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

Avishek Khanal*

University of Southern Queensland, Toowoomba, Australia. *Email: avishek.khanal@usq.edu.au

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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 (CO_2) 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 CO_2 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 necessity from day to day life to commercial use, plays significant role and is in increasing trend. Energy plays a significant role in the economic development of a country and economic growth is of fundamental significance for the advancement of any nation. 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 (CO_2) emissions (Hossain, 2011). Thus, the worldwide temperature boost from carbon emission has been, perhaps, the main natural issues of this century because of the higher energy utilization (Bose, 2010). As indicated by the International Energy Agency, worldwide energy-related carbon emissions (CO_2) increased by 1.7% in 2018, reaching a high of 33.1Gt of CO_2 (IEA 2019). Moreover, 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 of 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 CO_2 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.

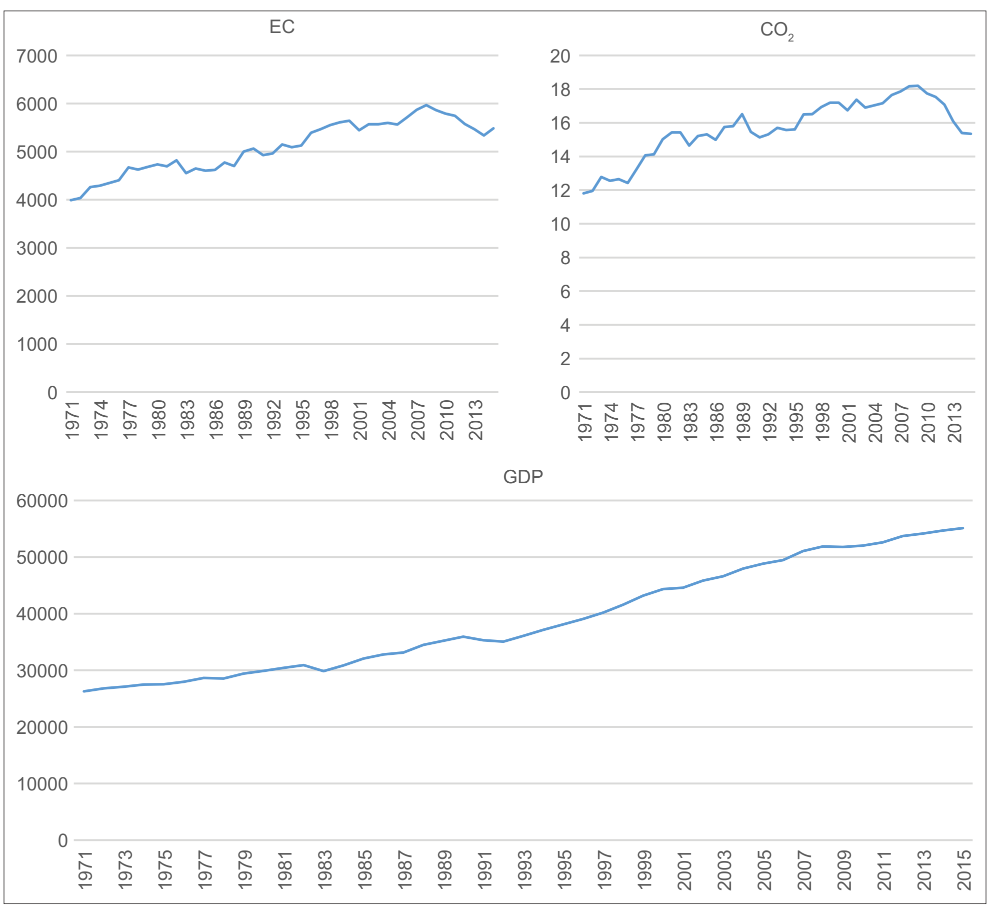
Energy consumption has increased by nearly 20 percent since the 1970s increasing from 4405.7 to 5483.82 oil equivalent per capita. Similarly, carbon emissions have increased by nearly 15% from 13.06 to 15.34 metric tons per capita. Likewise, GDP has doubled, with 27954.01 to 55079.90 per capita (constant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

The projected per capita energy consumption in Australia, Table 1, shows that there is an increasing trend until 2011 with from 4405.7 to 5745.23 kg of equivalent per capita. However, there is fluctuation seen from 2012 to 2015. Similarly, projected carbon emissions have shown an increase until 2012 and some downward trends were apparent in the years 2013, 2014, and 2015 with 16.10, 15.40, and 15.34 respectively. And there has been seen 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

Figure 1: The trend of energy consumption, carbon emissions and GDP in Australia from 1971-2015



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 (CO_2) 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) **i**nvestigated the relationship between EC, GDP, and CO2 from 1973-2008 in 15 MENA countries. They used panel unit root tests, cointegration methods, and causality tests to find the causality between the variables. The key findings were that there is short-run causality from energy consumption and to CO_2 emissions and results indicate that an increase in energy consumption may lead to an increase in CO_2 emissions.

Several studies examined the presence of causality using different methodological estimation strategies. Granger causality tests are one of the most commonly used methods to investigate the relationship between energy and carbon. In a study of 19 countries, Al-Mulali and Sab (2012) investigated the impact of energy consumption on economic and financial development using panel Granger causality tests. They found that 75% of fossil fuel consumption from the total energy consumption play an important role in increasing the level of pollution. This result was similar to the result of Al-Mulali and Sab (2018) in UAE where energy consumption increased 160% from 267.2 million Btu per person in 1980 to 704.8 million Btu per person in 2009. This has caused an increase in CO_2 which rose from 30.3 million metric tons to 195.8 million metric tons between 1980 and 2008.Likewise, using the Johanesn-Juleius (JJ) cointegration test, VECM and the Granger causality test, Dar and Asif (2017) and Mirza and Kanwal (2017) reported that an increase in energy consumption will also lead to high CO_2 emissions in the economy in the long run and vice versa and bidirectional causality exists between them.

There is increasing interest in testing the environmental Kuznets curve (EKC) hypothesis for environmental quality and economic performance. In a recent study (Hasnisah et al., 2019) of 13 developing countries in Asia, the study confirmed the existence of the inverted U-shape EKC hypothesis. The results from FMOLS and DOLS long-run estimates indicated that a 1% increase in energy use from electricity consumption contributed 38.7% and 36.49% of carbon emissions in the long-run for 13 Asian countries However, it failed to prove that renewable energy is capable of contributing positively to the environment and therefore it is insignificant. Nevertheless, an econometric study of the impact of economic growth and energy use on carbon emissions in 58 countries from 1990 to 2012 was undertaken by Kais and Sami (2016).In their empirical investigation, they found that 1% increase in per capita energy use will lead to a 0.843% increase in per capita carbon emissions globally, 0.993% in the European and North Asian regions, 0.744% in Latin America and the Caribbean, and finally 0.788% in the Middle Eastern, North African and sub-Saharan regions. They concluded through the EKC hypothesis that per capita energy use has a positive impact on carbon emissions and follows the U-shaped pattern.

Focusing on industrialized countries, Hossain (2011) investigated the relationship between carbon emissions, energy consumption, trade openness, and urbanization using the Johansen Fisher panel cointegration test over the 1971-2007 period. The findings revealed that in the long run, a 1% increase in energy use increased CO_2 by 1.2%. As a result, higher energy consumption in the newly industrialized countries gave rise to more CO_2 emissions, causing environmental pollution. Acheampong (2018), in another study, examined the dynamic causal relationship between economic growth, carbon emissions, and energy consumption using a system –generalized method of moment (System-GMM) and panel vector auto regression (PVAR) in 116 countries. He found that 1% increase in carbon emissions would decrease energy consumption by 0.07% global level, EC does not cause carbon emissions in the Asia Pacific, energy consumption uni-directionally causes carbon emissions and the direction of causality is negative in the Caribbean - Latin America and sub-Saharan Africa, EC positively causes carbon emissions in the MENA region.

On the other hand, increasing population is another important contributor to energy consumption (Khan et al., 2020). According to Khan et al. (2020), an increase in the population increases high per-capita energy consumption affecting the environmental quality especially ecological footprint and CO_2 emissions of the USA. In another paper, Mirza and Kanwal (2017) examined, the effect of human activities and energy consumption. They concluded from the most flexible ecological framework that population growth is a significant factor for higher energy consumption and a contributor to carbon emissions in Pakistan.

Numerous analysts have expanded their examination for energy use to improve the financial sector. The results are mixed for financial development and energy utilization. Financial development has led to an improvement in environmental quality as revealed by Dar and Asif (2017).To support this, a study conducted on 129 countries by Al-Mulali et al. (2015) has revealed that financial development enhances the energy efficiency and performance of industries, thus helps in reducing energy consumption and carbon emissions. As opposed to this, Sadorsky (2010) claimed that financial development increased the demand for energy in emerging economies. Consequently, from the literature discovered that financial development could be a crucial variable and an interesting way to study the nature of the relationship between energy consumption and financial development along with the other independent variables.

Finally, in the context of Australia, only two empirical investigations have been undertaken to investigate the nexus of energy consumption and carbon emissions. Shahbaz et al.

(2017) explored the long-run dynamics of CO_2 emissions, economic growth, and population growth along with the effects of globalization, tested as contributing factors over 1970-2012. The Cointegration and causality tests and impulse response function explained that a 1.35% increase in CO_2 emissions is associated with a 1% rise in energy consumption. In conclusion, increasing energy consumption and population growth has been shown to consistently and positively affect CO_2 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 CO_2 emissions. Based on the above findings, they recommended that further studies forecasting the magnitude of the impact of energy consumption on CO_2 emissions for next 10 years may be useful for the formulation of future energy policy for Australia.

Thus, our study will fill the gap in the existing literature by revealing the impact of energy consumption on environmental pollution (proxy by CO_2 emissions) in Australia. Further, this study will also discuss financial development, as no other study has incorporated financial development as a control variable in the context of Australia. With 45 years of data from 1971-2015 and employing the cointegration technique of Johansen and Juselius (JJ) and Bayer-Hanck (BH), this study will investigate the long-run and short-run relationship between energy consumption and carbon emissions with GDP, total population, and financial development as control variables using the ARDL model. The ARDL approach is another widely used technique to examine the impact of energy consumption and environmental pollution (Ali, Abdullah, & Azam, 2016; Dar and Asif, 2018; Mirza & Kanwal, 2017; Van and Bao, 2018).

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 CO_2 emissions, energy consumption, economic growth, total population, and financial development are tested from the yearly time series data over the period of 1971-2015. The dependent variable CO_2 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:

$$CO_2 = f\,(EC, GDP, TP, FD) \quad (1)$$

The natural logarithm of all variables is used in the above econometric analysis to gain growth impacts of independent variables on the dependent variables.

$$\ln CO_2 = f\,(\ln EC, \ln GDP, \ln TP, \ln FD) \quad (2)$$

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

$$CO_{2t}=\beta_0+\beta_1\, EC_t+\beta_2\, GDP_t+\beta_3\, TP_t+\beta_4\, FD_t+\varepsilon_t \quad (3)$$

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)

$$\text{Ln } CO_{2t}=\beta_0+\beta_1 \ln EC_t+\beta_2 \ln GDP_t+\beta_3 \ln TP_t+\beta_4 \ln FD_t+\varepsilon_t \quad (4)$$

Where β_0, β_1, β_2, β_3, β_4, and β_5 are the slope coefficients ε_t is the error term, tis the time period and _*ln* is the natural logarithm.

3.1. Estimation Procedures

3.1.1. Stationarity and unit root test

The statistical properties, i.e. stationary properties, should be implemented before undertaking the analysis of the data to fulfil the guidance on the choice of an appropriate model for the analysis. The stationary levels for the time series analysis are determined by employing 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.

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 lagged differences of the dependent variable (Gujarati and Porter, 2009). Hence, the PP test is considered an alternative as it allows for milder assumptions on the distribution of errors and presents an opportunity to control for higher-order serial correlation in the time series variables, and is robust against heteroscedasticity (Kouakou, 2011). Therefore, the ADF test and PP test are used in the study to check for stationarity following.

ADF model tests unit root as follows

$$\Delta y_t = \mu + \delta y_{t-1} + \beta_t + \sum_{i=1}^{k} d_i \Delta y_{t-i} + e_t \quad (5)$$

Where, k=number of lags, t–i =1,……, k, $\delta = \alpha - 1$, α = coefficient of y_{t-1} and Δy_t = first difference of y_t and e_t = 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.

PP model tests the unit root as follows

$$\Delta y_t=\mu+\delta y_{t-1}+\beta_t+e_t \quad (6)$$

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

(ZA) (Zivot and Andrews, 1992) structural break unit root test, we have applied the ZA unit root test prior for cointegration have been applied, stemming in the variables.

Zivot-Andrews method contains consistency of structural breaks inside series which is performed by running the following equations adapted from Ertugrul et al. (2016).

$$\Delta y_t = c + cY_{t-1} + \beta t + dDU_t + dDT_t + \sum_{j=1}^{k} d_j \Delta Y_{t-j} + \varepsilon_t \quad (7)$$

Where DU_t is shift dummy variable showing shift occurred at each point break date and DT_t is trend shift dummy variables (Ertugrul et al., 2016). They can be identified as:

$$DU_t = \begin{cases} 1 & \text{if } t > TB \\ 0 & \text{if } t < TB \end{cases} \text{ and } DT_t = \begin{cases} t - TB & \text{if } t > TB \\ 0 & \text{if } t < TB \end{cases} \quad (8)$$

The null hypothesis of unit root break date is $c = 0$ which indicates that the series is not stationary with a drift not having information about structural breakpoint while $c < 0$ hypothesis implies that the variable is found to be trend-stationary with one unknown time break. It is necessary to choose a region where the endpoints of the sample period are excluded (Shahbaz et al., 2013).

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. J.J 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 λ_{trace} and λ_{max} statistics. Trace statistics investigates the null hypothesis of r cointegrating relations against the alternative of N cointegrating relations and is computed as:

$$\lambda_{trace} = N \sum_{i=r+1}^{n} \log(1 - \lambda_i) \quad (8)$$

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

$$\lambda_{max} = N \log(1 - \lambda_r + 1) \quad (9)$$

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 significance level (*p*-values) of the individual cointegration test with the following formulae:

$$EG \text{ “-”} JOH = -2[\log(pEG) + (pJOH)] \quad (10)$$

$$EG\text{-}JOH\text{-}BO\text{-}BDM = -2[\log((pEG) + (pJOH)] + (pBO) + (pBDM))] \quad (11)$$

Where pEG, pJOH, 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 statistics 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 Anaika 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 and short-run coefficients is applied. The ARDL approach to cointegration helped in identifying cointegrating vector(s). That is, each of the underlying variables stands as a single long-run relationship equation. If one cointegrating vector (i.e. the underlying equation) was identified, the ARDL model of the cointegrating vector was reparametrized into the Error Correction Model (ECM). 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). After establishing the long-run relationship, the vector error correction model (VECM) was then specified, from which the error correction term (ECT) could be estimated.

If the cointegration was established among the variables, the run long and short-run models of ARDL specification could be seen in the following equations.

Long-run

$$nCO_2 = \beta_0 + \beta_1 lnCO_{2t-1} + \beta_2 lnEC_{2t-1} + \beta_3 lnGDP_{t-1}$$
$$+\beta_4 lnTP_{t-1} + \beta_5 lnFD_{t-1} + \sum_{i=1}^{p} \gamma_i lnCO_{2t-i} + \sum_{j=1}^{q} \delta_j lnEC_{t-j}$$
$$+\sum_{k=1}^{q} \mu k lnGDP_{t-k} + \sum_{n=1}^{q} \tau n lnGFCF_{t-n} + \sum_{l=1}^{q} \rho l\, lnFD_{t-l} + \varepsilon_t$$

Short-run

$$\Delta lnCO_2 = \beta_0 + \beta_1 lnCO_{2t-1} + \beta_2 lnEC_{2t-1}$$
$$+\beta_3 lnGDP_{t-1} + \beta_4 lnTP_{t-1} + \beta_5 lnFD_{t-1} + \sum_{i=1}^{p} \gamma_i lnCO_{2t-i}$$
$$+\sum_{j=1}^{q} \delta_j \Delta lnEC_{t-j} + \sum_{k=1}^{q} \mu k \Delta lnGDP_{t-k} + \sum_{l=1}^{q} \rho l \Delta lnTP_{t-l}$$
$$+\sum_{m=1}^{q} \vartheta m \Delta lnFD_{t-1} + \alpha \mathrm{ECT}_{t-1} + \varepsilon_t$$

Where the coefficient of the error correction term (ECT) is denoted 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 implication that the data are not likely to provide spurious findings.

4.1. ADF & PP Unit Root and ZA Structural Break Test

The three different kinds of unit root tests: Augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1979), Phillips-Perron (PP) (Phillips and Perron, 1988), and Zivot-Andrews (ZA) (Zivot and Andrews, 1992) were applied Sto avoid any spurious relationship. The results of the unit root test are reported in Table 3. We can see that the ADF and PP tests indicate that the variables are stationary at first differences, i.e. I (1).

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	$lnCO_2$	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	0.1093	–0.0026	–0.1445
Kurtosis	2.9239	2.0997	1.6004	1.8855	1.4821
Variance	0.0133	0.01167	0.0590	0.0307	0.3643
Observations	45	45	45	45	45

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.

These results in Table 4 suggest that we can reject the null of unit root at a 5% significance level. Since the calculated T-statistics value at the level is below the critical values, the variables are non-stationary. The null hypothesis can be rejected when the critical value of (1%, 5%, and 10%) are greater than the test statistic value. After the first difference, all T-statistics values, which are above the critical values, show evidence of stationarity. The results of the the Zivot-Andrews test further confirm that all the series are first difference stationary, i.e. I (1) in the presence of a single structural break in the series.

4.2. J.J 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 confirms the conclusion that there is one cointegrating relationship 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% of 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 3: Unit root test

Tests	$lnCO_2$	lnEC	lnGDP	lnTP	lnFD
Augmented Dickey-Fuller					
At level I (0)	–2.659	–2.482	–0.075	0.310	–0.569
At first difference I (1)	–4.005***	–4.561***	–4.728***	–3.796***	–3.870***
Philips and Perron					
At level I (0)	–2.611	–2.391	–0.093	–0.079	–0.591
At first difference I (1)	–6.095***	–7.085***	–5.790***	–4.929***	–4.904***

*is for<0.1, ** for<0.05, *** for<0.01 significance level. AIC criteria was selected for optimal lag

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

Variable	At level		At first Difference	
	T-statistics	Time break	T-statistics	Time break
$lnCO_2$	–1.697 (0)	1978	–7.445 (0)***	1993
lnEC	–2.588 (0)	2008	–8.265 (0)***	1989
lnGDP	–3.552 (0)	1997	–6.402 (0)***	1993
lnTP	–2.735 (1)	1997	–6.421 (0)***	2008
lnFD	–3.379 (0)	1988	–6.372 (0)***	1983

Lag order shown in parenthesis. Critical values: 1%: –5.34, 5%: –4.80, 10%: –4.58 where *** for <0.01 significance level

Table 5: J.J cointegration test

Rank	Trace Statistic	5% Critical Value	Max-Eigen Statistic	5% Critical Value
0	73.4109	68.52	34.3999	33.46
1	39.0110*	47.21	22.5545	27.07
2	16.4565	29.68	10.1639	20.97
3	6.2927	15.41	6.2285	14.07
4	0.0642	3.76	0.0642	3.76

* Shows the number of cointegration on 5% critical value

Once the JJ and BH cointegration approaches confirm the cointegration among the variables, the lag length of all variables is identified through the Akaike Information Criterion (AIC). Then the long-run and short-run coefficients are estimated using these lags (1 1 1 2 2). The lag length selection results are shown in Table 7 to estimate for the ARDL approach.

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

The long-run equilibrium relationship among the variables estimated using the ARDL (1 1 1 2 2) approach using the error correction model is given in Table 8. Results reported for long-run estimated coefficient estimates show that energy consumption has a positive and significant impact on metric tons per capita of CO_2 emissions. The results show that a 1% increase in energy consumption, in the long run, is associated with a 26.3% increase in metric tons per capita CO_2 emissions at a ($P<0.05$) significance level, other things remaining constant. Thus the impact of energy consumption on carbon dioxide is stronger. However, economic growth, total population, and financial development have a negative coefficient and have no impact on carbon emissions.

The Table 9 shows the estimated error correction model adjustment term ECM (-1) is negative (-0.1533) and statistically significant at a 1% significance critical level (0.00295). This result supports the 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 (CO_2) for Australia is given in Table 9.

The short-run results reveal that the lag value energy consumption causes an increase in 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 also have a positive but insignificant relationship with carbon emissions in the short run.

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 using the Breusch-Godfrey LM test for autocorrelation, the Breusch-Pagan / Cook-Weisberg test for heteroscedasticity, and the Jarque-Bera 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 stability of the long-run coefficient is tested by the short-run dynamics. Once the ECM model given by equation (1) has been estimated, the cumulative sum of recursive residuals (CUSUM) and the CUSUM of square (CUSUMQ) test are applied to assess parameter stability (Pesaran and Pesaran, 1997). Figures 2 plot the results for both tests. The results indicate the absence of any instability of the coefficients because the plot of CUSUM and CUSUMQ statistics fall inside the critical bands of the 5% confidence interval of parameter stability.

The present study also assesses the constant of short-run beta coefficients in the ARDL method by taking the cumulative sum (CUSUM) and the CUSUM of squares test on the recursive residuals. The following figure displays the outcomes of the CUSUM and the CUSUM square test, which propose no structural inconstancy of CO_2 emission with independent variables and are bounded within the 5% level of significance, which confirm the stability of the model.

5. DISCUSSION

The study investigated variable's stationarity at first differences using Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Zivot-Andrews (ZA) to avoid any spurious relationships. Johansen- Juselius and Bayer-Hanck cointegration techniques

Figure 2: The results of the stability test of CUSUM and CUSUMQ

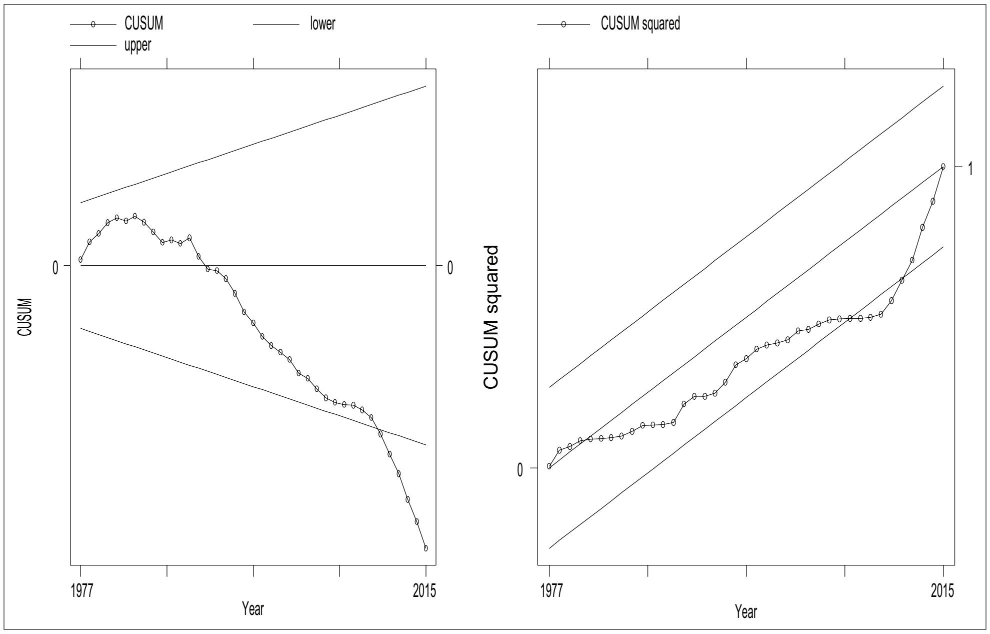


Table 6: Bayer –Hanck cointegration test

Model Specification	Fisher Type Test statistics				Cointegration decision
	EG-J	5% critical value	EG-J-BG-Bo	5% critical value	
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
$lnCO_2$	–1.92029	–4.09662**	–4.0543	–4.01113	–3.96279	1
lnEC	–1.92439	–4.57696**	–4.55016	–4.5023	–4.46933	1
lnGDP	–0.094284	–5.45254**	–5.41374	–5.38018	–5.33262	1
lnTP	–0.815685	–8.88643	–8.91328**	–8.88334	–8.84642	2
lnFD	1.74611	–3.02219	–3.09505**	–3.04659	–3.00077	2

Indicates lag order selected by the AIC criterion at a ** for <0.05 significance level

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
lnEC	2.6316	2.17	0.038**
lnGDP	–0.0858	–0.09	0.930
lnTP	–0.2713	–0.19	0.853
lnFD	–0.2339	–0.92	0.366
Diagnostic test			
Serial correlation (Breusch-Godfrey LM test for autocorrelation)	27.783 (0.0000)	Heteroscedasticity (Breusch-Pagan/ Cook-Weisberg test for heteroscedasticity)	5.46 (0.0194)
Normality Jarque-Bera	0.8856	F-statistics	75.75
R^2	0.8834	Adjusted R^2	0.8717

** for <0.05 significance level

Table 9: Short-run dynamics using the ARDL approach

Variables	Coeff.	t-stats	Prob.
lnEC	0.5993	2.15	0.040**
lnGDP	0.0331	0.10	0.919
lnTP	1.2140	0.96	0.345
lnFD	0.1443	1.54	0.135
ECM(–1)	–0.1533	–1.07	0.295***

** for <0.05 and *** for <0.01 significance level

were used for cointegration analysis for this paper. The long run-association among all our considered variables was established according to the JJ and BH cointegration tests.

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 estimated coefficient show that energy consumption has a positive and significant impact on metric tons per capita of CO_2 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 reveals that economic growth, total population, and financial development also have a positive but insignificant relationship with carbon emissions. The Australian energy sector represents 5% of gross industry value-added, 20 percent of total export value, and supports a large range of manufacturing industries (Geoscience Australia, 2020). The energy demand is expanding as Australia's economy, financial sector and population growth. However, the relationship between energy consumption and GDP contradicts the results with Van and Bao (2018) and Al-Mulali and Sab (2018), total population with Mirza and Kanwal (2017) and Khan et al. (2020), and financial development with Sadorsky (2010) in the long-run growth nexus.

6. CONCLUSION

This study explores the linkages between environmental quality, energy consumption, economic growth, financial development, 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 in carbon emissions in Australia. This study is significant for the reason that Australia has large variations in the environment which is exposed to floods and dry seasons. Therefore, this investigation is focused on the fundamental determinants of pollution emissions (CO_2), and also it attempts to capture their impact in order to understand the future damage they might cause. Therefore, policymakers and strategy creators can consider techniques to lessen energy consumption, ensure that environment is cared for, and diminish the risk of floods and droughts in Australia.

The study overall evaluates the impacts of energy consumption on carbon emissions taking into account economic growth, population, and financial development. However, the specific 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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