Journal of Sustainable Development; Vol. 15, No. 5; 2022
ISSN 1913-9063 E-ISSN 1913-9071
Published by Canadian Center of Science and Education

Drivers of Energy Efficiency in West African Countries

Auguste K. Kouakou[1] & Nibontenin Soro[2]

[1] LAREG, Economic Department, Jean Lorougnon Guede University, Cote d'Ivoire

[2] LAMPE, Department of Economics and Development, Alassane Ouattara University, Cote d'Ivoire

Correspondence: Auguste K. Kouakou, LAREG, Economic Department, Jean Lorougnon Guede University, Address: PO box 727 Abidjan 20, Cote d'Ivoire. Tel: 225-07-5773-7389. E-mail: augustekk@yahoo.fr

Received: July 9, 2022 Accepted: August 17, 2022 Online Published: August 22, 2022

doi:10.5539/jsd.v15n5p39 URL: https://doi.org/10.5539/jsd.v15n5p39

Abstract

The ideas behind the energy intensity turn out to be fundamental to the transition to a low-carbon society. This transition requires efforts both in low-emission technology choices and in moving away from path dependency. This entails significant costs in the short and long run for African countries. This paper analyses drivers of energy intensity in 13 West African countries focusing on education and investment over the period 1990 to 2015. Panel data technics are suitable for the analysis. After testing for stationarity and cointegration, we use the Fully Modified Ordinary Least Square method (FMOLS) with cross-sectional independence and the Common Correlated Effect Pooled Mean Group approach (CCEPMG) for cross-sectional dependence. Our main findings show robust evidence that education, energy price and income above a certain threshold play an important role in improving energy intensity in the long run. By controlling for cross-sectional dependence, we find that investment and the urbanization rate become positive and statistically significant. Our empirical findings show that increasing the education level is important to improve energy use, calling for policy action encompassing both sectoral and global measures that is crucial to achieve energy efficiency.

Keywords: energy intensity, investment, education, panel data, ECOWAS

1. Introduction

The Earth Summit held in Rio in 1992 after Stockholm 1972, marked a major landmark for international environmental action. The adoption in 2015 of the Sustainable Development Goals by the United Nations system is another turning point. For developing countries, improving energy efficiency to mitigate a higher vulnerability to climate change is a concern (IPCC, 2007). During the last decade, the growing dynamism of West African economies has undoubtedly contributed to an increase in demand for all forms of energy. This raises concerns for energy access, energy security, environmental protection for West African countries (ECOWAS, 2015; Diedhiou, 2020). This is even more significant given that improving energy efficiency has been included in the Sustainable Energy for All (SE4ALL), ECOWAS (Note 1) Centre for Renewable Energy and Energy Efficiency (ECREEE) and the commitment made at COP21 by West African countries, on a potential emission reduction of around 900 MtCO2 by 2030.

To move towards sustainable development, it is essential to use energy more efficiently and to reduce its intensity. Energy intensity, that's energy consumed to produce a unit of economic output, has been widely used in the literature as a proxy for energy efficiency. However, it is argued that energy intensity can mask certain structural and behavioral factors that do not necessarily imply energy efficiency improvements (IEA, 2014). At best, therefore, energy intensity can be used as a rough proxy for energy efficiency.

In ECOWAS countries, Energy intensity has certainly decreased, nearly 11.09 percent over the period 1990-2015, or at an average annual rate of 0.47 percent per year (World Bank-WDI, 2019). In addition, the region's energy resources consist mainly of traditional biomass and fossil fuels (gas, oil) which remain highly polluting.

Energy intensity is of crucial importance for the preservation of the environment and the restructuring of the energy-economy model (Miketa, 2001; IEA, 2009). Therefore, understanding the main factors influencing energy intensity in ECOWAS will have important implications in achieving the objectives of SE4ALL, ECOWAS Energy Efficiency Policy (EEEP) and COP21.

Several studies have analyzed the determinants of energy intensity (Hang and Tu, 2007; Destais et al., 2007; Song and Zheng, 2012; Herrerias et al., 2013;). They focus mainly on the relevance of technology, economic growth, energy prices and structural change. These studies do not abound in West African countries even if we can notice those of Djezou (2013) in the West African Economic and Monetary Union (WAEMU), Adom and Kwakwa (2014) in Ghana and Adam (2015) in Nigeria.

Moreover, few of them address the effects of education and investment (Van den Branden, 2015; Sequeira, 2018). Studies on these two variables have mostly been limited to micro-level analyses. However, comprehensive studies at the aggregate level with cross-country data can provide a broader picture of energy intensity.

ECOWAS countries face huge investment needs in energy-intensive infrastructure. For example, between 1998 and 2014, the World Bank approved 40 energy operations, totaling $1.45 billion, for ECOWAS member states (AfDB, 2015). However, increased investment to meet development imperatives should be coupled with broad awareness of efficient energy use. Information and education for change play a strategic role in improving energy intensity in the ECOWAS region.

Motivated by this background, our study endeavors to analyze the determinants of energy intensity, focusing on investment and education in West African countries.

A two-step empirical strategy is used. The first, more standard, uses Phillips and Moon's (1999) Fully Modified Ordinary Least Square method (FMOLS hereafter) with cross-sectional independence and the second, is Chudik and Pesaran's (2015) Common Correlated Effect Pooled Mean Group approach (CCEPMG hereafter). Unlike the standard approach, it considers the cross-sectional dependence of the observations in addition to the heterogeneity of the parameters and the non-stationarity of the variables.

The remainder of this article is organized as follows. Section 2 presents a preliminary analysis of energy and energy intensity of the ECOWAS. Section 3 reviews the related literature. The methodology and data are introduced in Section 4. Main findings and discussion are presented in Section 5. The final section concludes by discussing the overall findings and policy implications.

2. Stylized Facts: Energy and Energy Intensity

2.1 ECOWAS Energy Situation

The ECOWAS region is characterized by a low rate of access to energy services. According to ECOWAS statistics (2016), only 45% of energy demand is met, and per capita energy consumption is only 150 kWh/day, one of the lowest in the world.

Per capita energy consumption in the Sub-Saharan Africa region is 0.68 Ktoe, far below the world consumption (1.92) and that of North America (7.05).

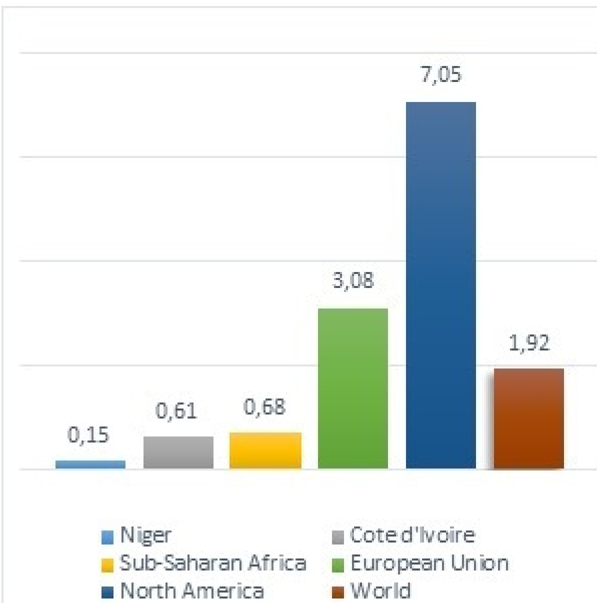

Figure 1. Energy consumption in 2014 (Ktoe/capita)

Biomass (wood, agricultural residues, charcoal, dung, etc.) and waste constitute the main source of energy supply for 70% to 90% of the West African population depending on the country.

Indeed, the role of traditional biomass in providing final energy consumption is noteworthy for nine countries in 2010 (UNEP, 2014) (Figure 2).

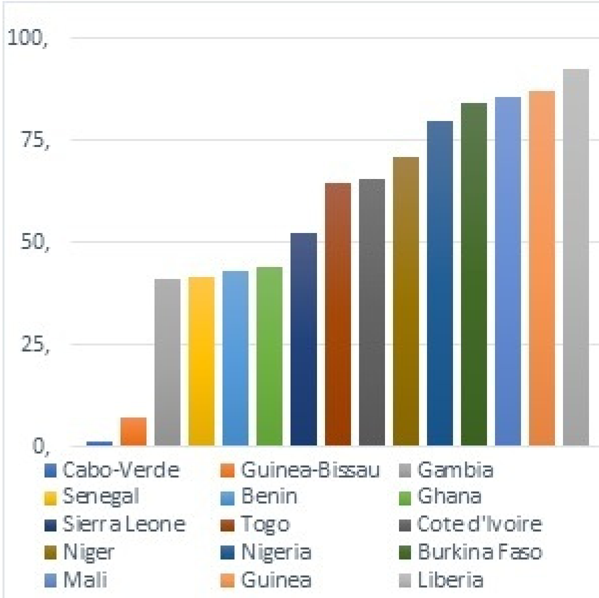

Figure 2. Share of traditional biomass in total final energy consumption (2010)

2.2 Energy Intensity Trends

Energy intensity improvements are among the most cost-effective solutions to rising energy costs, unpredictable and unstable energy supplies, and environmental conservation (IEA, 2014).

ECOWAS Heads of State have given high priority to energy efficiency with the adoption in 2013 of the ECOWAS Energy Efficiency Policy (EEEP). Many actions such as the introduction of energy saving lamps and energy audits are meaningful.

Noticeably, higher patterns of energy intensity are observed during 1970s. However, this trend has been reversed and this intensity has steadily decreased (Adom and Kwakwa, 2014). The average energy intensity of the 15 ECOWAS member states fluctuated over the period 1990-2015. It is 8.25 MJ/dollar in 2015, higher than that of Cabo Verde (Figure 3). The low intensity in some countries can be explained by the economic structure dominated by services. Energy-intensive countries are also those that are highly dependent on traditional biomass. Furthermore, we find that the overall energy intensity of the region decreases over time (Figure 4).

On average, the region’s primary energy intensity decreased by 11.09% between 1990 and 2015 at an average rate of 0.47% per year despite the enormous challenges that remain.

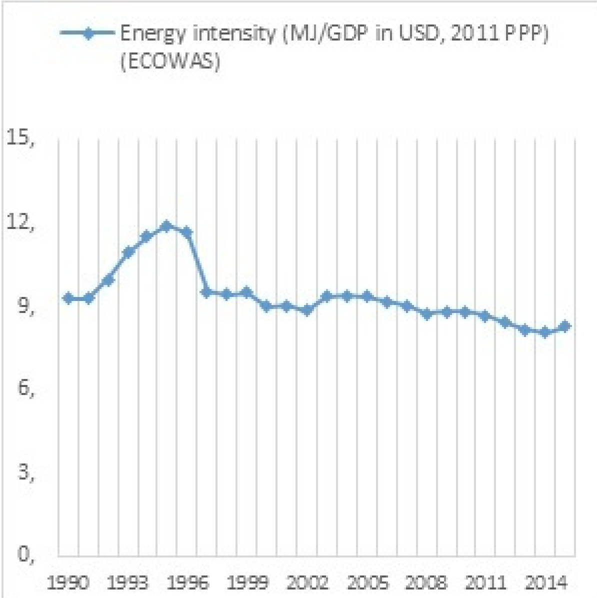

Figure 3. Evolution of energy intensity from 1990 to 2015

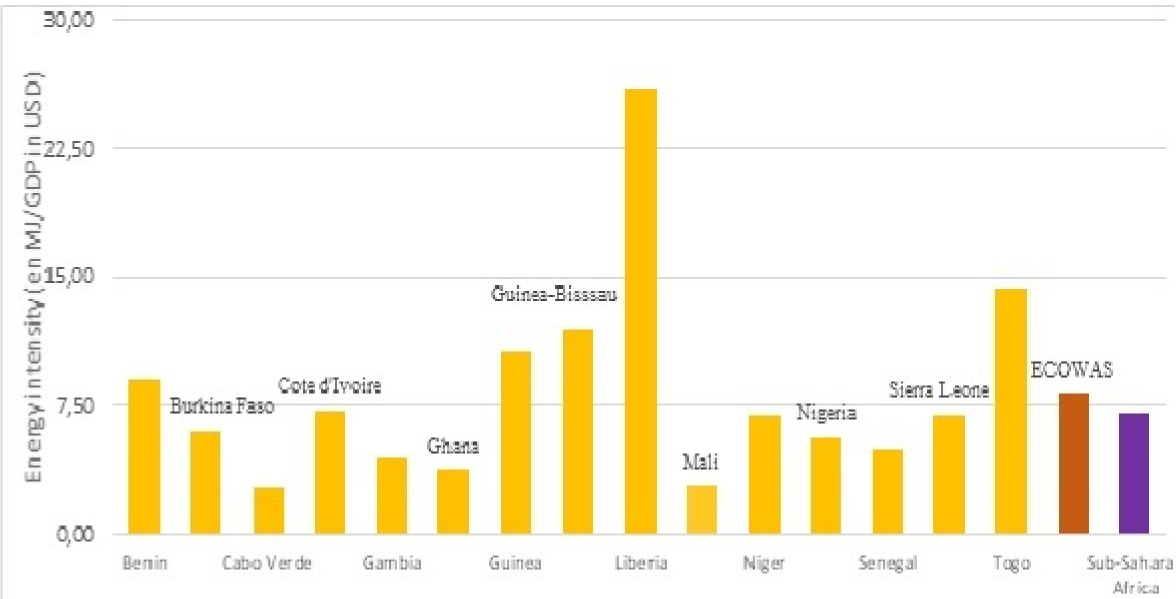

Figure 4. Final energy intensity of ECOWAS member states (2015)

3. A Brief Empirical Literature Review

Energy intensity has been the subject of much aggregate or sectoral work using time series or panel data techniques (Metcalf, 2008).

The empirical evidence on the role of investment and education is generally ambiguous. Given the mixed relationship between energy and financial development factors, Hübler and Keller (2010) question the energy savings potential of new capital investments. Thus, investment absorbs part of the composition effect: if energy-intensive sectors are also capital-intensive, an increase in investment may reflect an expansion of energy-intensive sectors and thus lead to an increase in energy consumption. Petrović et al. (2018) find the same results for European countries over the period 1995-2015, showing a positive impact of gross fixed capital formation.

Miketa (2001) shows that gross fixed capital formation also increases energy intensity in 10 manufacturing industries for some industrialized and developing countries over the period 1971-1996. Similarly, public infrastructure also has an impact on energy intensity. Public investment stimulates the development of energy-intensive industries, such as the steel and cement industries (Zeng et al., 2014; Ma, 2015), increasing energy constraints for the economy. Meanwhile, public resources invested in energy-efficient physical capital can ease the constraints on economic and social development. (Cho et al., 2007; Privitera and La, 2018).

Research on the effect of human capital is sparse despite its importance for African countries. Sequeira and Santos (2018) considering education at the national level, show a decreasing effect of primary education on energy intensity. Also, if students in secondary schools were relatively familiar with energy challenges, positive attitudes toward conservation may appear in Taiwan (Yeh et al., 2017). In addition, students with more educated parents tended to have better knowledge than others. In Greece, Ntanos et al. (2018) and Lefkeli et al. (2018) reveal the importance of education in raising environmental awareness and implementing energy conservation and environmentally friendly practices.

Van den Branden (2015) argues that schools need to rely on updated curricula and activities based on advanced knowledge including what motivates human learning to increase environmental awareness. Ashouri et al (2020) showed that average years of schooling and university enrollment have a positive effect on energy intensity.

Other studies have established the importance of some other factors such as economic indicators, demography, technology, and international trade in reducing energy intensity. Notwithstanding, focusing on West African countries with alternative empirical strategy is one of the main challenges in this paper.

Table 1. Summary of the literature on other energy intensity variables

Author(s)	Period	Methodology	Conclusions
		Economic indicators	
Mulder and De Groot (2013)	1987-2005	Decomposition approach	Energy declined only marginally in the overall economy and in the manufacturing sector but increased in the services.
Andersson and Karpestam (2013)	1973-2007	Decomposition approach	In the long run, changes in the composition of the capital stock and the real price of oil reduce energy intensity.
Chang (2015)	1999-2008	Panel threshold regression approach	Energy consumption generally increases with per capita income, except for economies with highly developed financial markets.
Adom (2015)	1971-2011	FMOLS and canonical cointegration regressions.	The impact of the price of crude oil is asymmetric and negative but becomes stronger after 1989.
		Demography	
Elliott et al. (2017))	1995-2012	Mean group estimation techniques	The direct impact of urbanization on energy intensity is generally positive, while the indirect impact measured through four different channels (construction, industrial modernization, transportation, and lifestyle change) tends to be negative.
Deichmann et al. (2018)	1990-2014	OLS, Models with individual and time fixed effects	The 0–14-year-old population reduces energy intensity; however, population density increases energy intensity.
Chen and Zhou (2021)	2000-2014	Panel threshold model	Increasing urbanization leads to higher energy intensity. However, this positive effect of urbanization on energy intensity can be dampened when institutional quality exceeds the threshold value.
		Technology and international trade	
Hübler and Keller (2010)	1975-2004	Ordinary Least Squares (OLS)	FDI flows reduce the energy intensity of developing countries.
Sultan (2013)	1995-2010	Stochastic frontier analysis and OLS.	Firms that produce more for export have a lower energy intensity because they address a larger market and can benefit from economies of scale.
Oak (2018)	1997-2015	Fixed effects model	No significant effect of exporting on energy intensity, while an increase in imports per unit of sales results in a decrease in energy intensity.
Cao et al. (2020)	1990-2014	Panel model and PSTR model	FDI has an insignificant impact on energy intensity in non-BRICS countries. However, a significant and negative effect IS NOTICED in BRICS countries.

Source: author’s summary

4. Methodology and Data

This section presents the econometric model and describe the data set.

4.1 Model Specification

Following Fisher-Vanden et al. (2004), Hübler and Keller (2010), Huang and Yu (2016), our specific setting derives from the following Cobb-Douglas cost minimization function:

$$C(\mathrm{P}_K, \mathrm{P}_L, \mathrm{P}_E, \mathrm{P}_M, Q) = A^{-1} P_K^{\alpha_K} P_L^{\alpha_L} P_E^{\alpha_E} P_M^{\alpha_M} Q \tag{1}$$

where Q is the quantity of output, $\mathrm{P_K}$, $\mathrm{P_L}$, $\mathrm{P_E}$, $\mathrm{P_M}$ represent respectively the prices of capital, labor, energy and materials.

α_X are the price elasticities of the vector $\mathrm{X}(X = K, L, E, M)$. The productivity term (*A*) is defined as:

$$A = \exp(\alpha_1 GFCF + \alpha_2 Educ) \tag{2}$$

where $GFCF$ is the gross capital formation (chosen as a proxy for investment); $Educ$ is the education (chosen as a proxy for human capital). α_1 et α_2 represent the coefficients of investment et education.

From Shephard's Lemma, the demand for energy is equal to the derivative of the cost function with respect to the price:

$$E = \frac{\alpha_E A^{-1} P_K^{\alpha K} P_L^{\alpha L} P_E^{\alpha E} P_M^{\alpha M} Q}{P_E} \tag{3}$$

Assuming,

$$P_Q = P_K^{\alpha_K} P_L^{\alpha_L} P_E^{\alpha_E} P_M^{\alpha_M} \tag{4}$$

Combining (3) and (4), the energy intensity (EI) becomes:

$$E = \frac{\alpha_E A^{-1} P_Q Q}{P_E} \quad \text{or} \quad \frac{E}{Q} = \frac{\alpha_E A^{-1} P_Q}{P_E} \quad \text{and} \quad EI = \frac{\alpha_E A^{-1} P_Q}{P_E} \tag{5}$$

By replacing A with its expression from (2) and taking the logarithm of both sides, we have:

$$\ln(EI) = \alpha_0 + \alpha_1 \ln(GFCF) + \alpha_2 \ln(Educ) + \alpha_3 \ln({}^{P_E}\!/_{P_Q}) + \upsilon \tag{6}$$

And the panel data form of the model is:

$$\ln(\mathrm{EI})_{i,t} = \alpha_0 + \omega_i + \theta_t + \alpha_1 \ln(\mathrm{GFCF})_{i,t} + \alpha_2 \ln(\mathrm{Educ})_{i,t} + \alpha_3 \ln({}^{P_E}\!/_{P_Q})_{i,t} + \upsilon_{i,t} \tag{7}$$

where ${}^{P_E}\!/_{P_Q}$ is the approximation of the price of energy.

Indeed, more efficient use of energy requires improved technology (captured by *GFCF*), on the one hand, and consumer sensitization and behavioral change (captured by education), on the other. Levels of income and urbanization can also control energy intensity. According to Furtado-Suslick (1993) and Hourcade (1993), energy intensities are more often U-shaped than saturated by economic components like income. Thus, following Galli (1998) and Djezou (2013), we opt for a non-linear relationship by favoring the quadratic form between energy intensity and income (*YPC*).

Therefore, the model (7) can be rewritten as follows:

$$\begin{aligned} \ln(\mathrm{EI})_{i,t} &= \alpha_0 + \omega_i + \theta_t + \alpha_1 \ln(\mathrm{GFCF})_{i,t} + \alpha_2 \ln(\mathrm{Educ})_{i,t} + \alpha_3 \ln(PE)_{i,t} + \alpha_4 \ln(\mathrm{YPC})_{i,t} + \\ &\quad \alpha_5 \ln(\mathrm{YPC}^2)_{i,t} + \alpha_6 \ln(\mathrm{URB})_{i,t} + \upsilon_{i,t} \end{aligned} \tag{8}$$

Where the subscripts *i* and *t* denote country and time, respectively. α_0, is the constant term, *ln* denotes the natural logarithm. *EI* is the energy intensity; *GFCF*, the gross fixed capital formation. *PE*, is the price of energy, *URB*, is the urbanization rate, *Educ* is the average number of years of schooling. *YPC* denotes the income and YPC^2, its quadratic form. ω_i, represents the individual (country) effect, θ_t, is the time-specific effect, then $\upsilon_{i,t}$ is the error term. The time-specific effect represents all variables that are common to all countries but vary over time, and the individual effects are specific to each country and constant over time.

4.2 Variable Description and Data Sources

The study uses annual data from the World Bank and UNDESA covering the period 1990-2015 for 13 ECOWAS (Note 2) countries based on data availability.

Primary energy intensity (EI) is the ratio between energy demand and gross domestic product measured in purchasing power parity. It measures the amount of energy used to produce a unit of economic output. It is measured in MJ/GDP in USD, 2011 PPP. This indicator is typically used in studies such as Cao et al. (2020).

The explanatory variables are as follow. Gross Domestic Product (YPC) per capita in constant 2011 international PPP is used as a proxy for income. The quadratic term of the YPC allows to check the non-linearity especially the "U-inverted" shape of the energy intensity curve in relation to income (Villa, 2000; Bilgili et al., 2017).

Physical capital accumulation (GFCF) represents the annual flow of investments made in a country and captures the effect of technology. This variable can be negatively related to energy intensity if a clean production technology is adopted (Sultan, 2013). We use GFCF to capture the effect of investment on energy intensity (Miketa, 2001). A negative sign of the GFCF variable is expected.

Human capital (Educ) is captured through the number of years in secondary school. An educated population is aware of the need for rational use of a resource that is becoming increasingly scarce (Lefkeli et al., 2018). A negative sign on energy intensity is expected.

The consumer price index (PE) is used as a proxy for energy price. Energy price is a signal that reflects energy supply and demand and has the power to drive consumers and businesses to choose clean energy and/or energy efficient technologies and equipment (Phoumin and Kimura, 2014; Adom, 2014). A negative sign on energy intensity is expected.

Urbanization (URB) is approximated by the urbanization rate as a percentage of the urban population. Urbanization drives energy consumption through demand from the residential, infrastructure, transportation, and building construction sectors, especially energy-intensive activities. Belloumi and Alshehry (2016) report the positive impact of urbanization on energy intensity in the short and long run in Saudi Arabia. Thus, the expected sign is positive. The statistical descriptions of all variables are reported in Table 2.

Table 2. The statistical description of all the variables

Variable	Obs.	Mean	Std. Dev	Min	Max	Description
EI	338	8.247	3.419	1.910	17.265	Energy intensity level of primary energy (MJ/$2011 PPP GDP). World Development indicators on-line, World Bank (WDI, 2019)
GFCF	338	18.857	8.342	-2.424	53.122	Gross fixed capital formation (% of GDP) (formerly gross domestic fixed investment). WDI, 2019
Educ	338	6.556	0.615	05	08	Secondary education, duration (years). WDI, 2019
PE	338	74.431	32.233	2.161	185.637	Consumer price index (2010 = 100). WDI, 2019
YPC	338	1858.041	925.907	754.855	5687.592	GDP per capita, PPP (constant 2011 international $). WDI, 2019
URB	338	35.732	10.003	13.815	59.228	Urbanization data is annual Percentage of Population at Mid-Year Residing in Urban Areas. It is collected from United Nations, Department of Economic and Social Affairs, Population Division (2018).

4.3 Econometric Approach

Our empirical strategy is based on addressing three key issues in panel data. The first one consists of testing the order of integration. In the econometric literature, several statistical tests are used to determine the degree of integration of a variable (Banerjee, 1999). The tests that will be used in this study are the "first generation" tests of Levin et al. (2002) (LLC) and Im et al (IPS) (2003) and the "second generation" test of Pesaran (2007).

The LLC test assumes non-heterogeneity of the autoregressive parameter, while the IPS test allows the heterogeneity. The CIPS unit root test relaxes the assumption of cross-sectional independence of the contemporaneous correlation. All of these tests use the null hypothesis of non-stationarity.

We perform also the Lagrange multiplier test developed by Breusch-Pagan (1980) and the Cross-Sectional (CD) test by Pesaran (2015) that controls for the presence of cross-sectional dependence. The cross-sectional dependence is likely since the energy shocks usually correspond to common shocks that affect the economies of different countries simultaneously. Also, technological advances that include the diffusion of ideas in the context of environmental protection are interdependent across countries.

The second step consists of examining the presence of co-integration relationships that may exist in the long run between the variables. This analysis will follow the panel data test procedure proposed by Kao (1999) and Westerlund (2007). The first is a first-generation test and the second is a second-generation test that considers individual dependence. The Kao (1999) test assumes the homogeneity of the co-integrating vectors in the individual dimension. The Westerlund (2007) test is based on four bootstrap tests.

These tests are based on estimating a standard Error Correction Model, where both the long-run and the short-run coefficients can vary across panel groups. Two of these tests are group-mean tests, while the other two are pooled panel tests.

Finally, given that co-integration is confirmed, we use Pedroni's (1996) and Phillips and Moon's (1999) FMOLS and Chudik and Pesaran's (2015) CCEPMG methods to estimate the co-integrating relationships. The FMOLS estimator accounts for possible serial correlation and endogeneity of regressors (Herzer and Nunnenkamp, 2012). It considers both individual coefficients (pooled panel) and group means (grouped panel).

To address the contemporaneous correlation problem, we use Ditzen's (2018) common correlated effects mean group (CCEPMG) technique.

CCEPMG estimation addresses concerns of potential heterogeneity and cross-sectional correlation by linking two different econometric techniques. The first is aggregate group mean (PMG) estimation, due to Pesaran, Shin, and Smith (1999), which imposes the restriction of long-run parameter homogeneity while allowing unrestricted heterogeneity of short-run parameters across cross-sectional units. The second is Pesaran's (2006) common correlated effects estimator, which accounts for the cross-sectional dependence of observations.

The technique of Ditzen (2018) has the advantage of being suitable for small sample sizes. To this end, we favor it and apply the mean recursive adjustment method to correct for small sample bias with respect to our sample size.

5. Results and Discussion

5.1 Panel Unit Root and Co-Integration Tests

Table 3 presents the level stationarity tests for each series. Almost all the variables are stationary in level except for LEduc with the LLC (2002) test with or without trend.

On the other hand, the results of these three tests in first difference summarized in Table 4 are univocal, except for the LEduc variable which cannot be rejected by considering the trend. The absence of results at the IPS level for the LEduc variable is likely due to the small size of this variable.

The Pesaran (2007) test is conditioned by the inter-individual dependence. The results are more conclusive for stationarity in first difference (Table 4). Thus, we consider that the variables are I (1) or quasi-I (1).

Table 3. Panel unit root tests

Variables	LLC test		IPS test		CIPS test	
	Level					
	Constant	Constant &Trend	Constant	Constant &Trend	Constant	Constant &Trend
LEI	-1.212 (0.113)	-1.976** (0.024)	-1.108 (0.134)	-1.020 (0.154)	-1.469* (0.071)	0.051 (0.520)
GFCF	-1.377* (0.084)	-3.548*** (0.000)	-0.946 (0.172)	-1.790 (0.037**	-1.290* (0.099)	-1.613* (0.053)
LEduc	6.521 (1.000)	6.618 (1.000)	-	-	10.862 (1.000)	10.283 (1.000)
LPE	-5.002*** (0.000)	-2.096** (0.018)	-0.565 (0.286)	2.482 (0.994)	1.646 (0.950)	-2.387*** (0.008)
LYPC	2.480 (0.993)	-1.838** (0.033)	3.879 (0.999)	0.143 (0.557)	1.278 (0.899)	0.772 (0.780)
LYPC2	2.646 (0.996)	-1.852** (0.032)	4.01 (1.000)	0.132 (0.552)	1.286 (0.901)	0.717 (0.763)
URB	10.128 (1.000)	-2.894*** (0.002)	19.233 (1.000)	-2.883*** (0.002)	-2.107** (0.018)	-1.569* (0.058)

Source: Author's own calculation

***, **, and * represent significance at a 1%, 5%, and 10% levels, respectively. Pvalue is in parentheses.

Table 4. Panel unit root tests

Variables	LLC test		IPS test		CIPS test	
	First difference					
	Constant	Constant &Trend	Constant	Constant &Trend	Constant	Constant &Trend
ΔLEI	-13.433*** (0.000)	-11.612*** (0.000)	-12.511*** (0.000)	-10.497*** (0.000)	-9.712*** (0.000)	-7.877*** (0.000)
ΔGFCF	-16.845*** (0.000)	-14.833*** (0.000)	-15.529*** (0.000)	-13.840*** (0.000)	-11.956*** (0.000)	-10.163*** (0.000)
ΔLEduc	-2.944*** (0.002)	-0.885 (0.188)	-	-	7.516 (1.000)	7.355 (1.000)
ΔLPE	-6.622*** (0.000)	-6.758*** (0.000)	-6.335*** (0.000)	-5.734*** (0.000)	-7.541*** (0.000)	-6.566*** (0.000)
ΔLYPC	-12.024*** (0.000)	-10.903*** (0.000)	-11.887*** (0.000)	-10.649*** (0.000)	-10.690*** (0.000)	-8.836*** (0.000)
ΔLYPC2	-11.864*** (0.000)	-10.776*** (0.000)	-11.760*** (0.000)	-10.527*** (0.000)	-10.579*** (0.000)	-8.693*** (0.000)
ΔURB	-5.595*** (0.000)	-8.806*** (0.000)	-3.141*** (0.000)	-2.625*** (0.004)	-4.541*** (0.000)	-3.739*** (0.000)

Source: Author's own calculation

***, **, and * represent significance at a 1%, 5%, and 10% levels, respectively. Pvalue is in parentheses.

The table below shows the inter-individual dependence tests developed by Breusch-Pagan (1980) and Pesaran (2015). Their result confirms the presence of inter-individual dependence.

Table 5. Breusch-Pagan (1980) and Pesaran (2015) cross-sectional dependence tests

	Statistic	P-value
Breusch-Pagan (1980)	109,2	0,012**
Pesaran (2015)	-2,319	0,020**

Source: Author's own calculation

Notes: ** denotes significance at the 5% level. The null hypothesis of the Breusch-Pagan LM test is that the residuals between entities are uncorrelated and relies on the chi2 statistic. Pesaran (2015) relies on the CD statistic. Rejection of the null hypothesis indicates the presence of inter-individual dependence.

As for the co-integration between variables, the Kao (1999) test is conclusive in identifying co-integrating relationships. The Kao statistic rejects the hypothesis of non-cointegration at 5 and 10% (Table 6). The Westerlund test (2007), which tests for co-integration of variables in the presence of possible dependence between observations, rejects the hypothesis of non-cointegration globally for each pair of variables (Table 7). These results conclude globally that there are co-integrating relationships between energy intensity and all explanatory variables.

Table 6. Kao Co-integration test results

	Coef.	P-value
Kao (Unadjusted modified Dickey-Fuller t)	-1.448	(0.074)
Kao (Unadjusted Dickey-Fuller t)	-1.296	(0.098)

Source: Author's own calculation

A P-value lower than 1, 5 and 10% indicates a rejection of H_0. Standard errors are reported in parentheses.

Table 7. Westerlund Co-integration test results

Statistic	GFCF	LEduc	LPE	LYPC	LYPC2	URB
Gt	-2.804 (0.040)	-2.779 (0.030)	-2.854 (0.010)	-2.895 (0.030)	-2.879 (0.060)	-2.937 (0.006)
Ga	-12.303 (0.020)	-8.736 (0.060)	-8.243 (0.460)	-10.456 (0.090)	-10.398 (0.090)	-2.641 (1.000)
Pt	-10.101 (0.060)	-7.252 (0.340)	-9.249 (0.160)	-9.149 (0.140)	-9.097 (0.180)	-6.648 (0.740)
Pa	-9.678 (0.170)	-5.590 (0.550)	-7.381 (0.460)	-8.416 (0.240)	-8.105 (0.350)	-3.409 (0.990)

Source: Author's own calculation

Note: All estimations include trend and one lag. Critical values bootstrapped under the null of no co-integration. P-values are those significant at least at the 10% level. Standard errors are reported in parentheses.

5.2 Results by FMOLS and CCEPMG Methods and Discussion

5.2.1 Results using FMOLS Procedure

Table 8 reports the results of the FMOLS methods. However, we use the Dynamic Ordinary Least Square (DOLS) method for robustness (Kao and Chiang, 2001). The coefficients of determination (R2-adjusted) of the two methods are respectively 95.6% for the FMOLS estimator and 95.5% for the DOLS estimator. Thus, the explanatory variables of the two methods globally explain the fluctuations of the dependent variable.

Focusing on the FMOLS method, we find that education matters for energy efficiency, as a 10% increase in LEduc leads to a 4.66% improvement in LEI. We postulate that an educated population learns not only how to improve energy use, but also how to decrease energy intensity in economic activities. Education can provide a basis for understanding best practices based on rational choices (Ashouri et al.,2020; Sequeira and Santos, 2018; Ntanos et al., 2018).

Also, the price of energy has a positive impact on the reduction of energy consumption, but only to a very small extent. Indeed, an increase in the price of energy would lead to a decrease in energy intensity of about 0.0796, ceteris paribus. This result may be due to the fact that the prices of electricity, oil, and natural gas are controlled by most ECOWAS governments with periodic adjustments based on the international price. This result agrees with Yang et al. (2016) who argue that energy price is less important than other driving forces of energy reduction in China. As well, energy intensity increases with per capita income but at a decreasing rate as indicated by the positive and negative coefficients of LYPC and LYPC2 at the 1% threshold.

The results confirm the "inverted U" relationship between income and energy intensity. There is therefore a level of income at which energy intensity decreases. This result is like those of Metcalf (2008) and Wu (2012), but contrary to those of Djezou (2013) who found a "U" shape for WAEMU countries. Moreover, the results of the DOLS estimator are almost equivalent to those of FMOLS, showing that the estimated effects are reliable and robust.

Table 8. FMOLS and DOLS estimation results

Dependent variable: Energy intensity (LEI)

Variables	FMOLS	DOLS
GFCF	0.0007 (0.334)	0.0005 (0.7560)
LEduc	-0.466*** (0.000)	-0.4589** (0.027)
LPE	-0.0796*** (0.000)	-0.0721*** (0.000)
LYPC	1.6785*** (0.000)	1.6904*** (0.000)
LYPC2	-0.1736**** (0.000)	-0.1769*** (0.000)
URB	0.0007 (0.773)	0.0028 (0.557)
R2-ajusté	0.956	0.955

Note: All variables are in natural logarithms, so all coefficients indicate percentage changes (elasticities).

***, **, * shows 1%, 5% and 10% of significance levels. Standard errors are reported in parentheses.

To account for inter-individual dependence added to heterogeneity across individuals, we re-estimate our models by the CCEPMG estimator of Chudik and Pesaran (2015).

5.2.2 Results using CCEPMG Approach

The possible inter-individual dependence seems highly probable to us insofar as energy shocks generally correspond to common shocks that simultaneously affect the economies of different countries. Therefore, the short and long run relationships are estimated through the CCEPMG and CCEMG estimators taking into account correlated common effects between countries. Table 9 shows the results and a Hausman specification test is carried out for comparison.

From the adjusted coefficient of determination, 75 and 64 percent for the CCEMG and CCEPMG respectively, we notice that the model is well specified. Error correction terms are negative and significant, supporting the evidence of a long-run relationship. The speed of adjustment to this long-run equilibrium is derived from the absolute value of the error correction term.

The Hausman test is used to examine the null hypothesis of no difference between CCEMG and CCEPMG estimators. The test statistic is 0,03 with a p-value of 0,866 and suggests that the consistent estimator, CCEPMG, is to be preferred over the efficient estimator, CCEMG. Hence, the CCEPMG estimator is reliable and robust.

Regardless of the model estimated (CCEPMG and FMOLS), education is always significant and is one of the main drivers of energy efficient in the long run. Moreover, the "inverted U" shape of income is also verified.

However, the positive influence of investment is statistically significant. A stock of investment in industrial activities facilitates mass production and consumption. These results are like those of Petrović et al. (2018), who explain it by the fact that investments are focused on increasing and modernizing production capacity in energy-intensive sectors, which are usually capital-intensive.

Also, the urbanization rate becomes statistically significant at the 1% level. Urbanization drives energy consumption through demand for infrastructure, transportation, and building construction, which are generally energy-intensive activities. This result is consistent with those of Poumanyvong and Kaneko (2010) who find that urbanization reduces energy consumption in low-income countries but increases energy demand in middle- and high-income countries.

In the short run, a one percentage point increase in income reduces energy intensity by 0.1525 percent. The early stages of growth for ECOWAS countries consume less conventional energy to the extent that their economies are based on non-motorized agriculture that is rather human energy intensive (Djezou, 2013). In addition, the short-term price of energy allows for energy savings.

Our results are robust since the CCEPMG estimator and CCEMG yield the same signs in the long run.

Table 9. CCEMG and CCEPMG estimation results

Dependent variable: Energy intensity (LEI)

Variables	CCEMG	CCEPMG
	Long term	
Ec	-0.6516*** (0.000)	-0.6100*** (0.000)
GFCF	0.0041*** (0.008)	0.0055* (0.060)
LEduc	-0.4337* (0.091)	-0.5682*** (0.000)
LPE	0.1883 (0.749)	-0.255 (0.902)
LYPC	1.3438* (0.098)	1.3366* (0.057)
LYPC2	-0.0958* (0.073)	-0.0739** (0.033)
URB	0.5315** (0.025)	0.4498*** (0.000)
C	5.2761 (0.773)	-2.2873 (0.338)
	Short term	
D.GFCF	0.0084 (0.802)	0.0026 (0.347)
D.LEduc	-0.2195 (0.289)	0.3102 (0.167)
D.LPE	-0.0487*** (0.000)	-0.0958* (0.07)
D.LYPC	-0.8101*** (0.000)	-0.1525*** (0.000)
D.LYPC2	0.0041 (0.656)	0.0014 (0.599)
D.URB	0.0138 (0.569)	0.0390 (0.593)
Obs.	325	325
Diagnostic tests	F(Prob.) = (0.000) *** R^2-adjusted 0.75	F(Prob.) = (0.000) *** R^2-adjusted 0.64
Hausman[b]	Statistic = 0,03 (0,866)	

Note: P-values are reported in parentheses. ***, ** and * indicate a significance level, respectively at 1, 5 and 10%. The null hypothesis of the Hausman test corresponds to the homogeneity of the long-run coefficients.

The results do not indicate major changes between the different methods used. Nevertheless, there are some slight discrepancies. The results obtained by considering the inter-individual dependency are more consistent than those obtained by the FMOLS method. Indeed, investment (GFCF) and the urbanization rate (URB) become positive and statistically significant.

6. Conclusion and Policy Implications

Energy concerns, in particular energy intensity, are central to ECOWAS' regional policy. The objective of this paper was to empirically assess the relationship between energy intensity and its influencing factors, in particular education and investment in 13 ECOWAS countries. Two panel data estimation methods were used, namely the FMOLS method with a heterogeneous specification, and the CCEPMG method which considers the dependence of common factors in addition to the heterogeneity of individuals. Both methods provide robust results.

Noticeably, empirical results with the FMOLS method indicate that education and energy price play an important role in improving energy intensity in the long run. Furthermore, the non-linear nature of the relationship between energy intensity and income shows that an increase in income above a threshold will lead to an increase in demand for environmentally friendly goods and services.

Controlling for cross-sectional dependence with the CCEPMG method, investment and urbanization become positive and significant. In contrast, the negative effect of energy price on energy intensity is no longer significant.

Thus, the positive effect of investment reflects the fact that investments are focused on increasing and modernizing production capacity, which is generally capital and energy intensive. Urbanization in ECOWAS countries is still poorly controlled as it increases energy consumption through the demand for infrastructure, transportation, and building construction.

For future research, we suggest studying a within country specific constraints in ECOWAS area as well as incentives mechanisms for energy efficiency.

Acknowledgments

The authors did not receive support from any organization for the submitted work. All authors conceived and designed the research. AK and NS acquired the data and analyzed the data. All authors discussed the research, wrote and approved the final version of the manuscript.

References

Adam, P. K. (2015). Asymmetric impacts of the determinants of energy intensity in Nigeria. *Energy Economics, 49*, 570–580. https://doi.org/10.1016/j.eneco.2015.03.027

Adom, P. K., & Kwakwa, P. A. (2014). Effects of changing trade structure and technical characteristics of the manufacturing sector on energy intensity in Ghana. *Renew. Sust. Energy Rev., 35*, 475–483. https://doi.org/10.1016/j.rser.2014.04.014

AfDB (2015). *Turn energy plans into action, ECOWAS countries told.* Retrieved from https://www.afdb.org/en/news-and-events/turn-energy-plans-into-action-ecowas-countries-told-14670

Andersson, F. N., & Karpestam, P. (2013). CO2 emissions and economic activity: Short- and long-run economic determinants of scale, energy intensity and carbon intensity. *Energy Policy, 61*, 1285–1294. https://doi.org/10.1016/j.enpol.2013.06.004

Ashouri, M., Parsa, H., & Heidari, E. (2020). Investigating the Factors Affecting Energy Intensity in Iran with an Emphasis on the Information and Communications Technology Index. *Environmental Energy and Economic Research, 4*(1), 27-41. https://doi.org/10.22097/EEER.2020.202920.1116

Banerjee, A. (1999). Panel data unit roots and cointegration: an overview. *Oxford Bulletin of Economics and Statistics, 61*, 607-630. https://doi.org/10.1111/1468-0084.0610s1607

Belloumi, M., & Alshehry, A. (2016). The Impact of Urbanization on Energy Intensity in Saudi Arabia. *Sustainability, 8*(4), 375. https://doi.org/10.3390/su8040375

Bilgili, F., Koçak, E., Bulut, Ü., & KuloGlu, A. (2017). The impact of urbanization on energy intensity: Panel data evidence considering cross-sectional dependence and heterogeneity. *Energy, 133*(15), 242-256. https://doi.org/10.1016/j.energy.2017.05.121

Breusch, T. S., & Pagan, A. R. (1980). The Lagrange multiplier test and its application to model specification in econometrics. *Review of Economic Studies, 47*(1), 239–253. https://doi.org/10.2307/2297111

Cao, W., Chen, S., & Huang, Z., (2020). Does Foreign Direct Investment Impact Energy Intensity? Evidence from Developing Countries. *Mathematical Problems in Engineering,* 11. https://doi.org/10.1155/2020/5695684

CEDEAO. (2016). La CEDEAO soucieuse de l'accès des populations rurales et périurbaines aux services énergétiques. Récupéré sur https://www.ecowas.int/la-CEDEAO soucieuse de l'accès des populations rurales et périurbaines aux services énergétiques – LACTUACHO.COM

Chang, S. (2015). Effects of financial developments and income on energy consumption. *Int. Rev. Econ. Financ., 35*, 28–44. https://doi.org/10.1016/j.iref.2014.08.011

Chen, Z., & Zhou, M. (2021). Urbanization and energy intensity: evidence from the institutional threshold effect. *Environmental Science and Pollution Research, 28*, 11142–11157. https://doi.org/10.1007/s11356-020-11386-8

Cho, Y., Lee, J., & Kim, T. Y. (2007). The impact of ICT investment and energy price on industrial electricity demand: Dynamic growth model approach. *Energy Policy, 35*, 4730–4738. https://doi.org/10.1016/j.enpol.2007.03.030

Chudik, A., & Pesaran, M. H. (2015). Common correlated effects estimation of heterogeneous dynamic panel data models with weakly exogenous regressors. *Journal of Econometrics, 188*(2), 393–420. https://doi.org/10.1016/j.jeconom.2015.03.007

Deichmann, U., Reuter, A., Vollmer, S., & Zhang, F. (2018). Relationship between Energy Intensity and Economic Growth: New Evidence from a Multi - Country Multi - Sector Data Set. *Policy Research Working Paper 8322*.

Destais, G., Fouquau, J., & Hurlin, C. (2007). Economic Development and Energy Intensity: A Panel Data Analysis. *The Econometrics of Energy Systems*, 98-120. https://doi.org/10.1057/9780230626317_5

Diedhiou, A. (2020). L'Afrique, une proie du réchauffement climatique. Environnement.

Ditzen, J. (2018). Estimating dynamic common-correlated effects in Stata. *The Stata Journal, 18*(3), 585–617. https://doi.org/10.1177/1536867X1801800306

Djezou, W. B. (2013). Analyse des déterminants de l'efficacité énergétique dans l'espace UEMOA. *European Scientific Journal, 9*(12), 1857-7431. https://doi.org/10.19044/esj.2013.v9n12p%25p

ECOWAS. (2015). *Ecowas at 40: Achievements, Challenges and Prospects.* 2015 Annual Report.

Elliott, R. J., Sun, P., & Zhu, T. (2017). The Direct and Indirect Effect of Urbanization on Energy Intensity: A Province level Study for China. *Energy, 123*, 677-692. https://doi.org/10.1016/j.energy.2017.01.143

Fisher-Vanden, K., Jefferson, G. H., Liu, H. M., & Tao, Q. (2004). What is driving China's decline in energy intensity? *Resour. Energy Economics, 26*, 77–97. https://doi.org/10.1016/j.reseneeco.2003.07.002

Furtado, A. T., & Suslick, S. B. (1993). Forcasting of petroleum consumption in Brazil using the intensity of energy technique. *Energy Policy*, 958-968. https://doi.org/10.1016/0301-4215(93)90184-H

Galli, R. (1998). The Relationship Between Energy Intensity and Income Levels: Forecasting Long Term Energy Demand in Asian Emerging Countries. *The Energy Journal, 19*(4), 85-105. Retrieved from http://www.jstor.org/stable/41322805

Hang, L. M., & Tu, M. Z. (2007). The impacts of energy prices on energy intensity: evidence from China. *Energy Policy, 35*, 2978–2988. https://doi.org/10.1016/j.enpol.2006.10.022

Herrerias, M. J., Cuadros, A., & Orts, V. (2013). Energy intensity and investment ownership across Chinese provinces. *Energy Economics, 36*, 286–298. https://doi.org/10.1016/j.eneco.2012.08.043

Herzer, D., & Nunnenkamp, P. (2012). The Effect of Foreign aid on Income Inequality: Evidence from Panel Cointegration. *Structural Change and Economic Dynamics, 23*(3), 245-255. https://doi.org/10.1016/j.strueco.2012.04.002

Hourcade, J. C. (1993). Modelling long-run scenarios: methodology lessons from a prospective study on low CO2 intensive country. *Energy Policy, 21*(3), 309-326. https://doi.org/10.1016/0301-4215(93)90252-B

Huang, J., & Yu, S. (2016). Effects of investment on energy intensity: evidence from China. *Chinese Journal of Population Resources and Environment, 14*(3), 197-207. https://doi.org/10.1080/10042857.2016.1215823

Hübler, M., & Keller, A. (2010). Energy savings via FDI? Empirical evidence from developing countries. *Environment and Development Economics, 15*(1), 59-80. https://doi.org/10.1017/S1355770X09990088

IEA (international Energy Agency). (2009). *Progress with Implementing Energy Efficiency Policies in the G8.* Internal Energy Agency Paper. Retrieved from http://www.iea.org/G8/docs/Efficiency_progress_g8july09.pdfS

IEA (International Energy Agency). (2014). *Energy Efficiency Indicators: fundamentals on statistics.* OECD/IEA, Paris.

Im, K. P., Pesaran, M. H., & Shin, Y. (1997). *Testing for unit root in heterogeneous panels.* DAE Working Paper, 9526, University of Cambridge.

Im, K. S., Pesaran, M. H., & Shin, Y. (2002). Testing for Unit Roots in Heterogenous Panels. *revised version of the DAE, Working Paper 9526*, University of Cambridge.

Im, K. S., Pesaran, M. H., & Shin, Y. (2003). Testing for Unit Roots in Heterogeneous Panels. *Journal of Econometrics, 115*, 53-74. https://doi.org/10.1016/S0304-4076(03)00092-7

IPCC. (2007). *Climate Change.* The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the IPCC.

Kao, C. (1999). Spurious regression and residual-based tests for cointegration in panel data. *Journal of Econometrics, 90*, 1-44. https://doi.org/10.1016/S0304-4076(98)00023-2

Kao, C., & Chiang, M.-H. (2001). On the Estimation and Inference of a Cointegrated Regression in Panel Data. *Advances in Econometrics, 15*, 179–222. https://doi.org/10.1016/S0731-9053(00)15007-8

Lefkeli, S., Manolas, E., Ioannou, K., & Tsantopoulos, G. (2018). Socio-Cultural Impact of Energy Saving: Studying the Behaviour of Elementary School Students in Greece. *Sustainability, 10*(3), 737. https://doi.org/10.3390/su10030737

Levin, A., Lin, C. F., & Chu., C. S. (2002). Unit Root Test in Panel Data: Asymptotic and Finite Sample Properties. *Journal of Econometrics, 108*, 1-24. https://doi.org/10.1016/S0304-4076(01)00098-7

Ma, B. (2015). Does urbanization affect energy intensities across provinces in China? Long-run elasticities estimation using dynamic panels with heterogeneous slopes. *Energy Econ., 49*, 390–401. https://doi.org/10.1016/j.eneco.2015.03.012

Metcalf, G. (2008). An empirical analysis of energy intensity and its determinants at the state level. *The Energy Journal, 29*(3), 1-26. Retrieved from https://www.jstor.org/stable/41323167

Miketa, A. (2001). Analysis of Energy Intensity Developments in Manufacturing Sectors in Industrialized and Developing Countries. *Energy Policy, 29*, 769-775. https://doi.org/10.1016/S0301-4215(01)00010-6

Mulder, P., & De Groot, H. L. (2013). Dutch sectoral energy intensity developments in international perspective, 1987–2005. *Energy Policy, 52*, 501-512. https://doi.org/10.1016/j.enpol.2012.09.072

Ntanos, S., Kyriakopoulos, G., Arabatzis, G., Palios, V., & Chalikias, M. (2018). Environmental Behavior of Secondary Education Students: A Case Study at Central Greece. *Sustainability, 10*(5), 1663. https://doi.org/10.3390/su10051663

Oak, H. (2018). Analysing factors influencing energy intensity of Indian cement industry. *International Journal of Engineering Technologies and Management Research, 5*(2), 213-220. https://doi.org/10.29121/ijetmr.v5.i2.2018.165

Pedroni, P. (1996). Fully Modified OLS for Heterogeneous Cointegrated Panels and the Case of Purchasing Power Parity. *Indiana University working papers in economics no. 96-020*.

Pesaran, M. H. (2006). Estimation and inference in large heterogeneous panels with multifactor error structure. *Econometrica, 74*, 967–1012. https://doi.org/10.1111/j.1468-0262.2006.00692.x

Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics, 22*(2), 265-312. https://doi.org/10.1002/jae.951

Pesaran, M. H. (2015). Testing Weak Cross-Sectional Dependence in Large Panels. *Econometric Reviews, 34*(6-10), 1089–1117. https://doi.org/10.1080/07474938.2014.956623

Pesaran, M. H., Shin, Y., & Smith, R. P. (1999). Pooled mean group estimation of dynamic heterogeneous panels. *Journal of the American Statistical Association, 94*, 621-634. https://doi.org/10.1080/01621459.1999.10474156

Petrović, P., Filipović, S., & Radovanović, M. (2018). Underlying causal factors of the European Union energy intensity: Econometric evidence. *Renewable and Sustainable Energy Reviews, 89*, 216-227. https://doi.org/10.1016/j.rser.2018.03.061

Phillips, P. C., & Moon, H. R. (1999). Linear regression limit theory for nonstationary panel data. *Econometrica, 67*(5), 1057-1112. https://doi.org/10.1111/1468-0262.00070

Phoumin, H., & Kimura, S. (2014). Analysis on Price Elasticity of Energy Demand in East Asia: Empirical Evidence and Policy Implications for ASEAN and East Asia. *ERIA Discussion Paper Series*.

Poumanyvong, P., & Kaneko, S. (2010). Does urbanization lead to less energy use and lower CO2 emissions? A cross-country analysis. *Ecological Economics, 70*(2), 434-444. https://doi.org/10.1016/j.ecolecon.2010.09.029

Privitera, R., & La, R. D. (2018). Reducing Seismic Vulnerability and Energy Demand of Cities through Green Infrastructure. *Sustainability, 10*(8), 2591. https://doi.org/10.3390/su10082591

Sequeira, T., & Santos, M. (2018). Education and Energy Intensity: Simple Economic Modelling and Preliminary Empirical Results. *Sustainability, 10*(8), 2625. https://doi.org/10.3390/su10082625

Song, F., & Zheng, X. (2012). What drives the change in China's energy intensity: Combining decomposition analysis and econometric analysis at the provincial level. *Energy Policy, 51*, 445–453. https://doi.org/10.1016/j.enpol.2012.08.044

Sultan, R. (2013). The determinants of energy intensity for the design of environmental strategies in the Mauritian textile sector. *Int. J. Sustainable Economy, 5*(2), 140-156.

UNDESA. (2018). World population prospects, 2018 revision. United Nations Department of Economic and Social Affairs (UNDESA).

Van den Branden, K. (2015). Sustainable Education: Exploiting Students Energy for Learning as a Renewable Resource. *Sustainability, 7*(5), 5471–5487. https://doi.org/10.3390/su7055471

Villa, P. (2000). Evolution sur longue période de l'intensité énergétique. *La revue de CEPII, n°82, deuxième trimestre*, la documentation française, Paris.

Westerlund, J. (2007). Testing for error correction in panel data. *Oxford Bulletin of Economics and Statistics, 69*(6), 709-748. https://doi.org/10.1111/j.1468-0084.2007.00477.x

World Bank. (2019). *World Development Indicators.* Washington (DC): World Bank.

Wu, Y. (2012). Energy intensity and its determinants in China's regional economies. *Energy Policy, 41*, 703–711. https://doi.org/10.1016/j.enpol.2011.11.034

Yang, J., Zhang, W., & Zhang, Z. (2016). Impacts of urbanization on renewable energy consumption in China. *Journal of Cleaner Production, 114*(15), 443-451. https://doi.org/10.1016/j.jclepro.2015.07.158

Yeh, S., Huang, J., & Yu, H. (2017). Analysis of Energy Literacy and Misconceptions of Junior High Students in Taiwan. *Sustainability, 9*(3), 423. https://doi.org/10.3390/su9030423

Zeng, L., Xu, M., Liang, S., Zeng, S., & Zhang, T. (2014). Revisiting drivers of energy intensity in China during 1997–2007: A structural decomposition analysis. *Energy Policy, 67*, 640–647. https://doi.org/10.1016/j.enpol.2013.11.053

Notes

Note 1. Economic Community of West African States (ECOWAS hereafter).

Note 2. The countries considered in our study are Benin, Burkina Faso, Cote d'Ivoire, Gambia, Guinea, Guinea-Bissau, Mali, Niger, Nigeria, Senegal, Sierra Leone. Cabo Verde and Liberia were excluded due to missing data.