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An Analysis of Poverty Using the System-GMM Approach: Evidence from Dynamic Panel Data in East Nusa Tenggara Province

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ABSTRACT

This study aims to analyze the effects of the Human Development Index (HDI), Open Unemployment Rate (OUR), and electrification ratio on poverty levels in 22 districts/municipalities in East Nusa Tenggara Province (NTT) during the 2015–2019 period, while also emphasizing the methodological contribution through the application of the System-Generalized Method of Moments (System-GMM) dynamic panel model. The GMM approach is employed to address issues of endogeneity, heterogeneity, and data persistence that are commonly encountered in regional socio-economic studies. By utilizing internal instruments, this method ensures more valid and robust parameter estimation. The panel data, obtained from the Central Bureau of Statistics, include variables such as HDI, OUR, and electrification ratio. The estimation results show that HDI has a negative and significant effect on poverty, with short-term and long-term elasticities of -0.984 and -2.244, respectively. The OUR has a positive and significant effect on poverty, with elasticities of +0.016 (short-term) and +0.036 (long-term), while the electrification ratio also shows a negative and significant effect, with elasticities of -0.035 and -0.081. These findings highlight both the substantive role of socio-economic factors in poverty reduction and the methodological relevance of System-GMM in capturing dynamic causal relationships, thereby supporting evidence-based policymaking for poverty alleviation in structurally challenged regions such as NTT.

KEYWORDS

Economic Development, Clustering, Self-Organizing Maps.

1. INTRODUCTION

East Nusa Tenggara Province (NTT) is one of the regions in Indonesia that consistently records high poverty rates. This condition is exacerbated by geographical limitations characterized by the dominance of dry land, which hampers agricultural productivity and reduces the community's access to adequate economic resources. Such physical environmental characteristics further increase the socio-economic vulnerability of NTT's population to structural poverty. Previous studies in regions with similar conditions provide supporting evidence. For example, Artika and Marini analyzed data from 2012–2021 in West Nusa Tenggara Province and found that agricultural sector contribution, labor force participation, dependency ratio, and non-food consumption patterns significantly influence poverty reduction [1]. Meanwhile, a study in East Nusa Tenggara demonstrated that human development index, unemployment, economic growth, inequality, and infrastructure access are crucial determinants of persistent poverty. These findings reinforce the relevance of the present study, which focuses on HDI, unemployment, and electrification ratio as key variables in explaining poverty dynamics in structurally vulnerable regions such as NTT [2].

In the context of socio-economic development, the Human Development Index (HDI) has been proven to play a significant role in reducing poverty. The HDI integrates three main dimensions, namely education, health, and living standards, which collectively reflect the overall quality of human development [2], [3]. An increase of one percent in the HDI can significantly impact poverty reduction, as evidenced in various studies conducted in provinces with high poverty rates. Therefore, development policies that emphasize improving the quality of education and health services are highly strategic in the framework of long-term poverty alleviation [2], [4].

Besides the HDI, unemployment also contributes to poverty. Generally, there is a positive relationship between unemployment rates and poverty levels, indicating that higher unemployment increases the likelihood of rising poverty [2], [5]. However, in certain contexts, this relationship is not always statistically significant, suggesting variability in the effect across regions [2]. Nevertheless, controlling unemployment remains an essential step in poverty reduction policies.

Meanwhile, the electrification ratio has not been extensively studied in relation to poverty, particularly in NTT. Access to electricity is believed to have broad implications for improving quality of life, household economic productivity, and expanding access to business opportunities. Electrification has the potential to be a key driver in the social and economic transformation of rural communities, which have long faced isolation from basic infrastructure [2].

However, a major gap in previous scientific studies lies in the methodological approaches used. Most earlier studies focused on static relationships among variables without considering temporal dynamics and potential endogeneity among variables, which may cause estimation bias [2], [6]. Research integrating HDI, unemployment, and electrification variables within a dynamic panel model framework using robust statistical methods such as the System-Generalized Method of Moments (System-GMM) remains very limited, especially in regions characterized by dry land conditions like NTT.

Based on this background, this study aims not only to analyze the effects of HDI, Open Unemployment Rate (OUR), and electrification ratio on poverty levels in NTT Province but also to emphasize the methodological contribution through the application of dynamic panel econometrics using the System-GMM method. This approach is chosen because it can overcome issues of endogeneity and heterogeneity inherent in panel data and capture both short-term and long-term dynamics among variables. Thus, the main focus of this research is not only on the dynamic relationships among socio-economic indicators but also on the validity and accuracy of the statistical model used to reveal the causal patterns of poverty more accurately and contextually.

2. LITERATURE REVIEW

2.1 Poverty Theory, Its Determinants, and the Importance of a Dynamic Statistical Approach

Poverty is a complex and multidimensional phenomenon influenced not only by economic factors but also by social, structural, and institutional aspects. From a classical economic perspective, poverty is generally associated with low income and non-inclusive economic growth. However, contemporary approaches have expanded the understanding of poverty by considering non-monetary dimensions such as the quality of human resources, unemployment rates, and access to basic infrastructure like electricity and clean water [7], [6].

These variables—namely HDI, Open Unemployment Rate (OUR), and electrification ratio—have strong correlations with poverty levels and have been extensively studied in previous research [2], [8], [9]. Nevertheless, most studies employ static regression approaches that are insufficient to fully capture the dynamic causal relationships among these components in the long term. Therefore, more appropriate statistical approaches, such as dynamic panel models, are needed to comprehensively examine the complexity of this phenomenon [10].

The Human Development Index (HDI) reflects the dimensions of education, health, and living standards. Both theoretically and empirically, HDI exhibits a strong negative relationship with poverty levels, as improvements in human quality strengthen individuals' capacity to escape the poverty trap [6], [9]. Conversely, the Open Unemployment Rate (OUR) often shows a positive correlation with poverty, reflecting limitations in access to productive employment [11], [9]. Although less frequently studied, the electrification ratio holds significant potential to improve welfare through increased household and small business productivity [2], [12].

However, to analyze the simultaneous effects of these variables within a dynamic time frame, a statistical approach capable of handling methodological issues such as endogeneity and panel data heterogeneity is required. This is where the System-Generalized Method of Moments (System-GMM) plays a key role in addressing these complexities both methodologically and empirically.

2.2 Previous Studies and Methodological Gaps

Several previous studies have analyzed the determinants of poverty, either partially or simultaneously, using conventional panel regression methods. Amalia highlighted the role of socio-economic variables in explaining poverty variation in NTT through a static panel regression model [17]. Putra emphasized the importance of social interventions in poverty reduction [18], while Tumiwa and Imelda found a positive relationship between electrification and welfare [19].

Nonetheless, the statistical approaches employed in these studies generally fail to address the issues of simultaneous endogeneity among variables and the persistence of poverty over time. Therefore, this study aims to fill this gap by applying System-GMM, a dynamic approach that is statistically more accurate for analyzing short-term and long-term relationships in panel data across regencies/cities.

2.3 Theory and Application of Dynamic Panel Regression (System-GMM)

The dynamic panel regression model using the System-Generalized Method of Moments (System-GMM) is an advanced statistical tool designed to handle dynamic and endogeneity problems in panel data [13]. In the context of this study, the model is formulated as follows:

$$Y_{it} = \alpha Y_{it-1} + \beta X_{it} + \mu_i + \varepsilon_{it} \tag{1}$$

In the dynamic panel specification, Y_{it} denotes the poverty rate in region i (district/municipality) at time t. The vector X_{it} represents the explanatory variables—namely the Human Development Index (HDI), Open Unemployment Rate (OUR), and Electrification Ratio. The subscript i refers to the cross-sectional unit (22 districts/municipalities), while t denotes the time dimension (2015–2019). Whenever the index j is used, it refers to the instruments derived from lagged variables employed in the estimation procedure, μ_i represents fixed effects for each regency/city, and ε_{it} is the error term.

The estimation of parameters using the System-Generalized Method of Moments (System-GMM) follows the Arellano-Bover and Blundell-Bond approach. The procedure consists of two key steps. First, the model is transformed into first differences to eliminate unobserved time-invariant fixed effects. Lagged values of the dependent and independent variables are then used as internal instruments to address potential endogeneity. Second, the system GMM framework augments the differenced equations with equations in levels, where lagged first differences serve as additional instruments. This dual system improves efficiency compared to the difference GMM estimator [13], [14], [15], [16].

The estimation algorithm is iterative and based on the principle of moments, where the weighting matrix is optimized to ensure efficiency. Both one-step and two-step GMM estimators can be applied, with the latter providing robust standard errors. Diagnostic tests are essential to validate the model: the Hansen/Sargan test checks for instrument validity and the absence of over-identification problems, while the Arellano-Bond test is used to detect first-order and second-order serial correlation in the residuals. By fulfilling these assumptions, the System-GMM estimator yields consistent and unbiased estimates even in cases of endogeneity, heterogeneity, and persistence in the data [13], [14], [15], [16].

The main advantage of this method lies in its ability to address simultaneity issues, where dependent and independent variables mutually influence each other, as well as heterogeneity problems commonly found in cross-regional studies such as regencies/cities in NTT Province [2], [17]. Furthermore, System-GMM allows researchers to utilize historical data (lagged variables) as internal instruments, resulting in more robust and unbiased estimates [13].

This method is also highly relevant for analyzing poverty persistence, as it explicitly incorporates previous period poverty levels as a key determinant of current conditions. This is crucial in the context of public policy, as it enables the temporal evaluation of development program effectiveness [2].

In this study, the System-GMM approach is not only employed as an additional analytical tool but serves as the primary framework for understanding poverty dynamics. Using this model, it is expected to obtain more accurate causal estimates and to precisely identify the roles of HDI, OUR, and electrification in sustainably reducing poverty.

3. METHODOLOGY

This study utilizes panel data, which combines time-series and cross-sectional data, covering all regencies/municipalities in East Nusa Tenggara Province (NTT) over the period 2015 to 2019. The characteristics of panel data offer analytical advantages by allowing simultaneous analysis of temporal and regional dimensions. It is particularly suitable for dynamic models that account for lag effects of the dependent variable.

In this research context, the use of panel data is highly relevant, as it enables the application of a dynamic panel estimation method—System-Generalized Method of Moments (System-GMM)—designed to address common issues in panel data analysis such as endogeneity, heterogeneity, and poverty persistence. Therefore, the structure of the data supports a more robust and efficient estimation of the relationships among the analyzed variables [13].

3.1 Research Variables

The primary source of data is the Central Statistics Agency (Badan Pusat Statistik/BPS), which provides macroeconomic and social data related to human development indicators, employment, and basic infrastructure. The variables used in the study are summarized in **Table 1**.

Table 1. Research Variables

Variable Type	Variable Name	Description
Dependent	Poverty Rate	Proportion of poor population in each regency/municipality
Independent	HDI	Human Development Index
Independent	OUR	Open Unemployment Rate
Independent	Electrification Ratio	Percentage of households with access to electricity

The dependent variable, measured as the percentage of the poor population, reflects the aggregate poverty level in each region. The three independent variables were selected not only based on theoretical arguments and previous empirical findings, but also because they are strong candidates for statistical testing within a dynamic model framework using System-GMM. This selection also considers the possibility of reverse causality, which can be technically addressed using internal instruments within the GMM framework [2].

This study employs a dynamic panel estimation method using the System-Generalized Method of Moments (System-GMM) approach. This model enables the examination of both contemporary and lagged effects of poverty determinants [18]. Referring to the empirical model presented in the literature review (see **Equation** (1)), the methodology section of this study adopts a dynamic panel model by incorporating the lagged variable of poverty, resulting in the specification shown in (see **Equation** (2)):

$$Pov_{it} = \alpha + \rho Pov_{i,t-1} + \beta_1 HDI_{it} + \beta_2 OUR_{it} + \beta_3 Electr_{it} + \mu_i + \varepsilon_{it} \tag{2}$$

where:

Pov_{it} : percentage of poor population in region i at time t,
HDI_{it}, OUR_{it}, Electr_{it} : values of Human Development Index, Open Unemployment Rate, and Electrification Ratio, respectively
ρ : lag coefficient of poverty, capturing temporal dynamics (persistence),
ε_{it} : error term.

The System-GMM approach is selected due to its advantages in:

1. Addressing endogeneity, particularly the potential two-way relationship between poverty and the independent variables,
2. Controlling for unobserved heterogeneity across regions,
3. Capturing poverty persistence, which reflects how past poverty conditions influence current outcomes.

This model uses internal instruments derived from the transformation of the variables themselves (through first-difference and level equations), ensuring more efficient and unbiased estimations [18].

3.2 Statistical Testing

To ensure the validity and reliability of the System-GMM model estimation used in this study, several statistical tests are conducted. Multicollinearity is assessed using the Variance Inflation Factor (VIF) to detect high correlations among independent variables that may compromise the stability of the estimates. Furthermore, unit root tests are performed using either the Levin-Lin-Chu method or the Augmented Dickey-Fuller (ADF) test to verify the stationarity of the panel data—an essential prerequisite for dynamic regression.

To test the validity of instruments employed in GMM, the Sargan Test is applied to evaluate whether the instruments are free from over-identification problems. Lastly, the Arellano-Bond Test is used to examine autocorrelation in the model residuals, particularly at the first and second orders, which, if left unaddressed, could bias the estimations [**?**].

3.3 Arellano-Bond Test for Serial Correlation

The Arellano-Bond test is applied to detect serial correlation in the error terms of the first-differenced equation. In dynamic panel models, first-order serial correlation is expected due to differencing, but the absence of second-order correlation is crucial for the consistency of the System-GMM estimator. Rejecting the null hypothesis at AR(1) but not at AR(2) validates the appropriateness of the model specification .

4. RESULT & DISCUSSION

4.1 Descriptive Statistics of Variables

Descriptive statistics provide a preliminary overview of the characteristics of the panel data comprising 22 regencies/municipalities in East Nusa Tenggara (NTT) during the 2015–2019 period. The average poverty rate is recorded at 24.17%, with considerable interregional variation (ranging from 15.82% to 38.85%), reflecting high socio-economic vulnerability [2].

Table 2. Descriptive Statistics of Research Variables

Variable	Unit	Mean	Min	Max	Standard Deviation
Poverty Rate	Percent (%)	24.17	15.82	38.85	5.12
HDI	Scale (0–100)	62.94	54.67	72.88	3.41
Open Unemployment Rate	Percent (%)	3.52	1.42	7.10	1.08
Electrification Ratio	Percent (%)	64.73	24.50	95.00	15.91

The average Human Development Index (HDI) value of 62.94 indicates that human development in most regions of NTT still requires improvement. Meanwhile, the variations in the Open Unemployment Rate (3.52%) and the Electrification Ratio (64.73%) show significant disparities in regional socio-economic conditions [2]. This descriptive information serves as a critical foundation for understanding the regional context before conducting further statistical model estimation.

4.2 Estimation Results of the Dynamic Panel Model

The System-GMM method allows the inclusion of the lagged dependent variable (poverty) as a predictor, providing insight into the persistence of poverty across regions. Moreover, the model employs internally generated instruments from valid variable transformations to produce robust estimates [13].

Table 3. Short-Run and Long-Run Elasticity Coefficients

Variable	Short-Run Elasticity	Long-Run Elasticity
HDI	-0.984	-2.244
OUR	$+0.016$	$+0.036$
Electrification Ratio	-0.035	-0.081

Based on the estimation results in **Table 3**, empirical prediction models can be formulated to explain the impact of the independent variables on poverty levels in both the short and long run.

Short-Run Model:

$$Pov_{it} = -0.984\, HDI_{it} + 0.016\, OUR_{it} - 0.035\, Electr_{it} + \varepsilon_{it}$$

Long-Run Model:

$$Pov_{it} = -2.244\, HDI_{it} + 0.036\, OUR_{it} - 0.081\, Electr_{it} + \varepsilon_{it}$$

4.3 Human Development Index (HDI)

The results show that an increase in the Human Development Index (HDI) has a significant negative effect on poverty. In the short run, a 1% increase in HDI reduces poverty by 0.984%, while in the long run, the effect becomes stronger, reducing poverty by 2.244%. This indicates that improvements in education, health, and living standards have a cumulative and sustained effect on poverty alleviation over time [2], [4].

4.4 Open Unemployment Rate (OUR)

In contrast, the Open Unemployment Rate (OUR) exhibits a positive relationship with poverty, although with relatively small elasticity values. In the short run, a 1% increase in unemployment raises poverty by 0.016%, while in the long run, the effect increases to 0.036%. This finding is consistent with labor market theory, as higher unemployment limits access to income and exacerbates poverty conditions [2], [5].

4.5 Electrification Ratio

Meanwhile, the electrification ratio (ER) demonstrates a negative and statistically significant impact on poverty. A 1% increase in electrification reduces poverty by 0.035% in the short run and by 0.081% in the long run. This suggests that broader access to electricity not only directly improves household living standards but also enhances economic productivity and entrepreneurial opportunities in the long run [2].

For illustration, a 5% increase in HDI is predicted to reduce poverty by approximately 4.92% in the short run and 11.22% in the long run. Similarly, a 10% increase in the electrification ratio is expected to lower poverty by about 0.35% in the short run and 0.81% in the long run. These simulations reinforce the empirical evidence that strategies aimed at improving human capital and basic infrastructure contribute substantially to accelerating poverty reduction in East Nusa Tenggara.

4.6 Interpretation of Elasticity Coefficients and GMM Process

Instrument validity was tested using the Sargan Test and Hansen J Test. The Sargan test result (p-value = 0.231) indicates no over-identification problem, thus confirming the statistical acceptability of the instruments used. The Hansen J test also produced a p-value of 0.384, further confirming that the instrument set is uncorrelated with the residuals.

The diagnostic results confirm the validity of the System-GMM estimation. The Arellano-Bond test shows significant first-order autocorrelation (AR(1)): z = -2.71, p = 0.006), which is expected in differenced models, while the absence of second-order autocorrelation (AR(2)): z = -0.98, p = 0.325) indicates that the model satisfies the key consistency requirement. Together with the Sargan and Hansen tests confirming instrument validity, these results ensure that the elasticity coefficients reported are robust and reliable. [13], [14], [15], [16].

In substantive terms, the estimated elasticities provide important policy insights. A 1% increase in the Human Development Index reduces poverty by 0.984% in the short run and 2.244% in the long run, demonstrating that investments in education, health, and living standards generate both immediate and cumulative effects in alleviating poverty. Conversely, a 1% increase in the Open Unemployment Rate leads to a rise in poverty of 0.016% in the short run and 0.036% in the long run, underscoring the structural vulnerability of households in NTT to labor market shocks. Similarly, the electrification ratio shows negative and significant elasticities (-0.035 short run; -0.081 long run), highlighting the role of improved access to electricity not only in raising household welfare but also in enhancing long-term economic opportunities in rural and remote areas [2].

These findings imply that poverty reduction strategies in NTT should prioritize simultaneous improvements in human capital, employment creation, and rural infrastructure. The robust validity of the GMM results ensures that these policy recommendations are supported by consistent and unbiased statistical evidence.

With this statistical foundation, the interpretation of both short-run and long-run elasticity coefficients is valid, reliable, and credible. The use of System-GMM ensures that the effects of HDI, unemployment, and electrification on poverty are estimated robustly against endogeneity bias and dynamic panel structure.

4.7 Methodological Relevance in Regional Context

The application of the System-GMM method is highly relevant in the context of regions like NTT, which exhibit distinct socio-economic dynamics and high potential endogeneity among variables. Given the short time span (2015–2019) and a reasonably large number of cross-sectional units (22 regencies/municipalities), this model is well-suited for analysis as it satisfies the efficiency assumptions of estimators in moderate N and T panel data settings [2].

5. CONCLUSION

This study not only examines the dynamics of the Human Development Index (HDI), Open Unemployment Rate (OUR), and electrification ratio in influencing poverty levels in East Nusa Tenggara (NTT) Province, but also methodologically emphasizes the application of a dynamic panel data model using the System-Generalized Method of Moments (System-GMM) approach. This method is employed to address the issues of endogeneity, cross-sectional heterogeneity, and temporal dynamics in the five-year panel data spanning 22 regencies/municipalities.

The GMM model estimation results indicate that all three key variables have statistically significant effects on poverty. A 1% increase in HDI is associated with a 0.984% decrease in poverty in the short term and a 2.244% decrease in the long term. These findings underscore the importance of improving human capital—through education, healthcare, and living standards—as a sustainable poverty alleviation strategy.

The Open Unemployment Rate exerts a positive and significant influence, whereby a 1% increase in OUR leads to a 0.016% rise in poverty in the short term and a 0.036% rise in the long term. These results reinforce the need for targeted interventions aimed at enhancing labor market absorption capacity, particularly in high-poverty-risk areas.

Meanwhile, a 1% increase in the electrification ratio is correlated with a 0.035% decrease in poverty in the short term and a 0.081% decrease in the long term. This highlights the structural impact of access to electricity on the economic and social well-being of the population.

Overall, the application of the System-GMM method has proven effective in capturing the dynamic relationships between development variables and poverty, yielding results that are robust to simultaneity bias and unobserved heterogeneity. Therefore, this study offers not only substantive contributions regarding the determinants of poverty but also methodological contributions in the context of statistical modeling for regional panel data.

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