Energy consumption and economic growth in the E7: a comprehensive analysis using random effect and PMG models

Oktavilia[1], *Nadia* Damayanti[2] , *Erman Denny* Arfinto[3], *Indah Fajarini Sri* Wahyuningrum[4]

[1] Economics Development, Universitas Negeri Semarang, Semarang, Indonesia
[2] Economics, Universitas Diponegoro, Semarang, Indonesia
[3] Management, Universitas Diponegoro, Semarang, Indonesia
[4] Accounting, Universitas Negeri Semarang, Semarang, Indonesia

Abstract. This study investigates the relationship between economic growth, agricultural practices, greenhouse gas emissions, and energy consumption in the E7 countries—Brazil, China, Indonesia, India, Mexico, Russia, and Turkey—using Random Effect and Pooled Mean Group (PMG) models. By analyzing panel data from 1992 to 2020, the research explores both short- and long-term impacts of GDP, agricultural land use (AGRI), greenhouse gas emissions (TGHG), and rice production (RICE) on energy consumption. The findings reveal that in the long run, GDP, AGRI, and TGHG have significant positive effects on energy consumption, indicating that economic growth, agricultural expansion, and environmental impact are key drivers of energy demand. However, RICE shows no significant long-term influence. In the short run, only TGHG remains a significant factor, while GDP and AGRI do not show immediate effects on energy consumption. These results underscore the importance of sustainable policies that address the long-term drivers of energy consumption, particularly in rapidly growing economies like the E7. The study contributes to the literature by providing insights into the unique dynamics of emerging economies, emphasizing the need for balanced strategies that promote economic growth while ensuring environmental sustainability

1 Introduction

Global energy demand continues to rise due to economic growth, population increases, and technological advancements, with significant environmental implications such as greenhouse gas emissions and resource depletion [1–4]. The E7 countries—Brazil, China, Indonesia, India, Mexico, Russia, and Turkey—are key players, accounting for a substantial portion of global energy demand due to rapid economic growth. Their strategies in managing energy demand and environmental concerns will influence global outcomes [5–9].

A strong relationship exists between GDP and energy consumption, where economic growth drives energy demand, as seen in long-term studies across various regions [10–14]. However, this growth raises sustainability challenges, particularly in the E7 nations experiencing rapid development. Additionally, energy consumption significantly correlates with greenhouse gas emissions, emphasizing the need for policies that improve energy efficiency to mitigate environmental impacts [15–21].
Agriculture is a major energy consumer in the E7, with total land use and practices like rice production influencing energy demand. Optimizing agricultural efficiency can help manage energy use while meeting production goals [22–29]. This study examines the short- and long-term dynamics of GDP, greenhouse gas emissions (TGHG), agricultural land use (AGRI), and rice production (RICE) on energy consumption in the E7 using Random Effect and Pooled Mean Group (PMG) models. These methods capture both temporal and cross-country variations, offering insights into how these variables interact over time [30–40]. The findings aim to guide policies balancing economic growth and environmental sustainability, addressing gaps in the literature by focusing on emerging E7 economies.

2 Method

2.1 Data

This study utilizes annual data from 1992 to 2020, covering seven countries that are part of the E7 economic group. The E7 consists of Brazil, China, Indonesia, India, Mexico, Russia, and Turkey. Data were obtained from FAOSTAT and the World Bank Open Data, with variable explanations provided in Table 1. Descriptive statistics are presented by variable and country in Tables 2 and 3. Panel data was chosen for this study to capture the dynamics of variable changes over time across different countries. The panel data used in this research is strongly balanced. Random-Effects GLS regression and Pooled Mean Group (PMG) regression models were employed to provide insights into both the short-term and long-term effects of the key variables on energy consumption [30,31,34,35,41–44].

Table 1. Definition of variables

Variables	Definitions	Unit of Measurements	Source
ENRG	Total final energy consumption	Tonnes of oil equivalent (toe)	FAOSTAT
GDP	Gross Domestic Products per capita	US Dollar	World Development Indicators, World Bank
AGRI	Total agriculture land area	Hectares	FAOSTAT
TGHG	Total greenhouse gas emissions	Kilo tonnes of CO2 equivalent	World Development Indicators, World Bank
RICE	Rice production	Tonnes	FAOSTAT

Source: Processed data, 2024

2.2 Statistic descriptive

The dataset includes 203 observations from 1992 to 2020, with an average year of 2006. GDP has a mean of 5862.72 (SD = 3369.97), ranging from 546.44 to 12,179.66. Energy consumption (ENRG) averages 380,993.3, with a wide range of 42,413.35 to 2,179,869. Agricultural land area (AGRI) averages 192,628.5, spanning 37,762 to 529,038.6, while greenhouse gas emissions (TGHG) have a mean of 2,155,327 and substantial variability (SD = 2,820,204), ranging from 215,375.1 to 12,900,000. Labor force (LBFR) averages 61.51, and rice production (RICE) shows the most variation, with a mean of 57,800,000 and values between 173,461 and 214,000,000.

First-differenced variables also exhibit wide fluctuations. D_ENRG averages 10,440.61, ranging from -77,284.1 to 150,828.8. D_GDP and D_AGRI show means of 132.17 and 99.24, respectively, with substantial ranges (-949.93 to 804.41 for GDP; -3,345 to 4,607 for AGRI). D_TGHG averages 62,496.15 with a range of -235,186 to 878,155.6, and D_RICE has a mean of 568,194.2, varying from -32,200,000 to 25,100,000.

Table 2. Descriptive statistics for research variables

Variables	Mean	Std. Dev.	Min	Max
Year	2006	8.39	1992	2020
ENRG	380993.3	463278.3	42413.35	2179869
GDP	5862.72	3369.97	546.44	12179.66
AGRI	192628.5	153803.1	37762	529038.6
TGHG	2155327	2820204	215375.1	1.29E+07
LBFR	61.51	7.39	45.52	78.71
RICE	5.78E+07	7.47E+07	173461	2.14E+08
D_ENRG	10440.61	26559.06	-77284.1	150828.8
D_GDP	132.17	272.05	-949.93	804.41
D_AGRI	99.24	842.68	-3345	4607
D_TGHG	62496.15	164243	-235186	878155.6
D_RICE	568194.2	4754886	-3.22E+07	2.51E+07

2.3 Unit root test

Panel data analysis involves datasets with both time series and cross-sectional dimensions. To determine if these datasets have a unit root, panel unit root tests are essential [45]. Some widely used panel unit root tests include the Levin, Lin, Chu test (LLC) and the Im-Pesaran-Shin's t-bar test (IPS), which are considered benchmark tests in this field [46,47]. This study attempts to use the first generation of unit root tests used to test cross-sectional independence [48–53]. These tests are crucial as they offer more power compared to single equation tests, making them advantageous for unit root testing [45]. The econometric analysis begins with the panel unit root test, adopting LLC and IPS methods to check the stationarity of the data to avoid spurious regressions [45]. Unit root test can be expressed below on the equation (1) and (2):

$$y_{1t} = p_i y_{it-1} + \varepsilon_{it} \quad (1)$$

H_0 : $p_i = 0 \forall i$, i.e the series contains a unit root
H_1 : $p_i = p<0$ for all i, where i is the country (2)

In this study, y_{it} corresponds to ENRG, making it the energy consumption of country i at time t. The parameter p_i denotes the autoregressive coefficient for country i, while y_{it-t} is the lagged value of the time series for entity at time t-1. The term ε_{it} represents the error term for country i at time t.

Table 3. Unit root test results for variables using levin-lin-chu (LLC) and im-pesaran-shin (IPS) methods

Variables	Statistics	p-value	LLC Results	IPS Results
ENRG	-2.6895	0.0583	Non-stationer	Non-stationer
GDP	-2.4282	0.2382	Non-stationer	Non-stationer
AGRI	-2.3553	0.4673	Non-stationer	Non-stationer
TGHG	-2.2497	0.1313	Non-stationer	Non-stationer

Variables	Statistics	p-value	LLC Results	IPS Results
RICE	-2.0472	0.4642	Non-stationer	Non-stationer
d_ENRG	-3.5466	0	Stationer	Stationer
d_GDP	-2.9638	0	Stationer	Stationer
d_AGRI	-4.6855	0	Stationer	Stationer
d_TGHG	-3.7576	0	Stationer	Stationer
d_RICE	-6.2037	0	Stationer	Stationer

Table 2 shows the results of the LLC test, indicating that all variables (ENRG, GDP, AGRI, TGHG, RICE) are non-stationary at their levels, with p-values exceeding 0.05, signifying the presence of unit roots and unstable trends. However, after first differencing, the LLC and IPS tests confirm that all variables become stationary, with p-values of 0.00, resolving the non-stationarity issue.

First differencing is essential in panel data analysis to address non-stationarity, which can otherwise lead to spurious regression results. This transformation removes trends, mitigates unit roots, and controls unobserved heterogeneity, ensuring the data meets the stationarity assumption for valid regression modeling. It also addresses autocorrelation and highlights short-term dynamics by focusing on changes in variables rather than their long-term levels.

3 Results and discussion

3.1 Cointegration test

The cointegration tests reveal a strong long-term relationship among the variables. The Pedroni and Kao tests show consistent evidence of cointegration, with the Phillips–Perron t and Augmented Dickey–Fuller t statistics in the Pedroni test and all Kao test statistics yielding p-values of 0.0000. These results confirm the existence of a long-term equilibrium relationship in the panel data.

However, the Westerlund test, with a variance ratio p-value of 0.3667, suggests no universal cointegration across the entire dataset. This implies potential cointegration in some panels but not uniformly across all. Despite this, the robust findings from the Pedroni and Kao tests provide a reliable foundation for analyzing long-term relationships, making them the primary reference for this study.

Table 4. Cointegration test

Test	Statistic	p-value	Interpretation
Pedroni Test			**H0: No cointegration; Ha: All panels are cointegrated**
Modified Phillips–Perron t	-1.5372	0.0621	Evidence of cointegration is weak, as p-value > 0.05
Phillips–Perron t	-7.0346	0	Strong evidence of cointegration
Augmented Dickey–Fuller t	-6.6716	0	Strong evidence of cointegration
Kao Test			**H0: No cointegration; Ha: All panels are cointegrated**
Modified Dickey–Fuller t	-11.8418	0	Strong evidence of cointegration
Dickey–Fuller t	-9.0576	0	Strong evidence of cointegration
Augmented Dickey–Fuller t	-4.5797	0	Strong evidence of cointegration

Test	Statistic	p-value	Interpretation
Unadjusted Modified Dickey–Fuller t	-15.6095	0	Strong evidence of cointegration
Unadjusted Dickey–Fuller t	-9.4817	0	Strong evidence of cointegration
Westerlund Test			**H0: No cointegration; Ha: Some panels are cointegrated**
Variance ratio	0.3406	0.3667	No evidence of cointegration in some panels

3.2 Autocorrelation test

In order to assess the presence of first-order autocorrelation in the panel data, a Wooldridge test was conducted see Table 5. The results indicated an F-statistic of 0.170 with a p-value of 0.6944. Given that the p-value exceeds the common significance level of 0.05, we fail to reject the null hypothesis of no first-order autocorrelation. Thus, the model does not exhibit significant autocorrelation issues.

Table 5. Wooldridge test for autocorrelation

Test	F-Statistic	p-value	Conclusion
Wooldridge Test	0.17	0.6944	No first-order autocorrelation detected

3.3 Random effect model

The random-effects GLS regression shows that GDP significantly increases energy consumption, with a coefficient of 8.69412 ($p = 0.003$), highlighting the positive impact of economic growth. Greenhouse gas emissions (TGHG) also have a strong positive effect (coefficient 0.143441, $p < 0.0001$), reflecting the link between emissions and energy use. In contrast, agricultural productivity (AGRI, coefficient -0.19401, $p = 0.823$) and rice production (RICE, coefficient 0.000213, $p = 0.164$) do not significantly affect energy consumption. The model explains 86% of the variance in energy consumption ($R^2 = 0.8584$) and is statistically significant overall (Chi-squared = 1157.61, $p < 0.000$), underscoring the collective impact of the variables.

Table 6. Random effect results

Metrics	Random Effect
d_GDP	
- Coefficient	8.69412
- Std. Err.	2.858545
- t/z-stat	3.04
-P> t/z	0.003
- [95% Conf. Interval]	[3.091475, 14.29676]
d_RICE	
- Coefficient	0.000213
- Std. Err.	0.000153
- t/z-stat	1.4
-P> t/z	0.164
- [95% Conf. Interval]	[-0.0000861, 0.0005125]

Metrics	Random Effect
d_TGHG	
- Coefficient	0.143441
- Std. Err.	0.004799
- t/z-stat	29.89
-P> t/z	0
- [95% Conf. Interval]	[0.1340356, 0.1528469]
d_AGRI	
- Coefficient	-0.19401
- Std. Err.	0.867867
- t/z-stat	-0.22
-P> t/z	0.823
- [95% Conf. Interval]	[-1.894999, 1.506977]
_cons	
- Coefficient	225.0462
- Std. Err.	822.7132
- t/z-stat	0.27
-P> t/z	0.785
- [95% Conf. Interval]	[-1387.442, 1837.534]
R-squared (Overall)	0.8584
Adjusted R-squared	
SE of Regression	10087.6
F-statistic	
Chi-squared	1157.61

3.4 Pooled Mean Group (PMG)

The Pooled Mean Group (PMG) regression reveals that in the long run, GDP, AGRI, and TGHG significantly and positively impact energy consumption, with coefficients of 1.1699, 1.0142, and 0.1910, respectively (all $p < 0.001$). However, RICE shows no significant long-term effect (coefficient 0.0004, $p = 0.695$). In the short run, none of the variables significantly influence energy consumption, as their p-values exceed 0.05. The constant term (_cons) is significant and negative (-38444.73, $p = 0.005$), indicating a notable short-term decrease in energy consumption when other variables are held constant.

Table 7. Pooled mean group results

Variables	Coefficient	Std Error	z	P>|z|	[95% Conf. Interval]
Long-Run Effects					
GDP L1.	1.169877	0.275054	4.25	0.000	0.630782 - 1.708973
AGRI L1.	1.014168	0.270388	3.75	0.000	0.4842174 - 1.544118
TGHG L1.	0.1910292	0.00741	25.8	0.000	0.1765058 - 0.2055527
RICE L1.	0.000446	0.001138	0.39	0.695	-0.0017843 - 0.0026763
Short-Run Effects					
GDP L1.	6.663747	19.08814	0.35	0.727	-30.74831 - 44.0758
AGRI L1.	1.142575	0.891784	128	0.200	-0.6052901 - 2.89044
TGHG L1.	0.1447671	0.016725	8.66	0.000	0.1119869 - 0.1775473
RICE L1.	0.0080797	0.006436	1.26	0.209	-0.0045337 - 0.0206931
Constant	-38444.73	13608.66	-2.83	0.005	-65117.21 - -11772.25

This study employs Random-Effects GLS and Pooled Mean Group (PMG) regression models to analyze the factors influencing energy consumption (D_ENRG) over time across countries. The Random-Effects GLS model accounts for cross-country differences, while the PMG model distinguishes between short-term and long-term relationships, providing a nuanced understanding of how GDP, agricultural land use (AGRI), greenhouse gas emissions (TGHG), and rice production (RICE) impact energy demand.

In the long run, GDP, AGRI, and TGHG significantly increase energy consumption, with GDP (coefficient 1.1699) and AGRI (coefficient 1.0142) showing robust positive effects, both significant at 1%. TGHG also has a significant positive impact (coefficient 0.1910), underscoring its link to energy use. Conversely, RICE does not significantly influence long-term energy demand (p-value 0.695). In the short run, GDP and AGRI show no significant effects on energy consumption, with p-values of 0.727 and 0.200, respectively. However, TGHG remains a significant driver (coefficient 0.1448, $p < 0.001$), reflecting its consistent impact. RICE continues to show no significant influence (p-value 0.209). This dual approach highlights the persistent and transitory dynamics shaping energy demand.

The comparison highlights that GDP and AGRI significantly influence energy consumption in the long run, reflecting enduring impacts from structural changes and investments. In the short run, their effects are less immediate, as economic or agricultural fluctuations do not directly impact energy demand. Meanwhile, TGHG remains consistently significant in both the short and long run, emphasizing its persistent influence on energy use and the potential for emission-reduction policies to yield both immediate and lasting effects [54–56]. RICE has no significant impact on energy consumption in either the short or long run, indicating its limited role. While economic growth and agricultural productivity affect energy demand more in the long term, greenhouse gas emissions consistently influence energy consumption in both timeframes, reflecting the complex relationship between economic, environmental, and energy factors.

The results from the Random-Effects GLS regression and the Pooled Mean Group (PMG) regression models have significant policy implications. The robust long-run relationship between GDP and energy consumption indicates that as economies grow, energy demand increases significantly [57–60]. This finding suggests the need for policies that encourage sustainable economic growth while managing energy consumption through energy efficiency measures and the adoption of renewable energy sources. Such policies could help mitigate the environmental impacts associated with higher energy use, especially in rapidly developing economies.

The significant long-run effect of agricultural productivity (AGRI) on energy consumption highlights the importance of the agricultural sector as a major energy consumer. Policymakers should prioritize initiatives that improve energy efficiency within agriculture, such as the promotion of energy-saving technologies and practices [61,62]. Additionally, integrating renewable energy into agricultural operations could help reduce the sector's carbon footprint without compromising productivity.

The consistent significance of greenhouse gas emissions (TGHG) in both short- and long-run models points to the necessity for stringent environmental policies that address energy-related emissions. Governments should enforce stricter emission regulations and facilitate the transition to low-carbon energy sources to manage both environmental impacts and long-term energy demand effectively [63,64]. Meanwhile, the insignificant impact of rice production (RICE) on energy consumption suggests that policy efforts might be better focused on other agricultural sectors with a more pronounced influence on energy use. However, continuing research on improving energy efficiency in rice production, particularly in regions where it is a staple crop, remains important.

Future research should focus on disaggregated analyses by sector or region to identify specific drivers of energy consumption and enable more targeted policy recommendations. Including variables on renewable energy adoption could clarify its impact on the relationship between economic growth and energy use. Additionally, exploring non-linear dynamics may uncover complex interactions between variables like economic growth and agricultural productivity. With advancing technologies, further studies could examine how innovations in energy efficiency and renewable technologies reshape these relationships over time.

4 Conclusion

The Random-Effects GLS and Pooled Mean Group (PMG) regression models reveal key insights into energy consumption's relationship with GDP, AGRI, TGHG, and RICE. The Random-Effects model shows GDP and TGHG significantly influence energy consumption, while AGRI and RICE do not. The high R-squared value indicates effective variance capture. The PMG model distinguishes short-run and long-run effects, showing GDP, AGRI, and TGHG have significant long-term impacts, while RICE remains insignificant. TGHG is significant in both timeframes. These findings underline the need for policies that balance economic growth with energy efficiency and environmental sustainability. Future research should explore renewable energy and technological advancements in shaping energy consumption dynamics.

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