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Regional prevalence and intensity of poverty in Slovakia in the context of polycrisis: An analysis using FGT indices

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Abstract

This study examines the relationship between poverty rate and intensity in Slovakia amid the cost-of-living crisis. Using Foster-Greer-Thorbecke indices, the research analyses poverty distribution across four income categories below the poverty line, moving beyond binary classifications toward interval measures. Data show that while 11.4% of the population in Slovakia suffered from income poverty in 2020, this had increased to 14.5% by 2024. Six of eight Slovak regions experienced an increase in poverty depth between 2022 and 2023, confirming a correlation between the poverty rate and its intensity. The study contributes methodologically by providing granular views of poverty intensity and challenging assumptions about economic hubs driving equitable growth, as evidenced by Bratislava's region, with a 36.7% poverty risk. It identifies regional vulnerabilities requiring targeted interventions and demonstrates that Slovakia's experience exemplifies the need for region-specific approaches to address poverty in the EU's polycrisis context.

Keywords: Poverty intensity, polycrisis, Foster-Greer-Thorbecke indices, cost-of-living crisis, income distribution, regions of Slovakia

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1. Introduction

Income poverty is currently on the rise in most countries of the world, including in many EU countries. This is largely the result of the polycrisis that has been underway for several years, particularly over the last 5 years, the cost-of-living crisis (CLC), which is a significant part of the overall polycrisis. The cost-of-living crisis is becoming a particularly important problem in Slovakia, where not only is the poverty rate increasing significantly, but so too are its depth and severity. Income poverty is becoming unbearable, especially in relation to purchasing power parity (PPP). Slovakia is the only EU country where income terms in PPP reached a negative value in the decade 2014–2023 (a decrease of –0.2%). The determinant of poverty growth in Slovakia has been income stagnation alongside ongoing dynamic growth and high inflation. In absolute terms, the quantity of income poverty increased from 614,000 (in 2020) to 778,000 (in 2024) – that is, an increase of up to 21.1% (Statistical Office of the Slovak Republic, 2024).

Along with the growth of the poor population, the intensity of poverty has also increased. Between 2020 and 2024, the share of the poor with an income below 50% of the median equivalent income increased by 37.3%, and the share with an income below 40% of the median equivalent income increased by 67.2% (Statistical Office of the Slovak Republic, 2024). The initial impetus for the gradual worsening of income poverty in Slovakia was the COVID-19 pandemic, which negatively affected inflation, led to income stagnation, increased the population's financial vulnerability, and, consequently, worsened poverty. At the same time, the increase in the number of the poor and the fall

of a significant proportion of the poor into even greater poverty indicate an ineffective policy of fiscal assistance to low-income and financially vulnerable households on the part of the state.

While some EU countries have used various measures and instruments to curb inflation (older Member States), others (especially in Central and Eastern Europe) have used various forms of fiscal aid to improve households' financial situations, Slovakia has gone in the opposite direction. By adopting three necessities but poorly designed consolidation packages aimed at improving public finances (a significant predominance of revenue-raising measures and almost no, or only symbolic, savings on the expenditure side), the state has further burdened household budgets. At the beginning of this year (2026), the measures of the third consolidation package came into effect, which include, among other things, an increase in health contributions for self-employed persons and an increase in social contributions, a reduction in unemployment benefits, exclusions or restrictions on energy assistance, and an increase in VAT on certain foods and beverages. In the context of the above measures, further poverty growth and its deepening in Slovakia can be expected (Múčka & Kandričák, 2025). The main objective of the paper is to determine whether the poverty rate determines the intensity of poverty at the national and regional levels, or whether the intensity of poverty increases with the growth of the poverty rate. To this end, the depth and severity of poverty have been analysed in more detail, based on the representation of the poor in the four income categories below the poverty line (PL). In a sense, this is a research transition from a binary definition of poverty status (poor versus non-poor) to a more detailed interval measure of poverty,

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which reflects the ‘interval’ decline in equivalised disposable income from the PL¹. This paper shows that a decomposition of poverty based on the concept of income distribution extends the possibilities for a deeper understanding of the intensity of poverty that cannot be detected from aggregate measures. At the same time, it highlights the importance of exploring and understanding spatiotemporally differentiated poverty intensity and points to the importance of tracing the relationship between the socio-economic and demographic characteristics of individuals/households and differences in their poverty.

2. Theoretical background

Measuring poverty is the first step towards understanding poverty. There is a large literature on poverty measurement (Atkinson, 1987; Bradshaw et al., 2007; Clark et al., 1981; Delamonica & Minujin, 2007; Foster et al., 1984; Haughton & Khandker, 2009; Sen, 1976²), and most poverty-related scholarship has long focused on the measurement of at-risk-of-income poverty (RIP). In particular, researchers have used a variety of methods and indicators to analyse the prevalence of income poverty across different groups of individuals or households. In these studies, all poor people are treated equally, regardless of how far their income is from the PL. For example, a person whose income falls just one euro below the PL contributes as much to the aggregate poverty rate as a person with zero income. The spectrum of ordinal poverty measures has been described by Hagenaars (1987), who identified key axioms for constructing a poverty index, including monotonicity, transmission sensitivity, and decomposability. These axioms are intended to ensure that the indices accurately and consistently reflect changes in poverty. A ‘new’ class of ordinal poverty measures defined using an aggregate generalised poverty gap has been used by Bossert et al. (2022) in their research. They used indices that do not explicitly depend on the number of poor or on the total population size, thus eliminating any direct effect of the headcount ratio on poverty comparisons. However, there is a broad consensus in the economics literature on poverty measurement, which involves measuring three basic aspects: prevalence, intensity, and inequality among the poor. Looking at multiple measures or indices of poverty provides a more useful view of poverty and better-tailored policies for poverty alleviation (Ciommi et al., 2021). For this reason, several scholars (Foster et al., 1984; Jenkins & Lambert, 1997; Kakwani, 1980; Sen, 1976; Thon, 1979) have proposed poverty indices that would identify not only the prevalence but also consider the intensity of poverty, which includes its depth (the distance of individual income from the PL) and severity (inequality among the poor).

There are now a large number of different poverty measures and indices, with one of the oldest and best known being the Sen-Shorrocks-Thon (SST) poverty intensity index, which is sometimes also referred to in the literature as the modified Sen poverty intensity index (Haughton & Khandker, 2009; Xu, 1998). The index is considered a quasi-comprehensive measure of poverty, as it jointly captures the incidence, depth, and severity/inequality of poverty. The advantage of this index is its decomposability – that is, its transparent decomposition of poverty into its component parts. An alternative formulation of the SST poverty intensity index, suitable for survey data with sampling weights, has been presented by Osberg and Xu (1999, 2000).

To measure the prevalence, intensity, and inequality of poverty, the Shapley decomposition approach has been widely used (Aristondo & Onadia, 2020; Ciommi et al., 2021). Other poverty measures and indices used include the Theil measure of inequality (Blackburn, 1989), a set of aggregate poverty measures (Zheng, 1997), graphical ways of measuring poverty (e.g. frequency density, distribution functions, Lorenz curves), ‘Three T’s of poverty curves’ (TIP³; Jenkins & Lambert, 1997), and the Watts poverty index (Morduch, 1998), as well as axiomatically derived alternatives to standard poverty measures that provide estimates not only of the prevalence of poverty, but also of the intensity and inequality of poverty (James & Ziliak, 2006). The poverty severity estimation method is also used by Muñoz et al. (2018), who used a basic approach of estimating the variance and constructing confidence intervals. The most important contributions of leading scholars in the field of poverty measurement have been presented by Klasen (2018), including articles on poverty measurement, conceptual and empirical approaches to setting the PL in national and international settings, multidimensional poverty indices, and ways to capture poverty dynamics. Because of the need to help the poor, the European Commission has introduced the measurement of the relative median poverty risk gap – the difference between the median equivalent disposable income of people below the poverty risk threshold and the threshold itself, expressed as a percentage of the poverty risk threshold (Social Protection Committee, 2015).

The creation and construction of poverty measures and indices have not escaped expert criticism, and many have been subjected to testing and rigorous scrutiny. Among the first papers to address the shortcomings of the poverty measurement methods used was Milanovic (2002), which proposed corrections and suggested improvements to several poverty measurement methods. Klasen and Launov (2007), in particular, criticised the complex methods used in poverty research and proposed a simple approach to measuring and assessing poverty. They developed analyses that, assuming the policymaker knows the costs of potential policy interventions, identify the most effective poverty-reduction strategy. Grusky and Kanbur (2006), drawing on the work of leading public intellectuals and poverty experts (i.e. Sen, Nussbaum, Bourguignon, Wilson, Massey, Fineman), concluded that conventional poverty indices, outdated approaches to poverty reduction and traditional modelling are inadequate, and that researchers and policymakers need to upgrade their knowledge of poverty, especially in the area of poverty measurement, in the context of modern challenges. Ravallion (2020) critically assessed current global poverty measures and concluded that new hybrid measures are needed that combine absolute and relative measures, in line with national PLs. Kyzyma (2020) focused her critique on aggregate poverty indices, which she criticised for obscuring individual experiences of poverty and providing limited opportunities to link poverty outcomes to individual or household characteristics.

Any measurement of poverty should be expressed as a function of three components or parameters of poverty – namely prevalence, intensity and inequality among the poor (Aristondo, 2018). In this paper, the FGT indices (Foster et al., 1984; Foster, 2006) were selected and used to measure these three components of poverty. The analysis of income gaps using the FGT indices is consistent with the traditional approach to poverty measurement, which focuses on identifying the proportion of individuals living

¹ That is, the income of the poor, whose income is below the poverty line, according to the four designated income bands.

² Sen’s seminal contribution set the stage for numerous subsequent studies, many of which are summarised in Zheng’s (1997) comprehensive surveys.

³ TIP curves are based on the distribution of income deficits from the PL and poverty gaps; their name is related to their ability to depict concisely and simultaneously what we refer to as the dimension of prevalence, intensity, and inequality of aggregate poverty (i.e. the poverty rate, depth, and severity of poverty).

in poverty (Kyzyma, 2020). The advantage of using individuals as the unit of analysis is that it allows for important personal characteristics to be considered while identifying the various determinants of the income deficits of the poor. The variables selected as potential predictors of the size of income gaps below the PL were household size (total number of members), number of dependent children, economic activity, unemployment, and post-reproductive age.⁴ In most similar studies (Duncan et al., 1993; Jenkins, 2011; Stevens, 1999), these variables have emerged as important and the most significant correlates of both the prevalence and intensity of poverty.

As a first step, the FGT indices used to analyse the aspects of poverty studied, with an emphasis on poverty intensity, are introduced. In the following step, the state of affairs and the development of poverty in Slovakia are briefly summarised, with an emphasis on its significantly worsening position within the EU. The third step presents the correlation analysis focusing on the association between the prevalence and depth of poverty and the prevalence and severity of poverty. This is followed by an inter-regional pairwise correlation between the poverty rate and the depth of poverty in the categories of the poor with different income levels. The intention of this survey was to determine which categories of the poor (by income) are most at risk of worsening poverty rates. To capture the significant deterioration in the poverty aspect of the situation in the regions, analyses were conducted to track changes in the distribution of the poor. Finally, the characteristics of the poor across different levels of poverty/income are analysed to identify those that determine the intensity of poverty.

The analyses and empirical part of the paper were based on two sources: An overview of poverty in Slovakia and its position within the EU was based on Eurostat data. The analyses focused on changes in poverty parameters, the characteristics of the poor, and the determinants of poverty, based on data from the EU-SILC surveys for Slovakia in 2020 and 2023 (Statistical Office of the Slovak Republic, 2024, 2025), which include household- and individual-level poverty and income data. In addition to the above indices, graphical and cartographic methods were used, namely, box plots, a dot plot of changes, and three maps. The graphs and maps clearly and in detail capture the situation and the significant changes that have occurred over the years under review.

3. Methods

There are several methods for measuring poverty prevalence and intensity, each with its own advantages and disadvantages. In this paper, the FGT indices, among the most widely used poverty metrics, were used to measure the prevalence, depth, and severity of poverty. The advantage of FGT indices is their decomposability, i.e. transparent distribution of poverty into its components. Decomposable poverty measures are particularly useful in poverty studies where a population is broken down into subgroups defined along ethnic, geographical, or other lines (Aguirregabiria, 2006). We can use these measures to obtain the contribution of each subgroup to total poverty and to estimate the effect of a change in subgroup poverty on total poverty. Aristondo (2018) classifies FGT indices as rank-independent poverty decomposition indices. FGT indices have a wide range of uses. Alkire and Foster (2007) used them, for example, to create a new methodology for measuring multidimensional poverty, Adjasi and Osei (2007) to identify the profile and nature of poverty in Ghana, Kyzyma (2020) to examine the depth of poverty in European countries, and Ogwang (2022) to create new multiplicative decompositions with poverty aversion parameters.

The first of the group of FGT indices is the poverty rate (sometimes also referred to as the prevalence of poverty in the literature), usually referred to as (P_0). The poverty rate is the proportion of the population whose income is below the PL. When the unit of analysis is the individual, this poverty rate is also called the poverty headcount index, because it is the ratio of the number of poor people to the total population. Mathematically, the poverty rate (P_0) is expressed by the following equation:

$$P_0 = \frac{1}{N} \sum_{i=1}^N I(y_i < z) = \frac{1}{N} \sum_{i=1}^q 1 = \frac{N_p}{N}$$

where N = total population, $I(\cdot)$ = indicator function, where the value of 1 (poor) if the expression in parentheses is true and 0 (non-poor) if the expression is false, y_i = welfare indicator, e.g. per capita consumption, z = poverty line, and N_p = number of poor in the population.

The advantages of the poverty measure are its construction, clarity, and ease of interpretation. In applied practice, it is a useful measure for assessing overall progress in poverty reduction. The disadvantages and limitations of the poverty measure are that it does not capture differences in poverty across groups of the poor. It assumes that all the poor are in the same situation, is equally insensitive to changes in individual poverty (as long as they remain below the PL), and does not account for the intensity of poverty.

The second poverty measure in the FGT indices is the poverty depth index (P_1). Overall, it is the average of the proportional differences between the income of poor people and the PL (given as their share below the PL). Mathematically, the poverty index is defined by the equation:

$$P_1 = \frac{1}{N} \sum_{i=1}^N \left(\frac{z - y_i}{z} \right) I(z - y_i) = \frac{1}{N} \sum_{i=1}^q \left(\frac{z - y_i}{z} \right)$$

where the variables are defined as in Equation 1. The poverty depth index measures the extent to which the average income of the poor differs from the PL. The advantage of P_1 is that it indicates the average (financial) deprivation of the poor and thus provides a better understanding of the depth of poverty. Another advantage of P_1 is that it shows how much the poor should receive (i.e. what financial amount) to bring their income to the PL, and this makes it easy to derive the minimum cost of poverty eradication using transfers from the index (i.e. the cost of poverty eradication with a perfect focus on the poor). The main limitation of P_1 is that it does not capture differences in the severity of poverty among the poor and ignores inequality among the poor themselves.

The third, least-used index among the FGT indices is the poverty squared gap index (P_2), which is more commonly referred to as the poverty severity index; it is defined similarly to the P_1 poverty index, except that the poverty gaps are equalised, thus giving the greatest weight to the largest poverty gaps. The square of the poverty index captures the differences in income levels among the poor. P_2 places greater weight on the poverty of the poorest individuals, making it a combined measure of poverty and income inequality and thus a popular choice in development economics. P_2 can be expressed by the equation:

$$P_2 = \frac{1}{N} \sum_{i=1}^q \left(\frac{z - y_i}{z} \right)^2$$

⁴ The selection of variables was based on their relevance to poverty intensity and was conditioned by the availability of necessary data, which are significantly limited at the regional level studied. The absence of additional relevant data predicts the need to expand the variables.

The advantage of P_2 is that it considers not only the distance that separates the poor from the PL, but also the inequality among the poor. The origin of the P_2 index is that the P_1 index may not adequately capture the distribution of change within the poor part of the population (e.g. the transfer of funds from an individual just below the PL to the poorest person). In contrast, P_2 can capture this transfer. The main limitation of P_2 is its lack of intuitive appeal, as it is difficult to interpret (Makoka & Kaplan, 2005).

Income distribution provides information about the intensity (depth and severity) of poverty, but it does not reveal the characteristics of the poor across different levels of poverty intensity. A three-stage multivariate framework consisting of classical multiple regression as a robust test, principal component analysis (PCA), and partial least squares regression (PLS) was used to identify the latent structure of the determinants of poverty intensity. Multiple linear regression, in which the dependent variable is the proportion of the poor in a particular income bracket and the explanatory variables are household characteristics and ordinal severity of the poverty bracket, offers simultaneous testing of multiple determinants of poverty intensity. The model estimates the partial impact of each characteristic while simultaneously controlling for all other factors. Since there are four observations per region in the data, robust standard errors clustered by region were used to mitigate bias from intra-regional dependence. The method also allowed us to determine whether household size remains significant even after controlling for the number of children, unemployment, and the number of pensioners. In socio-economic research, this is a standard way to distinguish the ‘pure’ effect of individual determinants from the apparent relationships created by a third variable. Since the original variables in the data are strongly correlated, the regression suffers from unstable coefficient estimates. This problem was solved by principal component analysis, which summarised several overlapping features into a few common factors. PCA from the original, mutually correlated variables created new uncorrelated latent dimensions. In this case, PCA was applied to the five monitored household characteristics, and the principal component scores were used as explanatory variables in the regression model for the share of the poor in individual bands. For the data used, multiple regression also showed multicollinearity and unstable estimates. Therefore, PLS regression was also used, which transformed the variables

into a small number of components optimised for predicting the dependent variable. In our case, this is very appropriate because the set is small, the variables are strongly correlated, and it serves not only to describe the structure but also to identify the determinants of the share of the poor in individual zones.

4. Results

4.1 Status and development of income poverty in Slovakia

The dynamic and extensive spatiotemporal changes in the examined poverty parameters (rate, depth, and severity) discussed above indicate that Slovakia is a suitable setting for examining the relationship between poverty rate and intensity. The significantly worsening situation in Slovakia is also confirmed by the loss of its relatively favourable position on poverty within the EU. The loss of position and Slovakia's decline within the EU are consequences of the rapid growth in poverty over the past 3 years. Figure 1 shows that, while poverty in the EU as a whole decreased by 1.1% over the last decade (from 17.3% in 2014 to 16.2% in 2023), in Slovakia it increased by 1.7% over the same period.

In 2023, Slovakia thus became the EU country with the third-highest poverty growth rate. According to the average annual growth index of RIP (Fig. 2), Slovakia fell another place and reached the second-worst position in the EU.

4.2 Changes in the distribution of the poor

Many external influences caused by the global polycrisis – as well as several internal economic problems in Slovakia (slow economic growth, public finance deficit, high inflation, low growth in real wages, rising cost of living, etc.) – caused not only a significant fall of a large number of people into poverty, but also worsened the situation of the poor themselves, who became even more impoverished. Figure 3 shows the significant changes in poverty intensity between 2022 (boxes on the left) and 2023 (boxes on the right). It provides a clear picture of the growth in the shares of the population with the lowest incomes. At first glance, the changes in the share of people across the three low-income intervals are obvious. Only the share of persons with an income up to 25% below the PL (the least poor) decreased. The remaining three low-income groups showed growth, indicating a deepening of poverty in Slovakia. This deepening of poverty was a consequence of

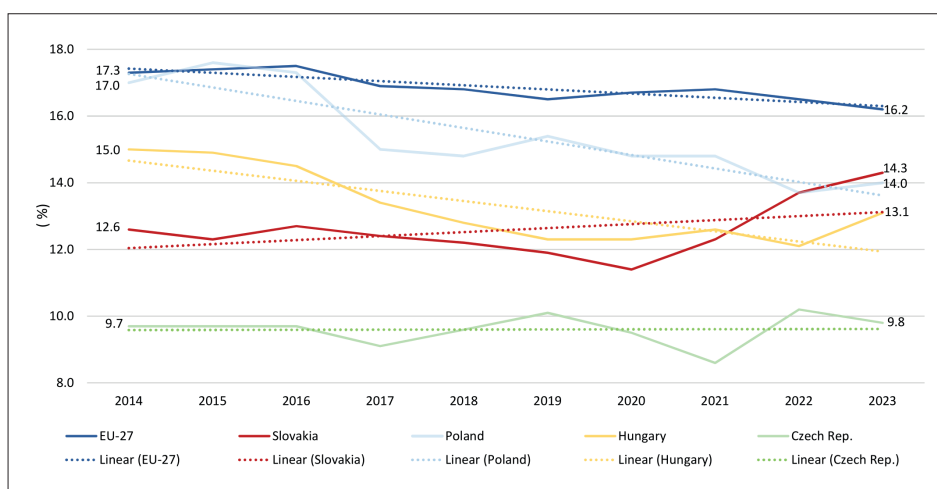


Fig. 1: Development of RIP in Selected EU Countries in 2014–2023

Source: Author's elaboration based on data from EUROSTAT (2024a; ilc_li02)

⁵ This is a method related to PCA, but unlike it, it does not construct latent components only according to the variability of the explanatory variables, but directly so that they best explain the dependent variable. The advantage of the method is its robustness in small sets and that it does not require as large a number of observations as classical models with many parameters.

a significant increase in the poverty rate, but also a consequence of the fall of the (already) poor into deeper poverty. The second significant and easily observable change in the graph (in 2023) is a protruding point (outlier) in the second group of the lowest incomes, which is represented by the Nitra region, which has seen an extreme growth in the share of poor with the indicated income from 1.5% to 7.1% in the course of one year.

4.3 Poverty intensity in Slovakia

Table 1 captures the exact values of the calculated FGT indices and illustrates the large inter-regional differences in all three poverty parameters. The poverty rate $FGT(P_0)$ was the highest

in the Prešov region at 22.6% and the lowest in the Bratislava region at 7.7%. The regions also had the same positions in terms of poverty depth $FGT(P_1)$ and poverty severity $FGT(P_2)$.

4.4 Results of correlation analysis

The results presented above showed that the depth and severity of poverty are reflected in the regions' poverty rates. Table 2 (interregional pairwise correlations) shows that regions with higher aggregate poverty rates have a smaller share (with lower/smaller depth) of the poor up to 25% below the PL and a higher share (with higher/greater poverty) of the poor deeper below the PL (above 50% or 75%). The highest association (0.769) is with

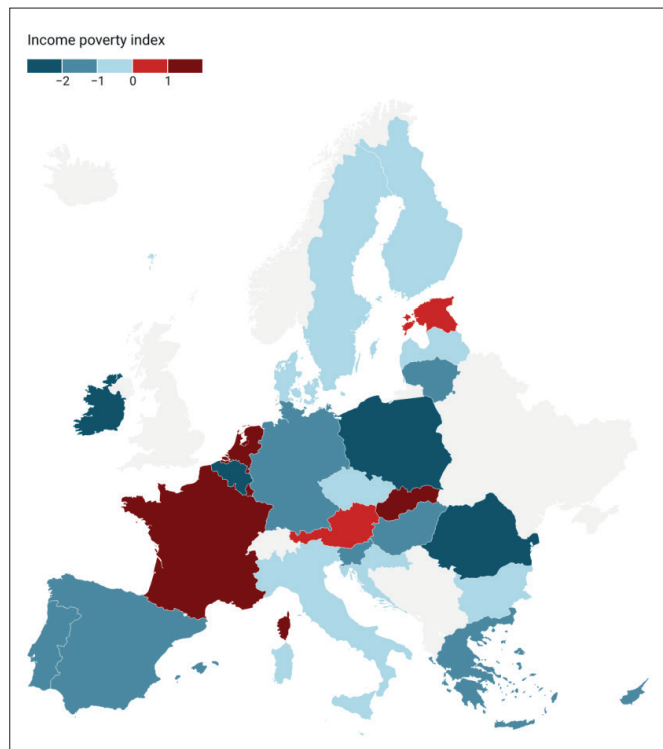


Fig. 2: Average Annual Growth/Decline Index of RIP in EU Countries, 2014–2023

Source: Author's elaboration based on data from EUROSTAT (2024a; ilc_li02)

Region	FGT(P_0)	FGT(P_1)	FGT(P_2)
Bratislava (BA)	0.077	0.0128	0.0164
Trnava (TT)	0.084	0.0143	0.0204
Trenčín (TN)	0.083	0.0138	0.0190
Nitra (NR)	0.132	0.0280	0.0784
Žilina (ZA)	0.117	0.0170	0.0289
Banská Bystrica (BB)	0.176	0.0260	0.0676
Prešov (PO)	0.226	0.0500	0.2500
Košice (KE)	0.211	0.0468	0.2190

Tab. 1: Values of Foster-Greer-Thorbecke poverty indices in the regions of Slovakia, 2023

Notes: FGT (0) – income poverty rate (headcount ratio); FGT (1) – average normalised poverty gap; FGT (2) – average squared normalised poverty gap; author's calculations

Source: Statistical Office of the Slovak Republic (2025; EU SILC, 2023 and 2024)

Poverty Indices	Percentage of the poor with different gaps of poverty			
	<25% below PL (the least poor)	25%–50% below PL	50%–75% below PL	>75% below PL (the poorest)
FGT (1)	0.628	0.613	0.757	0.769
FGT (2)	0.429	0.595	0.714	0.714

Tab. 2: Pairwise correlations of the summary measures of poverty with the share of the poor having poverty gaps of a certain size

Notes: FGT (1) – average normalised poverty gap; FGT (2) – average squared normalised poverty gap; author's calculations

Source: Statistical Office of the Slovak Republic (2025; EU SILC, 2023 and 2024)

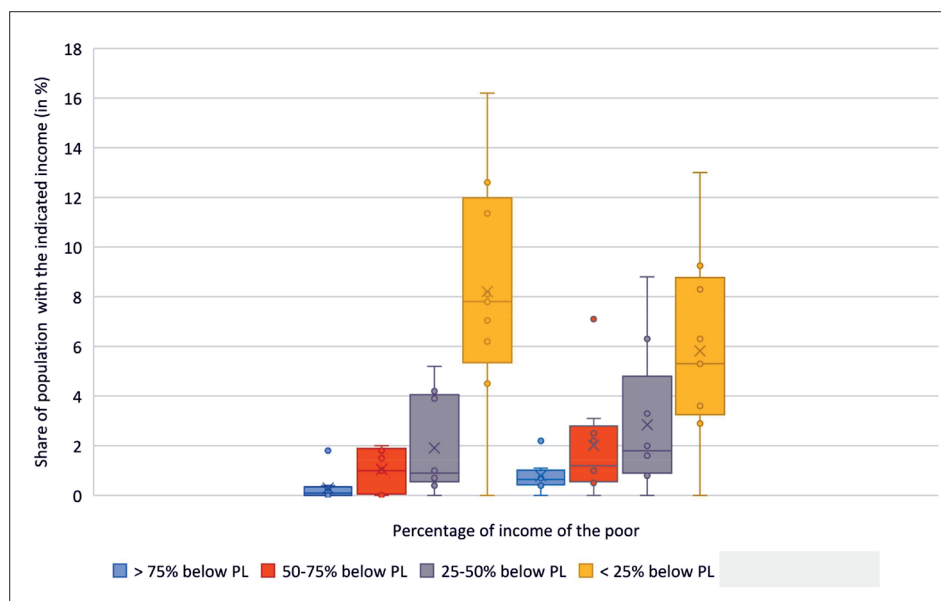


Fig. 3: Box-plots of the shares of individual poverty depth levels across Slovak regions in 2022 and 2023; own processing (Note: PL – poverty line)

Source: Author's elaboration based on data from Statistical Office of the Slovak Republic (2025; EU SILC, 2023 and 2024)

a high aggregate poverty rate and high/great depth of poverty (see Tab. 2). In all regions, approximately two-thirds of the poor have an income up to 50% below the PL. The highest share of the poor (16.3%) with an income below 50% of the PL is in the poorest Prešov region, which also has the highest share (5.9%) of the extremely poor (75% below the PL). The second-highest share of poor people (10.7%) with an income 50% below the PL is in the Nitra region (with a 1.4% share of poor people with an income 75% below the PL), although this region is only fourth in terms of poverty.

Lower correlation values, however, indicate that there is not always a significant relationship between the poverty rate and the depth and severity of poverty at the regional level. As the results themselves show, for example, the Banská Bystrica region, which has a high poverty rate (third-highest), has a lower poverty depth than the Nitra region, which has a lower poverty rate. The same applies to the intensity of poverty in both regions. The association between the rate and depth of poverty and the rate and severity of poverty is captured in Figures 4 and 5. The regions below the estimated regression line (Žilina [ZA] and Banská Bystrica [BB]) have a relatively better composition of the poor than would be expected given their poverty rate values.

The distribution of the poor across different levels of income deficit, or their distance from the PL, differs significantly across regions, even when regions have similar poverty rates. This fact is shown in Figure 6, which compares the income distribution of all poor (with incomes below the PL) across regions with similar poverty rates. The figure compares the distributions of the poor across different income levels in two economically developed regions, Trnava (TT) and Trenčín (TN), and two economically lagging regions, Prešov (PO) and Košice (KE), with similar poverty rates. The comparison of the selected regions shows not only differences in the income distribution of the poor across individual pairs of regions, but also significant differences in the income distribution between regions with different socio-economic conditions. It is clear that, when comparing the Trnava and Trenčín regions, the former has a worse distribution of the poor (a higher share of the poor with lower incomes or greater depth of poverty). In the Trenčín region, the poor with a smaller income gap from the PL prevail, as evidenced by the significantly steeper development of the (proportional) curve on the right side of the graph. A high share of the poor with an income 50% below the PL can be observed in the poor regions of Prešov and Košice. It can be said that their overall poverty rate largely coincides with the distribution of the poor or, rather, with a high share of the poorest

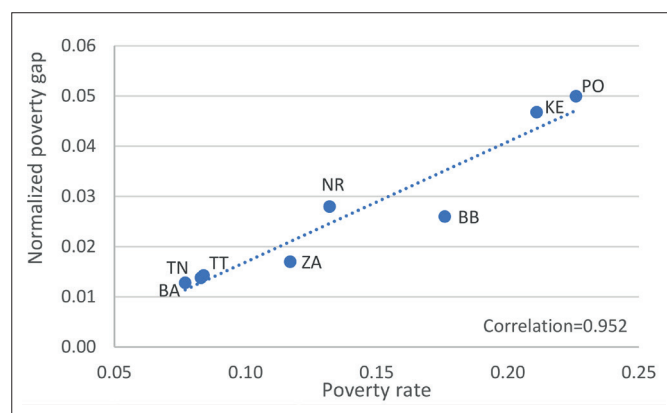


Fig. 4: Relationship between the Income Poverty Rate FGT (0) and the Average Normalised Poverty Gap FGT (1) across Regions, 2023 (Note: The trend line represents a two-way linear prediction plot for poverty rates derived from a linear regression of poverty rates on normalised poverty gaps; own processing)

Source: Author's calculations based on data from Statistical Office of the Slovak Republic (2025; EU SILC, 2023 and 2024)

with the lowest incomes. The higher representation of the poor (larger shares of the poor in lower-income bands farther from the PL) in Prešov and Košice is evident from comparing their share curves with those of the richer regions of Trnava and Trenčín.

The observed disparities in the monitored FGT poverty indices result from causal connections across the entire spectrum of socio-economic and demographic parameters. These and other facts confirm that the poverty rate itself captures the problems and situation of the poor in the regions to a significant extent, but not completely. In other words, the correlation between the monitored indices is not perfect. This is not surprising, given how the monitored characteristics (FGT poverty indices) are derived (and from what data). The prevalence (rate) of poverty, as calculated in this paper, is the percentage of individuals living below the PL, defined as 60% of the country's median income.

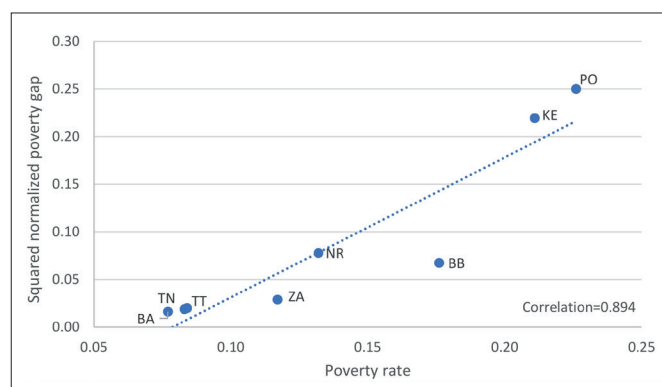


Fig. 5: Relationship between the Income Poverty Rate FGT (0) and the Average Squared Normalised Poverty Gap FGT (2) across Regions, 2023 (Note: The trend line represents a two-way linear prediction plot for poverty rates derived from a linear regression of poverty rates on normalised poverty gaps; own processing)

Source: Author's calculations based on data from Statistical Office of the Slovak Republic (2025; EU SILC, 2023 and 2024)

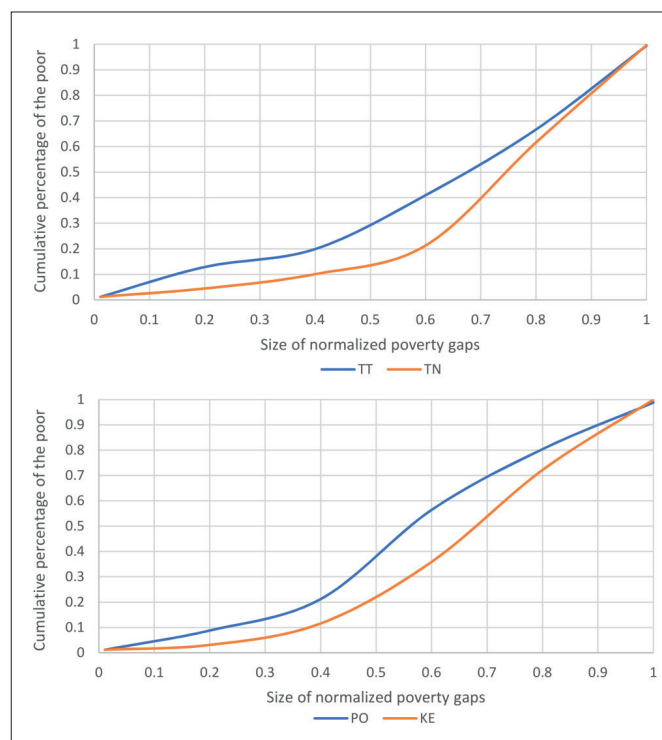


Fig. 6: Cumulative distribution functions of normalised poverty differences between regions with a similar (low) poverty rate (top) and with similar (high) poverty rates (bottom)

Source: Author's elaboration based on data from Statistical Office of the Slovak Republic (2025; EU SILC, 2023 and 2024)

Once someone's income falls below the PL, they are considered poor and contribute to the aggregate poverty prevalence rate. For this indicator, any additional information about the size of the income deficits of the poor from the PL is irrelevant. In contrast, the poverty depth (P_1) and poverty severity (P_2) indices depend primarily on how far the incomes of the poor fall below the PL. The average normalised poverty gap and the average squared normalised poverty gap are derived by averaging individual poverty gaps across the entire population, including those who are not poor. As a result of this measurement approach, regions with high poverty prevalence but small poverty gaps (when many individuals are just below the PL) can have the same average (squared) normalised poverty gap as regions with low poverty prevalence but large income gaps below the PL.

A cartographic representation is well-suited to capturing poverty rates, poverty depth, and poverty severity across individual regions with great clarity. Maps can clearly express the state and changes in all three monitored poverty characteristics, as shown in the three maps created using the following procedure. The first step was to convert the calculated values for all three FGT indices into percentages, which provides a quick overview and makes the results easier to interpret. The second step was to divide the values into four equal quartiles, each with the same number of regions. In

the maps that capture extreme values, the intervals were adjusted so that regions (at most 3) with similar/mostly extreme values were grouped into a single interval. This set of maps provides a quick overview of the state and changes in the monitored poverty characteristics in the studied regions. Figure 7 shows that the share of the poor increased more in the rich regions, especially in Žilina, Nitra, and Trenčín. This fact is confirmed to some extent by the decrease in the poverty rate in the Banská Bystrica region, which is among the poorest in Slovakia in the long term.

Figure 8 also shows deterioration in poverty depth across six regions. The Nitra and Žilina regions deteriorated the most, as the poverty depth increased to the level of the poorest regions. Again, only two regions (Banská Bystrica and Trenčín) recorded a favourable change/decrease in poverty depth. The best situation appeared in the Banská Bystrica region, which recorded an improvement of two degrees (intervals on the map). While the region had the highest poverty depth in 2022, it showed the largest decrease in poverty depth among all regions in 2023. This meant that, in 2023, the Banská Bystrica region had the second-lowest poverty depth. This favourable state and shift in a short period of time were unexpected, given its long-term high poverty levels, as well as the overall trend and changes, during which most regions recorded an increase in poverty depth.

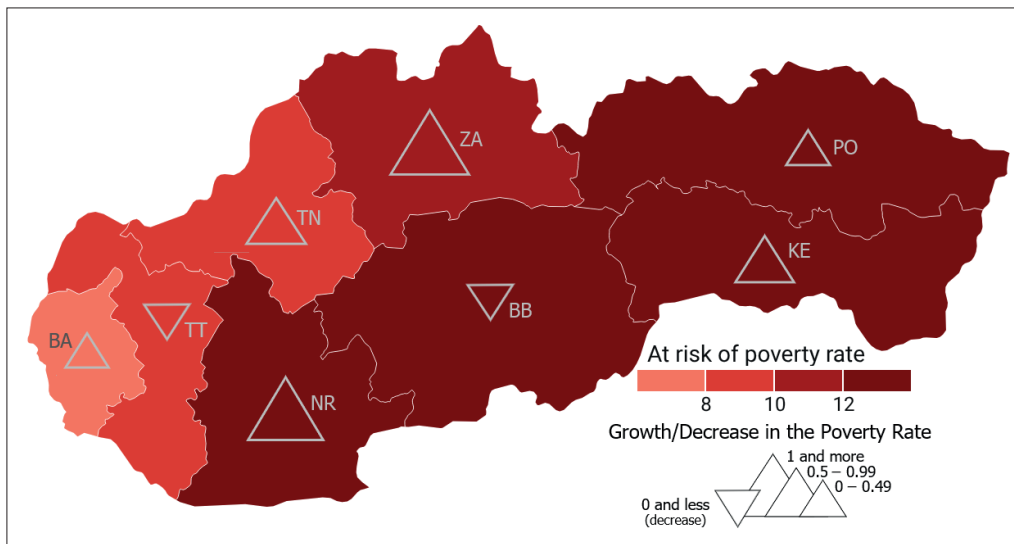


Fig. 7: Poverty rate in Slovakia in 2023 and its growth/decline compared to 2022

Source: Author's elaboration based on data from Statistical Office of the Slovak Republic (2025; EU SILC, 2023 and 2024)

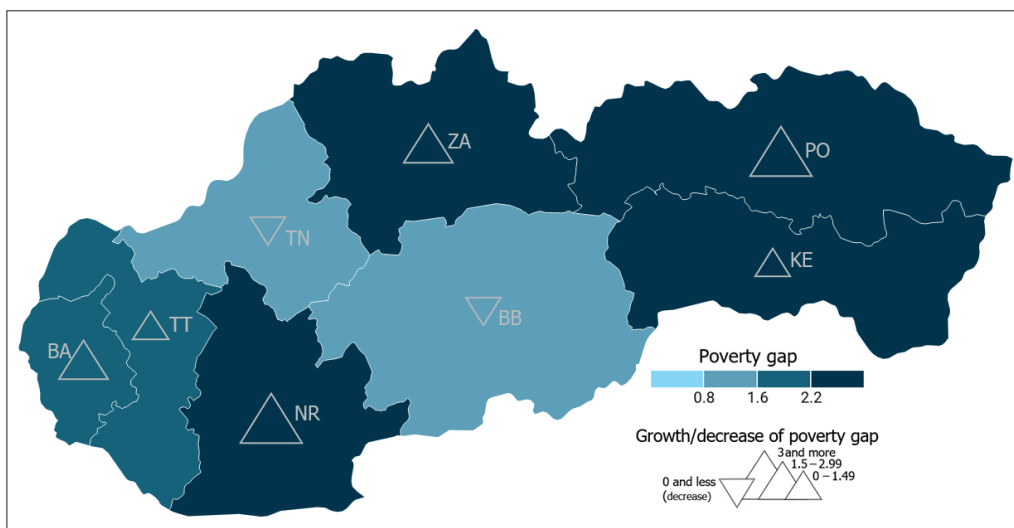


Fig. 8: Poverty gap in Slovakia in 2023 and its growth/decline compared to 2022

Source: Author's elaboration based on data from Statistical Office of the Slovak Republic (2025; EU SILC, 2023 and 2024)

Figure 9 shows that, as with the depth and severity of poverty, Nitra and Prešov regions worsened the most, and the severity of poverty also increased significantly in the Bratislava region. While this was expected in the case of the Prešov region, it was somewhat surprising in the case of the Nitra region, because the region has better long-term values not only in the poverty rate, but also in other socio-economic characteristics. A favourable change/decrease in poverty severity was again recorded in two regions (Banská Bystrica and Trenčín). In the quartile breakdown, both regions moved by two intervals.

The changes in poverty intensity (by quartiles) across regions are well captured in Figure 10, which reveals several important insights into the deepening of poverty in Slovakia during the period studied. The first is that the poverty of the poor in all regions recorded significant growth, though unevenly. The share of the poor increased significantly in the first interval/category – the least poor with income up to 25% below the PL, by 49.5 p.p. It increased the least, which is positive, among the poorest, by ‘only’ 3.6 p.p. On the other hand, the downside is that these are the poorest, and their growth has been highest in recent years. This was confirmed by the fact that poverty in the region with the highest poverty rate (Prešov) also deepened by 20.8 p.p. A positive factor was the low deepening

of poverty in the second-poorest (Košice) region, where the depth of poverty increased by only 1.8 p.p., compared with 5.4 p.p. in Bratislava, the richest region. The situation of the poor in all income categories significantly worsened in the Žilina and Nitra regions.

The situation was slightly different regarding changes in the poor's individual income categories. From the perspective of the poorest, the poorest region of Prešov again recorded the worst change, where their share increased by 1.8 p.p., which represents more than half of their total growth in Slovakia. The significant increase (the second- and third-highest) in the share of the poorest in the two richest regions was unexpected, by 1.1 p.p. in Trnava and 0.6 p.p. in Bratislava. There appears to be a significant concentration of the second-poorest group (income 50–75% below the PL) in two regions (Nitra and Žilina), where the increase accounted for over 85% of their total increase in Slovakia. The largest increase in the share of the poor at this level was recorded in the Nitra region, where their share increased by 5.6 p.p.

4.5 Determinants of poverty intensity

Although income distribution data provide important information on the intensity of poverty, they do not by themselves explain which household characteristics are associated with

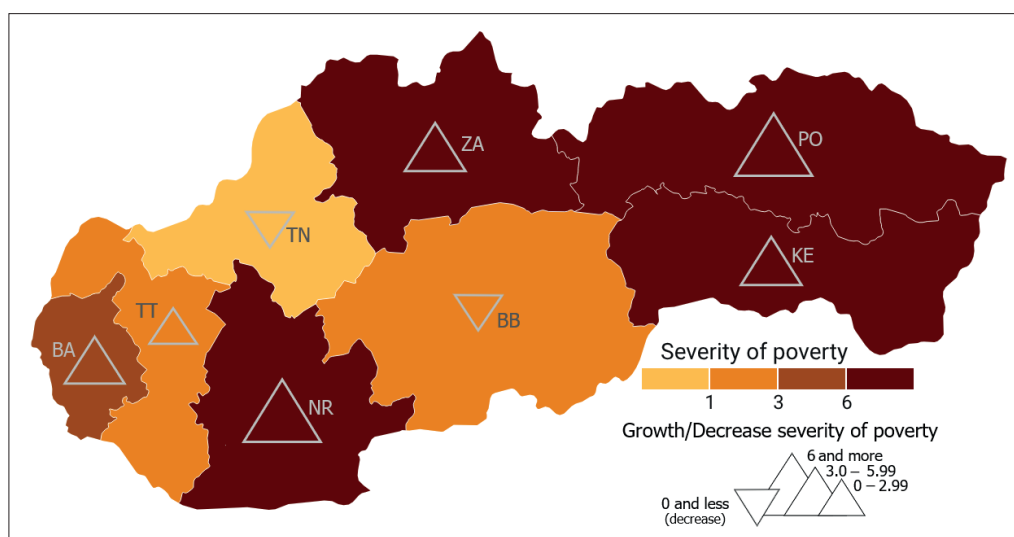


Fig. 9: Severity of poverty in Slovakia in 2023 and its growth/decline compared to 2022

Source: Author's elaboration based on data from Statistical Office of the Slovak Republic (2025; EU SILC, 2023 and 2024)

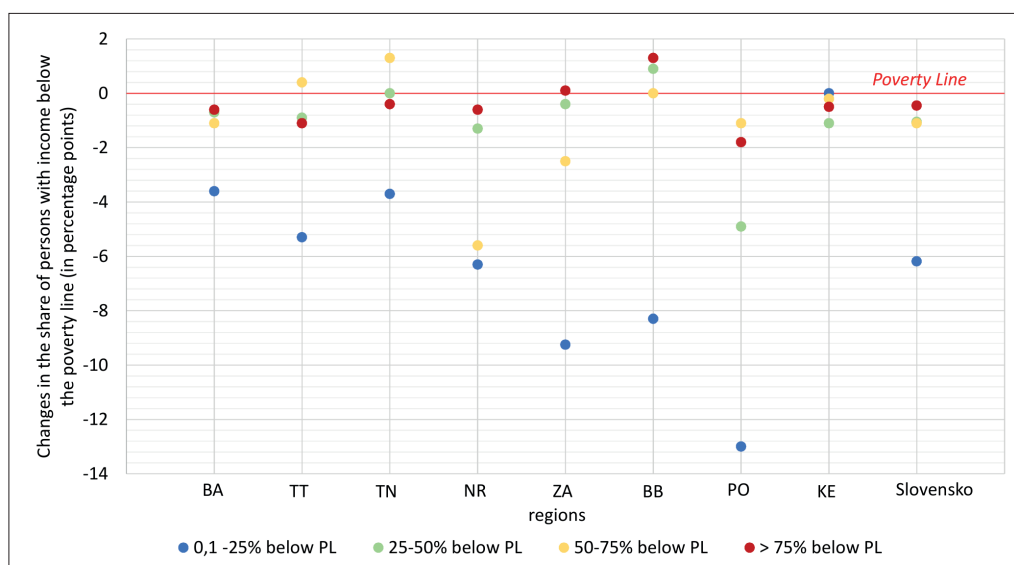


Fig. 10: Growth/decrease intensity of poverty (by quartiles) in 2022 and 2023

Source: Author's elaboration based on data from Statistical Office of the Slovak Republic (2025; EU SILC, 2023 and 2024)

different poverty depths. As previously mentioned, a three-stage multivariate framework comprising PLS regression, classical multiple regression, and PCA was used to identify the latent structure of determinants of poverty intensity. The PLS results show that the most stable core of the determinants of poverty intensity is household composition (Tab. 3). Household size and the number of dependent children achieve the highest VIP scores

	VIP (PLS)
Household size	1.171
Dependent children	1.181
Employed	0.870
Unemployed	1.132
Pensioners	0.443

Tab. 3: VIP scores of variables in the PLS model

Note: VIP values above 1 indicate variables with an above-average contribution to explaining the poverty structure

Source: Author's calculations

and display consistently positive relationships, especially for the categories 25–50% below the poverty line and less than 25% below the poverty line (Fig. 11). This means that in regions where poor households are larger and face a higher family burden in the form of dependent children, the representation of households in medium-deep and shallower, yet numerically widespread, forms of poverty is higher.

The PLS model also indicates that unemployment remains an important complementary determinant, particularly for the 25–50% and up to 25% poverty bands. By contrast, labour-market activity has a predominantly protective character once the shared structure of the determinants is taken into account, although a positive coefficient also appears for the category more than 75% below the poverty line. This should be interpreted cautiously, given the very small number of regional observations and the data's aggregation. The share of pensioners has the lowest VIP score and therefore the weakest overall contribution to explaining differences in poverty intensity.

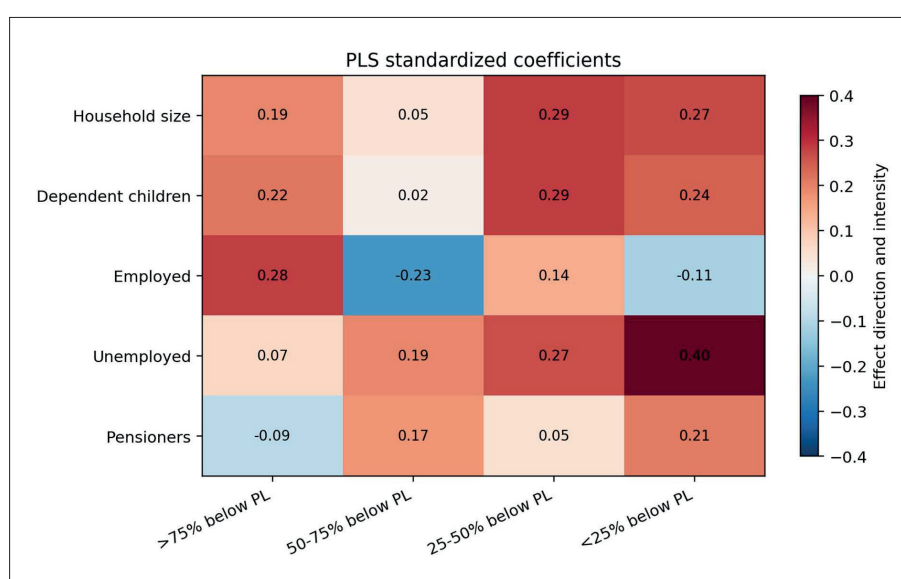


Fig. 11: Heatmap of standardised PLS coefficients

Note: Darker red tones indicate stronger positive relationships, while blue tones indicate negative relationships

Source: Author's calculations

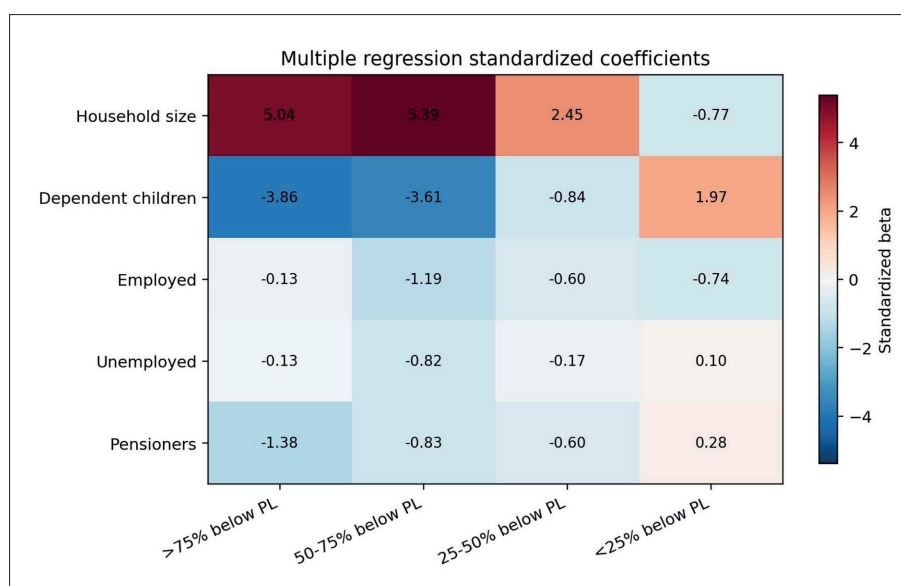


Fig. 12: Heatmap of standardised multiple-regression coefficients (Note: The volatility of the coefficients across models reflects the high sensitivity of OLS estimates to multicollinearity and a very small number of observations)

Source: Author's calculations

Classical multiple regression was then used as a robustness test. Its purpose was not to replace the PLS model, but to verify whether the direction and substantive logic of the relationships remain visible in a conventional specification. In this step, however, the problem of multicollinearity became fully apparent. VIF (Variance Inflation Factor) statistics reach extremely high values, especially for household size, dependent children, and the number of employed persons, confirming that isolated OLS coefficients are highly unstable in this type of dataset (Tab. 4).

	>75% below PL	50–75% below PL	25–50% below PL	<25% below PL
Household size	5.036	5.392	2.453	– 0.767
Dependent children	– 3.859	– 3.612	– 0.836	1.969
Employed	– 0.132	– 1.189	– 0.598	– 0.737
Unemployed	– 0.125	– 0.817	– 0.165	0.102
Pensioners	– 1.382	– 0.826	– 0.598	0.281

Tab. 4: Standardised coefficients of the multiple regression (robustness test)

Note: The results should be interpreted cautiously; the purpose of the table is to demonstrate directional stability together with the instability of individual OLS estimates under small-sample, high-collinearity conditions

Source: Author's calculations

In substantive terms, the OLS models confirm that household size and the number of dependent children play a major role in the structure of poverty, but individual coefficients vary substantially across models and in some cases even change sign (Fig. 12). This instability is not an argument against the underlying substantive relationships; rather, it demonstrates that simple correlations and standard regression coefficients may produce an overly simplified and potentially misleading picture when working with aggregated regional data. Methodologically, the multiple regression therefore reinforces the use of PLS regression as the primary analytical framework (Tab. 5).

	Adjusted R ²
>75% below PL	0.207
50–75% below PL	– 0.784
25–50% below PL	0.703
<25% below PL	0.937

Tab. 5: Adjusted R² of the multiple regression by poverty band

Source: Author's calculations

	PC1	PC2
Household size	0.561	– 0.012
Dependent children	0.538	– 0.213
Employed	0.415	– 0.490
Unemployed	0.422	0.389
Pensioners	0.214	0.750

Tab. 6: Variable loadings in the PCA. Note: A higher absolute value means a stronger connection of the variable to the given latent dimension. Source: Author's calculations

To clarify the internal structure of the determinants, principal component analysis (PCA) was subsequently applied. The results show that the determinants of poverty intensity can be reduced to two dominant latent dimensions. The first principal component explains about 63% of the total variance and is loaded mainly by household size, dependent children, employed persons, and unemployed persons (Tab. 6). This dimension can be interpreted as a factor of family burden and socio-economic pressure. The second component explains roughly 21% of the variance and is mainly associated with the share of pensioners and, to a lesser extent, with unemployment, thus representing a more age-status-related dimension (Tab. 7).

	Share of explained variance
PC1	0.630
PC2	0.214

Tab. 7: Share of explained variance in the PCA

Source: Author's calculations

The relationship of the PCA components to the individual poverty bands confirms the main findings of the PLS model. The first component is most strongly associated with the category 25–50% below the poverty line and also with the band up to 25% below the poverty line (Tab. 8). This means that the main regional differentiation of poverty intensity in Slovakia is not tied to a single isolated variable, but rather to a broader structural profile combining larger households, a higher number of dependent children, and a weaker socio-economic position. The second component is much less important, again suggesting that the concentration of pensioners alone does not explain the main regional differences in poverty intensity.

	>75% below PL	50–75% below PL	25–50% below PL	<25% below PL
PC1	0.611	0.116	0.851	0.757
PC2	– 0.268	0.363	– 0.073	0.209

Tab. 8: Correlations of the principal components with the poverty bands. Note: The strongest relationship of PC1 is visible in the 25–50% and 0–25% poverty bands

Source: Author's calculations

In summary, the three methods used provided a methodologically strong and content-conclusive picture of the determinants of poverty intensity. The results show that the decisive determinants of regional poverty intensity in Slovakia are household size and the presence of dependent children, while labour-market position plays an important but secondary role. Employment has a predominantly protective character, unemployment a risk character, and the share of pensioners only has limited explanatory power. From the perspective of applied policy, this implies that poverty-alleviation measures should be less uniform and more differentiated according to the demographic structure of poor households, particularly in favour of larger families with dependent children.

The results should nevertheless be interpreted with an awareness of the limitations of the analysed dataset. Only a small number of aggregated regional observations and a limited set of explanatory variables were available. The models, therefore, identify statistically and substantively meaningful associations, but they do not provide a basis for strong causal claims. Even so, compared with simple correlation analysis, they represent a substantially more robust basis for identifying the determinants of poverty intensity and for explaining why regions with similar poverty rates may differ markedly in the internal structure and depth of poverty.

5. Discussion

The study has its limitations, partly due to data constraints. The contribution is based on EU-SILC data, which do not allow for capturing, e.g. social, health, mental, behavioural, and other significant aspects of poverty. The lack of disaggregated data, in turn, limits research into micro-level mechanisms and the possibility of causal attribution between specific poverty rates or intensities and household groups defined by various characteristics. The study noted the lack of quantitative data, the need to expand them to include several key variables, and the need to monitor them at smaller spatial scales as well. Their existence would expand the possibilities for specifying the categories of the poor

not only in terms of the monitored FGT indices, but also in terms of the characteristics of the bearers of poverty. The absence of the aforementioned data also partly limits methodological options and narrows the range of methods available.

The analysis of changes in three poverty measures in Slovakia provided a picture and insights into the multidimensional nature of the cost-of-living crisis and its uneven socio-economic impacts across regions. The results of this paper confirm Kerr et al.'s (2025) findings that the cost-of-living crisis increases all poverty measures, especially for residents in areas experiencing long-term poverty. Although this study effectively uses the Foster-Greer-Thorbecke indices (FGT) to quantify poverty intensity, its methodological framework requires examination in the light of broader research across several EU countries. Eurostat data from 2023 show that 21.4% of the EU population faced poverty, with capital city regions typically achieving values below the national average (Eurostat, 2024b). However, the Bratislava region shows a completely opposite trend, recording a 36.7% share of households at risk of poverty, in sharp contrast to its position as an economic centre (Eurostat, 2024b). This anomaly is not unique; it has also been found in Belgium and Austria, where capital city regions showed higher poverty rates than the national average. This indicates not only regional differences across countries, but also that poverty in some EU countries has accelerated considerably and significantly affected urban economic centres. The deterioration of all poverty parameters in urban regions is mainly due to high and ever-increasing housing costs and stratified labour markets (Eurostat, 2024b). This fact is also confirmed by Vera-Toscano et al. (2024), who, based on the results of analyses in England, conclude that rural residence can currently be considered a significant 'poverty buffer'. This phenomenon, called the 'rural advantage effect', is related to significantly higher living expenses in cities, where housing costs in particular represent a significant part of household expenses. The authors state that while the share of people in income poverty before housing costs was 16% in rural areas and 18% in urban areas, after taking them into account (housing costs), the share of income-poor people in rural areas increased by only 1 percentage point to 17%, but in cities by up to 6 percentage points to 24% (in London up to 28%). Not only in London but also in other large cities, high housing costs have become the main driver of poverty. Similarly, Francis-Devine (2025), based on an analysis of the latest data, considers the disproportionately high housing costs, which significantly cut into household incomes, to be the main cause of the increase in poverty in cities in the United Kingdom. Our results confirm that, in Slovakia as well, significantly higher housing expenditures are associated with a higher share of the poor, especially in low-income households. For example, in 2020, arrears on mortgages, loans, or operating costs related to housing or regular services were reported by 6.7% of Slovaks; in 2024, their share increased to 8.4%. Although complete data for 2025 is not yet available, available statistics and analyses indicate that their share may reach double digits.

The study's emphasis on income-based poverty metrics overlooks the multidimensional drivers of deprivation highlighted in some recent work. For example, Ciommi et al. (2021) have shown that southern regions of Italy experienced intensified poverty due to complex factors, such as limited access to healthcare and educational disparities – variables that are missing from our analysis. Similarly, Calvo and Sánchez (2011) argued that regional poverty disparities in Spain stemmed from structural inequalities in the distribution of public services, rather than from income disparities alone (Calvo et al., 2011). By focusing exclusively on income thresholds, our study fails to capture the 'hidden poor', in particular those facing ever-increasing energy poverty or digital exclusion, as reported in the European Commission's 2023 Regional Vulnerability Assessments (Eurostat, 2024b).

The results of several studies (Dunga, 2024; Agyepong & Kuuwill, 2025; Marletta & Mussini, 2026) show that, at the household level, several factors can explain the different depths of poverty households find themselves in. The correlation between increasing poverty severity (FGT-P2) and household size in Slovakia mirrors the patterns observed in Poland and Hungary, where large families in rural areas faced a disproportionate impact of rising living costs (Decancq et al., 2014). However, the study's results, which show reduced correlation between unemployment and poverty depth, contradict Muñoz et al.'s (2018) finding that job loss is the primary factor in the intensification of poverty in Mediterranean EU countries. Even lower dependency and, at the same time, lower poverty depth can be observed among pensioners, where the relatively stable pension system in Slovakia significantly protects the elderly population from deep poverty. In recent years, however, this system (social security) has been failing younger households and working households – a nuance that requires deeper examination.

Regional disparities in poverty indicators in Slovakia also pose a challenge for the EU cohesion policy framework and national-level regional policy. While the poverty rate in the Prešov region at 22.6% is in line with structurally disadvantaged areas such as the north-east of Romania, the rapid deterioration in the Nitra region (an increase in extreme poverty of 5.6 percentage points) highlights the vulnerability of semi-industrialised zones to global market shocks (Eurostat, 2024b; Calvo et al., 2011). These findings confirm Kyzyma's (2020) observation that aggregate poverty indices often mask localised crises that require spatially targeted interventions (Decancq et al., 2014). The article, in agreement with Marletta and Mussini (2026), showed that the overall poverty gap results from alternative combinations of changes in the incidence of poverty, observed household structures, and spatial disparities, in particular, socio-economic inequalities. The importance or impact of space and significant territorial differences on the incidence and depth of poverty in Italy was confirmed by Ciommi et al. (2021), in Germany and Italy by Benedetti and Crescenzi (2023), and in England by Vera-Toscano et al. (2024).

6. Conclusions

This study underscores the multifaceted socio-economic ramifications of Slovakia's cost-of-living crisis, positioning it as a critical case study for understanding regional inequality in the EU. Three key contributions emerge:

6.1 Methodological rigor and gaps

The application of FGT indices provides a granular view of poverty intensity, confirming the limitations of binary (poor/non-poor) metrics. However, the absence of multidimensional indicators – such as access to healthcare or digital infrastructure – restricts the study's utility for holistic policy design. Future research should integrate the EU's revised 2025 multidimensional poverty framework to capture compounding deprivation factors.

Regional Disparities as a Policy Challenge: Slovakia's paradoxical poverty patterns, particularly the deterioration of its capital region, challenge the EU's assumption that economic hubs inherently drive equitable growth. The poverty risk in Bratislava demands urgent scrutiny of urban housing policies and wage stagnation, mirroring interventions in Vienna and Brussels, where targeted rent controls alleviated low-income precarity (Eurostat, 2024b).

6.2 Implications for EU cohesion

The study's finding that six of eight Slovak regions experienced worsening poverty depth between 2022 and 2023 signals systemic vulnerabilities in Central European economies. These trends align with broader CLC impacts in Hungary and Poland but contrast with Mediterranean nations where tourism rebounds mitigate

deprivation (Ciommi et al., 2021; Calvo et al., 2011). To address this, the EU's 2026–2030 cohesion policy must prioritise region-specific fiscal mechanisms, such as Slovakia's need for energy subsidy reforms versus Greece's tourism infrastructure investments.

6.3 Limitations and future directions

While the study's reliance on EU-SILC data ensures comparability, its cross-sectional design obscures longitudinal poverty dynamics. Subsequent work should employ panel data to track household trajectories, as demonstrated in Germany's Socio-Economic Panel (Decancq et al., 2014). Additionally, the exclusion of qualitative insights into coping mechanisms – a strength of the Council of Europe's 2024 CLC study – leaves critical behavioural factors unexplored.

In conclusion, Slovakia's experience exemplifies the inadequacy of one-size-fits-all approaches to the EU's polycrisis. Policymakers must balance immediate fiscal interventions with structural reforms addressing regional inequities, ensuring that cohesion strategies reflect the nuanced realities revealed by disaggregated poverty metrics.

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