

# The Role of ICT and Energy Consumption on Carbon Emissions: An Australian Evidence Using Cointegration Test and ARDL Long-run and Short-run Methodology

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Received: 22 April 2021

Accepted: 04 July 2021

DOI: <https://doi.org/10.32479/ijeeep.11419>

## ABSTRACT

Information and communication technology (ICT) and energy consumption have substantially increased use over the last decade. It has become one of the essential aspects for improving the standard of life for many people. This study investigates the impact of internet use and energy consumption on the carbon emissions (CO<sub>2</sub> emissions) using annual data from 1990 to 2019 in Australia. For this investigation, ADF and PP unit root tests were applied with the Zivot-Andrews structural break for the unit root test. The paper implements the ARDL cointegration test, JJ cointegration test, and Bayer-Hanck test to check the long-run relationship between carbon dioxide emissions (CO<sub>2</sub>), internet use, and energy consumption with GDP and total population. The cointegration test results show that there exists a long-run relationship between the variables. The long-run findings reveal a negative impact of ICT on the environment, whereas energy consumption has a positive and significant impact on the environment. According to the short-run dynamics results, both internet usage and energy consumption have a positive and statistically significant impact. Thus, the government should increase subsidies and boost the adoption of high-efficiency appliances to lower energy usage.

**Keywords:** Information and communication technology, Energy Consumption, CO<sub>2</sub>, Cointegration Tests, Autoregressive distributed lag, Australia

**JEL Classifications:** O30, Q43, Q54, Q56

## 1. INTRODUCTION

Information and communication technology (ICT) and energy consumption have substantially increased use over the last decade. It has become one of the essential aspects for improving the standard of life for many people (Moyer and Hughes, 2012). ICT includes the internet, computers, mobile phones, and other communication mediums; these play a vital role in making life a luxury. ICT is increasing in demand due to smart technologies like i-pads, touch screens, and touch monitors. Generally, through Bluetooth and wireless technologies, the efficiency of both humans and machines has increased and their productivity over time.

ICT not only helps in easing life but has also become one of the factors contributing to economic growth for a nation. Through the

use of ICT, there has been improved communication throughout the world; this has coined the term “global village.” Globally, ICT has proven to be one of the primary sources that a country can use for its development (Danish et al., 2018).

However, the internet is so highly used nowadays; users are responsible for a large amount of the energy consumed (Salahuddin and Alam, 2015). Ease of access and reduction in the cost of ICT has resulted in a considerable increase in energy consumption from production, distribution, and consumer use. From the developmental perspective, energy consumption is vital for economic growth as it is now the basis for the modern world. Also, Energy has been demonstrated to provide facilities for many areas, including household consumption, mining resources, transportation, and industrial production.

Although ICT may result in economic growth, there may be critical environmental consequences resulting from higher energy consumption due to ICT. Energy production is closely related to the concentration of carbon gases in the atmosphere, which may ultimately result in climate change (Akhmat et al., 2014). ICT and energy consumption contribute to the pollution of the environment as carbon emissions increase (Lee and Brahmarsene, 2014). Some members of society are concerned about the negative environmental impact of ICT. Although ICT is an essential tool for sustainable development, it causes a decline in the health of the environment due to the carbon emissions that occur during the engineering and processing of the equipment utilized in ICT (Godil et al., 2020).

According to Prosperity Media, the global population has reached approximately 7.77 billion people, of which 4.54 billion people are active internet users globally (Keats, 2021). In Australia, the number of internet users recorded in January 2021 was 22.31 million, with an internet penetration of 88%. Table 1 portrays the trend, energy consumption, and carbon emissions related to internet use in Australia from 1990 to 2019.

Australia’s internet use, energy consumption per capita, and CO<sub>2</sub> have shown an upward trend from 1990 to 2019. Figure 1 shows a significant rise in NET, EC, and CO<sub>2</sub> in Australia in 1996. In 1990, an internet user in Australia was <1% of the total population, which rose to 2.8 percent in 1995. In 2000, the number of people using the internet increased by 94% compared to 1995. However, from 2015 to 2019, the number of internet users in the country was stable for four consecutive years, i.e. 86.5% of the total population. Energy consumption and carbon emissions have shown a gradual rise from 1990 to 2019.

This study investigates the impact of internet usage and energy consumption on the environment. The analysis of the ICT and energy use to increase carbon dioxide emissions (CO<sub>2</sub>) in Australia, this paper will be the first of its nature. To investigate this relationship, three different cointegration tests (ARDL bound test, J.J cointegration test, and Bayer –Hanck cointegration test) are included to examine the long-run relationship between variables.

The rest of the paper consists of the following sections: (1) Literature review of existing works of literature (2) Empirical methodologies and data: This section provides information about the model specification and data sources; (3) Results: This section describes and analyses the results and discusses the result in section (4) Discussion; section (5) is the conclusion, providing the conclusion of the study, including the clear policy implications.

## 2. LITERATURE REVIEW

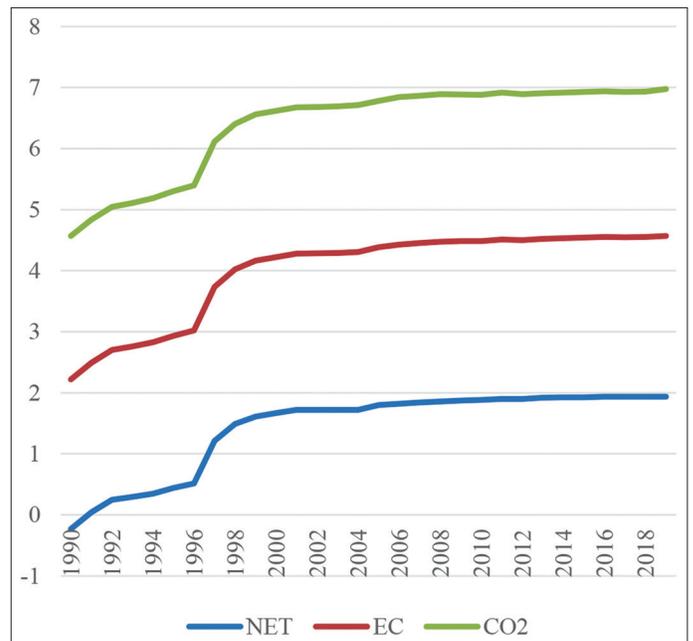
ICT is considered to be one of the biggest stimulators for economic growth throughout the world. Recent studies (Godil et al., 2020; Magazzino et al., 2021; Raheem et al., 2020) reiterate the negative influence of internet usage and energy consumption and concludes that growing internet use adversely affects the environment because of its energy consumption.

**Table 1: Trend of internet user, energy consumption and CO<sub>2</sub> emissions in Australia**

Year	NET	EC	CO <sub>2</sub>
1990	0.6	224.4	282.2
1995	2.8	233.1	311.5
2000	46.8	249.0	358.2
2005	63.0	250.7	383.1
2010	76.0	248.1	402.6
2015	84.6	243.9	411.3
2016	86.5	242.5	411.8
2017	86.5	238.8	409.6
2018	86.5	240.8	411.1
2019	86.5	254.3	428.3

The data is presented for only selected years to avoid large data table size. NET= Internet user (% of Population), EC= Energy consumption per capita (Primary), and CO<sub>2</sub>=Carbon dioxide Emissions (Million tonnes)

**Figure 1: Logarithm trend of NET, EC and CO<sub>2</sub> in Australia**



The data is presented for only selected years to avoid large data table size. NET= Internet user (% of Population), EC= Energy consumption per capita (Primary), and CO<sub>2</sub>=Carbon dioxide Emissions (Million tonnes)

Dehghan and Shahnazi (2019) explored the short-run and long-run causality between energy consumption, gross domestic product (GDP), CO<sub>2</sub> emissions, and ICT from 2002 to 2013 in several Iranian economic sectors. The authors used the dynamic ordinary least square (DOLS) technique with the estimated outcomes indicated that ICT is the principal cause of energy consumption in the industry. Furthermore, the results suggested a bidirectional short-run causality between ICT and CO<sub>2</sub> in the industrial and transportation sectors and a unidirectional causal relationship between ICT and CO<sub>2</sub> in the services sector. Finally, there was a unidirectional long-run causality running from ICT, GDP, and energy consumption to CO<sub>2</sub> emissions. These findings were further supported by Lee and Brahmarsene (2014), who investigated the relationships between ICT, carbon emissions, and economic growth. Their results, showing that ICT leads to an increase in CO<sub>2</sub> emissions and is statistically significant at the 0.05 level.

A 1% increase in ICT development increases economic growth by 0.672% and CO<sub>2</sub> emissions by 0.660%. Hence, ICT shows significant to highly significant positive effects on both economic growth and CO<sub>2</sub> emissions.

Similarly, Moyer and Hughes (2012) explored the dynamic impacts of ICT on interacting global systems, including economic and energy systems and resultant carbon emissions. The authors argued that ICT could have a low impact on overall carbon emissions across a 50-year time horizon. However, the net effect of ICT is limited, and if policymakers are concerned with substantial reductions in overall stocks of carbon in the atmosphere, their model shows that ICT promotion must be coupled with a global carbon price. In another study, the following empirical results are established from panel mean group (MG) and augmented mean group (AMG) estimation methods: first, the ICTs significantly affect CO<sub>2</sub> emissions; second, the moderating effect of ICT and financial development stimulates the level of CO<sub>2</sub> emissions; third, economic growth contributes to CO<sub>2</sub> emission. However, the interaction between ICT and GDP mitigates the level of pollution. (Danish et al., 2018). Cheng et al. (2019) explored information technology's effect on environmental pollution using spatial econometric models in 285 cities in China from 2003 to 2016. The spatial auto-correlation analysis results show a significant positive spatial auto-correlation between information technology and environmental pollution, and the spatial path dependence characteristics are apparent. The estimation results of the spatial econometric models show that information technology has significantly increased environmental pollution. The rebound effect of information technology on environmental pollution has played a leading role.

Recently, using the EKC hypothesis test and Cluster analysis, Arshad et al. (2020) examined the effect of ICT, trade, economic growth, financial development, and energy consumption on carbon emissions. They found that ICT degraded the quality of the environment in the SSEA region. Similarly, research conducted in G7 countries (Raheem et al., 2020) examined the role of ICT and financial development concerning CO<sub>2</sub> emissions and economic growth. The study found that ICT has a long-run positive effect on emissions. Godil et al. (2020) examined the impact of financial development, information and communication technology, and institutional quality on CO<sub>2</sub> emissions using quarterly data from 1995 to 2018. They implemented the quantile autoregressive distributed lag (QARDL) model. As a result, it concluded that financial development and ICT harm CO<sub>2</sub> emissions irrespective of the emission level in the country, which shows that if economic enhancement and ICT increase, carbon emissions decrease. In a recent study, Magazzino et al. (2021) investigated the relationship between Information and Communication Technology (ICT) penetration, electricity consumption, economic growth, and environmental pollution in EU countries Dumitrescu-Hurlin panel causality tests. These tests revealed that there is a one-way causality running from ICT usage and electricity consumption, causing a rise in CO<sub>2</sub> emissions and at the same time improving GDP.

However, there is a contrasting view regarding the impact of ICT on the environment. Ozcan and Apergis (2018) analysed

the effect of Internet use, employed as a proxy for information and communication technologies (ICTs), on CO<sub>2</sub> emissions. The panel causality test results highlighted a unidirectional causality running from Internet use to CO<sub>2</sub> emissions. They concluded from the results that increased Internet access results in lower levels of air pollution. This result was supported by Lu (2018) where he conducted a study with panel data to investigate the effects of information and communication technology (ICT), energy consumption, economic growth, and financial development on carbon dioxide emissions. The author used the Pedroni panel cointegration test and causality test to ascertain the impacts. The results revealed that a 1% increase in ICT would reduce carbon emissions by 0.06%. Thus, ICT does not necessarily impact a nation's environment, and hence internet usage can be promoted there without causing significant concern about any environmental degradation it causes (Salahuddin et al., 2016).

According to our knowledge, only one study (Salahuddin and Alam, 2015) investigated the impact of internet usage in Australia, estimating the short- and long-run effects of internet usage and economic growth on electricity consumption. The results revealed that internet usage and economic growth have positive and significant effects while these effects in the short run are insignificant. However, this study investigated the 2012 data set and did not examine the direct impact of internet usage on CO<sub>2</sub> emissions. Thus, this study will fill the existing literature gap by revealing the direct impact of internet usage on the CO<sub>2</sub> of Australia. With 30 years of data from 1990-2019 and employing three different cointegration tests: ARDL bound test, Johansen and Juselius (JJ), and Bayer-Hanck (BH) cointegration technique, this study will investigate the long-run and short-run relationship between internet use and carbon emissions. This study includes total population and determinants impacting CO<sub>2</sub> emissions (Shahbaz et al., 2016).

### 3. DATA AND METHODOLOGY

#### 3.1. Data

The principal aim of this study is to examine the role of the internet and energy consumption on CO<sub>2</sub>. To accomplish this aim, the time series data of Australia from 1990 to 2019 were taken into consideration. Data were extracted from the Australian Bureau of Statistics (2020), World Development Indicator (2020), and BP Statistical Review (2020). Data definitions, data sources, and variable definitions are summarized in Table 2.

#### 3.2. Empirical model and Econometric Methods

Following Salahuddin and Alam (2015), this study develops the following model

$$CO_2 = f(\text{NET}, \text{EC}, \text{GDP}, \text{TP}) \quad (1)$$

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

$$\ln CO_2 = f(\ln \text{NET}, \ln \text{EC}, \ln \text{GDP}, \ln \text{TP}) \quad (2)$$

**Table 2: Variable description and data source**

Symbol	Variables	Definition	Source
CO <sub>2</sub>	Carbon dioxide emissions	CO <sub>2</sub> emissions stemming from the burning of fossil fuel (Million tons)	BP stats
NET	Internet user per 100	Individuals using the Internet (% of the population)	WDI
EC	Energy consumption	Primary energy consumption	BP stats
GDP	GDP per capita	GDP per capita (constant 2010 US\$)	WDI
TP	Total population	Total number of population-based on the de facto definition of the population with mid-year estimates	WDI

ABS=Australian Bureau of Statistics (2020), WDI= World Development Indicator, (2020) BP stats= BP Statistical Review (2020)

**3.2.1. Estimation Procedures**

**3.2.1.1. Stationarity and unit root test**

Non-stationary data can obtain spurious results; thus, this study employs Augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1979) and Phillips –Perron (PP) (Phillips and Perron, 1988) unit root test to check the stationarity of the variables. The ADF tests the data’s stationarity, but it can be a non-robust test for unit root. To be exact, stationarity results from an additional test for the unit root; The Phillip Perron (PP) test is applied. The PP test is a non-parametric statistical method that takes note of serial correlation without using the dependent variable’s lagged differences (Gujarati and Porter, 2009). Hence, the PP test is considered a useful alternative. It allows for milder assumptions on the distribution of errors and presents an opportunity to control higher-order serial correlation in the time series variables, and is robust against heteroscedasticity (Kouakou, 2011). Therefore, the ADF test and PP test are both used in the study to check for stationarity.

ADF model tests unit root as follows

$$\Delta y_t = \mu + \delta y_{t-1} + \beta_t + \sum_{i=1}^k d_i \Delta y_{t-i} + e_t \tag{3}$$

Where k=number of lags, t-i=1... k,  $\delta = \alpha - 1$ ,  $\alpha =$  coefficient of  $y_{t-1}$ , and  $\Delta y_t =$  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 the variables 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

$$\Delta y_t = \mu + \delta y_{t-1} + \beta_t + e_t \tag{4}$$

**3.2.1.2. Zivot-Andrews unit root test**

The ADF test and PP test may provide biased and spurious results due to not having information about structural breakpoints in the series (Baum, 2003). Following Zivot-Andrews (ZA) (Zivot and Andrews, 1992) structural break unit root test is applied to the ZA unit root test before cointegration, 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).

$$\Delta y_t = c + c Y_{t-1} + \beta t + dDU_t + dDT_t + \sum_{i=1}^k d_i \Delta y_{t-i} + \varepsilon_t \tag{5}$$

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:

$$DU_t = \begin{cases} 1 & \text{if } t > TB \\ 0 & \text{if } t < TB \end{cases} \text{ and } DT_t = \begin{cases} t - TB & \text{if } t > TB \\ 0 & \text{if } t < TB \end{cases} \tag{6}$$

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 the  $<0$  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).

**3.2.2. Cointegration analyses**

The cointegration approaches like the ARDL cointegration test, Johansen and Juselius (JJ) test, and Bayer-Hanck (BH) cointegration test are applied to assess the long-term relationship between internet usage, energy consumption, and the environment in this study.

**3.2.2.1. ARDL or bound cointegration testing approach**

When the variables are stationarity, the ARDL bounds testing approach is applied; further, they can test the existence of cointegration between the variables for long-run relationships. The ARDL approach of cointegration gives realistic and efficient estimates of the long-term relationship between the variables. The ARDL bound test developed by Pesaran et al. (2001) provided two asymptotic critical value bounds when the independent variables are either  $I(0)$  or  $I(1)$ . It is assumed that the test statistics exceed their Upper Critical Bound (UCB), so it can be concluded that a long-run relationship among the variables exists.

The following equation is used to estimate cointegration relationships among variables.

$$\begin{aligned} \ln CO_2 = & \beta_0 + \beta_1 \ln CO_{2t-1} + \beta_2 \ln NET_{t-1} + \beta_3 \ln EC_{t-1} \\ & + \beta_4 \ln GDP_{t-1} + \beta_5 \ln TP_{t-1} + \sum_{i=1}^p \beta_6 \ln CO_{2t-i} + \sum_{j=1}^q \beta_7 \ln NET_{t-j} \\ & + \sum_{k=1}^r \beta_8 \ln EC_{t-k} + \sum_{l=1}^s \beta_9 \ln GDP_{t-l} + \sum_{m=1}^t \beta_{10} \ln TP_{t-m} + \varepsilon_t \end{aligned} \tag{7}$$

Where  $\varepsilon_t$  is white noise and  $\Delta$  is the white noise term, the bounds testing procedure is based on the joint F-statistic to determine the joint significance of the lagged variables’ coefficient. In this regard, the null hypothesis  $H_0: \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$  explains that the cointegrating relationship does not exist among the regressors against the alternative of  $H_1: \beta_r \neq 0$  where  $r=1, 2, 3, 4, 5$ .

**3.2.2.2. J.J cointegration testing approach**

When there are multiple cointegrating vectors, ARDL cointegration is not implacable. Thus, (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  $\lambda_{\text{trace}}$  and  $\lambda_{\text{max}}$  statistics. Trace statistics investigates the null hypothesis of  $r$  cointegrating relations against the alternative of  $N$  cointegrating relations and is computed as:

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

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

$$\lambda_{\text{max}} = -M \log(1 - \lambda_r + 1) \tag{9}$$

Where  $N$  is the number of observations, and is the ordered Eigen-value of matrices.

### 3.2.2.3. Bayer-hanck (BH) cointegration testing approach

Bayer and Hanck’s (2013) cointegration test blend measures various test statistics ranging from Engle and Granger (1987), Johansen (1991), Boswijk (1995), and Banerjee et al. (1998). Bayer and Hanck (2013) proposed the combination of the computed significance level (P-values) of the individual cointegration test with the following formulas:

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

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

Where pEG, pJOH, pBO, and pBDM are the p-values of cointegration tests of Engle and Granger (1987); Johansen (1991); Boswijk (1995) and Banerjee et al. (1998) respectively. According to Bayer and Hanck (2013), when the calculated Fisher statistics is greater than the critical values, the null hypothesis of cointegration cannot be rejected.

### 3.2.3 Lag length test

The lag order selection results are based on Anaika Information Criterion (AIC), which affords the best model to be selected. The AIC criteria for lag length selection are suitable for the ARDL estimation (Etokakpan et al., 2020).

## 3.4. Long-run and Short-run Dynamics

The estimation of short-run and long-run relationships between the variables is the next econometric step of the study. Firstly, if the series has any cointegration among the variables are tested. If one cointegration is identified, the ARDL model of the cointegration is reparametrized into the Error Correction Model (ECM), which gives long-run relationship and short-run dynamics results among the variables of a single model (Nkoro and Uko, 2016). After establishing the long-run relationship, the vector error correction model (VECM) is then specified from which the error correction term (ECT) can be estimated.

The long-run and short-run models of ARDL specification in the following equations.

### 3.4.1. Long-run

$$\begin{aligned} \ln CO_2 = & \beta_0 + \beta_1 \ln CO_{2t-1} + \beta_2 \ln NET_{t-1} + \beta_3 \ln EC_{t-1} \\ & + \beta_4 \ln GDP_{t-1} + \beta_5 \ln TP_{t-1} + \sum_{i=1}^p \beta_6 \ln CO_{2t-i} + \sum_{j=1}^q \beta_7 \ln NET_{t-j} \\ & + \sum_{k=1}^r \beta_8 \ln EC_{t-k} + \sum_{l=1}^s \beta_9 \ln GDP_{t-l} + \sum_{m=1}^t \beta_{10} \ln TP_{t-m} + \varepsilon_t \end{aligned} \tag{12}$$

### 3.4.2. Short-run

$$\begin{aligned} \Delta \ln CO_2 = & \beta_0 + \beta_1 \ln CO_{2t-1} + \beta_2 \ln NET_{t-1} + \beta_3 \ln EC_{t-1} \\ & + \beta_4 \ln GDP_{t-1} + \beta_5 \ln TP_{t-1} + \sum_{i=1}^p \beta_6 \ln CO_{2t-i} + \sum_{j=1}^q \beta_7 \Delta \ln NET_{t-j} \\ & + \sum_{k=1}^r \beta_8 \Delta \ln EC_{t-k} + \sum_{l=1}^s \beta_9 \Delta \ln GDP_{t-l} + \sum_{m=1}^t \beta_{10} \Delta \ln TP_{t-m} \\ & + \alpha \text{ECM}_{t-1} + \varepsilon_t \end{aligned} \tag{13}$$

Where the coefficient of the error correction term (ECM) is denoted by which shows the speed of adjustment of the variables toward long-run convergence. In addition, denotes the difference operator and the  $\ln CO_2$ ,  $\ln NET$ ,  $\ln EC$ ,  $\ln GDP$  and  $\ln TP$  are the log value of  $CO_2$  emissions, internet users, energy consumption, gross domestic product (GDP) and total population respectively  $\varepsilon_t$  is the disturbance term.

## 4. RESULTS

The descriptive statistics show some statistical measures of variables (Table 3). The standard deviations are low, which means that the data is dispersed evenly around the mean. This allowed us to progress further with given datasets to develop estimation and empirical investigations.

Table 4 shows that all the variables are stationary at the first difference, i.e.  $I(1)$ , which is significant at 1% critical level. To get the structural breaks in the data, Zivot and Andrews (1992) structural break trended unit root test is implemented.

Table 5 results suggest that the null of unit root at a 5% significance level can be rejected. Since the calculated T-statistics value at the level is below the critical values, the variable is non-stationary. The null hypothesis can be rejected when the critical value of (1%, 5%, and 10%) are greater than the test statistic value. Thus, the

**Table 3: The descriptive statistics**

Descriptive statistics	$\ln CO_2$	$\ln NET$	$\ln EC$	$\ln GDP$	$\ln TP$
Mean	5.901	3.294	5.495	10.747	16.836
Median	5.952	4.054	5.500	10.787	16.824
Maximum	6.060	4.461	5.566	10.954	17.049
Minimum	5.642	-0.536	5.391	10.464	16.652
St. Deviation	0.136	1.605	0.048	0.163	0.121
Skewness	-0.768	-1.220	-0.747	-0.435	0.198
Kurtosis	2.175	2.841	2.766	1.797	1.821
Variance	0.0183	2.575	0.003	0.026	0.014
Observations	29	29	29	29	29

variables are stationary at  $I(1)$  in the presence of single structural break in the series from Zivot-Andrews structural break trended unit root test.

Table 6 shows the Akaike Information Criterion (AIC) of lag order used in this study. The bound test for the cointegration hypothesis states that if the F statistics is lower than  $[I_0]$  series, there is no-cointegration, and if F-statistics is higher than  $[I_1]$  series, there is cointegration. Thus, our results show there is cointegration among the variables and reveals the existence of a long-run relationship between the variables. This is due to the calculated F-statistics (14.81) being greater than the UCB  $[I_1]$  (3.52).

**Table 4: Unit root test**

Tests	lnCO <sub>2</sub>	lnNET	lnEC	lnGDP	lnTP
ADF					
At level I(0)	-2.388	-2.332	-2.217	-2.618	2.957
At first difference I(1)	-4.297*	-3.471*	-4.373*	-3.790*	-3.548*
PP					
At level I(0)	-2.046	3.27	-1.611	-1.203	3.715
At first difference i(1)	-4.397*	-3.467*	-4.421*	-3.790*	-3.540*

\*Is 1% significance level. ADF: Augmented Dickey Fuller, PP: Philips and Perron

**Table 5: Zivot-Andrews structural break trended unit root test**

Variable	At level		At first Difference	
	T-statistics	Time break	T-statistics	Time break
lnCO <sub>2</sub>	-2.795(0)	2008	-5.83(0)*	2009
lnNET	-4.339(0)	2009	-4.59(0)***	2000
lnEC	-3.079(0)	2009	-4.87(0)**	2008
lnGDP	-2.318(0)	1997	-4.96(0)**	2008
lnTP	-19.976(0)	1997	-7.27(0)*	2008

Lag order shown in parenthesis. Critical values: 1%: -5.34, 5%: -4.80, 10%: -4.58 where \* is 1%, \*\* is 5% and \*\*\* is 10% significance level respectively

**Table 6: Lag length selection and bound testing for cointegration**

Lag length selection		Bounds testing for co-integration			
Lags order	AIC	Model	F-statistics $[I_0]$ $[I_1]$		
0	-16.5507	lnCO <sub>2</sub> =f(lnNET,lnEC, lnGDP, lnTP)	14.81*	2.45	3.52
1	-28.1185				
2	-28.2307				
3	-28.541				
4	-35.1519*				

\*Is 1% critical value for the bound test

**Table 7: J.J cointegration test**

Rank	Trace statistic	5% Critical value	Max-eigen statistic	5% Critical value
0	68.5453	68.52	26.0683	33.46
1	42.4770**	47.21	23.0064**	27.07
2	19.4706	29.68	13.6995	20.97
3	5.7711	15.41	5.7660	14.07
4	0.0051	3.76	0.0051	3.76

\*\*Is 5% significance level

JJ cointegration has a null hypothesis that if the trace and max value is greater than 5% critical value, the null hypothesis of no-cointegration is rejected. Here, the Trace statistics are less than 5% critical value, Table 7; thus, the null hypothesis meaning that there is one cointegration in both Trace and Max-Eigen statistic is accepted, which guides a substantial long-run relationship exists among the series of variables.

Table 8 shows that the calculated statistics (EG-J and EG-J-BG-Bo) values are higher than the 5% critical value; the null hypothesis of no-cointegration is rejected. This test confirmed the cointegration among the variables, which also revealed the presence of a long-run relationship between the study variables.

Table 9 reveals the lag length of all variables is identified through Akaike Information Criterion (AIC). Now the estimate of the long-run and short-run coefficients using these lags (1 2 1 1 1) length selection is carried out.

The results presented in Table 10 are from 1990 to 2019. The ARDL approach results show that internet usage has a negative but significant impact on Australia’s environmental degradation. The results revealed that a 1% increase in internet usage reduces CO<sub>2</sub> emissions by 0.018% in the long-run. Moreover, the total population has a negative impact on the environment. However, energy consumption and GDP have a positive impact on CO<sub>2</sub> emissions. An increase of 1% in energy consumption results in a 0.656% increase in CO<sub>2</sub> (million tonnes), and similarly, a 1% increase in GDP increases 1.156% million tonnes of CO<sub>2</sub> emissions into the environment.

**4.1. Diagnostic test Result**

Table 10 further demonstrates the Breusch-Godfrey Langrage Multiplier (LM) test for the autocorrelation test for serial correlation. The results revealed that there is no serial correlation. The Breusch-Pagan/Cook-Weisberg test for Heteroskedasticity test shows that there is no Heteroscedasticity in the data. To explore the normality of the series, test of Normality Jarque-Bera is conducted. Here, the P-value is lower than the Chi-squared  $[Chi(2)]$  value, so the null hypothesis cannot be rejected. As in Table 10, Chi (2) is 27.71 is greater than 0.96. Therefore residuals are normality distributed.

Accordingly, the results of the short-run dynamics using the ARDL approach (Table 11) indicate that internet users have a positive and statistically significant impact on the environment, which shows that a 1% increase in internet usage will increase CO<sub>2</sub> by 0.01% in the short run. Similarly, energy consumption also has a positive and significant impact on carbon emissions, and a 1% increase in energy usage will lead to a 0.497% increase in environmental degradation. Likewise, the total population has a positive impact, and GDP has a negative impact on CO<sub>2</sub>, although, are not statistically significant. The ECM value shows the speed of adjustment from short-run to long-run equilibrium. The coefficient is statistically significant at the 1% level, and the significant value of the estimated ECM is also negative (Table 11). Thus the value of ECM in this model reveals that the short-run deviations from the long-run equilibrium are corrected by 52.7%

**Table 8: Bayer –Hanck cointegration test**

Model specification	Fisher type test statistics				Cointegration decision
	EG-J	5% critical value	EG-J-BG-Bo	5% critical value	
$\ln\text{CO}_2 = f(\ln\text{NET}, \ln\text{EC}, \ln\text{GDP}, \ln\text{TP})$	55.399	10.576	110.66107	20.143	Cointegrated

**Table 9: Lags defined through VAR of variables**

Lag	0	1	2	3	4	Selected lags
	AIC	AIC	AIC	AIC	AIC	
$\ln\text{CO}_2$	-1.74238	-5.17105*	-5.11871	-5.04363	-4.96725	1
$\ln\text{NET}$	3.04555	0.356051	0.335038*	.410287	.456513	2
$\ln\text{EC}$	-3.98264	-5.15294*	-5.0778	-5.00296	-4.9284	1
$\ln\text{GDP}$	-1.16818	-6.85462*	-6.77835	-6.70806	-6.63975	1
$\ln\text{TP}$	-1.56582	-8.96752*	-8.89105	-8.91518	-8.84251	1

Akaike Information Criterion (AIC) criteria. \* is 1% significance level

**Table 10: Long-run dynamics using the ARDL approach. ARDL (1 2 1 1 1) model coefficients**

Variables	Coeff.	t-stats	Prob.
Constant	-1.044	-0.46	0.652
$\ln\text{NET}$	-0.018	-2.13	0.048**
$\ln\text{EC}$	0.656	2.26	0.037**
$\ln\text{GDP}$	1.156	3.26	0.005***
$\ln\text{TP}$	-0.481	-1.32	0.204
Diagnostic test			
Serial correlation (Breusch-Godfrey)	6.331(0.0119)	Heteroskedasticity (Pagan / Cook-Weisberg test for heteroscedasticity)	0.00(0.9921)
LM test for autocorrelation)		F-stat(Prob.)	4.555(0.018)
Normality Jarque-Bera	27.71 (0.96)	Adjusted R <sup>2</sup>	0.9181
R <sup>2</sup>	0.9484		

\*\*Is 5% and \*\*\* is 10% significance level respectively

**Table 11: Short-run dynamics using the ARDL approach**

Variables	Coeff.	t-stats	Prob.
$\Delta\ln\text{NET}$	0.010	2.09	0.052***
$\Delta\ln\text{EC}$	0.497	2.19	0.043**
$\Delta\ln\text{GDP}$	-0.098	-0.61	0.553
$\Delta\ln\text{TP}$	0.694	1.28	0.217
ECM(-1)	-0.527	-3.08	0.007*

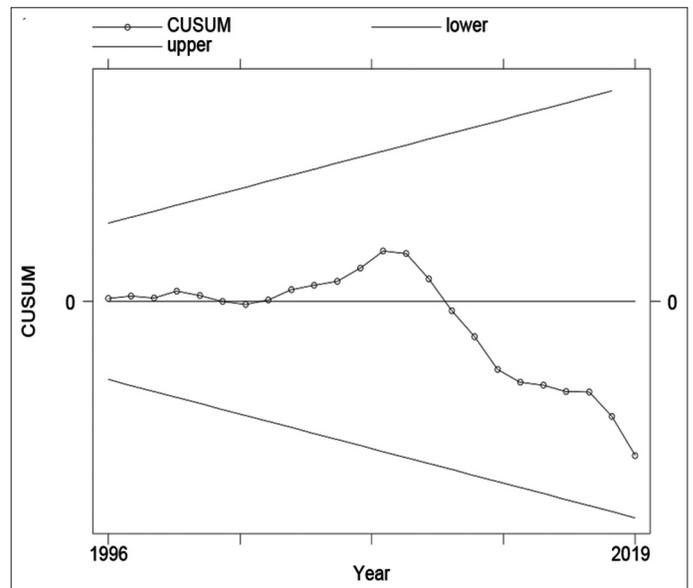
\*Is 1%, \*\* is 5% and \*\*\* is 10% significance level respectively

toward the long-run equilibrium path each year. The negative and statistically significant sign of the ECM coefficient states that any long-run disequilibrium among the model variables will move or draw together to the long-run equilibrium.

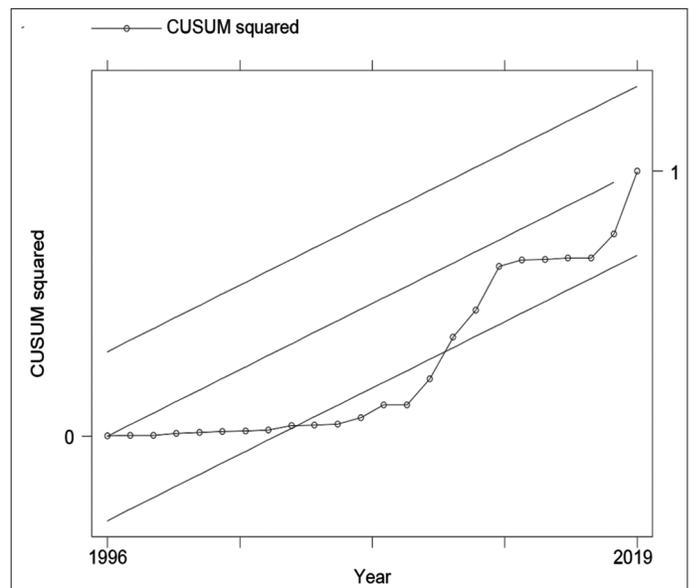
**4.2. Stability of Short-run Model**

The short-run dynamics test the stability of the parameters. Once the ECM model given by equation (1) has been estimated, the cumulative sum (CUSUM) of square (CUSUMQ) test is applied (Figure 2) to assess parameter stability and the cumulative sum of recursive residuals (CUSUM) (Figure 3) (Pesaran and Pesaran, 1997). This study assesses the constancy of short-run beta coefficients in the ARDL method by taking the CUSUM and the CUSUM of squares test on the recursive residuals. The following figure displays the outcomes of the CUSUM and the

**Figure 2: A plot of the cumulative sum of residuals**



**Figure 3: A plot of the cumulative sum of the square of recursive residuals**



CUSUM square test, which propose no structural inconstancy of CO<sub>2</sub> emissions with independent variables and are bounded within the 5% level of significance. These confirm the stability of the model.

## 5. DISCUSSION

Since Australia is dependent on the internet for development, it is crucial to examine its impact. Thus, this study analyses the long-run and short-run relationship between CO<sub>2</sub> emissions and internet users (per 100) and energy consumption, GDP, and the total population in Australia. The estimated long-run relationship results revealed that internet usage does not increase CO<sub>2</sub> emissions. This result is consistent with the outcome of Salahuddin and Alam (2015), who revealed that rapid growth in the use of the internet is still not a threat to Australia's environment. However, energy consumption is a severe threat that gives rise to carbon emissions. This study found that an increase of 1% in energy usage will lead to a 0.497% increase in environmental degradation due to CO<sub>2</sub> emissions. These results are comparable with other studies between energy consumption and CO<sub>2</sub> emissions by Lu (2018), resulting in a 1% increase in energy consumption causes a 0.59% increase in carbon emissions and Khanal (2021) in his recent study found that energy consumption impacts the environment in the long-run in Australia.

GDP has a statistically significant impact on the environment and is consistent with Lee and Brahmastre (2014). This study indicates that the total population does not increase carbon emissions in the long-run. However, according to Shahbaz et al. (2016), an increase in population growth causes a 0.66% increase in CO<sub>2</sub> emissions in Australia; our findings are not consistent with this result.

According to the short-run dynamic results using the ARDL approach, internet users have a positive and statistically significant impact on the environment; an increase of 1% in internet usage will increase carbon dioxide emissions by 0.01% million tonnes in the short-run. This result contradicts the result of Salahuddin and Alam (2015) in the short-run. Like the long-run impact, energy consumption has a positive and significant impact on energy consumption in the short-run. Similar findings were presented by Shahbaz et al. (2016) and Khanal (2021). In contrast with the long-run result, GDP has a negative and statistically insignificant impact on carbon emissions in the short-run. The GDP and the environment nexus result is not in line with Lu (2018) findings. The total population has a positive but insignificant impact on the deterioration of the environment. The total population findings of this study are similar to those of Begum et al. (2015).

## 6. CONCLUSIONS

This study aims to understand the long-run and short-run relationship between carbon dioxide emissions (CO<sub>2</sub>), energy consumption and the internet usage, using data from 1990 to 2019. The ARDL bounds test for cointegration, Bayer-Hanck cointegration, and J.J cointegration were used to analyse the data presented in this study. All three cointegration tests provide

evidence of cointegration between the series. Further, the long-run and short-run dynamics from the ARDL approach are used in the model to analyse the long-run and short-run relationships among the variables.

The long-run relationship between internet users and the environment states that the internet decreases carbon emissions in the long term. However, energy consumption and GDP have a positive impact on CO<sub>2</sub> emissions. The short-run dynamics assessed by estimation of the error correction models indicate an average adjustment coefficient of  $-0.527$ . According to the results of the short-run dynamics, internet users have a positive and statistically significant impact on the environment, showing that an increase in internet usage will increase carbon emissions in the short run. Similarly, energy consumption also has a positive and significant impact on carbon emissions, and an increase in energy usage will lead to increase in environmental degradation. Thus, to conclude, internet usage impacts the environment in the short-run while energy consumption degrades the environment both in the long-run and short-run in Australia.

The results of this investigation have numerous implications for policymakers in Australia. To maintain sustainable development, policymakers need to monitor the usage of the internet in the short-run. Besides, the Australian government should mainly focus on energy consumption, other than from ICT, in the Australian environment. It has a positive and significant impact on carbon emissions in both the long-run and short-run. To achieve this, the government should increase subsidies and boost high-efficiency appliances that minimize energy usage. Promotion of alternative energy like renewable energy should be focused regardless of the maximum use of energy. However, policymakers should be aware of the usage of the internet, which increases rapidly over time, and further investigation should be conducted regarding electricity consumption caused by internet usage and its impact on the environment.

## REFERENCES

- Akhmat, G., Zaman, K., Shukui, T., Sajjad, F. (2014), Does energy consumption contribute to climate change? Evidence from major regions of the world. *Renewable and Sustainable Energy Reviews*, 36, 123-134.
- Arshad, Z., Robaina, M., Botelho, A. (2020), The role of ICT in energy consumption and environment: An empirical investigation of Asian economies with cluster analysis. *Environmental Science and Pollution Research*, 27(26), 32913-32932.
- Australian Bureau of Statistics. (2020), Overseas Arrivals and Departures (Cat. No. 3401.0), Canberra, Australia. Available from: <https://www.abs.gov.au/ausstats/abs@.nsf/glossary/3401.0>.
- Banerjee, A., Dolado, J., Mestre, R. (1998), Error-correction mechanism tests for cointegration in a single-equation framework. *Journal of Time Series Analysis*, 19(3), 267-283.
- Baum, C.F. (2003), A review of Stata 8.1 and its time series capabilities. In: *Working Papers in Economics* No. 23.
- Bayer, C., Hanck, C. (2013), Combining non-cointegration tests. *Journal of Time Series Analysis*, 34(1), 83-95.
- Begum, R.A., Sohag, K., Abdullah, S.M.S., Jaafar, M. (2015), CO<sub>2</sub> emissions, energy consumption, economic and population growth in

- Malaysia. *Renewable and Sustainable Energy Reviews*, 41, 594-601.
- Boswijk, H.P. (1995), Efficient inference on cointegration parameters in structural error correction models. *Journal of Econometrics*, 69(1), 133-158.
- BP Statistical Review. (2020), *Statistical Review of World Energy*. Available from: <https://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy.html>.
- Cheng, Z., Li, L., Liu, J. (2019), The effect of information technology on environmental pollution in China. *Environmental Science and Pollution Research International*, 26(32), 33109-33124.
- Dehghan, Z.S., Shahnazi, R. (2019), Energy consumption, carbon dioxide emissions, information and communications technology, and gross domestic product in Iranian economic sectors: A panel causality analysis. *Energy*, 169, 1064-1078.
- Dickey, D.A., Fuller, W.A. (1979), Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, 74(366a), 427-431.
- Engle, R.F., Granger, C.W. (1987), Co-integration and error correction: Representation, estimation, and testing. *Econometrica: Journal of the Econometric Society*, 55(2), 251-276.
- Ertugrul, H.M., Cetin, M., Seker, F., Dogan, E. (2016), The impact of trade openness on global carbon dioxide emissions: Evidence from the top ten emitters among developing countries. *Ecological Indicators*, 67, 543-555.
- Etokakpan, M.U., Solarin, S.A., Yorucu, V., Bekun, F.V., Sarkodie, S.A. (2020), Modeling natural gas consumption, capital formation, globalization, Co<sub>2</sub> emissions and economic growth nexus in Malaysia: Fresh evidence from combined cointegration and causality analysis. *Energy Strategy Reviews*, 31, 100526.
- Godil, D.I., Sharif, A., Agha, H., Jermisittiparsert, K. (2020), The dynamic nonlinear influence of ICT, financial development, and institutional quality on Co<sub>2</sub> emission in Pakistan: New insights from QARDL approach. *Environmental Science and Pollution Research International*, 27(19), 24190-24200.
- Gujarati, D.N., Porter, D.C. (2009), Causality in economics: The Granger causality test. In: *Basic Econometrics*. New York: McGraw-Hill. p652-658.
- Johansen, S. (1991), Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models. *Econometrica: Journal of the Econometric Society*, 59, 1551-1580.
- Johansen, S., Juselius, K. (1990), Maximum likelihood estimation and inference on cointegration-with applications to the demand for money. *Oxford Bulletin of Economics and Statistics*, 52(2), 169-210.
- Keats, M. (2021), *Australian Internet Statistics 2021*. Available from: [https://www.prosperitymedia.com.au/australian-internet-statistics/#:~:text=there%20are%207.77%20billion%20people,people%20are%20active%20internet%20users.and text=there%20were%2022.31%20million%20internet,%25\)%20between%202019%20and%202021](https://www.prosperitymedia.com.au/australian-internet-statistics/#:~:text=there%20are%207.77%20billion%20people,people%20are%20active%20internet%20users.and text=there%20were%2022.31%20million%20internet,%25)%20between%202019%20and%202021).
- Khan, N., Baloch, M.A., Saud, S., Fatima, T. (2018), The effect of ICT on CO<sub>2</sub> emissions in emerging economies: Does the level of income matters? *Environmental Science and Pollution Research*, 25(23), 22850-22860.
- Khanal, A. (2021), Does energy consumption impact the environment? Evidence from Australia using the JJ Bayer-Hanck cointegration technique and the autoregressive distributed lag test. *International Journal of Energy Economics and Policy*, 11(4), 185-194.
- Kouakou, A.K. (2011), Economic growth and electricity consumption in Cote d'Ivoire: Evidence from time series analysis. *Energy Policy*, 39(6), 3638-3644.
- Lee, J.W., Brahmasrene, T. (2014), ICT, Co<sub>2</sub> emissions and economic growth: Evidence from a panel of ASEAN. *Global Economic Review*, 43(2), 93-109.
- Lu, W.C. (2018), The impacts of information and communication technology, energy consumption, financial development, and economic growth on carbon dioxide emissions in 12 Asian countries. *Mitigation and Adaptation Strategies for Global Change*, 23(8), 1351-1365.
- Magazzino, C., Porri, D., Fusco, G., Schneider, N. (2021), Investigating the link among ICT, electricity consumption, air pollution, and economic growth in EU countries. *Energy Sources, Part B: Economics, Planning, and Policy*, 2021, 1-23.
- Moyer, J.D., Hughes, B.B. (2012), ICTs: Do they contribute to increased carbon emissions? *Technological Forecasting and Social Change*, 79(5), 919-931.
- Nkoro, E., Uko, A.K. (2016), Autoregressive distributed lag (ARDL) cointegration technique: Application and interpretation. *Journal of Statistical and Econometric Methods*, 5(4), 63-91.
- Ozcan, B., Apergis, N. (2018), The impact of internet use on air pollution: Evidence from emerging countries. *Environmental Science and Pollution Research International*, 25(5), 4174-4189.
- Pesaran, M.H., Pesaran, B. (1997), *Working with Microfit 4.0: Interactive Econometric Analysis*. Oxford: Oxford University Press.
- Pesaran, M.H., Shin, Y., Smith, R.J. (2001), Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics*, 16(3), 289-326.
- Phillips, P.C., Perron, P. (1988), Testing for a unit root in time series regression. *Biometrika*, 75(2), 335-346.
- Raheem, I.D., Tiwari, A.K., Balsalobre-Lorente, D. (2020), The role of ICT and financial development in Co<sub>2</sub> emissions and economic growth. *Environmental Science and Pollution Research International*, 27(2), 1912-1922.
- Salahuddin, M., Alam, K. (2015), Internet usage, electricity consumption and economic growth in Australia: A time series evidence. *Telematics and Informatics*, 32(4), 862-878.
- Salahuddin, M., Alam, K., Ozturk, I. (2016), The effects of internet usage and economic growth on Co<sub>2</sub> emissions in OECD countries: A panel investigation. *Renewable and Sustainable Energy Reviews*, 62, 1226-1235.
- Shahbaz, M., Bhattacharya, M., Ahmed, K. (2016), Co<sub>2</sub> emissions in Australia: Economic and non-economic drivers in the long-run. *Applied Economics*, 49(13), 1273-1286.
- Shahbaz, M., Hye, Q.M.A., Tiwari, A.K., Leitão, N.C. (2013), Economic growth, energy consumption, financial development, international trade and Co<sub>2</sub> emissions in Indonesia. *Renewable and Sustainable Energy Reviews*, 25, 109-121.
- World Development Indicator. (2020), Available from: <https://www.datacatalog.worldbank.org/dataset/world-development-indicators>.
- Zivot, E., Andrews, D.W.K. (1992), Further evidence on the great crash, the oil-price shock, and the unit-root hypothesis. *Journal of Business and Economic Statistics*, 10(3), 251-270.