

Article

Rethinking Poverty Metrics: How Outlier Management Affects Poverty Estimates in Mexico

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Abstract

The Food Energy Intake (FEI) method is among the most widely used approaches for establishing income poverty lines, particularly in low- and middle-income countries where it is often used as a baseline to define official poverty lines. This method links poverty measurement to the consumption of calories and other essential nutrients, identifying households that lack the resources necessary to meet minimum nutritional requirements. However, due to data limitations, the construction of poverty lines based on the FEI method relies on a series of assumptions that are often left to the discretion of specialists, without adequate discussion regarding their appropriateness or potential implications. These assumptions can significantly influence the resulting poverty lines and, consequently, the poverty estimates derived from them. In this study, we focus on the Mexican official method of poverty measurement to explore an often overlooked step in poverty measurement: the treatment of extreme values in nutrient availability estimates constructed using household survey data. While this may initially appear to be a minor technical consideration, we demonstrate that the criteria used to identify and potentially exclude outlying observations exert a substantial influence on poverty metrics, which reveals weak fulfillment of the FEI assumptions, as well as important limitations in the expenditure data. This underscores the critical importance of adopting transparent, rigorous, and consistent methodologies for managing outliers, alongside a careful evaluation of other assumptions that are commonly overlooked during the poverty line construction process. We assess the sensitivity of poverty estimates in Mexico employing twelve different outlier-handling methodologies. For each method, we compute the corresponding poverty lines and poverty rates. Our findings reveal substantial variation in extreme poverty rates—ranging from 10.7% to 26.7%—solely attributable to the criteria adopted for the treatment of extreme values. Our analysis suggests that such sensitivity may originate in the decision to use income, rather than expenditure, as the underlying welfare measure in the implementation of the FEI method. We conclude that addressing the treatment of outliers is essential for ensuring consistent and reliable poverty measures, but a thorough revision of the method adopted by the Mexican government to measure poverty is essential.

Keywords: poverty measurement; poverty lines; food energy intake method; nutritional requirements; Mexico



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1. Introduction

Despite the increasing adoption of multidimensional poverty measures (MPPN) globally (MPPN 2025), income-based poverty measures remain a crucial tool for developing countries in monitoring poverty and guiding policy interventions (Alvaredo and Gasparini 2015; Chen and Ravallion 2007), as monetary measures of household income or expenditures serves as a fundamental indicator of access to essential resources, directly influencing a household's ability to meet basic needs like food, shelter, and clothing. In many developing countries, where immediate survival is a pressing concern, absolute poverty lines¹ offer a straightforward and easily interpretable metric for assessing the adequacy of a household income or expenditure to meet their basic needs (Ravallion 2016). Furthermore, the availability and comparability of income and expenditure data—usually collected in well-established surveys developed by national statistical offices—allows for consistent tracking of income poverty trends over time and across regions, enabling policymakers to identify areas where poverty reduction efforts are most needed (Deaton and Zaidi 2002). For similar reasons, income-based measures are often more amenable to rigorous econometric analysis, facilitating the identification of causal relationships between poverty and other socioeconomic factors to inform the design of interventions aimed at addressing the root causes of poverty (Duflo and Abhijit 2011).

Absolute poverty lines are “meant to reflect the cost of obtaining a given reference level of utility or standard of living that defines the threshold of poverty,” usually linked to nutritional requirements (Tarp et al. 2002, p. 78). Although multiple methods exist to estimate such thresholds (see Ravallion 2016), the most commonly used approach in empirical applications combines the Food Energy Intake (FEI) and Cost of Basic Needs (CBN) methods (Ravallion 2012). The FEI method, introduced by Greer and Thorbecke (1986), estimates households' caloric intake to establish a food poverty line that accounts for regional dietary preferences and price variations. Despite widespread implementation and ongoing methodological refinements, the approach has faced substantial criticism. Several theoretical and empirical issues remain unresolved, including the comparability of multiple poverty lines (Ravallion and Bidani 1994; Mahrt et al. 2022), price adjustments, and equivalence scales, among other measurement challenges (Amendola et al. 2024).

This article contributes to the literature by examining how methodological decisions regarding the measurement of caloric consumption affect poverty estimates derived using the FEI method in Mexico. Specifically, we analyze how alternative techniques for identifying and treating outliers in caloric consumption influence income-based poverty measurement, using Mexico's official poverty measurement as a case study to empirically demonstrate the implications of applying different statistical approaches.

Our results reveal that poverty estimates in Mexico (and possibly those in other countries using similar approaches) are highly sensitive to the methodology used to detect and handle outlying observations in nutritional intake. Food poverty rates can vary by as much as 16 percentage points—or up to 30 points when no method is applied. We find that certain approaches, such as threshold-based criteria (e.g., applying minimum or maximum recommended caloric intake cutoffs), may fail to eliminate the influence of outliers effectively. These thresholds often do not reflect actual consumption behaviors, which can hinder the accurate identification of poverty conditions, suggesting that the assumptions on which the FEI method are based may not hold in the Mexican data. Conversely, mean-based methods are sensitive to the underlying data distribution and may yield unreliable results, as well.

We also find that the treatment of outliers has a greater impact on rural food poverty estimates than on urban ones. Rural areas present unique conditions—such as subsistence production and post-harvest food storage—that are rarely accounted for in existing litera-

ture. These factors can lead to a biased estimation of food poverty in rural contexts and amplify the sensitivity of measurement results.

Given that poverty estimates guide public policy decisions related to resource allocation and the design of poverty reduction strategies, obtaining an accurate picture of household consumption is essential. Reliable poverty diagnostics depend on sound caloric consumption measurement, and the proper identification and treatment of outliers is a critical component in defining robust poverty lines.

To our knowledge, this is the first study to explicitly highlight the significance of outlier treatment in poverty measurement, as well as the potential pitfalls in the Mexican methodology to define poverty that make them so relevant in setting the poverty rates. It underscores the need for transparency and thorough methodological discussion by institutions responsible for official poverty statistics. Moreover, this study offers concrete recommendations for improving poverty measurement methodologies—not only in Mexico but also in other countries employing similar approaches—to strengthen the evaluation and design of effective poverty alleviation interventions.

2. Related Literature

Poverty lines estimated using the Food Energy Intake (FEI) method aim to determine the minimum level of resources a household requires to meet the nutritional needs of all its members. These nutritional needs are typically based on international standards—such as those established by the World Health Organization ([World Health Organization 2023](#))—while also incorporating local food preferences and price structures ([Greer and Thorbecke 1986](#)). One of the key strengths of the FEI method lies in its simplicity and ease of interpretation ([Tarp et al. 2002](#)). However, the estimation of household-level caloric availability is highly sensitive to the availability, precision, and reliability of underlying data sources, so that in multiple applications it is usually combined with the Cost of Basic Needs (CBN) approach to define the poverty lines to improve their consistency and specificity ([Ravallion 2012](#); [Wodon 1997](#)).² Challenges such as missing data, misreporting, and irregular consumption patterns can significantly distort the caloric thresholds used to define poverty ([Ravallion 2016](#)). Although many empirical applications of the FEI method have not adequately addressed these issues, recent efforts have increasingly focused on identifying its theoretical, methodological, and empirical limitations to improve the accuracy of poverty measurement ([Amendola et al. 2024](#)).

As part of this broader research agenda, one area that remains underexplored in the literature is the role of outlier detection and treatment in estimating household nutrient availability—particularly caloric intake. Caloric availability is central to the FEI method, as it forms the basis for assessing whether household members meet minimum nutritional requirements and, consequently, for identifying the subset of the population used to derive the composition and monetary value of the food basket that defines the poverty line.

Outliers in dietary data are common and can arise from various sources, including measurement error, unobserved food quality differentials, and the aggregation of diverse food items into broad consumption categories ([Gibson and Kim 2007](#)). Food consumption data are especially prone to biases such as rounding, recall error, poorly designed survey instruments, and inaccurate estimation of portion sizes—many of which are difficult to correct ([Burcham et al. 2023](#)).

In the context of household expenditure surveys (HCES)—the primary data source for poverty measurement and analysis—these challenges are exacerbated by the fact that reported food acquisition (from purchases, own production, or gifts) is typically used as a proxy for actual consumption ([Fiedler 2013](#)). This proxy may diverge from true intake due to factors like food waste, spoilage, consumption from pre-existing stocks, or foods purchased for non-human use (particularly in rural settings). Staples—often purchased

in bulk—are particularly prone to such distortions, especially when the recall period is short. The combination of these issues can result in highly skewed distributions, where some households report no acquisition, and others report exceptionally high quantities. Identifying whether extreme values reflect reporting errors, data entry mistakes, or genuine consumption behavior is complex, and usual treatment of such values (exclusion from the analysis) may not be enough to address the problem, or even magnify it. Moreover, standard practices such as excluding extreme values from the analysis may undermine the validity of sampling design and compromise the statistical estimates (Fiedler et al. 2012). Therefore, an adequate treatment of outliers is essential for producing reliable estimates of caloric intake.

Despite the importance of addressing outliers in the context of poverty measurement, there is currently no universally accepted standard for detecting or treating them. Furthermore, the literature lacks a systematic discussion of how poverty estimates respond to different outlier-handling strategies. In practice, outliers are typically treated using conventional techniques adapted from disciplines such as epidemiology, statistics, or nutritional science. However, few studies rigorously examine the implications of adopting one method over another. As a result, methodological choices are often made arbitrarily or based on convenience, rather than being guided by a critical assessment of their effects on key welfare indicators, including caloric thresholds and poverty rates.

Sompolska-Rzechuła and Kurdyś-Kujawska (2022) applied a winsorization procedure to caloric consumption data, replacing extreme values located outside the interquartile range (IQR) with the corresponding boundary values. While this method aims to mitigate the influence of outliers, the authors did not conduct a comparative evaluation against alternative techniques or assess the impact of their approach on core welfare metrics.

Similarly, Bocoum et al. (2014) explored the effects of outlier treatment on caloric intake and food expenditure estimates used to measure food insecurity. They applied three variants of the IQR approach: (1) 1.0 IQR from the median (Q2), (2) 2.0 IQRs from Q2, and (3) 6.0 IQRs from Q2. In all cases, fewer than 10% of observations were identified as outliers and subsequently replaced with the median, effectively centralizing the distribution. While this adjustment lowered food expenditure estimates relative to official benchmarks, the authors did not disaggregate their results by detection method, leaving the differential impact of each approach unclear.

In epidemiological research, a range of strategies have been employed to manage dietary outliers. Crozier et al. (2006), for example, excluded observations in which caloric intake exceeded six standard deviations for any food group. More comprehensive evaluations can be found in studies such as Horn et al. (2001), which compared Dixon's test and Tukey's lower and upper fence tests by introducing synthetic outliers into samples of healthy individuals. Their results showed that in the absence of true outliers, data exclusion had little effect. However, when 5% of the sample consisted of genuine outliers, Tukey's test more effectively reduced the influence of extreme values, improving the accuracy of reference group estimates.

Burcham et al. (2023) conducted a systematic comparison of five outlier detection strategies for macronutrient intake data: (1) fixed caloric intake thresholds; (2) values beyond ± 2 standard deviations from the mean; (3) Tukey's fences using 1.5 and 3.0 IQRs from Q3; (4) Tukey's fences using only the 3.0 IQR threshold; and (5) values above the 99th percentile. Their findings indicate that non-parametric, median-based methods—such as Tukey's fences and percentile-based cutoffs—are more robust, particularly in skewed or heteroskedastic distributions, where mean-based methods may produce biased results.

Similarly, Massara et al. (2023) evaluated four outlier detection methods in the context of child growth monitoring using simulated anomalies. The methods included: (1) fixed

cutoff values based on WHO recommendations; (2) WHO-based thresholds with a ± 2 SD adjustment over a two-year period; (3) ± 2 SD from the mean of the reference population; and (4) unsupervised clustering using k-means. Their results show that clustering-based techniques, particularly k-means, are highly sensitive to extreme values, which can distort cluster composition and shift the centroid of the distribution.

Collectively, these studies highlight the diversity of outlier detection techniques used across disciplines, and the absence of a unified methodological standard. While each approach offers specific advantages and limitations, the variability in their outcomes underscores the importance of critically assessing their implications—especially when such methodological choices directly affect key welfare statistics. In this article, we evaluate the extent to which alternative outlier detection and treatment methods influence poverty estimates produced using the FEI method, focusing on Mexico's official poverty measurement method as a case study.

3. Methodology

Although multiple data sources have been employed to operationalize the Food Energy Intake (FEI) method in developing countries, a significant number of applications rely on existing Household Income and Expenditure Surveys (HIES). These surveys, initially designed to update the weights of the Consumer Price Index (CPI), are available in both high- and low-income countries and typically contain granular information on food acquisition, including total expenditure, quantities purchased, type of retail outlet, and other contextual variables. To illustrate the methodological implications of our analysis, we examine the case of Mexico, where the FEI method is used to construct official monetary poverty lines, which are estimated based on data from the national HIES (CONEVAL 2012).

Although Mexico's official poverty measurement framework is multidimensional in nature (CONEVAL 2010), one of its central components is the assessment of economic well-being. Within this dimension, the FEI method is used to identify households whose income is insufficient to purchase a basic food basket that meets the minimum caloric requirements of all members. This condition corresponds to what is officially classified as extreme income poverty; however, for simplicity, we refer to this indicator hereafter as income poverty (as explained in the next section). The adoption of the FEI method in Mexico is consistent with international best practices for poverty measurement (CONEVAL 2012), so similar approaches are used in several countries, so that the Mexican experience may be of relevance in multiple settings.

To contextualize the subsequent discussion on the influence of outlier detection and treatment in poverty estimation, we first present a brief overview of the current methodology used to construct the official poverty lines in Mexico. We then outline the analytical strategy adopted in this study to evaluate the sensitivity of poverty estimates to alternative procedures for identifying and addressing extreme values in nutritional intake data.

3.1. Measuring Poverty in Mexico

The construction of the poverty lines used in Mexico's income poverty measurement involves the following steps (CONEVAL 2012, 2019):

1. *Conversion of food purchases into nutrients:* Food purchase data are converted into calories and other macro- and micronutrients available for household consumption using food-to-nutrient conversion tables (see Hernández-Solano et al. 2022).
2. *Estimation of household caloric requirements:* Caloric needs are estimated based on the age, sex, and rural or urban location of household members.
3. *Calculation of the Adequacy Coefficient (AC):* The AC is defined as the ratio of available calories to the caloric requirements of the household.

4. *Outlier identification and removal*: Households with an AC exceeding 4.9—i.e., those whose reported food purchases imply an intake greater than 4.9 times the household's total caloric requirements—are excluded from the estimation sample. Notably, the methodological documentation does not provide an explicit justification for the selection of the 4.9 threshold or for the decision to remove the corresponding observations, rather than using other alternatives.
5. *Ranking households by income*: Households are ordered from lowest to highest per capita income and grouped into percentiles.
6. *Identification of the Population Reference Stratum (PRS)*: An iterative procedure is used to determine the group of households that, on average, meet their nutritional requirements with the lowest possible income. Starting with percentiles 1 to 20, the average AC is calculated. If it is equal to or greater than 1, this group is designated the PRS. If not, the window is shifted (e.g., percentiles 2 to 21, 3 to 22, etc.) until a group with an average $AC \geq 1$ is found.
7. *Definition of the food basket*: The PRS is used to determine the composition and shares of the food basket. Items that are infrequently consumed or represent a negligible share of total food expenditure are typically excluded.³
8. *Nutrient adequacy adjustment*: The quantities in the basket are adjusted to ensure compliance with recommended dietary requirements for proteins, vitamins, and minerals.
9. *Valuation of the poverty line*: The monetary value of the food basket is calculated using average unit prices for each food item, defined as the ratio of total expenditure to the quantity purchased, based on observations within the PRS.

As in many countries, the construction of poverty lines in Mexico combines elements of the FEI method and the Basic Needs approach, as it uses as reference the food basket obtained from the FEI approach, and then adjust it to nutritional and experts' criteria to define the final basket. In addition, the process is conducted separately for rural and urban areas to account for systematic differences in consumption patterns and relative price structures across these regions. Once the caloric requirements are translated into a region-specific food basket, the cost of non-food necessities is estimated using the Engel coefficient (also referred to as the Orshansky coefficient), defined as the inverse of the share of total household expenditure allocated to food (Hanson 2008; CONEVAL 2010). Consequently, the monetary value of the poverty line serves as the foundational input for computing the total income poverty line. This implies that any bias in the estimation of the extreme income poverty (or food poverty) threshold is propagated and potentially magnified in the derivation of overall income poverty rates. To simplify our exposition, from now on focus exclusively on the food component of the income poverty line and refer to it as the poverty line, in the understanding that the overall poverty lines require to be adjusted using the Engel coefficient.

3.2. Identification and Treatment of Outliers

While each of the aforementioned steps involves important methodological considerations, our analysis focuses on Step 4, which, as we demonstrate, can substantially influence national poverty estimates. Specifically, we evaluate the sensitivity of both the poverty lines and the resulting poverty rates to alternative strategies for identifying and treating outliers in caloric intake data. To this end, we estimate poverty lines and corresponding income poverty rates under twelve distinct decision rules (summarized in Table 1): nine derived from the five most commonly used outlier detection methods in the empirical literature; two based on the criteria employed in Mexico's official poverty measurement methodology; and one baseline scenario in which no outlier treatment is applied. For

comparability, all decision rules apply a consistent criterion of removing all observations identified as outliers, as is standard practice in Mexico’s official methodology.

Table 1. Strategies for identifying and handling outliers in caloric intake data.

Method	Decision Rule	Source
Baseline	- No outlier removal	
Mexico Official Methodology (2012)	- Remove households with AC > 4.0	CONEVAL (2012)
Mexico Official Methodology (2019)	- Remove households with AC > 4.9	CONEVAL (2019)
Daily Consumption Limit	- Remove if per capita calorie intakes > 5000 kcal	Burcham et al. (2023); Massara et al. (2023)
Standard Deviation	- Remove values > 2 SD away from the mean - Remove values > 6 SD away from the mean	Crozier et al. (2006); Burcham et al. (2023)
Tukey’s Upper Fence Test	- Remove values above $Q3 + (1.5 \times IQR)$ - Remove values above $Q3 + (3.0 \times IQR)$	Horn et al. (2001); Sompolska-Rzechuła and Kurdyś-Kujawska (2022); Burcham et al. (2023)
Percentiles	- Remove values above the 99th percentile	Burcham et al. (2023)
IQR	- Remove values above $Q2 + (Q3 - Q1)$ - Remove values above $Q2 + (2.0 \times IQR)$ - Remove values above $Q2 + (3.0 \times IQR)$	Bocoum et al. (2014)

Notes: AC refers to Adequacy Coefficient (See Section 3.1). SD refers to Standard Deviation. IQR refers to Interquartile Range, while Q1, Q2, Q3 refers to Quartiles 1, 2 or 3. Source: Authors.

Our analysis concentrates on the upper tail of the caloric intake distribution, as extreme values in this range can lead to an overestimation of average caloric intake levels, thereby distorting the identification of nutritional deficits and biasing poverty estimates. By addressing these high-end outliers, we seek to improve the precision of poverty measurements and prevent the misrepresentation of underlying consumption patterns.

The empirical analysis is based on data from the 2016 edition of the National Survey on Household Income and Expenditure (ENIGH), conducted by Mexico’s National Institute of Statistics and Geography (INEGI) (INEGI 2017). The use of the 2016 dataset aligns with the most recent update of the official income poverty lines in Mexico, thus allowing for direct comparability between our results and those published by CONEVAL (CONEVAL 2019) since then.

4. Results

Table 2 presents three key indicators used to evaluate the performance of each decision rule for outlier treatment:

- Percentage of the Sample Removed:* Refers to the proportion of observations identified as outliers and excluded from the estimation sample. This indicator provides insight into the stringency of each method or decision rule in classifying observations as outliers.
- Percentile included in the Population Reference Strata (PRS):* Expressed as the range of income percentiles retained for constructing the PRS. A range concentrated near the lower percentiles suggests that households with relatively low incomes are deemed

capable of meeting their nutritional requirements. Conversely, a range skewed toward the upper percentiles implies that only the households of high income are considered able to afford the required caloric intake.

- c. *Income poverty rates*: Represents the share of the population living in households whose total income is insufficient to afford the cost of the food basket identified by the corresponding method or decision rule.

Given that the estimation procedure is conducted separately for urban and rural areas, results are disaggregated by region, with national averages reported where applicable.

On average, the decision rules for outlier removal presented in Table 2 exclude 3.21% of the estimation sample. However, the proportion of excluded observations varies substantially across methods, ranging from as low as 0.10% (when excluding observations exceeding 6 SD from the mean) to as high as 16.10% (when excluding values beyond one interquartile range from the median).

A notable pattern emerges when examining the percentile range included in the PRS: the greater the number of observations identified and excluded as outliers, the higher the household income required to meet the nutritional threshold. While this relationship is theoretically expected, the magnitude of the shift highlights the critical role outliers play in shaping poverty estimates (see Section 4.1 for details). For example, when no outlier removal is applied, households in the bottom 20% of the rural income distribution may be considered capable of meeting their caloric needs. However, the exclusion of just 0.17% of households—those with the highest average caloric availability—results in the PRS shifting upward to the 59th to 78th percentiles.

As larger shares of the sample are excluded, more low-income households—often those with implausibly high reported caloric intakes—are removed from the estimation. This reduces the representation of low-income households deemed capable of meeting nutritional requirements, thereby pushing the PRS toward higher-income groups. Ultimately, excluding only 5% of households with the highest adequacy coefficient, the PRS moves to the top 20% of the income distribution in both areas, underscoring the sensitivity of the poverty line to even small changes in the treatment of outliers.

The quantities and types of foods consumed by households within the PRS serve as the foundation for constructing the food baskets for the poverty lines. Consequently, a rightward shift in the PRS implies that the consumption patterns of higher-income households are used as the benchmark, thereby increasing the cost of meeting nutritional requirements. As a result, the removal of a greater number of outliers raises the poverty threshold and, in turn, increases the share of the population classified as poor.

For instance, applying a decision rule that excludes values beyond 1.0 IQR from the median—resulting in the exclusion of 16.1% of the sample—yields a national income poverty rate of 26.7%. This figure is nearly 80% higher than the estimate produced using Mexico's official methodology, which has applied a more conservative outlier rule since 2019 and excludes only 0.5% of the sample. Employing a slightly less stringent rule—removal of values beyond 2.0 IQRs—excludes 6.1% of the sample and results in an income poverty rate of 24.5%. Although no consensus exists regarding the most appropriate method for identifying outliers in caloric intake data, the magnitude of exclusion under the 1.0 IQR rule raises concerns about its validity. The proportion of excluded observations far exceeds the maximum levels commonly reported in the literature on caloric consumption (Bocoum et al. 2014), calling into question the appropriateness of this rule. In such cases, further investigation into data quality is warranted to assess whether the presence of extreme values is justified.

Table 2. Performance Metrics for Outlier Treatment Rules.

Decision Rule	Percentage of the Sample Removed ¹			Percentiles Included in the PRS ²		Income Poverty Rates ³		
	National	Urban	Rural	Urban	Rural	National	Urban	Rural
Baseline (no outlier removal)	0.00%	0.00%	0.00%	[50,69]	[1,20]	10.70%	10.20%	12.20%
Remove values > 6 SD from the mean	0.10%	0.09%	0.17%	[55,74]	[1,20]	11.20%	10.90%	12.30%
CONEVAL (2019)	0.50%	0.43%	0.76%	[59,78]	[59,78]	14.90%	11.20%	27.00%
Remove values above Q2 + (6.0 × IQR)	0.60%	0.50%	0.83%	[60,79]	[59,78]	15.30%	11.80%	27.00%
CONEVAL (2012)	1.00%	0.82%	1.27%	[61,80]	[68,87]	16.40%	11.90%	31.20%
Remove values above 99th percentile	1.00%	0.84%	1.28%	[61,80]	[68,87]	16.40%	12.00%	31.20%
Remove values > 2 SD from the mean	1.60%	1.43%	1.99%	[67,86]	[74,93]	17.40%	12.80%	32.80%
Remove values above Q3 + (3.0 × IQR)	2.00%	1.73%	2.39%	[68,87]	[77,96]	17.80%	13.10%	33.50%
Remove if per capita calorie intakes > 5000 kcal	5.20%	4.30%	6.70%	[81,100]	[81,100]	24.40%	20.90%	35.90%
Remove values above Q3 + (1.5 × IQR)	5.70%	5.39%	6.15%	[81,100]	[81,100]	24.40%	21.10%	35.50%
Remove values above Q2 + (2.0 × IQR)	6.10%	5.83%	6.67%	[81,100]	[81,100]	24.50%	21.20%	35.60%
Remove values above Q2 + IQR	16.10%	15.71%	16.72%	[81,100]	[81,100]	26.70%	23.40%	37.60%

Notes: ¹ Refers to the number of observations identified as outliers based on the estimated total caloric availability at the household level. ² Indicates the lower bound of the per capita income percentile range within which the average AC equals 1. ³ Represents the percentage of the population residing in households whose total income is insufficient to meet their caloric requirements, even if fully allocated to food purchases. Source: Authors' calculations using ENIGH 2016 data ([INEGI 2017](#)).

In general, the use of IQR-based decision rules tends to be more stringent. For example, applying thresholds of 1.5 or 2.0 IQRs—whether from the median (Q2) or the upper quartile (Q3), as in Tukey’s Upper Fence Test—can result in the exclusion of over 6% of the sample. This is considerably higher than the exclusion rates typically reported in the literature, which are generally below this threshold (Burcham et al. 2023). Accordingly, we recommend that IQR-based rules be applied with caution.

Moreover, selecting Q2 or Q3 as reference points is not as straightforward as it may appear. The underlying distribution of caloric consumption plays a critical role. When caloric intake is relatively homogeneous across households, applying thresholds based on Q2 or Q3 may yield similar outcomes. For instance, using Tukey’s test results in the exclusion of 5.7% of the sample and an estimated poverty rate of 24.4%—only 2.2 percentage points lower than the result obtained using the 1.0 IQR-from-the-mean rule, despite the latter excluding nearly three times as many observations. This similarity suggests that mistakenly excluding non-outliers may have a limited effect on aggregate poverty estimates, but also underscores the importance of carefully selecting a method for outlier treatment.

Finally, while excluding non-outlier observations may have a modest impact, entirely foregoing any outlier detection may produce markedly different results. Specifically, when no outliers are removed, the national income poverty rate falls to 10.7%—approximately 50% lower than the estimate produced under the current official methodology (14.9%). This finding illustrates the substantial influence of outlier treatment on poverty measurement and highlights the need for transparency and methodological rigor in this step of the estimation process.

The preceding analysis can be extended by progressively excluding households with the highest values of the AC, as shown in Figure 1.

Figure 1 illustrates how estimated income poverty rates increase as households with the highest AC values are incrementally excluded from the sample. Rather than exhibiting a linear trend, the graph reveals discrete jumps in the poverty rate at specific thresholds, such as after 0.3%, 2.0% and 3.0% of the sample is removed. A key finding is that although the irregular pattern continues around the 0.3% and 2.0% marks, after the 3.0% exclusion mark further removal of high-AC households yields only marginal changes in the estimated poverty rate. This pattern suggests that, at least in this data, once a critical share of extreme values is excluded, the influence of remaining outliers on aggregate poverty estimates diminishes substantially.

The extreme sensitivity of the poverty rate to the chosen outlier rule underscores three fundamental concerns: (i) potential violations of the assumptions underlying the FEI method; (ii) persistent and unresolved quality deficiencies in the expenditure data; and (iii) the limited robustness of Mexican poverty measurement to alternative methodological choices. These findings point to the need for a systematic reconsideration of the procedures employed in constructing the Mexican poverty lines. Beyond documenting these limitations, our analysis highlights the critical importance of rigorously assessing the impact of outlier treatment on poverty estimates. In large samples, additional removals beyond a certain point may lead to negligible analytical benefits and risk discarding valid data. Overly aggressive outlier treatment can thus result in the unnecessary loss of information without significantly improving the accuracy of poverty estimates. These findings support a more balanced approach to outlier detection—one that prioritizes methodological rigor and data quality over arbitrary exclusion thresholds.

Interestingly, the exclusion of the top percentile of the AC distribution produces results that closely align with those obtained under Mexico's official poverty measurement methodology in 2012, despite differences in the criteria used. In contrast, the exclusion of values greater than six standard deviations from the mean has virtually no effect on the poverty rate, indicating that such a rule is too lenient and fails to meaningfully address the presence of extreme values. Standard deviation and percentile-based thresholds are highly sensitive to the distribution of the data. Given that similar results can be achieved using less distribution-sensitive methods, we argue that these rules do not meaningfully enhance the accuracy of poverty measurement and should generally be avoided.

Conversely, the removal of households reporting per capita caloric consumption above 5001 kilocalories may reflect that a relatively lax criterion can exclude an important number of households (5.2 percent). This is particularly concerning given that the caloric thresholds employed in this analysis are not disaggregated by sex, age, or adjusted for household size. Such simplifications may inflate estimated caloric availability, as they overlook the fact that children, elderly individuals, and adults have distinct nutritional requirements. Applying a single, undifferentiated caloric threshold risks underestimating poverty by overestimating households' capacity to meet nutritional needs.

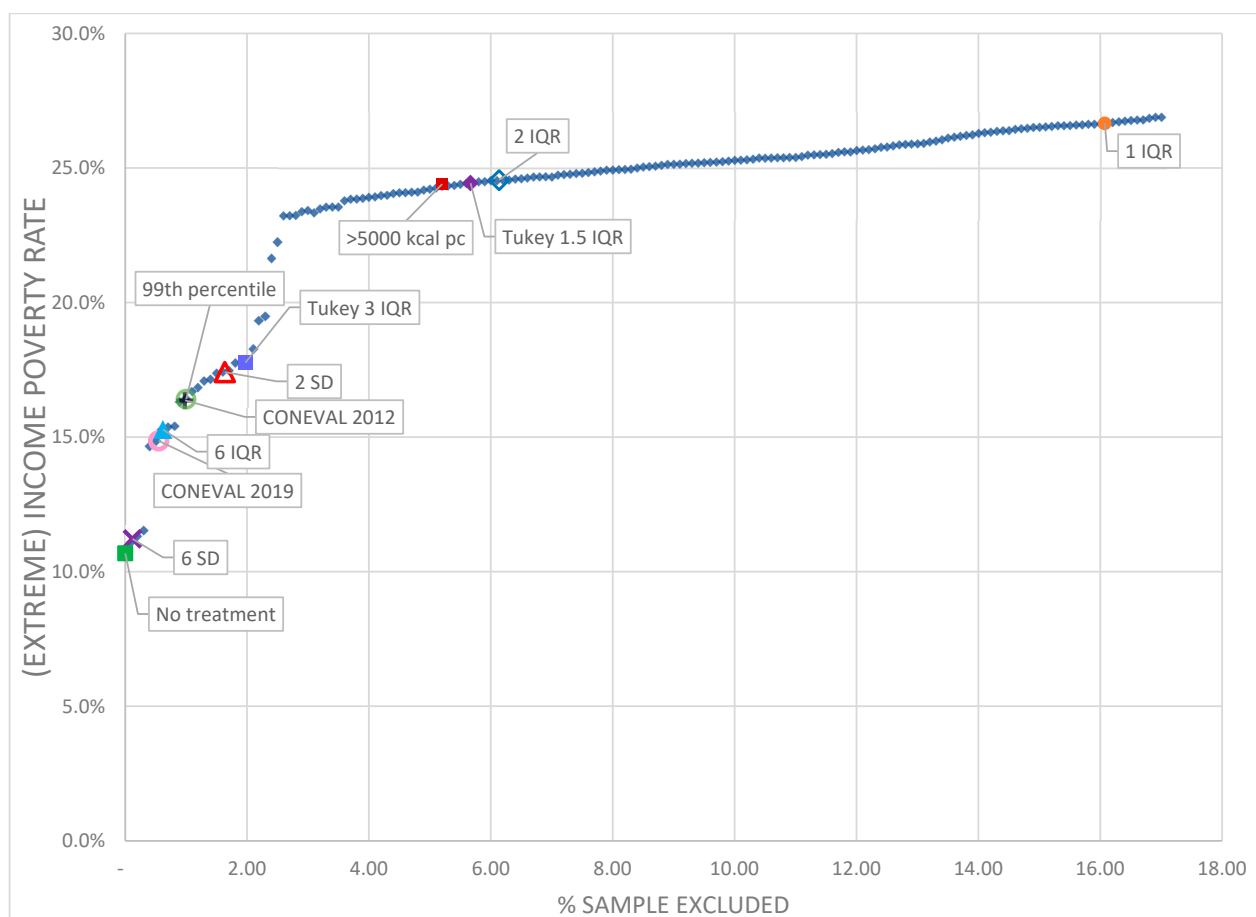


Figure 1. Sensitivity of the Income Poverty Rate to the Progressive Exclusion of Households with the Highest Adequacy Coefficients. *Notes:* The x-axis represents the cumulative percentage of the sample excluded by sequentially removing 0.1% of households with the highest values of the Adequacy Coefficient—that is, households where the ratio of available calories to the nutritional requirements of their members is greatest. The y-axis displays the corresponding income poverty rate at each level of exclusion. Data point labels indicate the percentage of the sample excluded under each decision rule described in Table 1. *Source:* Authors' calculations using ENIGH 2016 data (INEGI 2017).

The sensitivity of poverty estimates to the method used for outlier treatment suggests that additional factors, beyond outlying observations, may be distorting the distribution of caloric availability. A particularly important element concerns the decision to rely on household income, rather than expenditure, to define the PRS (step 5 in Section 3.2). Unlike standard implementations of the FEI method, which ensure consistency between household resources and caloric intake by using expenditure as the welfare indicator, the reliance on income tends to exacerbate biases linked to food purchases. This undermines both the internal consistency of the estimation and its key assumption: that the expected value of food energy intake, conditional on income (or expenditure), is strictly increasing (Ravallion 1998; Greer and Thorbecke 1986).

To address these concerns, we re-estimated the poverty lines and poverty rates based on the relationship between caloric intake and household expenditure, closely following the approach applied in most FEI studies in the literature. The new estimates (see Table 3) are considerably more stable across different methods of outlier treatment, although—particularly in rural areas—substantial variation in poverty estimates persists depending on the outlier-handling strategy employed. From this exercise, we derive two preliminary conclusions: (1) when income is used instead of expenditure in the FEI method applied to define Mexican poverty lines, a careful and detailed analysis of outlier identification methods is required; (2) future revisions of the Mexican poverty lines should consider relying on household expenditure and explicitly verify the assumptions underlying the FEI method.

4.1. On the Sensitivity of the Poverty Estimates

A central element behind the pronounced shifts in poverty incidence, despite the exclusion of a relatively small fraction of the estimation sample, lies in the weak monotonicity between caloric availability and household resources, whether measured by income or expenditure. Unlike in the theoretical formulation of the FEI method, in the Mexican data the relationship is not linear, and households located in the lower income percentiles frequently report unusually high caloric availability. These extreme cases exert a disproportionate influence on the calculation of the adequacy coefficient, artificially raising the average caloric intake of the PRS and thereby anchoring it to the very bottom of the income distribution (see Figure 2).

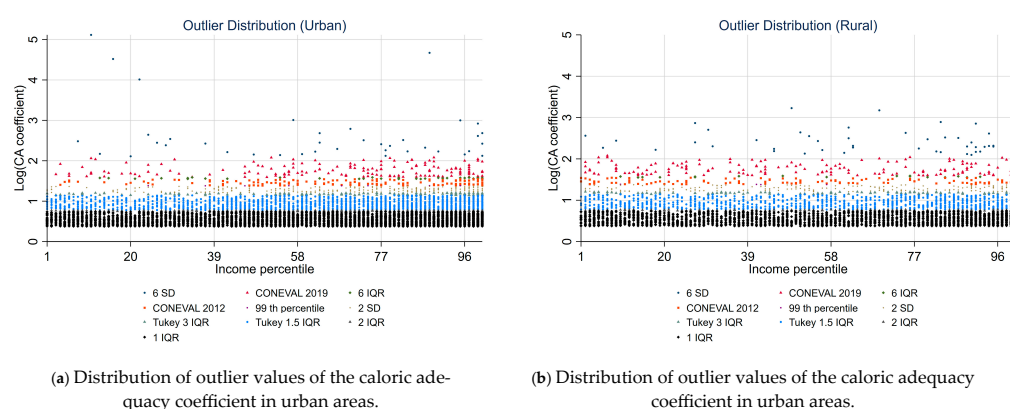


Figure 2. Location of the extreme values of the caloric adequacy coefficient across the percentiles of per capital household income in urban and rural areas, Mexico, 2026. *Notes:* The y-axis is expressed in natural logarithms. Only outlying observations are included, considering the different decision rules described in Table 1. Stricter criteria (colors at the top of the Y-axis) identify a smaller set of outliers. As more relaxed criteria are applied (colors at the bottom), the number of detected cases increases, but cumulatively: all outliers flagged by stricter criteria are also included under the more relaxed ones. *Source:* Authors' calculations using ENIGH 2016 data (INEGI 2017).

Table 3. Performance Metrics for Outlier Treatment Rules Using an Alternative Poverty Line Estimation Based on the Caloric Intake–Expenditure Relationship.

Decision Rule	Percentage of the Sample Removed ¹			Percentiles Included in the PRS ²		Income Poverty Rates ³		
	National	Urban	Rural	Urban	Rural	National	Urban	Rural
Baseline (no outlier removal)	-	-	-	[46,65]	[36,55]	12.06%	9.43%	20.82%
Remove values > 6 SD from the mean	0.15	0.12	0.21	[47,66]	[39,58]	12.26%	9.52%	21.42%
CONEVAL (2019)	0.52	0.39	0.75	[48,67]	[47,66]	12.64%	9.57%	22.91%
Remove values above Q2 + (6.0 × IQR)	0.64	0.51	0.86	[49,68]	[47,66]	12.73%	9.67%	22.95%
CONEVAL (2012)	0.93	0.76	1.21	[52,71]	[51,70]	13.22%	9.95%	24.11%
Remove values above 99th percentile	1.00	0.83	1.30	[52,71]	[51,70]	13.24%	9.98%	24.13%
Remove values above Q3 + (3.0 × IQR)	1.97	1.71	2.42	[55,74]	[55,74]	13.77%	10.40%	25.03%
Remove values > 2 SD from the mean	1.98	1.71	2.43	[55,74]	[55,74]	13.81%	10.39%	25.20%
Remove if per capita calorie intakes > 5000 kcal	4.93	4.04	6.48	[73,92]	[74,93]	18.95%	15.39%	30.84%
Remove values above Q3 + (1.5 × IQR)	5.70	5.38	6.25	[81,100]	[73,92]	23.34%	21.12%	30.77%
Remove values above Q2 + (2.0 × IQR)	6.16	5.79	6.80	[81,100]	[76,95]	23.59%	21.28%	31.32%
Remove values above Q2 + IQR	16.03	15.60	16.80	[81,100]	[81,100]	26.08%	23.40%	35.03%

Notes: ¹ Refers to the number of observations identified as outliers based on the estimated total caloric availability at the household level. ² Indicates the lower bound of the per capita expenditure percentile range within which the average AC equals 1. ³ Represents the percentage of the population residing in households whose total income is insufficient to meet their caloric requirements, even if fully allocated to food purchases. Source: Authors' calculations using ENIGH 2016 data ([INEGI 2017](#)).

Figure 2 illustrates this mechanism by showing the distribution of outliers across income percentiles under alternative detection rules. The graph highlights two important features: first, that extreme caloric values are not confined to the tails of the distribution but are scattered across all percentiles; and second, that their magnitude is considerable large relative to the nutritional requirements of the household. These patterns imply that removing a seemingly small share of households can substantially alter the statistical foundations of the FEI method, particularly when extreme values are concentrated in the lower percentiles. In these cases, the exclusion of outliers leads to a discontinuous upward shift of the PRS, explaining why poverty rates may change by 5–10 percentage points after discarding only a handful of observations.

When outliers are removed, even if only 1–2% of the sample, the composition of the PRS changes substantially. This occurs because the initial identification of households capable of meeting nutritional requirements is highly sensitive to the presence of extreme values. Once these atypical households are excluded, the average caloric adequacy of the lower percentiles no longer reaches the nutritional threshold, forcing the PRS to shift upward along the income distribution. Consequently, the composition of the food basket is determined by households located at higher percentiles, which leads to a higher valuation of the poverty line and a corresponding increase in measured poverty incidence.

4.2. Rural and Urban Differences

Table 2 also illustrates the extent to which different decision rules for outlier treatment affect estimated rural and urban income poverty levels. Notably, these effects are not proportional across regions. For example, when comparing estimates produced without any outlier removal to those based on Mexico's current official methodology, the national income poverty rate increases by 4.2 percentage points. However, this overall change masks significant heterogeneity: urban poverty rises by only 1.0 percentage points, while rural poverty increases by 14.8 percentage points.

On average, the differential impact of decision rules across rural and urban areas results in a differential of poverty rates of approximately 7.6 percentage points. The largest disparity is observed when comparing the official methodology with the no-treatment scenario, which yields a rural-urban difference of 14.9 percentage points.

The decision rule that most closely replicates the results of not removing any outliers is the six standard deviation (6 SD) criterion. However, as previously discussed, rules based on standard deviations are highly sensitive to the underlying distribution of the data. Consequently, the 6 SD rule often produces results nearly identical to the no-treatment scenario, suggesting it may be too lenient to effectively manage extreme values.

The uneven effects of different decision rules on rural and urban poverty estimates reflect the structural and socio-economic differences between these populations. Rural areas often face specific challenges, such as limited access to services, lower employment density, and a greater reliance on subsistence agriculture. These factors lead to distinct consumption patterns—such as the home production of food—which may result in caloric availability values that differ systematically from urban norms. When national-level outlier detection methods are applied uniformly across both areas, these rural-specific consumption patterns may be misclassified as outliers, leading to a disproportionate exclusion of rural households from the estimation sample (as shown in Table 2) and an overestimation of rural poverty.

Applying outlier detection rules at the national level, without accounting for rural-urban heterogeneity, can introduce systematic biases. In urban areas, atypical observations may be retained because they are not considered outliers within the broader national distribution, leading to a PRS that includes households with lower incomes and thus underestimates urban poverty. Conversely, rural households with higher caloric availability—

common due to subsistence production—are more likely to be identified as outliers. This pushes the rural PRS toward higher-income households, thereby inflating the estimated poverty rate in rural areas.

These findings underscore the importance of designing poverty measurement methodologies that are sensitive to the distinct characteristics of rural and urban populations. A uniform approach may obscure meaningful differences in living conditions and misrepresent the true extent of poverty across regions. Therefore, policymakers should consider adopting differentiated criteria that more accurately capture local realities, ensuring that poverty assessments are both methodologically sound and policy-relevant.

5. Conclusions

This study highlights the significant impact that outlier detection and treatment methods can have on poverty estimates based or derived using the Food Energy Intake (FEI) method, particularly when household income, rather than expenditure, is used to identify the Population Reference Strata (PRS). Drawing on Mexico's official poverty measurement framework, and using nationally representative household data (ENIGH), we show that methodological decisions regarding the identification and exclusion of extreme caloric values can substantially alter both national and subnational poverty estimates. These findings show that poverty estimates in Mexico are highly sensitive to outlier treatment, reflecting weak compliance with FEI assumptions, unresolved expenditure data issues, and limited methodological robustness, while underscoring the need for a thorough revision of the procedures used in constructing the poverty lines. This requires greater transparency and rigor not only in handling outliers—an often overlooked yet consequential step in poverty measurement—but also across other key aspects of poverty line construction.

Our results make clear that the choice of such decision rule is not neutral. Excluding even a small fraction of observations—particularly those in the upper tail of the caloric distribution—can shift the PRS, increase the monetary value of the food basket, and, consequently, bias the resulting poverty rates. Conversely, overly permissive approaches, such as using high standard deviation thresholds or no outlier treatment at all, tend to underestimate poverty levels.

Although no universal standard exists for outlier detection in caloric intake data, our findings support several best practices applicable, although their idoneity for a specific case is highly dependent on the data used. However, from our analysis, we derive a few recommendations for researchers involved in defining poverty lines:

First, we recommend excluding outliers only from the upper end of the distribution. Removing low-calorie observations may suppress the visibility of food deprivation among vulnerable populations—particularly in settings characterized by food insecurity or structural poverty. While such values may appear statistically abnormal, they often reflect lived constraints such as insufficient income or limited access to food. Their removal risks masking undernutrition and undermining the design of effective social protection policies.

Second, we advise against the use of fixed caloric thresholds (e.g., 5001 kcal) as exclusion criteria. As shown in prior literature (e.g., [Burcham et al. 2023](#)), such methods fail to account for variation in demographic characteristics (e.g., age, sex, physical activity) and may lead to systematic misclassification. Likewise, mean-based rules should be applied with caution in skewed distributions, given their sensitivity to extreme values.

Our analysis also raises concerns about the current implementation of Mexico's official methodology, particularly the extreme sensitivity of poverty rates to the rule adopted for identifying and excluding outlying observations. As shown in the exercise where household expenditure was used instead of income to define the poverty rates, variations in the PRS and estimated poverty rates across different outlier-selection methods are

considerably reduced. This finding suggests that relying on income may violate the assumptions underlying the FEI method. This calls for a re-evaluation and refinement of official poverty measurement practices.

Importantly, we find that rural poverty estimates are more sensitive to outlier treatment than urban estimates. This reflects structural differences in household behavior, such as the storage and consumption of self-produced food in rural areas, which may not be captured adequately by short-term recall periods. When national-level exclusion rules are applied uniformly, they risk overestimating poverty in rural areas and underestimating it in urban ones. We therefore recommend applying outlier detection methods separately for rural and urban subpopulations to better account for their distinct consumption patterns.

From a public policy perspective, we argue that it is preferable to adopt more conservative outlier detection rules—even if they identify a larger proportion of extreme values—because they reduce the likelihood of underestimating the population in need. While this may lead to some over-identification, it is a more cautious and inclusive approach, especially in low- and middle-income countries where the consequences of exclusion are severe.

In sum, we advocate for the use of robust, non-parametric decision rules tailored to the characteristics of different population groups. Such refinements can improve the reliability and policy relevance of poverty estimates, not only in Mexico but also in other contexts where the FEI method or similar approaches are used. A more rigorous and context-sensitive approach to outlier treatment will help ensure that poverty statistics more accurately reflect the realities of food access and deprivation among the world's most vulnerable populations.

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Notes

- ¹ We emphasize the term “absolute” to distinguish it from relative poverty, a distinction commonly made in the poverty measurement literature. Absolute poverty refers to a condition in which households lack the resources necessary to achieve a minimum standard of welfare deemed essential for all individuals, regardless of societal context. In contrast, relative poverty is defined with respect to a fixed proportion of the median income, thereby reflecting shifts in overall living standards and income distribution (Ravallion 2016). This article focuses on absolute poverty lines, as they are the most commonly employed metric in the context of developing countries.
- ² Both the Food Energy Intake (FEI) and Cost of Basic Needs (CBN) methods aim to define poverty lines based on the principle of meeting essential human needs—typically operationalized as meeting minimum caloric (and potentially micronutrient) requirements. However, they differ substantially in their implementation. The FEI method is behaviorally anchored, deriving the poverty line from observed consumption patterns at which individuals meet the nutritional threshold. In contrast, the CBN method is normatively anchored, constructing the poverty line by costing a basket of essential goods—both food and non-food—that reflect a socially acceptable minimum standard of living. The food component is designed to meet nutritional requirements based on the consumption patterns of a reference population (e.g., the near-poor), ensuring both adequacy and cultural relevance (Ravallion and Sen 1994; Wodon 1997; Ravallion 2016). In practice, some applications use the FEI method to identify the reference group, followed by normative adjustments consistent with the CBN approach (Ravallion 2016).
- ³ From this point onward, the construction of the food basket incorporates multiple normative criteria, thereby combining elements from both the FEI and CBN approaches. While it maintains the behavioral foundation of the FEI method, it introduces normative adjustments to ensure that the resulting bundle meets minimum nutritional requirements and aligns with socially accepted standards.

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