Does Energy Consumption Impact The Environment? Evidence from Australia Using the JJ Bayer-Hanck Cointegration Technique and the Autoregressive Distributed Lag Test

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Received: 07 February 2021  Accepted: 2 April 2021  DOI: https://doi.org/10.32479/ijeep.11163

ABSTRACT

This study investigates the impact of energy consumption on environmental pollution in Australia using time series data from 1971 to 2015. Gross domestic product (GDP), total population (TP), and financial development (FD) are included as control variables. In achieving the objective, this study employ unit root test, cointegration test, and autoregressive distributed lag (ARDL) long-run and short-run methodology to examine the nexus between energy consumption, carbon dioxide (CO2) emissions, Gross Domestic Product (GDP), total population (TP), and financial development (FD). The results of ARDL long-run and short-run reveals that energy consumption is the most substantial determinant that impacts environmental pollution. However, the empirical findings suggest that GDP, TP, and FD are insignificant in contributing to an increase in CO2 emissions. Thus, this study concludes that policymakers and attention on energy consumption trend and pattern is crucial for effective policies on environmental pollution.

Keywords: Electricity Consumption, Carbon Dioxide Emissions, GDP, Bayer-Hanck Cointegration Technique, Autoregressive Distributed Lag

JEL Classifications: O13, Q43, Q54, Q56

1. INTRODUCTION

Energy use was the part of human civilization and now being QHFWLL Wolff SRF GFR **3 WWD OR SXS ODWL RQ 73 DO6G @QDQFL DOGHY HRS RSH QW) 1 DUH LQFOXG HGDVF RQWUROYDULDEOHV QDFK. The economic development of the country and economic growth is RII XGDPHWO DOL JQFQH IRUWKH GDY QDFHWHQ. In 2018, worldwide energy utilization expanded at almost double the normal pace of development since 2010, driven by a vigorous global economy (IEA 2019). Globally, the role of energy is assertive and thus undeniable economic integration as it is essential for producing goods and services.

Many researchers have focused on the economic and environmental impact of energy consumption, which has become an increasingly popular issue of debate. Global energy demand has increased since World War II and is expected to increase by more than one-third by 2035 (Toka et al., 2014). Unfortunately, although industrialization is related to economic development, it has caused higher energy consumption which, in industrialized countries, gives rise to more carbon dioxide (CO2) emissions (Hossain, 2011). Thus, the worldwide trend from carbon emission has been, perhaps, the main natural issues of this century because of the higher energy utilization indicated by the International Energy Agency, worldwide energy-related carbon emissions (CO2) increased by 1.7% in 2018, reaching a high of 33.1Gt of CO2 (IEA 2019).

M oreover, environmental standards have been continuously degraded by increased energy consumption (Dar and Asif, 2018) and therefore, currently, the world is confronting a mounting challenge like air pollution because of environmental degradation and environmental changes throughout the world (Li et al., 2012). On the other hand, the increasing trend of temperature due to climate change eventually increases because of the energy consumption for all sectors; including domestic and industrial (Saboori and Sulaiman, 2013).
Population growth is another important aspect that increases energy consumption (Khan et al., 2020). Even though, population influences the economic aspects of the country, it impacts the natural environment by utilizing more energy for domestic and business purposes (Zaharia et al., 2019). Population growth will drive higher energy demand and can therefore have negative consequences for the climate. Additionally, the improvement in the financial sector in a nation assumes a significant role in achieving financial growth (Sadorsky, 2010). It is significant because it increases the economic growth of a nation’s monetary framework. However, financial development can also influence people to purchase goods with high energy use like cars, air conditioners, refrigerators, or washing machines leading to higher energy consumption (IEA, 2019). The interaction between changing climate, population, and economic growth increases energy consumption and may have an adverse role in the natural environment.

The amount of CO₂ emissions from energy consumption has rapidly increased in Australia in recent years. Australia is the world’s twentieth largest consumer of energy and fifteenth in terms of per capita energy use (Geoscience Australia, 2020). Australia’s primary energy consumption is dominated by coal (around 40%), oil (34%), and gas (22%). Coal produces approximately 75% of the energy for electricity generation, followed by gas (16%), hydro (5%), and wind (2%) (Geoscience Australia, 2020). Figure 1 shows the trend of energy consumption, carbon emissions, and GDP growth from 1971 through 2015.

Energy consumption has increased by nearly 20 percent since the 1970s increasing from 4405.7 to 5483.82 oil equivalent per capita. Similarly, carbon emissions have increased by nearly 15% from 13.06 to 15.34 metric tons per capita. Likewise, GDP has doubled, with 27954.01 to 55079.90 per capita (constant 2010 US$).

The projected per capita energy consumption in Australia, Table 1, shows a decreasing trend until 2011 with from 5745.23 kg of equivalent per capita. However, there is a steady rise since the 1970s in economic growth (GDP per capita).

A small number of investigations have been carried out on energy consumption and its impact on the environment (Dar and Asif, 2017; Farhani and Ben Rejeb, 2012; Hasnisah et al., 2019; Khan et al., 2020). However, to our knowledge, there is no studies focusing on Australian evidence with the latest large-scale time-series data. Also to the best of our knowledge, population has not previously been considered as an exploratory variable for energy consumption. Thus, this study employs more explanatory variables compared to previous studies (Salahuddin and Khan, 2013).

The main objective of this study is to examine the impact of energy consumption on the environment in the Australian context using the time series data for 45 years from 1971-2015, using...
cointegration and the autoregressive distributed lag (ARDL) approach. The organization of this study is as follows: Section 2 shows the past work, i.e. the literature review; Section 3 describes the data and the methodology. Section 4 demonstrates the empirical results and section 5 presents the conclusion.

2. LITERATURE REVIEW

Energy consumption increases carbon dioxide (CO₂) emissions. In the last decade, numerous studies have examined the causal relationships between energy consumption, carbon emissions, and economic growth. In the case of Australia, the literature on energy economics has been relatively scarce until recently.

A large number of empirical studies have analysed the causality between energy consumption, carbon emissions, and economic growth. Farhani and Rejeb (2012) investigated the relationship between EC, GDP, and CO₂ from 1973-2008 in 15 MENA countries. They used panel unit root tests, cointegration methods, and distributed lag methods to find the causality between the variables. The results indicate that there is short-run causality from energy consumption and CO₂ emissions, and results indicate that an increase in energy consumption may lead to an increase in CO₂ emissions. Acheampong (2018), in another study, examined the dynamic causal relationship between economic growth, carbon emissions, and energy consumption using a vector autoregression (VAR) model.

In the last decade, numerous studies have examined the relationship between energy consumption and carbon emissions. Shahbaz et al. (2016) investigated the impact of energy consumption on economic and financial development using the inverted U-shaped EKC hypothesis. The results from FMOLS and system-GMM approaches indicate that energy consumption is a significant factor for higher energy consumption and a contributor to CO₂ emissions.

Numerous analysts have expanded their examination for energy use with a focus on energy efficiency and energy utilization. Financial development has led to an improvement in environmental quality as revealed by Dar and Asif (2017). The study found that financial development could be a crucial variable and an interesting way to study the nature of the relationship between energy consumption and carbon emissions. Shabbaz et al. (2013) and Khan et al. (2020) investigated the impact of financial development and energy utilization. Financial development has led to an improvement in environmental quality as revealed by the EKC hypothesis. The results from FMOLS and system-GMM approaches indicate that energy consumption is a significant factor for higher energy consumption and a contributor to CO₂ emissions.
In contrast, using the Johansen cointegration technique, VAR, and impulse response, Salahuddin and Khan (2013) suggest that there is no stable long-run relationship between economic growth, energy consumption, and CO2 emissions. Based on the above magnitude of the impact of energy consumption on CO2 emissions for next 10 years may be useful for the formulation of future energy policy for Australia.

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In accordance with the past studies, this study estimates the relationship between energy consumption and environment, while controlling other variables. The linkages between CO2 emissions, energy consumption, economic growth, total population, and CO2 emissions per capita is a proxy for environmental pollution and an independent variable is energy consumption (EC). The control variables are Gross Domestic Product (GDP) per capita (constant 2010US$), Total Population (TP), and the Financial Development (FD) (% of GDP). The general form of the empirical equation is modelled as follows:

\[ \ln CO_2 = \beta_0 + \beta_1 \ln EC + \beta_2 \ln GDP + \beta_3 \ln TP + \beta_4 \ln FD + \epsilon_t \]  

(3)

To get the direct elasticities of coefficients and to make the estimation process smooth we take the log of the variables are taken which helps to select suitable time series models derived from eq (2)

\[ \ln CO_2 = \beta_0 + \beta_1 \ln EC + \beta_2 \ln GDP + \beta_3 \ln TP + \beta_4 \ln FD + \epsilon_t \]  

(4)

Where, \( \beta_0, \beta_1, \beta_2, \beta_3, \beta_4 \) and \( \epsilon_t \) are the coefficients and error term, \( t \) is the time period and \( \ln \) is the natural logarithm.

3. EMPIRICAL MODEL AND ECONOMETRIC METHODS

In accordance with the past studies, this study estimates the relationship between energy consumption and environment, while controlling other variables. The linkages between CO2 emissions, energy consumption, economic growth, total population, and CO2 emissions per capita is a proxy for environmental pollution and an independent variable is energy consumption (EC). The control variables are Gross Domestic Product (GDP) per capita (constant 2010US$), Total Population (TP), and the Financial Development (FD) (% of GDP). The general form of the empirical equation is modelled as follows:

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(2)

To investigate the long-run relationship between the variables, we employed the following equation derived from eq (1) is employed.

\[ \ln CO_2 = \beta_0 + \beta_1 \ln EC + \beta_2 \ln GDP + \beta_3 \ln TP + \beta_4 \ln FD + \epsilon_t \]  

(3)

3.1. Estimation Procedures

3.1.1. Stationarity and unit root test

The statistical properties, i.e. stationary properties, should be revealed the impact of energy consumption on environmental pollution (proxy by CO2 emissions) in Australia. Further, the ARDL model approach is another widely used technique to examine the long-run and short-run relationship between energy consumption and CO2 emissions.

Thus, our study will fill the gap in the existing literature by revealing the impact of energy consumption on environmental pollution. Hence, this study will investigate the long-run and short-run relationship between energy consumption and CO2 emissions. The ARDL approach is another widely used technique to examine the impact of energy consumption and environmental pollution (Ali, Abdullah, & A zam, 2016; Dar and A sif, 2018; M irza & K anwal, 2017; Van and B ao, 2018).

In accordance with the past studies, this study estimates the relationship between energy consumption and environment, while controlling other variables. The linkages between CO2 emissions, energy consumption, economic growth, total population, and CO2 emissions per capita is a proxy for environmental pollution and an independent variable is energy consumption (EC). The control variables are Gross Domestic Product (GDP) per capita (constant 2010US$), Total Population (TP), and the Financial Development (FD) (% of GDP). The general form of the empirical equation is modelled as follows:

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3.1.2. Zivot-Andrews unit root test

The ADF test is mostly a non-robust test for the unit root. So, to be sure, an additional test for the unit root, the Phillip Perron (PP) (Phillips and Perron, 1988) unit root tests. They test the null hypothesis: a series has a unit root (non-stationary) while the alternative is that there is stationarity.

The ADF test is mostly a non-robust test for the unit root. So, to be sure, an additional test for the unit root, the Phillip Perron (PP) test, is undertaken. The PP test is a non-parametric statistical method that takes care of serial correlation without using the Augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1979) and Phillips –Perron (PP) (Phillips and Perron, 1988) unit root tests. They test the null hypothesis: a series has a unit root (non-stationary) while the alternative is that there is stationarity.

In accordance with the past studies, this study estimates the relationship between energy consumption and environment, while controlling other variables. The linkages between CO2 emissions, energy consumption, economic growth, total population, and CO2 emissions per capita is a proxy for environmental pollution and an independent variable is energy consumption (EC). The control variables are Gross Domestic Product (GDP) per capita (constant 2010US$), Total Population (TP), and the Financial Development (FD) (% of GDP). The general form of the empirical equation is modelled as follows:

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PP model tests the unit root as follows

\[ \Delta y_t = \mu + \delta y_{t-1} + \beta_1 + \sum_{i=1}^{k} \beta_i \Delta y_{t-i} + \epsilon_t \]  

(5)

Where, \( k \) is number of lags, \( \delta = 0 \) and \( \epsilon_t \) is white noise disturbance. The ADF’s null hypothesis is that \( \delta = 0 \) against the alternative hypothesis of \( \delta < 0 \). If we do not reject the null, the series is non-stationary whereas rejection means the series is stationary.

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3.1.2. Zivot-Andrews unit root test

ADF test and PP test may provide biased and spurious results due to not having information about structural breakpoints that occurred in the series (Baum, 2003). Following Zivot-Andrews
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3.2. Cointegration Analyses
The long-term relationship between energy consumption and the environment in this study is investigated by using cointegration approaches i.e. Johansen and Juselius (JJ) test and Bayer-Hanck (BH) cointegration test.

3.2.1. JJ cointegration testing approach
Johansen and Juselius (1990) cointegration method is used to estimate the long-run relationship among the series. The Johansen and Juselius cointegration technique is constructed on \( \lambda_n \) and \( \lambda_{max} \) statistics. Trace statistics investigates the null hypothesis of \( r \) cointegrating relations against the alternative of \( N \) cointegrating relations and is computed as:

\[
\lambda_n = N \sum_{i=r+1}^{N} \log(1-\lambda_i) \tag{8}
\]

Where \( N \) is the number of observations, is the ordered Eigen-value of matrices.

The maximum Eigen-value statistics tests the null hypothesis of \( r \) cointegrating relations against the

\[
\lambda_{max} = N \log(1-\lambda_r+1) \tag{9}
\]

Where \( N \) is the number of observations, is the ordered Eigen-value of matrices.

3.2.2. Bayer-Hanck (BH) cointegration testing approach
The Bayer and Hanck (2013) cointegration tested blend various test statistics ranging from Engle and Granger (1987); Johansen (1991); Boswijk (1995) and Banerjee et al. (1998). The current study also used the BH cointegration test to assess possible cointegration between the environment and energy consumption. Bayer and Hanck (2013) proposed a combination of the computed \( V_L \) QL\( \phi \)DQFH OHYHOP \( p \)-values of the individual cointegration test with the following formulae:

\[
\begin{align*}
\text{EG} - \text{J OH} &= -2[\log (pEG) + (pOH)] \\
\text{EG-J OH-BO-BDM} &= -2[\log (pEG) + (pOH)] + (pBO) + (pBDM)) \tag{10}
\end{align*}
\]

Where \( pEG \), \( pOH \), \( pBO \), and \( pBDM \) are the \( p \)-values of cointegration tests Engle and Granger (1987); Johansen (1991); Boswijk (1995) and Banerjee et al. (1998) respectively. According to Bayer and Hanck (2013), the decision rule holds that where the calculated Fisher statistic is greater than the critical values, the null hypothesis of cointegration can be rejected.

3.3. Lag Length Test
The lag order selection results are based on the Akaika Information Criterion (AIC) which affords the best model. The AIC criteria for lag length selection are suitable for this study (Etokakpan et al., 2020). Thus, we selected the lag-length of one model for ARDL estimation is selected.

3.4. Long-run and Short-run Dynamics
After testing the stationarity properties of the series and various cointegration approaches, we applied ARDL testing to examine the long-run relationship and short-run dynamics (i.e. traditional ARDL) among the variables of a single model (Nkoro and Uko, 2016). A vector error correction model (ECM) was then specified, from which the reparametrized result gave a long-run relationship and short-run dynamics (i.e. traditional ARDL) among the variables of a single model (Nkoro and Uko, 2016).

If the cointegration was established among the variables, the run ORQDQV KRUWUXQP RGH0V R1S5VSHFLOFDWLRQFRX OEH in the following equations.

\[
\begin{align*}
n\text{CO}_2 &= \beta_0 + \beta_1\text{lnCO}_2t-1 + \beta_2\text{lnEC}_2t-1 + \beta_3\text{lnGDP}_t-1 + \beta_4\text{lnTP}_t-1 + \beta_5\text{lnFD}_t-1 + \sum_{j=1}^{q}\delta_j\text{lnEC}_{t-j} + \sum_{k=1}^{q}\delta_k\text{lnGFCF}_{t-k} + \sum_{n=1}^{q}\phi_n\text{lnFD}_{t-n} + \epsilon_t
\end{align*}
\]
Short-run

\[ \Delta \ln CO_2 = \beta_0 + \beta_1 \ln CO_{2t-1} + \beta_2 \ln EC_{2t-1} + \beta_3 \ln GDP_{t-1} + \beta_4 \ln TP_{t-1} + \beta_5 \ln FD_{t-1} + \sum_{i=1}^{p} \gamma_i \Delta \ln CO_{2i-1} + \sum_{j=1}^{q} \delta_j \Delta \ln EC_{t-j} + \sum_{k=1}^{q} \eta_k \Delta \ln GDP_{t-k} + \sum_{l=1}^{q} \theta_l \Delta \ln TP_{t-l} + \sum_{m=1}^{q} \beta_m \Delta \ln FD_{t-m} + \alpha \varepsilon_{t-1}, \]

\[ \Delta \ln TP = \beta_0 + \beta_1 \ln TP_{2t-1} + \beta_2 \Delta \ln TP_{t-1} + \beta_3 \Delta \ln TP_{t-1} + \sum_{i=1}^{p} \gamma_i \Delta \ln TP_{2i-1} + \sum_{j=1}^{q} \delta_j \Delta \ln TP_{t-j} + \sum_{k=1}^{q} \eta_k \Delta \ln TP_{t-k} + \sum_{l=1}^{q} \theta_l \Delta \ln TP_{t-l} + \sum_{m=1}^{q} \beta_m \Delta \ln TP_{t-m} + \alpha \varepsilon_{t-1}, \]

by which shows the speed of adjustment of the variables toward long-run convergence.

4. EMPIRICAL RESULTS AND ANALYSIS

The empirical results were obtained from STATA 14.2 software. The descriptive statistics between the variables were measured in natural logarithms and were found to be normally distributed (See Table 2) within a reasonable range. This would allow the Phillips-Perron (PP) (Phillips and Perron, 1988), and Zivot-Andrews (ZA) (Zivot and Andrews, 1992) structural break unit root test was applied to examine the status of the unit-root test and the presence of a structural break in our series.

These results in Table 4 suggest that we can reject the null of unit root by which shows that the ADF and PP tests indicate that the variables are stationary DW øU VW GL ÙH HQ FHV LHV,

Moreover, we have applied Zivot and Andrews (1992) structural break unit root test was applied to examine the status of the unit-root test and the presence of a structural break in our series.

4.2. JJ Cointegration Test

To check the cointegration, we used the Johansen-Juselius (JJ) test (Johansen and Juselius, 1990) was used to determine whether the JJ test showed any combination of the variables that are cointegrated. The results are presented in Table 5.

Here, the Trace statistic is less than 5% critical value, so we accept the null hypothesis meaning that there is one co-integration in both Trace statistics and this guides a substantial long-run relationship existing among the series of variables. JJ cointegration has a null hypothesis that if the trace and max value is greater than 5% critical value, we reject the null hypothesis of no cointegration. This FRQ øUP VWK HQR FQ FOX LRO WQK DWW K KUHL VRQ HFRL QW HJUDW amongst the variables.

4.3. Bayer–Hanck Cointegration Test

The third approach of cointegration is Bayer and Hanck cointegration test. To enhance the power of the cointegration, this study uses the cointegration test suggested by Bayer and Hanck (2013) to check the presence of cointegrating relationships among the variables suggested by Shahbaz et al. (2015). The result of the Bayer and Hanck test of combined cointegration, as of Table 6, shows that the calculated test statistic values of EG-J and EG-J-BG-BO, which are 55.7569 and 111.0201 are higher than 5% critical value, i.e. 10.419 and 19.888 respectively. Hence, we reject the null hypothesis of no cointegration was rejected. Thus, these tests all supported the JJ and ARDL cointegration test which also revealed the presence of a long-run relationship between the study variables.

4.4. Lag Length Selection

The ARDL bound test of cointegration can now be co-opted to explore the cointegration between the variables. Primarily we selected the Akaike Information Criterion (AIC) to estimate the lag length of considered variables to examine the long-run relationship between the series. The outcome of the lag length is given in Table 7:

Table 1: Trend of energy consumption, carbon emissions and GDP per capita in Australia

| Time Period | Energy consumption (kg of oil equivalent per capita) | Carbon emissions (metric tons per capita) | GDP per capita (constant 2010 US$) |
|-------------|-------------------------------------------------------------|------------------------------------------|----------------------------------|
| 1970s       | 4405.7                                                      | 13.06                                     | 27954.01                         |
| 1980s       | 4748.35                                                     | 15.45                                     | 32557.86                         |
| 1990s       | 5292.48                                                     | 16.17                                     | 38993.59                         |
| 2000s       | 5694.56                                                     | 17.48                                     | 48982.67                         |
| 2011        | 5745.23                                                     | 17.54                                     | 52567.76                         |
| 2012        | 5575.23                                                     | 17.07                                     | 53682.03                         |
| 2013        | 5468.39                                                     | 16.10                                     | 54129.94                         |
| 2014        | 5334.68                                                     | 15.40                                     | 54679.42                         |
| 2015        | 5483.82                                                     | 15.34                                     | 55079.90                         |

Source: Author’s estimation

Table 2: The descriptive statistics

| Descriptive Statistics | lnCO2 | lnEC | lnGDP | lnTP | lnFD |
|------------------------|-------|------|-------|------|------|
| Mean                   | 2.7425| 8.5293| 10.5424| 16.6808| 4.0740|
| Median                 | 2.7470| 8.5350| 10.4938| 16.6872| 4.1495|
| Maximum                | 2.9014| 8.6936| 10.9165| 16.9859| 4.9150|
| Minimum                | 2.4689| 8.2914| 10.1759| 16.3756| 3.1634|
| St. Deviation          | 0.1151| 0.1080| 0.2429| 0.1752| 0.6036|
| Skewness               | -0.8384| -0.3660| 0.1933| -0.0026| -0.1445|
| Kurtosis               | 2.9239| 2.0997| 1.6004| 1.8855| 1.4821|
| Variance               | 0.0133| 0.0116| 0.0590| 0.0307| 0.3643|
| Observations           | 45    | 45    | 45    | 45    | 45 |
Table 3: Unit root test

| Tests                         | lnCO₂     | lnEC      | lnGDP     | lnTP      | lnFD      |
|-------------------------------|-----------|-----------|-----------|-----------|-----------|
| Augmented Dickey-Fuller       |           |           |           |           |           |
| At level I (0)                | -2.659*** | -2.482*** | -0.075*** | 0.310***  | -0.569*** |
| Phillips and Perron           |           |           |           |           |           |
| At level I (0)                | -2.611*** | -2.391*** | -0.093*** | -0.079*** | -0.591*** |

Once the JJ and BH cointegration approaches confirm the cointegration among the variables, the lag length of all variables were determined using Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Zivot-Andrews structural break trended unit root test.

4.5. ARDL (Long-run and Short-run) Approach

The long-run equilibrium relationship between carbon dioxide (CO₂) emissions and the long-run equilibrium relationship between carbon dioxide (CO₂) emissions and energy consumption for Australia is given in Table 7.

Table 4: Vivot-Andrews structural break trended unit root test

| Variable | At level | At first difference |
|----------|----------|---------------------|
| lnCO₂    | -1.697   | -7.445 (0)***       |
| lnEC     | -2.588   | -8.265 (0)***       |
| lnGDP    | -3.552   | -6.402 (0)***       |
| lnTP     | -2.735   | -6.421 (0)***       |
| lnFD     | -5.790   | -6.372 (0)***       |

The short-run results reveal that the lag value energy consumption causes an increase in carbon emissions. The impact of energy consumption on carbon emissions is stronger. However, economic growth, total population, and financial development also have a positive but insignificant impact on carbon emissions. The impact of energy consumption is positive (0.5993) and significant (0.04) at a 5% significance level in the short run, similar to the results of the long-run estimates. Likewise, economic growth, total population, and financial development have a negative coefficient and have no significant impact on carbon emissions. The impact of energy consumption has a positive and significant impact on metric tons per capita CO₂ emissions.

5. DISCUSSION

The Table 9 shows the estimated error correction model adjustment and the estimated error correction model adjustment for long-run equilibrium relationship between carbon emissions and energy consumption for Australia. The results of the short run, independent variables (energy consumption) on dependent variable i.e. carbon emissions (CO₂) for Australia is given in Table 9.

4.6. Diagnostic Test Result

As presented in Table 8, we ran some diagnostic tests were ran to check the serial correlation, heteroscedasticity, and normality of the residuals. The Breusch-Godfrey LM test for autocorrelation, the Breusch-Pagan / Cook-Weisberg test for heteroscedasticity, and the Jarque-Bera test for normality. The Breusch-Godfrey LM test for autocorrelation showed no serial correlation, the Breusch-Pagan / Cook-Weisberg test for heteroscedasticity indicated no heteroscedasticity in the data and the Jarque-Bera test revealed that the residuals were normally distributed.

4.7. Stability of Short-run Model

The present study also assesses the constant of short-run beta that the residuals were normally distributed.
Figure 2: The results of the stability test of CUSUM and CUSUM Q

![Figure 2: The results of the stability test of CUSUM and CUSUM Q](image)

Table 6: Bayer–Hanck cointegration test

| Model Specification | Fisher Type Test statistics | Cointegration decision |
|---------------------|-----------------------------|------------------------|
|                     | EG-J 5% critical value      | EG-J-BG-Bo 5% critical value | Cointegration decision |
| \( CO_2 = f (EC, GDP, TP, FD) \) | 55.517709 | 10.576 | 63.452129 | 20.143 | Cointegrated |

Table 7: Lags of variables

| Lag | 0 | 1 | 2 | 3 | 4 | Selected lags |
|-----|---|---|---|---|---|--------------|
|     | AIC | AIC | AIC | AIC | AIC | AIC |
| \( \ln CO_2 \) | -1.92029 | -4.09662** | -4.0543 | -4.01113 | -3.96279 | 1 |
| \( \ln EC \) | -1.92439 | -4.57696** | -4.55016 | -4.5023 | -4.46933 | 1 |
| \( \ln GDP \) | -0.094284 | -5.45254** | -5.41374 | -5.38018 | -5.33262 | 1 |
| \( \ln TP \) | -0.815685 | -8.88643 | -8.91328** | -8.88334 | -8.84642 | 2 |
| \( \ln FD \) | 1.74611 | -3.02219 | -3.09505** | -3.04659 | -3.00077 | 2 |

Table 8: Long-run dynamics using the ARDL approach.

| ARDL (1 1 1 2 2) model coefficients |
|-------------------------------------|
| Variables | Coeff. | t-stats | Prob. |
| Constant | -2.0402 | -0.57 | 0.571 |
| \( \ln EC \) | 2.6316 | 2.17 | 0.038** |
| \( \ln GDP \) | -0.0858 | -0.92 | 0.366 |
| \( \ln TP \) | -0.2339 | -0.92 | 0.366 |
| \( \ln FD \) | 0.2713 | 2.17 | 0.038** |

Table 9: Short-run dynamics using the ARDL approach

| Variables | Coeff. | t-stats | Prob. |
|-----------|--------|---------|-------|
| \( \ln EC \) | 0.5993 | 2.15 | 0.040** |
| \( \ln GDP \) | 0.0331 | 0.10 | 0.919 |
| \( \ln TP \) | 1.2140 | 0.96 | 0.345 |
| \( \ln FD \) | 0.0443 | 1.54 | 0.135 |
| \( \text{ECM} (-1) \) | -0.1533 | -1.07 | 0.295*** |

We implemented the ARDL approach to investigate long-run and short-run relationship. The long-run dynamics from the ARDL results show that the energy consumption causes an increase in carbon emissions in Australia. Results reported for long-run and short-run relationship. The long-run dynamics from the ARDL model coefficients show that energy consumption has a positive and significant impact on metric tons per capita of CO₂ emissions of Australia. The impact of energy consumption is positive and significant at a 5% significance level in the short run, similar to the results of the long-run estimates. Our results are consistent with the findings of Shahbaz et al. (2017), Tang and Tan (2015), and Ali et al. (2016) who found evidence that energy consumption...
leads to carbon dioxide (\(CO_2\)) emissions in the long-run. This is because energy consumption has increased by nearly 20 percent since the 1970s increasing from 4405.7 to 5483.82 oil equivalent per capita until 2015.

Likewise, our results reveal that economic growth, total SRSXODWRQDOQGGdqDQFRLDQGHYHORSRPHQWDVRKDYFSVXMVWUDLDO energy sector represents 5% of gross industrial value-added, 20 percent of total export value, and supports a large range of manufacturing industries (Geoscience Australia, 2020). The HQQHU]GHPDQGQLVH[DQGGLQD]SVXVWUDLDO produces nexus between energy consumption and GDP contradicts the results with Van and Bao (2018) and AI-Mulali and Sab (2018), total population with OLUJDDQGDOQDFRLQDGKDQHWWDDQGDOQDFLDO development with Sadorsky (2010) in the long-run growth nexus.

6. CONCLUSION

This study explores the linkages between environmental quality, HQHU]FRQVXPSWLRQHFRRQPLFJURZWK\@QDFRLQDGKDQHWWDDQGDOQDFLDOI and total population for Australia from 1971 to 2015 by employing the ARDL model. Australia is one of developed economies in the world and largely depends on energy for the development and economic growth. This dependence causes considerable carbon emissions in the atmosphere. Thus this paper analyses the nexus between energy consumption and carbon emissions for 44 observations.

The results of the cointegration tests showed that the sampled variables were cointegrated and a long-run relationship between the variables existed in Australia. The long-run dynamics from the ARDL results show that the energy consumption causes an increase LQFDUERQHPLVLRQLQXSVXVWUDLDO7KLVVXGLVVLQROK\@QDFRLQDGKDQHWWDDQGDOQDFLDO reason that Australia has large variations in the environment which LHVHISRVHGVRQDGDUQHDKVQTVKHUIRGHULQKLVLQJKWVXGLVVLQROKQGDDQGDL. This study overall evaluates the impacts of energy consumption on carbon emissions taking into account economic growth, SRSXODWRQDOQGGdqDQFRLDQGHYHORSRPHQWRZHURYHUWDDQGDOQDFLDO components of energy consumption like energy use and/or renewable or non-renewable energy from the industrial sector have not been addressed and these areas should be more closely addressed by future researchers.

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