Regional disparities and spatial convergence of multidimensional energy poverty in Indonesia

Ikhlasul A'mal*, Fitri Kartiasih
Politeknik Statistika STIS, Jakarta, Indonesia

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Abstract

Energy plays a fundamental role in advancing global sustainability across social, economic, and environmental dimensions. The issue of access to adequate and affordable modern energy remains a crucial problem in various countries, including Indonesia. This condition reflects energy poverty, which has a widespread impact on all aspects of community life. This study investigates the convergence of energy poverty across Indonesian provinces during 2016–2024, using balanced panel data comprising 306 observations. This analysis utilizes 34 provinces to ensure data consistency throughout the research period, particularly for the development of the Multidimensional Energy Poverty Index (MEPI). Sigma convergence is assessed by examining the evolution of cross-sectional variation in MEPI, while beta convergence is tested using a spatial dynamic panel analysis. The research results indicate that energy poverty across provinces experienced both sigma and beta convergence. Per capita GRDP, urbanization rate, energy prices, higher education level, and regional spatial influence play an essential role in accelerating the process of energy poverty convergence. Based on these findings, the government is expected to strengthen policies that support the expansion of access to modern energy, as well as encourage the role of socioeconomic factors to accelerate the process of energy equalization across regions.

Keywords: modern energy; energy poverty; spatial convergence; spatial dynamic panel
JEL Classification: Q4; R11; C23

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*Corresponding Author : 212112105@stis.ac.id

1. Introduction

Energy use serves as a key catalyst for advancing human welfare and economic growth (Kartiasih, Syaukat and Anggraeni, 2012). In this regard, discussions about energy often emphasize accessibility and affordability, particularly in the context of modern energy. Modern energy has become a global concern due to its crucial role in driving economic, social, and environmental sustainability (Gunnarsdottir *et al.*, 2021). In this context, we focus on two primary indicators: electricity and cooking fuels, which include electricity, liquefied petroleum gas (LPG), and city gas/natural gas. Affordable, sustainable access to modern energy has become a prerequisite for improving people's quality of life. Global commitment to this issue is also reflected in the Sustainable Development Goals (SDGs), particularly in Goal 7, which explicitly targets universal access to modern energy services, especially for developing countries (Poblete-Cazenave *et al.*, 2021).

However, the issue of access to modern energy remains a global concern to this day. According to World Bank data, in 2019, around 8.6% of the world's population still lacked access to electricity, and approximately 26% of the world's population also did not have access to modern energy for cooking (Jayasinghe, Selvanathan and Selvanathan, 2021). The global energy conditions cause most households to experience problems in consuming daily energy (Drescher and Janzen, 2021), which is often associated with energy poverty.

The problem of energy poverty undoubtedly exists in Indonesia. Managing the energy trilemma, energy security, affordability/energy poverty, and climate change mitigation, is a major challenge in national energy governance (Muzayanah *et al.*, 2022). Although Indonesia's per capita energy consumption has increased in recent years, it is still relatively low, at around 8.37 MWh, placing Indonesia fourth in the ASEAN region. Other energy access indicators also reflect progress: the electrification rate reached 99.78% and household LPG usage reached 86.91% in 2023. However, this progress only reflects the national condition in aggregate and does not necessarily represent equal access across all regions.

In contrast, Indonesia's energy sector has significant economic value. According to the International Trade Administration (ITA), total energy exports reached USD 82.2 billion in 2022. They remained in the range of USD 68.7 billion in 2024, demonstrating Indonesia's strategic position in the global energy market. However, the size of this market value does not automatically guarantee equal access to energy for the public. Geographical challenges, high distribution costs, and limited infrastructure keep remote and underdeveloped areas behind, potentially leading to a continued significant energy gap between regions (Setyowati, 2021; Erdiwansyah *et al.*, 2021).

The Indonesian government has implemented several initiatives to improve access to modern energy services, such as the LPG conversion program, the development of electricity infrastructure, and tariff subsidies for low-income households. The steps taken by the government have indeed proven capable of increasing access to modern energy. However, this is not yet widespread, as many people still lack access to modern energy services. Data from BPS-Statistics Indonesia, as of 2024, indicates that some villages still lack access to electricity, particularly in the provinces of Papua, Nusa Tenggara Timur, and Sumatra Utara. The availability of clean energy for cooking also shows the same condition. The results of the National Socioeconomic Survey (*Susenas*) reveal disparities in access between western regions, which have almost completely transitioned to clean energy sources, and eastern regions, which still rely on dirty energy sources such as firewood and charcoal.

Nevertheless, in the long run, regions with a high number of villages without electricity and dirty energy users for cooking in the initial period experienced the most significant decline compared to areas that already showed low figures. This pattern indicates the initial hypothesis of energy poverty convergence in Indonesia. Convergence in this context refers to the condition in which a lagging region experiences faster improvement than a more advanced region, thereby gradually reducing interregional disparities (Battisti, Di Vaio and Zeira, 2022). This sends a positive signal toward achieving energy justice in the medium-to long-term.

In macroeconomic studies, the term convergence is often used to explain the dynamics of economic growth between (Islam, 1995). In energy studies, this concept has evolved into an analytical tool for examining whether there is a pattern of decreasing disparity in energy access and use across regions. Several empirical studies have found convergence in various energy indicators, such as energy consumption and energy poverty, at both the global and regional levels (Ngoc and Khoi, 2021; Huang, Ming and Duan, 2022; Salman, Zha and Wang, 2022; Anastasiou and Zaroutieri, 2023). Findings from Salman, Zha and Wang (2022), who studied global convergence in energy poverty, found that each country exhibits a distinct convergence pattern. Several developing countries, such as the Philippines, India, Vietnam, Indonesia, and Thailand, demonstrate bottom-up convergence, starting with high levels of energy poverty and showing steady improvement. However, the pace of convergence often remains moderate due to challenges like unequal infrastructure, reliance on traditional fuels, and geographical constraints. Beyond global analysis, further evidence from ASEAN was provided by Ngoc and Khoi (2021), who confirmed β-convergence in per capita electricity consumption across the 10 ASEAN countries and highlighted strong spatial dependence. Although their study did not focus on multidimensional energy poverty, the ASEAN findings provide a relevant regional benchmark that strengthens the rationale for examining convergence patterns in provincial energy poverty in Indonesia. Collectively, these studies underscore the importance of assessing convergence at the regional level, particularly for developing countries, to inform more targeted and effective policymaking.

Many academics have studied the convergence of energy poverty, but most of their work still focuses on the national level (Huang, Ming and Duan, 2022; Salman, Zha and Wang, 2022; *et al.*, 2024). Given the uneven distribution of modern energy access across Indonesian provinces, it is essential to examine energy poverty convergence at the subnational level. Statistically, data from BPS-Statistics Indonesia show that the availability of modern energy varies considerably across provinces and changes from year to year. This variation reflects development gaps and differences in spatial characteristics, infrastructure, and energy distribution, which highlights the importance of considering the spatial dimension in the analysis (Jia and Wu, 2022; Lu and Ren, 2024).

Existing studies in Indonesia remain limited. Previous work has focused mainly on energy intensity (Azaliah *et al.*, 2024), while research on convergence in energy poverty using household-based indicators is still lacking. Moreover, no study has explicitly examined whether provinces in Indonesia exhibit absolute and conditional beta convergence of energy poverty, accounting for spatial dependence.

This study seeks to fill that gap by analyzing the dynamics of energy poverty convergence across 34 provinces in Indonesia during 2016–2024. Energy poverty is measured using the Multidimensional Energy Poverty Index (MEPI), while sigma convergence is tested through the evolution of cross-sectional variation and beta convergence is estimated using a spatial dynamic panel framework. Specifically, this study aims to answer two questions: (i) does energy poverty in Indonesia experience absolute and conditional beta convergence across provinces when spatial effects are considered? and (ii) which socioeconomic and regional factors play a role in accelerating convergence?

Energy poverty has become a significant challenge hindering the achievement of sustainable development, particularly in developing countries that still face gaps in energy access. Energy poverty is defined as the lack of sufficient options to access adequate, affordable, reliable, high-quality, safe, and environmentally friendly energy services to support economic and human development (Sy and Mokaddem, 2022). The consequences of energy poverty encompass various aspects of life, including the economy, health, education, and the environment, and can hinder social and economic progress. Limited access to modern energy drives communities' reliance on traditional fuels for cooking (firewood, charcoal, and kerosene), which produces harmful pollutants such as carbon monoxide, sulfur dioxide, and delicate particulate matter, and increases the risk of acute respiratory infections, cardiovascular disease, and even premature death (Lee and Yuan, 2024). Limited access to electricity in households, especially for nighttime lighting, can restrict the quality of school-aged children's learning activities (George E Halkos and Gkampoura, 2021). Not only that, the low availability of energy as a primary input is directly proportional to low productivity, which significantly impacts sustainable economic development, especially in developing countries (Amin *et al.*, 2020; Kartiasih and Setiawan, 2020; Doğanalp, Ozsolak and Aslan, 2021).

Beyond its technical and economic dimensions, energy poverty is also understood as a social justice issue through the lens of energy justice. This framework emphasizes that the unequal distribution of energy benefits and burdens, minimal community involvement in decision-making processes, and the neglect of vulnerable groups are forms of energy injustice that deepen the vulnerability of energy-poor households (Sovacool, 2012; Jenkins *et al.*, 2016). In the Indonesian context, energy injustice is reflected in geographical disparities, particularly in remote and island regions, where high distribution costs, limited infrastructure, and unequal access to energy persist. Thus, the socio-economic and spatial factors that shape energy poverty are not merely technical issues but also reflect structural inequalities within the national energy system.

Understanding of energy poverty continues to evolve from a purely technical issue to a complex socioeconomic and spatial one. After considering the energy justice aspect, which highlights the unequal distribution of energy services, the literature also emphasizes that various structural factors shape households' vulnerability to energy poverty. Generally, the driving factors of energy poverty can be grouped into three aspects: socioeconomic, regional structure, and sociodemographic characteristics. Socioeconomic characteristics include aspects of society's economic conditions, such as income and energy prices. Huang, Ming and Duan (2022) state that households with higher incomes are more able to purchase and use modern energy to meet their daily needs. This condition aligns with the energy ladder hypothesis, which describes the transition of households from using more traditional energy to more modern energy as their well-being or income increases (Meried, 2021). Meanwhile, energy prices reflect the cost consumers must pay to obtain a specific unit of energy. Energy prices in a region significantly affect the affordability of modern energy for all segments of society. When prices rise, there are consequences for limited access to modern energy for certain groups, such as low-income groups (Cyrek *et al.*, 2024). This condition creates a substitution effect, in which households shift their consumption from modern energy to cheaper traditional energy sources, thereby potentially exacerbating energy poverty.

Regarding the structural characteristics of the region, Mahumane and Mulder (2022) and Lyu *et al.* (2023) state that urbanization is one of the factors that can influence energy poverty in a region. Urbanization generally improves household access to modern energy due to the development of energy infrastructure and the availability of cleaner and more efficient energy technologies in urban areas (Dong, Dou and Jiang, 2022). At the same time, education plays a crucial role in shaping household energy choices. A higher level of education not only increases awareness and responsiveness to energy efficiency policies but also enhances the likelihood of adopting electricity and clean fuels (Drescher and Janzen, 2021; Dong, Dou and Jiang, 2022; Said, 2024). Moreover, education contributes to better economic opportunities and higher purchasing power, thereby strengthening households' ability to access modern energy services.

2. Methodology

This study employs balanced panel data covering 34 provinces in Indonesia over the period 2016–2024. The analysis is conducted at the provincial level based on the administrative division of 34 provinces, prior to the expansion into 38 provinces. Accordingly, provinces that were later divided are still incorporated in the analysis by merging them with their original provinces. This approach ensures a consistent and comprehensive representation of interprovincial conditions throughout the study period. The research period of 2016–2024 was selected due to the consistent and updated availability of data across all variables, particularly for the calculation of the MEPI variable, which is derived from the *Susenas*.

The dataset is primarily obtained from BPS–Statistics Indonesia, drawing on raw data from the National Socioeconomic Survey (*Susenas*) and complemented by several official publications, including the People's Welfare Statistics, Indonesian Labor Market Indicators, and the Regional Gross Domestic Product of Provinces in Indonesia. Table 1 provides an overview of the variables employed in the study, detailing their definitions, notations, measurement units, and data sources.

Energy poverty still lacks a uniform and universally accepted definition at both internationally and regionally level (Kashour and Jaber, 2024). The complexity of this concept has created challenges in its measurement. Several researchers have sought to develop appropriate metrics, including composite indices that simplify diverse information into standardized levels and scales, making them easier to analyze. In this study, energy poverty is measured using the Multidimensional Energy Poverty Index (MEPI) proposed by Nussbaumer, Bazilian and Modi (2012). The MEPI is calculated through the Alkire-Foster method developed by the Oxford Poverty and Human Development Initiative (OPHI), which determines energy poverty based on household deprivations across five dimensions: cooking, lighting, household appliances, entertainment/education, and communication (Table 2). The resulting index ranges from 0 to 1. However, the indoor pollution indicator cannot be applied in this study due to data limitations in Indonesia, particularly the absence of such information in the Susenas.

Table 1.
Definitions of research variables and data sources

Variable	Notation	Definition	Units	Source
Multidimensional Energy Poverty Index	MEPI	Composite index is structured based on five dimensions: cooking, lighting, household appliances, entertainment or education, and communication, with a value range of 0-1	index	Author's calculations from raw data *Susenas*
Per Capita Gross Regional Domestic Product (GRDP)	PGRDP	The total value of final goods and services produced from all economic activities in a region, divided by the population of that region. Per capita GRDP used is based on constant market prices (2010=100)	thousand rupiah	BPS-Statistics Indonesia
Urbanization rate	URBAN	Percentage of the population living in urban areas compared to the total population of each province in Indonesia	percent	BPS-Statistics Indonesia
Electricity prices	PRICE	Average electricity tariff per kilowatt-hour (kWh) paid by household consumers of each province in Indonesia	kWh/ rupiah	BPS-Statistics Indonesia
High education rate	EDU	Percentage of workers with higher education compared to the total working population of each province in Indonesia	percent	BPS-Statistics Indonesia

Source: Processed by Author

In analyzing energy poverty convergence, this study incorporates several independent variables supported by previous empirical findings. Socioeconomic characteristics are represented by per capita Gross Regional Domestic Product (GRDP) and energy prices. GRDP per capita serves as a proxy for average income and welfare levels, measured at constant 2010 prices to eliminate inflation effects and better reflect real regional economic growth. Energy prices are represented by household electricity tariffs, measured as the average cost per kilowatt-hour (kWh) paid by household consumers in each province, based on *Susenas* data. Electricity prices are used because they constitute a primary indicator of household energy expenditure, given electricity's central role in modern energy consumption, including lighting, household appliances, and other basic needs.

In addition, structural and sociodemographic factors are considered. The level of urbanization is measured using *Susenas* data on household classification by residential area (urban or rural). This variable reflects the degree of urban development in a region, which is typically associated with better energy-related infrastructure. Education, identified as the most influential sociodemographic factor in previous studies, is measured by the percentage of the employed population with higher education qualifications (diploma, bachelor's, master's, doctoral, or professional degrees) in each province. This variable reflects the quality of human resources, which affects productivity, technological adaptability, and purchasing power, thereby influencing access to modern energy.

Table 2.
Dimensions and corresponding indicators with deprivation cut-offs, including relative weights

Dimensions: Indicators	Deprivation Cut-Off (poor if ...)	Weight	
		Nussbaumer et al. (2012)	Indonesia Study
Cooking: Modern cooking fuel	Households use traditional fuel such as firewood, charcoal, and kerosene.	0.200	0.400
Cooking: Indoor pollution	Households cook on a stove or open fire (no hood/chimney), indoors, using fuels such as firewood, charcoal, and kerosene	0.200	N.A.
Lighting: Electricity access	Households does not have access to electric lighting	0.200	0.202
Household appliances: Household appliance ownership	Households does not own a refrigerator	0.133	0.134
Entertainment/Education: Entertainment or education appliance ownership	Households does not own either a television or a computer/laptop	0.133	0.132
Communication: Telecommunication means	Household does not own a landline or mobile phone	0.133	0.132
Total Weight		**1.000**	**1.000**

Source: Processed by Author

In the context of energy poverty across Indonesian regions, the study uses a dynamic spatial panel data regression model to examine both absolute and conditional beta convergence. Following the econometric framework of Hao and Peng (2017), the rate of convergence in energy poverty is assessed using the coefficient δ associated with the lagged dependent variable in the estimation model. Convergence is said to occur if $\delta < 1$ and is statistically significant, indicating that energy poverty between provinces tends to move towards long-term equilibrium. The smaller the value of δ, the faster the convergence process occurs. To test for absolute beta convergence, the model is estimated without accounting for spatial effects using a dynamic panel regression. This is in line with argument by Spiru (2008), which states that absolute beta convergence does not depend on the specific characteristics of the observation units, such as economic or geographical factors.

The dynamic panel data regression model for testing absolute β-convergence is presented in Equation (1). This specification represents the baseline non-spatial dynamic model, where convergence is assessed by examining the effect of the lagged level of energy poverty on its current value.

$$MEPI_{it} = \delta\, MEPI_{i(t-1)} + \varepsilon_{it} \tag{1}$$

In Equation (1), $MEPI_{it}$denotes the Multidimensional Energy Poverty Index in province i at time t, while $MEPI_{i(t-1)}$represents its one-period lag. The coefficient δcaptures the speed of convergence, with a value less than 1 indicating the presence of absolute β-convergence in energy poverty across provinces. The error term ε_{it}reflects idiosyncratic shocks. Considering the potential spatial interdependence between provinces in Indonesia and the presence of temporal dynamics, this study extends the baseline specification in Equation (1) by employing a Dynamic Spatial Lag Model (SDM) to analyze energy poverty convergence during the period 2016–2024. This model allows energy poverty conditions in one province to be influenced not only by its own past values but also by the energy poverty levels of geographically connected provinces.

To represent spatial structure, this study constructs a customized spatial weight matrix that incorporates both geographic proximity and non-geographic connectivity. Geographic proximity is defined using the k-nearest neighbors (k-NN) approach with $k = 3$, which is more suitable for Indonesia's archipelagic structure, where shared land borders do not always capture spatial interactions. In addition, a non-geographical, data-based component capturing inter-provincial migration flows is incorporated to reflect socio-economic interactions that may influence energy demand patterns and the spatial transmission of energy poverty (Bu et al., 2022). To ensure that the choice of spatial weight specification does not drive the empirical results, a sensitivity analysis is conducted using alternative spatial matrices commonly applied in spatial econometric studies: (i) an inverse-distance matrix and (ii) a queen contiguity matrix of order two. Robustness is evaluated by assessing whether (a) the sign and statistical significance of key parameters remain stable across specifications and (b) Moran's I statistics confirm the presence of spatial autocorrelation in the MEPI variable under different spatial weight matrices. This procedure follows the recommendations of Anselin (1988) and Elhorst et al. (2014) regarding robustness checks in spatial panel modelling.

The spatial model determination is based on the results of the Lagrange Multiplier (LM) and robust LM tests to determine the most appropriate model specification according to the methodological framework by Elhorst *et al.* (2014). In this context, conditional beta convergence is analyzed by explicitly incorporating spatial effects and adding control variables such as per capita GDP, urbanization, energy prices, and education levels, which reflect the different structural conditions of the region. The dynamic spatial lag model in this study is shown in Equation (2).

$$\begin{aligned} MEPI_{it} = {} & \delta\, MEPI_{i(t-1)} + \rho \textstyle\sum_{j=1}^{n} w_{ij}\, MEPI_{jt} + \beta_1\, ln(PGRDP_{it}) + \beta_2\, URBAN_{it} \\ & + \beta_3\, ln(PRICE_{it}) + \beta_4\, EDU_{it} + \varepsilon_{it} \end{aligned} \tag{2}$$

In Equation (2), $MEPI_{it}$denotes the Multidimensional Energy Poverty Index in province i at time t. The coefficient δcaptures the degree of dynamic persistence in energy poverty through the inclusion of the one-period lagged dependent variable $MEPI_{i(t-1)}$. The term $\sum_{j=1}^{n} w_{ij}\, MEPI_{jt}$ represents the spatial lag of energy poverty, where w_{ij} denotes the elements of the spatial weight matrix that quantify the spatial interaction between provinces i and j, and ρ measures the magnitude of spatial spillover effects. The vector of control variables includes the natural logarithm of per capita Gross Regional Domestic Product ($\ln(PGRDP_{it})$), the urbanization rate ($URBAN_{it}$), the natural logarithm of electricity prices ($\ln(PRICE_{it})$), and the higher education attainment rate (EDU_{it}). The associated coefficients β_1–β_4 capture the influence of economic development, demographic structure, energy cost conditions, and human capital on energy poverty dynamics. The error term ε_{it} represents unobserved idiosyncratic shocks. This dynamic spatial lag specification allows the analysis of conditional β-convergence by jointly accounting for temporal dependence, spatial spillovers, and structural heterogeneity across provinces.

In this study, the dependent variable is the Multidimensional Energy Poverty Index (MEPI), which measures the level of energy poverty in province i at time t. The explanatory variables include provincial per capita Gross Regional Domestic Product (PGRDP), the urbanization rate (URBAN), electricity prices (PRICE), and the higher education attainment rate (EDU). These variables are included to capture differences in economic development, demographic structure, energy cost conditions, and human capital across provinces.

Sigma convergence analysis relates to the tendency for dispersion among regions to decrease. To measure the dispersion of energy poverty across regions, cross-sectional variation is used, as specified by the formula in equation (3).

$$\sigma_t^2 = \frac{1}{n}\sum_{i=1}^{n}(y_{it} - \mu_t)^2 \tag{3}$$

In Equation (3), σ_t^2 represents the cross-sectional variance of energy poverty across regions at time t, which is used to assess σ-convergence. The variable y_{it} denotes the level of energy poverty in region i at time t, while μ_t is the cross-sectional mean of energy poverty across all regions at time t. A declining trend in σ_t^2 over time indicates a reduction in regional dispersion of energy poverty, providing evidence of σ-convergence. Sigma convergence captures whether disparities in energy poverty across regions decrease over time, complementing the β-convergence analysis, which focuses on the speed at which initially disadvantaged regions catch up to more advanced ones. While σ-convergence examines changes in dispersion, β-convergence is assessed using dynamic panel models that account for temporal dependence through lagged variables.

Meanwhile, beta-convergence analysis aims to test whether lagging regions are improving faster than advanced regions. To capture the dynamics of time more accurately, this analysis is generally conducted within the framework of a dynamic model, which includes lagged variables.

In estimating Equation (1), which is a dynamic panel data model with a lagged dependent variable, this study uses the Generalized Method of Moments (GMM) estimation approach. Meanwhile, to estimate conditional beta convergence while considering spatial effects in Equation (2), this study uses the Spatially Corrected Blundell-Bond (SCBB) estimator. This approach is an extension of the System-GMM and has been adapted in the spatial literature to account for interdependence between geographical units in dynamic panel models.

The empirical analysis employs the System GMM estimator proposed by Arellano and Bover (1995) and Blundell and Bond (1998), which is appropriate for panels with a relatively small time dimension and persistent variables, such as provincial MEPI. The first-difference transformation removes time-invariant provincial fixed effects Arellano and Bond (1991), ensuring that unobserved heterogeneity across provinces is fully controlled for without the need to include province dummy variables explicitly. To maintain instrument validity and avoid instrument proliferation, we follow Roodman (2009) by limiting lag depth and collapsing instruments. All results are estimated using two-step GMM with Windmeijer-corrected standard errors (Windmeijer, 2005). Model specification checks include the Arellano–Bond AR(1) and AR(2) tests for serial correlation and the Hansen J-test for over-identifying restrictions.

For the GMM estimation results to be reliable, two main conditions must be met. First, the model should not experience second-order autocorrelation. To check this, Arellano and Bond (1991) recommend testing using AR(1) and AR(2) statistics, where the presence of autocorrelation is considered a problem if the test value is significant, leading to the rejection of the null hypothesis. Second, the validity of the instrumental variables is tested using the Sargant statistic. In this case, the null hypothesis states that the instruments are valid; if the test is significant, it indicates that the instruments are not suitable for the model.

3. Results and Discussion

Based on Table 3, the descriptive statistics show that the average MEPI across 34 provinces from 2016 to 2024 is 0.155, with a minimum of 0.0042 and a maximum of 0.651, indicating significant disparities in energy poverty levels between provinces. GDP per capita, as a proxy for community income, also shows considerable variation, with an average of around 43.96 thousand rupiah and a standard deviation of 32.92 thousand rupiah. Urbanization is recorded to have a relatively high average of 48.12 percent, meaning almost half of the population resides in urban areas. However, there is an interprovincial gap ranging from 20.27 percent to 100 percent. The price of electricity per kWh shows an average of 983.61 rupiah and a maximum of 1,615.57 rupiah, reflecting differences in energy costs that can affect household energy affordability. Additionally, higher education is represented by an average of 11.87 percent of workers with at least a diploma, ranging from 5.46 percent to 24.30 percent, indicating disparities in human resource capacity that can affect energy choices and household energy resilience in each province.

Energy poverty is measured using the MEPI approach, which ranges from 0 to 1. The higher the value, the greater the number of households experiencing energy poverty, or the worse the level of multidimensional energy poverty in a region. Based on the calculations, Indonesia's MEPI value has continued to decline from 2016 to 2024, from 0.2199 in 2016 to 0.1151 in 2024. If we look at the numbers, they indicate that Indonesia's multidimensional energy poverty level is not particularly concerning, as it falls into the low category (2016) and the very low category (2024). However, the national MEPI value may not accurately reflect the conditions between regions, so MEPI calculations were also conducted at the provincial level.

Table 3.
Summary Statistics

Variable	Units	Mean	Std. Deviation	Min.	Max.	Obs.
MEPI	index	0.155	0.138	0.004	0.651	306
PGRDP	thousand rupiah	43,956.410	32,921.300	11,468.800	201,315.130	306
URBAN	percent	48.120	18.590	20.270	100.000	306
PRICE	kWh/rupiah	983.610	212.580	384.770	1,615.570	306
EDU	percent	11.870	3.600	5.460	24.300	306

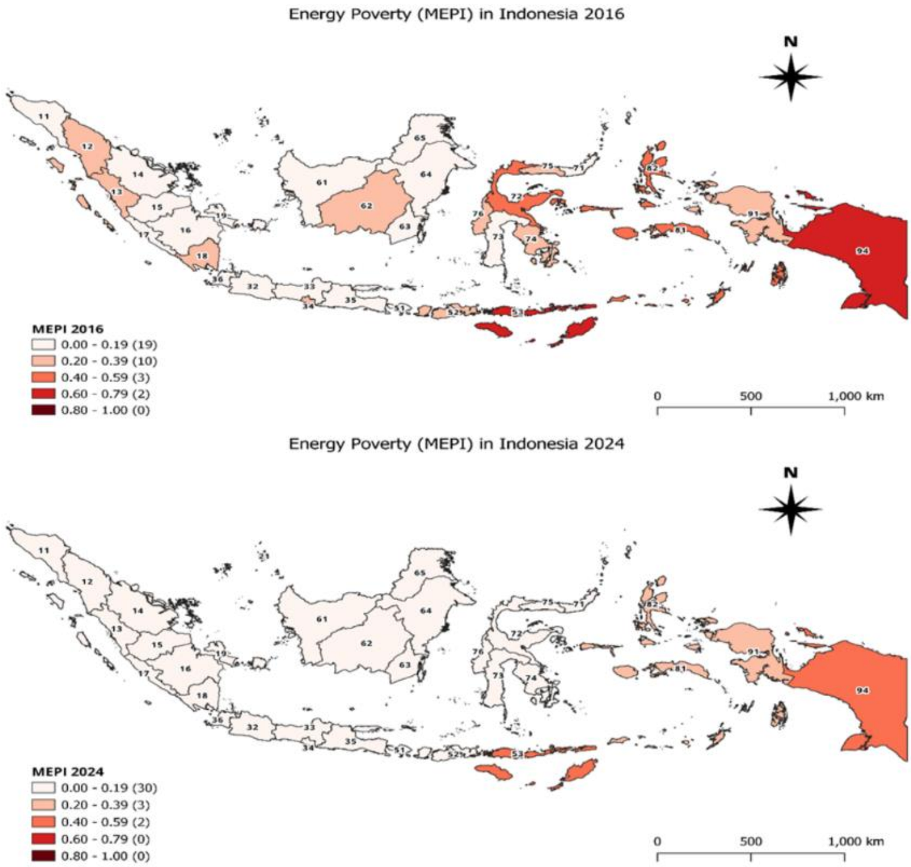
Source: Processed by Author

Figure 1 shows the comparison of MEPI value distribution between provinces at the beginning and end of the study period. The darker the colour displayed on the map, the higher the MEPI value of a province. The comparison of the two maps shows significant progress: in 2016, many provinces were still darkly coloured, indicating a high level of energy poverty. Meanwhile, in 2024, most provinces experienced a shift to a lighter shade, indicating a decrease in energy poverty levels. However, there are still disparities or gaps between regions. Provinces with high MEPI scores are concentrated in the eastern region, such as Papua and Nusa Tenggara Timur. On the other hand, the western region is dominated by provinces with low MEPI scores, ranging from 0 to 0.19.

The results of the dynamic panel data estimation are presented in Table 4, which reports the estimation outcomes for both absolute and conditional β-convergence in energy poverty. The absolute convergence model is estimated using the System Generalized Method of Moments (SYS-GMM) to address potential endogeneity arising from the inclusion of the lagged dependent variable and to control for unobserved heterogeneity. The conditional convergence specification is estimated using the Spatially Corrected Blundell–Bond (SCBB) estimator, which extends the dynamic panel framework by explicitly accounting for spatial dependence across provinces. This approach enables a more accurate assessment of convergence dynamics by incorporating potential spatial spillover effects in energy poverty. To estimate the parameters in the absolute β-convergence equation, a dynamic panel regression is employed, with the corresponding estimation results reported in Column (2) of Table 4.

Referring to Islam (1995), the lagged MEPI coefficient has a significant and positive impact of less than one, which means there is absolute beta convergence. This condition indicates that if it is assumed that all provinces have similar characteristics, then provinces with higher energy poverty levels tend to experience a faster decline in energy poverty than provinces with already low energy poverty levels. The disparity in energy poverty in Indonesia will decrease by 7.59 percent each year, so it will take about 9.13 years to reduce half of the energy poverty disparity that occurred at the beginning of the period.

Figure 1.
Spatial Distribution of Energy Poverty (MEPI) in Indonesia, 2016 and 2024



Source: Processed by Author

However, the analysis of absolute beta convergence has limitations for explaining the dynamics of energy poverty reduction because it considers only the lagged dependent variable, without controlling for other factors that may influence the convergence process. Thus, the analysis will continue with conditional beta convergence to examine the influence of different variables on the process of energy poverty convergence. To analyze conditional beta convergence, a dynamic spatial panel data regression model is used that accommodates spatial dependence between regions.

To identify the spatial correlation of energy poverty between provinces in Indonesia, Moran's I test was conducted. In this study, the Moran's I test used a modification of the spatial weighting matrix for panel data thru the Kronecker product. The results of the Moran's I test showed a p-value less than 0.05, indicating that energy poverty in Indonesia has a global spatial correlation, making it suitable for spatial analysis.

Table 4.
Dynamic panel estimation for energy poverty convergence

Variables	Absolute convergence SYS-GMM	Conditional convergence SCBB
MEPI (t-1)	0.927***	0.830***
	[0.000]	[0.000]
PGRDP (log)	–	−0.019***
		[0.000]
URBAN	–	−0.000***
		[0.006]
PRICE (log)	–	0.031***
		[0.000]
EDU	–	−0.001***
		[0.000]
W		
MEPI	–	0.109***
		[0.000]
AR(1)	−3.533***	−3.413***
	[0.000]	[0.001]
AR(2)	1.589	1.641
	[0.112]	[0.101]
Sargan	33.657	32.496
	[0.484]	[0.999]
Wald Test	1.75e+08***	275,600***
	[0.000]	[0.000]
Speed of Convergence (λ)	7.590	18.620
Half-life Convergence (t^*)	9.130	3.720

The value in the square brackets are the p-value.
Significant, *p<0.1, **p<0.5, ***p<0.01

Source: Processed by Author

The Lagrange Multiplier (LM) test is used to determine the most appropriate spatial effect specification for the model. Bouayad-Agha and Vedrine (2010) stated that the LM test is not yet available for development for dynamic panel data models, so this test is performed on static panel data models. Based on Table 5, the LM test results indicate that spatial dependence occurs in both the lag and error effects. Subsequently, further testing is needed using robust LM lag and robust LM error. The results of these tests indicate that spatial dependence only occurs in the lag effect, so the model suitable for analyzing conditional beta convergence is the Spatial Autoregressive (SAR) model.

It is also known that the lagged MEPI coefficient has a significant, positive impact of less than 1, indicating the presence of conditional beta convergence. This means that if provinces differ in characteristics, provinces with higher energy poverty levels tend to experience a faster decline than those with lower energy poverty levels. The disparity in energy poverty in Indonesia will decrease more rapidly, at a rate of 18.62

percent per year, and it can reduce half of the energy poverty disparity that occurred at the beginning of the period in just about 3.72 years. The spatial effect is reflected in the coefficient of 0.1086, which indicates a significant, positive spatial correlation with the level of energy poverty levels. These findings suggest the presence of spatial spillover between provinces, in which the energy poverty conditions in one area are influenced by those in surrounding areas.

Table 5.
Results of spatial dependence tests on the static panel regression model

LM test	Statistic	P-value
LM *lag*	190.911	0.000***
LM *error*	176.863	0.000***
Robust LM *lag*	14.756	0.000***
Robust LM *error*	0.708	0.400

Note: Significant, *p<0.1, **p<0.5, ***p<0.01

Source: Processed by Author

The results of this study indicate a negative and significant relationship between per capita GDP and the level of energy poverty. This study is in line with previous research conducted by Halkos and Gkampoura (2021), Barkat, Alsamara and Mimouni (2023), and Cyrek *et al.* (2024). A region with a high per capita GDP indicates that the average income of the community is also increasing. Thus, the ability of households to meet their energy needs will also increase, such as paying electricity and gas bills, or purchasing cooling appliances. This study also found that the urbanization rate has a negative relationship with energy poverty. This finding is consistent with studies conducted by George E. Halkos and Gkampoura (2021), which show that an increasing urbanization rate in a region can reduce the level of energy poverty in that region. A high urbanization rate plays a vital role in reducing energy poverty by increasing access to modern energy and energy efficiency, which is caused by better energy infrastructure development in urban areas (Dong, Dou and Jiang, 2022).

Energy prices have a positive relationship with energy poverty, which is in line with the findings of Cyrek *et al.* (2024) and George E Halkos and Gkampoura (2021). The increase in energy prices, especially electricity, will raise the financial burden on households to pay their energy bills. This forces them to reduce energy consumption or switch to traditional energy sources at lower prices, worsening energy poverty. Meanwhile, the relationship between higher education in this study was found to be negative and significantly affected energy poverty. These results are supported by previous research by Lyu *et al.* (2023) and Said (2024), which states that more educated individuals tend to understand better the importance of energy efficiency and its impact on the environment. Additionally, workers with higher levels of education tend to have better economic status, allowing them to access modern energy sources.

The results of the dynamic spatial panel regression model estimation discussed earlier confirm that convergence of energy poverty β occurs in Indonesia, both in absolute and conditional terms. This indicates that provinces with higher levels of energy poverty at the beginning of the period tend to experience faster growth compared to more advanced provinces, demonstrating a catch-up effect. These results also align with the results of the convergence test for σ, which was measured using cross-sectional variation. Based on Figure 2, the cross-sectional variation of MEPI in Indonesia shows a decreasing trend, from 0.0207 in 2016 to 0.0165 in 2020. However, there was a temporary increase in the value of cross-sectional variation in 2021 and 2023, driven by major economic shocks such as the COVID-19 pandemic and uneven post-pandemic economic recovery across regions (Brussevich, Liu and Papageorgiou, 2022). Although there was an increase in some years, overall, the cross-sectional variation value shows a decreasing trend from the initial to the final period. Thus, there is an indication of convergence in the MEPI across provinces in Indonesia, leading to a tendency for regional disparities to decrease over time.

Figure 2.
Cross-sectional variation in MEPI in Indonesia 2016-2024

Source: Processed by Author

To ensure the reliability of the dynamic spatial panel estimation results, a sensitivity test was conducted using various specifications of the spatial weight matrix, including K-nearest neighbors (k=3), inverse-distance, and Queen contiguity, combined with inter-provincial migration flows. The estimation results proved stable across all specifications (Appendix 1). The β-convergence coefficients remain positive and highly significant across all matrices (0.784–0.830), indicating that the evidence of provincial energy poverty convergence is not sensitive to the choice of spatial weights. Likewise, the spatial lag parameter is consistently positive and significant, and the global Moran's I value for MEPI remain substantial and significant under all specifications (0.662–0.814). These results confirm that both the convergence patterns and spatial spillovers are robust to alternative representations of spatial connectivity.

As a robustness check for the convergence finding, we estimated the dynamic model using the First-Difference GMM (FD-GMM) estimator. The results (Appendix 2) are consistent with the System GMM estimates, with the lagged MEPI coefficient remaining positive and significant, confirming the robustness of the β-convergence finding. The post-estimation diagnostics support model validity: the null hypothesis rejection criteria for the AR(2) test show no second-order serial correlation, and the Sargan/Hansen tests confirm that the instruments are valid because the Prob > Z values exceed 0.05. Overall, the FD-GMM results reinforce the robustness of the convergence conclusion.

4. Conclusion

This study analyzes the dynamics of energy poverty convergence among households across all provinces in Indonesia during the period 2016–2024 using a spatial dynamic panel model. Energy poverty, measured by the MEPI, declined during that period, but the decline was not uniform across all provinces, resulting in energy poverty gaps between provinces in Indonesia. Estimates of the beta convergence model confirm the occurrence of beta convergence in energy poverty levels across provinces. When all provinces have similar characteristics, the time required to reach half-convergence is 9.13 years, with a convergence rate of 7.59 percent. However, if the conditions of each province have different characteristics, in this case considering socioeconomic variables and aspects of inter-regional (spatial) connectivity, then the convergence of energy poverty rates between provinces will accelerate both in terms of time and the rate of convergence. This could indicate a narrowing of the energy poverty gap between provinces in Indonesia, supported by the contribution of socioeconomic variables and inter-regional connectivity.

The results of this research yield several essential policy recommendations, particularly regarding the equitable availability of modern energy access. First, the central and local governments need to strengthen and expand policies, such as the use of energy-efficient solar-powered lamps (LTSHE), especially in the eastern regions, which also have high solar energy potential. In addition, efforts need to be made to rebuild LPG terminals and distribute LPG sub-bases evenly across Indonesia to ensure subsidized LPG distribution reaches its target and prices remain affordable for the public. Second, formulating a comprehensive policy strategy in line with energy poverty factors, such as maintaining the sustainability of energy subsidies for low- and middle-income households, improving equitable access to education thru the development and improvement of educational infrastructure across all regions, and promoting the improvement of inter-regional infrastructure not only in terms of transportation (roads, bridges, ports) but also in terms of modern energy infrastructure including electricity grids, renewable energy generation, and energy storage facilities.

While this study contributes to the empirical literature on energy poverty convergence, it is not without limitations. First, the scope of analysis is restricted to the provincial level, which does not capture the dynamics of energy poverty at more micro levels, such as districts/cities or rural–urban areas. Second, the relatively short observation period of 9 years (2016–2024), constrained by the availability of *Susenas* data, may limit the ability to observe long-term convergence dynamics fully. Considering these limitations, future research should investigate energy poverty convergence at lower administrative levels and make use of household-based microdata, such as the Indonesian Family Life Survey (IFLS), which offers the potential for long-term panel analysis (if available). Such approaches would provide a more comprehensive understanding of the long-run trajectory of energy poverty convergence.

5. References

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Appendix 1. Sensitivity of dynamic spatial panel estimates to alternative spatial weight

Spatial Weight Matrix		β-convergence coefficient	Spatial lag coeffcient	Moran's I (MEPI)
Geographic	Non-Geographic			
KNN (k=3)	Migration	0.8301***	0.1085***	0.7730***
Inverse-distance	Migration	0.8260***	0.1074***	0.6620***
Queen contiguity	Migration	0.7843***	0.1367***	0.8140***

Note: Significant, *p<0.1, **p<0.5, ***p<0.01

Appendix 2. Robustness of β-convergence: First-Difference GMM results

Variables	Absolute convergence FD-GMM	Conditional convergence FD-GMM
MEPI (t-1)	0.7882***	0.6183***
	[0.0000]	[0.0000]
PGRDP (log)	–	−0.0394***
		[0.0000]
URBAN	–	0.0005***
		[0.0000]
PRICE (log)	–	0.0427***
		[0.0000]
EDU	–	−0.0005***
		[0.0000]
W		
MEPI	–	0.3074***
		[0.0000]
AR(1)	−3.5318***	−3.1513***
	[0.0004]	[0.0016]
AR(2)	1.5019	1.4246
	[0.1331]	[0.1543]
Sargan	30.8705	32.3385
	[0.2765]	[0.9915]
Wald Test	124202.21***	66012.44***
	[0.0000]	[0.0000]

Note: The value in the square brackets are the p-value. Significant, *p<0.1, **p<0.5, ***p<0.01