Renewable energy transition paradox: How capacity and consumption share differentially affect energy poverty in the European Union

Chatchai Khiewngamdee[1*], *Terdthiti* Chitkasame[1], and *Nachattapong* Kaewsompong[1]

[1]Center of Innovation in Economics Finance and Investment, Faculty of Economics, Chiang Mai University, Chaing Mai, Thailand, 50202

Abstract. This study examines the relationship between renewable energy deployment and energy poverty across 25 European Union member states from 2015 to 2023. Employing multiple panel regression specifications, we analyze how renewable electricity capacity per capita and renewable energy share affect energy poverty. Panel unit root tests confirm variable stationarity, enabling robust panel estimation. Results reveal a paradoxical relationship: renewable electricity capacity per capita demonstrates negative associations with energy poverty, while renewable energy share exhibits positive relationships in fixed effects models, suggesting that rapid renewable penetration increases temporarily exacerbate affordability challenges through transition-related costs. Income inequality emerges as the strongest predictor across all specifications. These findings indicate that achieving a just energy transition requires restructuring renewable energy financing mechanisms away from regressive consumer levies toward progressive funding sources, while implementing compensatory measures protecting vulnerable households from short-term transition costs that disproportionately burden low-income populations.

1 Introduction

Energy poverty remains a persistent challenge across European Union member states, affecting millions of households' ability to access affordable and adequate energy services. This multidimensional problem encompasses both the inability to maintain adequate home warmth and difficulties paying utility bills, with significant implications for health, wellbeing, and social equity. As the EU pursues ambitious renewable energy targets to achieve climate neutrality, understanding how this energy transition affects vulnerable populations has become increasingly critical for policymakers.

Recent scholarship reveals a nuanced and often contradictory relationship between renewable energy deployment and energy poverty outcomes. Several studies have documented renewable energy's potential to alleviate energy poverty through enhanced energy security and reduced dependence on volatile fossil fuel prices [1, 2]. However, emerging evidence suggests this relationship is more complex than initially assumed. Yüksel

* Corresponding author: chatchai.kh@cmu.ac.th

et al. [3] identified startup costs and geographical conditions as critical barriers to renewable energy projects effectively addressing energy poverty, while Kolati and Raghutla [4] found that renewable energy consumption and energy-related uncertainty can actually promote energy poverty in certain contexts. This paradoxical effect has been further substantiated by multiple European studies. Muhammad *et al.* [5] demonstrated that renewable energy at early transition stages does not reduce energy poverty but instead promotes energy price increases, while Simionescu and Cifuentes-Faura [6] documented how renewable energy simultaneously reduces some energy poverty indicators while exacerbating others, particularly through high taxes and surcharges associated with renewable deployment. Simionescu *et al.* [7] confirmed that renewable energy consumption per capita enhanced arrears on utility bills across EU countries from 2003 to 2021, and Soto *et al.* [8] identified an insufficient effect of renewable energy penetration on energy poverty reduction in the European Union from 2004 to 2022.

Theoretical explanations for these contradictory findings emphasize the importance of distinguishing between renewable energy capacity and consumption share, transition timing, and mediating mechanisms. Lee *et al.* [9] revealed that renewable energy technology innovation's effect on energy poverty is moderated by climate risk, exhibiting threshold effects whereby benefits materialize only after certain development levels. Wang *et al.* [10] found that marketization levels significantly influence how renewable energy technology innovation alleviates energy poverty, with effects varying substantially across regions. Beyond renewable energy characteristics, socioeconomic factors play fundamental roles in energy poverty dynamics. Income inequality consistently emerges as a significant predictor, with distributional considerations proving essential for understanding vulnerability patterns [6]. Economic development level, measured through GDP per capita, demonstrates strong negative associations with energy poverty across multiple studies, while foreign direct investment patterns have shown potential to alleviate energy demand pressure [8].

Despite this growing body of evidence, significant research gaps remain. Most studies focus on single renewable energy measures without comparing capacity versus consumption share effects and lack consensus on whether renewable energy impacts reflect cross-country differences or within-country transition dynamics, with limited panel evidence accounting for unobserved heterogeneity. This study addresses these gaps by employing multiple panel regression specifications to examine how both renewable electricity capacity per capita and renewable energy share relate to energy poverty across 25 EU member states from 2015 to 2023, while carefully controlling for economic development and income inequality. By distinguishing between pooled, fixed effects, and random effects estimates, we provide nuanced insights into whether renewable energy relationships with energy poverty primarily reflect structural cross-country differences or dynamic within-country transition processes.

2 Methodology

2.1 Panel unit root test

To ensure the reliability of our panel regression estimates and avoid spurious regression problems, we first test the stationarity properties of all variables in our dataset. We employ two complementary panel unit root tests to examine the stationarity of our variables: the Levin-Lin-Chu (LLC) test and the Fisher-type test.

The LLC test, proposed by Levin et al. [11], assumes a common unit root process across all cross-sectional units and tests the null hypothesis that all panels contain a unit root against the alternative that all panels are stationary. The test is based on the following augmented Dickey-Fuller (ADF) specification for each panel:

$$\Delta y_{it} = \alpha_i + \rho y_{it-1} + \sum_{k=1}^{n} \phi_{ik} \Delta y_{it-k} + \delta_i t + \theta_i + \varepsilon_{it}, \quad (1)$$

where y_{it} represents the variable of interest for country i at time t, α_i represents individual fixed effects, δ_{it} allows for panel-specific time trends, and θ_t captures time-specific effects. The parameter ρ is the number of lags included to address serial correlation, and ε_{it} is the error term. The LLC test evaluates whether $\rho = 0$ (unit root) against $\rho < 0$ (stationarity) under the assumption that the autoregressive coefficient ρ is homogeneous across panels.

The Fisher-type test, developed by Maddala and Wu [12] and Choi [13], provides a more flexible alternative by allowing for heterogeneity in the autoregressive coefficients across panels. This test combines the p-values from individual ADF tests for each cross-sectional unit using Fisher's [14] result that the test statistic:

$$P = -2 \sum_{i=1}^{N} ln(p_i) \quad (2)$$

follows a chi-square distribution with $2N$ degrees of freedom under the null hypothesis, where p_i is the p-value from the unit root test for panel i and N is the number of panels. The Fisher-type test is advantageous because it does not require a balanced panel and allows for heterogeneous autoregressive processes across countries, making it more suitable for our diverse sample of European Union member states.

2.2 Panel regression model

Following confirmation of stationarity, we estimate the relationship between renewable energy deployment and energy poverty using panel regression analysis. Panel data methodology offers several advantages over pure cross-sectional or time-series approaches, including increased sample size, greater degrees of freedom, reduced collinearity among variables, and the ability to control for unobserved heterogeneity across countries. We estimate four alternative panel regression specifications to assess the robustness of our findings and understand how different modelling assumptions influence the estimated relationships.

Following Wooldridge [15] and Hsiao [16], our baseline empirical model takes the following general form:

$$ENP_{it} = \beta_0 + \beta_1 ln(REC_{it}) + \beta_2 RES_{it} + \beta_3 ln(GDP_{it}) + \beta_4 INI_{it} + \mu_i + \lambda_t + \varepsilon_{it}, \quad (3)$$

where ENP_{it} represents energy poverty in country i at time t; $ln(REC_{it})$ is the natural logarithm of renewable electricity capacity per capita; RES_{it} is the renewable energy share in gross final energy consumption; $ln(GDP_{it})$ is the natural logarithm of GDP per capita; INI_{it} represents income inequality measured by the Gini coefficient; The component μ_i captures country-specific fixed effects, λ_t captures time fixed effects, and ε_{it} is the composite error term.

3 Data

This study employs an annual panel dataset comprising 25 European Union member states over the period 2015-2023, yielding 225 country-year observations. The selection of this timeframe allows us to capture recent developments in renewable energy deployment and energy poverty dynamics while maintaining data consistency across countries. Our dependent variable, energy poverty, is constructed following the multidimensional approach adapted from Muhammad [5], calculated as the average of two key indicators: the percentage of households with arrears on utility bills and the share of population unable to keep their homes adequately warm, both sourced from Eurostat. Higher values of this composite measure indicate greater prevalence of energy poverty. For our primary independent variables, we utilize two complementary proxies to capture different dimensions of renewable energy penetration. First, renewable electricity capacity per capita, obtained from Our World in Data, reflects the availability of renewable power infrastructure relative to population size. Second, the renewable energy share in gross final energy consumption, extracted from Eurostat's sustainable development goals database, represents the overall penetration of renewables in the national energy mix, encompassing electricity, heating and cooling, and transport sectors.

To address potential omitted variable bias and control for confounding factors, we incorporate two key macroeconomic control variables drawn from the World Bank's World Development Indicators. Specifically, we include GDP per capita, measured in constant international dollars to ensure cross-country comparability, as a proxy for overall economic development and living standards. Additionally, we control for income inequality using the Gini coefficient, which captures the distribution of equivalized disposable income within each country. This specification allows us to isolate the effect of renewable energy penetration on energy poverty while accounting for fundamental economic conditions and distributional factors that may independently influence households' ability to afford essential energy services. Table 1 presents the descriptive statistics for all variables used in the analysis.

Table 1. Descriptive statistics.

	ENP	REC	RES	GDP	INI
Mean	9.450	996.170	24.300	72.920	31.570
Median	6.800	837.040	21.560	70.740	31.600
Maximum	35.650	3606.290	66.390	98.190	41.300
Minimum	1.650	179.460	4.990	53.780	24.000
Std. Dev.	7.680	671.580	11.990	12.570	3.770
Skewness	1.470	1.590	1.020	0.220	0.120
Kurtosis	1.860	2.590	1.040	-1.040	-0.400
Jarque-Bera	115.660***	161.230***	50.138***	11.403***	3.047
Observations	225	225	225	225	225

*** indicate the significance levels at 1%

4 Empirical results and discussions

4.1 Panel unit root test result

Prior to conducting panel regression analysis, we examine the stationarity properties of all variables to ensure econometric validity and avoid spurious regression problems. Table 2 reports results from two complementary panel unit root tests: the Levin-Lin-Chu (LLC) test and the Fisher-type test. Both tests consistently reject the null hypothesis of a unit root for all variables at the 1% significance level, confirming that energy poverty, renewable electricity capacity per capita, renewable energy share, GDP per capita, and income inequality are all stationary processes integrated of order zero, I(0). These findings satisfy the stationarity requirement for standard panel regression techniques, allowing us to proceed with panel data estimation.

Table 2. Panel unit root test.

Variables	Levin-Lin-Chu test	Fisher-test
Energy poverty	-5.868***	258.360***
log(Renewable capacity per capita)	-11.553***	346.590***
Renewable energy share	-9.335***	-5.465***
log(GDP per capita)	-12.069***	587.480***
Income inequality	-72.409***	-21.786***

*** indicates the significance levels at 1%

4.2 Panel regression analysis

Table 3 presents estimation results from four alternative specifications: a bivariate model without control variables, pooled OLS, fixed effects, and random effects models. This approach allows us to assess robustness and understand how controlling for unobserved heterogeneity influences the estimated relationships.

Renewable electricity capacity per capita exhibits a consistently negative association with energy poverty across most specifications. In the pooled OLS model, a 1% increase in renewable capacity per capita corresponds to a 2.213 percentage point decrease in energy poverty. This relationship remains negative in the random effects model and the model without controls. However, the fixed effects specification yields a statistically insignificant coefficient, though maintaining the negative sign. This loss of significance likely reflects limited within-country temporal variation, as renewable capacity deployment has been gradual and path-dependent over the study period. The fixed effects estimator, relying exclusively on within-country changes, may lack sufficient identifying variation to precisely estimate this relationship. The negative relationship can be explained through several mechanisms. First, increased renewable capacity enhances energy security and reduces dependence on volatile fossil fuel prices, stabilizing household energy costs. Second, distributed renewable technologies (e.g., rooftop solar) enable households to generate their own electricity, directly reducing expenditures. Third, renewable capacity expansion often accompanies grid modernization, improving service reliability and reducing system costs.

In contrast, the relationship between renewable energy share and energy poverty presents a more complex picture. While the pooled OLS model shows a small, insignificant negative coefficient, the fixed effects specification reveals a significantly positive relationship. This suggests that within-country increases in renewable energy share are associated with higher energy poverty levels. This finding aligns with several recent empirical studies in the European context [5-8]. This counterintuitive finding likely reflects short-term transition costs. Policy mechanisms such as feed-in tariffs and renewable energy surcharges are often financed through electricity bill additions, disproportionately burdening lower-income households. Additionally, renewable intermittency necessitates investments in grid infrastructure and backup capacity, with costs passed to consumers. The divergence between pooled OLS and fixed effects results highlights the importance of distinguishing cross-sectional from within-country relationships. Pooled OLS captures both between-country differences (e.g., Nordic countries with high renewable shares and low energy poverty) and within-country changes. In contrast, fixed effects isolates within-country dynamics, suggesting that rapid renewable share increases may temporarily exacerbate energy poverty during transition phases. This aligns with a "renewable transition paradox" wherein long-term benefits for energy affordability may be preceded by short-term distributional challenges, as documented by Muhammad *et al.* [5] who showed that when renewable energy permeates the system and becomes a dominant energy supply source, it eventually helps reduce energy poverty.

https://doi.org/10.1051/e3sconf/202671206004

Regarding control variables, GDP per capita demonstrates a negative and significant relationship with energy poverty across all specifications. The magnitude varies substantially, with the fixed effects model yielding a particularly large coefficient compared to pooled OLS and random effects. The strong negative relationship is theoretically expected: higher economic development provides greater household purchasing power for essential energy services. Additionally, wealthier countries possess better housing stock, more developed social safety nets, and greater resources for energy infrastructure modernization. The exceptionally large fixed effects coefficient warrants attention. This magnitude suggests that within-country GDP changes have substantially stronger associations with energy poverty than cross-country differences. One explanation relates to our dependent variable's sensitivity to short-term economic fluctuations. Energy poverty indicators (utility bill arrears, inability to maintain warmth) respond rapidly to economic contractions and recoveries. Furthermore, the fixed effects specification controls for time-invariant characteristics (climate, housing infrastructure), isolating the direct impact of income fluctuations on households' capacity to meet energy needs.

Income inequality, measured by the Gini coefficient, exhibits a positive and highly significant relationship with energy poverty across all specifications. In pooled OLS, a one-point Gini increase associates with a 1.224 percentage point energy poverty increase. This remains strongly positive in fixed effects and random effects models. This finding is consistent with Simionescu and Cifuentes-Faura [6], who demonstrated that the Gini index, reflecting income inequality, shows a positive and significant association with all energy poverty indicators, highlighting the disproportionate burden of energy costs in poor homes. Greater income inequality implies more households occupy the lower income distribution tail, where vulnerability to energy poverty peaks. These households spend disproportionate income shares on energy, leaving them susceptible to price fluctuations. Moreover, inequality correlates with unequal access to energy-efficient housing and technologies. Wealthier households invest in efficiency improvements and renewable systems, reducing expenditures, while lower-income households reside in poorly insulated housing with inefficient appliances, creating higher energy costs relative to income. This consistency across specifications strengthens confidence in the finding that distributional considerations are fundamental to understanding energy poverty dynamics.

Comparison of the four model specifications reveals that the pooled OLS model achieves the highest adjusted R-squared, indicating superior fit compared to fixed effects and random effects. This suggests substantial variation in energy poverty is attributable to cross-country differences rather than within-country changes over time, consistent with energy poverty being influenced by slowly-changing structural factors (climate, housing stock, infrastructure, social protection systems).

Table 3. Panel regression parameter estimation.

Variables	Without control variables	Pooled OLS	Fixed effects	Random effects
Constant	39.611***	6.938		58.685**
	(5.764)	(10.403)		(28.864)
log(Renewable capacity per capita)	-4.729***	-2.213***	-1.753	-2.011*
	(0.954)	(0.826)	(1.203)	(1.110)
Renewable energy share	0.064	-0.003	0.176**	0.008
	(0.051)	(0.041)	(0.089)	(0.073)
log(GDP per capita)		-4.965**	-119.683***	-14.701**
		(2.408)	(22.366)	(6.733)
Income inequality		1.224***	0.567***	0.852***
		(0.101)	(0.166)	(0.151)
Adj. R-squared	0.108	0.472	0.195	0.230

***, **, and * indicate the significance levels at 1%, 5%, and 10%, respectively

5 Conclusion

This study examined the relationship between renewable energy deployment and energy poverty across 25 European Union member states from 2015 to 2023, employing multiple panel regression specifications to analyze renewable electricity capacity per capita and renewable energy share while controlling for economic development and income inequality.

The empirical findings reveal a paradoxical relationship challenging simplistic assumptions about green energy transitions. Renewable electricity capacity per capita demonstrates a consistently negative association with energy poverty, suggesting that expanding renewable infrastructure alleviates energy vulnerability through enhanced security and reduced fossil fuel dependence. However, this relationship loses significance in fixed effects models, indicating benefits primarily reflect cross-country structural differences rather than short-term within-country changes. Conversely, renewable energy share exhibits a positive relationship with energy poverty in fixed effects specifications, confirming that rapid renewable penetration increases may temporarily exacerbate affordability challenges through feed-in tariff surcharges and grid infrastructure costs disproportionately passed to consumers.

These findings carry substantial policy implications for achieving multiple Sustainable Development Goals simultaneously, particularly SDG 7 (Affordable and Clean Energy), SDG 1 (No Poverty), and SDG 10 (Reduced Inequalities). Since renewable energy share increases correlate with higher energy poverty during transition phases, policymakers should cap renewable energy surcharges on electricity bills for low-income households or exempt them entirely from transition cost levies, ensuring that climate action (SDG 13) does not inadvertently increase poverty. Furthermore, given that renewable capacity expansion shows beneficial effects while share increases prove problematic, governments should prioritize direct public investment in renewable infrastructure rather than financing mechanisms that pass costs to consumers through utility bills. This approach would promote a just energy transition that simultaneously advances clean energy deployment and poverty reduction, recognizing that the path to sustainable development must address both environmental and social dimensions equitably to leave no one behind in the transition to climate neutrality.

References

1. J. Zhao, K. Dong, X. Dong, M. Shahbaz, Renewable Energy **186**, 299-311 (2022)
2. I. Bąk, K. Wawrzyniak, M. Oesterreich, Energies **17**, 6241 (2024)
3. [3] S. Yüksel, S. Eti, H. Dinçer, D. Pamucar, M. Acar, K. Köklü, V. Simic, Renewable Energy **256**, 124285 (2026)
4. Y. Kolati, C. Raghutla, Energy Strategy Rev. **58**, 101687 (2025)
5. S. Muhammad, Y. Pan, X. Ke, M.H. Agha, P.S. Borah, M. Akhtar, Renewable Energy **208**, 181-190 (2023)
6. M. Simionescu, J. Cifuentes-Faura, Energy Res. Soc. Sci. **115**, 103640 (2024)
7. M. Simionescu, M. Radulescu, J. Cifuentes-Faura, D. Balsalobre-Lorente, Energy Policy **183**, 113826 (2023)
8. G.H. Soto, X.-H. Nghiem, X. Martinez-Cobas, Energy **320**, 135350 (2025)
9. C.-C. Lee, Z. Yuan, C.-C. Lee, Y.-F. Chang, Energy Econ. **116**, 106427 (2022)
10. W. Wang, W. Xiao, C. Bai, Technol. Soc. **68**, 101933 (2022)
11. A. Levin, C.-F. Lin, C.-S. James Chu, J. Econom. **108**, 1-24 (2002)
12. G.S. Maddala, S. Wu, Oxf. Bull. Econ. Stat. **61**, 631-652 (1999)
13. I. Choi, J. Int. Money Finance **20**, 249-272 (2001)
14. R.A. Fisher, Statistical Methods for Research Workers (Oliver & Boyd, Edinburgh, 1932, 4th edn.)

15. J.M. Wooldridge, Introductory Econometrics. A Modern Approach (Cengage Learning, 2016, 6th edn.)
16. C. Hsiao, Analysis of Panel Data (Cambridge University Press, Cambridge, 2014, 3rd edn.)