

Article

Modelling Multidimensional Poverty and Social Exclusion in the EU and Türkiye: Evidence from SDG 1 Indicators

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Abstract

Poverty and social exclusion remain major challenges to social sustainability, social cohesion and quality of life in Europe, and their reduction is a central objective of Sustainable Development Goal (SDG) 1. The present study examines the relationship between macroeconomic factors and poverty and social exclusion across the EU-27 and Türkiye. The analysis employs the EU's headline at-risk-of-poverty-or-social-exclusion (AROPE) indicator and its three components: relative income poverty (AROP), severe material and social deprivation (SMSD), and very low work intensity (VLWI). Whilst the majority of cross-country studies utilise the composite rate or a single component and exclude Türkiye, this study estimates the comparative sensitivity of all three components to the same regressors within a panel that treats Türkiye as a structurally distinct case. Utilizing two-way fixed-effects models with country-clustered standard errors across 28 countries from 2015 to 2024, in conjunction with a range of robust checks, our study identifies three salient findings. First, Gross Domestic Product (GDP) per capita is the sole factor with a robust association with the headline rate. In particular, a 10% increase in GDP per capita is associated with a reduction in the AROPE rate of approximately 1.7 percentage points (an approximate semi-elasticity). Conversely, inequality and employment emerge as significant factors only under classical inference. Secondly, the associations demonstrated in this study are dimension-specific. Income is associated with material deprivation, inequality with relative income poverty, labour market conditions with work intensity, and social spending with material deprivation. Thirdly, the exclusion of Türkiye results in the reversal of the signs of the inflation and early-school-leaving coefficients, indicating a poverty dynamic that is structurally distinct. The analysis suggests that strengthening social sustainability requires not only economic growth, but also inclusive labour markets, effective social protection and reduced inequality.

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1. Introduction

Poverty remains one of the most persistent socio-economic challenges in Europe, despite the relatively high level of economic development, extensive welfare systems and long-standing social cohesion policies implemented across the European Union (EU). From the perspective of social sustainability, poverty and social exclusion undermine

social cohesion, limit equal participation in economic and social life, and reduce the capacity of societies to achieve inclusive development. The importance of poverty reduction has been strongly emphasized in the United Nations 2030 Agenda for Sustainable Development, where SDG 1 aims to “end poverty in all its forms everywhere.” This goal is not limited to the elimination of extreme poverty, but also includes reducing relative poverty, improving social protection systems, ensuring equal access to basic services, and strengthening the resilience of vulnerable groups. In the European context, poverty is commonly understood as a multidimensional phenomenon that extends beyond insufficient income. Eurostat monitors SDG 1 by focusing on several aspects of poverty and social exclusion, including people at risk of poverty or social exclusion, monetary poverty after social transfers, severe material and social deprivation, very low work intensity, housing deprivation and unmet needs for medical care. This broader approach reflects the fact that poverty is shaped not only by household income, but also by labour market conditions, redistributive policies, access to public services and the overall macroeconomic environment. Although the EU has made progress in reducing some dimensions of poverty, the problem remains substantial. In 2024, 93.3 million people in the EU, representing 21% of the population, were at risk of poverty or social exclusion. This was a slight decrease compared with 2023, when 94.6 million people, or 21.3% of the population, were affected. These figures indicate that, despite improvements, approximately one in five EU residents still faces poverty-related risks. Such persistence highlights the need for further empirical investigation into the economic determinants of poverty reduction and the effectiveness of socio-economic policies across countries. Economic factors play a crucial role in shaping poverty outcomes. Higher employment levels, rising household incomes, stable economic growth and effective redistributive mechanisms can contribute to poverty reduction. At the same time, inflation, labour market segmentation, income inequality, insufficient social protection and regional disparities may weaken the poverty-reducing effects of economic development. Therefore, analysing poverty solely through the lens of GDP growth may be insufficient. A more comprehensive approach should consider how different economic variables interact with social policy instruments and how these relationships differ across countries.

The inclusion of Türkiye in the analysis provides an important comparative perspective. As a candidate country and a major economy closely connected with the EU through trade, migration, institutional cooperation and regional development processes, Türkiye offers a valuable case for examining poverty dynamics beyond the EU Member States. Comparing EU countries with Türkiye may reveal both common and country-specific mechanisms influencing poverty reduction, particularly in relation to economic growth, employment, income distribution, social transfers and material deprivation. Indicators used in SDG-related monitoring for Türkiye include, among others, people at risk of poverty after social transfers, poverty headcount ratios and severe material and social deprivation rates.

This article aims to examine the economic factors associated with poverty and social exclusion in EU countries and Türkiye using selected SDG 1 indicators. The study focuses on identifying the relationships between poverty-related indicators and key economic conditions, with particular attention to cross-country differences. By adopting a comparative perspective, the article contributes to the discussion on sustainable development, social cohesion and evidence-based policy design. The findings may provide useful insights for policymakers seeking to strengthen poverty reduction strategies and improve progress towards SDG 1 in both EU Member States and Türkiye. The present study is of significance in three respects. Firstly, whereas most cross-country research relies on the composite AROPE rate or a single component, this study estimates the comparative sensitivity of all three components (AROP, SMSD and VLWI) to an

identical set of macroeconomic factors within one panel. This reveals factor–dimension correspondences that the composite indicator conceals. Secondly, the study incorporates Türkiye, a country that is typically excluded from European studies despite the existence of EU-comparable Eurostat data. As an EU candidate with a deep trade and institutional relationship but a structurally distinct hybrid welfare regime—characterised by relatively low social-protection expenditure (approximately half the EU average), significant labour-market informality, and a family-based social safety net—Türkiye serves as a different comparator for testing whether the macro-poverty associations established for European welfare states also hold in a divergent institutional setting. Thirdly, given the shortness of the panel and the paucity of clusters, the estimates are subjected to cluster-robust and Driscoll–Kraay standard errors, a wild cluster bootstrap and a leave-one-country-out jackknife. This is to ensure that the reported associations do not depend on a particular error structure. The structure of the article is as follows. The next section presents the theoretical background and previous research on poverty reduction and its economic determinants. The following section describes the data, variables and methodological approach. The empirical results are then presented and discussed in relation to SDG 1 objectives. The final section provides conclusions, policies and suggestions for future research.

2. Literature Review

2.1. *Measuring Poverty in the European Union: Multidimensional Frameworks*

The conceptualisation of poverty has undergone a significant shift, transitioning from one-dimensional, income-based definitions towards multidimensional frameworks that capture the intricate nature of deprivation [1–4]. This paradigm shift is reflected in the manner in which the EU is monitoring SDG 1. The EU’s headline measure, the AROPE rate, classifies a person as at risk if they meet at least one of three criteria: AROP, SMSD, and the living situation of the subject (i.e., whether they resided in a (quasi-)jobless household; VLWI). Each person was counted once. Adopted under the Europe 2020 strategy and retained for the 2030 target, AROPE has been described as the highest-profile policy application of multidimensional poverty measurement to date [5,6]. Consequently, the reduction of poverty is a priority and a key issue in many nations, as it is a key component in achieving the SDGs. It is imperative to comprehend the dimensions of poverty and the processes through which it intensifies in order to address this priority. In this context, the complex nature of the problem can be comprehended through consideration of the measurability of the extent and intensity of poverty [7].

The broad scope of AROPE is characterised by its ability to amalgamate disparate experiences of poverty under a unifying “union” definition. This approach, as outlined in the extant literature, involves the classification of individuals as poor based on their deprivation in at least one dimension. Each indicator provides information regarding overall performance within a single dimension and potentially the shape of the distribution. However, this design exhibits an analytical blind spot in that it fails to disclose the relationship between the components, thus leading to an erroneous assumption that a person in a high-income household who cannot afford a fixed set of material items is equivalent to an unemployed person in a jobless household with income below the threshold [4,8,9]. Empirical evidence indicates that the components exhibit only partial overlap and are associated with different demographic groups. The selection of measurement methodology has been demonstrated to engender fluctuations in measured rates, with a potential variation of up to ten percentage points [3]. A non-trivial proportion of those not classified as at risk by AROPE are, nevertheless, impoverished according to a stricter combined-deprivation criterion.

A limitation specific to the income-poverty component is that each member state's poverty line is defined against its own income distribution, so the threshold does not reflect inequalities between states [1,10–13]. Following the expansion of the European Union, the classification of an individual as impoverished in a member state with a lower income may result in their position exceeding that of the state's own average. This phenomenon can introduce bias in cross-country comparisons. Notwithstanding these criticisms, AROPE remains the EU's reference indicator, with the 2030 Action Plan targeting a reduction of at least 15 million in the AROPE population relative to 2019 [6,14]. In order to ensure comparability with the EU's own monitoring framework, this study therefore takes the AROPE rate and its three components as dependent variables, while recognising that the composite rate can mask heterogeneity across those components.

However, as Wagle's [15] work elucidates, a multidimensional approach may prove essential in determining policy design, a conclusion further reinforced by the limitations of unidimensional measurements. It is evident that the 2030 UN Sustainable Development Agenda, which acknowledges the significance of a multidimensional understanding, establishes the objective of eradicating poverty in all its forms and dimensions. According to the monitoring report by Eurostat [6], the EU has achieved improvements in all three AROPE components. Nevertheless, the realisation of the target set for 2030 will require additional efforts. The present study is informed by extant research that formed the methodological framework for this study, which in turn drew upon findings from the literature and Eurostat data, thus providing results. The composite AROPE rate obscures both the heterogeneity of poverty experiences across its three components and the distortions introduced by country-specific relative thresholds. Therefore, focusing on a single headline indicator to assess the decisive role of economic factors would risk producing findings that are both statistically significant and fundamentally misleading. Consequently, the present study adopts the AROPE rate as the primary dependent variable in order to ensure comparability with the EU's own monitoring framework.

2.2. Economic Factors and Poverty

The correlation between economic growth and poverty reduction has been a subject of considerable academic debate. The relationship is by no means uniform. The extent to which economic growth exerts an impact on poverty remains the subject of ongoing debate, particularly with regard to the degree to which poverty is elastic with respect to growth. These vary substantially across different contexts, with the extent of this variation being largely dependent upon how the gains from growth are distributed and on the structural characteristics of the economy [16–18].

The magnitude is sensitive to three factors: the composition of the sample, the time period in question, and the poverty measure employed [18]. When economic growth is accompanied by increasing inequality, its ability to reduce poverty is weakened. An analysis of China reveals that income growth and deteriorating distribution can act in contradictory ways. The gains from income growth are significantly offset by deteriorating distribution. In the context of economic analysis, inequality functions as a mediating condition that operates between the variables of growth and poverty [19]. The present model incorporates both GDP per capita, measured in purchasing-power standards, and the post-transfer Gini coefficient, thus enabling an examination of the distinct roles of growth and distribution as explanatory variables.

In instances where growth alone does not alleviate poverty, the redistributive capacity of the welfare state assumes a central role. Van Kersbergen and Vis [20] report a strong negative association between social expenditure and relative poverty across OECD countries. This suggests that achieving low poverty is difficult without substantial social spending. The magnitude of this effect is contingent, however, on the welfare regime.

Esping-Andersen and Myles [21] found that redistribution reduced market poverty among households, with the most significant impacts observed among households with children, particularly in social-democratic regimes. Greve [12] demonstrated that the inequality-reducing effect of transfers varied considerably across different regime types and shifted during the 2010–2020 period. It is important to note that social expenditure does not invariably reach the economically disadvantaged. Cantillon [22] and Van Kersbergen and Vis [20] have documented that the proliferation of social investment occurred in tandem with the stagnant or rising prevalence of poverty among working-age individuals, a phenomenon referred to as the “Matthew effect.” This suggests that financial assistance programmes are disproportionately benefiting middle-income groups. The effectiveness of social protection is thus contingent on its institutional design and targeting. Consequently, the share of social expenditure in GDP is included in this study without an a priori expectation about the sign of its coefficient.

Employment is recognised as a component of well-being, with evidence demonstrating that it has a direct impact on household income and living standards. Moreover, employment is instrumental in facilitating income generation, consumer spending, and social engagement. The ‘very low work intensity’ element of AROPE is measured using this pathway [3]. Consequently, the employment and unemployment rates are proxies for both income generation and labour-market exclusion. The cost of living exerts its influence through a distinct mechanism affecting material deprivation. Energy poverty varies considerably across countries, and household energy prices rose sharply in 2022–2023. Consequently, this variation may be indicative of a pattern that is specific to the regime in question with respect to the cost of living [23–25]. It can be demonstrated that a correlation exists between consumer price inflation and not only income poverty but also severe material and social deprivation.

Finally, inequality exerts a significant influence on the capacity of other factors to reduce poverty. As the level of inequality rises, so does the growth elasticity of poverty; in turn, the effectiveness of targeted transfers is diminished, and the returns to employment become dependent on wage distribution and contractual security [12,26]. The Gini coefficient is therefore entered into the analysis not merely as a control, but as a variable of central interest. Within this framework, GDP per capita in Purchasing Power Standards (PPS) is indicative of economic growth; the unemployment and employment rates are reflective of labour-market conditions; social-protection expenditure is indicative of redistribution; the Gini coefficient is an indicator of distribution; and the Harmonised Index of Consumer Prices (HICP) is a measure of cost-of-living pressures. The phenomenon of early school leaving, in conjunction with the age dependency ratio amongst the elderly population, has been identified as a contributing factor to the manifestation of poverty outcomes.

2.3. Welfare Regimes and Cross-Country Heterogeneity

The indicators of poverty are subject to systematic influence by the prevailing welfare regime. The fundamental typology proposed by Esping-Andersen [27] categorises regimes—social democratic, conservative and liberal—according to de-commodification, social stratification and the combination of public and private welfare provision. Ferrera’s [28] argument for a distinct Southern European type was based upon the existence of social assistance programmes and strong family ties. Despite Esping-Andersen’s initial rejection of the incorporation of a Southern European welfare regime into the classification, on the grounds that ‘the distinction between the Conservative and Mediterranean models was too small to be taken into account’, subsequent studies have largely adopted this proposal [20,29,30]. Utilising the contributions of Greve [12,31] and Aspalter [32], a six-regime classification was operationalised through the incorporation of

the Southern European, Eastern European, and Baltic clusters, in addition to the original classification. This approach was applied to the entirety of the 28 EU member states. These welfare regimes form the analytical framework of this study's comparative structure. It has been demonstrated that the welfare regime classification is associated with marked disparities in terms of outcomes pertaining to poverty and inequality. Greve [12] asserts that during the 2010–2020 period, inequality was most pronounced in the Baltic countries, followed by liberal and Southern European regimes, with the lowest levels observed in the Scandinavian welfare states. The Eastern European and continental clusters occupied intermediate positions.

However, the framework, comprising six welfare regimes, excludes Türkiye—a candidate country that falls outside the EU-27 classification—yet it has been incorporated into the analysis on the basis that it provides analytical support to this study. It is asserted that Türkiye exhibits numerous structural similarities with the Southern European paradigm. These characteristics include the presence of a significant informal economy, a fragmented social insurance sector linked to formal employment, and a notable reliance on family-based solidarity to act as a safeguard against poverty [20,28,33,34]. Concurrently, Türkiye diverges from the Southern European paradigm in a number of significant respects. A major restructuring of the pension system was undertaken in the 2000s, while the social assistance system is expanding rapidly and is still described as evolving towards a coherent regime [35]. The hybrid status of Türkiye offers a valuable opportunity to examine whether the economic factors that determine poverty, as defined within the EU context, function in a comparable fashion within a structurally distinct institutional framework. Should the coefficients for growth, employment and social transfers differ significantly between Türkiye and the EU-27, this could be indicative of the influence of the characteristics of the welfare regime on the poverty-reducing effectiveness of macroeconomic variables. The empirical strategy employed involves the initial analysis of the full sample of 28 countries, with subsequent robustness checks excluding Türkiye in order to determine whether the inclusion of a non-EU welfare state affects the estimated relationships.

2.4. Research Gap and Hypotheses

The EU's headline indicator combines three qualitatively different forms of deprivation under a single Union definition. However, the overlap between its components is empirically limited, and they are associated with different demographic groups [5,36]. Concurrently, the economic factors associated with poverty, including growth, employment, social transfers, inequality, and the cost of living, function through partially independent channels whose magnitude is subject to variation by welfare regime [12,20]. Türkiye demonstrates a social protection architecture that is structurally distinct from European regimes [35,37]. Consequently, the question remains unanswered as to whether the economic factors associated with the various AROPE components are consistent in direction and magnitude or whether different components respond to different factors. Existing cross-country studies of poverty in Europe have tended to rely on the composite AROPE rate or to examine a single component in isolation. The work closest to the present design [38] modelled income poverty and material deprivation separately, but excluded the work-intensity component, used the pre-2021 indicator definitions, and did not extend beyond EU member states. To the best of our knowledge, no study has systematically estimated the comparative sensitivity of all three AROPE components (AROP, SMSD, and VLWI) to the same set of macroeconomic factors within a single panel that also includes Türkiye.

The hypotheses are derived from the conceptual nature of the three components. The concept of AROP is defined in relation to a relative income threshold, while SMSD is

defined against a fixed list of deprivation items. The third component, VLWI, captures the phenomenon of household labour-market attachment.

H1. *The hypothesis is that GDP per capita will be negatively associated with the composite AROPE rate, with the effect concentrated in particular components. The evidence suggests that this effect will be more pronounced for material deprivation, whose threshold is fixed, than for relative income poverty, whose threshold shifts with national income.*

H2. *Social protection expenditure as a share of GDP is expected to reduce all three components, but its effect is expected to be stronger for income poverty and VLWI than for SMSD.*

H3. *A strong correlation is expected between unemployment and the component known as VLWI. This is due to the fact that the component is directly related to labour market attachment.*

H4. *In view of the sensitivity of the relative threshold to the income distribution, it is to be expected that the Gini coefficient will be associated above all with AROP.*

H5. *It is hypothesised that consumer-price inflation, by eroding the purchasing power required for the items defining the deprivation threshold, is most closely associated with SMSD.*

H6. *The inclusion of Türkiye in the sample is expected to modify the estimated associations, particularly for social-protection expenditure and the employment rate.*

To test the hypotheses in question, a panel dataset for the period between 2015 and 2024 is employed. The dataset includes both the EU-27 and Türkiye, and it has been analysed with two-way fixed effects and country-clustered standard errors. The robustness of the estimates is assessed through a variety of means, including the use of alternative dependent variables, a Türkiye-excluded subsample, alternative specifications, and the jackknife and wild cluster bootstrap.

3. Methodology

3.1. Data and Variables

The analytical approach encompasses a nearly balanced panel comprising 27 EU Member States and Türkiye over the 2015–2024 period, encompassing 28 cross-sectional units and a ten-year span ($T = 10$), yielding 280 country-year observations. In this case, the dependent variables are the AROPE rate and the three sub-components that constitute this rate (see Dependent Variable). The delimitation of the sample period is predicated on two considerations. The first is the starting year of the United Nations 2030 Agenda for Sustainable Development, which provides the study's conceptual framework. Secondly, the "Europe 2030" definition of the AROPE indicator underwent revision in 2021 under the Action Plan of the European Pillar of Social Rights. The three components employed in the analysis have been compiled in accordance with the revised definition. The period under consideration concludes in 2024, the most recent year for which observations are consistently available from Eurostat.

The inclusion of Türkiye within the same panel constitutes a fundamental design decision. Notwithstanding its candidacy for EU membership, Türkiye has a welfare regime that is structurally distinct from European models. The discussion of this configuration is situated within a theoretical framework that is rooted in "inegalitarian corporatism," a concept previously advanced by Seekings (2004) [34] and described as an idiosyncratic regime that shares features of the Southern European model [34,35]. This divergence is quantitatively pronounced, with Türkiye's social protection expenditure averaging 11.3% of GDP over the period, in contrast to the EU-27's 22.6%. As such,

Türkiye offers a case for assessing whether the poverty–macroeconomy relationships hold beyond the core European welfare states (H6).

3.2. Dependent Variable

The primary dependent variable in this study is the AROPE rate. AROPE is the European Union’s official headline indicator for monitoring poverty and social exclusion under SDG 1 and the European Pillar of Social Rights [6,14], which is why it is adopted here; to avoid the aggregation blind spots noted in Section 2.1, it is analysed both as the composite rate and through its three components, each modelled separately. The AROPE rate combines three distinct deprivation statuses under a unified “union” rule. An individual is classified as “at risk” if they fulfil at least one of three criteria: AROP, SMSD, or VLWI. If an individual fulfils more than one condition, they are considered “at risk.” The components are in accordance with the 2021 revision. AROP is defined as the share of individuals with equivalised disposable income (after transfers) below 60% of the national median, representing a relative measure. SMSD is defined as the share of the population unable to afford at least seven of thirteen material and social items (replacing the pre-2021 four-of-nine measure). The term ‘VLWI’ is used to denote the proportion of the population aged between 0 and 64 years who resided in households where the working-age adults had utilised no more than 20% of their work-time potential in the previous year (in place of the pre-2021 0–59 definition). The series under consideration are AROPE (ilc_peps01n), AROP (ilc_li02), SMSD (ilc_md07), and VLWI (ilc_lvhl11n, ages 0–64), with the pre-2021 VLWI (ages 0–59) retained for comparison.

Despite the fact that the union rule engenders a powerful headline indicator, it reduces qualitatively distinct deprivation experiences to a single rate. The populations identified by income poverty and material deprivation are largely different [5,36], and estimating macroeconomic effects on the composite rate may mask offsetting effects on the components. The study therefore adopts a multi-equation strategy, estimating the same regressors for each component as well as on AROPE.

3.3. Explanatory Variables and Functional Forms

The explanatory variables comprise the macroeconomic factors associated with poverty in the relevant literature, namely growth, the labour market, social transfers, inequality and inflation, as well as two structural/demographic control variables. All variables were obtained from Eurostat in order to encompass the EU-27 and Türkiye for the 2015–2024 period. Supplementary Table S1 lists the definitions, units of measurement, and Eurostat series codes.

All variables, with the exception of GDP per capita, are rates, shares or indices and enter in levels, with coefficients interpreted per percentage point. GDP per capita, measured in purchasing power standards (a real, volume measure that already adjusts for cross-country price differences), enters logarithmically; the variables are not otherwise normalised or standardised. This finding is indicative of the diminishing effect of income on poverty: A given percentage rise is more effective at reducing poverty in lower-income countries. This phenomenon is linearised by the log transform (see Wooldridge [39]). The data fit is notably superior ($R^2 = 0.473$ versus 0.361 in level form; see Robustness Strategy, R4); however, the level form is retained as a robustness check.

Inflation is defined as the annual average rate of change in the HICP (Eurostat RCH_A_AVG). The unemployment and employment rates are both retained deliberately, as they each convey distinct information. It is important to note that, while the unemployment rate is a measure of those who are actively seeking work, the employment rate reflects the proportion of the working-age population that is employed. For a more

detailed discussion of this topic, please refer to the section on Functional Form and Multicollinearity.

3.4. Panel Specification and Estimators

The panel data structure makes it possible to control for unobserved unit heterogeneity. The study's general unobserved-effects model can be written as [39]:

$$\text{AROPE}_{(it)} = \beta_0 + \sum_{(k)} \beta_k X_{(kit)} + a_i + \lambda_t + u_{it} \quad (1)$$

where AROPE_{it} is defined as the AROPE rate (or one of its components) for country i in year t ; X_{kit} is the k -th explanatory variable ($k = 1, 2, \dots, 8$; selected on the theoretical grounds set out in Section 2); a_i is the country-specific unobserved effect; λ_t is the year-specific (cross-country common) effect; and u_{it} is the independent (idiosyncratic) error term. The four estimators employed in the study differ in their treatment of a_i and λ_t .

The pooled OLS model operates under the assumption that there is no unobserved heterogeneity. It is reported solely for the purpose of comparison. The random effects (RE) model treats the country effect as uncorrelated with the regressors and is estimated by feasible GLS. The one-way fixed effects model eliminates the country effect through the within transformation, but it is unable to identify time-variant variables. The two-way fixed-effects model, which is adopted as the study's main specification, additionally removes the year-specific effects through the transformation:

$$\widetilde{(\text{AROPE})}_{(it)} = \text{AROPE}_{(it)} - \overline{(\text{AROPE})}_i - \overline{(\text{AROPE})}_{(t)} + \overline{(\text{AROPE})} \quad (2)$$

This transformation incorporates both country-specific permanent differences and annual shocks shared among all countries (λ_t), including the 2020 pandemic [39]. As common shocks are characterised by cross-sectional dependence, the two-way fixed-effects model is adopted as the study's primary specification.

The utilisation of two-way fixed effects serves to eliminate time-invariant country heterogeneity and the annual shocks that are endemic to all countries. However, these studies do not address contemporaneous simultaneity. The present study acknowledges the possibility that some explanatory variables may be jointly determined with poverty outcomes. Prolonged periods of elevated levels of poverty have been demonstrated to exert a detrimental effect on economic growth, with a concomitant effect on GDP per capita. It is evident that social protection expenditure responds to the economic cycle, thereby providing a cushioning effect against poverty. Moreover, employment and poverty have been shown to be mutually reinforcing. It is imperative to acknowledge that all regressors are entered concurrently. This finding indicates that the estimated coefficients are more likely to reflect within-country co-movements rather than causal effects [39–41]. Consequently, the estimated coefficients may be biased by reverse causality or by time-varying factors common to poverty and its correlates. Consequently, the results are interpreted as associations, and instrumental-variable estimation and dynamic panels are identified as routes to causal identification in future work. In order to perform a partial check on the timing of these associations, Section 4.1.5 re-estimates the model with the regressors lagged by one year.

3.5. Functional Form and Multicollinearity

The functional forms under discussion may be found in the section on Explanatory Variables and Functional Forms. The GDP per capita variable is entered logarithmically [39], whilst the remaining variables, which are rates or shares, are entered in levels. It is acknowledged that high collinearity can inflate coefficient variances. Therefore, multicollinearity was investigated prior to estimation by means of the variance inflation factor (VIF), as outlined in Supplementary Table S2.

The highest VIF is for the employment rate (2.95), which is well below both the conservative threshold of 5 and the conventional threshold of 10 [39,40]. Furthermore, no pairwise correlation among the regressors exceeds 0.80 (the strongest being -0.70 between unemployment and employment). Consequently, the model exhibits no substantial multicollinearity. Despite the observed correlation between the variables, both are retained due to the unique insights they offer. Unemployment rate captures individuals actively seeking employment, whereas the employment rate represents the employed share of the working-age population, thereby offering an indirect measure of the inactive population. Therefore, due to their distinct informational content, these variables are considered non-interchangeable.

3.6. Cross-Sectional Dependence and Standard Errors

In cross-country panels, errors may be cross-sectionally dependent through common shocks or spillovers; therefore, standard errors that ignore this are inconsistent [42]. This was tested using the Pesaran [43] CD test, which is suitable for short-T, large-N panels. The test was used in a comparable European poverty panel by Canale and Liotti [44]. The CD test was applied in three distinct specifications, as delineated in Table 1.

Table 1. Pesaran CD test (N =28, T = 10).

Specification	CD	<i>p</i>	mean <i>q</i>
Raw AROPE	14.96	<0.001	0.525
One-way (entity) FE residuals	5.92	<0.001	0.422
Two-way FE residuals	−1.39	0.165	0.388

Source: Own calculations based on Eurostat data. Notes: H_0 = cross-sectional independence [43] (Pesaran, 2004). The two-way specification removes the dependence present in the raw series.

The raw AROPE series demonstrates a strong cross-sectional dependence (CD = 14.96). The introduction of country fixed effects serves to reduce, though not entirely eliminate, this dependence (CD = 5.92). Conversely, the year fixed effects appear to absorb common shocks, resulting in the two-way FE residuals becoming dependence-free (CD = -1.39 , $p = 0.165$). As the CD statistic is designed to average signed correlations, the possibility of residual dependence cannot be completely excluded (the mean absolute pairwise correlation remains at 0.388). Inference is thus rendered robust to the choice of standard errors: the primary estimates employ country-level cluster-robust standard errors [45], with Driscoll–Kraay [46] standard errors serving as a check, given their robustness to cross-sectional and temporal dependence. Given that cluster-robust validity depends on a large number of clusters and Driscoll–Kraay validity on a long panel, and given that our sample lacks both (28 clusters, $T = 10$), the key coefficients were assessed via the wild cluster bootstrap and the jackknife (see Robustness Strategy).

3.7. Model Selection

The choice between fixed and random effects is contingent on whether the unobserved country effect is correlated with the regressors, which is traditionally tested using the Hausman [47] test. In this case, the classical statistic ($\chi^2(8) = 13.20$, $p = 0.105$) did not reject RE, but the FE–RE covariance difference was not positive definite. This rendered the classical test unreliable and unstable across runs. The selection of the model was therefore made using the more robust Mundlak [48] correlated-random-effects approach in cluster-robust form [39], with the RE model augmented by the group means of the time-varying regressors. The Wald test ($\chi^2(8) = 12.59$, $p = 0.127$) also did not reject RE (Table 2). Despite the fact that neither test rejects RE, the two-way fixed-effects model is adopted as the primary specification (with RE reported as a check) for four reasons. Firstly, the tests

do not exclude FE either, and FE is consistent whether or not the country effect is correlated with the regressors, with minimal efficiency loss (all one-way FE–RE slope differences < 0.17). Secondly, the two-way specification absorbs the common annual shocks identified in Cross-Sectional Dependence and Standard Errors. Thirdly, the EU-27-plus-Türkiye set is very nearly a complete universe rather than a random sample, making RE’s random-draw assumption conceptually inappropriate (a justification also given by Ribeiro et al. [41] for the same two-way FE model). Finally, the main findings remain unchanged when RE estimates are reported alongside FE.

Table 2. Model selection (fixed vs. random effects).

Test	Statistic	<i>p</i>	Outcome
Hausman (classical)	$\chi^2(8) = 13.20$	0.105	Does not reject RE; FE–RE covariance difference not positive definite, hence unreliable
Mundlak/CRE Wald)	(cluster-robust $\chi^2(8) = 12.59$	0.127	Does not reject RE

Source: Own calculations based on Eurostat data. Notes: Two-way FE is adopted as the primary specification (RE reported as a check) for the four reasons given in the text.

The two-way specification also bears on the question of time trends. The incorporation of a comprehensive set of year fixed effects facilitates the absorption of any factor common to all countries in a given year, including a common time trend, in a more flexible manner than would be possible with a single linear trend term. Conversely, the country fixed effects have the capacity to assimilate time-invariant regional heterogeneity. The incorporation of welfare regime—or country-specific linear trends—was deemed unnecessary, as the ten-year period per unit would have resulted in a significant loss of degrees of freedom for minimal gain. It was determined that the year fixed effects adequately capture the predominant common-time variation, including the impact of the pandemic shock.

3.8. Robustness Strategy

In view of the few-cluster and short-T limits mentioned above, robustness was gauged along four lines, with comprehensive results available in the Results section. The model was re-estimated with each of the alternative dependent variables (AROP, SMSD, and VLWI) as the dependent variable (R1), since AROPE is a union of three components. This multi-equation strategy has been demonstrated to correspond with the findings of the closest comparison study, which employed both a composite index and AROPE [49]. This approach was adopted to unveil dimension-specific effects that may be obscured by the headline indicator.

The investigation of sample and specification variations was conducted to ensure that the findings were not influenced by Türkiye. Consequently, the model was re-estimated on the EU-27 alone (R2). The influential observation subsets (namely, the pandemic years, observations of very high inflation above 20%, and 2024) were eliminated rather than implementing a split of the short panel (R6). Moreover, a jackknife analysis that excluded one country at a time was utilised to ascertain that no individual country exerted a significant influence on the key coefficients. The study utilised a comprehensive set of economic indicators, encompassing social-protection expenditure as a percentage of GDP, as well as its real per capita measure (R3). Additionally, GDP per capita was analysed in both logarithmic and level forms (R4), and the labour market was assessed with unemployment and employment data entered separately (R5). Finally, in order to assess whether the associations reflect contemporaneous timing rather than a lagged relationship, the main model was re-estimated with all macroeconomic regressors lagged

by one year (R7). This is particularly relevant for social-protection expenditure, whose budget is set in the preceding year.

In the context of few-cluster inference, it is important to note that cluster-robust standard errors tend to over-reject in cases where clusters are few. To address this issue, the key coefficients were also assessed using the wild cluster bootstrap-t [49] (null imposed, $B = 999$). This approach serves to correct the over-optimistic significance of conventional tests in the 5–30-cluster range, a range that includes the sample under consideration.

The estimation of all models was conducted in R (v4.5.2), with independent reproduction occurring in Python (v3.11.14). The two-way fixed-effects estimates, the classical and country-clustered standard errors, and the within- R^2 were obtained using the fixest package (v0.13.2). The Hausman and Mundlak/correlated-random-effects tests and the Driscoll–Kraay standard errors were computed using the plm (v2.6.7) and sandwich packages (v3.1.1) [50–52]. The wild cluster bootstrap was implemented manually following Cameron et al. [49], using Rademacher weights with the null imposed. To guard against implementation error, the results were then independently reproduced in Python using NumPy (v2.3.5) and SciPy (v1.16.3) and cross-checked against a base-R least-squares dummy-variable regression; all three approaches yielded identical results.

3.9. Cluster Analysis

Cluster analysis is a widely used multivariate statistical technique aimed at grouping objects into relatively homogeneous clusters based on their similarities or dissimilarities. The primary objective of this method is to ensure that objects within the same cluster are as similar as possible, while objects from different clusters are as distinct as possible [53]. This approach is particularly useful in socio-economic research, where complex and multidimensional data structures require classification and pattern recognition.

Cluster analysis belongs to the broader category of unsupervised learning methods, as it does not rely on predefined group labels [54]. Instead, it explores the inherent structure of the data, allowing researchers to identify natural groupings based on selected variables. Depending on the methodological approach, cluster analysis can be divided into hierarchical methods (e.g., agglomerative and divisive techniques) and non-hierarchical methods, such as k-means clustering [55,56]. The choice of clustering method depends on the nature of the data and the research objectives. Hierarchical clustering is often used for exploratory analysis and provides a visual representation of the clustering process in the form of a dendrogram, while k-means clustering is more suitable for larger datasets and requires the researcher to specify the number of clusters in advance [57]. An important step in cluster analysis is the selection of an appropriate distance measure, such as Euclidean distance, which determines the similarity between objects.

In socio-economic studies, cluster analysis is frequently applied to identify groups of countries or regions with similar development patterns, levels of innovation, or living standards. It enables researchers to simplify complex datasets and support decision-making processes by revealing hidden structures in the data [58].

In this study, cluster analysis was applied as a complementary exploratory tool to identify groups of countries with similar profiles in terms of the analysed variables. The use of hierarchical clustering and k-means is justified by the need to examine whether the studied units form internally coherent groups that reflect broader structural differences. While regression-based methods are used to assess statistical associations between variables, clustering allows us to explore multidimensional similarity and heterogeneity across units. This exploratory grouping also allows us to examine whether the theory-

based welfare-regime typology outlined in Section 2.3 finds empirical support in the observed data.

Hierarchical clustering was first used to determine the potential structure of the data without imposing a predefined number of groups. This approach enabled the identification of natural patterns of similarity between units. Subsequently, k-means clustering was applied to refine the grouping and to obtain a clearer partition of the sample into clusters with distinct profiles. Therefore, the two methods were used in a complementary way: hierarchical clustering supported the selection and interpretation of the cluster structure, while k-means provided a final classification of units based on their multidimensional characteristics.

The cluster analysis should be interpreted as exploratory rather than confirmatory. Its purpose is not to establish causal relationships, but to support the interpretation of differences between groups and to provide additional evidence on the structural heterogeneity of the analysed units. It is important to note that the partitioning of a small number of units is sensitive to both the variable set and the number of clusters. Consequently, the resulting grouping is interpreted descriptively rather than as a definitive classification.

Based on the hierarchical clustering results and the inspection of the dendrogram, a four-cluster solution was selected for the subsequent k-means analysis. The number of clusters is denoted as ($C = 4$) in order to avoid confusion with the subscript (k), which is used elsewhere in the study to denote explanatory variables. The four-cluster solution provides a meaningful classification of the analysed countries and allows the identification of distinct multidimensional profiles. The number of clusters was not selected to optimise a single internal-validity index—for a cross-section of this size, these criteria need not point to a single value—but was chosen from the dendrogram for interpretability and for its correspondence to the welfare-regime distinctions in Section 2.3, consistent with the exploratory purpose of the analysis.

4. Results

The data were retrieved from Eurostat databases for the years 2015–2024. Variables were selected based on correlation analysis in order to eliminate multicollinearity. Highly correlated indicators ($|r| > 0.8$) were excluded, and representative variables were retained for each dimension of socio-economic development.

4.1. Model Results

4.1.1. Main Model Estimates and Few-Cluster Inference

The primary model is AROPE, estimated with the two-way fixed-effects estimator on 278 observations (within- $R^2 = 0.473$). The coefficients, along with their significance under three different standard-error approaches (classical, country-clustered, Driscoll–Kraay) and the wild cluster bootstrap p -value, are presented in Table 3.

Table 3. Main model: AROPE, two-way FE ($N = 278$).

Variable	β	Classical SE (p)	Cluster SE (p)	D–K SE (p)	WCR-Boot p
ln(GDP)	−17.67	2.479 (0.000)	4.561 (0.001)	2.488 (0.000)	0.010
Unemployment rate	0.05	0.095 (0.616)	0.205 (0.818)	0.095 (0.618)	—
Gini	0.33	0.096 (0.001)	0.203 (0.116)	0.191 (0.086)	0.228
Inflation	0.02	0.038 (0.565)	0.037 (0.562)	0.026 (0.401)	—
Employment rate	−0.31	0.109 (0.005)	0.185 (0.104)	0.066 (0.000)	0.101
Early school leaving	−0.02	0.063 (0.741)	0.110 (0.851)	0.030 (0.491)	—
Old-age dependency	0.01	0.131 (0.914)	0.226 (0.951)	0.121 (0.907)	—

Social protection exp. −0.08 0.092 (0.416) 0.138 (0.592) 0.057 (0.190) —

Source: Own calculations based on Eurostat data. Primary SE = country-clustered [45] (Liang–Zeger). WCR = wild cluster bootstrap-t, B = 999.

The data demonstrate a strong negative correlation between GDP per capita and AROPE ($\beta = -17.67$), a finding that remains consistent across all three analytical approaches (clustered $p < 0.01$). In contrast, the Gini coefficient (+0.33) and the employment rate (−0.31) are only significant under classical standard errors and lose significance once country-clustered standard errors are employed ($p = 0.116$ and 0.104 , respectively). The remaining variables are insignificant throughout.

Due to the fact that cluster-robust standard errors over-reject when there are a small number of clusters, a decision was taken that the significance of the key coefficients should be re-assessed using the wild cluster bootstrap-t and a leave-one-country-out jackknife (Table 4).

These findings serve to substantiate the robustness of GDP per capita, with the coefficient demonstrating significance across all 28 jackknife runs (range −19.76 to −14.46) and a bootstrap p -value of 0.010, thereby indicating that no single country exerts a predominant influence on the outcome. In contrast, the Gini and employment coefficients are only significant in one of the 28 runs, with bootstrap p -values (0.228 and 0.101) failing to reach statistical significance. Consequently, the employment rate is deemed non-robust.

Table 4. Few-Cluster inference: jackknife (28 runs) and wild cluster bootstrap-t.

Variable	Full-Sample β	JK Min	JK Max	JK 5%-Significant	Cluster p	WCR-Boot p
ln(GDP)	−17.67	−19.76	−14.46	28/28	0.001	0.010
Gini	0.33	0.19	0.51	1/28	0.116	0.228
Employment rate	−0.31	−0.55	−0.18	1/28	0.104	0.101

Source: Own calculations based on Eurostat data.

The resulting conclusion is that GDP per capita is the only significant factor associated with the AROPE outcome. As GDP enters logarithmically, the coefficient of −17.67 is an approximate semi-elasticity [39]. This coefficient provides the change in AROPE per one-unit increase in ln(GDP)—an e-fold rise in income. Therefore, a 10% higher GDP per capita is associated with a roughly 1.7-percentage-point lower AROPE rate. This single-factor result gives rise to two further questions: firstly, on which dimension the apparently influential inequality and employment variables operate, and secondly, how Türkiye fits within this picture.

4.1.2. Dimensional Decomposition: Alternative Dependent Variables

The re-estimation of the model, with each AROPE component designated as a separate dependent variable (see Table 5), has revealed that the union obscures dimension-specific mechanisms. GDP per capita has been identified as the headline indicator, and, most significantly, for SMSD. However, it has been found to be insignificant for AROP. Conversely, inequality is significant only for AROP (Gini +0.50), as expected for a measure defined relative to the median. The labour-market variables operate mainly on very low work intensity (unemployment +0.33, employment −0.21; both $p < 0.01$).

Table 5. Alternative dependent variables: two-way FE, country-clustered SE.

Explanatory	AROPE	AROP	SMSD	VLWI (0–64)	VLWI (0–59)
ln(GDP)	−17.67 ***	−2.28	−40.42 ***	−4.68	−5.66 **
Unemployment rate	0.05	−0.04	0.22	+0.33 ***	+0.37 ***

Gini	0.33	+0.50 ***	−0.04	0.15	+0.17 *
Inflation	0.02	−0.01	−0.03	+0.05 **	+0.05 **
Employment rate	−0.31	−0.09	−0.13	−0.21 ***	−0.21 ***
Early school leaving	−0.02	+0.08 *	−0.04	0.05	0.05
Old-age dependency	0.01	0.11	−0.04	+0.25 *	+0.30 ***
Social protection exp.	−0.08	0.06	−0.60 **	0.12	0.10
N	278	278	276	278	278
within-R ²	0.473	0.374	0.525	0.499	0.553

Source: Own calculations based on Eurostat data. VLWI (0–64) is the main definition; VLWI (0–59) is the Europe 2020 definition. Significance based on country-clustered standard errors: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Social-protection expenditure is significant and negative only for material deprivation (−0.60). Income, as a result, is the most significant factor, affecting diverse areas. Inequality, the labour market, and social expenditure are all effective within specific areas, however, and are thus diminished within the union, meaning an analysis based on the headline indicator may overlook policy-relevant heterogeneity.

4.1.3. Türkiye's Structural Distinctiveness

Türkiye deviates significantly from the rest of the panel, both in terms of its level of poverty and its overall macroeconomic structure (see Table 6).

Table 6. Türkiye and EU-27 averages (2015–2024).

Variable	Türkiye	EU-27	Difference
AROPE	31.31	21.53	9.78
Relative poverty (AROP)	22.28	16.55	5.73
Severe material deprivation (SMSD)	29.26	13.74	15.53
Inflation	27.47	2.92	24.55
Gini	43.24	29.62	13.62
Early school leaving	27.21	8.76	18.45
Employment rate	55.02	73.83	−18.81
Social protection expenditure	11.30	22.60	−11.30
Old-age dependency	13.20	30.04	−16.84

Source: Own calculations based on Eurostat data.

The AROPE rate in this region is approximately 10 percentage points higher than the EU-27 average, with a particularly pronounced disparity in material deprivation (a gap of +15.5 percentage points). Additionally, it occupies a structurally distinct position, characterised by inflation that is almost ten times the EU average (27.5% versus 2.9%), significantly higher levels of inequality, and a higher rate of early school leaving. The region also exhibits a substantially lower employment rate and social-protection expenditure that is approximately half the EU average. The significance of these structural differences in relation to levels and estimated relationships was investigated through the re-estimation of the model with Türkiye excluded (see Table 7).

Two findings emerge from the research. Firstly, the GDP-per-capita effect remains strong and negative when Türkiye is excluded from the analysis (−17.67 to −15.70; both $p = 0.001$), thus indicating that the central result is not driven by Türkiye. Secondly, excluding Türkiye reverses the sign of the inflation and early-school-leaving coefficients. Within the EU-27, early school leaving carries its expected positive sign and approaches significance ($p = 0.100$), whereas inflation, which was weakly positive in the full panel,

turns negative (though itself insignificant, $p = 0.387$). Excluding Türkiye results in an alteration of the directions of these coefficients rather than their significance.

Table 7. Türkiye-excluded model (R2) versus full model (selected coefficients).

Variable	Full Model β (p)	Türkiye-Excluded β (p)
ln(GDP)	−17.67 (0.001)	−15.70 (0.001)
Inflation	+0.02 (0.562)	−0.07 (0.387)
Early school leaving	−0.05 (0.851)	+0.13 (0.100)

Source: Own calculations based on Eurostat data.

This analysis indicates that Türkiye does not constitute a comparable entity within the EU panel; rather, it is considered a structurally distinct and influential case. In other words, the presence of both extremely high levels of early school leaving and a distinct poverty structure in Türkiye obscures the education-poverty relationship that is evident within the EU-27. Furthermore, whereas the EU effectively absorbed the inflationary effects of the pandemic through the implementation of social support measures, the severe inflation experienced by Türkiye gives rise to a distinct inflation-poverty dynamic. It is important to note that Türkiye should not be analysed as a comparison unit pooled with the EU-27, but rather as a distinct case whose poverty dynamics are systematically different. It is possible to interpret Türkiye as a dynamically distinctive and influential case in the panel, particularly with respect to inflation and poverty-related changes over time.

4.1.4. Robustness of the Income-Poverty Relationship

The robustness of the negative income-poverty relationship was tested through a series of specification and sample variations (Supplementary Table S3). The income coefficient maintains its robust and negative significance across all specifications ($p < 0.01$), oscillating within a constrained range (−15.70 to −18.94). When examining social protection expenditure per capita in lieu of its proportion of GDP (R3), excluding the pandemic years, the most elevated inflation observation (Türkiye 2023, 54%) and 2024 (R6), and excluding Türkiye entirely (R2), the coefficient remains constant. The functional form has also been confirmed; in level form, the within- R^2 falls to 0.361 against 0.473 in logarithmic form (R^4), and in the leave-one-country-out jackknife, the coefficient is significant in all 28 runs (−14.46 to −19.76). Therefore, it can be inferred that the outcome is not influenced by the specific actions of any individual nation.

As shown in Table S4, entering the labour-market variables separately (R5) has no effect on the income finding. GDP per capita remains robust and exhibits a negative trend in both the unemployment-only specification (−21.18, $p < 0.001$) and the employment-only specification (−17.33, $p = 0.001$). The unemployment rate was found to be insignificant ($p = 0.153$). However, the employment rate became significant under clustered standard errors (−0.35, $p = 0.008$) once the strongly correlated unemployment rate ($r = -0.70$) was removed. This was deemed to be a consequence of collinearity rather than a robust effect, since the employment rate was not found to be significant under the conservative bootstrap. Across all checks, then, the only consistently robust relationship at the AROPE-union level is the negative income-poverty relationship; the other factors either act on specific dimensions of poverty or remain fragile under robust inference.

4.1.5. Timing: Lagged-Regressor Robustness

In order to assess the dependence of the estimated associations on contemporaneous timing, a key concern for social-protection expenditure, the budget of which is determined in the previous year (see Section 3.4), the model was re-estimated with the macroeconomic

regressors lagged by one year. This results in the panel being reduced to nine years ($T = 9$); a static specification with lagged covariates is employed rather than a dynamic (lagged-dependent-variable) estimator, which with 28 clusters and a short time dimension would be susceptible to instrument proliferation. The results of the study are presented in Table 8.

Table 8. Lagged-regressor robustness (two-way FE, country-clustered standard errors).

Dependent Variable	Specification	ln(GDP)	Key Component Coefficient	Within-R ²	N
AROPE	Contemporaneous (baseline)	−17.67 ***	—	0.473	278
AROPE	All regressors lagged one year	−15.98 ***	—	0.435	251
AROP	All regressors lagged one year	−5.03 ***	Gini +0.28 ***	0.234	251
SMSD	All regressors lagged one year	−34.96 ***	Soc. protection −0.63 ***	0.548	250
VLWI	All regressors lagged one year	−5.42 **	Unemployment +0.40 ***	0.531	251

Source: Own calculations based on Eurostat data. Own calculations based on Eurostat data. Significance based on country-clustered standard errors: *** $p < 0.01$, ** $p < 0.05$. One-year lag; sample covers 2016–2024. Standard errors are clustered by country (t distribution, $G - 1 = 27$ df). N varies across rows owing to listwise deletion. VLWI uses the main (0–64) definition. Coefficients on ln(GDP) are semi-elasticities; component coefficients are in levels (percentage points).

The primary finding remains constant: The ln(GDP) coefficient maintains its negative and significant status (−15.98, $p = 0.002$), approximating its contemporaneous value of −17.67; it is also resilient when solely social-protection expenditure is lagged (−16.47). The dimension-specific pattern is preserved, with income being associated with severe material deprivation, inequality with relative income poverty, and unemployment with very low work intensity. It is noteworthy that the correlation between social protection expenditure and severe material deprivation intensifies following a one-year delay, with a decrease from −0.63 to −0.60 when considering contemporaneous data. This finding aligns with the institutional lag between budgetary decisions and their impact on households, suggesting that the institutional processes that determine social protection expenditure can influence the timing of its effect on households. Consequently, the lagged estimates provide support for the contemporaneous results, rather than offering additional information.

4.2. Cluster Analysis Results

To identify groups of countries with similar socio-economic characteristics, a k-means cluster analysis was performed using selected variables that were previously screened for multicollinearity. All variables were standardized prior to analysis to ensure comparability. Based on the dendrogram and the interpretability of the solution, four clusters were identified. The number of clusters was not selected to optimise a single internal-validity index—for a cross-section of this size these criteria do not uniquely favour one value—but was chosen for interpretability and correspondence to established welfare-regime distinctions, consistent with the exploratory purpose of the analysis. The cluster analysis is based on averaged country-level characteristics over the analysed period and therefore captures similarities in the general socio-economic profiles of countries rather than temporal dynamics.

The cluster analysis ($k = 4$) resulted in the identification of four distinct groups of countries. Cluster 0 includes Poland, Türkiye, and several Central, Eastern, and Southern European countries (Poland, Türkiye, Romania, Bulgaria, Hungary, Slovakia, Croatia, Latvia, Lithuania, Estonia, Greece, Spain, Italy, Portugal), characterized by moderate development and structural challenges. Cluster 1 consists of highly developed Western and Northern European economies: Belgium, Germany, Sweden, Finland, France, Ireland,

Denmark, and the Netherlands. Cluster 2 includes Czechia and Slovenia, representing upper-middle, stable economies. Cluster 3 comprises high-income but structurally specific countries such as Luxembourg, Austria, Malta, and Cyprus.

The four-cluster solution provides a more refined classification of countries, allowing for a clearer distinction between different socio-economic profiles. The largest group (Cluster 0) includes a heterogeneous set of countries, primarily from Central and Eastern Europe, as well as Southern Europe. These countries, including Poland and Türkiye, are characterized by moderate levels of economic development combined with structural challenges such as higher poverty rates, labour market vulnerabilities, and income inequalities. Cluster 1 represents highly developed economies with strong institutional capacity, high income levels, and favourable labour market conditions. These countries exhibit the most stable socio-economic structures. Cluster 2 consists of countries with relatively strong and balanced performance, representing a transitional group approaching the level of highly developed economies. Cluster 3 includes high-income but structurally specific economies, whose economic indicators differ due to unique national characteristics, such as economic size or sectoral specialization. Because the partitioning of a small number of units is sensitive to the variable set and the number of clusters, the resulting grouping is interpreted descriptively rather than as a definitive classification.

5. Discussion: Conclusions Based on the Robustness Analysis

The study's key finding is that GDP per capita is the only factor robustly associated with poverty at the AROPE-union level; inequality and employment are significant only under classical standard errors and prove fragile under conservative inference (clustering, the wild bootstrap, the jackknife). This fragility is partly a power problem, as evidenced by the following characteristics: few clusters, a short panel, and low within-group variation. However, the dimensional decomposition reveals that this is not the sole cause. It is evident that each factor operates on a specific dimension, as opposed to exerting its influence on the union. GDP per capita is significant for the headline indicator and, most significantly, SMSD, but is insignificant for AROP. The latter is defined against a moving 60%-of-median threshold and is thus unresponsive to proportional income gains. In contrast, inequality operates solely on AROP, labour-market variables exclusively on VLWI, and social-protection expenditure solely on material deprivation. The primary outcome is not solely income-related; income is pertinent across all dimensions, whereas the other factors are dimension-specific.

5.1. Income and Dimensional Decomposition

The robustness analysis based on alternative dependent variables confirms that the economic correlates of poverty and social exclusion differ depending on the dimension considered. The two-way fixed effects models indicate that poverty and social exclusion are multidimensional phenomena and that their correlates are not identical across all SDG 1-related indicators. The results show that GDP remains one of the factors most strongly associated with poverty-related outcomes. The coefficient for $\ln(\text{GDP})$ is negative and statistically significant for AROPE, SMSD, and VLWI measured for the 0–59 age group. This indicates that higher levels of economic development are associated with lower poverty and social exclusion, particularly in relation to broader deprivation indicators. However, the insignificant association of GDP with AROP suggests that income poverty is not explained by economic growth alone and may depend more strongly on income distribution and redistributive mechanisms.

This finding is in line with Darvas's [59] observation that the AROP rate essentially measures income inequality rather than poverty and is largely equivalent to the Gini coefficient. A proportional rise in income will also increase the threshold. GDP has no

effect on AROP, but the Gini coefficient is significantly associated with it because it reflects the distribution. Therefore, the Gini coefficient can be considered a predictable reflection of this indicator of inequality equivalence rather than an independent finding. In this sense, the Gini–AROP association can be considered a definitional correspondence rather than a substantive empirical result. This is due to the fact that both statistics are computed from the same income distribution. Consequently, a dispersion measure (Gini) will necessarily track a relative below-threshold headcount (AROP) [10]. The coefficient is retained not as a novel result but because it validates the decomposition, confirming that the procedure isolates the inequality dimension onto the component defined in inequality terms. The broader implication is that the AROPE union, by collapsing several dimensions into one figure, can conceal factor–dimension correspondences that are pertinent to policy. These include material deprivation, which calls for income growth and social protection; relative poverty, which calls for redistribution; and work-intensity poverty, which calls for labour-market measures. The notion that such union indicators may obscure dimension-specific effects is further substantiated by Notten [11], who demonstrates that income-poverty and material-deprivation measures frequently diverge in their identification of low-income groups. This discordance has the potential to introduce variability in the estimates of the poverty-reducing effect of social transfers.

This pattern is consistent with the findings of the closest comparison study. Ribeiro et al. [41] assert that, when larger-scale deprivation measures are employed, growth becomes less significant in explaining deprivation. However, they contend that it exhibits a strong positive correlation with poverty reduction when deprivation is more monetarily biased in definition. Furthermore, although a decrease in the rate of unemployment results in a statistically significant reduction in multidimensional poverty, net social benefits reduce poverty only according to specific measures. In the present study, the findings align with the broader conclusions of Ribeiro et al. [41], specifically highlighting the association of income with work intensity and of social expenditure with material deprivation.

It is imperative to interpret these pooled estimates within the context of welfare-regime heterogeneity. As the specification incorporates country fixed effects, time-variant regime membership is incorporated into these effects. Consequently, the coefficients represent the mean within-country relationships, as opposed to regime-specific elasticities. This finding is pertinent to the social-protection outcome, which demonstrates that the impact is only significant in the context of material deprivation. The finding that the effect is fragile at the headline level is consistent with the extant literature, which indicates that the poverty-reducing efficacy of transfers is contingent on the regime and targeting mechanisms. Specifically, redistribution cuts market poverty to a greater extent in social-democratic than in liberal regimes [21], and the inequality-reducing effect of transfers varies considerably across regime types [12]. The average coefficient combines these contrasting experiences, which is one reason the aggregate effect is less pronounced. In a similar vein, the correlation between employment and work intensity, as opposed to income-based poverty, is in alignment with the extant literature on in-work poverty [26]. In this literature, the protective value of a job is found to depend on factors such as wages and contractual security. Consequently, the regime framework is introduced not as an estimated parameter but as the interpretive context for these averages.

5.2. Welfare Regimes and Türkiye's Structural Position

The findings demonstrated that Türkiye was diverging systematically from the EU-27 with regard to poverty levels, the surrounding macroeconomic structure, and the sign changes in the inflation and early-school-leaving coefficients when it was excluded. The root cause of this divergence can be attributed to the structural distinctiveness of Türkiye's

welfare regime [34]. This exclusion is evident in social protection expenditure, which remains approximately half the EU-27 average. This phenomenon contributes to the understanding of why social transfers function in a different manner in Türkiye than in the EU.

The hypothesis that Türkiye relies on economic growth as a means of poverty reduction is supported by evidence specific to the country. As demonstrated by Şeker and Jenkins [60], absolute poverty underwent a precipitous decline during the period of high growth (2003–2008). However, this decline stagnated when growth slowed after 2008. Furthermore, the research indicates that this decline was driven predominantly by growth rather than redistribution. In their 2025 study, Öktem and Leisering [35] placed Türkiye between the Southern European welfare states and the Global South. It was contended that social insurance coverage was inadequate and, given the high level of informality, the safety net relied on discretionary social assistance rather than comprehensive insurance. The EU's comprehensive protection mechanisms have largely absorbed the impact of the pandemic; however, the weaker structure of Türkiye means that shocks are transmitted to poverty more directly. In the absence of a transfer buffer, income becomes the predominant channel.

The present structure provides a cogent account of the sign changes that are observed when Türkiye is excluded. The high inflation rate in the country (27.5% compared to 2.9%) in combination with inadequate social protection generates an inflation-poverty dynamic that is distinct from that observed in the EU. Additionally, the high rate of early school leaving (27.2% compared to 8.8%) within a different informal and labour market structure masks the education-poverty relationship that is evident in the EU, where low educational attainment and weak school-to-work transitions are well-established drivers of youth poverty and NEET status [61,62]. The coefficient for early school leaving exhibits a positive relationship with the country's removal, which is consistent with the observed findings. When considered as a whole, these results indicate that it is not a comparable unit that can be grouped with the EU-27; rather, it is a structural outlier. The value of including it lies precisely in making that divergence visible.

5.3. Evaluation of Hypotheses

Table 9 summarises how each of the six hypotheses fares against the empirical estimates. The findings substantiate the existence of two distinct channels, namely labour and inequality. The association of unemployment with VLWI (H3) is particularly robust and unique, while the Gini coefficient manifests significance predominantly and specifically in relation to AROP (H4). The cautious version of H1 is also supported: The data indicate that GDP per capita is associated with lower AROPE, with the effect concentrated on material deprivation and absent for relative income poverty. This is in line with predictions when the relative threshold absorbs income gains.

Two predictions were not supported, and both reflect the dimensional structure of poverty rather than a failure of the underlying mechanism. In contrast to the findings of H2, the correlation between social-protection expenditure and poverty is observed to be solely in the SMSD, as opposed to the dimension of AROP. This contrast is coherent and has a direct policy reading. Material deprivation is measured against a fixed basket of goods; therefore, transfers that raise households' purchasing power relieve it directly. By contrast, AROP is defined against a moving threshold set at 60% of the national median, which rises as average incomes rise [10,11]. Consequently, untargeted transfers can lift the poverty line by as much as they lift the incomes of the poor. The implication for policymakers is that cash and in-kind transfers are effective instruments against material hardship, whereas reducing relative income poverty additionally requires distributionally targeted measures rather than across-the-board spending [22,63]. In

contrast to the H5 hypothesis, inflation is associated with minimal work intensity rather than material deprivation. The anticipated cost-of-living channel was plausibly mitigated by pandemic-era price and energy support, as well as by the delayed response of the deprivation measure. Consequently, the macroeconomic effect is transmitted partly through fiscal and institutional channels [64].

Table 9. Comparison of hypotheses with the findings.

H	Expectation (Summary)	Finding	Outcome
H1	GDP↓AROPE; effect varies across components	GDP↓AROPE; concentrated in SMSD, insignificant in AROP	Supported
H2	Social spending reduces all three components; weakest in SMSD	Significant only in SMSD (−0.60)	Not supported
H3	Unemployment most strongly related to VLWI	Unemployment significant only in VLWI (+0.33)	Supported
H4	Gini raises all components; especially AROP	Gini significant only in AROP (+0.50)	Partly
H5	Inflation most related to SMSD	Inflation insignificant in SMSD; in VLWI (+0.06)	Not supported
H6	TR changes the coefficients (especially soc_exp and employment)	TR changes the inflation and ESL coefficients	Partly

Source: Own calculations based on Eurostat data. “↓” denotes a negative (poverty-reducing) association; e.g., “GDP↓AROPE” indicates that a higher GDP per capita is associated with a lower AROPE rate.

The H6 result corroborates the prevailing anticipation that changes in the coefficients are to be expected, yet it only partially aligns with respect to the predicted channels. The exclusion of Türkiye has been demonstrated to have a negligible effect on the coefficients relating to social protection expenditure and the employment rate. However, it has been evidenced that this exclusion does result in a marked alteration of the coefficients pertaining to inflation and early school leaving. In essence, the observed structural difference in Türkiye exerts a discernible influence on the coefficients, albeit through variables that diverge from those projected in the hypothesis.

5.4. Interpretation of the Cluster Analysis

The k-means clustering method utilises period-averaged, cross-sectional level profiles, whereas the fixed-effects regression approach employs within-country variation over time. It is noteworthy that a country may share a level-profile group with EU members while exhibiting distinct estimated within-country associations. It is important to note that both analyses are static in nature; however, one is cross-sectional and the other is longitudinal within units. This exploratory grouping also allows us to examine whether the theory-based welfare-regime typology outlined in Section 2.3 finds empirical support in the data.

The cluster analysis groups the 28 countries by their broader socio-economic profiles, and the resulting groups are broadly consistent with the welfare-regime distinctions discussed in Section 2.3. The most stable cluster combines the Scandinavian regimes, the larger Continental economies, and liberal Ireland, while the higher-vulnerability cluster brings together most of the Eastern and Southern European regimes and all three Baltic states. The typology demonstrates that the countries assigned to the more decommodifying, higher-spending regimes also display the most favourable poverty and labour-market profiles. However, it is important to note that the correspondence is not perfect. Specifically, the two strongest Central European economies, namely the Czech Republic and Slovenia, form a transitional cluster. In addition, a fourth cluster, which

includes Luxembourg, Austria, Malta and Cyprus, cuts across regime boundaries. This cluster is notable for its tendency to group high-income countries according to their economic size rather than their regime type. The clustering is thus broadly consistent with the regime framework while exposing within-regime heterogeneity, particularly among the Eastern and Southern European countries.

The mean profile of Türkiye places it in the same cluster as Poland and several Central, Eastern and Southern European countries, indicating similarity in average levels of the selected indicators rather than in temporal dynamics. The regression, which exploits within-country variation over time, demonstrates that Türkiye is nevertheless a dynamically distinctive and influential case. Excluding it results in a change in the signs of the inflation and early-school-leaving coefficients (though not their significance). The two analyses are therefore complementary rather than contradictory—the clustering identifies similarities in average country profiles, while the regression highlights sensitivity in longitudinal associations. The analysis indicates that the clusters substantiate the dimensional output: labour-market and distributional indicators, rather than income alone, distinguish the groups, thereby suggesting that priorities differ across them. This suggests that targeting and in-work poverty may be more significant in the more developed group; employment, human capital and social protection are priorities in the less developed group; and, in Türkiye, particular attention may be necessary regarding labour-market informality and the effectiveness of social-policy instruments.

5.5. Limitations

The study's findings must be assessed in light of its limitations. The first of these is that the model is static. It is evident from the specification that no consideration is given to the persistence of poverty or state dependence, that is, the prediction of poverty in one year as a predictor of the next. A dynamic panel approach (see, for example, the Arellano–Bond Generalised Method of Moments used by Canale and Liotti [44]) could have addressed this issue; however, the short time dimension ($T = 10$) of our sample renders dynamic estimation difficult (owing to instrument proliferation and a weak time dimension), and the static form was therefore deliberately retained. Consequently, the coefficients demonstrate not adjustment dynamics but co-movements within a fixed-effects framework.

Secondly, the inferential process is constrained by a limited number of clusters and a short panel. Utilising a total of 28 clusters (i.e., the cross-sectional units used for clustered standard errors) over a decade, it is evident that both the cluster-robust and the Driscoll–Kraay standard errors function in proximity to their asymptotic limits. Notwithstanding this, the employment of wild cluster bootstrap and jackknife techniques is effective in ameliorating this effect. However, the validity of marginal variables remains dubious. Within-group variation in some variables was found to be low (inequality, social protection expenditure). This further reduced the power of fixed-effects estimation and undermined the reliability of the Hausman test (the covariance difference was not positive definite). Consequently, the Mundlak/CRE alternative was used for model selection.

Thirdly, a particular data limitation is specific to Türkiye. The income and living-conditions survey excludes the refugee and asylum-seeker population. Additionally, in 26 country-years, the standalone SMSD value exceeds that of the AROPE union. This is because the two series originate from different table vintages. Consequently, this only affects the use of SMSD for robustness and does not impact the main results.

Finally, the analysis did not incorporate several potential factors, including institutional and governance indicators and the output gap. Within the confines of a fixed-effects framework, the analysis identifies associations rather than establishing causality. As discussed in Section 3.4, the estimates may be affected by contemporaneous

simultaneity and reverse causality. These issues could be addressed in future work by instrumental-variable or dynamic-panel designs.

6. Conclusions

The study examined the economic factors associated with poverty and social exclusion in the EU-27 and Türkiye using SDG 1 indicators over the period 2015–2024. The results show that poverty and social exclusion are strongly associated with macroeconomic conditions, but the relationship is multidimensional and heterogeneous. At the headline AROPE level, GDP per capita is the only factor whose association with poverty and social exclusion remains robust across alternative inference methods and specifications. When assessed against the hypotheses of the study (see Section 5.3), the evidence supports Hypotheses 1 and 3, partially supports Hypotheses 4 and 6, but does not support Hypotheses 2 or 5. A 10% increase in GDP per capita is associated with an approximately 1.7 percentage-point reduction in AROPE.

The component-level analysis shows that poverty indicators are associated with different factors. Material deprivation is most strongly related to GDP per capita and social protection expenditure. Relative income poverty is most strongly related to inequality. Very low work intensity is most strongly related to unemployment and employment. These findings indicate that the headline AROPE rate masks distinct mechanisms and that separate analysis of its components is necessary for policy design.

Türkiye is not simply an additional EU-like observation. Its higher poverty levels, high inflation, higher inequality, lower employment and lower social protection expenditure create a distinct macro-social structure. Excluding Türkiye does not change the core GDP result, but it alters the signs of selected coefficients. This confirms the importance of treating Türkiye as a structurally distinct comparative case.

The study contributes to the literature by estimating the comparative sensitivity of AROPE, AROP, SMSD and VLWI to the same macroeconomic regressors within one panel framework and by combining econometric results with cluster analysis. When evaluated in relation to the study's hypotheses outlined in Section 5.3, the evidence appears to support Hypotheses 1 and 3 to a certain extent and offers partial support for Hypotheses 4 and 6. However, it does not provide substantial evidence in support of Hypotheses 2 and 5. The present study makes a contribution to the existing literature by estimating the comparative sensitivities. Given that the economic correlates of poverty are dimension-specific, a single aggregate figure cannot be used to guide policy across all three dimensions. The results imply that material hardship calls primarily for income growth and social transfers, relative income poverty for distributionally targeted redistribution, and work-intensity poverty for labour-market activation [11,22]. The central policy message of the study is that this dimensional targeting, rather than undifferentiated pro-poor growth, is the optimal approach. Future research could extend the analysis using regional data, household-level microdata, dynamic panel models and more detailed institutional variables describing welfare-state design and transfer targeting.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/su182010409/s1>. Table S1: Explanatory variables, definition, and unit; Table S2: Variance inflation factors (VIF); Table S3: Robustness of the $\ln(\text{GDP})$ coefficient; Table S4: Labour-market specification (R5; AROPE, two-way FE, country-clustered SE).

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Abbreviations

The following abbreviations are used in this manuscript:

SDG	Sustainable Development Goal
AROPE	At-Risk-of-Poverty-or-Social-Exclusion
AROP	Relative Income Poverty
SMSD	Severe Material and Social Deprivation
VLWI	Very Low Work Intensity
GDP	Gross Domestic Product
EU	European Union
UN	United Nations
PPS	Purchasing Power Standard
HICP	Harmonised Index of Consumer Prices
RE	Random Effects
OLS	Ordinary Least Squares
VIF	Variance Inflation Factor
FE	Fixed Effects

References

1. Bossert, W.; Chakravarty, S.R.; D'Ambrosio, C. Multidimensional poverty and material deprivation with discrete data. In *Poverty, Social Exclusion and Stochastic Dominance; Themes in Economics*; Chakravarty, S., Ed.; Springer: Singapore, 2019. https://doi.org/10.1007/978-981-13-3432-0_12.
2. Stiglitz, J.; Sen, A.; Fitoussi, J.-P. Report by the Commission on the Measurement of Economic Performance and Social Progress. 2009. Available online: <https://ec.europa.eu/eurostat/documents/8131721/8131772/Stiglitz-Sen-Fitoussi-Commission-report.pdf> (accessed on 5 June 2026).
3. Martínez, R.; Ruiz-Huerta, J. Immigrant–native differences in multidimensional poverty after the great recession: A comparison of five European countries. In *Measuring Multidimensional Poverty and Deprivation; Global Perspectives on Wealth and Distribution*; White, R., Ed.; Palgrave Macmillan: Cham, Switzerland, 2017. https://doi.org/10.1007/978-3-319-58368-6_7.
4. Decancq, K. Chapter 4: Cumulative deprivation: Identification and aggregation. In *The Research Handbook on Poverty and Inequality*; Edward Elgar Publishing: Cheltenham, UK, 2023. <https://doi.org/10.4337/9781800882300.00010>.

5. Alkire, S.; Foster, J.; Seth, S.; Santos, M.E.; Roche, J.M.; Ballon, P. *Multidimensional Poverty Measurement and Analysis: A Counting Approach*; Oxford University Press: Oxford, UK, 2015. <https://doi.org/10.1093/acprof:oso/9780199689491.001.0001>.
6. Eurostat. *Sustainable Development in the European Union—Monitoring Report on Progress Towards the SDGs in an EU Context—2026 Edition*; Publications Office of the EU: Luxembourg, 2026.
7. Chakravarty, S.R.; Silber, J. Measuring multidimensional poverty: The axiomatic approach. In *Quantitative Approaches to Multidimensional Poverty Measurement*; Kakwani, N., Silber, J., Eds.; Palgrave Macmillan: New York, NY, USA, 2008; pp. 192–209.
8. Atkinson, A.B.; Cantillon, B.; Marlier, E.; Nolan, B. *Social Indicators: The EU and Social Inclusion*; Oxford University Press: Oxford, UK, 2002.
9. Decancq, K. Copula-based measurement of dependence between dimensions of well-being. *Oxf. Econ. Pap.* **2014**, *66*, 681–701. <https://doi.org/10.1093/oep/gpt038>.
10. Decerf, B. Chapter 3: Absolute and relative income poverty measurement: A survey. In *The Research Handbook on Poverty and Inequality*; Edward Elgar Publishing: Cheltenham, UK, 2023. <https://doi.org/10.4337/9781800882300.00009>.
11. Notten, G.; De Neubourg, C. Monitoring absolute and relative poverty: ‘Not enough’ is not the same as ‘much less’. *Rev. Income Wealth* **2011**, *57*, 247–269.
12. Greve, B. Chapter 20: Poverty and inequality in European welfare states. In *The Research Handbook on Poverty and Inequality*; Edward Elgar Publishing: Cheltenham, UK, 2023. <https://doi.org/10.4337/9781800882300.00028>.
13. White, R.; Lindley, L.-N. Examination of the effects of variation in the measurement of multidimensional poverty in the United States. In *Research Handbook on Poverty and Inequality*; Wagle, U.R., Ed.; Edward Elgar Publishing: Cheltenham, UK, 2023; pp. 138–171.
14. European Commission. *The European Pillar of Social Rights Action Plan*; Publications Office of the EU: Luxembourg, 2021.
15. Wagle, U. (Ed.) *Research Handbook on Poverty and Inequality*; Edward Elgar Publishing: Cheltenham, UK, 2023. <https://doi.org/10.4337/9781800882300>.
16. Alvaredo, F.; Gasparini, L.C. Chapter 9—Recent trends in inequality and poverty in developing countries. In *Handbook of Income Distribution*; Elsevier: Amsterdam, The Netherlands, 2013; Volume 2; pp. 697–805. <https://doi.org/10.1016/B978-0-444-59428-0.00010-2>.
17. Fosu, A.K. Growth, inequality, and poverty reduction in developing countries: Recent global evidence. *Res. Econ.* **2017**, *71*, 306–336. <https://doi.org/10.1016/j.rie.2016.05.005>.
18. Garza-Rodriguez, J. Chapter 21: Poverty in Mexico: Trends, determinants, and policies. In *The Research Handbook on Poverty and Inequality*; Edward Elgar Publishing: Cheltenham, UK, 2023. <https://doi.org/10.4337/9781800882300.00029>.
19. Wang, X. The evolution of thinking about the concept of poverty. In *Multidimensional Poverty Measurement. International Research on Poverty Reduction.*; Springer: Singapore, 2022. https://doi.org/10.1007/978-981-19-1189-7_1.
20. Kersbergen, K.V.; Vis, B. *Comparative Welfare State Politics: Development, Opportunities, and Reform*; Cambridge University Press: Cambridge, UK, 2014; pp. 207–240. <https://doi.org/10.1017/CBO9781139021852>.
21. Esping-Andersen, G.; Myles, J. Economic inequality and the welfare state. In *The Oxford Handbook of Economic Inequality*; Nolan, B., Salverda, W., Smeeding, T.M., Eds.; Oxford Academic: Oxford, UK, 2011; pp. 639–664. <https://doi.org/10.1093/oxfordhb/9780199606061.013.0025>.
22. Cantillon, B. The paradox of the social investment state: Growth, employment and poverty in the Lisbon era. *J. Eur. Soc. Policy* **2011**, *21*, 432–449. <https://doi.org/10.1177/0958928711418856>.
23. European Commission. *Directorate-General for Employment, Social Affairs and Inclusion. Labour Market and Wage Developments in Europe 2023*; Publications Office of the European Union: Luxembourg, 2023. <https://doi.org/10.2767/1277>.
24. European Commission. *Directorate-General for Employment, Social Affairs and Inclusion. Labour Market and Wage Developments in Europe—Annual Review 2024*; Publications Office of the European Union: Luxembourg, 2024. <https://doi.org/10.2767/888580>.
25. European Commission. *Directorate-General for Employment, Social Affairs and Inclusion. Labour Market and Wage Developments in Europe—Annual Review 2025*; Publications Office of the European Union: Luxembourg, 2025. <https://doi.org/10.2767/1810636>.
26. Brülle, J.; Gangl, M.; Levanon, A.; Saburov, E. Changing labour market risks in the service economy: Low wages, part-time employment and the trend in working poverty risks in Germany. *J. Eur. Soc. Policy* **2019**, *29*, 115–129. <https://doi.org/10.1177/0958928718779482>.
27. Esping-Andersen, G. *The Three Worlds of Welfare Capitalism*; Polity Press: Cambridge, UK, 1990.
28. Ferrera, M. The “Southern Model” of Welfare in Social Europe. *J. Eur. Soc. Policy* **1996**, *6*, 17–37. <https://doi.org/10.1177/095892879600600102>.

29. Kaya, S. Avrupa refah rejimlerinde çalışan yoksulluğu: Birleşik Krallık, Almanya, İspanya ve İsveç örnekleri. In *Sosyal Politika Ekseninde Yoksulluk Güncel Sorunlar Ve Tartışmalar*; Öcal, A.T., Ed.; Gazi Kitabevi: Ankara, Turkey, 2022; pp. 1–37.
30. Aykaç, M.; Kaya, S. İşgücü Piyasasında Yaşanan Dönüşümler: Standart Dışı İstihdam ve Çalışan Yoksulluğu İlişkisi. *Sosyoekonomi* **2024**, *32*, 413–453. <https://doi.org/10.17233/sosyoekonomi.2024.04.20>.
31. Greve, B. (Ed.) *Routledge International Handbook of Poverty*, 1st ed.; Routledge: London, UK, 2019. <https://doi.org/10.4324/9780429058103>.
32. Aspalter, C. Welfare regime analysis: 30 years in the making. *Int. Soc. Work* **2019**, *62*, 76–88. <https://doi.org/10.1177/0020872817710551>.
33. Kaya, S. Çocuk Hakları Perspektifinden Güney Avrupa Ülkeleri ve Türkiye’de Çocuk Yoksulluğu (Tez No. 945545). Ph.D. Thesis, Marmara University, Istanbul, Turkey, 2025.
34. Buğra, A.; Keyder, Ç. The Turkish Welfare Regime Transformation. *J. Eur. Soc. Policy* **2006**, *16*, 211–228. <https://doi.org/10.1177/0958928706065593>.
35. Öktem, K.G.; Leisering, L. Emerging social assistance regimes in middle income countries: Turkey in comparative perspective. *Glob. Soc. Policy* **2025**, *25*, 433–459. <https://doi.org/10.1177/14680181251384653>.
36. Whelan, C.T.; Layte, R.; Maitre, B.; Nolan, B. Income, deprivation, and economic strain. An analysis of the European community household panel. *Eur. Sociol. Rev.* **2001**, *17*, 357–372.
37. Dlugosch, D. *Labour Market and Education Reforms Are Needed to Create More and Better Jobs in Türkiye*; OECD Economics Department Working Papers, No. 1782; OECD Publishing: Paris, France, 2023. <https://doi.org/10.1787/54657452-en>.
38. European Commission. *Poverty Developments in the EU After the Crisis: A Look at Main Drivers*; ECFIN Economic Brief No. 31; Publications Office of the European Union: Luxembourg, 2014. Available online: https://ec.europa.eu/economy_finance/publications/economic_briefs/2014/eb31_en.htm (accessed on 25 June 2026).
39. Wooldridge, J.M. *Introductory Econometrics: A Modern Approach*; Cengage Learning: Boston, MA, USA, 2019.
40. Sahay, A. *Applied Regression and Modeling: A Computer Integrated Approach*; Business Expert Press: New York, NY, USA, 2016.
41. Ribeiro, A.P.; Silva, S.T.; Guimarães, D. Macroeconomic Fundamentals of Poverty and Deprivation: An Empirical Study for Developed Countries. *Eur. J. Dev. Res.* **2015**, *27*, 37–66.
42. Sarafidis, V.; Yamagata, T.; Robertson, D. A test of cross section dependence for a linear dynamic panel model with regressors. *J. Econom.* **2009**, *148*, 149–161.
43. Pesaran, M.H. *General Diagnostic Tests for Cross Section Dependence in Panels*; Cambridge Working Papers in Economics 0435; Faculty of Economics, University of Cambridge: Cambridge, UK, 2004.
44. Canale, R.R.; Liotti, G. Absolute Poverty and Sound Public Finance in the Eurozone. *J. Econ. Inequal.* **2022**, *20*, 327–344. <https://doi.org/10.1007/s10888-021-09498-3>.
45. Liang, K.-Y.; Zeger, S.L. Longitudinal Data Analysis Using Generalized Linear Models. *Biometrika* **1986**, *73*, 13–22. <https://doi.org/10.1093/biomet/73.1.13>.
46. Driscoll, J.C.; Kraay, A.C. Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data. *Rev. Econ. Stat.* **1998**, *80*, 549–560. <https://doi.org/10.1162/003465398557825>.
47. Hausman, J.A. Specification Tests in Econometrics. *Econometrica* **1978**, *46*, 1251–1271. <https://doi.org/10.2307/1913827>.
48. Mundlak, Y. On the Pooling of Time Series and Cross Section Data. *Econometrica* **1978**, *46*, 69–85. <https://doi.org/10.2307/1913646>.
49. Cameron, A.C.; Gelbach, J.B.; Miller, D.L. Bootstrap-Based Improvements for Inference with Clustered Errors. *Rev. Econ. Stat.* **2008**, *90*, 414–427.
50. Massaron, L.; Boschetti, A. *Regression Analysis with Python*; Packt Publishing Ltd.: Birmingham, UK, 2016.
51. Hill, C.; Du, L.; Johnson, M.; McCullough, B.D. Comparing programming languages for data analytics: Accuracy of estimation in Python and R. *Wiley Interdiscip. Rev. Data Min. Knowl. Discov.* **2024**, *14*, e1531.
52. McNulty, K. *Handbook of Regression Modeling in People Analytics: With Examples in R and Python*; Chapman and Hall/CRC: Boca Raton, FL, USA, 2021.
53. Everitt, B.S.; Landau, S.; Leese, M.; Stahl, D. *Cluster Analysis*, 5th ed.; John Wiley & Sons: Hoboken, NJ, USA, 2011.
54. Kaufman, L.; Rousseeuw, P.J. *Finding Groups in Data: An Introduction to Cluster Analysis*; John Wiley & Sons: Hoboken, NJ, USA, 2005.
55. Hair, J.F.; Babin, B.J.; Anderson, R.E.; Black, W.C. *Multivariate Data Analysis*, 8th ed.; Cengage Learning: Andover, UK, 2019.
56. Tan, P.-N.; Steinbach, M.; Karpatne, A.; Kumar, V. *Introduction to Data Mining, What’s New in Computer Science Series*, 2nd ed.; Pearson: New York, NY, USA, 2019.

57. James, G.; Witten, D.; Hastie, T.; Tibshirani, R.; Taylor, J. *An Introduction to Statistical Learning*; Springer: Berlin/Heidelberg, Germany, 2023.
58. Mięła-Warchoł, A. *Modeling Socio-Economic Development in EU Countries*; Oficyna Wydawnicza Politechniki Rzeszowskiej: Rzeszów, Poland, 2021.
59. Darvas, Z. Why is it So Hard to Reach the EU's Poverty Target? *Soc. Indic. Res.* **2019**, *141*, 1081–1105. <https://doi.org/10.1007/s11205-018-1872-9>.
60. Şeker, S.D.; Jenkins, S.P. Poverty trends in Turkey. *J. Econ. Inequal.* **2015**, *13*, 401–424. <https://doi.org/10.1007/s10888-015-9300-8>.
61. Caroleo, F.E.; Rocca, A.; Mazzocchi, P.; Quintano, C. Being NEET in Europe Before and After the Economic Crisis: An Analysis of the Micro and Macro Determinants. *Soc. Indic. Res.* **2020**, *149*, 991–1024. <https://doi.org/10.1007/s11205-020-02270-6>.
62. Cimpoeu, S. What Triggers Poverty of Young Nationals and Young Migrants? A Comparative Macroeconomic Approach. *J. Soc. Econ. Stat.* **2020**, *9*, 13–29. <https://doi.org/10.2478/jses-2020-0010>.
63. Leventi, C.; Sutherland, H.; Tasseva, I.V. Improving poverty reduction in Europe: What works best where? *J. Eur. Soc. Policy* **2019**, *29*, 29–43. <https://doi.org/10.1177/0958928718792130>.
64. Canale, R.; Liotti, G.; Marani, U. Structural public balance adjustment and poverty in Europe. *Struct. Change Econ. Dyn.* **2019**, *50*, 227–236. <https://doi.org/10.1016/j.strueco.2019.07.002>.

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