Journal of Regional Economics and Development, Volume 3, Number 2, 2026, *Page*: *1-15*

# Urban-Rural Disparities in Multidimensional Poverty: A Cross-Country Econometric Analysis Using MPI Data

**Shilpa Sree R[1]*, Anurag Vikram Singh[2]**

[1]Independent Researcher, PhD in Economics, Vijayanagar Sree Krishnadevaraya University, Ballari, Karnataka, India
[2] M.Sc. Economics and Data Analytics, Department of Economics, Central University of Andhra Pradesh, Ananthapuramu, India

DOI:
https://doi.org/10.47134/jred.v3i2.1070
*Correspondence: Shilpa Sree R
Email: shilparcuap@gmail.com

Received: 19-12-2025
Accepted: 19-01-2026
Published: 19-02-2026



**Abstract:** Urban–rural disparities in poverty remain a persistent challenge despite significant global progress in poverty reduction. Conventional income based measures often fail to capture the multiple and overlapping deprivations experienced by households, particularly in rural areas. This study aims to examine the magnitude, structure, and determinants of urban–rural disparities in multidimensional poverty using the global Multidimensional Poverty Index (MPI). Employing a cross-country econometric research design, the study integrates national-level and subnational-level MPI data covering more than 100 countries and approximately 1,000 regions. The empirical analysis combines descriptive techniques, ordinary least squares (OLS) regression, and linear mixed-effects modeling to capture both between-country and within-country variations in multidimensional poverty. The results reveal substantial and unevenly distributed urban–rural MPI gaps across countries, with particularly pronounced disparities observed in several Sub-Saharan African economies. Regression findings indicate that differences in poverty incidence, measured through the headcount ratio gap, are the dominant driver of the urban–rural MPI gap, while differences in deprivation intensity play a statistically significant but secondary role. The multilevel analysis further demonstrates a strong and near-proportional transmission of national-level multidimensional poverty to regional outcomes, underscoring the importance of national development trajectories in shaping subnational poverty patterns. The study concludes that urban–rural disparities in multidimensional poverty are primarily driven by unequal access to basic services and opportunities rather than solely by the depth of deprivation. These findings highlight the need for multidimensional and multi-level policy interventions that simultaneously reduce poverty incidence and address overlapping deprivations, particularly in rural areas, to achieve inclusive and balanced development.

**Keywords:** Multidimensional Poverty Index (MPI); Urban–Rural Disparities; Poverty Decomposition; Econometric Analysis; Mixed-Effects Modeling

## Introduction

Urban–rural disparities remain a central concern in development economics, particularly in the context of poverty reduction and inclusive growth. While substantial progress has been made in reducing global poverty over recent decades, the benefits of development have not been evenly distributed across space. Rural areas continue to exhibit systematically higher levels of deprivation than urban areas due to structural constraints such as limited access to education, healthcare, infrastructure, and productive employment opportunities. These spatial inequalities highlight the need for poverty measurement frameworks that move beyond income-based indicators and capture the multidimensional nature of human deprivation.

Recent advances in poverty measurement have increasingly adopted multidimensional approaches, most notably the Multidimensional Poverty Index (MPI), which captures overlapping deprivations in health, education, and living standards. A growing body of empirical research using MPI data has documented persistent urban–rural poverty gaps across countries and regions. Existing studies generally employ descriptive analyses, national-level comparisons, or single-level regression techniques to examine these disparities. Some strands of the literature focus on identifying key contributors such as education, infrastructure, and access to basic services, while others analyze changes in multidimensional poverty over time. However, much of the existing research remains limited in three important ways: first, by treating national and subnational poverty patterns separately; second, by relying largely on descriptive decompositions rather than econometric analysis of MPI components; and third, by overlooking the hierarchical structure of poverty data in which regions are nested within countries.

Therefore, despite the growing use of MPI, there is limited empirical evidence that jointly analyzes cross-country and within-country urban–rural disparities within a unified econometric framework. In particular, few studies explicitly decompose the urban–rural MPI gap into its incidence (headcount) and intensity components using regression-based methods, and even fewer incorporate multilevel modeling to account for intranational heterogeneity. This study addresses these gaps by integrating national and subnational MPI data within a combined ordinary least squares and mixed-effects modeling framework. The novelty of this research lies in its simultaneous examination of the structural drivers of urban–rural MPI gaps and the transmission of national poverty conditions to regional outcomes. Accordingly, the objective of this study is to quantify urban–rural disparities in multidimensional poverty, identify the relative contributions of poverty incidence and intensity to these disparities, and assess how national-level multidimensional poverty shapes subnational poverty patterns across countries.

## Literature Review

Poverty measurement literature has undergone a sig nificant transformation over the last 30 years, moving from uni-dimensional monetary metrics towards multi-dimensional frameworks that capture the entire range of human deprivation. The Alkire Foster method has been one of the leading proponents of this change in direction, as it provides a flexible, axiomatic method that enables the identification of poor households by multiple indicators and the linkage of poverty aspects into one summarised measure. The works of Alkire and Santos (2010) and Alkire et al. (2015) have led to the empowerment of the MPI as a tool for the comparison of poverty levels across countries and as a source of insight into different poverty profiles. Moreover, the MPI's endorsement by the United Nations Development Pro gramme (UNDP) in its Human Development Reports has greatly contributed to its importance as a leading global poverty measure. 1 Differences between the urban and rural areas have been one of the most frequently mentioned aspects in the context of poverty in the literature. The phe nomenon of better-developed cities and towns issues with rural areas over the years has been disclosed in the range of research undertaken in different places on the subject. Authors such as Ravallion, Chen, and San graula (2007) argued that global poverty plummeted dramatically between 1981 and 2005; however, the prob lem of rural poverty was only marginally alleviated. Recent studies leveraging on MPI data (OPHI, 2022; UNDP, 2023) indicate that rural settings are more than twice as likely as urban ones to be poor in at least eight of the ten dimensions and conditions defined in the MPI, with the most significant instances of deprivation occur ring in cooking with clean fuel, electricity, sanitation, and education. The disparities highlighted in this para graph are not only a result of income differences but also structural inequalities in service provision and dis tribution of opportunities. The regression models, widely used in econometric studies, serve as one of the main tools for the identifica tion of poverty drivers which in a contemporary fashion are shown to be multidimensional. Thus, researchers like Santos et al. (2019) have applied regression de composition techniques to pinpoint that the attainment of educational levels and the availability of infrastruc ture good quality are the two biggest contributors to ruralurban divides. Yalonetzky (2014) in his study, em ploying panel data, found that in different territories the multidimensional poverty situation varies dynami cally, sometimes developing in a way leading to conver gence of regions and in a different way leading to diver gence of them. Nevertheless, the question of incorporat ing national and subnational MPI data into one econo metrical model that takes account of cross-country and within-country variability is still unresolved. This pa per deals with the issue by combining OLS and mixed effects models so as to present a more comprehensive explanation of the structural factors causing MPI dis parities. 3. Research Gap The existing literature on poverty measurement and ru ralurban disparities has made substantial progress by moving beyond income-based indicators toward multi dimensional frameworks such as the Multidimensional Poverty Index (MPI). Several studies have documented that rural areas consistently exhibit higher levels of mul tidimensional poverty than urban areas and have high lighted the role of education, health, and infrastructure in shaping these disparities. However, despite these ad vances, important gaps remain in the empirical under standing of ruralurban MPI differentials. First, much of the empirical literature focuses either on national-level MPI comparisons across countries or on subnational poverty patterns within individual coun tries. There is a relative lack of studies that inte grate both cross-country and within-country perspec tives within a single econometric framework. As a re sult, the linkages between national poverty structures and regional or subnational MPI outcomes remain in sufficiently explored. Second, while MPI is constructed from headcount and intensity components, limited attention has been given to decomposing the ruralurban MPI gap econometri cally in order to assess the relative contribution of in cidence versus intensity differences. Most studies de scribe these components descriptively, but few provide formal regression-based evidence on how variations in headcount and intensity jointly explain observed MPI gaps across countries. Third, the majority of cross-country analyses rely on single-level regression models that do not account for the hierarchical nature of poverty data, where regions are nested within countries. Ignoring this structure may obscure important intranational heterogeneity and lead to incomplete inferences about the transmission of na tional poverty conditions to subnational outcomes. Finally, there remains a shortage of empirical stud ies that combine ordinary least squares regression with multilevel mixed-effects modeling using recent global MPI data to provide a comprehensive explanation of ruralurban poverty disparities. This paper seeks to ad dress these gaps by jointly analyzing national and sub national MPI data, decomposing the ruralurban MPI gap into its core components, and explicitly modeling the hierarchical structure of poverty across regions and countries.

## Research Method

This study adopts a quantitative, cross-sectional econometric research methodology to examine urban–rural disparities in multidimensional poverty using national and subnational data derived from the global Multidimensional Poverty Index (MPI). The methodological approach is designed to capture both cross-country variation and within-country heterogeneity in multidimensional poverty outcomes, thereby ensuring analytical rigor, validity, and reliability of the findings.

### Research Design

The research employs a non-experimental, explanatory research design based on secondary data analysis. A cross-country econometric framework is used to analyze urban–rural MPI gaps at the national level, complemented by a multilevel mixed-effects modeling approach to assess the transmission of national poverty conditions to subnational outcomes. This integrated design allows for simultaneous examination of structural determinants of poverty disparities across countries and hierarchical variation across regions nested within countries.

### Population, Sample, and Sampling

The population of the study comprises all countries and regions for which Multidimensional Poverty Index data are available in the global MPI database maintained by the Oxford Poverty and Human Development Initiative (OPHI). From this population, the study constructs two analytical samples.

The first sample consists of national-level MPI data for more than 100 countries, disaggregated by urban and rural populations. Countries were included based on the availability of complete information on MPI values, headcount ratios, and deprivation intensity for both urban and rural areas. Countries with missing or incomplete disaggregation were excluded from the analysis to ensure consistency and comparability across observations.

The second sample comprises subnational MPI data covering approximately 1,000 regions across 78 countries. These regions represent administrative units such as states, provinces, or districts, depending on country-specific data availability. Inclusion criteria required that each region be linked to a corresponding national MPI estimate, allowing for hierarchical modeling. Regions lacking reliable MPI estimates or not matched with national-level data were excluded from the final sample.

The sampling process is census-based rather than probabilistic, as it includes all eligible observations meeting predefined inclusion criteria. This approach minimizes sampling bias and enhances the external validity of the findings.

**Intervention Procedure**

This study does not involve experimental manipulation or intervention procedures, as it relies exclusively on secondary data analysis. No treatments, behavioral interventions, or controlled exposures were administered to human subjects. Consequently, this subsection is not applicable in the experimental sense but is acknowledged here to clarify the non-interventional nature of the research design.

**Instrument**

The primary instrument used in this study is the Multidimensional Poverty Index (MPI), a globally recognized composite measure developed using the Alkire–Foster methodology. The MPI captures multidimensional deprivation across three dimensions—health, education, and living standards—using ten standardized indicators. Poverty is measured through two components: the headcount ratio, which reflects the proportion of multidimensionally poor individuals, and the intensity of deprivation, which captures the average breadth of deprivations among the poor.

National-level and subnational-level MPI data, including urban and rural disaggregation, were obtained directly from the OPHI global MPI database. No modifications were made to the original construction of the MPI indicators, ensuring methodological consistency with international standards. The dependent variables include the urban–rural MPI gap at the national level and regional MPI values at the subnational level, while explanatory variables include headcount and intensity gaps and national MPI measures.

**Data Analysis Techniques**

The analysis proceeds in three stages. First, descriptive statistics and graphical analysis are employed to examine the distribution of urban–rural MPI gaps across countries and regions. Second, ordinary least squares (OLS) regression is used to estimate the contribution of headcount and intensity differentials to the observed urban–rural MPI gap at the national level. Regional dummy variables are included to control for broad geographic heterogeneity.

Third, a linear mixed-effects model is applied to subnational data to account for the hierarchical structure of regions nested within countries. A country-level random intercept is introduced to capture unobserved heterogeneity across countries and to assess the extent to which national-level poverty conditions influence regional MPI outcomes. Estimation is conducted using restricted maximum likelihood (REML) procedures.

### Validity, Reliability, and Trustworthiness

The validity of the study is supported by the use of internationally standardized MPI data, which ensures construct validity and comparability across countries and regions. Internal validity is strengthened through robustness checks, including alternative specifications, heteroscedasticity-robust standard errors, and diagnostic tests for multicollinearity and model fit. Reliability is ensured by relying on publicly available, replicable datasets and established econometric techniques. The transparency of data sources and estimation procedures enhances the trustworthiness and reproducibility of the findings.

### Ethical Considerations

All data used in this study are secondary, anonymized, and publicly available. The research does not involve direct interaction with human subjects, nor does it use identifiable personal information. As such, ethical approval and informed consent requirements are satisfied through compliance with the ethical standards of the data-providing institutions. The study adheres to principles of responsible data use and academic integrity.

## Result and Discussion

The empirical analysis is based on a comprehensive dataset combining national-level and subnational-level Multidimensional Poverty Index (MPI) information, allowing for a detailed examination of both cross-country and within-country variations in multidimensional poverty. National-level data are sourced from the global MPI database maintained by the Oxford Poverty and Human Development Initiative (OPHI) and include measures of MPI, headcount ratios, and deprivation intensity for rural and urban populations across more than 100 countries. Complementing this, subnational MPI data provide disaggregated regional-level information for approximately 1,000 regions across 78 countries, thereby enabling an assessment of intranational heterogeneity in poverty outcomes.

In the cross-country analysis, the primary outcome variable is the rural–urban MPI gap, defined as the difference between rural MPI and urban MPI values. Positive values of this gap indicate a higher level of multidimensional poverty in rural areas relative to urban areas. The key explanatory variables are the headcount ratio gap and the intensity gap, which capture differences in the incidence and depth of deprivation between rural and urban populations, respectively. In addition, regional dummy variables are incorporated to control for unobserved geographic and structural characteristics across major world regions.

For the multilevel analysis, regional MPI is used as the dependent variable, while national MPI serves as the primary explanatory variable. A country-level random intercept is included to account for unobserved heterogeneity across countries and to reflect the hierarchical structure of regions nested within countries.

**Table 1.** presents a description of the variables employed in the analysis.

| Variable | Description |
|---|---|
| **MPI_gap** | Difference between rural MPI and urban MPI at the national level; positive values indicate higher multidimensional poverty in rural areas. |
| **Headcount_gap** | Difference between rural and urban headcount ratios, capturing differences in the incidence of multidimensional poverty. |
| **Intensity_gap** | Difference between rural and urban deprivation intensity, reflecting differences in the average breadth of deprivations among the poor. |
| **MPI_National** | National-level Multidimensional Poverty Index value used to explain regional MPI outcomes in the mixed-effects model. |
| **MPI_Regional** | Subnational (regional) Multidimensional Poverty Index, used as the dependent variable in the multilevel analysis. |
| **Region dummies** | Binary indicators for major world regions (e.g., Africa, Asia, Latin America) included to control for regional heterogeneity in the cross-country regressions. |

***Note:*** MPI data are sourced from the global Multidimensional Poverty Index database compiled by the Oxford Poverty and Human Development Initiative (OPHI).

The empirical strategy follows a structured analytical framework. First, descriptive statistics and graphical techniques are used to examine the distribution of rural–urban MPI gaps across countries and to explore preliminary relationships between the MPI gap, headcount gap, and intensity gap. Second, a cross-country ordinary least squares (OLS) regression model is estimated to quantify the contribution of headcount and intensity differentials to the rural–urban MPI gap. Third, a linear mixed-effects model is applied to subnational data to assess the transmission of national-level multidimensional poverty to regional outcomes while explicitly accounting for the hierarchical structure of the data.

The cross-country OLS regression model is specified as:

$$MPI\_gap\_i = \beta_0 + \beta_1 \text{ Headcount\_gap\_i} + \beta_2 \text{ Intensity\_gap\_i} + \gamma \text{ Region\_i} + \varepsilon\_i$$

where MPI_gap_i denotes the difference between rural and urban MPI for country i, Headcount_gap_i represents the difference between rural and urban headcount ratios, and Intensity_gap_i captures the difference in deprivation intensity between rural and urban populations. Region_i is a vector of regional dummy variables included to control for unobserved geographic and structural heterogeneity, $\beta_0$ is the intercept term, and ε_i is the random error term.

The coefficients $\beta_1$ and $\beta_2$ measure the marginal effects of headcount and intensity differentials on the rural–urban MPI gap, respectively. Given that MPI is constructed from headcount and intensity components, the OLS results are interpreted as a decomposition framework that quantifies the relative contribution of poverty incidence and deprivation depth to observed MPI disparities rather than as evidence of strict causal relationships.

Post-estimation diagnostic tests are conducted to evaluate the validity of the OLS model assumptions. These include residual analysis to assess heteroscedasticity and normality, examination of fitted-versus-observed plots to evaluate model fit, and calculation of variance inflation factors (VIF) to detect potential multicollinearity among explanatory variables. Robust standard errors are also considered to ensure the stability of coefficient estimates.

To capture intranational heterogeneity and further exploit the hierarchical structure of the data, a linear mixed-effects model is estimated using subnational MPI observations. The model is specified as:

$$MPI\_ij = \alpha + \beta \, MPI\_National\_j + u\_j + \varepsilon\_ij$$

where MPI_ij denotes the MPI value for region i in country j, MPI_National_j represents the national-level MPI, $\alpha$ is the fixed intercept, and $\beta$ measures the association between national and regional MPI. The term u_j denotes the country-specific random intercept, assumed to be normally distributed with mean zero and variance $\sigma^2$_u, and $\varepsilon$_ij is the idiosyncratic error term.

This multilevel specification enables a clear distinction between between-country variation and within-country variation in multidimensional poverty, thereby providing a more accurate and policy-relevant representation of poverty dynamics across regions nested within countries.

**Empirical Results**

One of the main results the empirical analysis provides is a set of findings that are consistent and mutually reinforcing to each other. The descriptive statistics indicate that the average of the urban–rural MPI gap for the whole sample of countries is around 0.18, with a standard deviation of about 0.11. Many countries have relatively balanced gaps; however, a considerable number of them, which are mainly located in Sub-Saharan Africa, have very disparate gaps. The top 15 countries with the largest rural–urban MPI gap are those where gaps of over 0.40 are reported by several countries (e.g., Guinea, Ethiopia, Burkina Faso, and Niger), showing extreme spatial inequality in the distribution of basic deprivations. Such areas are visible on the map and bar chart presenting the spatial clustering of large gaps, which indicate that these high MPI gaps are not randomly distributed but are localized in geographic regions that share common long-term structural constraints such as weak public infrastructure, limited market access, and low human capital endowments.

Furthermore, distributional data reveal that the MPI gap is strongly related to the headcount ratio gap (correlation coefficient > 0.9) and weakly linked with the intensity gap, indicating that the primary source of MPI differences lies in incidence differences between rural and urban populations. The depth of deprivation (intensity), while less dominant, acts as an important auxiliary factor, particularly where overlapping deprivations are more pronounced.

The ordinary least squares model that applies the headcount gap and intensity gap to forecast the MPI gap achieves a very high explanatory value. The main coefficients are reported in Table 2. The coefficient on Headcount_gap is 0.00477 (SE = 0.00021, t = 22.37, p < 0.001), while the coefficient on Intensity_gap is 0.00825 (SE = 0.00082, t = 10.05, p < 0.001).

The intercept is −0.0169998 (SE = 0.0042014, t = −4.046, p = 0.000103). Model diagnostics indicate a Multiple $R^2$ of 0.9553 and an Adjusted $R^2$ of 0.9544 ($F(2, 99) = 1057$, $p < 0.001$).

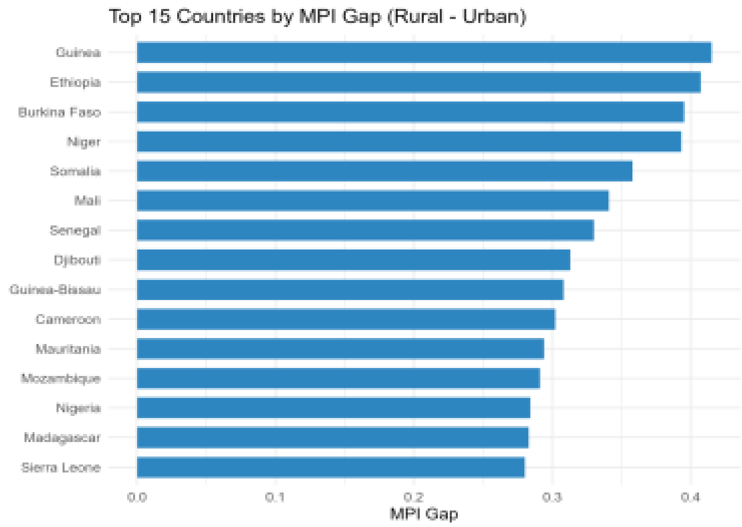


**Figure 1.** Top 15 Countries by Rural–Urban MPI Gap
**Source:** Authors calculation using global MPI national dataset

It is worth noting that despite the very high R2 for a cross-country specification, these findings should be considered within the context of the MPI construction, since MPI is a function of both headcount and intensity so this regression can be seen as a breakdown of the MPI gap illustrating how much of it follows from incidence versus intensity. Visual diagnostics are good at showing the alignment of the prediction with the actual values. The predicted versus-observed scatterplot is tightly clustered near the 45-degree line, which means that the linear model cap tures central tendencies quite accurately and that there are not many high-leverage outliers that distort the fit.

**Table 2.** Ordinary Least Squares Regression Results Pre dicting Urban–Rural MPI Gap (N = 102)

| Predictor | B | SE | t | p |
|---|---|---|---|---|
| Intercept | −0.0170 | 0.0042 | −4.05 | 0.0001 |
| Headcount_gap | 0.00477 | 0.00021 | 22.37 | < 0.001 |
| Intensity_gap | 0.00825 | 0.00082 | 10.05 | < 0.001 |

***Note:*** *Model statistics: Multiple* $R^2 = 0.955$, *Adjusted* $R^2 = 0.954$, $F(2, 99) = 1057$, $p < 0.001$.
***Source:*** *Authors' calculation based on national MPI dataset*

Residual analysis reveals modest heteroscedasticity at the extremes of the predicted range, suggesting slight underprediction for countries with very low MPI gaps and minor under- or overprediction at higher gap levels. These patterns do not undermine the main results but suggest that nonlinearities or additional covariates may improve model fit at the tails. Variance inflation factors for the regressors are well below conventional thresholds (VIF < 2), indicating that multicollinearity does not materially affect coefficient estimates.

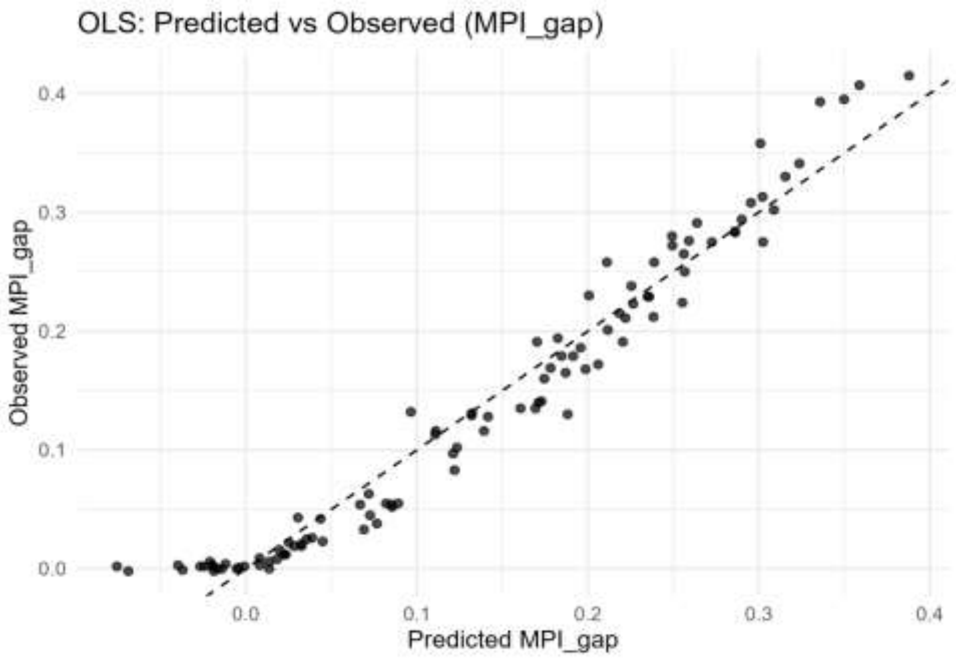


**Figure 2:** Predicted vs. Observed Values for OLS Regres sion
**Source:** Authors estimation using ordinary least squares model, based on MPI_national.csv data.

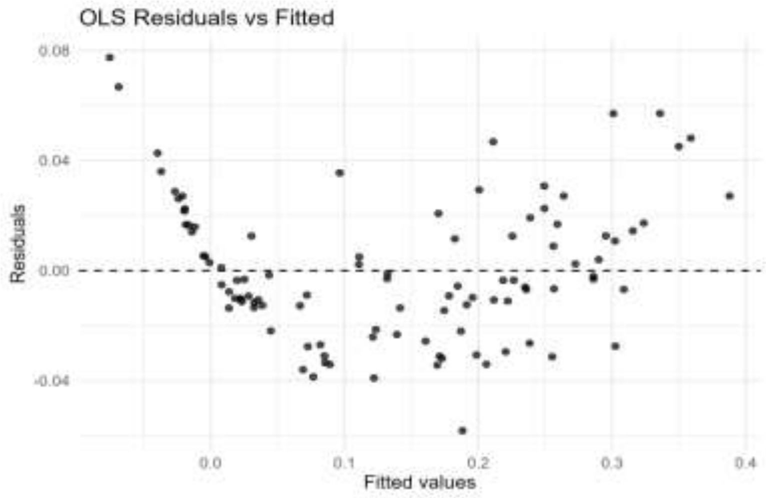


**Figure 3.** Residuals vs. Fitted Values for OLS Regression
**Source:** Authors diagnostic plots generated from OLS regression residuals, using R statistical software.

**Table 3.** Linear Mixed-Effects Regression Results Predicting Regional MPI

| Predictor | B | SE | t |
|---|---|---|---|
| Intercept | 0.01078 | 0.00509 | 2.12 |
| MPI_National | 0.98379 | 0.01954 | 50.35 |

**Note:** Random effects: Country (intercept) variance = 0.0000559 (SD = 0.00748); Residual variance = 0.008789 (SD = 0.09375). Model fit: REML criterion = −1844.4.
**Observations = 983; Countries = 78.**
**Source:** Author’s calculation using *MPI_subnational.csv* dataset.

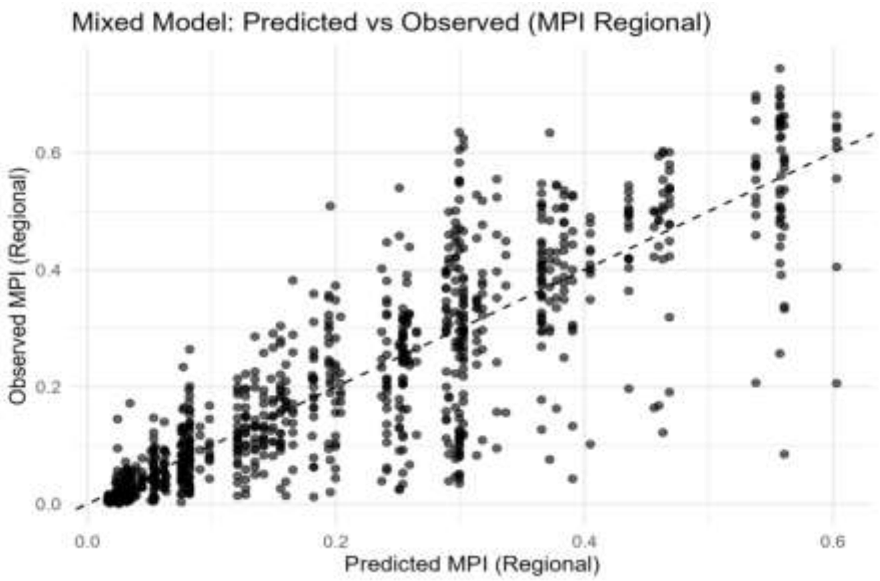


**Figure 4.** Predicted vs. Observed Values for Mixed-Effects Model
**Source:** Authors estimation using linear mixed-effects model (lme4 package in R) with MPI_subnational.csv data.

To examine whether the cross-country results generalize to within-country patterns, a linear mixed-effects model is estimated using subnational MPI as the dependent variable, with a country-level random intercept and national MPI as the main predictor. The results, reported in Table 3, show a fixed-effect estimate on MPI_National of 0.983785 (SE = 0.019540, t ≈ 50.35) and an intercept of 0.010775 (SE = 0.005088, t ≈ 2.118).
Graphical diagnostics for the mixed-effects model reveal a similarly tight predicted-versus-observed pattern and no evidence of systematic bias across most of the regional distribution. These findings support the generalization of the cross-country decomposition results to subnational contexts.

Additional robustness checks—including heteroscedasticity-robust standard errors, alternative functional forms, winsorization of extreme values, quantile regression, and sensitivity analyses excluding high-leverage observations do not materially alter the qualitative conclusions. The results consistently indicate that headcount and intensity differentials remain the principal drivers of the MPI gap, and that the relationship between national and regional MPI remains close to proportionality.

## Discussion

The empirical results have several implications beyond descriptive patterns. The dominance of the headcount-gap coefficient suggests that rural–urban MPI disparities are primarily driven by differences in poverty incidence rather than by the depth of deprivation alone. This finding is consistent with a framework in which urbanization and public-service diffusion raise access to education, health care, and basic infrastructure more rapidly in urban areas than in rural regions, leading to faster reductions in the proportion of multidimensionally poor households in cities.

Although intensity-gap effects are smaller in magnitude, they remain substantively important. In rural areas where households experience multiple, overlapping deprivations—such as inadequate sanitation, poor health outcomes, and limited educational attainment—reductions in poverty incidence alone may not be sufficient to generate sustained improvements in well-being. Policies that focus exclusively on lowering headcount ratios without addressing the overlapping nature of deprivations may therefore fail to improve living conditions among the poorest households in a durable manner.

The near-unity coefficient on national MPI in the mixed-effects model highlights a key structural dynamic: subnational poverty outcomes closely track national poverty conditions. This indicates that macro-level policies, national development strategies, and institutional capacity play a central role in shaping regional poverty patterns. At the same time, the presence of intranational variation underscores the continued importance of geographically targeted interventions to address localized pockets of severe deprivation.

Finally, it is important to recognize that because MPI is constructed from headcount and intensity components, regressing the MPI gap on these components is mechanically partially tautological. Nevertheless, this decomposition-based approach remains analytically valuable, as it provides a transparent assessment of the relative importance of incidence and intensity in explaining observed rural–urban disparities. The analysis should therefore be interpreted as descriptive and decompositional rather than causal, with causal inference requiring alternative empirical strategies such as instrumental-variable approaches or panel-data methods exploiting exogenous variation.

**Policy Implications**

The empirical findings of this study provide several important policy implications for the design and implementation of multidimensional poverty alleviation strategies, particularly in addressing persistent rural–urban disparities. The dominance of the headcount gap in explaining rural–urban MPI differences suggests that policies aimed at reducing the incidence of poverty in rural areas should be prioritized. At the same time, the statistically significant role of intensity differentials highlights the need for interventions that address overlapping and deep-rooted deprivations faced by the rural poor.

First, policy interventions should adopt a dual-track approach that simultaneously targets poverty incidence and deprivation intensity. Measures such as conditional cash transfers, school-feeding programs, and employment guarantee schemes can effectively reduce the proportion of multidimensionally poor households, thereby lowering headcount ratios. However, these interventions must be complemented by long-term investments in health, education, sanitation, clean cooking fuel, and rural infrastructure to reduce the intensity of deprivation among households that remain poor.

Second, the strong and near-proportional relationship between national and subnational MPI outcomes revealed by the mixed-effects model underscores the importance of macro-level policy coordination. National development strategies, including fiscal decentralization, social protection floors, and pro-poor public expenditure frameworks, play a critical role in shaping regional poverty outcomes. Well-designed national policies can generate broad-based improvements across regions, while poorly targeted macroeconomic policies risk reinforcing existing spatial inequalities.

Third, the presence of intranational heterogeneity implies that national-level interventions alone are insufficient. Geographic targeting mechanisms should be used to identify regions with exceptionally high rural–urban MPI gaps and allocate additional resources accordingly. This calls for the integration of MPI-based targeting into budgetary allocation processes, enabling policymakers to prioritize districts and regions where multidimensional deprivations are most severe.

Fourth, the robustness of the results across alternative specifications highlights the importance of strengthening data systems and monitoring frameworks. Regular collection of subnational MPI data, improved survey coverage in rural areas, and the integration of administrative data can enhance the effectiveness of policy evaluation and enable dynamic adjustment of poverty alleviation strategies.

## Conclusion

This study has examined rural–urban disparities in multidimensional poverty using cross-country and subnational data derived from the global Multidimensional Poverty Index (MPI). By integrating descriptive analysis, cross-country ordinary least squares (OLS) regression, and linear mixed-effects modeling, the paper provides a comprehensive empirical assessment of the magnitude, structure, and transmission mechanisms underlying rural–urban MPI gaps.

The results demonstrate that rural–urban disparities in multidimensional poverty are both substantial and unevenly distributed across countries, with particularly large gaps observed in several Sub-Saharan African economies. The decomposition of the MPI gap reveals that differences in poverty incidence, as captured by the headcount gap, constitute the dominant driver of rural–urban disparities, while differences in deprivation intensity play a significant but secondary role. These findings highlight that spatial inequality in multidimensional poverty is shaped primarily by unequal access to basic services and opportunities rather than solely by the depth of deprivation among the poor.

The multilevel analysis further shows that national-level multidimensional poverty is strongly and almost proportionally transmitted to subnational outcomes. The small variance associated with country-level random effects relative to within-country variation suggests that national development trajectories and macroeconomic policy choices exert a pervasive influence across regions. At the same time, the presence of intranational heterogeneity underscores the need for geographically targeted interventions to address localized pockets of severe deprivation.

Overall, the findings emphasize the importance of adopting a multidimensional and multi-level policy framework to address persistent rural–urban poverty disparities. Policies that focus exclusively on income growth or single-sector interventions are unlikely to achieve sustained reductions in multidimensional poverty. Instead, a combination of broad-based national strategies and targeted regional policies aimed at reducing both the incidence and intensity of deprivation is required to foster inclusive and balanced development.

Future research may extend this analysis by incorporating panel data, causal identification strategies, and policy-specific evaluations to further strengthen the evidence base for multidimensional poverty reduction.

## References

Alkire, S., & Foster, J. (2011). Counting and multidimensional poverty measurement. Journal of Public Economics, 95(7–8), 476–487. https://doi.org/10.1016/j.jpubeco.2010.11.006

Alkire, S., & Santos, M. E. (2010). Acute multidimensional poverty: A new index for developing countries. Human Development Research Paper No. 38. United Nations Development Programme. https://hdr.undp.org

Alkire, S., Jindra, C., Robles, G., Seth, S., & Vaz, M. A. (2015). Global Multidimensional Poverty Index 2015. Oxford Poverty and Human Development Initiative. https://ophi.org.uk

Alkire, S., Kanagaratnam, U., & Suppa, N. (2020). The global Multidimensional Poverty Index (MPI): 2020 revision. OPHI Working Paper. https://ophi.org.uk

Atkinson, A. B. (2003). Multidimensional deprivation: Contrasting social welfare and counting approaches. Journal of Economic Inequality, 1(1), 51–65. https://doi.org/10.1023/A:1023908006047

Bourguignon, F., & Chakravarty, S. R. (2003). The measurement of multidimensional poverty. Journal of Economic Inequality, 1(1), 25–49. https://doi.org/10.1023/A:1023913831342

OPHI. (2022). Global Multidimensional Poverty Index 2022: Unpacking deprivation bundles. Oxford Poverty and Human Development Initiative. https://ophi.org.uk/global-mpi-2022/

Ravallion, M., Chen, S., & Sangraula, P. (2007). New evidence on the urbanization of global poverty. Population and Development Review, 33(4), 667–701. https://doi.org/10.1111/j.1728-4457.2007.00193.x

Santos, M. E., Dabus, C., & Delbianco, F. (2019). Growth, inequality and poverty: Assessing the links. World Development, 122, 1–18. https://doi.org/10.1016/j.worlddev.2019.05.010

Sen, A. (1999). Development as Freedom. Oxford University Press. https://global.oup.com

Thorbecke, E. (2008). Multidimensional poverty: Conceptual and measurement issues. In N. Kakwani & J. Silber (Eds.), The Many Dimensions of Poverty (pp. 3–19). Palgrave Macmillan. https://link.springer.com

UNDP. (2023). Global Multidimensional Poverty Index 2023. United Nations Development Programme. https://hdr.undp.org

World Bank. (2020). Poverty and Shared Prosperity 2020: Reversals of Fortune. World Bank Publications. https://www.worldbank.org

World Bank. (2022). World Development Report 2022: Finance for an Equitable Recovery. World Bank Publications. https://www.worldbank.org

Yalonetzky, G. (2014). Multidimensional poverty measurement: Theoretical and empirical advances. Journal of Economic Inequality, 12(1), 121–137. https://doi.org/10.1007/s10888-013-9242-6