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Can Clean-Tech Patents and Energy Productivity Enhance Carbon Productivity in a Fossil Fuel Exporting Economy? Lessons from Australia

Virgiline Kongni FOPA^{1*}, Mohamed YUFENYUY¹, Kwaku ADDAI²

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ABSTRACT

Within the concept of sustainable development, economic growth should be driven by low-carbon practices and improved carbon productivity. While several studies have focused on low-carbon economy delivery, little has been done on carbon productivity and its relationship with innovative green technologies. This study assesses the effect of green-tech patents and energy productivity on the carbon productivity of Australia using the ARDL long run form and bounds test between 1990 and 2020. The Westerlund's variance ratio cointegration estimates indicate that all variables are integrated. The ARDL long-form and bounds estimates indicate that both green-tech patents and energy productivity help in the delivery of low-carbon productivity in Australia. The ARDL long form estimates further suggest that rising economic growth hinders improvements in carbon productivity levels of the Australian economy. Finally, the empirical outcomes of the Toda-Yamamoto test indicate (i) a one-directional causality from green-tech patents to both energy and carbon productivity; (ii) a rebound causal effect between economic growth and carbon productivity. For policy suggestions, the government of Australia could heavily invest in innovations in environmental technologies to improve carbon productivity levels and to determine progress towards reducing climate change by supporting corporations to consider carbon as a useful component and not a waste product. Second, the government could ground the carbon productivity concept in its commitments to reducing fossil carbon consumption. Corporations that perform well in delivering carbon dioxide emissions productivity could benefit from tax incentives and government grants. Finally, given that rising economic growth reduces or improves the Australian economy's carbon productivity levels, the government could institute non-monetary awards for individuals or corporations with strong records of registered green-tech patents and green energy technologies.

INTRODUCTION

Globally, carbon dioxide emissions (CO₂E) productivity has become central in academic and policy discussions owing to its climate change and emission reduction potential. In this global discussion, energy productivity is differentiated from carbon productivity, such that as fossil fuel consumption reduces, it theoretically implies that green or environmental technology utilization has improved in the economy, helping to decouple carbon dioxide productivity from energy productivity. Historically, environmental scientists have claimed that dynamics in the energy section remain a central factor to the escalating human-induced CO₂E found to cause climate change (Atasoy, 2017). Because of this climate change peril, existing biophysical assets are endangered. A recent study of global environmental change by Kirikkaleli *et al.* (2022) also reported that, in comparison with the 1880s, the temperature of the world has risen by almost 1.4°F, causing about 75% of global flora and fauna species to become extinct. Additionally, apart from its menace to wellbeing and human health, this climate danger also causes a fall in global food production, air pollution, inequality and wildfires. In comparison to pre-modern era, scientists claim that, the upsurge in world temperatures must be reduced to a tolerable 1.5°C through policy measures. Additionally, for many years, global climate crusaders or

leaders have reechoed on the exigency of policy needed to curb CO₂E and climate perils.

To beef up global policy insight, recent scholars have emphasized environmental technology policy as the most effective pathway to improving carbon productivity without compromising output (Ekins *et al.*, 2012; Shao *et al.*, 2014). Environmental technologies directly support carbon productivity delivery (i.e., energy-use technologies and carbon technologies), including carbon reduction, zero carbonization, and decarbonization technologies. Theoretically, environmental and economic experts claim that the process of delivering low-carbon-based economic transformation requires an environmental innovation-driven pathway (Berna *et al.*, 2022). Several scholars claim that achieving carbon emissions reduction objectives requires an innovation-driven economy (Yang *et al.*, 2019; Chen *et al.*, 2022) as knowledge innovations improve energy and environmental technologies, promoting commercial application of green technologies (Yang *et al.*, 2019). Across the world, innovations in environmental technologies are influencing global energy consumption. For example, renewable energy innovations (such as solar energy) promote global transition from fossil-based towards a carbon-neutral economy (Guo *et al.*, 2019), and reduces our reliance on unclean energy (Brathwaite *et al.*, 2010).

¹ Department of Business Management, Faculty of Business, Girne American University, Kyrenia, Northern Cyprus, TR-10 Mersin, Turkey

² Department of Business Management, Faculty of Business Management, Noble International Business School (NIBS) University, Accra, Ghana

* Corresponding author's e-mail: virgilinefopa@gau.edu.tr

There are, however, some academic critics who argue on the contrary. According to Dauda *et al.* (2021), technological improvement can reduce carbon emissions in the advanced economies, but intensify it in poor countries. Similarly, in his study, Ganda (2019) found 1% upwards adjustment of patent family-count leads to 0.05% rise in carbon emissions. Further, by studying OECD member states, Koçak and Ulucak (2019) noted that investments in renewable energy innovations provide unclear outcomes about reducing carbon emissions. Until now, the debates on the effect of environmental technology innovations on CO₂E productivity remains unsettled (Zhang *et al.*, 2021). The persistent question for the academics involves whether the claim on the role of environmental technologies can be validated, especially at country level. This study seeks to provide answers and close this scholarly gap

by exploring the role of green-tech patents in carbon dioxide productivity debate for the case of Australia due to their rising rates of environmental technologies but questionable emission records. Globally, Australia is one of the largest energy-consuming economies and carbon dioxide (CO₂) emitters, and as a result, it urgently seeks policy options to reduce its CO₂E. The country's average carbon emissions rose from at least 263630 kt in 1990 to 386530 kt in 2019, with a slight improvement in 2014. Additionally, Australia is an advanced economy with annual growth rate in GDP averaging 3.37 percent between 1960 until 2022. Figure 1 illustrates Australia's latest data from 2025, showing economic growth of 1.35 percent, and time series covering the period from 1960 to 2025.

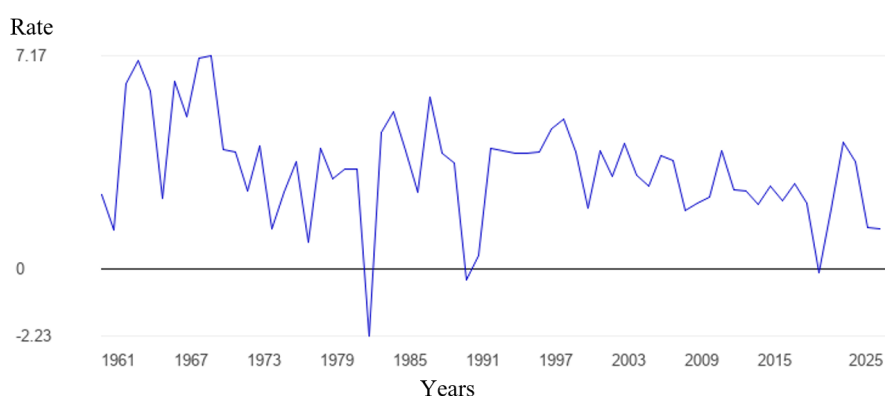


Figure 1: Australia's growth trend from 1960 to 2025.

Source: *theglobaleconomy.com* (2026): https://www.theglobaleconomy.com/Australia/Economic_growth/

The country's science, research and innovation (SRI) budget tables indicate that Australia Government's total investment in R&D amounted to AUS\$11.8 billion in 2021 to 2022 financial year. Regarding Intellectual Property (IP), applicants submitted 32,397 standard patents in 2021 signifying an eleven percent increase from applications received in 2020, thus representing the second largest upsurge in a decade; compared to the spike in filings between 2012 and 2013. Although this

represented a fall, given that the global innovation index for Australia was 47.1 compared to 53.07 index in 2013, ranking 25th among 132 economies in 2021(GNI, 2022). For renewable energy supply, Australia saw a rise from 8.29% in 2012 to 10.13% in 2019. However, the average carbon emissions value for Australia in 2024 was 383 Mt, a marginal fall since 2017 value of 411Mt as shown in Figure 2. In 2024, the carbon emissions figure represented a minimum of 161 metric tons in per capita terms.

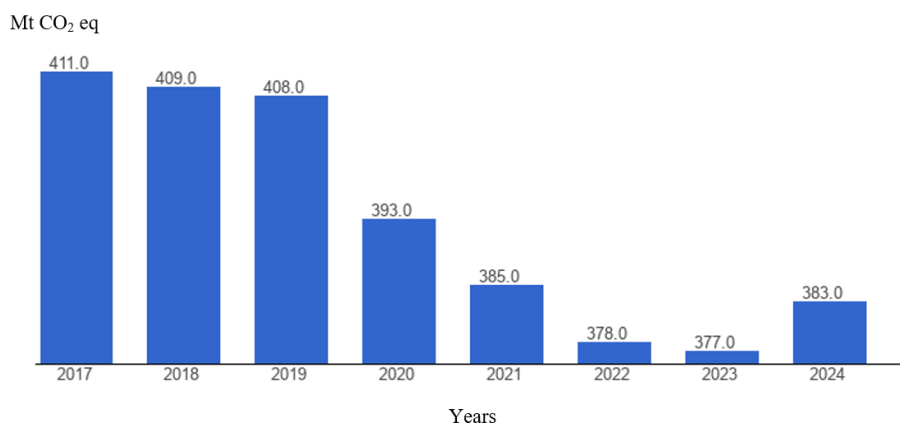


Figure 2: Australia's carbon emissions record since 2017.

Source: https://www.theglobaleconomy.com/Australia/Carbon_dioxide_emissions/

Further, concerns have been expressed about the fluctuating states in the filing of provisional patent applications recently. For instance, in 2018, 2757 provisional patent applications were filed, indicating

an outstanding increase compared to 2014 (with 1988 patent applications). However, filed applications dropped steadily to 2368 in 2020 before regaining momentum in 2021 as shown in Figure 3.

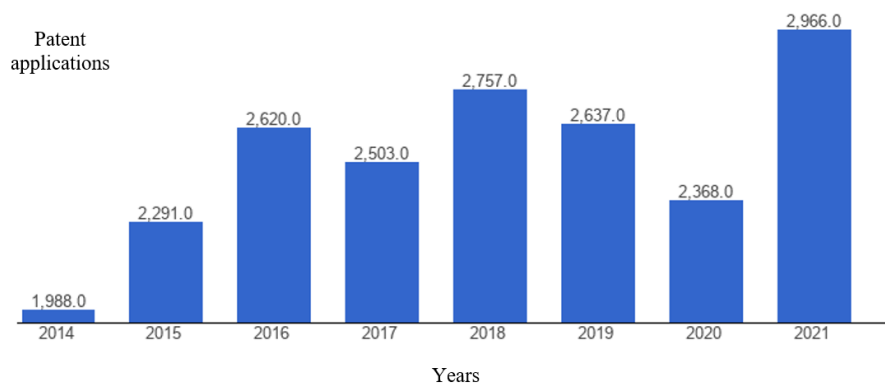


Figure 3: Patent applications by residents.

Source: https://www.theglobaleconomy.com/Australia/Patent_applications_by_residents/

With the above narratives, assessing the role of green-tech patents on CO₂E productivity for the case of Australia will provide policy cues not only to Australia but also to economies across the world with similar records. Using data from 1990 to 2020, this research made use of the auto-regressive distributive lag (ARDL) long run and bound form methods to assess the long run equilibrium features of Australia's green technologies and carbon emissions productivity. To realize the set objective, the research controls economic growth and energy productivity factors, which are historically validated to participate in global carbon dioxide emissions productivity policy discussions. The contribution of this paper is manifold. First, it aims to provide a thorough account of how carbon emissions productivity has evolved in Australia. Second, it aims to shed light on how green-tech patents play a significant role in determining emissions productivity of an economy. Third, the paper develops a comprehensive environmental innovation variable system, consisting of four dimensions, i.e., technology performance, resources, knowledge and environment. Fourth, to separate the policy effect of green-tech on carbon emissions productivity and circumvent selection prejudice, the study controls for economic growth and energy productivity variables in Australia. Finally, the paper uses a robust estimator, ARDL long run form and bounds test to determine the role of green-tech patents, economic growth and energy productivity of Australia. The paper is further organized as: section two reviews relevant literature; section three describes data, variables definitions and methodology for the empirical analysis; section four presents and discuss the empirical outcomes; while section five concludes the study with policy insights.

LITERATURE REVIEW

Carbon productivity concept is described as a component of wider change in perspectives where pioneering individuals and organisations are "reimagining" how

to control the rising carbon emissions. One major methodological perspective is the full deployment of green-tech patents in the pursuit of carbon dioxide productivity while delivering social and financial value. This section examines studies about relationships between relevant factors related to global climate change agenda and carbon productivity delivery pathways. By definition, carbon productivity describes economic gains realized per unit of CO₂E. Its attainment implies that more economic value is realized for every unit of CO₂E produced.

According to experts, carbon productivity is generally measured in two ways: (i) single-factor (Kaya and Yokobori 1997) and total-factor (Aldy, 2022) measurements. The single factor determines single linkage between carbon dioxide emissions regarding economic growth. This factor considers only economic productivity and ignores the role of capital and labor input factors. Total factor measures input and outputs of production factors into an integrated model. This makes outcome more comprehensive and reliable. In this literature review, the paper frames three hypothetical concepts geared towards the realization of objectives for the study as:

Hypothesis 1 (H1): The ever-increasing economic growth positively affects rising carbon emissions in Australia.

Theoretically, pursuing economic growth can undermine environmental standards, and culminate in the production of toxic wastes that pollute the environment (Farmery *et al.*, 2021). Empirically, it is found that due to rising economic growth over the last decade, there has occurred increases in levels of global carbon emissions compared to 1990 levels. Several scholars insinuate that the startling level of environmental degradation emanates from economic growth that is achieved through unclean energy consumption (Addai *et al.*, 2022; Serener *et al.*, 2022; Shahbaz *et al.*, 2021). Studying the asymmetric effect of environmental technologies and pollution in developing

economies, Yu-Ke *et al.* (2022) confirmed pollution caused by unclean energy use. Similarly, studying rising use of fossil-based fuel, industrial growth and environmental pollution, Huan *et al.* (2022) found fossil-based fuel over-consumption to cause environmental degradation in Australia. Shikwambana *et al.* (2022) in South Africa validated these findings. Based on these findings, the paper assumes that the ever-increasing economic growth positively affect CO₂E emissions in Australia, i.e.,

$$\vartheta_1 = \frac{\partial LCO_2}{\partial LGDP} > 0; \vartheta$$

LCO₂ refers to the log of CO₂ as proxy variable for carbon productivity; LGDP is the log of GDP per capita as proxy variable for economic growth; a study by Umar *et al.* (2020) aligns closely with is assumption.

Hypothesis 2 (H2): Investments in energy productivity has negative effects on rising carbon emissions in Australia In recent times, economies across the world have resorted to promoting energy productivity in their policy decisions. The primary goal is to reduce rising CO₂E associated with expanding economic growth. Theoretically, energy productivity improvements generate economic viability by lessening product cost and increasing green technological innovations (Paramati *et al.*, 2021). However, critics claim that productivity policies on energy use do not yield ‘win-win’ results at the macro level due to energy consumption rebound effect (Takase and Kondo, 2005; Dimitropoulos, 2007). Scientific demonstration by Saunders (2000) showed that investing in energy productivity within a neoclassical growth theory is not energy efficient. Expanding this argument, Wei *et al.* (2020) claimed that rising fossil consumption is interlinked with rising economic output. This means that energy productivity measures which create reduction in energy consumption will ultimately lead to decreasing economic output. However, critics contend that, Sounder’s theoretical explanation is limited and over-hyped since income impacts due to energy productivity investments is not comparable to gains from technology processes (Howarth, 1997, Krarti *et al.*, 2019). Studying the impact of productive policies from 2000 and 2004, Krati *et al.*, (2017) observed that elementary energy retrofitting in residential facilities in Saudi Arabia generated both economic and environmental gains. Webster and Ayataksi (2013) studied UK’s tax policies on energy consumption and found them to exert negative impacts on carbon emissions in 2009. Because of these findings, this paper hypothesizes that investments in energy productivity has adverse effects on rising CO₂E in Australia . i.e.,

$$\vartheta_4 = \frac{\partial LCO_2}{\partial LENPRO} < 0; \vartheta$$

LCO₂ refers to log of CO₂ as proxy variable for carbon productivity; LENPR is log of energy productivity; this assumption aligns with Umar *et al.* (2020).

Hypothesis 3 (H3): Rising rates of green-tech patents improves on carbon productivity in Australia. Historically, scholars have found that green technological

applications are the most robust pathways for transitioning to low-carbon economy. They claim that rising patents on environmental innovations signals green transition. Scholars further claim that knowledge improvements on green technologies and patents records in environmental technologies encompass other product innovations, which promote environmentally friendly industrial activity, and helps to reduce carbon emissions (Gallagher *et al.*, 2006). According to Chen *et al.* (2018), driven by policy, several economies have experienced huge economic growth rates with falling carbon emissions due to energy productivity improvements. Based on this, the paper hypothesized that rising rates of environmental technologies improves carbon productivity in Australia. i.e.,

$$\vartheta_4 = \frac{\partial LCO_2}{\partial LPATENT_{it}} < 0$$

LCO₂ refers to the log of CO₂ as proxy variable for carbon productivity; LPATENT is the log of patents as proxy variable for green-tech patents; studies by Li *et al.* (2020) and Wahab *et al.* (2021) corroborates with this hypothesis respectively.

Given this comprehensive literature review, it is apparent that studies on carbon emissions productivity require further investigation to provide clarity that supports sustainable economic growth through innovations in environmental technologies, as it is essential to realizing carbon productivity gains. The review process has validated the assumed hypothesis established. Additionally, given this review, there is a sense that despite its importance to the global economy, the exact impact of green technologies on CO₂E productivity is still not conclusively determined. This study investigates the case of Australia under the augmented green Solow framework.

MATERIALS AND METHODS

Data on (i) carbon productivity was sourced from the International Energy Agency database as a proxy variable for CO₂E productivity. This variable describes the financial and environmental value generated when utilizing energy from unclean fossil sources like natural gas, oil and coal. Carbon productivity measurements are intended for corporations that are engaged in product value chains as well as those intended to improve environmental implications of a products’ life cycle, such as guiding green innovations. (ii) Economic growth was proxied by Gross domestic product per capita (GDP; in constant 2015 US\$), obtained from the World Bank database. GDP per capita is measured by splitting the overall value of all resident producers by mid-year population while including any product taxes not accounted for during output valuation (Lewis, 2013; Jones, 2022). (iii) Energy productivity data was obtained from Eurostat to quantify economic gains per unit of energy consumed. Its measurement is done by dividing the overall economic output by consumed energy in electricity kilowatts utilized or barrels of oil equivalent (Ding *et al.*, 2021). (iv) Green-tech patents refers to the application of green technologies to conserve, monitor

or reduce detrimental effects of human actions on the environment. It also refers to environmental technologies. In accordance with the World Intellectual Property Organization, green-tech patents are filling counts for Climate Change Mitigation technologies (CCMTs) anchored within the International Patent System and

spearheaded by a sharp increase in solar energy generation, battery technology, and electric vehicle drive systems (World Intellectual Property Organization, 2025). Data on patents was collected as a proxy for green technologies. It is measured by the number of patents recorded (Baumann *et al.*, 2021). Table 1 describes the variables of interest.

Table 1: Variable description.

Variable	Abbreviation	Definition	Reference
Carbon dioxide productivity	CO2	Emissions pollution	Aldy, (2022)
Gross domestic product to capture economic growth	GDP	Technology performance	Zhang <i>et al.</i> (2016)
Patent of environmental technologies or Green-tech patents	Patent	Intellectual property rights to prevent environmental damage	Serener <i>et al.</i> (2022)
Energy productivity	ENPR	Technology performance	Addai <i>et al.</i> (2022)

Theoretical Framework and Model Specification

One of the biggest policy problems worldwide in recent decades has been the attempt to decouple environmental pollution from rising economic growth. Scholars have, over the years, made framework contributions to explain environmental degradation and the likelihood of further worsening in growth pursuit in the absence of policy action. To make a policy contribution, this paper accounts for the effect of technology use on CO2 productivity in Australia.

To realize this objective, the paper adopts the augmented Solow model, which sees exogenous advancement in technological applications towards economic growth while improving environmental quality. The model follows Copeland and Taylor (1997), who argued that every unit change in economic activity ('F') has an associated unit of pollution ('Y') generated to create a product. Here, an assumption is made that the pollution generated differs across economies depending on the degree of abatement action taken. According to this model, pollution abatement is a function of total economic activity and the abatement action due to technical progress. The abatement action at level A, which deals with ΩA units of pollution on total output, can be framed as:

$$\begin{aligned}
 E &= \text{Pollution created} - \text{Pollution abated} \\
 &= \Omega F - \Omega A (F, F^A) \\
 &= \Omega F - |1 - A \left(1 - \frac{F^A}{F}\right)| \\
 &= F e(\theta) \text{ where } e(\theta) \cong \Omega |1 - A(1,0)| \text{ and } \theta \cong \frac{F^A}{F}
 \end{aligned} \quad (1)$$

where pollution abated is F^A ; the 3rd line is a linear homogeneity follow-up of A, the 4th line θ is the fraction of economic activity dedicated to abatement; economic activity 'F' is determined by production techniques $e(\theta)$; and F^A in F.

The environmental Kuznets Curve (EKC) recognition process differs, as this model does not account for recognition of composition effects, increased pollution abatement intensity, the political process, or cross-border trade. CO₂E per unit of GDP reduce in the transition process and along the balanced growth path. Hence,

augmenting technological progress increases abatement rates. Based on this framework, the paper models the effect of economic growth, energy productivity and green-tech patents on carbon productivity in Australia as

$$CO2_t = GDP_t, ENPR_t, PATENT_t, e_t \quad (2)$$

$$Y = f(X_{1t}, X_{2t}, X_{3t}) \quad (3)$$

To initiate the assessment, we converted all parameters of interest into their logarithm form in order to minimize scaling issues as:

$$LCO2_{it} = \vartheta_0 + \vartheta_1 LGDP_{it} + \vartheta_2 LENPR_{it} + \vartheta_3 LPATENT_{it} + e_{it} \quad (4)$$

From equation (4) i, represents our case study or country under investigation, t stands for the time scope of the study (1990-2020), ϑ denotes the series coefficients and ϵ for the error term. A positive connection is expected between LGDP and LCO2 as hypothesized in the literature review ($\vartheta_1 = (\vartheta LCO2 / \vartheta LGDP) > 0$), where economic growth is proxied by the log of GDP and carbon productivity is proxied by the log of CO₂E in Australia. Additionally, a negative association is expected between LENPR and LCO2; i.e. ($\vartheta_2 = (\vartheta LCO2 / \vartheta LENPR) < 0$) where LCO₂ is the log of CO₂E as a proxy for carbon productivity in Australia; LENPR is the log of energy productivity. Finally, a negative association is expected between LPATENT and LCO2 ($\vartheta_3 = (\vartheta LCO2 / \vartheta LPS) < 0$), where LCO₂ is the log of CO₂E as a proxy for carbon productivity in Australia; LPATENT is the log of green-tech patents or patents on environmental technologies.

Unit root test

By following good practices in econometric analysis, scholars realized that variances occur in data over time and such non-stationarity usually give rise to false regression outcomes. To assess the integration order of parameters, we utilized the Augmented Dickey Fuller (ADF) unit root tests with a breakpoint as in equation (5),

$$x_t = \mu + \rho x_{t-1} + e_t \quad (5)$$

From the equation, the target parameter is represented by x_t , while μ and e_t represents the constant and error terms respectively. After differencing, the model translates to $\Delta x_t = \mu + e_t$; where $\Delta = (1-B)$; and ρ denotes the parameter slopes for lagged variables, which turns to 1 in case a unit root occurs. The alternate stationarity for ADF with breaks is written as:

$$x_t = \mu + \beta_t \delta D U_t + \theta D(T_B)_t + e_t \quad (6)$$

When the augmented factors is applied, the re-specification of the error correction form for then ADF with break becomes like:

$$\Delta x_t = \mu + \beta_t + \gamma_1 \sin\left(\frac{2\pi k_t}{N}\right) + \gamma_2 \cos\left(\frac{2\pi k_t}{N}\right) + (\rho - 1)x_{t-1} + \sum_{i=1}^p c_i \Delta x_{t-i} + \varepsilon_{t-1} \quad (7)$$

From equation (7), the slope parameter of the augmented portions is represented by c while p denotes the lag length with the lowest information criteria values in the augmentation process. T_B denotes the date of the structural break whereas λ is the fraction break and k stands for regularity

Co-integration test

Experts on economic theories observed that movements in time series data happens in a coordinated manner around the equilibrium in the long run, which is measured and tested under the concept of co-integration. Co-integration happens in the testing process when two of more non-stationary parameters exhibit long run equilibrium characteristics such that their linear consolidation ends up sharing a common stochastic trend.

To realize this, the paper adopts Westerlund's 2005 and Søren Johansen trace approaches. These tests permit more than one co-integrating connection, better than the traditional Engle–Granger test on outcome reliability.

Long and short-run equilibrium test

Next, the paper adopts the ARDL Long-run and bound form to test the short and long run association. The approach is chosen because the method is superior to several other co-integration tests. After all, first, it is applicable regardless of the integration order of selected parameters, next the short-run adjustments becomes integrated with the long run equilibrium through the error correction model (ECM); and finally, the approach is free from residual correlation, helping to avoid endogeneity problems. The long-run equilibrium co-integration is written as:

$$Y_t = \beta_0 + \beta_1 X_t + \mu_t \quad (8)$$

From equation (8) Y_t represents the predicted parameter, X_t stands for the explanatory variables while β_1 describes changes in Y_t due to unit changes in X_t . To control for the effects of technological innovation, the study adopted the Augmented Solow framework and the model becomes:

$$CO2_t = \beta_0 + GDP + ENPR + PATENT + \mu_t \quad (9)$$

The parameters are then, converted into their respective logarithms form as in equation (10) before conducting

the econometric assessment,

$$\Delta LCO_{2t} = \beta_0 + \beta_1 LCO_{2,t-1} + \beta_2 LGDP_{t-1} + \beta_3 LENPR_{t-1} + \beta_4 LPATENT_{t-1} + \sum_{i=1}^{p-1} \delta'_i \Delta LCO_{2,t-i} + \sum_{i=1}^{p-1} \delta'_i \Delta LGDP_{t-i} + \sum_{i=1}^{p-1} \delta'_i \Delta LENPR_{t-i} + \sum_{i=1}^{p-1} \delta'_i \Delta LPATENT_{t-i} + e_t \quad (10)$$

Where β represents the constant term and the time scope is denoted by t . LCO_2 is the log of CO_2E as the proxy for CO_2 productivity; $LGDP$ is the log gross domestic product as the proxy for economic growth; $LENPR$ is the log of energy productivity; $LPATENT$ is the log of patents as a proxy for green-tech patents; and e_t is the error term.

To ensure long-run co-integration, the paper additionally conducts the ARDL with bounds testing capabilities (Pesaran *et al.*, 2001). $H_0: \lambda_1 = \lambda_2 = 0$, indicating no association among the parameters in the long term against $H_1: \lambda_2 \neq \lambda_1 \neq 0$, meaning there is a long term connection among the studied parameters. Rejection of the null hypothesis (i.e., H_0) means to accept the alternative hypothesis (H_1).

Causality test

Finally, the paper determines the directions of causality using Toda & Yamamoto (1995), which is validated to provide reliable estimates (Shahbaz and Sinha, 2019). Toda Yamamoto introduced a causality test that applies a modified Wald Test (MWALD) with a chi-square (X^2) dissemination capable of restricting the parameters of the VAR (k); where k denotes the proper lag length of the VAR system. Yamamoto's technique further expands the existing order (k) by an optimum order of integration (d_{max}), allowing VAR $K+d_{max}$ to be estimated.

RESULTS AND DISCUSSION

This paper is a dynamic investigation of the long-run effect of green-tech patents on carbon dioxide productivity in Australia, with the time scope from 1990 to 2020. Table 2 describes the parameter used for this investigation.

Following good practices in econometric assessment, the paper performs a unit root test. Nevertheless, before the unit root, the paper undertakes the Broock *et al.*, (1996) test of the stochastic time series dataset towards detecting possible hidden nonlinearities. The BDS assessment is generally beneficial for several analytical reasons.

These may include its ability to guard against misspecification and judgmental errors in the model. The BDS estimates also indicate the p-values are significant; and therefore, a rejection of the null hypothesis suggests non-linearity for the case of the Australia, paving the way for the stationarity test to be performed using non-linear approaches. Previous studies by Sowah & Kirikkaleli (2022) align perfectly with these outcomes.

Based on the Unit Root with Beaks (Adf) estimates (Table 4), variables are integrated at mixed orders and with breakpoints at 1998Q1, 1990Q1 and 1990Q3. This result supports previous work by Addai *et al.* (2022) and enables the paper to conduct co-integration assessments using several econometric techniques.

Table 2: Descriptive Statistics

Description	LCO2	LGDP	LENPR	LPATENT
Mean	17.60809	40182.63	7187.672	218.9353
Median	17.43373	41918.89	6676.933	251.2939
Maximum	19.28614	49927.34	9413.077	320.6167
Minimum	14.96329	26807.12	5823.804	123.2745
Std. Dev.	1.083219	7667.896	1143.397	60.58995
Skewness	0.008609	-0.358001	0.865834	-0.358877
Kurtosis	1.714969	1.732423	2.391506	1.654122
Jarque-Bera	779.2114	999.9193	1589.439	1097.650
Probability	0.000000*	0.000000*	0.000000*	0.000000*
Sum	199376.4	4.55E+08	81386008	2479004.
Sum Sq. Dev.	13284.82	6.66E+11	1.48E+10	41564669
Observations	11323	11323	11323	11323

For the Johansen Trace Test for co-integration (Table 5), the rule is to proceed with assessments if the model contains one co-integration relationship (Hoxha, 2010). Since the outcomes revealed a 1% statistically significance

level for all cases, it is appropriate to discard the null hypothesis and accept its alternative, thus confirming the long run connection among the parameters.

Table 3: BDS Test

LCO2				
Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
2	0.209123	0.000392	533.9316	0.0000*
3	0.355747	0.000617	576.5256	0.0000*
4	0.458561	0.000728	629.9464	0.0000*
5	0.530659	0.000751	706.2096	0.0000*
6	0.581216	0.000718	810.0096	0.0000*
LENPR				
Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
2	0.208178	0.000634	328.3844	0.0000*
3	0.354662	0.001005	352.9704	0.0000*
4	0.457745	0.001193	383.6952	0.0000*
5	0.530288	0.001240	427.7839	0.0000*
6	0.581338	0.001192	487.8302	0.0000*
LGDP				
Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
2	0.209938	0.000433	485.0124	0.0000*
3	0.356891	0.000681	524.2247	0.0000*
4	0.459756	0.000802	573.3723	0.0000*
5	0.531773	0.000826	643.4752	0.0000*
6	0.582187	0.000788	738.8915	0.0000*
LPATENT				
Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
2	0.211546	0.000542	390.3954	0.0000*
3	0.358682	0.000848	422.9394	0.0000*
4	0.461003	0.000994	463.7291	0.0000*
5	0.532146	0.001020	521.8164	0.0000*
6	0.581596	0.000968	600.9366	0.0000*

Note: * denote statistically significant at 1% level.

Table 4: Unit Root with Beaks (Adf)

Variables	Level	Diff	Order	Breaks
LCO2	-4.949133	-4.443649	0	-4.506537(1998Q1)
LPATENT	-4.949133	-4.443649	0	-4.506537(1998Q1)
LENPR	-4.949133	-4.443649	1	-90.66774 (1990Q3)
LGDP	-4.949133	-4.443649	0	-13.09229(1990Q1)

The outcomes from Tables 5 and 6 indicate that variables are co-integrated. This finding lends support to Adebayo *et al.* (2022). In economic theory, time series datasets move

together and fluctuate around a long-run equilibrium. This long-run equilibrium could be tested with the concept of cointegration. Based on this, the paper employs ARDL

Table 5: Co-integration Test

Rank/Trace test			
Variables	LR- stats	Lag order	Prob.
LCO2	0.143621	4	0.0000*
LGDP	0.000432	4	0.0000*
LENPR	-0.001756	4	0.0000*
LPATENT	-0.021095	4	0.0000*

Star * represents 1% level of statistical significance.

long form and bounds methods for this assessment. As reported in Table 7, since the F-statistic value (149.7448) surpasses the critical values, there is a sense of connection between our outcome variable and predictor

variables (i.e. LCO2, LPATENTS, LGDP, and LENPR), implying that, through the ARDL bound test method, a long-run association exists between our variables of interest.

Table 6: Variance Ratio Test

Variance Ratio Cointegration Test (Westerlund, 2005)			
Joint Tests		Df	Probability
Max z (at period 16)*		11322	0.0000*
Individual Tests			
Period	Var. Ratio	z-Statistic	Probability
2	1.158058	10.46661	0.0000*
4	1.473072	16.79469	0.0000*
8	2.098472	24.83076	0.0000*
16	3.329120	35.87255	0.0000*

Star * represents 1% level of statistical significance.

Error correction model (ECM) captured the (ECT) term, where the Coint Eq (-1*) coefficient value (0.000342) is significant at 0% statistical level as illustrated in Table 8. The ECT (negative) value is significant at 5% level and

exposed, reflecting a long-term connection between the regressors. Additionally, the error correction speed shows the time elapsed between the short-term imbalance and long-term adjustment to the equilibrium position.

Table 7: ARDL Long-run Bounds Diagnostic estimates

F-Bounds Test	Null Hypothesis: No levels relationship			
	Asymptotic: n=1000			
	Value	Signif.	I(0)	I(1)
F-Statistics	149.7448	10%	2.37	3.2
K	3	5%	2.79	3.67
		1%	3.65	4.66
Asymptotic: n=1000				

Because of the cointegrated variables, the paper estimated the long-term variations in the predictor parameters and how they affect the outcome variable. The long-run outcomes and values of the estimated coefficient

(as illustrated in Table 9) capture the directions and magnitudes of LCO2 on LGDP, LENPR and LPATENT, respectively. The ARDL Long Run Co-integration Diagnostic estimates indicate that both LENPR and

Table 8: Short term ARDL outcomes with error correction representation.

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
D(GDP)	7.13E-05	3.82E-06	18.68902	0.0000*
D(ENPR)	8.82E-05	4.45E-06	19.80486	0.0000*
D(PATENT)	0.002190	6.00E-05	36.50088	0.0000*
CointEq(-1)*	0.000342	1.25E-05	27.36767	0.0000*

*represent 1% levels of significance.

LPATENT are significant with coefficient values of -9.51E-05 and -0.002548, respectively. Also, the estimates indicate that LGDP is significant and has a coefficient of 7.13E.05.

First, the ARDL long run co-integration diagnostic estimates indicate that LENPR is significant, and possesses a coefficient value of -9.51E-05. The implication is that statistically, 1% upward adjustment in LENPR helps to

Table 9: ARDL Long Run Co-integration Diagnostic estimates

Dependent Variable: LCO2				
Method: ARDL (4, 1, 2, 4)				
Variable	Coefficient	Std. Error	t-Statistic	Prob.*
LGDP	7.13E-05	4.60E-06	15.51049	0.0000
LENPR	-9.51E-05	6.78E-06	-14.01880	0.0000
LPATENT	-0.002548	9.21E-05	-27.65901	0.0000
C	-0.005514	0.000455	-12.10621	0.0000

reduce LCO2 by 9.51% in Australia. This implies that energy productivity investments by the government could yield significant carbon productivity benefits. This finding align with the stated hypothesis of the paper (i.e., H1: Investments in energy productivity improve on carbon productivity in Australia); and the outcome also supports recent findings by Serener *et al.* (2022). Instructively, the country's science, research and innovation (SRI) budget tables indicate that Australia Government's total investment in R&D amounted to AUS\$11.8 billion in 2021 to 2022 financial year. Regarding Intellectual Property (IP), applicants submitted 32,397 standard patents in 2021 signifying an eleven percent increase from applications received in 2020, thus representing the second largest upsurge in a decade; compared to the spike in filings between 2012 and 2013. Despite criticisms that it represented a downward slide, the global innovation index for Australia showed 47.1 ranking, 25th among 132 economies in 2021 (GNI, 2022). It is instructive to observe that the increasing supply and deployment of innovative and environmental technologies have been observed to contribute to the rising carbon productivity in Australia. This outcome validates Sharif *et al.* (2020) findings.

Second, as presented in Table 9, the long-run outcome of the ARDL reveal that LPATENT is significant and has a

coefficient value of -0.002548. This means that 1% rise in LPATENT reduces LCO2 by 0.002548% in Australia. This implies that for the government of Australia to witness improvements in carbon dioxide productivity, policies to ensure the development of environmental technologies (proxied by LPATENT) are vital. The outcome is a validation of the hypothesis made for the statistical analysis as part of the literature review process (i.e., H2: Rising rates of environmental technologies improve carbon productivity in Australia). Theoretically, rising LPATENTS on environmental technologies are required for the process of a low-carbon economy (Serener *et al.*, 2022; Yang *et al.*, 2019; Chen *et al.*, 2022). As knowledge innovations aim to boost science and technology in the energy sector, so is green-tech patents, aimed at encouraging the viable promotion of leading edge green energy and other related technologies. The finding indicates that with a rising number of Intellectual Property (IP) and standard patent applications (i.e., 32,397 in 2021, representing an 11% increase from 2020 levels, the second largest growth in a decade). Australia is likely to experience a downward trend in LCO2 reduction and an improvement in carbon productivity.

Third, long-run results of the ARDL in Table 9 show that LGDP is significant and has a coefficient value of

713E-05. This means that 1% rise in LGDP results in an increase in LCO₂ by 7.1% in Australia. This estimate implies that for the period studied, policies for economic growth have caused upward adjustments in carbon dioxide productivity. The outcome is a validation of the hypothesis made for the statistical analysis as part of the literature review process (i.e.H3: Economic growth has positive effects on carbon emissions in Australia). Australia is recognized as one of the largest energy-consuming economies evident by the increasing economic growth. Due to economic growth pursuit, Australia's average carbon emissions rose from at least 263630 kt in 1990 to 386530 kt in 2019; seeing only a minor improvement in 2014. Additionally, Australia is an advanced economy with annual growth rate in GDP averaging 3.37 percent between 1960 until 2022. This is a worrying trend warranting policies to reverse the rate of emissions in economic growth rates.

In the nutshell, the ARDL long run form and Bounds estimates indicate that the variables are integrated, and their individual or collective variations have effect on the dependent variable, (i.e., LCO₂) in Australia. Policy

makers could review and invest in existing policies on LGDP, LENPR and LPATENT in Australia towards ensuring reductions in emissions productivity of growth. The diagnostic estimates (CUSUM and CUSUM of squares) in Figure 4 and 5 respectively of the empirical ARDL long run and Bounds model indicate substantial stability in the model.

Tables 10, 11 and 12 shows the model diagnostic tests utilized in this study. The outcomes (Table 10) failed to reject the null hypothesis, proving that the model is homoscedastic. Furthermore, Table 11 also failed to reject the null hypothesis of no serial correlation at up to 2 lags, showing that no serial correlation of up to 2 lags was noticed in the data. Lastly, the correctness and stability of the specified model is confirmed in Table 12 as evident by the probability values at more than 5% significance level. The empirical outcomes of Toda-Yamamoto (1995) test (Table 13) indicate that (a) there is a bi-direction causality between LGDP and LCO₂. This means a rising LGDP results in rising demand for fossil energy for production leading to rising LCO₂ in Australia. This outcome provides support to Saint *et al.* (2019) in the

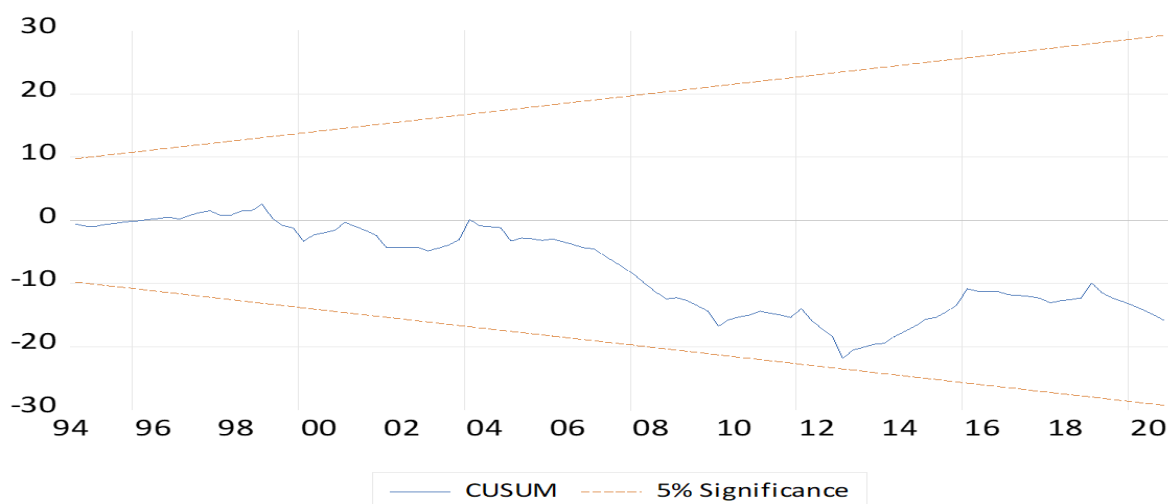


Figure 4: CUSUM.

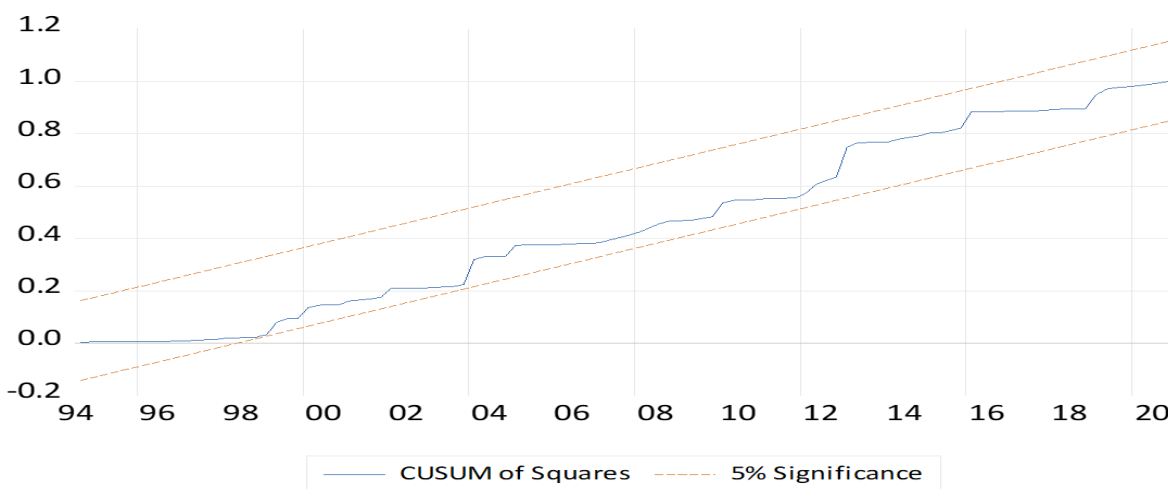


Figure 5: CUSUM of Squares.

work on growth, energy usage and carbon emissions. (b) (Table 13), which indicates that a shift away from unclean energy towards green energy and increasing investments

Table 10: Heteroskedasticity Test: Breusch-Pagan-Godfrey.

Null hypothesis: Homoskedasticity			
F-statistic	0.371651	Prob. F(10,110)	0.9565
Obs*R-squared	3.954551	Prob. Chi-Square(10)	0.9494
Scaled explained SS	8.411928	Prob. Chi-Square(10)	0.5887

Table 11: Breusch-Godfrey Serial Correlation LM Test.

Null hypothesis: No serial correlation at up to 2 lags			
F-statistic	0.233484	Prob. F(2,108)	0.7922
Obs*R-squared	0.520924	Prob. Chi-Square(2)	0.7707

Table 12: Ramsey RESET Test.

	Value	Df	Probability
t-statistic	0.167668	109	0.8672
F-statistic	0.028113	(1, 109)	0.8672
Likelihood ratio	0.031204	1	0.8598

in research and development lower CO₂ emissions in Australia. Therefore increasing the demand for green technologies and services results an increases in energy productivity. This finding supports earlier findings by Sharif *et al.* (2020). (c) The TY estimates indicate a one-

direction causality from LPATENT to LENPR and LCO₂. This means that rising demand for fossil energy for production leading to increasing levels of LCO₂ in Australia. Also, the results indicate that rising supply and use of innovative green and other environmental

Table 13: Toda Yamamoto (1995) causality estimates.

Dependent variable: LCO ₂			
Direction of causality; Null hypothesis (H ₀)	Chi-sq	Prob.	Decision
LGDP → LCO ₂	17.04750	0.0002*	Accept H ₀
LENPR → LCO ₂	4.134613	0.1265	Reject H ₀
LPATENT → LCO ₂	15.08594	0.0005*	Accept H ₀
LCO ₂ → LGDP	13.47006	0.0012*	Accept H ₀
LPATENT → LENPR	6.668815	0.0356**	Accept H ₀

The stars **, and *represent 5%, and 1% levels of significance, respectively.

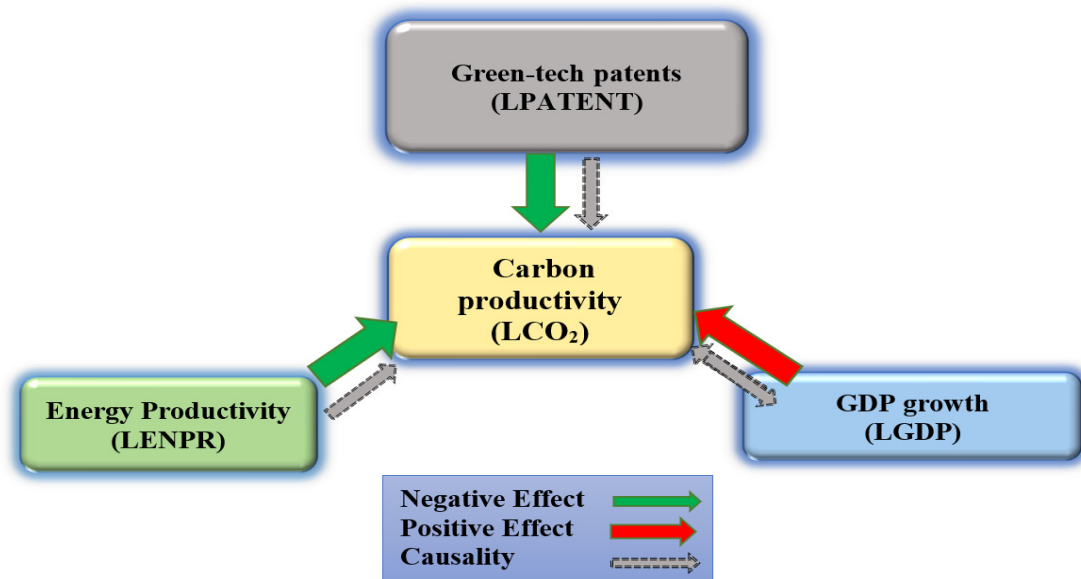


Figure 6: Illustrates the summary of the empirical outcomes.

technologies will culminate in energy productivity; supporting the reports of Sharif *et al.* (2020). Figure 6 illustrates the summary of the empirical outcomes.

CONCLUSION

This study assesses the impact of green-technology patents and energy productivity on carbon productivity in Australia using ARDL long-run and bound form estimators alongside the Toda-Yamamoto causality test. Results demonstrate a long-term association among the variables, showing that green-tech patents and energy productivity significantly enhance carbon productivity, while economic growth hinders it. Additionally, unidirectional causality flows from green-tech patents to green energy and carbon productivity, alongside a rebound effect between economic growth and carbon productivity.

To address these empirical findings, Australian authorities should allocate budgetary resources toward green technology and energy productivity. Key policy recommendations include offering technical support schemes for small and medium-sized enterprises, providing tax incentives or grants for high-performing corporations, and instituting national award programs for green-tech patent holders to balance economic growth with emissions goals.

Future research could address the study's limitations by testing cubic model specifications, evaluating comparative economies with similar economic and emissions profiles, and incorporating additional determinants such as energy consumption behaviors, regulatory quality, and environmental taxation.

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