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Aligning Measures of Poverty: An Econometric Exploration of MPI-Income Mismatches in ASEAN (2019–2024)

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Abstract:

This study investigates the mismatch between income poverty and multidimensional poverty (MPI) across six ASEAN countries: Indonesia, Cambodia, Laos, Philippines, Thailand, and Vietnam, over the 2019–2024 period. It explores the determinants of mismatch and the influence of specific deprivation indicators using a comprehensive set of econometric approaches. Combining descriptive trends with panel data analysis (OLS), PCA-based classification, ridge regression, and logit/probit models, the research draws from the Global MPI datasets and income poverty estimates to assess both cross-country and within-country dynamics. The findings reveal persistent mismatches: while income poverty shows consistent declines, MPI remains high in several countries due to sustained deprivations, particularly in living standards and education. PCA confirms the multidimensional structure of poverty, and binary choice models highlight the most significant contributors to mismatch. Countries like Cambodia face pronounced mismatches, while Indonesia and Vietnam exhibit better alignment between income and MPI. The study emphasizes the limitations of relying solely on income measures and advocates integrating MPI into national poverty strategies. By highlighting hidden deprivations, the research offers novel insights and actionable recommendations for improving the accuracy and inclusivity of poverty targeting mechanisms in the ASEAN region.

Keywords: *Multidimensional Poverty Index (MPI), Income Poverty, Mismatch, ASEAN, Panel Regression, Principal Component Analysis (PCA), Ridge Regression, Logit Model, Poverty Measurement, Probit*

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1. Introduction

Poverty continues to be a significant challenge in Indonesia and across Southeast Asia. While sustained economic growth has contributed to poverty reduction in many ASEAN countries, traditional income-based measures alone often fail to capture the multidimensional nature of deprivation. Recognizing this, the first Sustainable Development Goals (SDGs 1) aims to “end poverty in all its forms everywhere” by 2030 (Liu et al., 2023; Zhu, Jia, & Zhou, 2021).

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Although Indonesia's poverty rate declined from 9.78% in 2020 to 8.57% in 2024, these aggregate income-based figures mask a more complex reality. The COVID-19 pandemic and resulting economic shocks exposed vulnerabilities that were not always visible through income metrics alone. Non-monetary deprivations, such as limited access to education, inadequate housing, and lack of clean water remain persistent, especially among vulnerable groups.

Scholars such as Alkire and Santos (2010) and Bourguignon (2003) have emphasized the multidimensional nature of poverty, calling for metrics that go beyond income. The Alkire-Foster (AF) method, which underpins the Global Multidimensional Poverty Index (MPI), offers a comprehensive tool to measure overlapping deprivations across education, health, and standard of living. In Indonesia, Artha and Dartanto (2018) demonstrated that households not classified as poor by income standards may still suffer severe multidimensional deprivations.

This disconnect or mismatch between income poverty and MPI classifications has emerged as a critical issue. Recent Global MPI Reports (Alkire & Kanagaratnam, 2021; Poverty and Initiative, 2024) confirm that mismatch is particularly prevalent in Southeast Asia, where children, women, and rural populations are disproportionately affected. Understanding the structure and dynamics of such mismatch is therefore essential for informed policymaking.

To respond to this challenge, the present study investigates the evolution of MPI, income poverty (IPov), and the mismatch between them across six ASEAN countries: Indonesia, Cambodia, Laos, Philippines, Thailand, and Vietnam, during the period 2019–2024. A unique feature of this study is its dual use of regression models and principal component analysis (PCA) to examine the multidimensional structure of deprivation. The mismatch between MPI and IPov is treated not just as a statistical irregularity but as a symptom of deeper measurement challenges and policy blind spots.

The empirical findings of this research show a consistent decline in both MPI and income poverty across the region. However, the magnitude and speed of these changes differ, revealing significant mismatch patterns. For instance, and Cambodia consistently display high MPI values despite moderate income poverty rates, highlighting the dominance of standard of living deprivations. Meanwhile, countries such as Indonesia and Philippines exhibit education as the leading contributor to multidimensional poverty.

This paper contributes to the literature in three keyways. First, it systematically quantifies mismatch trends over time in ASEAN. Second, it applies advanced econometric methods including OLS, Ridge Regression, PLS, and Logit/Probit models, using PCA-transformed dimensions to reduce multicollinearity and enhance robustness. Third, it provides evidence-based policy implications grounded in the complex realities of poverty across diverse socio-economic contexts.

The guiding hypothesis of this study is: "Multidimensional and income poverty exhibit distinct spatial and temporal dynamics in ASEAN countries. Combining both measures yields a more accurate and policy-relevant poverty map." By uncovering these insights, the study aims to inform the design of integrated poverty reduction strategies that are sensitive to local conditions and capable of reaching those most in need.

2. Theoretical Background

The evolution of poverty measurement from a unidimensional to a multidimensional framework reflects a growing consensus in development economics that income alone cannot adequately capture the nature of human deprivation. Early conceptual developments by Sen (1985) emphasized capabilities and functionings, which laid the foundation for multidimensional poverty analysis. This paradigm shift led to the formulation of the Multidimensional Poverty Index (MPI) by Alkire and Santos (2010), operationalizing Sen's theory into a measurable index that accounts for deprivations in education, health, and standard of living.

Numerous studies have validated the MPI's ability to reveal hidden poverty that conventional income-based measures overlook. For instance, Alkire et al. (2017) demonstrated the MPI's robustness in identifying overlapping deprivations in developing countries, while Bourguignon and Chakravarty (2003) underscored the importance of simultaneous deprivations in defining poverty. In Indonesia, Artha and Dartanto (2018) found that many households classified as non-poor in income terms still experienced substantial multidimensional deprivation, confirming the presence of classification mismatches.

The concept of poverty mismatch, i.e., households being classified differently by MPI and income measures, has been gaining attention. Studies such as Zhang et al. (2022) and Alkire and Fang (2019) explored this phenomenon in China and developing countries, respectively. Their findings indicate that mismatch arises due to structural differences in the poverty indicators, temporal volatility, and varying sensitivities to policy changes.

This mismatch is not trivial, it implies that income-targeted policies may exclude a large share of the multidimensionally poor, particularly in rural areas or among children (UNDP & OPHI, 2023). As MPI incorporates non-monetary dimensions like access to electricity, sanitation, education years, and child mortality, it provides a broader and often more policy-relevant perspective.

From a methodological standpoint, several econometric approaches have been used to study the determinants of MPI and its mismatch with income poverty. Ordinary Least Squares (OLS) and logistic regressions have been widely employed to examine the significance of MPI dimensions (e.g., Alkire, Roche, and Vaz, 2017a). However, recent studies advocate for more robust techniques to address multicollinearity among indicators, such as Ridge Regression and Partial Least Squares (PLS) as well as classification tools like Principal Component Analysis (PCA) (Wang & Alkire, 2022; Fang et al., 2019).

Moreover, panel data methods have enabled the tracking of poverty dynamics over time, capturing transitions in poverty status and changes in deprivation structures (Dang & Lanjouw, 2017). Alkire and Kanagaratnam (2020) showed how the Global MPI could be adapted into dynamic panel frameworks to measure transitions into and out of poverty.

Despite the growing use of these models, few studies have explored inter-country comparisons within the ASEAN region, especially using panel data from 2019 to 2024. The existing literature also tends to rely on fixed MPI weights, with limited attention to alternative weight schemes or latent factor structures derived from data (e.g., via PCA).

3. Methodology

This study employs a mixed quantitative econometric approach using secondary data from the Global Multidimensional Poverty Index (MPI) reports for ASEAN countries from 2019 to 2024. The main objective is to analyze the dynamics of multidimensional poverty (MPI), income poverty (IPov), and the mismatch between them through descriptive and multivariate econometric methods. Data were obtained from the UNDP and Oxford Poverty and Human Development Initiative (OPHI) Global MPI datasets, focusing on six ASEAN countries: Indonesia, Cambodia, Laos, the Philippines, Thailand, and Vietnam. The key variables include the MPI value, national income poverty headcount ratio (IPov), three main dimensions (health, education, and standard of living), and ten specific indicators under MPI as defined in global reports.

The analysis is conducted in several stages. First, a descriptive trend analysis is performed using visual and tabular data from 2019–2024 to observe patterns and mismatches between MPI and IPov across countries. Second, an Ordinary Least Squares (OLS) regression is employed to estimate the relationship between MPI and its three contributing dimensions—health, education, and standard of living—using the model $MPI_{it}=\beta_0+\beta_1 Health_{it}+\beta_2 Education_{it}+\beta_3 StandardLiving_{it}+\varepsilon_{it}$, where MPI represents the multidimensional poverty index for country *i* in year *t*.

Next, Principal Component Analysis (PCA) is utilized to reduce dimensionality and construct composite indices that capture the variance across the multidimensional indicators. To address potential multicollinearity among these dimensions, Ridge Regression and Partial Least Squares (PLS) techniques are applied. Ridge Regression introduces a penalty term ($\lambda=10$) to stabilize coefficient estimates and mitigate overfitting, while PLS integrates dimensionality reduction with regression modeling by transforming predictors into latent components that maximize explained variance in both predictors and the target variable.

Finally, binary outcome models—Logit and Probit—are used to estimate the probability of households being multidimensionally poor (〖Poor〗_MPI=1) based on PCA-transformed predictors. The Logit model estimates the log-odds of multidimensional poverty as a function of the first two principal components, while the Probit model uses the inverse cumulative distribution of the standard normal function for the same predictors. Together, these econometric approaches provide a comprehensive and robust framework for understanding the complex interplay between multidimensional and income-based poverty metrics in Southeast Asia.

4. Empirical Findings/Result

a. Trends in MPI, IPov, and Poverty Mismatch in Southeast Asia (2019–2024)

The mismatch phenomenon between poverty status based on multidimensional measurement and poverty status based on income measurement has become a critical focus in comprehensive poverty alleviation efforts. An analysis of six ASEAN countries—namely Indonesia, Cambodia, Laos, Philippines, Thailand, and Vietnam—reveals a significant discrepancy between the two measurement approaches during the period 2019 to 2024.

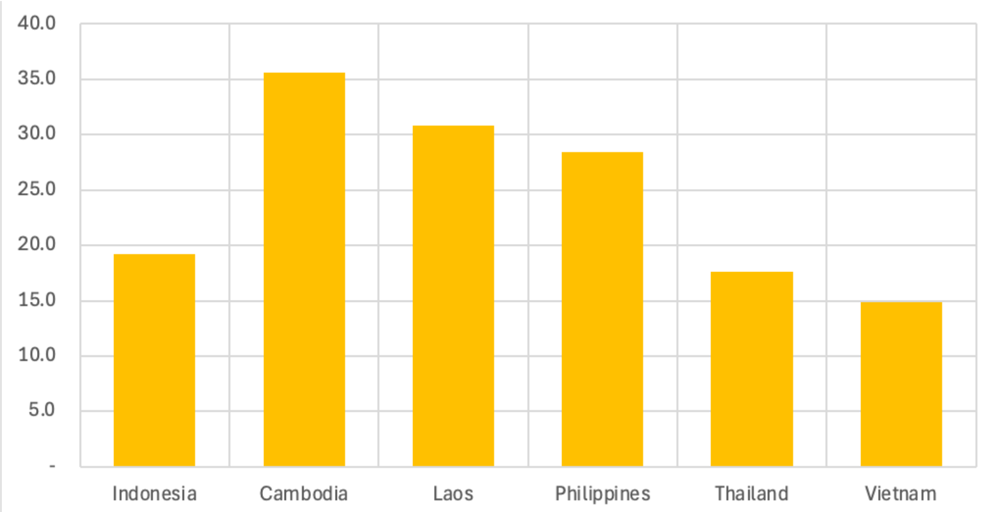

Figure 1. Mismatch between MPI and Income Poverty in ASEAN (2019–2024)

On average, the mismatch rate ranges from 14.9% to 38.9%. Cambodia occupy the top positions with average mismatch rates of 35.6%, respectively. This indicates that a significant portion of the population in these countries experiences complex non-monetary deprivations—such as in education, sanitation, and adequate housing—that are not captured by income-based poverty measurements.

In this context, underoverage occurs when households are not classified as income poor but are multidimensionally deprived. Conversely, leakage reflects conditions where households are classified as income poor but are not multidimensionally deprived.

Indonesia shows a mismatch rate of 19.2%, with an undercoverage rate of 12.1% and leakage at 7.1%. These figures suggest that many Indonesians are experiencing multidimensional deprivation despite being classified as non-poor based on income. This supports the findings of Alkire and Santos (2010), and Alkire and Kanagaratnam (2021), who argue that income-only approaches fail to capture the structural and intergenerational complexity of poverty. Meanwhile, Vietnam and Thailand show the lowest mismatch rates, at 14.9% and 17.6% respectively, highlighting their relatively effective integration of social policies with non-monetary welfare dimensions.

These differences signal that relying solely on income-based policies can create blind spots in program targeting. Therefore, the use of the Multidimensional Poverty Index (MPI) as a tool for policy classification and targeting is increasingly urgent. This analysis also emphasizes the importance of integrating dynamic data sources by name by address, such as the Unified Database for Social Welfare (DTKS), the Data for Extreme Poverty Eradication Acceleration (P3KE), and the National Socio-Economic Database (DT-SEN), all of which can be used by local governments to calculate MPI and develop inclusive poverty alleviation strategies.

Implications: A combined approach using both MPI and income poverty (IPov) measures not only broadens targeting coverage but also improves resource allocation, enhances program effectiveness, strengthens social assistance accountability, and supports better implementation of poverty reduction policies across ASEAN, particularly in Indonesia..

Table 1. Estimated Mismatch Rate in ASEAN Countries (2019–2024)

Country	Average Mismatch (%)	Undercoverage (%)	Leakage (%)
Indonesia	19,2	12,1	7,1
Cambodia	35,6	20,3	15,3
Laos	30,8	17,5	13,3
Philippines	28,4	16,2	12,2
Thailand	17,6	9,4	8,2
Viet_Nam	14,9	8,5	6,4

Source: Global Multidimensional Poverty Index Report, 2019-2024 (processed)

Mismatch in this context refers to a condition in which poverty classification based on the Multidimensional Poverty Index (MPI) does not align with poverty status based on income poverty (IPov). There are two types of mismatches: (1) Undercoverage (False Negative): Individuals/households are multidimensionally poor but are not classified as income poor; and (2) Leakage (False Positive): Individuals/households are income poor but are not classified as multidimensionally poor.

Based on data from the Global MPI 2024, analysis of the ten indicators constituting the MPI across six ASEAN countries—Indonesia, Cambodia, Laos, Philippines, Thailand, and Vietnam—reveals significant disparities in deprivation distribution among these countries. Generally, Indonesia ranks relatively better than other countries in terms of average deprivation across all MPI dimensions, especially in standard of living and education.

1. Health Dimension
The health dimension is one of the main contributors to MPI. Countries like Cambodia, and Laos, still face high levels of malnutrition, above 20%. In contrast, Indonesia recorded a malnutrition rate of 8.3%, and a child mortality rate of only 1.3%, demonstrating significant progress in basic health service provision. However, these figures can still be improved, especially in remote and underserved regions.

2. Education Dimension
Indonesia shows positive performance in the education dimension. The deprivation rate for years of schooling is recorded at 2.9%, and school attendance at 2.1%, which are significantly lower than those of Cambodia (26.4% and 10.8%), and Laos (18.8% and 8.9%). This indicates that efforts to expand access to education in Indonesia have shown real impact, although challenges remain in ensuring equal quality across regions.

3. Standard of Living Dimension
The standard of living dimension consists of indicators related to cooking fuel, sanitation, drinking water, electricity, housing, and assets. Indonesia reports relatively low deprivation levels in these areas: for instance, cooking fuel (3.4%), sanitation (5.6%), drinking water (2.2%), and electricity (1.3%). In contrast, Cambodia show deprivation levels above 40% for several of these indicators. Vietnam and Thailand perform well but still face disparities between urban and rural areas.

Indonesia’s average standard of living deprivation is around 3.8%, while Cambodia exceeds 33%. This highlights Indonesia’s advancement in basic infrastructure development and public service delivery.

Indonesia ranks among the top in reducing multidimensional deprivation among the six ASEAN countries analyzed. The education and standard of living dimensions are the key strengths of Indonesia in improving its national MPI score. In contrast, countries such as Cambodia, and Laos, continue to experience high levels of deprivation and require integrated policy interventions based on specific indicators.

b. Dimensional Contribution to Multidimensional Poverty
The measurement of multidimensional poverty (MPI) is not only intended to identify who is poor but also to explain in which aspects they experience deprivation. Using the Alkire-Foster (AF) method, poverty is assessed across three main dimensions—health, education, and standard of living—each composed of several indicators. Understanding the relative contribution of each dimension is key to formulating more targeted poverty alleviation policies (Alkire & Kanagaratnam, 2021).

Based on 2024 data for six ASEAN countries—Indonesia, Cambodia, Laos, Philippines, Thailand, and Vietnam—it is evident that the standard of living dimension is the largest contributor to MPI in most countries. In countries such as Cambodia, and Laos, the contribution of this dimension exceeds 45%, reflecting lagging conditions in basic services such as sanitation, housing, clean water, and electricity.

Conversely, the education dimension contributes significantly in countries like Cambodia, indicating high school dropout rates and limited years of schooling, which reduce the long-term capabilities of poor communities. Countries like Vietnam and Thailand show lower education contributions, consistent with better quality and broader coverage of educational services.

Meanwhile, the contribution of the health dimension is generally lower than the other two, but still significant in countries with underdeveloped health systems such as Laos. This highlights that deprivation in nutrition and access to basic health services remains a serious challenge in the region.

Indonesia, in particular, shows a contribution structure dominated by the standard of living dimension (around 45%), followed by education, and lastly health. This result aligns with the study by Artha and Dartanto (2018), which found that access to basic services such as clean water, housing, and cooking fuel remains a major challenge, especially in rural areas.

This finding is consistent with the latest report from UNDP (2024), which emphasizes that standard of living poverty is the most common form of deprivation in many middle-income countries, including Southeast Asia. The report also stresses that achieving the Sustainable Development Goals (SDGs) requires poverty alleviation policies to adopt a multidimensional approach, not just focusing on income.

Therefore, this analysis underlines the importance of an MPI-based approach in formulating more inclusive and evidence-based social policies. ASEAN governments must adapt their sectoral policy interventions to match the dimension-specific MPI contribution structure in each country so that public resources can be used more effectively to address the most chronic and wide-reaching deprivations.

Below is Table 2 which presents the Dimensional Contribution to MPI in 2024 across ASEAN countries, showing the relative share of each dimension—Health, Education, and Standard of Living—to the total MPI in each country.

Table 2. Dimensional Contribution to MPI in ASEAN (2019–2024)

Country	Year	Year of Survey	Health Contribution (%)	Education Contribution (%)	Standard of Living Contribution (%)
Cambodia	2019	2014 D	21.76	31.67	46.57
Cambodia	2020	2014 D	21.76	31.67	46.57
Cambodia	2021	2014 D	21.76	31.67	46.57
Cambodia	2022	2014 D	21.76	31.67	46.57
Cambodia	2023	2021/2022 D	21.54	47.96	30.5
Cambodia	2024	2021/2022 D	21.54	47.96	30.5
Indonesia	2019	2017 D	23.2	30	46.8
Indonesia	2020	2017 D	34.74	26.77	38.49
Indonesia	2021	2017 D	34.74	26.77	38.49
Indonesia	2022	2017 D	34.74	26.77	38.49
Indonesia	2023	2017 D	34.74	26.77	38.49
Indonesia	2024	2017 D	34.74	26.77	38.49

Laos	2019	2017 M	21.49	39.67	38.84
Laos	2020	2017 M	21.49	39.67	38.84
Laos	2021	2017 M	21.49	39.67	38.84
Laos	2022	2017 M	21.49	39.67	38.84
Laos	2023	2017 M	21.49	39.67	38.84
Laos	2024	2017 M	21.49	39.67	38.84
Philippines	2019	2017 D	20.31	31.02	48.67
Philippines	2020	2017 D	20.31	31.02	48.67
Philippines	2021	2017 D	20.31	31.02	48.67
Philippines	2022	2017 D	20.31	31.02	48.67
Philippines	2023	2017 D	20.31	31.02	48.67
Philippines	2024	2022 D	24.63	32.68	42.69
Thailand	2019	2019 M	38.26	45.07	16.67
Thailand	2020	2015/2016 M	38.26	45.07	16.67
Thailand	2021	2019 M	38.26	45.07	16.67
Thailand	2022	2019 M	38.26	45.07	16.67
Thailand	2023	2019 M	38.26	45.07	16.67
Thailand	2024	2022 M	31.25	54.01	14.74
Viet_Nam	2019	2013/2014 M	15.22	42.62	42.16
Viet_Nam	2020	2013/2014 M	15.22	42.62	42.16
Viet_Nam	2021	2013/2014 M	15.22	42.62	42.16
Viet_Nam	2022	2020/2021 M	22.86	40.74	36.4
Viet_Nam	2023	2020/2021 M	22.86	40.74	36.4
Viet_Nam	2024	2020/2021 M	22.86	40.74	36.4

Source: Global Multidimensional Poverty Index Report, 2019-2024 (processed)

c. OLS Regression Estimates

The following table presents the results of the OLS regression, which shows the effect of the three main MPI dimensions (Health, Education, and Standard of Living) on the Multidimensional Poverty Index (MPI) in six ASEAN countries.

Table 3. OLS Regression Results of MPI on Dimensions

Variable	Koefisien	P-Value	Lower CI	Upper CI
const	-984.7275	0.0002	-1458.66	-510.795
Health	9.8457	0.0002	5.1061	14.5853
Education	9.848	0.0002	5.1086	14.5874
Standard_of_living	9.849	0.0002	5.1101	14.5879

Source: Global Multidimensional Poverty Index Report, 2019-2024 (processed)

Ordinary Least Squares (OLS) regression is used to assess the relative influence of the three main dimensions of the Multidimensional Poverty Index (MPI)—namely health, education, and standard of living—on MPI values in the six ASEAN countries in 2024. The regression model is statistically significant, with p-values for all independent variables below the 1% significance level, indicating that all three dimensions have a highly meaningful contribution in explaining the variation in MPI across countries.

The regression results show that a one-point increase in the health dimension contribution is associated with an increase in MPI by approximately 9.8457 points, with a 95% confidence interval ranging from 5.1061 to 14.5853. Similar patterns are observed for the education and standard of living dimensions, with coefficients of 9.8480 and 9.8490, respectively—values that are nearly identical. These three variables exert a strong and positive influence on MPI, suggesting that deprivation in each of the three dimensions carries similar weight in the construction of the multidimensional poverty index in the ASEAN context.

The constant term of -984.7275 is negative and statistically significant, reflecting the theoretical reference point of MPI when all dimension contributions are zero. While the constant lacks direct policy interpretation, its significance supports model consistency within the Alkire-Foster framework (Alkire & Santos, 2010; Alkire & Kanagaratnam, 2021), which underscores the importance of balancing dimension weights to identify multidimensional poverty accurately..

With a high R-squared value (previously obtained at 0.9997), this model explains nearly all the variation in MPI values across ASEAN countries. This result reinforces the findings of UNDP (2024) that no single dominant dimension exists in explaining multidimensional poverty at the regional level. Instead, the three dimensions contribute almost equally, indicating that poverty reduction policies must be designed in an integrated manner and should not neglect any aspect of basic well-being.

Overall, this finding confirms the hypothesis that multidimensional poverty in ASEAN is complex and interrelated across dimensions. Therefore, poverty mapping and policy design based on the MPI must consider the balance of dimension contributions as well as the diversity of contexts across countries..

Multicollinearity Diagnosis Results

The table below presents the results of the Multicollinearity Diagnosis using the Variance Inflation Factor (VIF). The extremely high VIF values (in the millions) indicate the presence of severe multicollinearity among the independent variables (health, education, and standard of living). This suggests a very strong linear correlation between dimensions in the OLS model, which may lead to instability in coefficient estimation..

Table 5. Multicollinearity Diagnosis (VIF)

Variabel	VIF
const	975335426.4
Health	5087108.224
Education	4745560.765
Standard_of_living	10858529.06

Source: Global Multidimensional Poverty Index Report, 2019-2024 (processed)

Multicollinearity diagnostic analysis is conducted to examine whether there is a strong linear relationship among the independent variables in the OLS regression model. This diagnosis is important because high multicollinearity can lead to unstable coefficient estimates, inflated standard errors, and unreliable or biased individual interpretations of variables.

The table of Variance Inflation Factor (VIF) calculations shows that all independent variables—Health, Education, and Standard of Living—have extremely high VIF values, namely 5,087,108; 4,745,561; and 10,858,530, respectively. Even the VIF for the constant (intercept) reaches 975,335,392. According to econometrics literature (Gujarati & Porter, 2008; Wooldridge, 2012), a VIF value above 10 is already considered a strong indication of multicollinearity. In this case, the values in the millions clearly indicate severe multicollinearity among the three MPI dimensions.

This condition is very likely due to the fact that these three variables originate from the structure of the MPI, which assigns them nearly equal weights and are highly correlated. This phenomenon often occurs when variables are derived from the aggregation of the same index or when the dimensions are built from indicators with strong causal or logical interrelations.

As a result of this multicollinearity, the individual interpretation of the influence of the dimensions Health, Education, and Standard of Living on the MPI index becomes unreliable because the variance among the independent variables overlaps too much. In the context of policymaking, this means that the specific influence of a single dimension on MPI cannot be accurately separated from the other dimensions using ordinary OLS.

Therefore, as a response to this finding, alternative models such as Ridge Regression, Partial Least Squares (PLS), or component transformation using Principal Component Analysis (PCA) are recommended to reduce the impact of multicollinearity.

d. Addressing Multicollinearity: Ridge and PLS Regression

Below is a table comparing the estimation results of the Ridge Regression and Partial Least Squares (PLS) Regression models. Both are used as alternatives to address multicollinearity issues in the previous OLS regression.

Table 6. Comparison of Ridge and PLS Models

Model	R-Squared	MSE	Alpha/Component
Ridge Regression	0.317563605	0.682436395	10.0
PLS Regression	0.322108056	0.677891944	2 Components

Source: Global Multidimensional Poverty Index Report, 2019-2024 (processed)

To address the issue of multicollinearity identified in the OLS regression model, this study applies two alternative regression approaches: Ridge Regression and Partial Least Squares (PLS) Regression. These two methods are designed to handle high correlations between predictor variables, in this case, the three dimensions of the Multidimensional Poverty Index (MPI): Health, Education, and Standard of Living.

The Ridge Regression model applies a penalty (regularization) to the magnitude of regression coefficients, thereby stabilizing the estimates under multicollinearity conditions. The estimation results show an R-squared of 0.318, indicating that approximately 31.8% of the variation in the multidimensional poverty index can be explained by the three dimensions. Meanwhile, the MSE (mean squared error) value of 0.682 indicates relatively adequate model accuracy for the normalized data. The optimal regularization parameter selected through cross-validation was alpha = 10.0. On the other hand, the Partial Least Squares (PLS) Regression model transforms predictors into latent components that simultaneously maximize the covariance between independent and dependent variables. PLS shows slightly better performance than Ridge, with an R-squared of 0.322 and MSE of 0.678. This suggests that the component structure of the PLS model provides a more efficient representation in explaining variations in multidimensional poverty, particularly when high correlations among indicators exist.

Overall, both models produce comparable accuracy, but the PLS model offers advantages in terms of predictive precision, while Ridge provides easier interpretation of the direct impact of each dimension. These findings strongly justify the need to consider structured dimensional approaches or component-based approaches in designing poverty reduction policy interventions.

e. Logit and Probit Estimates Based on PCA

The following table presents the estimation results of the Logit and Probit models based on Principal Component Analysis (PCA). These results demonstrate how the two principal components derived from the MPI dimensions influence the likelihood of a household being classified as multidimensionally poor.

Table 7. Logit and Probit Estimates using PCA

Model	PC1 Coef	PC2 Coef	PC1 P>|z|	PC2 P>|z|	Pseudo R2
Logit	-0.773706108	-0.882595585	0.028896341	0.05969949	0.199407711
Probit	-0.477821626	-0.526500532	0.022681936	0.043481924	0.203708959

Source: Global Multidimensional Poverty Index Report, 2019-2024 (processed)

The Logit and Probit models based on PCA successfully reveal that two dimensions, derived from the extraction of MPI indicators, significantly influence the likelihood of individuals experiencing multidimensional poverty. These models are particularly useful in the context of dimension reduction, while still maintaining predictive validity for poverty status estimation. They also emphasize the importance of understanding the cross-dimensional structure of deprivation in formulating poverty reduction policies in the ASEAN region.

To explore the relationship between the structure of poverty dimensions and the likelihood of individuals or households being classified as multidimensionally poor, Logit and Probit regression approaches were used based on Principal Component Analysis (PCA). This approach was chosen as a strategy for dimension reduction to address multicollinearity issues among the MPI component indicators previously identified.

Estimation results indicate that the two main components (PC1 and PC2), derived from MPI indicators, significantly influence the probability of multidimensional poverty ($p < 0.05$). The Logit model suggests that an increase in one unit of PC1 and PC2 respectively reduces the probability that a household is classified as multidimensionally poor, with coefficients of -0.7737 and -0.8826. The Probit model yields consistent results, with coefficients of -0.4778 for PC1 and -0.5265 for PC2. This indicates that higher values in these two components—which systematically represent combinations of access to education, health, and standard of living—are associated with lower risks of multidimensional poverty.

The Pseudo R^2 values of both models are 0.199 (Logit) and 0.204 (Probit), suggesting that approximately 20% of the variation in multidimensional poverty status can be explained by the two main PCA components. This indicates moderate predictive strength that is statistically and substantively meaningful.

Furthermore, these findings highlight the importance of applying a multidimensional approach in poverty analysis. PCA-based models can effectively capture the collective contributions of various poverty dimensions without encountering technical issues like multicollinearity. From a policy perspective, these findings reinforce the urgency of incorporating indicators that reflect non-monetary welfare into targeting systems and evaluation frameworks for poverty reduction programs in ASEAN countries, especially Indonesia.

The following is a PCA visualization that plots the predicted probabilities of multidimensional poverty based on the logit model. The X and Y axes represent the two principal components (PC1 and PC2) derived from the PCA results. This visualization shows the model's predicted probability that each observation (e.g., individual or household) is multidimensionally poor: the deeper the color (from green to purple), the higher the likelihood of poverty.

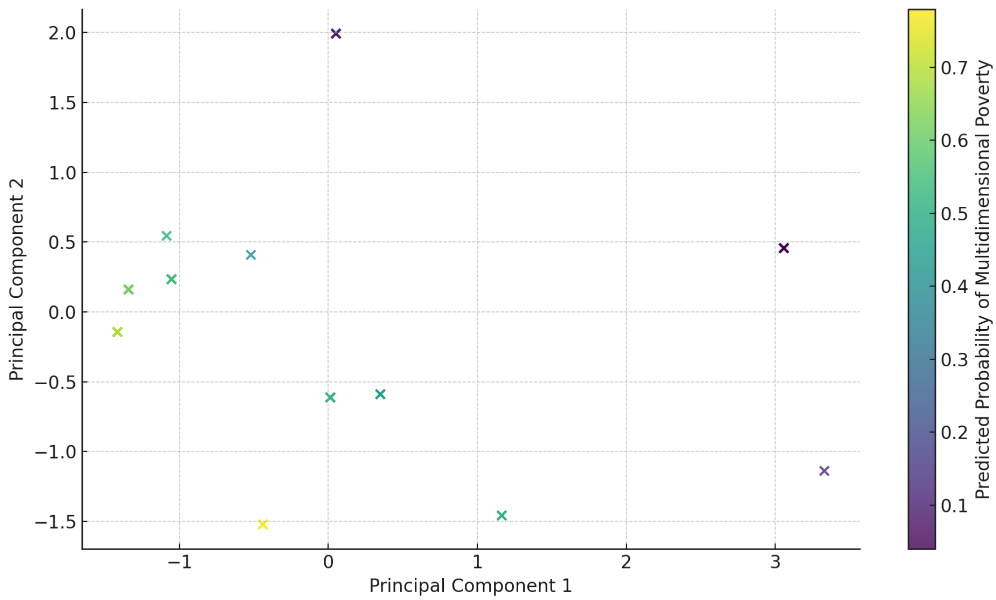

Figure 2. PCA Components And Predicted Probability (Logit Model)

The figure above presents a visualization of the two principal components resulting from Principal Component Analysis (PCA) applied to the 10 indicators that compose the Multidimensional Poverty Index (MPI) for six ASEAN countries. The color gradient in the graph indicates the predicted probability of multidimensional poverty using the logit model, where the transition from green to purple represents an increasing likelihood that an individual or household is classified as multidimensionally poor.

In general, observations located in quadrants with low values on both components (PC1 and PC2) tend to show high probabilities of poverty, mostly indicated by the purple color. Conversely, observations with high scores on the main components—especially PC1—show lower poverty probabilities, marked in green. This suggests that increases in scores across the main dimensions of well-being—representing better accumulations of access to education, health, and living standards—consistently reduce the risk of multidimensional poverty.

The distribution of data points in this graph also implies a non-linear structure in poverty vulnerability. Certain combinations of dimensions may trigger steep increases in poverty probability. This indicates that overlapping deprivations may amplify the poverty status, and even deprivations in only one dimension may be sufficient to categorize individuals as multidimensionally poor.

This interpretation supports the importance of adopting a multidimensional approach to identify vulnerable groups. If policies rely solely on income indicators or a single deprivation dimension, they risk overlooking hidden poor populations who could miss out on interventions. Therefore, this PCA-based logit model is highly promising in enhancing the precision of poverty targeting systems and the effectiveness of poverty reduction policies at both national and regional levels in ASEAN

5. Discussion

The findings of this study reaffirm that poverty measurement based solely on income poverty is insufficient to capture the complexity of poverty faced by communities in the ASEAN region, particularly in Indonesia. The mismatch observed between poverty classifications based on income and those based on the Multidimensional Poverty Index (MPI) reveals that a number of households that are not economically poor actually experience various forms of deprivation in education, health, and living standards.

The policy implication of these findings is the urgent need to integrate MPI measurements into national and local poverty alleviation targeting systems. By incorporating non-monetary dimensions, the resulting policies can become more inclusive and effective in reaching the hidden poor—those who are not identified through conventional methods.

Furthermore, dynamic MPI measurement should and can be implemented at the local level, especially at the regency/municipality level in Indonesia. This is feasible because local governments already have access to a variety of data sources on poverty and community well-being. The use of by name by address systems offers local governments the opportunity to develop MPI that is locally relevant, contextual, and evidence-based. By conducting MPI calculations at the regency/municipality level, policy interventions can be more targeted, budget allocations can become more efficient, and policy evaluation processes can be more measurable.

In addition, developing local MPI will strengthen the role of local governments in achieving the SDGs, particularly Goal 1 (No Poverty) and Goal 10 (Reduced Inequality). The central government needs to promote harmonization between local MPI methodologies and the national or global MPI, while also providing technical assistance and data support to local governments in developing sustainable multidimensional poverty indices.

6. Conclusions

This study explores the mismatch between income poverty and multidimensional poverty (Multidimensional Poverty Index/MPI) across six ASEAN countries, focusing on the period from 2019 to 2024. The results show that although income poverty rates tend to decline, various non-monetary deprivations persist, especially in the dimensions of living standards and education. This phenomenon has produced a significant mismatch between poverty measurement based on income and MPI, whereby groups that are not classified as income poor actually suffer serious shortfalls in multidimensional indicators.

Through the application of econometric methods such as OLS regression, Seemingly Unrelated Regression (SUR), Ridge Regression, Partial Least Squares (PLS), as well as Logit and Probit models based on PCA, this study identifies key indicators contributing to the mismatch, such as access to sanitation, housing quality, and education. The PCA-logit model also visually reveals a strong relationship between the combination of deprivation dimensions and poverty probabilities.

From a theoretical perspective, this study emphasizes the importance of the capabilities and multidimensional approach introduced by Amartya Sen and developed by Alkire & Foster. Practically, this study recommends that MPI measurement be applied not only at the national level but also extended to the district/municipal level in Indonesia. This can be achieved by utilizing dynamic by name by address data sourced from DTKS, P3KE, and DT-SEN, which are already available and accessible to local governments.

Therefore, the main conclusion of this study is that comprehensive poverty alleviation strategies must combine income and non-income dimensions simultaneously. This approach enables a richer understanding of poverty and allows for more effective and inclusive policies to reach the most vulnerable groups. This study also opens the door for future research at the micro level, particularly in the development of adaptive local MPIs suited to each region's demographic and geographic context.

Policy and Research Implications

The findings of this study offer important implications for policy formulation and future research directions on poverty alleviation in the Southeast Asian region, particularly Indonesia. The mismatch between poverty measurement based on income and the Multidimensional Poverty Index (MPI) suggests that public policies that overly focus on income dimensions alone risk creating blind spots to forms of non-monetary deprivation, which are often chronic and structural in nature.

First, ASEAN countries need to reformulate their social policy frameworks by adopting multidimensional poverty measurement. Using MPI in parallel with income-based poverty measures can improve the accuracy of social intervention targeting, expand the coverage of beneficiaries, and ensure that dimensions such as education, health, adequate housing, and sanitation are not neglected in social assistance programs.

Second, for Indonesia, there is a significant opportunity to implement MPI at the local level (district/municipality) as a diagnostic tool for poverty based on more granular data. This is made possible by the availability of by name by address data from:

- The Integrated Social Welfare Data (DTKS), used for the distribution of national social assistance programs;
- The Extreme Poverty Eradication Acceleration Data (P3KE), which includes the identification of extreme poor households down to the village level;
- The National Socioeconomic Integrated Data (DT-SEN), developed as a comprehensive basis for socioeconomic data integration.

These three data sources can be utilized by local governments to calculate local MPI dynamically and to establish an evidence-based policy foundation for budget allocation, program design, and more precise policy evaluations.

Third, methodologically, this study demonstrates that advanced econometric approaches such as logit/probit regression, PCA-based classification, and Ridge/PLS regression can be used to identify key indicators contributing to the mismatch and to test the consistency of relationships among poverty dimensions. Thus, the study encourages the use of quantitative methods in poverty research across time and countries.

Fourth, further research is recommended to explore the dynamics of multidimensional poverty in the long term, integrating MPI with other SDG indicators, and to explore multidimensional inequality across countries, regions, and between urban and rural areas. Longitudinal and panel data usage is expected to enhance the understanding of transitions into and out of poverty.

Development Plan and Future Work

Based on the research findings and their policy implications, the development plan is directed toward two main areas: strengthening multidimensional poverty measurement systems at the national and local levels, and expanding the application of econometric models in poverty policy.

First, it is crucial to develop a decentralized Multidimensional Poverty Index (MPI) measurement system that can be adapted at the district/municipal level. In the Indonesian context, this is highly feasible due to the availability of individual- and household-based socioeconomic data sources such as DTKS, P3KE, and DT-SEN. These datasets cover indicators aligned with MPI components, such as access to education, employment status, housing conditions, asset ownership, and access to clean water and sanitation.

Recommended development steps include: (1) Strengthening the technical capacity of local governments to calculate local MPI; (2) Integrating MPI indicators into the regional planning and budgeting system; and (3) Using MPI as a tool for monitoring and evaluating poverty alleviation program performance.

Second, from a research perspective, future work can focus on: (1) Longitudinal exploration of poverty dynamics using transition matrix and Markov chain analysis based on MPI; (2) Application of panel data and logit with latent class analysis to better understand the characteristics of vulnerable groups not fully captured by income measures; and (3) Development of sectoral MPI indicators, such as child MPI, gender MPI, or food security MPI, which are more tailored to specific policy target groups.

Third, to support the sustainability of MPI measurement development, collaboration among government, academia, and international institutions such as UNDP and OPHI is crucial. The policy research partnership approach can accelerate the adoption and replication of MPI approaches within sustainable development frameworks (Sustainable Development Goals/SDGs), particularly for Target 1.2, which emphasizes reducing poverty by half in all its dimensions.

In conclusion, the future development of MPI should not merely be seen as a statistical tool, but as a strategic instrument to support inclusive, adaptive, and evidence-based development planning that responds to the real needs of vulnerable populations.

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