprehensive, integrated coverage that mitigates source-specific errors, though survey-method limitations remain. SWIID (Solt, 2009) also combines multiple sources and includes more government-provided and fiscally-based inputs. However, the main difference between the two databases lies in their approach to data standardization. Both use econometric estimations, but SWIID follows the LIS methodology as its gold standard (Solt, 2020), whereas GCIP applies its own quintile-specific consumption-income ratio method and additionally interpolates missing data. The World Income Inequality Database (WIID), compiled by WIDER, aggregates income data from numerous sources and studies into a single accessible dataset but does not standardize them, which distinguishes it from the two previous databases (UNU-WIDER, 2022). Similarly, the OECD’s Income Distribution Database (IDD) combines multiple sources, mainly surveys, with occasional tax data. However, results may differ due to its correction procedure, which adjusts all household income components by the square root of household size (OECD, 2017; OECD, 2023).

World Inequality Database (WID) takes a completely different approach than previous databases. When it is possible for some fiscal data to appear in other databases, they are not subject to special treatment, at most averaged with the rest of the data. WID, on the other hand, assumes that survey data accurately reflect the income of the lowest part of society but underestimate the highest income, quite the opposite of fiscal data, therefore, it combines these data in an appropriate way to obtain more balanced results (Alvaredo, Atkinson, Chancel, Piketty, Saez, Zucman, 2016).

Among the selected databases, the majority relies on survey data, often combined with additional data from national offices. However, substantial differences between them can significantly impact the obtained results. An exception is WID, which innovatively employs fiscal and survey data. Notably absent are purely fiscal data sources, due to variations in their availability among countries and possible discrepancies between providers of such data.

2.4. Empirical studies on the variation of income inequality depending on the method of measurement, measure and database

Based on the presented data collection methods, inequality measures, and databases, clear differences emerge that can lead to variation in estimated inequality levels. Empirical studies show that estimates from administrative tax data often differ markedly from survey-based results, both in levels and trends over time. Moreover, methodological factors, including the choice of measure or database, can produce similar discrepancies due to differences in harmonisation and data interpolation.

Studies comparing survey and tax-adjusted data show differences of several percentage points (p.p.) in Gini coefficients, while maintaining consistent long-term trends. Jenkins (2017) indicates that the Gini coefficient for gross individual income in the UK estimated from tax data rose by 7–8%, whereas survey data showed a 5% decline over the same period. According to Bartels and Metzing (2019), the income shares of the top 1% in Germany were higher in the tax data than in the surveys by 3–6 p.p., but the estimates of the income share of the top 10–5% and top 5–1% are of similar magnitude in both data sources. Their research also indicates the relevance of the choice of data pooling method, as their integrated approach indicated slightly lower levels of income inequality than the decomposition method (Alvaredo, 2011). Similar gaps were found elsewhere: about 6 p.p. in the US (Burkhauser et al., 2012), 12–14 p.p. in Russia (Novokmet et al., 2018), and 14% in Spain (Ayala, Perez, and Prieto-Alaiz, 2021). In Poland (1994–2015), Brzezinski, Myck and Najsztub (2022) found that adjusting survey data with fiscal data on top incomes increased Gini values by 14–26% (4–8 p.p.) relative to unadjusted estimates. The authors also show that the adjustment changed the development trend of Ginis, with a sharp change in the level of inequality of income distribution, which was invisible in survey-only data.

In terms of databases, Bartels and Metzing (2019) comparing nine countries using EU-SILC and WID, found that differences are minor for some countries but reach up to 9% for others. However, differences can also arise with similar methods. Similar conclusions are also indicated by analyses focused on other databases such as LIS, OECD, EU-SILC, and WDI (Galbraith et al., 2016). Jenkins (2015), based on two secondary databases, SWIID and WIID, shows that differing data implementation can distort inequality estimates, with SWIID tending to over-smooth results. Ferrerira, Lustig and Teles (2015), comparing eight databases (including LIS, WIID, SWIID, IDD, among others), found a high degree of consistency in long-term trends across most countries. However, for specific country–year observations, methodological differences cause substantial discrepancies, sometimes leading to divergent conclusions depending on the chosen dataset. These discrepancies concern not only inequality levels but sometimes even the direction of year-to-year changes. In a similar comparison, Galbraith et al. (2016) also presented the overall consistency with the occurrence of large differences in specific countries, and added indications of significant deviations from other databases compared to data from the WDI.

Moreover, in terms of the measures, according to Trapeznikova (2019), research shows general agreement on trends and rankings of countries in terms of levels of income inequality, although the author notes the importance of including measures sensitive to changes in marginal income in order to arrive at more precise conclusions. However, Goda (2016) argues that due to methodological issues, the choice of a particular measure can indicate divergent development trends, even if they are often similar between the measures.

The literature has examined how the above aspects affect income distribution equality. Researchers note fluctuations between countries, varying degrees of data smoothing depending on the source, and inconsistent long-term trends or rankings across measures. However, most studies focus on individual countries or groups of countries from Western Europe or the US. Post-socialist countries have experienced some of the largest observed changes in income inequality in recent decades, with significant changes occurring both in individual countries and the group as a whole. However, research in this area has mainly focused on a few examples like Poland, Russia, or the Czech Republic, leaving a gap in studies analyzing the group as a whole. This article aims to address that gap.

Based on the analyzed studies, three research hypotheses were formulated. First, the analysis will examine whether post-socialist countries exhibit long-term trend consistency across different measures and databases. Second, the study will assess the consistency of country rankings within the group at specific points in time. While measures and databases may show similar inequality trends for a given country, rankings can still differ in identifying which countries are most or least equal at a given time. The differential ranking may be the result of significant differences in the measurement of values, for this reason, consistency of the measurement of inequality levels over the entire study period will also be tested. The research hypotheses are:

- H1: A cohesive pattern is evident in the evolution of income inequality trends among post-socialist countries, irrespective of the measures and databases used;
- H2: The classification of post-socialist countries based on income inequality reveals a consistent homogenization within the same measures from different database;
- H3: Values for the same inequality measures exhibit consistent stability and limited variation across different databases in post-socialist countries.

3. Data selection and analytical strategy

This analysis examines the consistency of income inequality levels and trends over 30 years across selected measures and databases. The study includes eight major sources: World Inequality Database, Standardized World Income Inequality Database, Luxembourg Income Study, OECD - Income Distribution Database, World Income Inequality Database, World Development Indicators, Eurostat, and Global Consumption and Income Project. These databases, both primary and secondary, differ in data collection, processing, and implementation. The selected inequality measures - Gini coefficient, income shares by decile, Atkinson index, and Palma ratio - capture both overall inequality and distributional segments. More details on these databases and measures were discussed in the previous section. Table 1 outlines the selected measures from each source, with variations due to data availability.

Table 1: Summary of variable and database selection

Database	Measure
World Inequality Database	Gini coefficient
	Income shares of individual deciles
	Palma ratio
Global Consumption and Income Project	Gini coefficient
	Atkinson index
	Palma ratio
	Income shares of individual deciles
Standardized World Income Inequality Database	Gini coefficient
Luxembourg Income Study	Gini coefficient
	Atkinson index
OECD - Income Distribution Database	Gini coefficient
	Palma ratio
World Income Inequality Database	Gini coefficient
	Palma ratio
	Atkinson index
	Income shares of individual deciles
World Development Indicators	Gini coefficient
Eurostat	Gini coefficient (EU SILC)
	Gini coefficient (EU SILC - experimental)

Source: own compilation.

To confirm each of the three hypotheses, the following analyses were conducted. For the first hypothesis (H1), which posits cohesive patterns in inequality trends, Pearson correlation coefficients were calculated to assess their consistency over time. These correlations were examined both between databases for the same measure (cross-source consistency) and between measures within the same database (internal consistency). To confirm H2, which concerns the consistency of country classifications based on income inequality, country rankings were created for each measure and compared across datasets. The rankings, ordered from most equal to most unequal, were generated separately for each measure and analyzed across selected years to assess whether countries maintained similar rankings within a given year. For the third hypothesis (H3), concerning the stability and limited variation of inequality, we statistically analyzed variation in inequality levels across measures. Detailed results are presented in Section 5.

4. Data on income inequality in post-socialist countries

Income inequality trends across countries, based on the previously discussed measures and databases, indicate an initial rise in inequality until around 1995 or 2000, varying by country. Future EU members generally experienced a milder and shorter polarization phase than other post-socialist nations, followed by a period of relative stability. The time-series evidence confirms a broad consistency among different databases and inequality measures regarding long-term dynamics, which aligns with the findings of Ferrerira, Lustig, and Teles (2015). Nonetheless, individual observations reveal some notable discrepancies.

Starting with the Gini coefficient, the only measure analyzed in the study with data available from the Standardized World Income Inequality Database, the trend analysis confirmed the issue identified by Jenkins (2015) regarding excessive smoothing of data from this database over time. Consistent with previous studies (Vermeulen, 2016; Alvaredo, 2011; Atkinson et al., 2011; Blanchet et al., 2018), the World Inequality Database reports the highest Gini values across nearly all countries. While long-term trends align, year-on-year changes differ between databases, as noted by Ferrerira, Lustig, and Teles (2015). At the country level, the average year-to-year difference between databases was 11.83 points (on a scale of 0-100). The Czech Republic and Hungary showed the highest consistency, with only minor deviations, whereas Azerbaijan exhibited the largest discrepancy - exceeding 30 points in a single year - suggesting significant income polarization.

The data on the Palma ratio confirm conclusions similar to those drawn from the Gini coefficient. Once again, the World Inequality Database exhibits the widest spread in values, with several significant outliers. This issue is particularly evident in Lithuania, where between 2018 and 2019, the Palma ratio surged from 3.23 to an implausible 16.32—an error also reflected in the pre-tax data, indicating an almost 24-fold increase in one year. Due to this anomaly, observations for Lithuania had to be partially excluded from subsequent analyses to prevent data distortion. A similar problem with outlier observations appeared in the Global Consumption and Income Project, affecting Armenia and Kyrgyzstan, as well as in the World Income Inequality Database for Kyrgyzstan and Russia, though in these cases, the maximum change was 10.7 points.

The Atkinson index differs due to varying parameter ε settings across databases: 0.5 in the World Income Inequality Database, 1.5 in the Luxembourg Income Study, and unspecified in the Global Consumption and Income Project. According to Latty (2015) the difference significantly affects the level of the obtained WIID data points out values from 1.87 to 27.34, the LIS value does not exceed 0.2, and in the case of GCIP it is a range of 0.9-0.93. Hence, the data are comparable only in terms of rankings and correlations, not absolute levels. Notably, WIID and GCIP provide data spanning a much longer period than LIS and cover all countries, revealing recurring development patterns consistent with previous measures, as well as similar cases of outlier observations.

The data on income shares by decile particularly highlighted the earlier differences between the databases. For the total income of the poorer half of the population, the databases again converge on the direction of change and the overall development trend. Consistency is particularly evident between the World Inequality Database and the Global Consumption and Income Project, where income shares stabilized after a period of significant declines. However, the World Income Inequality Database indicates an additional partial increase in shares during the later period. Similar patterns are observed for the top 10% of income. All databases in this case show an increase in shares, with the largest changes occurring until around 1995, though the magnitude of these changes varies significantly between countries. This example also illustrates why WID shows the highest inequality among the measures, as its post-2000 values exceeds the highest values indicated by WIID, reflecting a much greater enrichment of the wealthy and impoverishment of the poorer population after 1989. This difference is particularly significant when examining the average inequality values over time, which are shown in Figure 1. WIID is the only database that shows an equalization of the incomes of the bottom 50% with the top 10%, followed by an increase in the incomes of the poorer 50%. These values also highlight the significant impact that the inclusion of non-survey data has on the final inequality measures. The WIID, based solely on survey data, indicated that on average during the period studied, the incomes of the richest 10% accounted for 0.95% of the incomes of the bottom 50%. The GCIP, which includes national accounts data, indicates a relationship of 122%, while the WID's inclusion of fiscal data results in a nearly doubled difference, at 199%. Given the significant methodological differences among the three databases, these discrepancies confirm De Maio's (2007) findings on differences in empirical results when targeting different parts of the income distribution, particularly in obtaining more precise data on the top decile. Moreover, the database containing fiscal data indicates greater fluctuations and more dynamic changes.

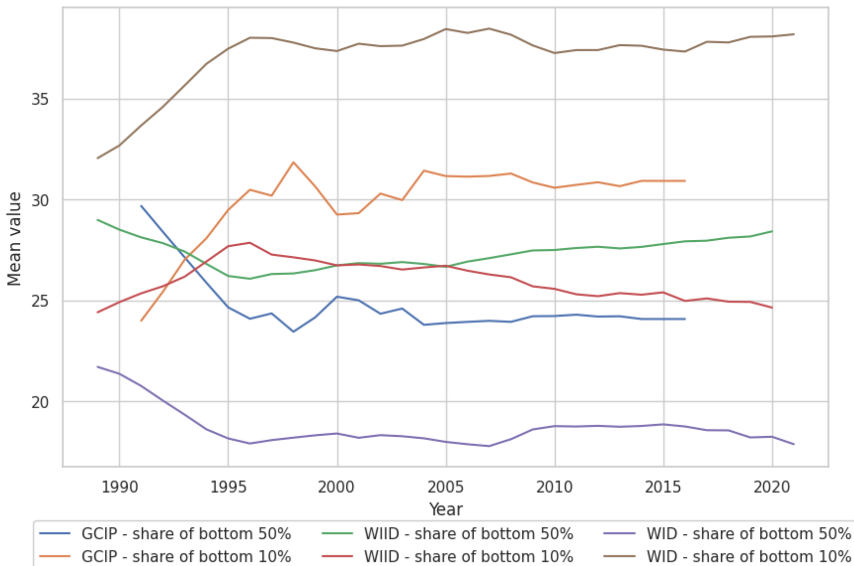

Figure 1: Average income shares of the 50% bottom earners and 10% top earners

Source: own compilation based on: Global Consumption and Income Project, World Income Inequality Database, World Inequality Database.

The data review confirms overall consistency in long-term trends but highlights inconsistencies in year-on-year changes, varying across countries. Outliers appear in each measure, with notable differences between EU and Central Asian countries. The analysis also reinforces concerns about data oversmoothing and the impact of survey-only vs. mixed data sources. This study further assesses how these inconsistencies influence income inequality research.

5. Findings

To properly conduct the study, the analysis was divided into three subsections aligned with the research hypotheses. The analysis begins with inequality trends previously observed in other country groups but not empirically verified for post-socialist countries. The focus then shifts to country rankings, moving from the level of individual countries to the entire group over time. The third stage involves value differentiation, which may not occur even if countries are ranked similarly and their development trends are perfectly correlated. Since differences in the data between EU and non-EU countries became apparent, the dataset was divided into subgroups for part of the analysis. In addition, because data availability for these subgroups is uneven, this division will provide more accurate results. Similarly, the issue of outlier observations and the inability to fully analyze variations in Atkinson index values due to differing ε parameters were addressed.

5.1. Consistency between the trends of income inequalities

The actual occurrence of consistency in income inequality trends was checked by analyzing correlation coefficients from available databases. This includes correlations within data for a single measure and between different measures, as methodological differences may result in more consistent data for specific metrics. The analysis covered the entire group of countries studied and two subgroups defined by membership in the European Union. Trend consistency analysis is particularly vulnerable to result distortion if there are unequal outcomes for any subgroup, as significantly higher (or lower) correlations in one group could skew the overall study results.

At the group level, correlation analysis of the Gini coefficient shows mostly high correspondences. The only low result (35%) was observed between Global Consumption and Income Project (GCIP) and World Development Indicators (WDI). World Inequality Database (WID) consistently exhibits lower correlations (0.63-0.83) with other datasets. This is expected as WID is the only database incorporating fiscal data which can inflate inequality estimates and capture fluctuations not visible in survey-based sources. All correlations are positive, confirming a consistent long-term trend, despite previously noted year-on-year inconsistencies. At the subgroup level, high correlations predominate among EU countries, where values exceed 0.9, reaching 0.98 in some cases, except for WID. Non-EU countries show much weaker or non-existent correlations, particularly in SWIID, WID, WIID, and GCIP, which provide the most data for this group.

Other measures show similar patterns. Palma ratios exhibit medium to high correlations across the entire group and EU countries, particularly after excluding Lithuania's 2019 outlier, which distorted results. Again, WID shows slightly lower correlations, but values remain high for EU countries (68–85%), compared to non-EU countries (37%–46%).

The correlation analysis for the Atkinson index leads to similar conclusions, with a correlation of 0.48 between GCIP and WIID (LIS provides single observations) for non-CEE countries. The last two measures examined—the income of the top 10% and bottom 50%—are also consistent with the above observations, showing a negative correlation as expected, since an increase in one measure should correspond to a decrease in the other. The lowest correlations were observed for WID, with -65% for EU countries and -22% for non-EU subgroups compared to WIID and GCIP. This highlights the impact of fiscal data on inequality estimates and the challenges of measuring inequality in post-Soviet countries. Methodological differences between databases, particularly the inclusion of fiscal data, result in higher recorded inequality levels (see Section 2) and distort comparisons with survey-based sources, which face their own methodological biases. Therefore, lower correlations reflect methodological rather than accuracy differences between fiscal and survey-based data.

Correlations occur not only within a single measure but also between different measures. Despite concerns that focusing on different parts of the income distribution could alter trends (Goda, 2016; De Maio, 2007), correlations remained high and positive between the Gini coefficient, Palma ratio, Atkinson index, and top 10% income shares. Likewise, high negative correlations were observed between bottom 50% income shares and the other indicators, as expected. Importantly, strong correlations were found not only within the same database (up to 99%, indicating internal consistency) but also across different databases measuring different inequality metrics. This suggests that regardless of the inequality measure chosen, the data indicate the same trend, minimizing the impact of methodological differences. For EU countries, the choice of income inequality measure does not affect the overall trend, as the data consistently reflect the same direction of change. In contrast, for non-EU countries, selecting the appropriate database and methodology is more crucial than the specific measure when analyzing long-term national trends.

In conclusion, for EU countries, high or very high correlations exist regardless of the measure or data source, with a consistent trend direction. This indicates stable relationships between inequality trends and long-term data consistency. The slightly lower correlations for WID, due to its inclusion of fiscal data, underscore the value of incorporating such data to capture inequality trends overlooked by survey-based sources, as observed in Poland (Bukowski & Novokmet, 2019) and Russia (Neef, 2020). In contrast, post-Soviet, non-EU countries show significant inconsistencies, with some datasets lacking any measurable correlation. The absence of fiscal data in these countries further complicates analysis, making dataset and measure selection crucial, as choices can substantially impact results. Finally, the apparent consistency of income inequality trends across measures and databases was largely driven by EU countries, masking methodological disparities and data availability issues. The inclusion of fiscal data in WID, contrasted with SWIID's excessive smoothing, further distorts inequality estimates, creating a misleading picture of actual trends. Ultimately, the first hypothesis is not confirmed for all post-socialist countries, shifting the analysis from long-term national trends to short-term group-level dynamics.

5.2. Consistency between the trends of income inequalities

The long-term consistency of development trends, particularly in EU countries, suggests persistent dependencies across individual nations. However, a dominant direction of change over time does not guarantee actual consistency, nor does it reflect relative changes between countries. To further investigate these findings, an individual-year analysis was conducted.

Following Trapeznikova (2019), who noted a consensus on country rankings by inequality, rankings for post-socialist countries were compiled across all datasets, sources, and measures. Rankings were prepared for key years: 1993, the earliest year with reliable data (earlier years, like 1991, posed analytical challenges); 2000, marking the stabilization of major inequality shifts; 2004, aligned with EU accession; and 2010, 2015, and 2020, representing later trends. Observing rankings at multi-year intervals allowed verification of trend consistency across different countries. For each dataset, the country with the lowest inequality received a rank of 1, while the country with the highest inequality was ranked 25. If fewer than 25 countries were available, rankings were adjusted accordingly. To ensure comparability, bottom 50% income shares were ranked inversely—higher values (indicating greater equality) received a rank of 1, aligning them with other measures where lower values indicate more equality.

Due to conceptual differences between measures, hypothesis H2 examines ranking homogeneity within the same measure rather than across different ones. Among the Gini coefficient, Palma ratio, Atkinson index, and income shares, no full consistency exists in rankings of post-socialist countries, and greater data availability often increases ranking discrepancies. Over time, ranking consistency does not show a clear improvement. However, when comparing complete or nearly complete rankings, noticeable differences emerge between measures. In the selected years, the Atkinson index exhibited the highest ranking stability (43% of observations had a maximum deviation of ±2 places), while the Palma ratio showed the greatest discrepancies (only 21% of observations within the same range). For the Gini coefficient and income shares, consistency within a ±2-place range was 27% and 26%, respectively.

The analysis also highlights differences between EU and non-EU countries. Splitting rankings into smaller subgroups reveals significant differences in consistency. Among EU countries, the Atkinson index rankings remained exactly the same in over 30% of cases, with a ±2-place deviation occurring in 91% of observations. Slightly lower consistency was found in income shares of the bottom 50% (45% and 74%), Palma ratio (39% and 70%), and top 10% income shares (38% and 67%). The Gini coefficient, which had the largest dataset, showed the lowest consistency—33% of rankings were identical, while 48% had only minor deviations. Among non-EU countries, the highest consistency was also observed for the Atkinson index (44% and 61%), while other measures ranged between 19% and 26%, with ranking differences reaching over 10 places in some years.

Subgroup analysis showed increasing ranking consistency over time for EU countries, a pattern not observed in non-EU nations. This improvement became apparent between 2004 and 2010, continued in 2015, and by 2020, rankings for Palma ratio and bottom 50% income shares remained within a ±2-place range for all countries.

Due to conceptual differences, comparing inequality measures is challenging. However, the Gini coefficient and Palma ratio allow for partial comparison, and databases that provide full rankings for both (WID and WIID) show very high consistency.

At the broadest level, rankings of the most and least income-equal countries show high consistency across measures and sources, remaining stable over time. Countries with low inequality in the 1990s—Czech Republic, Slovakia, Slovenia, Hungary, and Belarus—have maintained their positions, although Belarus's ranking may be influenced by unreliable data. Conversely, the most unequal countries are post-Soviet, non-EU states, including Armenia, Azerbaijan, Turkmenistan, and Georgia. This pattern holds even in incomplete rankings, where Georgia, for example, has appeared in positions "8" or "18", depending on dataset coverage.

In conclusion, full homogeneity in rankings of the same inequality measures across sources cannot be confirmed, although the Atkinson index rankings show the highest consistency. However, marginal rankings remain stable over time, particularly in EU countries, where rank variation is lower. Additionally, comparable measures show strong internal consistency when sourced from the same database. Given that databases differ significantly in methodology, choosing the right data source is more impactful than selecting a specific inequality measure, as it has a greater effect on final rankings.

5.3. Variation in income inequality values

The previous analysis assessed consistency in individual country trends and group-wide rankings over time. In both cases, some degree of inconsistency emerged, which can be linked to data variance. High variance can distort inequality trends and rankings, particularly when it affects multiple countries. To quantify this variation, statistical methods including analysis of variance, coefficient of variation, and data range were applied. Table 2 presents average values of these measures for the Gini coefficient, Palma ratio, bottom 50% income share, and top 10% income share, based on all available sources. The Atkinson index was excluded due to variability in the ε parameter, which prevents meaningful cross-source comparisons. While trends and rankings could still be analyzed, value variance was assessed separately for each measure due to their different scales.

Table 2: Summary of average values of variation and range of data on income inequality

country	Gini coefficient			Palma ratio			Bottom 50%			Top 10%		
	s^2	CV	max-min	s^2	CV	max-min	s^2	CV	max-min	s^2	CV	max-min
CZ	3.26	0.16	4.18	1.24	0.37	0.80	0.01	0.18	0.07	0.01	0.35	0.13
HU	10.06	0.09	7.56	0.17	0.24	0.85	0.00	0.12	0.07	0.01	0.24	0.11
SI	14.35	0.13	8.96	0.22	0.33	1.02	0.00	0.15	0.08	0.01	0.30	0.14
MK	14.91	0.08	8.33	0.41	0.25	1.30	0.00	0.12	0.08	0.01	0.28	0.11
BG	19.55	0.17	10.38	1.35	0.36	1.56	0.01	0.17	0.10	0.01	0.34	0.12
LV	21.98	0.11	10.54	0.63	0.34	1.65	0.00	0.14	0.09	0.01	0.32	0.13
SK	22.89	0.13	11.39	5.00	0.35	0.89	0.00	0.16	0.07	0.01	0.31	0.14
TM	25.18	0.13	5.89	4.87	0.35	4.01	0.00	0.16	0.18	0.01	0.31	0.13
GE	30.09	0.11	10.68	2.29	0.34	2.68	0.01	0.15	0.13	0.00	0.30	0.09
RU	31.90	0.10	9.48	3.03	0.46	2.90	0.01	0.21	0.16	0.01	0.34	0.13
LT	35.69	0.12	12.04	76.9	0.37	6.22	0.00	0.13	0.09	0.01	0.32	0.12
EE	36.02	0.14	13.71	1.32	0.42	2.36	0.01	0.18	0.13	0.01	0.35	0.14
TJ	36.94	0.10	9.49	1.48	0.39	2.25	0.01	0.19	0.14	0.01	0.33	0.13
BY	37.58	0.16	11.75	0.60	0.36	1.36	0.00	0.18	0.12	0.01	0.31	0.14
UA	37.89	0.13	12.02	4.71	0.35	1.45	0.01	0.16	0.12	0.01	0.31	0.13
AL	38.73	0.12	12.38	0.53	0.26	1.50	0.00	0.13	0.09	0.00	0.30	0.11
HR	40.01	0.16	14.00	0.47	0.33	1.50	0.00	0.15	0.09	0.01	0.32	0.14
UZ	41.74	0.10	9.07	4.85	0.51	3.77	0.01	0.22	0.18	0.01	0.08	0.12
PL	43.17	0.17	16.44	0.79	0.39	1.85	0.01	0.19	0.12	0.01	0.31	0.13
AM	43.24	0.14	13.26	1.99	0.35	2.44	0.01	0.16	0.13	0.00	0.33	0.12
RO	44.34	0.16	16.35	1.17	0.39	2.06	0.01	0.20	0.13	0.01	0.31	0.12
MD	46.55	0.15	13.84	0.74	0.28	1.79	0.00	0.13	0.09	0.01	0.32	0.13
KG	59.55	0.16	14.49	1.80	0.34	2.16	0.01	0.17	0.13	0.00	0.31	0.11
KZ	62.75	0.17	14.88	1.59	0.39	2.32	0.01	0.19	0.14	0.01	0.34	0.14
AZ	187.2	0.29	25.77	1.96	0.47	2.43	0.01	0.24	0.17	0.01	0.34	0.17

Where: s^2- variance, CV - coefficient of variation.

Source: own compilation.

Compared to the previous two aspects of data consistency tested, value consistency showed the greatest variation. For EU countries (excluding Poland), the range of income shares (bottom 50% and top 10%) does not exceed 20 p.p., with the average variation between the maximum and minimum value of the bottom 50% income share being less than 10 p.p. and 11-15 p.p. for the top decile. In non-EU countries, average variation exceeds 10 p.p., and in some cases, data sources are less consistent in estimating bottom 50% shares than top 10% shares. Across the entire group, standard deviation remains below 10%, but the coefficient of variation highlights issues with top-income measurement. While for lower-income groups it remains below 20% (except for Azerbaijan—24%, Uzbekistan—22%, and Russia—21%), at the top decile, even in countries with previously high consistency (e.g., Czech Republic), it exceeds 30%. This explains trend correlation differences found earlier in the analysis.

The Gini coefficient results showed different patterns. At the national level, the average difference between sources each year was 11.83 (on a 0-100 scale), meaning a country could be placed in different inequality groups in the same year. Czech Republic (4.18) and Hungary (7.58) showed the highest consistency, while Azerbaijan (25.77, and a maximum exceeding 30) exhibited the greatest variation. Poland (16.44) was the second least consistent, with twice the difference reported by Brzezinski, Myck, and Najsztub (2022). Regarding the coefficient of variation, most countries remained around 15%, except Azerbaijan (26%). Notably, both Czech Republic and Kyrgyzstan had the same variation level (16%), though their absolute data ranges differed significantly—3.3 vs. 60, respectively. This suggests a large spread in values despite a relatively stable ratio to the mean.

The Palma ratio again reveals substantial differences between subgroups. In EU countries (excluding Lithuania), the average variation between maximum and minimum values remained below 2, with Czech Republic (0.8) and Poland (1.85) showing the lowest fluctuation. In contrast, Central Asian countries exhibited significantly higher variation, with Uzbekistan (3.77) and Turkmenistan (4.01) indicating an average difference of nearly 4 in the income shares of the richest two deciles vs. the bottom 40%.

The value consistency analysis found no widespread stability in measures, disproving hypothesis 3. While EU countries exhibited lower variation, differences between subgroups persisted. In some cases, specific measures showed relatively stable values with low dispersion, but this stability was country-specific rather than measure-specific. The observed variation aligns with Bartels and Metzing (2019), who found that some countries exhibit minimal fluctuations, while others show significant discrepancies.

6. Conclusions

This article examines the consistency of income inequality data in post-socialist countries, from Central and Eastern Europe and Central Asia, across common measures and databases, considering the impact of methodological differences. Such analyses were mainly carried out for single measures, databases, or selected countries, and this article aimed to fill the research gap for a selected group of countries. The formulated hypotheses tested the consistency of development trends, the stability of country rankings, and the constancy of values across different measures. The analysis covered both long-term trends for individual countries and comparisons across time periods. Data were sourced from leading inequality databases—including WID, SWIID, WIID, OECD-IDD, GCIP, WDI, and Eurostat—and examined using the Gini coefficient, Palma ratio, Atkinson index, and income shares of the bottom 50% and top 10%.

The analysis of hypothesis H1 confirmed high consistency in long-term income inequality trends for EU countries where different measures showed aligned trajectories. In contrast, non-EU countries exhibited lower consistency, with occasional contradictory trends (Goda, 2016; De Maio, 2007). While databases focused solely on inequality and broader economic datasets produced similar trends, methodological differences remained relevant, particularly in WID data, which diverged due to its fiscal-data focus. For EU countries, correlations often exceeded 90%, confirming stable trends regardless of measure or source. However, in non-EU countries, database choice played a much greater role in determining trends.

Methodological choices significantly affected data consistency, particularly SWIID's oversmoothing and WID's fiscal-data inclusion, which lowered correlations in some cases (De Maio, 2007; Alvaredo et al., 2016). This conclusion particularly applies to post-Soviet countries that are not part of the EU, where the richest individuals may have disproportionately more income than in most CEE countries, and where access to high-income data may be more difficult, resulting in significantly lower data consistency.

Hypothesis H2 tested the stability of country rankings over time. Results showed that EU countries exhibited greater ranking consistency, particularly after 2004, likely due to improved data quality from EU statistical integration. In contrast, non-EU countries showed significant variation, with rankings shifting by up to 10 places for some measures.

Despite inconsistencies, some ranking patterns remained stable. Czech Republic, Slovakia, Slovenia, and Hungary consistently ranked among the least unequal, while Georgia and Turkmenistan were among the most unequal. Within each database, rankings remained largely consistent, typically shifting by only one place. This suggests that for non-EU countries, the choice of database has a stronger impact than the choice of measure.

Hypothesis H3 examined value consistency across databases, revealing that full consistency was not found. Variation was more limited in EU countries, while non-EU countries showed greater inconsistencies, particularly for measures like the Palma ratio.

In conclusion, the article indicates a high level of consistency in income inequality trends over the long term and highlights strong correlations between different data sources for the same measures. However, they are inflated by the high consistency of data for EU countries, which is why only for this subgroup it would be possible to truly confirm the existence of consistent trends. The ranking of countries is most consistent in the context of extreme equality or inequality and between measures from the same database, while the occurrence of full consistency in the values of individual measures practically does not occur, which is the result of inconsistency at the level of the values of given measures, even if the level of their variance is moderate.

The key finding is that data selection is crucial when studying income inequality, requiring awareness of methodological challenges across measures, sources, and countries. The analysis revealed that SWIID's oversmoothing and WID's use of fiscal data led to significant data divergences, sometimes even producing contradictory year-on-year trends. The extent of these issues depends on the country and research focus. For EU countries, data from a single database tend to show consistent development trends, regardless of the measure. However, in international comparisons, where country differences play a larger role, the choice of data source becomes more critical—although its influence weakens over time. For instance, selecting a Palma ratio dataset for 2000 requires greater caution than for 2020 due to historical inconsistencies. For non-EU post-socialist countries, low correlations between datasets, significant discrepancies between measures, and unstable rankings highlight the need for careful selection of both the measure and data source. In such cases, any choice can lead to vastly different results, making methodological justification essential. This applies both to analyses for single countries and especially to broad international comparisons.

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