IJEEP
INTERNATIONAL JOURNAL OF ENERGY ECONOMICS AND POLICY
EJ EconJournals
ISSN: 2146-4553

International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2024, 14(5), 372-379.

EJ EconJournals

Energy Consumption, Bank Credit and Manufacturing Industry Performance: A Panel ARDL Analysis in Western Indonesia

Amaluddin Amaluddin*, Rina Indiastuti, Nury Effendi, Cupian Cupian

Economics and Business Faculty, Universitas Padjadjaran, Bandung, Indonesia. *Email: amaluddin21001@mail.unpad.ac.id

Received: 25 April 2024 **Accepted:** 30 July 2024 **DOI:** https://doi.org/10.32479/ijeep.16625

ABSTRACT

The energy growth nexus is still being debated due to mixed empirical findings. This study seeks to establish a relationship between energy consumption, bank credit, and the performance of the manufacturing industry. This study also aims to determine the pattern of the dynamic causal relationship between energy use, bank credit, and the performance of the manufacturing industry in 17 provinces in western Indonesia. This study used secondary data from the Central Bureau of Statistics and the Financial Services Authority. Panel data are from 17 provinces in western Indonesia, spanning from Q1 2010 to Q4 2022 (2010Q1-2022Q4). We employed the panel ARDL and causality test to explore the connection between the variables of interest. The panel ARDL confirms that energy consumption and bank credit play a crucial role in boosting the performance of the manufacturing industry in the long term. This study found strong evidence to support the long-term feedback hypothesis of the energy-output growth nexus. However, in the short term, bank credit was statistically insignificant at all confidence levels. We recommended several policies to local governments and stakeholders, prioritizing the provision of more adequate energy infrastructure and greater access for industrial businesses to utilize banking services. Advancing infrastructure and developing the utilization of new renewable energy are proposed to support sustainable economic development.

Keywords: Energy, Bank Credit, Manufacturing Industry, Autoregressive Distributed Lag, Causality
JEL Classification: Q43, O14, G21

1. INTRODUCTION

The manufacturing industry is a sector that plays a vital role in regional development as the main driving force and support for the national economy. Most countries, including Indonesia, consider industrialization necessary for long-term economic development. In addition, developing the industrial sector helps boost the economy, creates jobs, and promotes growth in other sectors. The Central Bureau of Statistics reports that Indonesia's manufacturing industry had the highest GDP contribution in 2010 (22.04%), but in 2022 it dropped to 18.34%. The industrial development in Indonesia is unbalanced, with Western Indonesia having an advantage over Eastern Indonesia due to its superior infrastructure and human resources. In 2010, the manufacturing industry in western Indonesia contributed 21.84% of GDP, and in 2022, it decreased to 19.87%. In recent years, Indonesia's manufacturing industry has become the second-largest energy user after the transportation sector. Industries that consume the most energy are food, beverage, and tobacco (18.5%), fertilizer, chemical, and rubber goods (18.1%), cement and non-metallic mineral goods (17.2%), textile, leather, and footwear (17%), and basic metals, iron, and steel (9.7%) (Kemenperin, 2020). Electricity is one of the main sources of energy for the industrial sector and is a determining factor for domestic industrial competitiveness. Electricity is necessary for setting up digital infrastructure and platforms to speed up the adoption of Industry 4.0 in industrial areas (Kemenperin, 2020).

Empirically, the energy-output growth nexus has gained attention since the first study by Kraf and Kraf in 1978, which motivated further research with precise analysis. In recent literature, studies emphasizing the use of dynamic econometrics are rapidly growing. For example, studies such as the study by Ozcan et al. (2020) used the GMM-PVAR method to uncover the dynamic relationship between energy consumption, economic growth, and environmental degradation in OECD countries. Khan et al. (2020) used ARDL to investigate the nexus of energy consumption, economic growth, and carbon dioxide emissions. Similarly, Xiong and Xu (2021) used ARDL to examine the link between energy consumption, economic growth, and environmental pollution in China. Çakmak and Acar (2022) used the GMM and Panel causality test. However, the energy-growth nexus is still debated because of mixed empirical findings. Payne (2010) highlights that the essence of the debate lies in the effect of energy on output and causality on both short-term and long-term relationships.

Regarding the finance-energy-growth nexus, most previous studies focus on the impact of energy consumption on economic growth influenced by various economic sectors. The novelty of this study lies in its emphasis on analyzing a specific sector, particularly the manufacturing industrial sector, using the dynamic ARDL analysis approach. Furthermore, the geographical focus solely on the Western Region of Indonesia will reveal unique and dynamic relationships between energy consumption, bank credit, and industrial sector performance. Additionally, past research has not given enough attention to how bank credit affects manufacturing industry performance; furthermore, the debate regarding the connection between energy consumption and output growth lies in inconsistent causality. As far as we know, studies related to this topic with an emphasis on the Western Region of Indonesia are still very limited. Therefore, this study has significant contributions to the advancement of knowledge and is expected to provide practical recommendations for stakeholders.

The main objective of this research is to investigate the dynamic relationship between energy consumption, bank credit, and industrial sector performance. Specifically, this study aims to: (1) Examine the dynamic impact of energy consumption on industrial performance in both the short and long term. (2) Investigate the dynamic influence of bank credit on manufacturing industrial performance. (3) Explore the causal relationship between energy consumption and manufacturing industrial performance. (4) Investigate the causal relationship between bank credit and manufacturing industrial performance. (5) Investigate the causal relationship between bank credit and manufacturing industrial performance. The remaining sections of this paper are as follows: Literature review, data and methods, results and discussion, and conclusion.

2. LITERATURE REVIEW

The manufacturing industry significantly contributes to the global economy, and its performance is determined by multiple factors, including energy consumption and finances. This literature review aims to summarize the main previous findings and synthesize the relevant past research on the interplay between energy consumption, bank credit, and manufacturing industry performance.

2.1. Energy Consumption and Manufacturing Industry

The availability of adequate energy consumption is one of the key factors determining the success of manufacturing industry development in the global economy. Numerous studies have consistently revealed findings that show energy consumption is one of the important determinants influencing the performance of the manufacturing industry (Çakmak and Acar, 2022; Ozcan et al., 2020; Khan et al., 2020; Xiong and Xu, 2021). However, the findings of those previous studies remain inconclusive because other research still debates the issue of causal relationships, categorizing hypotheses into four groups, including energy-led growth, conservation hypothesis, feedback hypothesis, and neutrality hypothesis.

In the context of the energy-led growth hypothesis, previous studies have suggested that an increase in energy consumption contributes positively and significantly to the improvement of economic performance, including the manufacturing industry sector. Studies falling under this category have found that the relationship between energy consumption and economic performance exhibits one-way causation, flowing from energy consumption to output growth, termed as unidirectional causality in econometrics (Inani and Tripathi, 2017; Wolde-Rufael, 2014; Iyke, 2015; Karanfil and Li, 2015).

Regarding inconsistent findings, studies supporting the feedback hypothesis have found that energy usage contributes to output growth, including manufacturing output, and that the rise in output growth also triggers an increase in energy usage, indicating a two-way relationship (feedback), or in econometrics, known as bi-directional causality. Supporters of this hypothesis include (Kasperowicz, 2014; Gurgul and Lach, 2012a and b; Hamdi et al., 2014; Tang and Tan, 2013; and Cowan et al., 2014). This view is challenged by the conservative hypothesis, which asserts that the relationship between the two variables occurs from output growth to energy consumption. Studies that support the conservative hypothesis include (Salahuddin and Alam, 2015; Adom, 2011; and Shaari et al., 2013). In contrast, other findings conclude that there is no significant relationship between output growth and energy consumption, supporting the neutrality hypothesis (Acaravci and Ozturk, 2010; Cowan et al., 2014).

The focus of studies on certain sectors, particularly the manufacturing industry sector, is still very limited. For example, Bassey et al. (2022) studied the impact of electricity usage on the performance of the manufacturing industry in Nigeria. They employed FMOLS, which covered the period from 1981 to 2019. Their findings indicate that increased electricity usage will greatly enhance the performance of manufacturing industries in Nigeria. However, Zou (2022) studied the dynamic link between primary energy use and the growth of key industrial sectors in China during the period from 1953 to 2018. The study concluded that industrial sectors cause energy use in the long run, supporting the conservation hypothesis. Energy use and three key industrial sectors had small elasticities and bidirectional causality in the short run. In their study, Li and Yuan (2021) established a connection between industrial growth and electricity usage in China, spanning from 1995 to 2017, utilizing a novel quantile-on-quantile approach. This empirical study concluded that there is a positive relationship between industrial growth and energy usage. However, the strength of the relationship depends on the level of energy usage and economic development.

Based on the findings of previous research, it can be synthesized that the majority of studies indicate that energy consumption plays a significant role in driving output growth. However, regarding causal relationships, previous research findings have resulted in inconsistent and uncertain outcomes regarding the direction of causality, giving rise to debated findings such as the energy-led growth hypothesis, conservation hypothesis, feedback hypothesis, and neutrality hypothesis. Previous studies have employed various analytical techniques.

2.2. Bank Credit and Manufacturing Industry

Bank credit plays a key role in the growth of the real economy including the manufacturing industry as indicated by theory and empirical studies. According to the finance-growth theory, the size of the financial sector affects the real sector of an economy directly. This theory is based on the role of banks in connecting people who have surplus funds with those who require them through financial intermediation (Mishkin, 2013). Schumpeter made the first hypothesis in 1911 that the growth rate of the real economy was determined by the financial sector. Moreover, some scholars also argue that the financial system helps in the growth of economies through the accumulation of capital and innovation (Levine, 1997) while King and Levine (1993) found that "innovation" stands out as the main channel through which finance affects growth in terms of output." Regarding the theory of finance and growth, the size of the financial sector directly impacts the real sector of the economy. This concept derives from the ability of banks to link those having much money inside up with those who require it via financial intermediation (Mishkin, 2013).

Empirically, Olusegun et al. (2020) examined the impact of bank financing on industrial sector growth in Nigeria from 2004 to 2018 empirically. The Fully Modified OLS (FMOLS) methodology was employed in this study. The study established that industrial growth was influenced by bank credits, money supply, and bank lending rates. The researchers proved that bank credit, domestic money supply, and industrial sector growth have a positive correlation. Furthermore, Akinlo et al. (2021) investigated how financial advancement affected the real sector in 38 African countries south of the Sahara during the period 1986-2015. Furthermore, this study uses the value added of the agriculture sector, the value added of the industrial sector, and labor productivity as proxies for the real sector. Financial development is proxied by private sector domestic credit, domestic credit, and money supply. The study found that, concerning labor productivity and industrial value added, financial development hinders real sector performance.

Similarly, Mesagan et al. (2018) analyzed how financial development is related to manufacturing growth in Nigeria from 1981 to 2015. In this study, various indicators like utilization, manufacturing output, and manufacturing value-added were used to represent manufacturing performance while money supply was measured as a percentage of GDP. Domestic credit to the private sector and liquidity ratio were used by the researchers as proxies for financial development. The short-run analysis indicated that credit and money supply had a positive but insignificant impact on capacity utilization and output. However, the relationship between private sector credit or financing and the performance of manufacturing was found to be negative. It was discovered in the study that in the long term, raising money and lending to the private sector has a positive effect on industrial manufacturing output.

Additionally, Balasubramanian (2022) used an ARDL model to examine the impact of long-term industrial credit on industrial growth in India, while controlling for other factors. The study established a relationship between long-term credit and industrial output in India. From both short-term and long-term perspectives, long-term bank credit has a positive influence on overall economic growth. Granger causality test indicated that long-term bank credit Granger causes GDP. The study proposed that the Indian government and Central Bank should establish policies to support long-term credit. Similarly, Majeed et al. (2019) used ARDL to show how banking credit affected output growth in Pakistan from 1982 to 2017 for both enterprises and households. The study found that enterprise credit positively influenced Pakistan's output growth during the sample period. In contrast, the other component of private credit, i.e., household credit, was not a positive driver of output growth.

Based on the findings of previous research, it can be synthesized that the majority of studies indicate that bank credit plays a significant role in driving output growth including the manufacturing industry sector. However, Akinlo et al. (2021) revealed that financial development hinders real-sector performance regarding labor productivity and industrial value added.

2.3. Hypothesis

Based on the literature review, we can formulate several hypotheses for this study as follows:

- H1: Energy consumption positively affects manufacturing industry performance both in the short and long term
- H2: Bank credit positively affects manufacturing industry performance both in the short and long term
- H3: Energy consumption causes manufacturing industry performance
- H4: Bank credit causes manufacturing industry performance
- H5: Manufacturing industry performance causes bank credit and energy consumption.

3. DATA AND METHODS

3.1. Data and Variable Measurement

This research utilizes data obtained from the Central Bureau of Statistics and Financial Services Authority. The panel data is from Western Indonesia containing 17 provinces, and the period of the study was from the first quarter of 2010 to the fourth quarter of 2022 (2010Q1-2022Q4). These 17 provinces in Western Indonesia are Aceh, West Sumatera, North Sumatera, Lampung, South Sumatera, Jambi, Bangka Belitung, Bengkulu, Riau Islands, Riau, Jakarta, West Java, East Java, Central Java, Jogyakarta, Banten, and Bali.

The data is processed and analyzed using Stata software version 17. The dependent variable for this study is manufacturing industry performance (*lnIND*). The dependent variables of this study are bank credit (*lnCR*) and energy consumption (*lnENR*). In the causality test, all variables are treated as endogenous variables. Energy consumption (*lnEC*) uses the electricity consumption of the manufacturing industry as a proxy. The quarterly data for the electricity consumption is not available. Therefore, we convert the annual data into quarterly data using the quadratic-match-last method. The manufacturing industry performance variable (*lnIND*) is measured by the value-added of the manufacturing industry. Bank credit is measured by the bank credit of the manufacturing industry. All data are converted into natural logarithms (*ln*).

3.2. Model Specification

This study employs the panel ARDL (Autoregressive Distributed Lag) to investigate the energy consumption and bank credit on the manufacturing industry performance in western Indonesia. We also perform the causality test through the Wald test of ARDL to ascertain the pattern of causality relationship for the variable used. The application of panel ARDL is preferred above the Dynamic Generalised Methods of Moments (GMM) and static panel data. The static panel estimator can't differentiate between short and long-run relationships. Additionally, GMM isn't effective when N < T. Panel ARDL has advantages for estimating short and long-term coefficients dynamically with three types of estimators: PMG (Pooled Mean Group), MG (Mean Group), and DFE (Dynamic Fixed Effect). The PMG assumes varied coefficients and variances for short-term effects while keeping the long-term effects constant across provinces. This model works better if the (N) units share a common characteristic in the long run, despite short-term differences due to external shocks, policy response, or financial crisis vulnerability, whereas the Mean Group technique allows all coefficients to be heterogeneous both in the long and short runs. The model needs a large enough dataset in both cross-sectional (N) and time identities (T) for it to be valid, consistent, and efficient. The assumption of the homogeneous slope leads to the setup of an alternative estimator known as dynamic fixed effects (DFE), where the slopes are fixed and the intercepts vary across provinces(Pedroni et al., 1999; Asteriou and Hall, 2016).

The formation of the basic model is as follows:

$$\ln IND_{it} = \beta_0 + \beta_1 lnEC_{it} + \beta_2 lnCR_{it} + v_{it} \quad (1)$$

Where *IND* is the manufacturing industry performance, *EC* is the energy consumption of the manufacturing industry, *CR* is bank credit of the manufacturing industry, I,t is provinces of western Indonesia and period (2010Q1-2022Q4).

The MG model for testing a long-run relationship between variables is as follows:

$$\ln IND_{it} = \theta + \beta_{0i} lnIND_{i,t-1} + \beta_{1i} lnEC_{i,t-1} + \beta_{2i} \ln CR_{i,t-1} + \varepsilon_{it} \quad (2)$$

According to equation (2), MG model estimation assumes that short-term and long-term coefficients vary by province. The model needs a large enough dataset in both cross-sectional (N) and time identities (T) for it to be valid, consistent, and efficient (Pedroni et al., 1999). The application of ARDL in this study chooses the optimal time lag using the Akaike Information Criterion (AIC) which requires a longer period (T=195) than the number of cross-sections (N=17).

This is the formulation of the long-run relationship model using the PMG and DFE estimators:

$$\ln IND_{it} = \alpha_i + \sum_{j=1}^{o} \lambda_{ij} \ln IND_{i,t-j}$$
$$+\sum_{j=0}^{p} \delta_{1ij} lnEC_{i,t-j} + \sum_{j=0}^{q} \delta_{2ij} lnCR_{i,t-j} + \varepsilon_{it} \quad (3)$$

Where, *i* represents the province (1, 2, 3….17), *t* is the period (2010Q1-2022Q4), and *o*, *p*, *q* is the optimum time lags. α_i is the province's specific effect, and ε_{it} refers to the error terms. The model includes an error-correction term that denotes a short-run relationship, which can be written as follows:

$$\Delta \ln IND_{it} = \alpha_i + \varphi_i (\ln IND_{i,t-1} - \lambda_1 lnEC_{i,t-1} - \lambda_2 lnCR_{i,t-1}$$
$$+\sum_{j=1}^{o} \lambda_{ij} \Delta \ln IND_{i,t-j} + \sum_{j=1}^{p} \lambda_{1ij} lnEC_{i,t-j} + \sum_{j=1}^{q} \lambda_{2ij} \ln CR_{i,t-j} + \varepsilon_{it} \quad (4)$$

The speed of adjustment of *lnIND* towards equilibrium following movements in lnEC and lnCR is measured by ϕi, with λi representing its long-term parameters. ϕi indicates the presence of a long-term relationship between the variables. If the coefficient ϕi is negative and significant, then *lnIND*, *lnEC*, and *lnCR* are cointegrated. All ECM dynamics (ε) are assumed to be independently and identically distributed. The model accurately estimates long-run coefficients for both stationary and non-stationary regressors I(1). Its parameter estimation is consistent and asymptotically normal. According to Pesaran et al. (1999), MG and PMG estimators work well for large cross-sections in panel data analysis (N) and for the time series (T). Nevertheless, the MG estimator works inefficiently in the presence of homogeneity. Under conditions of homogeneity, the maximum likelihood-based PMG estimator is the most efficient (Asteriou and Hall, 2016).

ARDL lags provide short-term relationship information. Within the framework of the ARDL model, the causality test/Wald test is used to examine the short-term causality relationship between three variables. The Wald test computes the test statistic as an unrestricted parameter, and the standard Wald statistic has a χ^2 distribution since the constrained covariance matrix is not singular. The t statistic of the error correction factor (ECT) can be used as an indicator of long-term effects in ARDL. The specification model used to test causality can be rewritten as:

$$\Delta \ln IND_{it} = \alpha_1 + \sum_{i=1}^{o} \beta_{11} \ln IND_{it-1} + \sum_{i=1}^{p} \beta_{12} \Delta \ln EC_{it-1} + \sum_{i=1}^{q} \beta_{13} \ln CR_{it-1} + \lambda_1 ECT_{it-1} + \mu_{1it} \quad (5)$$

$$\Delta \ln EC_{it} = \alpha_2 + \sum_{i=1}^{o} \beta_{21} \ln EC_{it-1} + \sum_{i=1}^{p} \beta_{22} \Delta \ln IND_{it-1} + \sum_{i=1}^{q} \beta_{23} \ln CR_{it-1} + \lambda_2 ECT_{it-1} + \mu_{2it} \quad (6)$$

$$\Delta \ln CR_{it} = \alpha_3 + \sum_{i=1}^{o} \beta_{31} \ln CR_{it-1} + \sum_{i=1}^{p} \beta_{32} \Delta IND_{it-1} + \sum_{i=1}^{q} \beta_{33} \ln EC_{it-1} + \lambda_3 ECT_{it-1} + \mu_{3t} \quad (7)$$

Where all variables are viewed as endogenous variables. Equation (5) specifies the *lnIND* variable as the dependent variable, which is a function of energy consumption (*lnEC*) and bank credit (*lnER*). *LnEC* and *lnER* in Equations (6) and (7) are treated as the dependent variable, respectively. ECT represents the long-term causality relationship.

3.2. Panel Unit Root Test

The panel ARDL technique requires that a panel unit root test be conducted first. If the data used for parameter estimation involves non-stationary series, spurious regression results are likely to arise because of unit roots. An important characteristic of stationary series is that their trends should be close to their mean value or have a constant mean and variance. The panel unit root test aims to determine whether the data is stationary or non-stationary. Additionally, the panel unit root test aims to ascertain whether the observed variables are stationary and to determine their levels of integration.

The data used can be identified as stationary in integration order at level I (0), first difference I (1), or a mixture of both I(0) and I(1) (Asteriou and Hall, 2016; Hansen, 2017). The panel unit root test is better than regular time series data because there are many observations and province-specific heterogeneity, so it can help us to reduce bias in estimation and possibly improve the accuracy of the estimates (Hansen, 2022). Levin et al. (2002) argue that using panel unit root tests is more efficient than testing for unit roots in time series. Different methods are applied by scholars to establish the presence of panel unit roots. This research adopts the panel unit root test method as proposed by Levin, Lin, and Chu (LLC) and Im, Pesaran, and Shin (IPS). Levin et al. (2002) utilized the Quah's generalization technique to incorporate individual effects as well as diverse error structures under homogenous AR(1) premise in their research. Another assumption is that while N is very large, T should be infinite, but it grows by a larger ratio to infinity; hence, N/T→0. Our panel data has a need for IPS as it considers each individual's unique variance and correlation with other research data. In contrast to LLC, this method demands more time series observations.

3.3. The Optimal Lag Length and Hausman Test

Using the Akaike Information Criterion (AIC), it is possible to establish the optimal lag length. The optimum lag length selected for the research variable is the lag number that is most frequently and commonly used in each province. Specifically, we choose the most frequent number for all provinces and for each variable used by referring to the AIC indicator. The best estimator among MG, PMG, and DFE is selected by applying the Hausman test. When the p-value obtained from the Hausman test exceeds 0.05, our preference shifts towards the PMG estimator rather than the MG estimator. If the Hausman test between PMG and DFE is not significant, it suggests that the null hypothesis is not rejected but rather favors PMG, which could be more efficient.

4. RESULTS AND DISCUSSION

4.1. Data Description

Table 1 presents descriptive statistics that summarize and explain the features of the data by providing a brief overview and measurements. This study includes the types of descriptive statistics commonly used in statistics, i.e.: The mean, standard deviation (std. dev), minimum (min), maximum (max), and the number of observations (N). We convert all variables of interest into natural logarithms (ln).

Table 1 reports a brief overview and measurements of the research data. The descriptive statistics explain that the number of observations (N) is 884, obtained by multiplying quarterly time series data (52) and cross-sectional data (17 provinces). The industry manufacturing performance (*lnIND*) as a dependent variable has the highest mean and minimum value of 9.296, and 6.040 respectively, while the bank credit variable (*lnCR*) as one of the independent variables has the lowest mean and minimum value of 3.400 and −1.205 respectively. The standard deviation is used in statistics to quantify how much the actual data differs from their mean values. The bank credit variable is greatly dispersed from its mean value, as shown by its high standard deviation of 3.244.

Table 2 displays a correlation matrix that helps predict variable correlation and detect multicollinearity issues. However, the correlation matrix cannot be utilized to explore cause and effect. Hence, we still need statistical tools like econometrics to analyze the causal relationship between these variables.

Presented in Table 2 are Pearson's coefficients showing the relationships among the variables. All variables under analysis exhibit positive relationships with one another. The variable *lnEC*, visible in Table 2, shows the highest relative correlation compared to other pairs of variables, indicating that lnEC as an independent variable has a moderate positive correlation with the dependent variable *lnIND* (industrial performance). Moreover, the pairwise independent variables *lnEC* and *lnCR* do not appear to be heavily related, having correlation coefficients below 0.30, hence reducing the potential for multicollinearity between them.

Table 1: Descriptive statistics

Variable	n	Mean	SD	Min	Max
lnIND	884	9.296	1.557	6.040	12.089
lnEC	884	5.199	2.077	0.374	8.730
lnCR	884	3.400	3.244	−1.205	12.117

Source: Authors' computation, 2023

Table 2: Correlation matrix

	lnIND	*lnEC*	*lnCR*
lnIND	1.0000		
lnEC	0.8372	1.0000	
lnCR	0.2034	0.2196	1.0000

Source: Authors' computation, 2023

The data must be tested to ensure the presence of stationery of the variables of interest. As a result, we apply a powerful panel unit root test to preliminary tests that justify the use of the panel ARDL and we expect to obtain regression parameters that avoid spurious regression. We employ a robust panel unit root test utilizing the Levin, Lin, and Chu (LLC) and Im, Pesaran, and Shin (IPS) approaches. The results are presented in Table 3.

Table 3: Panel unit root test results

Variable	Levin, Lin, and Chu		Im, Pesaran, Shin	
	Level	First-difference	Level	First-difference
lnIND	−8.387***	−5.579***	−3.169***	−12.635***
lnEC	−1.902**	9.5121***	−1.531*	−5.511***
lnCR	−0.581	9.840***	−1.464*	−1.259

Source: Authors' computation, 2023. ***, **, * indicate the significance levels of 1%, 5% and 10%, respectively

Table 3 presents the outcomes of the panel unit root test using both the LLC and IPS methods. The LLC test results indicate that the variables lnIND and lnCR are statistically significant, whereas lnEC is not. This implies that lnEC fails to reject the null hypothesis at the first difference, indicating that all selected variables are stationary at levels of I(0) and I(1) integration orders. However, according to the IPS methodology, the lnEC variable is statistically significant at the level or order of integration I(0). Despite the differences in the LLC and IPS test results, they both lead to the same conclusion: the variables exhibit a mixed-order integration pattern of I(0) and I(1). Therefore, it can be concluded that applying the panel ARDL is appropriate for this study.

In this study, we attempt to determine the optimal lag length for the ARDL (p, q, o) model. Subsequently, we interpret the results of different estimations (e.g., MG, PMG, and DFE). We select the most common lag length among provinces, specifically by identifying the most frequently occurring number for all provinces and each variable, guided by the AIC indicator. Ultimately, we select the best lag length for the ARDL model as (1, 1, 1). Table 4 presents the short-term and long-term estimated results of the relationship in the ARDL model.

Table 4 shows that the Hausman test is used to select the best estimation method among PMG, MG, and DFE for determining the long-run relationships in panel data. The test results indicate that the null hypothesis of no systematic difference in coefficients cannot be rejected. Specifically, the Prob $>Chi^2$ values are 0.43 and 0.99, both exceeding the 0.05 threshold, indicating that the PMG estimator is appropriate in both cases. Given that the Hausman test supports the use of the PMG estimator, the final interpretation of the panel results is based on this method. This allows for the analysis of both short-term heterogeneity and long-term homogeneity coefficients. The Error Correction Term (ECT) coefficient in the PMG estimation confirms the findings from the MG and DFE estimations, showing a significant and negative relationship, which is crucial for establishing the validity, consistency, and efficiency of the long-term relationship between the variables. The ECT coefficient measures the speed at which short-term imbalances are corrected to achieve long-term stability. The ECT coefficient of −0.0794 suggests that variables in western Indonesia adjust by approximately 7.94% each quarter to return to long-run equilibrium from short-run disequilibrium, indicating a relatively fast adjustment process.

Regarding the long-term relationship of PMG estimation, all independent variables (*lnEC* and *lnCR*) are significant at the 1% significance level. In the long run, energy consumption (*lnEC* has a significant impact in boosting manufacturing industry performance with a coefficient of 0.151. This suggests that in the long run, a 1% increase in energy consumption would lead to an increase of 0.15 % in the manufacturing industry performance. This finding is consistent with the findings reported by Inani and Tripathi (2017), Wolde-Rufael, (2014), Iyke (2015), Karanfil and Li (2015), Gurgul and Lach (2012), Hamdi et al. (2014); Tang and Tan (2013), and Cowan et al. (2014). The coefficient of bank credit has a statistically significant impact on the manufacturing industry's performance. The coefficient of bank credit is statistically significant at the 1% level and has a positive coefficient of 0.0201. This means that a 1% increase in bank credit would result in a 0.02% increase in the manufacturing industry performance in the long run. This finding is in line with the findings reported by Olusegun et al. (2020), Akinlo et al. (2021), Balasubramanian (2022), Effiong et al. (2022), and Majeed et al. (2019). However, the finding was not consistent with the study of Mesagan et al. (2018).

Table 4 also presents the results of the short-term relationship of the PMG model which are inconsistent with the MG and DFE models. The results of PMG model estimation in the short run confirm that the energy consumption variable (*lnEC)* exerts a statistically significant and positive coefficient of 0.0848, this means that a 1% increase in energy consumption will lead to a 0.02% increase in production. This empirical evidence suggests that in the short term, energy consumption plays a significant role in improving the manufacturing industry performance in 17 provinces of western Indonesia. Nevertheless, the bank credit variable (*lnCR*) is statistically insignificant at all confidence levels.

The causality test using the t-statistic and Wald test of PMG estimation can provide some information relating to the causal relationship among the research variables both in the short run and long term. The causality test results are presented in Table 5.

Table 4: The panel ARDL estimation results

Variable	PMG coefficient	t-stat	MG coefficient	t-stat	DFE coefficient	t-stat
Short-run						
ECT	−0.0794	4.86***	−0.2686	−6.44***	−0.0512	−5.95***
Δ*lnEC*	0.0848	2.76***	0.0138	0.53	0.0014	0.17
Δ*lnCR*	0.0231	1.24	0.0212	0.67	−0.0043	−0.76
C	0.6434	4.97***	2.1704	5.46***	0.4499	6.01***
Long-run						
lnEC	0.1511	7.52***	0.2101	1.93*	0.1184	2.34***
InCR	0.0201	2.99***	0.0621	2.03**	0.0181	0.95
Hausman test: MG or PMG[1] 1.690 PMG or DFE[2]						0.000
P=0.431						0.998

Source: Authors' estimation. Dependent variable: Δ*lnIND*. ARDL (1, 1, 1). [1]PMG is an efficient estimation than MG under the null hypothesis. [2]PMG is an efficient estimation than DFE under the null hypothesis. ***, **, * indicate the significance level of 1%, 5% and 10%, respectively. ARDL: Autoregressive distributed lag

Table 5: The short and long-run causality test

Dependent variable	Independent variable	Short-run		Long-run	
		t-stat	Chi^2-stat	t-stat	Chi^2-stat
LnIND	lnEC	2.76***	7.62***	7.52***	56.60***
	lnCR	1.24	1.53	2.99***	8.95***
lnEC	lnIND	0.06	0.95	7.99***	63.79***
	lnCR	−1.02	1.04	1.10	1.21
lnCR	lnIND	−0.52	0.27	−1.42	2.01
	lnEC	0.02	0.00	2.06**	4.25**

Source: Authors' computation

***, **, * indicate the significance level of 1%, 5% and 10%, respectively

Table 5 presents a statistical summary of the causality test using the t-statistic and the Wald test (Chi-square statistic). In the short term, we can identify a unidirectional causal relationship running from energy consumption (*lnEC*) to manufacturing industry performance (*lnIND*), indicated by the significant t-statistic and Chi-square of the Wald test at the 1% significance level. However, the results of the short-term causality test are inconsistent compared to the long-term relationship. In the long run, it proves the existence of a two-way causality and supports the feedback hypothesis, confirming that increased energy consumption, such as electricity usage, has a significant impact on increasing the performance of the manufacturing industry, and vice versa. The improvement in the performance of the manufacturing industry leads to an increase in energy use. These results are consistent with the studies of Kasperowicz (2014), Tang and Tan (2013), Wolde-Rufael (2014), and Gurgul and Lach (2012). Regarding the finance-output nexus, both the t-statistic and Wald tests fail to reject the null hypotheses of the feedback hypotheses. However, in the long run, we find clear evidence supporting unidirectional causality from bank credit (*lnCR*) to manufacturing (*lnIND*). The results of this empirical study are consistent with the work of Balasubramanian (2022), Olusegun et al. (2020), and Majeed et al. (2019).

5. CONCLUSION AND RECOMMENDATIONS

This study attempts to highlight the impact of energy consumption and bank credit on manufacturing industry performance. In addition, this study also aims to investigate the pattern of dynamic causality link between energy consumption, bank credit, and manufacturing industry performance in 17 provinces of western Indonesia. We employ a panel ARDL and causality test to obtain an appropriate analysis for exploring the relationship between the interest variables. The panel ARDL confirms that energy consumption and bank credit play a significant role in boosting the manufacturing industry's performance in the long run. This empirical study finds strong evidence to support the long-run feedback hypotheses relating to the energy-output growth nexus. However, in the short run, bank credit is statistically insignificant at all confidence levels.

The results of this study contribute significantly, particularly to theory and practical implications. In the context of theoretical implications, future theoretical frameworks need to involve and provide a comprehensive overview of the dynamic causal relationship between the role of energy in output growth or economic development performance and expand its scope to include the important role of new renewable energy.

Practically, we recommend several policies to local governments and stakeholders. First, the government and stakeholders are advised to prioritize the development of adequate energy infrastructure and ensure it reaches all regions of Indonesia, as this is a crucial factor in supporting the long-term sustainability of national economic development. Second, the government and stakeholders should advance infrastructure and develop the utilization of new renewable energy to support sustainable future economic development. Third, we propose to develop and prioritize the integration between emerging ICTs (the Internet of Things [IoT], Artificial Intelligence [AI]) and digital financial services to facilitate efficient, secure, and accessible financial services for all communities, including the poor and isolated regions.

However, this study has several limitations, particularly regarding the scope of the analysis, which is solely focused on provinces in the western region of Indonesia. Future studies should strive to unveil dynamic relationships with a broader regional scope. Another limitation is found in the measurement of the energy consumption variable, which solely comprises electricity consumption indicators. Therefore, future research is recommended to incorporate multiple indicators to measure energy consumption.

6. ACKNOWLEDGMENT

This research is financially supported by the Indonesia Endowment Funds Agency for Education (LPDP).

REFERENCES

Acaravci, A., Ozturk, I. (2010), Electricity consumption-growth Nexus: Evidence from panel data for transition countries. Energy Economics, 32, 604-608.

Adom, P.K. (2011), Electricity consumption-economic growth Nexus: The Ghanaian case. International Journal of Energy Economics and Policy, 1, 18-31.

Akinlo, T., Yinusa, D.O., Adejumo, A.V. (2021), Financial development and real sector in sub-Saharan Africa. Economic Change and Restructuring, 54(2) 417-455.

Asteriou, D., Hall, S.G. (2016a), Applied Econometrics. 3rd ed. United Kingdom: Macmillan Education.

Asteriou, D., Hall, S.G. (2016b), Applied Econometrics. United Kingdom: Macmillan Education.

Azadi, M., Moghaddas, Z., Farzipoor Saen, R., Hussain, F.K. (2021), Financing manufacturers for investing in industry 4.0 technologies: Internal financing vs. External financing. International Journal of Production Research. https://doi.org/10.1080/00207543.2021.1912431

Balasubramanian, R. (2022), Role of long-term bank credit in the economic growth of India. Global Business Review, 1-12.

Bassey, C.E., Oduneka, A.E., Ikpe, IK. (2022), Electricity consumption and industrial performance in Nigeria. Journal of Economics and Public Finance, 8(2), p1.

Çakmak, E.E., Acar, S. (2022), The Nexus between economic growth, renewable energy and ecological footprint: An empirical evidence from most oil-producing countries. Journal of Cleaner Production, 352, 131548.

Cowan, W.N., Chang, T., Inglesi-Lotz, R., Gupta, R. (2014), The nexus of electricity consumption, economic growth and CO_2 emissions in the BRICS countries. Energy Policy, 66, 359-368.

Gurgul, H., Lach, L. (2012a), The electricity consumption versus economic growth of the Polish economy. Energy Economics, 34(2), 500-510.

Gurgul, H., Lach, L. (2012b), The electricity consumption versus economic growth of the Polish economy. Energy Economics, 34(2), 500-510.

Hamdi, H., Sbia, R., Shahbaz, M. (2014), The Nexus between electricity consumption and economic growth in Bahrain. Economic Modelling, 38, 227-237.

Hansen, B.E. (2017), Econometrics. Wisconsin: Department of Economics, University of Wisconsin.

Hansen, B. (2022), Econometrics. United States: Princeton University Press.

Inani, S.K., Tripathi, M. (2017), The Nexus of ICT, electricity consumption and economic growth in India: An ARDL approach. International Journal of Indian Culture and Business Management, 14, 457-479.

Iyke, B.N. (2015), Electricity consumption and economic growth in Nigeria: A revisit of the energy-growth debate. Energy Economics, 51, 166-176.

Karanfil, F., Li, Y. (2015), Electricity consumption and economic growth: Exploring panel-specific differences. Energy Policy, 82(1), 264-277.

Kasperowicz, R. (2014), Electricity consumption and economic growth: Evidence from Poland. Journal of International Studies, 7, 46-57.

Kemenperin. (2020), Provision of Electrical Energy Supports Industrial Growth. Available from: https://www.kemenperin.go.id/artikel/22105/penyediaan-energi-listrik-dukung-pertumbuhan-industri [Last accessed on 2023 Oct 10].

Khan, M.K., Khan, M.I., Rehan, M. (2020), The relationship between energy consumption, economic growth and carbon dioxide emissions in Pakistan. Financial Innovation, 6(1), 1.

King, R.G., Levine, R. (1993), Finance and growth: Schumpeter might be right. Quarterly Journal of Economics, 108(3), 717-737.

Kraft, J., Kraft, A. (1978), On the relationship between energy and GNP. The Journal of Energy and Development, 3(2), 401-403.

Levin, A., Lin, C.F., James Chu, C.S. (2002), Unit root tests in panel data: Asymptotic and finite-sample properties. Journal of Econometrics, 108(1), 1-24.

Levine, R. (1997), Financial development and economic growth: Views and agenda. Journal of Economic Literature, 35(2), 688-726.

Li, K., Yuan, W. (2021), The Nexus between industrial growth and electricity consumption in China - New evidence from a quantile-on-quantile approach. Energy, 231, 120991.

Majeed, S., Iftikhar, S.F., Atiq, Z. (2019), Modeling the impact of banking sector credit on growth performance: An empirical evidence of credit to household and enterprise in Pakistan. International Journal of Financial Engineering, 6(2), 1950012.

Mesagan, E., Olunkwa, N., Yusuf, I. (2018), Financial development and manufacturing performance: The Nigerian case. Studies in Business and Economics, 13(1), 97-111.

Mishkin, F.S. (2013), The Economics of Money, Banking, and Financial Markets. 10th ed. New York: Pearson Education.

Olusegun, A.A., Efuntade, O.O., Efuntade, A.O. (2020), Banks financing and industrial sector performance in Nigeria. International Journal of Accounting, Finance and Risk Management, 5(3), 157-166.

Ozcan, B., Tzeremes, P.G., Tzeremes, N.G. (2020), Energy consumption, economic growth and environmental degradation in OECD countries. Economic Modelling, 84, 203-213.

Payne, J.E. (2010), A survey of the electricity consumption-growth literature. Applied Energy, 87, 723-731.

Pedroni, P. (1999), Critical values for cointegration tests in heterogeneous panels with multiple regressors. Oxford Bulletin of Economics and Statistics, 61, 653-670.

Pesaran, M.H., Shin, Y., Smith, R.P. (1999), Pooled mean group estimation of dynamic heterogeneous panels. Journal of the American Statistical Association, 94(446), 621-634.

Salahuddin, M., Alam, K. (2015), Internet usage, electricity consumption, and economic growth in Australia: A time series evidence. Telematics and Informatics, 32, 862-878.

Shaari, M.S., Hussain, N.E., Ismail, M.S. (2013), Relationship between Energy consumption and economic growth: Empirical evidence for Malaysia. Business System Review, 2(1), 17-28.

Tang, C.F., Tan, E.C. (2013), Exploring the Nexus of electricity consumption, economic growth, energy prices and technology innovation in Malaysia. Applied Energy, 104, 297-305.

Wolde-Rufael, Y. (2014), Electricity consumption and economic growth in transition countries: A revisit using bootstrap panel granger causality analysis. Energy Economics 44, 325-330.

Xiong, J., Xu, D. (2021), Relationship between energy consumption, economic growth and environmental pollution in China. Environmental Research, 194, 110718.

Zou, G. (2022), The relationships between energy consumption and key industrial sector growth in China. Energy Reports, 8(9), 924-935.