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Energy Poverty Among Households in EU Countries: A Panel Data Analysis*

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Abstract

The household is a key subject of economic analysis, particularly in the context of inequalities in access to essential goods. One manifestation of these constraints is energy poverty, defined as a situation in which excessive expenditure on energy prevents households from achieving an optimal consumption pattern. Energy, as a basic good with low demand elasticity, is difficult to reduce, especially in the short term. Rising energy prices therefore lead to budgetary pressure and the sacrifice of other needs. The problem is exacerbated by the low energy efficiency of homes and a lack of funds for modernisation, creating an energy poverty trap. The aim of this article is to analyse the determinants of energy poverty in the European Union. Panel analysis was used for this purpose, as it allows for the observation of units over multiple time periods. The analysis revealed that the most significant factor influencing the level of energy poverty is the unemployment rate (particularly among the new Member States). The impact of GDP per capita (PPS) also proved to be significant. Furthermore, the share of tenant households is of particular importance among the new Member States. The share of renewable energy in the energy mix also proved significant, as it can both reduce energy poverty (in the new Member States) and increase it (in the old Member States).

Keywords: energy market, energy poverty, households, international comparisons, panel analysis

Introduction

The household, as the fundamental unit of the economy, holds a central place in ongoing research and analysis, frequently attracting the attention of both the state and organisations such as the European Union. Of particular concern is the issue of inequality in access to resources and limited consumption opportunities concerning goods essential to everyday life. A particular case of such decision-making constraints in the area of meeting basic needs is undoubtedly the problem of energy poverty, that is, a situation in which a household is unable to achieve an optimal consumption pattern due to an excessive burden of energy costs. The high share of energy costs in a household budget limits the ability to meet other needs, leading to forced substitution of goods or partial reduction in consumption. Energy, as a basic good without close substitutes, is characterised by low price elasticity of demand. The limited ability to reduce energy consumption, particularly in the short term, means that rising energy prices do not lead to a proportional decline in consumption, but rather to a shift in household expenditure patterns. Consequently, budgetary pressure intensifies, particularly for low-income households. Additionally, the low energy efficiency of the housing stock, resulting in part from a lack of investment in thermal retrofitting, generates higher operating costs. At the same time, low-income households lack the financial means to undertake such investments, which perpetuates their unfavourable economic situation and creates the so-called energy poverty trap. Moreover, rapid economic growth and technological progress, leading to a growing demand for energy and ever-increasing consumption, mean that households are becoming increasingly vulnerable to any interruptions or disruptions in supply, which can stem from a variety of causes. As a result, more and more households are

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experiencing difficulties in accessing energy. This phenomenon stems primarily from several key factors: fluctuations in energy prices (particularly evident in Europe since the outbreak of the war in Ukraine), high inflation, low household incomes, and insufficient energy efficiency in buildings. This article attempts to answer the key question: what determines, across the EU-27 (over time), the proportion of the population stating that they cannot afford to heat their homes adequately? This problem is, after all, well-known and experienced in many, if not all, countries of the European Union. Following a long-term downward trend, since 2021 we have observed an increase in the proportion of households reporting difficulties in heating their homes.

The literature consistently shows that households are one of the primary sources of energy demand and that not only do they consume energy, but also help shape the market through their purchasing, investment and saving decisions (Nguyen et al., 2024; Link, Axinn and Ghimire, 2012). In Polish studies, Trębska (2018) points out that households account for a large share of final energy consumption, and that energy expenditure constitutes a significant item in household budgets. This conclusion is consistent with international analyses, which treat the household as a microeconomic entity that responds to market incentives. In economic literature, energy is often described as an essential good, as it is a prerequisite for carrying out basic daily activities: heating, cooking, lighting and ensuring comfort. The classic study by (Meier, Jamasb and Orea, 2013) explicitly examines whether energy is a necessity or a luxury. In economic and social practice, energy is often treated as a basic necessity, particularly in countries with colder climates and in lower-income households. This means that demand for energy is less elastic than for discretionary goods, and a lack of access to energy can lead to a reduction in the basic standard of living (Link, Axinn and Ghimire, 2012; Meier, Jamasb and Orea, 2013). The structure of expenditure on energy is an important aspect of household budget research, as it shows a household's share of income spent on energy and how this burden changes in line with prices and income. An analysis by the Polish researcher (Trębska, 2018) highlights that energy constitutes a significant item in household expenditure, and statistical data also show the considerable importance of solid fuels in the structure of energy consumption (Meier, Jamasb and Orea, 2013).

Energy poverty is a complex and multidimensional phenomenon, and as such has been studied by many authors. The most frequently encountered perspective relates to energy justice (e.g. (Ferrall-Wolf, Gill-Wiehl and Kammen, 2023; Chapman, McLellan and Tezuka, 2018; Dudka, Magnani and Koukoufikis, 2024; Siciliano et al., 2021). Historically, the concept of energy poverty (often referred to as 'fuel poverty' in developed countries) was based on the burden of energy costs (Antunes et al., 2023). The landmark definition from 1991 stated that a household is affected by this problem if it has to spend more than 10% of its income on energy services in order to maintain a comfortable indoor temperature (Boardman, 1991).

Over the years, broader and more multidimensional definitions have emerged. The first of these is the European Union's approach, under which (based on the revised Energy Efficiency Directive (EED) of 2023) energy poverty has been formally defined as a household's lack of access to essential energy services that ensure a basic standard of living and health (EU 2023/1791). This includes, among other things, adequate heating, hot water, cooling, lighting and power for appliances, and this situation results from a combination of factors such as lack of affordability, insufficient income, high energy expenditure and poor energy efficiency of buildings (Koukoufikis, Ozdemir and Uihlein, 2024). The International Energy Agency (IEA), however, points to the difficulties in clearly defining energy poverty and selecting an indicator to reflect it. This is because it can be viewed in several ways: as households spending a large proportion of their income on energy bills, as consuming too little energy to meet household needs, as being unable to heat one's home, or as having debts relating to utility bills. Each approach leads to the identification of different population groups as energy-poor (IEA, 2026). In conclusion, energy poverty is a complex phenomenon characterised by a household's inability to access or afford adequate energy services, which constitutes a growing threat to citizens' health, comfort and productivity (Ozdemir and Koukoufikis, 2024).

The literature on energy poverty and methods for measuring it is extensive. A study by (Ferrall-Wolf, Gill-Wiehl and Kammen, 2023) analysed over 4,000 articles published between 1983 and 2023. Another detailed review of the literature on energy poverty in EU Member States was conducted by (European Commission: Directorate-General for Energy & Energy Poverty Advisory Hub (EPAH), 2025). Research into energy poverty is also being carried out in many countries, including Germany (Drescher and Janzen, 2021), Greece (Halkos and Kostakis, 2023), Poland (Karpinska and Śmiech, 2021) and Spain (Pourkhanali et al., 2023). International research focusing on the persistence of energy poverty in the EU includes studies by (Karpinska and Śmiech, 2020) and also (Ozdemir and Koukoufikis, 2024). Meanwhile, the research by (Wojewódzka-Wiewiórska, Dudek and Ostasiewicz, 2024) focuses on assessing household energy poverty based on objective and subjective indicators of energy poverty.

Energy poverty is a multi-dimensional phenomenon resulting from a complex combination of various determining factors. The most important of these include: economic factors, the technical condition and characteristics of buildings, socio-demographic factors (in particular: household size and composition, age, education and employment status, migration background, housing market status, environmental and geographical conditions, and the habits and knowledge of household members). The primary cause of energy poverty is low household income. Households in the lowest income deciles and quintiles have to spend a disproportionately large (often more than double) share of their income on basic energy services, compared to higher-income households (IEA, 2026; Koukoufikis, Ozdemir and Uihlein, 2024). This situation is dramatically exacerbated by rising and volatile energy prices and the high burden of general housing costs, which directly compound the difficulties in paying utility bills (Makridou, Matsumoto and Doumpos, 2024; Llera-Sastresa et al., 2017; Koukoufikis, Ozdemir and Uihlein, 2024; Ozdemir and Koukoufikis, 2024).

Alongside income, the second key issue is the low energy efficiency of residential buildings. Poor insulation, draughty and leaking roofs, damp and rotting window frames drastically increase the energy required to achieve thermal comfort (Antunes et al., 2023; Świerszcz and Grenda, 2018). Outdated, inefficient heating and cooling systems are also a significant factor (Llera-Sastresa et al., 2017; Świerszcz and Grenda, 2018). Susceptibility to this phenomenon also increases depending on the specific nature of the dwelling - the problem is more acute in overcrowded flats (Makridou, Matsumoto and Doumpos, 2024) and in detached houses, which, due to the lack of shared walls, require significantly more energy for heating and cooling than, for example, flats in multi-family buildings (Koukoufikis, Ozdemir and Uihlein, 2024; Makridou, Matsumoto and Doumpos, 2024; Świerszcz and Grenda, 2018).

Methodology and Data

Panel data allow for the observation of units (e.g., individuals, firms, regions, countries) over multiple time periods. This means that panel analysis uses two-dimensional data. This is the fundamental methodological advantage of two-dimensional data over ordinary time series and cross-sectional data (data of a homogeneous type). Time series allow the observation of a single object and any changes over time, but it is impossible to compare objects with one another. Cross-sectional data allow the observation of many units simultaneously at a single point in time, meaning that differences between them are observed, but the variability of these differences over time is overlooked. Panel data provide a complete picture and allow for better modelling of the complexity of the phenomenon under observation (Hsiao, 2007).

The analysed countries differ in terms of characteristics that are difficult to observe and measure - such as the institutional environment, geographical conditions, and energy culture - meaning there is unobservable heterogeneity, which poses a significant risk of biased results in traditional modelling (Baltagi, 2021). Panel models allow for the control of this unobservable heterogeneity by incorporating individual effects into the model (μ_i) (Hausman and Taylor, 1981).

There are two ways to model these effects, depending on the chosen variant - Fixed Effects or Random Effects. The first is used under the assumption that there is a correlation between individual effects and explanatory variables, and as a result, it eliminates this component through a within transformation. The Random Effects variant assumes the absence of such correlation, and the individual effect is combined with a random error component, which is the advantage of this variant, as differences between countries are not overlooked (Hsiao, 2007). Both versions of the panel analysis can be enhanced with time effects δ_t, which are the same for all countries (units) under analysis in a given year. Their inclusion allows us to capture shared shocks such as changes in common regulations, recessions, and energy crises. A model that accounts for both individual and time effects can be called a two-way fixed/random-effects model (Baltagi, 2021). Time effects are commonly captured by including a set of year dummy variables in the regression and estimating their coefficients (Angrist and Pischke, 2008; Cameron and Trivedi, 2005).

The formal criterion for choosing between the Fixed Effects and Random Effects models is the Hausman test (Hausman, 1978). It is used to assess whether or not there is a correlation between individual effects and explanatory variables. If the p-value is > 0,05, there is no reason to reject the null hypothesis, meaning that the β coefficients are similar in both variants of the panel analysis, supporting the use of the RE model. Otherwise, the FE model should be used. In this study, the Hausman test was conducted six times - for the full EU-27 sample and for the Old and New EU subgroups, all in variants with and without lags. Due to limitations of the Python library (linearmodels), the standard errors of the FE and RE models were calculated differently, so the difference in the covariance matrices may be singular. The solution to this problem is to apply the absolute value of the test statistic (Schreiber, 2008). In four out of six cases, the test indicated the RE model, in all three variants of the lagged specification. The purpose of this article is to examine how cross-country differences affect energy poverty;

therefore, eliminating these differences by automatically applying the FE model would be methodologically unjustified (Bell and Jones, 2015).

The Augmented Dickey-Fuller test was applied to the dependent variable for each country separately to verify the stationarity of the time series (Dickey and Fuller, 1979). The null hypothesis assumes that the time series is non-stationary, while the alternative hypothesis assumes that it is stationary. A non-stationary time series may be associated with spurious regression. A problem with the testing is the length of the time series; eleven years is a fairly short panel that cannot be extended due to the lack of adjusted Gini coefficient data, so the test's power is relatively low. The results for some countries did indeed indicate non-stationarity in the time series, which was addressed by introducing time effects as year dummies to eliminate any potential spurious regression (Baltagi, 2021).

The Breusch-Pagan test was used to verify the assumption of homoscedasticity of the residuals. If there is no basis for rejecting the null hypothesis, it is assumed that the variance of the error term is constant across all observations; the alternative hypothesis assumes heteroscedasticity (Breusch and Pagan, 1979). An incorrect assumption regarding the variance of the residuals can lead to biased standard errors and incorrect conclusions. Due to the inability to calculate clustered standard errors within the linearmodels library for RE, ordinary standard errors were used, which means that any conclusions must be drawn with some caution. Any alternative methods that could potentially ensure robustness to heteroscedasticity (e.g., bootstrap) are ineffective due to the insufficient number of clusters (27) (Colin Cameron and Miller, 2015).

The final diagnostic step for the panel model was to calculate the Durbin-Watson (DW) statistic for each country in order to assess the presence of autocorrelation in the residuals - that is, a potential correlation between the error term from period t and the error term from the previous period (t-1) (Durbin and Watson, 1992). Values close to 2 indicate the absence of autocorrelation, values close to 0 may be associated with positive autocorrelation, and values close to 4 with negative autocorrelation. Analysing DW statistics is of an auxiliary nature, as this statistic was not designed for panel analysis. In many countries, DW statistic values are close to 2; the averages for the old and new EU are 2.61 and 2.58, respectively, meaning there are no significant differences between the groups. This means that the results are perfectly acceptable, especially in the context of panel analysis.

Based on the Hausman test and additional methodological criteria, the Random Effects model was selected for estimation. Based on the diagnostic tests conducted - verification of time series stationarity (ADF), homoscedasticity of residuals (Breusch-Pagan), and autocorrelation (Durbin-Watson) - year dummies were included in all specifications as a safeguard against spurious regression. The choice of this model is justified, among other things, by the desire to preserve cross-country variability while eliminating external factors that affect all observed units.

The model can be formally specified as follows:

$$EP_{it} = \alpha + \beta_1 \ln\_elec\_price_{it} + \beta_2 unemployment_{it} + \beta_3 gini_{it} + \beta_4 renewables_{it} + \gamma_1 \ln\_gdp\_pps_{it} + \gamma_2 \ln\_hdd_{it} + \gamma_3 tenants_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (1)$$

where: EP_{it} - share of the population unable to keep their home adequately warm in country i in year t (dependent variable), $\ln\_elec\_price_{it}$ - log of electricity price for households in country i in year t, $unemployment_{it}$ - unemployment rate in country i in year t, $gini_{it}$ - Gini coefficient of equivalised disposable income in country i in year t, $renewables_{it}$ - share of renewables in gross final energy consumption in country i in year t, $\ln\_gdp\_pps_{it}$ - log of GDP per capita in purchasing power standards in country i in year t, $\ln\_hdd_{it}$ - log of Heating Degree Days in country i in year t, $tenants_{it}$ - share of tenant households in country i in year t, μ_i - individual country effect, δ_t - time effect for year t, ε_{it} - error term; unexplained deviation for country i in year t.

A logarithmic transformation was applied to variables exhibiting right-skewed distribution. Specifically, these were: electricity prices, GDP per capita PPS, and Heating Degree Days. All other explanatory variables and the dependent variable remained unchanged. Treating some variables in this way is intended not only to address the issue of asymmetry, but also to facilitate interpretation. For example, a 1% change in the price of energy corresponds to a change in energy poverty of β/100 percentage points (Wooldridge, 2020).

Additionally, given the theoretical grounds for the delayed impact of selected explanatory variables on energy poverty, an extended specification was estimated using one-year lags of electricity prices, the unemployment rate, and the Gini coefficient. It can be assumed that not every factor contributes to energy poverty immediately upon its occurrence, but only after some time has passed. For example, losing one's job should not prevent a household from heating its home, as some people have savings, whether large or small. Furthermore, the time spent looking for a new job will directly affect the need to use savings, and subsequently, energy poverty. This approach makes sense only when there are strong indications that a causal relationship exists between the dependent variable and the previous values of the independent variables (Bellemare, Masaki and Pepinsky, 2017). The use of lagged explanatory variables aims to reduce the risk of reverse causality and endogeneity (Siuda, 2026).The model with lagged explanatory variables can be formally specified as follows:

$$EP_{it} = \alpha + \beta_1 \ln\_elec\_price_{i,t-1} + \beta_2 unemployment_{i,t-1} + \beta_3 gini_{i,t-1} + \beta_4 renewables_{it} + \gamma_1 \ln\_gdp\_pps_{it} + \gamma_2 \ln\_hdd_{it} + \gamma_3 tenants_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (2)$$

where the subscript t-1 denotes a one-year lag. All remaining symbols are as defined in equation (1).

Table 1 contains the dependent variable and main explanatory variables. The dependent variable is the share of the population unable to keep their home adequately warm - energy_poverty (Eurostat, 2026, sdg_07_60). The main explanatory variables are electricity price for households - ln_elec_price (Eurostat, 2026, nrg_pc_204), unemployment rate - unemployment (Eurostat, 2026, une_rt_a), Gini coefficient of equivalised disposable income - gini (Eurostat, 2026, ilc_di12), and share of renewables in gross final energy consumption - renewables (Eurostat, 2026, nrg_ind_ren).

Table 1. Sample of panel data for Austria and Sweden, 2014 - 2024: energy poverty (%), electricity price (EUR/kWh), unemployment rate (%), Gini coefficient, and renewables share (%)

country	year	energy_poverty	elec_price	unemployment	gini	renewables
AT	2014	3,2	0,2004	6	27,6	33,55
AT	2015	2,6	0,1996	6,1	27,2	33,497
AT	2016	2,7	0,2022	6,5	27,2	33,37
AT	2017	2,4	0,1964	5,9	27,9	33,136
…						
SE	2021	1,7	0,2359	8,9	26,8	62,527
SE	2022	3,3	0,2509	7,5	27,6	66,287
SE	2023	5,9	0,24215	7,7	29,5	66,393
SE	2024	4,1	0,23925	8,4	27,6	62,846

Table 2 contains the control variables: GDP per capita in purchasing power standards - gdp_pps (Eurostat, 2026, nama_10_pc), Heating Degree Days - hdd (Eurostat, 2026, nrg_chdd_a), and share of tenant households - tenants (Eurostat, 2026, ilc_lvho02).

Table 2. Sample of panel data for Austria and Sweden, 2014 - 2024: GDP per capita in purchasing power standards (PPS), Heating Degree Days, and share of tenant households (%)

country	year	gdp_pps	hdd	tenants
AT	2014	34668,5	3195,4	42,8
AT	2015	35681,9	3371,08	44,3
AT	2016	36385,1	3480,26	45
AT	2017	37012,2	3559,94	45
…				
SE	2021	39670,2	5220,65	35,1
SE	2022	40905,5	4939,74	35,8
SE	2023	42507	5201,02	35,1
SE	2024	44414,4	4817,57	35,2

The dataset was divided into three groups: the main (overall) group, and—based on the date of EU accession—the old and new EU countries. The new EU countries are those that joined in 2004 or later. In total, 27 countries are analysed.

Results and discussion

The purpose of the study was to identify the determinants of energy poverty in European Union countries. Based on Eurostat data (2014 - 2024), RE models were estimated for the entire EU, the old EU, and the new EU in two specifications - without (Sample A) and with a one-year lag for energy prices, unemployment, and the Gini coefficient (Sample B). Table 3 presents the model fit results for each variant and information on the number of observations. Tables 4 and 5 present the estimation results (β/γ) for each group in specifications A and B, respectively. The statistical significance of the coefficients is indicated in Tables 4 and 5 based on p-value thresholds. Results with a p-value < 0,01 are underlined, bold, and italic; p-values < 0,05 bold and italic; at p-values < 0,1 italic only.

The R^2 overall and R^2 between values in samples A and B are nearly identical for each model, which means that the inclusion of lagged variables does not significantly alter the models' explanatory power, suggesting that the models are stable. The values of the coefficients of determination (R^2 overall) for the new and old EU countries are very high, ranging between 0,7 and 0,86. R^2 between takes on even higher values, always exceeding 0,84. It can be concluded that the models are capable of effectively explaining the structural differences between countries, which is the main objective of this article. The R^2 values for the EU as a whole are significantly lower (below 0,3), as the differences between the old EU countries and, for the most part, the former post-communist countries cannot be explained by a single set of explanatory variables.

Table 3. Overview of Model Fit - Random Effects Models for EU-27, Old EU and New EU across Sample A (2014 - 2024, without lags) and Sample B (2015 - 2024, with one-year lags)

Model	Sample	R2 overall	R2 between	N
RE EU-27	A	0,2919	0,2723	297
RE Old EU	A	0,8428	0,9212	154
RE New EU	A	0,6996	0,8364	143
RE EU-27	B	0,2769	0,2622	270
RE Old EU	B	0,8561	0,9362	140
RE New EU	B	0,7061	0,8416	130

The most important factor determining energy poverty is the unemployment rate. Unemployment showed the highest statistical significance in every group and in both samples (A and B). A particularly strong impact on energy poverty can be observed in the new EU member states (1,32 - 1,46). Mostly post-communist countries are three times more vulnerable to labour market shocks. GDP per capita (PPS) across the EU was highly statistically significant in both samples. The coefficient is negative, meaning that a 1% increase in this variable results in a decrease in energy poverty of approximately 0,18 percentage points.

Table 4. Estimated Coefficients (β/γ) and Standard Errors (SE) - Random Effects Models for EU-27, Old EU and New EU (Sample A, 2014 - 2024, without lags)

Variable	RE EU-27	RE EU-27 SE	RE Old EU	RE Old EU SE	RE New EU	RE New EU SE
const	***202,6819***	-30,045	***100,7174***	-12,4131	43,5482	-51,6066
gini	*-0,2465*	-0,1364	0,2359	-0,1661	***1,4884***	-0,1294
ln_elec_price	-1,7012	-1,2366	-0,7573	-1,1123	1,7881	-2,4994
ln_gdp_pps	***-17,6408***	-2,5161	*-2,488*	-1,3293	***-9,1243***	-4,3389
ln_hdd	-2,4227	-1,8227	***-10,4841***	-1,4556	1,7383	-1,1955
renewables	-0,0177	-0,0716	***0,0851***	-0,0282	***-0,6482***	-0,0853
tenants	***0,2323***	-0,0796	0,0151	-0,0446	***0,2529***	-0,0867

unemployment	***0,5293***	-0,1057	***0,4826***	-0,1018	***1,3193***	-0,269

In the subgroups, GDP loses significance, suggesting that it explains the differences between the old and new EU well, but within these groups there are other, more significant variables. The percentage of tenants is significant in the new EU, but not in the old one. One could hypothesize that rental properties are not a priority in terms of improving their energy efficiency (e.g., insulation), meaning they are more expensive to heat. The number of days on which heating is required shows greater significance in the model with lagged variables. It is worth noting that in the new EU, a higher number of such days increases poverty, whereas in the old EU it does not. This can be linked to the previous observation regarding differences in infrastructure quality.

Table 5. Estimated Coefficients (β/γ) and Standard Errors (SE) - Random Effects Models for EU-27, Old EU and New EU (Sample B, 2014/15 - 2024, with one-year lags)

Variable	RE EU-27	RE EU-27 SE	RE Old EU	RE Old EU SE	RE New EU	RE New EU SE
const	***205,514***	-31,1199	***96,8894***	-11,8767	-5,0846	-54,2896
gini_L1	-0,1617	-0,1363	0,2304	-0,1582	***1,4931***	-0,1307
ln_elec_price_L1	-1,3836	-1,2357	-0,6024	-1,0336	0,351	-2,6665
ln_gdp_pps	***-18,5166***	-2,6816	*-2,3818*	-1,2767	-5,3693	-4,529
ln_hdd	-1,685	-1,764	***-9,9572***	-1,3841	***2,594***	-1,2302
renewables	-0,0404	-0,0706	***0,0818***	-0,0266	***-0,6498***	-0,0857
tenants	***0,2206***	-0,0763	0,0075	-0,0422	***0,2612***	-0,0854
unemployment_L1	***0,4585***	-0,1108	***0,4254***	-0,0961	***1,4605***	-0,2682

The share of renewable energy sources in total energy consumption is also statistically significant; however, it is worth noting that, once again, this impact differs between the old and new EU. In the new EU countries, investments in renewable energy sources may reduce energy poverty, while in the old EU they may slightly increase energy poverty. It is certainly worth examining this phenomenon in future studies and analysing national regulations in this area. All significance tests should be treated with caution due to the lack of clustered standard errors. In future studies, it would be worthwhile to consider expanding the list of countries studied beyond the EU, which should allow for the calculation of reliable clustered standard errors and a reassessment of the significance of the explanatory variables.

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