

# Threshold Effects and Classification Bias in Poverty Measurement: Evidence from Alternative Poverty Lines

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## ABSTRACT

This study examines threshold effects and classification bias in poverty measurement by analyzing how incremental changes in poverty lines affect cumulative poverty headcounts. Using income-band distribution data and applying elasticity and reclassification bias metrics, the study evaluates the sensitivity of poverty measurement across alternative thresholds. A detailed case analysis of Albania is complemented by cross-country comparisons with Brazil, India, and Indonesia. The findings reveal substantial non-linearity in poverty responsiveness. Elasticity estimates exceed 3.5 within the \$5–\$10 per day range, indicating that small proportional increases in the poverty line generate disproportionately large increases in measured poverty. Classification bias is similarly concentrated within these lower-middle thresholds, with reclassification effects exceeding 150 percent in some cases. A clear structural break emerges around the \$10 threshold, separating a high-instability regime from a relatively stable upper-income regime. Cross-country analysis further demonstrates that threshold sensitivity varies according to national income distribution structures, suggesting that poverty measurement is context-dependent rather than universally stable. The results indicate that poverty statistics are not threshold-neutral and that binary poverty classification may generate substantial volatility when poverty lines intersect regions of income clustering. These findings highlight the importance of incorporating distributional density considerations into poverty line selection and policy interpretation.

**Keywords** Threshold Effects, Poverty Measurement, Classification Bias, Income Distribution, Elasticity Analysis

## INTRODUCTION

Poverty measurement plays a central role in economic policy, social protection design, and international development assessment. Official poverty statistics influence resource allocation, determine eligibility for social assistance programs, and shape public discourse regarding economic progress [1]. Traditionally, poverty is measured using a fixed monetary threshold that classifies individuals as either poor or non-poor depending on whether their income falls below or above a predefined cutoff [2]. Although this binary framework offers simplicity and comparability, it implicitly assumes that poverty measurement is stable with respect to small adjustments in the poverty line.

Recent developments in poverty research emphasize the multidimensional nature of deprivation and the importance of distribution-sensitive indices [3]. The Foster–Greer–Thorbecke (FGT) class of poverty measures incorporates income shortfalls below the poverty line and accounts for poverty depth and severity [4]. Similarly, Sen’s poverty index integrates income distribution and inequality considerations into poverty measurement [5]. Multidimensional poverty indices further expand the analytical framework by incorporating non-monetary indicators such as health, education, and living standards [6]. Despite

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these methodological advances, most empirical poverty assessments continue to rely heavily on threshold-based headcount measures [7].

The existing literature has extensively examined poverty trends, inequality dynamics, and the relationship between economic growth and poverty reduction [8], [9]. Other strands of research analyze the robustness of poverty lines under Purchasing Power Parity (PPP) revisions and alternative price deflators [10]. However, relatively limited attention has been given to the structural instability that may arise when poverty thresholds intersect regions of high-income clustering. While the normative choice of poverty lines has been widely debated [11], the quantitative sensitivity of poverty headcounts to marginal threshold adjustments remains underexplored.

Welfare economics suggests that poverty outcomes depend not only on the level of the poverty line but also on the distribution of incomes relative to that line [12]. When a large proportion of households is concentrated near a cutoff, small increases in the poverty threshold may generate disproportionately large changes in measured poverty. Conversely, in income distributions characterized by gradual dispersion, threshold adjustments may produce only marginal effects. Despite this theoretical insight, empirical studies rarely quantify elasticity and reclassification bias associated with incremental poverty line changes [13].

This study addresses this gap by examining threshold effects and classification bias in poverty measurement using income-band distribution data. Specifically, the research estimates the elasticity of cumulative poverty with respect to incremental threshold adjustments and quantifies reclassification instability across alternative poverty lines. By doing so, the analysis moves beyond static headcount comparisons and evaluates the structural responsiveness of poverty statistics to definitional changes.

The contribution of this study is threefold. First, it introduces an elasticity-based framework to measure poverty line sensitivity across income bands. Second, it develops a classification bias metric to capture reclassification instability between adjacent thresholds. Third, it provides cross-country evidence demonstrating that threshold sensitivity varies according to national income distribution structures. This comparative perspective highlights the context-dependent nature of poverty measurement and challenges the assumption that poverty statistics are invariant to marginal threshold adjustments.

By integrating elasticity analysis, structural break identification, and cross-country comparison, this research advances the literature on poverty measurement and distribution-sensitive welfare analysis. The findings contribute to ongoing debates regarding the reliability of threshold-based poverty statistics and provide empirical evidence that poverty measurement is not threshold-neutral but structurally dependent on income distribution density.

## Literature Review

### Foundations of Poverty Measurement

The theoretical foundations of poverty measurement are rooted in welfare economics and distribution-sensitive social evaluation [14]. Early poverty metrics focused primarily on headcount ratios, which measure the proportion of individuals below a predefined poverty line. While simple and intuitive, the headcount index does not capture the depth or severity of poverty and is

insensitive to income transfers among the poor [15].

To address these limitations, the FGT class of poverty measures was introduced, incorporating poverty gaps and squared poverty gaps to reflect both incidence and intensity [16]. The FGT framework allows poverty measurement to account for the distribution of income below the poverty line, making it more sensitive to inequality among the poor. Similarly, Sen's poverty index integrates both the headcount ratio and the Gini coefficient among the poor, emphasizing the distributional dimension of poverty [17].

Despite these theoretical advancements, the majority of empirical poverty assessments continue to rely heavily on headcount measures derived from fixed monetary thresholds [18]. The simplicity and policy relevance of binary poverty classification have sustained its dominance in applied research and official statistics.

### **Poverty Line Determination and Sensitivity**

The determination of poverty lines has long been debated in the literature. Absolute poverty lines are typically based on minimum consumption requirements, while relative poverty lines are defined as a proportion of median income [19]. International organizations frequently employ PPP-adjusted thresholds to facilitate cross-country comparisons [20].

Several studies have examined how poverty estimates respond to revisions in price indices, PPP adjustments, and methodological changes in consumption measurement [21]. These analyses highlight that poverty rates may shift substantially when poverty lines are recalibrated. However, most of this literature focuses on discrete methodological changes rather than on the marginal responsiveness of poverty headcounts to incremental threshold adjustments.

A smaller strand of research acknowledges that poverty measurement may be sensitive to income distribution density near the cutoff [22]. When households cluster around a specific income band, minor changes in the poverty line can produce disproportionately large shifts in measured poverty. Nevertheless, empirical quantification of this threshold elasticity remains limited, and systematic measurement of reclassification instability across adjacent thresholds is rarely conducted.

### **Distributional Density and Threshold Effects**

Distribution-sensitive poverty analysis emphasizes that the impact of a poverty line depends not only on its absolute value but also on the shape of the income distribution [23]. If the income distribution is smooth and gradually dispersed, changes in poverty thresholds will result in modest adjustments to headcount ratios. Conversely, when income density is concentrated near a specific range, threshold adjustments may trigger abrupt reclassification effects.

Recent contributions in development economics and welfare analysis suggest that poverty statistics may exhibit non-linear behavior when poverty lines intersect zones of income clustering [24]. These non-linearities imply that poverty measurement may operate under different regimes depending on threshold location. However, formal identification of structural breaks in poverty elasticity across income bands remains underexplored in empirical literature.

Cross-country comparative studies further indicate that income distribution

structures vary significantly across developing and emerging economies [20], [21]. As a result, the same international poverty line may generate different degrees of statistical sensitivity depending on national income density patterns. Yet, few studies directly compare elasticity responses across countries within a unified analytical framework.

## Research Gap

While existing literature provides substantial insights into poverty measurement theory, inequality-adjusted indices, and methodological robustness, several gaps remain. First, prior studies largely focus on static poverty levels rather than on the responsiveness of poverty headcounts to marginal threshold adjustments. Second, the concept of classification instability between adjacent poverty lines has not been systematically formalized in empirical analysis. Third, cross-country heterogeneity in threshold sensitivity has received limited quantitative attention.

This study addresses these gaps by introducing an elasticity-based framework to measure poverty line sensitivity, developing a classification bias metric to quantify reclassification instability, and conducting cross-country comparisons to examine heterogeneity in threshold responsiveness. By integrating these elements, the research advances the literature beyond conventional headcount analysis and contributes to a deeper understanding of how poverty statistics respond to threshold selection within different income distribution contexts.

## Methods

### Data Source and Structure

This study uses income-band distribution data derived from harmonized income or consumption measures expressed in constant 2021 international dollars per day. The dataset reports the number of individuals within predefined income intervals, ranging from \$3 to \$40 per day. These bands enable the reconstruction of cumulative poverty counts under alternative poverty thresholds.

For the main case analysis, Albania (2020) is selected as a representative example to illustrate threshold effects. Cross-country comparisons are conducted using the same methodology.

### Variable Construction

The key variables used in the analysis are summarized in [table 1](#).

Variable	Description	Unit	Construction
Threshold	Poverty line threshold	USD per day	Defined income bands (\$3–\$30)
Population_band	Population within income interval	Number of people	Raw dataset value
Cumulative_poverty	Population below threshold	Number of people	Cumulative sum of income bands

The poverty threshold represents the upper bound of each income band. Population\_band refers to the number of individuals whose daily income lies within a specific interval. Cumulative\_poverty is constructed by summing all population bands up to a given threshold. This cumulative measure

approximates the poverty headcount that would result if the poverty line were set at that threshold.

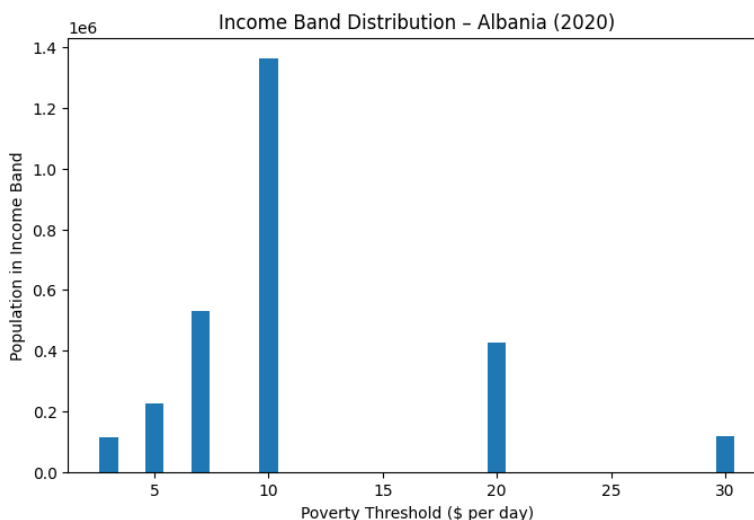
### Poverty Band Distribution

The empirical analysis begins with a descriptive examination of income distribution across bands. Table 2 reports the distribution of the population across income intervals for Albania in 2020.

**Table 2 Poverty Band Distribution (Albania, 2020)**

Threshold (\$/day)	Population Band	Cumulative Poverty
3	112,782	112,782
5	227,528	340,310
7	531,300	871,610
10	1,363,433	2,235,043
20	426,462	2,661,505
30	117,081	2,778,586

The largest population segment is concentrated within the \$7–\$10 income band. This clustering is central to the identification of threshold sensitivity in subsequent analysis. Figure 1 visualizes the distribution of the population across income bands.

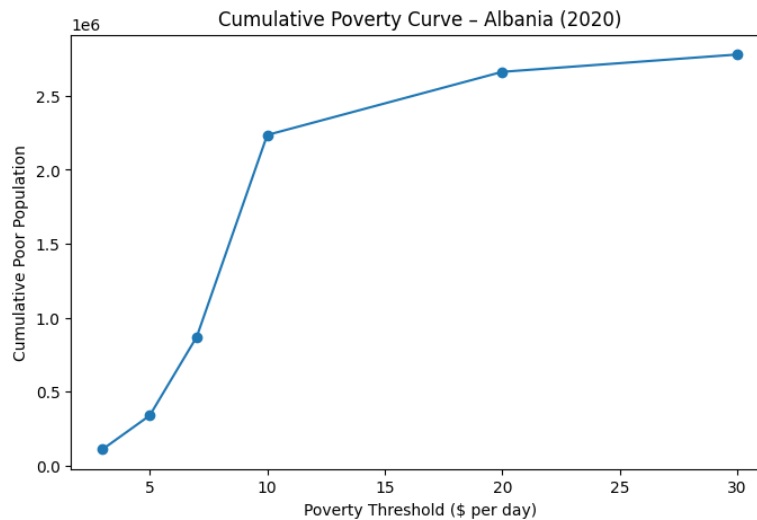


**Figure 1 Income Band Distribution – Albania (2020)**

The bar chart shows a pronounced concentration of households in lower-middle income ranges. The uneven distribution suggests that incremental changes in poverty thresholds within this interval may generate substantial reclassification effects.

### Cumulative Poverty Curve

To examine how poverty headcounts evolve as thresholds increase, cumulative poverty is plotted against poverty thresholds.



**Figure 2 Cumulative Poverty Curve – Albania (2020)**

The cumulative poverty curve exhibits a steep slope between \$5 and \$10 per day, followed by a gradual flattening beyond \$10. The steep section reflects dense income clustering, while the flatter segment indicates diminishing marginal additions to the poor population at higher thresholds.

### Elasticity Estimation

Threshold elasticity is computed to measure the responsiveness of cumulative poverty to proportional changes in poverty thresholds. Elasticity is defined as:

$$Elasticity = \frac{\% \Delta \text{Cumulative Poverty}}{\% \Delta \text{Threshold}} \quad (1)$$

This measure captures how sensitive poverty headcounts are to incremental threshold adjustments. High elasticity values indicate strong threshold effects and potential measurement instability.

### Classification Bias

To assess reclassification instability, classification bias is estimated as:

$$\text{Classification Bias} = \frac{|P_{Z+\delta} - P_Z|}{P_Z} \quad (2)$$

$P_Z$  denotes cumulative poverty at threshold  $Z$ . This metric quantifies the proportion of reclassified individuals resulting from marginal changes in the poverty line.

### Cross-Country Comparison

To evaluate whether threshold sensitivity is structurally country-specific rather than a universal feature of poverty measurement, the analytical framework described above is applied to three additional countries: Brazil, India, and Indonesia. These countries were selected to represent different income distribution profiles and stages of economic development, thereby allowing comparative assessment of threshold effects under heterogeneous distributional conditions.

For each country, the most recent year available in the dataset is selected to

ensure temporal consistency. Using identical income-band definitions and threshold intervals (\$3, \$5, \$7, \$10, \$20, and \$30 per day), cumulative poverty is constructed following the same procedure applied to the baseline case. Elasticity is then computed as the proportional change in cumulative poverty relative to proportional changes in poverty thresholds. Classification bias is similarly calculated to quantify reclassification instability between adjacent income bands.

Maintaining methodological uniformity across countries ensures comparability of elasticity estimates and avoids distortions arising from differences in poverty line construction. This standardized approach isolates the role of income distribution density in explaining cross-country variation in threshold responsiveness. To visualize heterogeneity, elasticity estimates across thresholds and countries are presented using a heatmap representation. The heatmap provides a matrix-based comparison in which rows represent countries and columns represent poverty thresholds. Color intensity corresponds to the magnitude of elasticity values. This visualization technique enables identification of threshold clustering zones and facilitates the detection of structural differences in income distribution regimes.

Cross-country comparison serves three methodological purposes. First, it tests the robustness of threshold effects beyond a single-country context. Second, it allows identification of whether structural breaks occur at similar threshold levels across economies. Third, it provides evidence on whether uniform international poverty lines may generate uneven statistical sensitivity across countries. By systematically applying the same elasticity and classification bias framework across multiple national contexts, the analysis moves beyond descriptive poverty comparisons and instead evaluates structural heterogeneity in poverty measurement responsiveness. This comparative dimension strengthens the external validity of the findings and provides a foundation for assessing the broader implications of threshold-dependent poverty statistics.

## Result

### Threshold Elasticity of Poverty Measurement

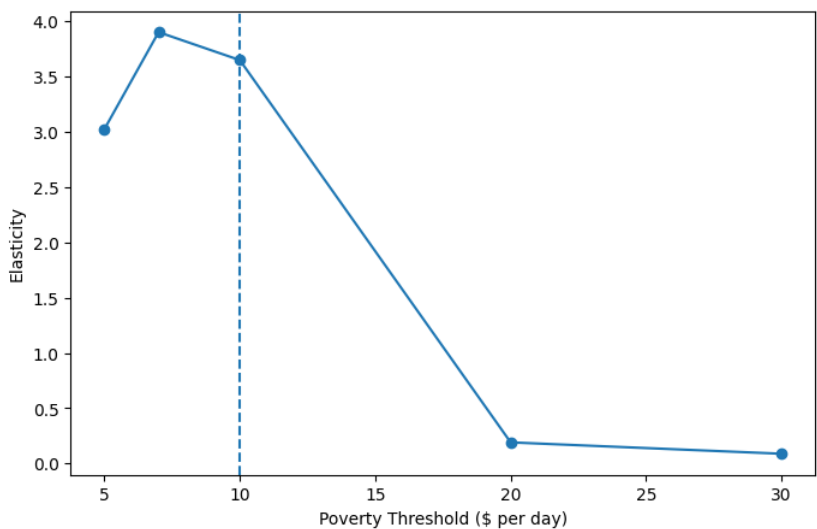
To evaluate how sensitive poverty measurement is to definitional adjustments, this study estimates the elasticity of cumulative poverty with respect to incremental changes in poverty thresholds. Elasticity captures the proportional response of the poverty headcount to percentage changes in the poverty line. A higher elasticity value indicates that small increases in the threshold produce disproportionately large increases in measured poverty. This metric therefore provides direct evidence of threshold sensitivity and potential measurement instability, particularly in income ranges where households cluster near poverty cutoffs. [Table 3](#) reports the estimated elasticity values across selected poverty thresholds for Albania in 2020.

Poverty Threshold (\$/day)	Elasticity
3	–
5	3.03
7	3.90
10	3.65

20	0.19
30	0.09

The results indicate substantial non-linearity in the responsiveness of poverty headcount to threshold variation. Elasticity rises sharply from 3.03 at the \$5 threshold to a peak of 3.90 at \$7. This implies that a 1 percent increase in the poverty line at \$7 per day produces nearly a 4 percent increase in measured poverty. Elasticity remains elevated at \$10 (3.65), suggesting continued high sensitivity within this lower-middle income range.

However, beyond \$10 per day, elasticity declines dramatically. At \$20, elasticity falls to 0.19, and at \$30 it declines further to 0.09. These values indicate that additional increases in higher poverty thresholds generate only marginal changes in poverty headcount. The abrupt shift between \$10 and \$20 suggests the presence of a structural change in the density of the income distribution. This non-linear relationship is illustrated in [figure 3](#).



**Figure 3 Elasticity vs Poverty Threshold – Albania (2020)**

[Figure 3](#) clearly demonstrates the steep upward slope between \$5 and \$7, the sustained high elasticity up to \$10, and the pronounced structural collapse thereafter. The curvature of the elasticity profile indicates that households are densely clustered within lower-middle income bands, particularly between \$7 and \$10 per day. Once the threshold surpasses this range, the marginal pool of households eligible for reclassification becomes significantly smaller, resulting in sharply reduced elasticity.

The observed pattern provides empirical evidence of threshold effects in poverty measurement. Poverty statistics appear highly sensitive to definitional adjustments within specific income intervals, especially those characterized by income clustering. This suggests that poverty measurement is not threshold-neutral and that the choice of poverty line within lower-middle income bands may substantially influence official poverty estimates.

### **Classification Bias and Reclassification Instability**

While elasticity measures proportional responsiveness of poverty headcount to threshold adjustments, it does not directly capture the magnitude of

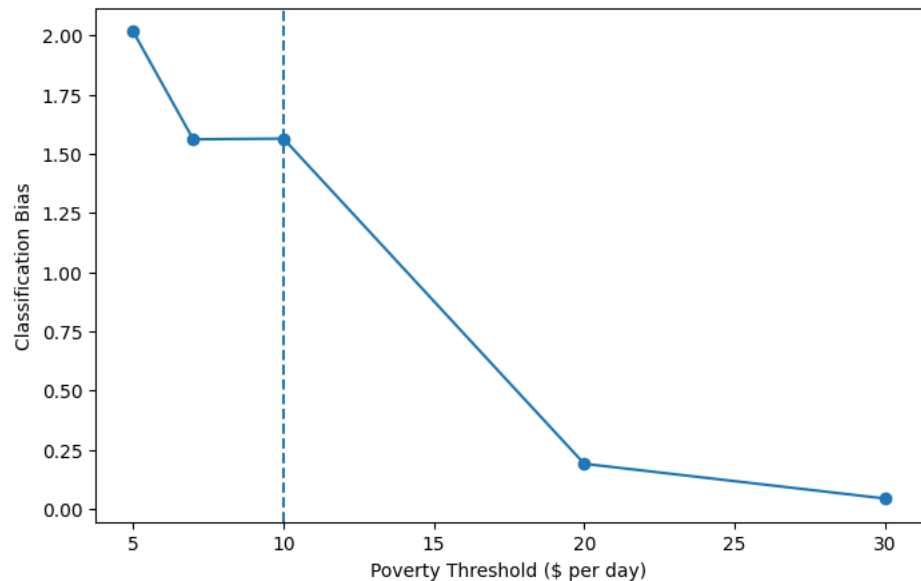
reclassification that occurs between adjacent poverty lines. To address this, this study estimates classification bias, defined as the proportional change in cumulative poverty resulting from incremental shifts in the poverty threshold. This measure provides a direct indication of reclassification instability and reveals how fragile poverty categorization may be when small definitional adjustments are introduced. Table 4 reports classification bias across selected poverty thresholds for Albania in 2020.

**Table 4 Classification Bias Across Poverty Thresholds (Albania, 2020)**

Poverty Threshold (\$/day)	Classification Bias
3	–
5	2.02
7	1.56
10	1.56
20	0.19
30	0.04

The results indicate substantial instability in poverty classification at lower-middle thresholds. Classification bias exceeds 200 percent at the \$5 threshold, implying that a marginal increase in the poverty line leads to reclassification effects that are more than twice the size of the previously identified poor population. Bias remains above 150 percent at both \$7 and \$10, confirming persistent reclassification volatility within this income range.

However, beyond \$10 per day, classification bias declines sharply. At \$20, bias falls to 0.19, and at \$30 it drops further to 0.04. These values indicate that poverty categorization becomes increasingly stable as the threshold moves into higher income ranges. The transition between \$10 and \$20 suggests a structural shift in the distribution of households relative to poverty cutoffs. This pattern is illustrated in figure 4.



**Figure 4 Classification Bias vs Poverty Threshold – Albania (2020)**

Figure 4 shows a steep downward trajectory after \$10, visually confirming that

instability is concentrated within lower-middle income thresholds. Above \$20 per day, additional threshold adjustments produce only minor reclassification effects. This evidence reinforces the findings from the elasticity analysis and demonstrates that binary poverty classification is particularly fragile in income intervals where households are densely clustered.

Taken together, the results suggest that poverty measurement is highly sensitive to threshold selection within specific income bands. When poverty lines are set near regions of income concentration, even small definitional changes can produce disproportionately large shifts in official poverty statistics. This instability raises important concerns regarding the reliability of poverty estimates and the potential for policy mis-targeting when thresholds are adjusted without accounting for underlying income distribution dynamics.

### Cross-Country Heterogeneity in Threshold Sensitivity

The previous analysis demonstrates strong threshold effects within a single-country context. However, an important question remains: are these sensitivity patterns universal features of poverty measurement, or do they vary across national income distributions? To address this, elasticity estimates were computed for Albania, Brazil, India, and Indonesia using the same methodological framework. Comparing countries allows us to assess whether threshold instability is structurally embedded in poverty measurement or contingent on country-specific income density patterns. Figure 5 presents the cross-country elasticity heatmap.

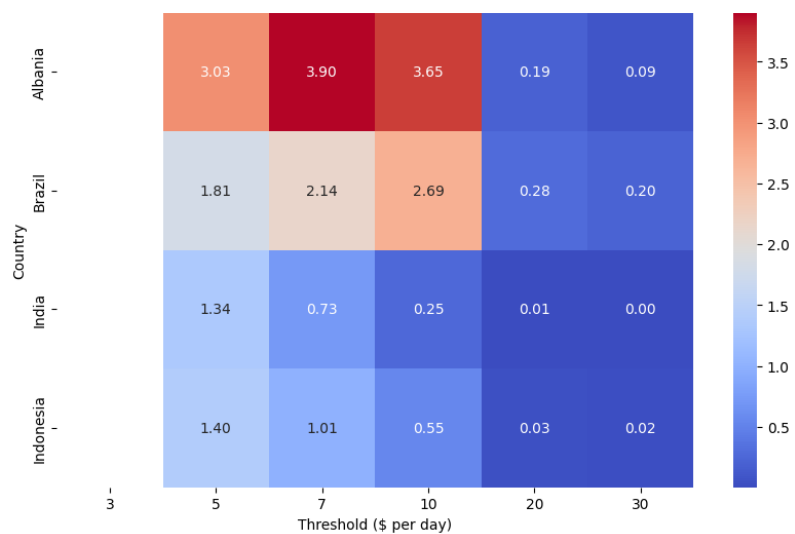


Figure 5 Elasticity Heatmap Across Countries

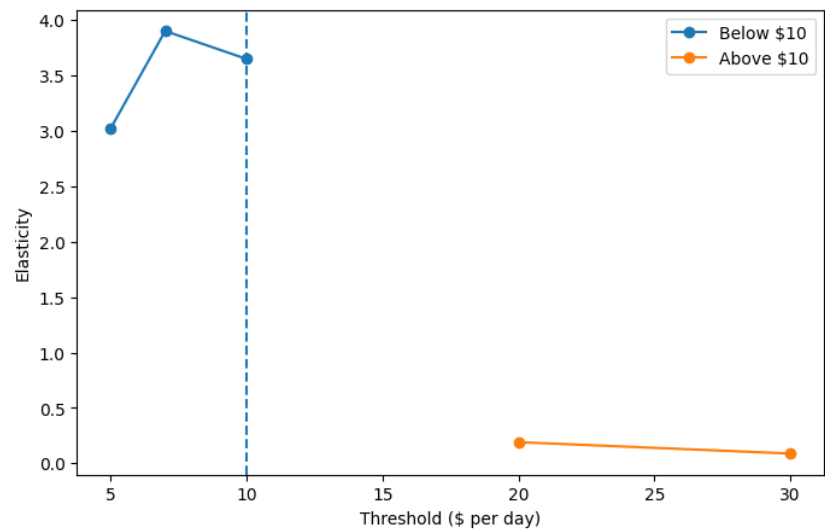
The heatmap reveals substantial heterogeneity in threshold responsiveness across countries. Albania exhibits extremely high elasticity between \$5 and \$10 per day, confirming strong clustering in lower-middle income bands. Brazil shows moderate elasticity within the same interval, indicating a noticeable but less pronounced concentration around these thresholds. Indonesia displays modest sensitivity, suggesting a more gradual income distribution across adjacent bands. In contrast, India demonstrates relatively low elasticity across most thresholds, implying a smoother distribution of households that reduces abrupt reclassification effects when poverty lines are adjusted.

These cross-country differences suggest that threshold effects are not inherent properties of poverty measurement itself but rather reflections of underlying income distribution structures. Countries with dense clustering near lower-middle thresholds exhibit sharp elasticity spikes and higher instability, while countries with more dispersed income distributions show smoother responsiveness patterns.

The heterogeneity observed in [figure 5](#) reinforces the argument that poverty measurement is context-dependent. Threshold sensitivity is shaped by national income distribution dynamics, implying that uniform global poverty thresholds may generate uneven measurement distortions across countries. This finding highlights the importance of incorporating distributional structure into poverty line selection and suggests that policy interpretations of poverty statistics should account for country-specific sensitivity regimes.

### Structural Break Evidence

The elasticity and classification bias results indicate a sharp decline in responsiveness after the lower-middle income range. To further examine whether this pattern reflects a structural change rather than a gradual decline, a structural break visualization was conducted. The objective is to identify whether poverty elasticity operates under distinct regimes across income thresholds. [Figure 6](#) provides visual evidence of a structural shift in poverty elasticity around the \$10 threshold.



**Figure 6 Structural Break Visualization – Albania**

The figure shows that elasticity remains consistently high below \$10 per day, with values exceeding 3 in the \$5–\$10 range. However, elasticity collapses sharply beyond this interval, falling below 0.2 at \$20 and approaching zero at \$30. The abrupt change in slope between \$10 and \$20 suggests the presence of a structural discontinuity rather than a smooth monotonic decline.

This discontinuity indicates the existence of two distinct poverty measurement regimes. The first regime, located below \$10 per day, is characterized by high elasticity and strong reclassification sensitivity. In this zone, small adjustments to the poverty line generate disproportionately large changes in measured poverty. The second regime, located above \$20 per day, exhibits low elasticity

and minimal classification instability, implying a more stable measurement environment.

The structural separation implies that poverty measurement behaves differently across income bands. Lower-middle thresholds represent a zone of significant measurement fragility, where definitional adjustments can substantially alter official poverty statistics. In contrast, higher thresholds reflect a regime of relative stability, where incremental changes in poverty lines produce only marginal effects on headcount estimates.

The presence of this structural break reinforces the earlier findings on threshold effects and classification bias. It suggests that poverty measurement is governed by distributional density dynamics and that the choice of threshold around income clustering zones may critically determine the volatility of poverty statistics.

## Discussion

The empirical findings of this study provide strong evidence that poverty measurement is highly sensitive to threshold selection, particularly within lower-middle income bands. The elasticity analysis demonstrates that small proportional changes in poverty lines between \$5 and \$10 per day generate disproportionately large increases in measured poverty. This pattern indicates a high density of households clustered around these income levels, making poverty classification extremely responsive to marginal definitional adjustments.

The classification bias results further reinforce this interpretation. Reclassification instability exceeding 150 percent in lower thresholds suggests that binary poverty categorization may not adequately capture the continuum of economic vulnerability. When households are densely concentrated near poverty cutoffs, even minor shifts in threshold definitions can substantially alter official poverty headcounts. This fragility raises concerns regarding the robustness and comparability of poverty statistics, particularly when poverty lines are revised due to methodological updates, inflation adjustments, or policy reforms.

The structural break analysis reveals that poverty elasticity operates under two distinct regimes. Below \$10 per day, poverty measurement exhibits high instability and strong responsiveness. Above \$20 per day, elasticity declines sharply and classification becomes relatively stable. This regime shift suggests that poverty measurement dynamics are shaped by income distribution density rather than by uniform statistical properties. In other words, poverty measurement is not inherently unstable; instability arises when thresholds intersect regions of concentrated income clustering.

The cross-country analysis strengthens this argument. The elasticity heatmap shows substantial heterogeneity across Albania, Brazil, Indonesia, and India. Countries with pronounced income clustering in lower-middle ranges exhibit extreme threshold sensitivity, while countries with smoother income distributions display more gradual responsiveness. This finding implies that global poverty thresholds may produce uneven measurement distortions across countries. A uniform poverty line may generate high volatility in some economies while remaining relatively stable in others.

These results have important implications for poverty policy and measurement frameworks. First, reliance on strict binary poverty cutoffs may underestimate

the degree of economic vulnerability in societies where income distribution is concentrated near lower-middle thresholds. Second, adjustments to official poverty lines should account for distributional density to avoid artificial volatility in poverty statistics. Third, alternative measurement approaches, such as vulnerability bands or graduated poverty indices, may provide more stable and policy-relevant assessments of economic hardship.

From a theoretical perspective, the findings align with welfare economics and distribution-sensitive poverty measurement theory. The Foster–Greer–Thorbecke framework emphasizes the role of distribution below the poverty line, but this study demonstrates that the location of the poverty line itself can significantly influence measured outcomes when income density is uneven. Threshold selection is therefore not merely a technical parameter but a structurally consequential decision.

Overall, the evidence suggests that poverty measurement is context-dependent and structurally sensitive to income distribution characteristics. Recognizing this sensitivity is essential for improving the credibility and stability of poverty statistics.

## Conclusion

This study examined threshold effects and classification bias in poverty measurement using income band data across multiple countries, with a detailed case analysis of Albania. By estimating elasticity and reclassification bias across alternative poverty thresholds, the analysis demonstrates that poverty headcounts are highly sensitive to definitional adjustments within lower-middle income ranges.

The results reveal three central findings. First, poverty elasticity is exceptionally high between \$5 and \$10 per day, indicating that small increases in the poverty line produce disproportionately large increases in measured poverty. Second, classification bias is concentrated in these same thresholds, confirming substantial reclassification instability. Third, a structural break occurs around \$10 per day, separating a high-instability regime from a more stable upper-income regime.

Cross-country comparisons further show that threshold sensitivity varies according to national income distribution structures. This heterogeneity suggests that poverty measurement is not universally stable and that uniform threshold applications may generate unequal distortions across countries.

The findings highlight the importance of incorporating distributional structure into poverty line selection and caution against relying solely on binary poverty classification. When poverty thresholds intersect zones of income clustering, official poverty statistics may become highly volatile and potentially misleading for policy design.

Future research may extend this analysis by employing formal structural break tests, panel regression models, or alternative poverty indices to further examine the interaction between income distribution density and poverty measurement sensitivity. Incorporating multidimensional poverty indicators may also provide a more comprehensive understanding of economic vulnerability.

In conclusion, poverty measurement is not threshold-neutral. The location of the poverty line relative to income distribution density plays a decisive role in

determining the stability and magnitude of measured poverty. Recognizing and accounting for this structural sensitivity is essential for producing reliable and policy-relevant poverty statistics.

## Declarations

### Author Contributions

Conceptualization: B.H. and D.T.S.; Methodology: D.T.S.; Software: B.H.; Validation: B.H. and D.T.S.; Formal Analysis: B.H. and D.T.S.; Investigation: B.H.; Resources: D.T.S.; Data Curation: D.T.S.; Writing Original Draft Preparation: B.H. and D.T.S.; Writing Review and Editing: D.T.S. and B.H.; Visualization: B.H.; All authors have read and agreed to the published version of the manuscript.

### Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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### Institutional Review Board Statement

Not applicable.

### Informed Consent Statement

Not applicable.

### Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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