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Impacts of wholesale electricity price under varying carbon price levels on carbon emissions and economic output in Australia

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ADB Working Paper Series

**IMPACTS OF WHOLESALE
ELECTRICITY PRICE UNDER
VARYING CARBON PRICE LEVELS
ON CARBON EMISSIONS AND
ECONOMIC OUTPUT IN AUSTRALIA**

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Abstract

Reducing global carbon emissions and mitigating the adverse impacts of climate change is a fundamental environmental challenge. Australia's target is to reduce carbon emissions by between 26% and 28% by 2030 compared to 2005 emission levels. Carbon pricing can be an effective market-based instrument for reducing carbon emissions. This paper examines the impact of varying carbon price levels on carbon emissions by incorporating the different carbon price levels in the electricity prices and eventually employing time series econometrics based on an autoregressive distributed lagged (ARDL) model. We use quarterly data spanning the period 2001 Q3 to 2019 Q1 and undertake varying scenario analysis. First, we design a scenario with a low and high carbon tax where we test and confirm the existence of a long-run equilibrium relationship among economic output, wholesale electricity price, and emissions under the high carbon tax scenario based on cointegration relationships. Our empirical results reveal that a stable wholesale electricity pricing with a carbon price and carbon emission nexus exists in the long run where a 1% hike in wholesale electricity price under a high carbon price scenario reduces carbon emissions by 0.57%. The vector error correction modeling-based Granger causality test suggests the presence of a bidirectional causality among electricity pricing, carbon prices, and carbon emissions in the long run. Therefore, Australia needs to implement a carbon emissions mitigation scheme that places a high tax rate on polluters such as fossil-based electricity generators to achieve reduced emissions and a sustainable economy.

Keywords: carbon emissions, carbon prices, Australia, VECM Granger causality

JEL Classification: Q54, P22, N57, C51

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1. INTRODUCTION

The Australian electricity sector is carbon-intensive and emissions from the electricity sector are one of the significant drivers of rising national emissions. For example, fossil fuels contributed 77% of total electricity generation in 2019, including coal (56%) and gas (21%). Therefore, decarbonization of the Australian electricity sector offers a natural pathway towards reducing carbon emissions in Australia and is a cornerstone of the Australian low-carbon economic transition (Garnaut 2019). More than 200 terawatt hours (twh) of electricity is traded through wholesale electricity generation via the Australian National Electricity Market (NEM), which consists of more than 9 million customers and a total electricity generating capacity of more than 50,000 megawatts (MW). However, until now, the impact of wholesale electricity pricing on emission reductions has received little detailed attention among researchers and policymakers in Australia. This study examines the impact of wholesale electricity prices with varying levels of carbon pricing on the reduction of carbon emissions in Australia while also incorporating the effect of economic output in a trivariate framework.

Australia introduced the Carbon Pricing Mechanism (CPM) from July 2012 to motivate the use of clean energy through a legislation package under the Clean Energy Act in 2011, and to meet the national longer-term target of reducing greenhouse gas (GHG) emissions to 80% below the 2000 levels by 2050. Carbon pricing is a crucial instrument for discouraging the largest carbon emitters and encouraging the adoption of, and investment in, sustainable and renewable energy sectors such as hydro, solar, wind, etc. (Quiggin, Adamson, and Quiggin 2014). Australia initiated the CPM from 1 July 2012 with a fixed price of AUD23/tCO₂e until 30 June 2013 and increased the carbon price to AUD24.15/tCO₂e from 1 July 2013 until 30 June 2014. The carbon price further increased to AUD25.40/tCO₂e from 1 July 2014 until 30 June 2015. The Emissions Trading Scheme (ETS) was also introduced in 2015, as a consequence of a new government being elected in July 2014, but it was ultimately shelved. How effective was the implementation of carbon pricing in reducing the carbon emissions from electricity generation in Australia?

This paper explores the impact of carbon prices in reducing carbon emissions by also incorporating the effect on economic output in Australia by focusing on the impacts of different levels of carbon taxes on carbon emissions. However, the limited experience with carbon pricing in Australia has also resulted in very few studies being available (Ding, Zhang, and Song 2019; Han et al. 2019; Lin and Jia 2019; Weibin et al. 2011; Diaz, Muñoz, and Moreno 2020). Australia does not have continuous historical time series data on carbon pricing either. The future of carbon pricing in itself is also unclear in Australia (Quiggin, Adamson, and Quiggin 2014). We therefore develop scenario modeling based on different carbon price scenarios, namely a low-price scenario, middle-price scenario, and high-carbon price scenario, and compare the emission reduction performance of these three different scenarios with the business-as-usual (BAU) scenario to address the future uncertainty around carbon pricing. The estimations are undertaken by applying the autoregressive distributed lagged model (ARDL) approach and further supported by alternative modeling specifications and techniques based on vector error correction modeling (VECM) for ensuring the robustness of results.

The carbon pricing literature also points to a scarcity of studies examining the impact of carbon pricing in reducing CO₂ emissions channeled through electricity prices while most of the existing studies are examined in a multivariable framework by incorporating economic growth, energy intensity, and other additional variables¹. Recent studies examining the impacts of carbon pricing on emission reduction include those by Diaz, Muñoz, and Moreno (2020) for Chile; Adetutu, Odusanya, and Weyman-Jones (2020) for the UK; Yuan et al. (2011) for the US; Wang et al. (2019) for the European Union; and Lin and Jia (2018), Ding, Zhang, and Song (2019), and Cao et al. (2019) for the People's Republic of China (PRC). The Australian evidence on the environmental impacts of carbon pricing, particularly focusing on emissions reduction, is also limited (Meng, Siriwardana, and McNeill 2013; Dwyer et al. 2013; Fahimnia et al. 2013; Bakhtiari 2018; Markham et al. 2018).

Yuan et al. (2011) reported that carbon and energy taxes are the most cost-effective instruments for reducing emissions and curbing total energy usage in order to maintain a range of energy and environmental quality. Diaz, Muñoz, and Moreno (2020) showed that carbon tax leads to more cuts in carbon emissions than normal pollution policies through imposing a tax on carbon-emitting power generators using an equilibrium model. Lin and Jia (2018) considered different taxes on carbon based on different industries to examine the effects of carbon tax on the economy and the environment using a computable general equilibrium (CGE) framework. The results showed that the carbon tax negatively impacts GDP, but a high tax scenario will not surpass 0.5%. The findings recommended that the PRC should adopt a carbon tax scheme and alongside impose a higher tax on energy-generating firms and businesses that are highly energy-intensive. Frey (2017) also applied a CGE model to examine the economic and environmental impacts of different carbon tax levels in Ukraine.

In the Australian context, a study by Meng, Siriwardana, and McNeill (2013) simulated the impact of different carbon tax scenarios on CO₂ emissions through a CGE model and also extending the social accounting matrix (SAM). The results showed that the carbon price is effective in reducing emissions but also brings about a small contraction in economic output. Likewise, Bakhtiari (2018) showed that the July 2012 to July 2014 implementation of the carbon pricing scheme in Australia accelerated the deployment of cleaner technology and thereby reduced emissions based on a data envelopment analysis. A report by the Australian Department of the Environment recorded that the Australian economy experienced a 2.9% decrease in carbon emissions after carbon tax implementation throughout the plan and an 8.9% decrease in the electricity emissions sector during the same period (NGGI 2017). A recent study by Han et al. (2019) investigated the wealth impacts brought about by the introduction of the Australian CPM, with findings showing that carbon-intensive businesses and industries suffer the most in terms of value destruction with these businesses losing a value of 6.97% compared to other firms' value losses of around 3.67%.

Most of the existing studies empirically examining the impact of carbon prices on carbon emissions are based on simulations where the quantitative analysis is based on CGE modeling as the main method (Timilsina 2018). Studies based on historical time series data to model the impacts of wholesale electricity pricing on emissions reductions are very limited in general and more so in the Australian context. Furthermore, the importance of carbon pricing as a useful market-based instrument for curbing emissions and mitigating adverse climate change impacts has been gaining renewed attention since the Paris Agreement on climate change. Therefore, our study

¹ We interchangeably use the terms "prices" and "taxes" throughout the paper when referring to carbon tax/price.

is also timely in terms of providing policy inputs to energy and climate policymakers on the enabling role of carbon pricing on emissions pricing through the realms of the carbon-intensive electricity sector such as in Australia.

The major findings of this paper include: (1) CO₂ emissions, carbon prices, and economic output are cointegrated, implying the presence of a long-run equilibrium relationship among the variables; (2) both carbon prices and economic output coefficients are significant with respect to CO₂ emissions; (3) a high carbon price plays a crucial role in mitigating carbon emissions. However, economic output is positively linked with CO₂ emissions. We also found a bidirectional (or feedback) relationship between CO₂ emissions and economic output while there is long-run Granger causality running from carbon prices to economic output and CO₂ emissions. The results from the impulse response functions (IRFs) showed that one standard deviation shock to carbon tax results in a gradual reduction of carbon emissions while economic output also starts to decline after a certain period. We also conducted a robustness check by applying an autoregressive distributed lagged model (ARDL) and vector error correction model (VECM). These empirical results from the robustness checks support our major results.

The rest of the paper is constructed as follows. Section 2 briefly discusses the wholesale electricity price formation in the Australian National Electricity Market (NEM). Section 3 outlines the model, the econometrics methods developed, and the data used in this study. The empirical findings for all of the estimation methods and the Granger causality tests are described in Section 4. Section 5 offers relevant policy recommendations and concludes the paper.

2. PRICE FORMATION IN THE NATIONAL ELECTRICITY MARKET (NEM) IN AUSTRALIA

The NEM is a wholesale electricity market that began operation in Australia in 1998 and comprises the physically interconnected states of South Australia, New South Wales, Queensland, Victoria, and the Australian Capital Territory. Tasmania joined the NEM in 2005, with a direct physical interconnection being operational from 2006. Therefore, the NEM globally is among the largest interconnected power markets, with transmission network lengths spanning a distance of around 5,000 km running from Port Lincoln in South Australia to Port Douglas in Queensland while being connected to Tasmania through the Bass Strait (Australian Energy Market Operator 2020). The NEM reform is an energy-only gross pool design with a real-time spot market for coordinated scheduling and dispatch and a forward derivatives market that addresses concerns around resource adequacy and new capacity. The price volatility risk for future electricity sales is managed by retailers and generators, who often enter into hedging contracts.

The Australian Energy Market Operator (AEMO) centrally coordinates the process of dispatching wholesale electricity while bearing in mind that the demand for electricity needs to be instantaneously matched with supply in real time as electricity storage is not possible. Therefore, the AEMO runs a spot wholesale exchange for electricity across the five physically interconnected regions where generators offer supply bids to the market with set amounts of electricity at set prices for set time periods (currently every five minutes), and with the possibility of resubmitting the offered amounts at any point in time. The AEMO then decides on the electricity generators to be deployed following a least-cost dispatch process where the cheapest generation will be put into operation first to meet demand. Meeting the electricity demand based on a least-cost

dispatch (or the most cost-efficient way) has served the NEM well in the past (Nepal and Foster 2016; Do, Nepal, and Smyth 2020) while the wholesale market has been an epitome of the microeconomic reform in Australia for most of the past two decades by virtually any metric (Simshauser 2019).

More than 100 electricity generators and retailers participate in the NEM where wholesale electricity is sold to large customers and retailers, and eventually gets sold to all consumers. Wholesale electricity prices in the NEM fluctuate at any point in time as per changing demand and supply conditions, implying that the wholesale price of electricity is based on generator offers to supply electricity to the market at specified volumes and prices at set times and the electricity demand at any given time. The National Electricity Rules have set a limit on the maximum spot price (also known as the “market price cap”) of \$14,200 per megawatt hour (MWh) and a minimum spot price in the form of a market price floor of -\$1,000 per MWh to achieve the NEM’s reliability standards.

3. EMPIRICAL MODEL, DATA, AND METHODOLOGY

Our aim is to examine the short- and long-run relationships between wholesale electricity prices and varying levels of carbon prices, carbon emissions, and economic output. The debate around carbon pricing has shifted from academic discussion to one of practical importance over the last 30 years with a general consensus around its effectiveness in reducing emissions (Meinshausen et al. 2009; Bureau 2011; Edenhofer and Kalkuhl 2011; Liang and Wei 2012). Thus, carbon pricing can affect the extent to which carbon emissions decrease desirably without reducing economic output, which needs to be examined in the Australian context.

3.1 Model

Previous studies have noted that carbon pricing is a key market-based instrument in reducing emissions (Fang et al. 2012, 2013; Tian and Jin 2012;). Therefore, the relationship between economic output with carbon price constraints and CO₂ emissions is expressed as below:

$$CO_{2t} = \beta_0 + \beta_1 \text{ wholesale electricity price (with varying levels of carbon prices)}_t + \beta_2 \text{ economic output}_t + \varepsilon_t \quad (1)$$

All the variables in Eq. (1) can be transformed into a natural logarithmic linear form and ε_t is the disturbance term. CO_{2t} represents carbon emissions at time t, wholesale electricity price is adjusted to include carbon prices under the three different scenarios as previously discussed, and GDP is used to capture the underlying economic output. The long-run elasticity parameters of emissions are respectively β_1 and β_2 with respect to wholesale electricity price with carbon prices and economic output.

3.2 Data

This study has collated and retrieved data on carbon emissions from the Department of the Environment and Energy of the Australian Government and wholesale electricity price data from the Australian Energy Market Operator (AEMO), and real GDP data are sourced from the Australian Bureau of Statistics (ABS). The data span from the third quarter (Q3) of 2001 to up to the first quarter (Q1) of 2019. The carbon emissions

(million tonnes CO₂ equivalent), wholesale electricity price (in AUD\$ per megawatt hour), and real GDP (in billion AUD) data variables are seasonally adjusted.

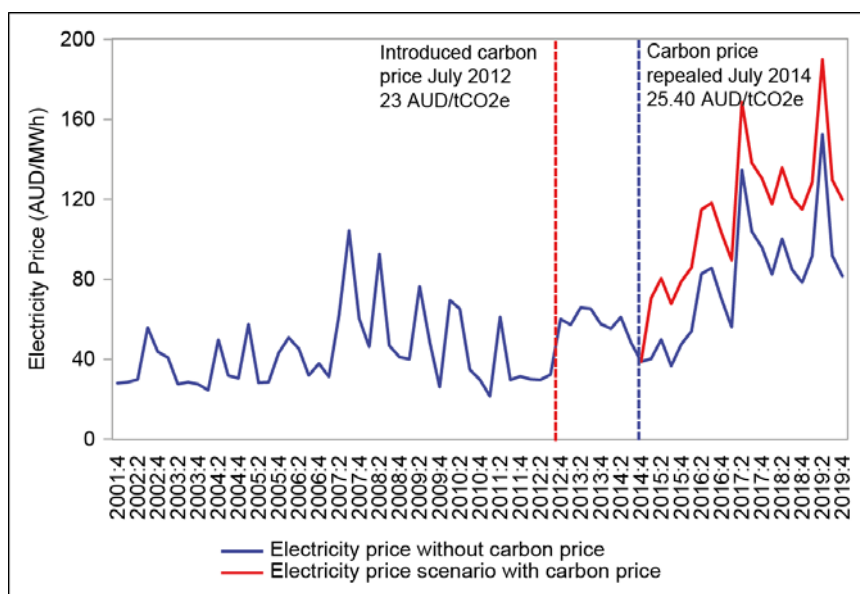
3.2.1 Scenario Design

We developed three scenarios to gauge the effect of carbon prices on emissions reductions: AUD23/t CO₂e (low carbon tax rate), AUD60/t CO₂e (medium carbon tax rate), and AUD80/t CO₂e (high carbon tax rate) (in 2012 dollars), respectively. We raised the tax rate by 5% each year, reflecting a rational range in many countries and regions of the world, and provided market-based policy instrument schemes (Chapple, Clarkson, and Gold 2013; Sarkis and Tamarkin 2005; Fahimnia et al. 2013). Table 1 shows the different carbon tax levels. Our BAU scenario does not include a carbon tax for the entire time span apart from its implementation between 2012 and 2014 in Australia. ELECP1², ELECP2, and ELECP3 scenarios assume that the government imposes a carbon tax of AUD23, AUD60, and AUD80 per ton of emissions, respectively. We convert the unit of tCO₂e to MWh³ to simplify our analysis. Figure 1 below shows that the wholesale electricity price was not changed drastically even after the Australian government introduced carbon prices (AUD23/tCO₂e) between 2012 and 2014.

Table 1: Scenario Design of Carbon Pricing

Scenarios	Carbon Prices (AUD/tCO ₂ e)
BAU	–
ELECP1	23
ELECP2	60
ELECP3	80

Figure 1: Electricity Price (AUD/MWh)



² ELECP refers to electricity price with carbon prices under varying carbon price scenarios (ELECP1, ELECP2, and ELECP3).

³ We convert the unit from tCO₂e to MWh according to the guidelines of the Department of the Environment and Energy produced by the Australian government.

3.3 Econometric Methodology

3.3.1 ARDL (Autoregressive Distributed Lag) Model

We employed the ARDL model advocated by Pesaran and Smith (1998) and Pesaran, Shin, and Smith (2001) to explore the dynamics and existence of long- and short-run relationships between carbon emissions, electricity prices with carbon prices, and economic output. ARDL estimations have many econometric benefits over other time series econometric frameworks. Most notably, Pesaran and Shin (1999) show that ARDL estimation handles a mixed order of integration of time series data variables whether the series integrated is of the order zero (I(0)) or 1 (I(1)). Moreover, the ARDL method, by following a simple linear transformation, enables the generation of a dynamic and unrestricted error correction model incorporating short-run dynamics with long-run equilibrium while not losing any long-run information. The ARDL representation for Eq. (1) is formally expressed in the following terms:

$$\begin{aligned}
 \Delta CO_{2t} = & \beta_0 + \beta_1 CO_{2t} + \beta_2 \text{electricity price with carbon prices}_{t-1} \\
 & + \beta_3 \text{economic output}_{t-1} + \sum_{i=1}^p \gamma_i \Delta CO_{2t-1} \\
 & + \sum_{j=0}^p \gamma_j \Delta \text{electricity price with carbon prices}_{t-j} \\
 & + \sum_{k=0}^p \gamma_k \Delta \text{economic output}_{t-k} + \varepsilon_t
 \end{aligned} \tag{2}$$

where the symbol Δ is the first-difference operator and refers to the dynamics of error correction dynamics, the terms with β_i are the parameters of the long-run relationships, and ε_t is iid (independent and identically distributed) error terms. The choice of the optimal lag length structure is based on the Akaike information criteria (AIC). We first estimated the F-test in the ARDL model based on Pesaran, Shin, and Smith (2001) and conducted an F-test of joint significance on the coefficient of the lagged variables. The specifications of the null hypothesis (H_0) of no cointegration and the alternative hypothesis (H_a) of cointegration among the variables are as follows: $H_0: \beta_1 = \beta_2 = \beta_3 = 0$ and $H_a: \beta_1 \neq \beta_2 \neq \beta_3 \neq 0$. The rejection of the null hypothesis of no cointegration is based on the calculated F-test statistics surpassing the upper critical bound and thereby suggesting a long-run relationship among the variables (Pesaran, Shin, and Smith 2001). The findings of long-run relationships are inconclusive when the F-statistic falls between the lower critical and upper bounds. We cannot reject the null hypothesis when the F-statistic is below the lower bound. We also performed different diagnostic tests to confirm the robustness of ARDL estimations: serial correlation, Gaussian error term normality tests, functional form (RESET), heteroskedasticity tests, and autoregressive conditional heteroskedasticity (ARCH) tests.

An error correction model (ECM) was also estimated to enable exploration of short-run dynamics and long-run adjustment based on the specification below:

$$\begin{aligned} \Delta CO_{2t} = & \beta_0 + \sum_{i=1}^p \beta_1 \Delta CO_{2t-i} \\ & + \sum_{i=1}^p \beta_2 \Delta \text{electricity price with carbon prices}_{t-i} \\ & + \sum_{i=1}^p \beta_3 \Delta \text{economic output}_{t-i} + \tau ECT_{t-1} + \epsilon_t \end{aligned} \tag{3}$$

The ECM model enables CO₂ emissions to converge towards their long-run equilibrium after experiencing a shock in the short run. The error correction term ECT_{t-1} captures the speed of adjustment in the short run towards the long-run equilibrium steady state. The cumulative sum of recursive (CUSUM) and the cumulative sum of recursive residual square (CUSUMSQ) tests are employed to check the stability of the coefficients.

The Johansen and Juselius (1990) cointegration technique is conducted to test for the long-run equilibrium relationships among emissions, carbon prices, and economic output in Australia. The Johansen cointegration test is based on the significance of the λ_{max} and λ_{trace} statistics. We can proceed sequentially from $r = 0$ to $r = k - 1$ until we fail to reject in determining the different number of cointegrating vectors (r). The maximum eigenvalue test is computed as follows:

$$\lambda_{max} = -T \log (1 - \lambda_{r+1}^*) \tag{4}$$

where $\lambda_i^*, r = 1, 2, \dots, k - 1$ indicates the estimated eigenvalues. The null hypothesis of r cointegrating relations is tested against the alternative hypothesis of $(r + 1)$ cointegrating relations.

The trace statistics under the null hypothesis of r cointegrating vectors that is tested against the alternative hypothesis k is estimated as follows:

$$\lambda_{trace} = -T \sum_{i=r+1}^k \log (1 - \lambda_i^*) \tag{5}$$

The cointegration test of the null hypothesis by Johansen and Juselius (1990) suggests that there is no long-run cointegration among the variables.

3.3.2 Granger Causality Test

The Granger causality must be at least in one direction if the variables form a long-run equilibrium relationship (i.e., cointegrated) (Granger 1988). The confirming of a cointegration relationship, therefore, merits the application of the Granger causality test based on the vector error correction modeling (VECM) framework as specified by Eq. (6) below in determining the direction of the causality among the variables:

$$\begin{aligned} \begin{matrix} \epsilon \\ \epsilon \\ \epsilon \\ \epsilon \\ \epsilon \end{matrix} \begin{matrix} \Delta CO_{2t-1} \\ \Delta Output_{t-1} \\ \Delta ELECP_{t-1} \end{matrix} &= j_0 + j_1 \begin{matrix} \epsilon \\ \epsilon \\ \epsilon \\ \epsilon \\ \epsilon \end{matrix} \begin{matrix} \Delta CO_{2t-1} \\ \Delta Output_{t-1} \\ \Delta ELECP_{t-1} \end{matrix} + \dots + j_k \begin{matrix} \epsilon \\ \epsilon \\ \epsilon \\ \epsilon \\ \epsilon \end{matrix} \begin{matrix} \Delta CO_{2t-k} \\ \Delta Output_{t-k} \\ \Delta ELECP_{t-k} \end{matrix} + f [ECT_{t-1}] + \begin{matrix} \epsilon_{1t} \\ \epsilon_{2t} \\ \epsilon_{3t} \end{matrix} \end{aligned} \tag{6}$$

where f is a 3×3 matrix containing the parameters of the explanatory variables (i.e., ΔCO_{2t} , ΔOutput_t , and ΔELECP_t). j is also a parameter matrix containing the lagged error correction term ECT_{t-1} , obtained from the long-run estimation, while h_{it} are white noise terms. The existence of short-run causality relationships is conditional on $f_k^{-1} 0_k$, from Eq. (7), while $j^{-1} 0$ implies the presence of long-run causality relationships. The determination of the direction of the short-run causality relationships is based on assessing the c^2 test statistic of the first difference of the lagged independent variable. We also obtain the t-test statistic on the coefficient of lagged error correction for one period to determine the long-run Granger causality relationships.

4. RESULTS AND DISCUSSION OF RESULTS FROM THE EMPIRICAL ANALYSIS

4.1 Testing of Unit Root and Results

We first undertake the unit root testing in our data variables consisting of carbon emissions, electricity prices with varying levels of carbon price, and economic output. We use three unit root tests for this purpose, namely the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) null stationary test, the augmented Dickey-Fuller (ADF) unit root test, and the Phillips-Perron (PP) test. We compare the unit root testing results of ADF and KPSS tests to ensure greater accuracy of results (Henricsson and Lundback 1995). The tests are performed to ensure that variables do not exceed the integration order of $I(1)$ and thereby justify the suitability of the ARDL method.

The results from the unit root tests conducted at the levels and first difference of the variables are reported in Table 2. ADF and PP test results for all variables at their levels confirm the nonrejection of the null hypothesis of a unit root presence. However, all variables, namely carbon emissions, electricity price with carbon prices, and economic output, are found to be stationary at their first-difference level. Therefore, the test results from both the ADF and PP confirm the presence of a unit root. Similarly, the findings of the KPSS unit root testing also reveal that the variables are integrated of the order 1 ($I(1)$). Thus, as our data variables have mixed orders of integration based on Table 2, the application of the ARDL estimations is as follows.

Table 2: Unit Root Test Results

Variable	ADF	PP	KPSS
$\ln\text{CO}_{2t}$	-1.202(1)	-1.500	0.377*
$\Delta\ln\text{CO}_{2t}$	-10.900***(0)	-10.856***	0.283
Output_t	-2.063(0)	-2.097	1.119***
ΔOutput_t	-8.165***(0)	-8.192***	0.329
BAU_t	-1.046(2)	-2.461	0.897***
ΔBAU_t	-9.967***(1)	-19.093***	0.273
ELECP1_t	-0.678(2)	-1.865	0.961***
ΔELECP1_t	-10.058***(1)	-18.690***	0.256
ELECP2_t	-0.357(2)	-1.000	1.002***
ΔELECP2_t	-10.122***(1)	-17.669***	0.253
ELECP3_t	-0.423(2)	-0.949	1.037***
ΔELECP3_t	-10.160***(1)	-19.093***	0.251

*** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

However, structural breaks due to policy, political, regulatory, and economic changes over time can impact the time series properties. Unit root testing must account for such structural breaks and the application of the unit root testing in the presence of structural breaks developed by Zivot and Andrews (1992) is justifiable for this purpose. The findings obtained from the Zivot-Andrews (Z&A hereafter) unit root test are reported in Table 3. All the variables are nonstationary at levels after allowing for both trend and intercept in the data variables while they are stationary at their first differences. Table 3 reports on the timing of the structural breaks. For example, significant structural breaks in carbon emissions and economic output occurred in 2014 and 2008, respectively. The structural break in 2008 in economic output can be attributed to the slowdown of the world economy and the global financial crisis (GFC), while the structural break in 2014 can be attributed to the Australian government's repeal of the carbon price.

Table 3: Results of Zivot-Andrews (1992) Test

Variable	Level Variables			1st Difference Variables		
	T-statistic	Timing	Outcome	T-statistic	Timing	Outcome
CO _{2t}	-3.032	6/1/2010	Unit Root	-12.204***	3/1/2014	Stationary
Output _t	-4.061	12/1/2008	Unit Root	-6.421***	6/1/2008	Stationary
BAU _t	-4.632	6/1/2010	Unit Root	-8.196***	6/1/2008	Stationary
ELECP1 _t	-4.603	6/1/2010	Unit Root	-8.243***	6/1/2008	Stationary
ELECP2 _t	-4.573	6/1/2010	Unit Root	-8.275***	6/1/2008	Stationary
ELECP3 _t	-4.569	6/1/2010	Unit Root	-8.282***	6/1/2008	Stationary

*** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

4.2 Cointegration Test

The optimum lag length is chosen to be 6 based on the Akaike information criteria after estimating the vector autoregression (VAR) model. The critical bounds used are based on Pesaran, Shin, and Smith (2001). The examination of the cointegration relationship is based on the Wald test of the computed F-statistics. The null hypothesis of no cointegration ($\beta_1 = \beta_2 = \beta_3 = 0$) is tested and compared against the results of the alternative hypothesis of cointegration in our model. Table 4 reports the results and shows that the computed F-statistics are 2.66, 4.175, 5.777, and 8.69, respectively. The computed F-statistics exceed the upper critical bound at the 10%, 5%, and 1% level of significance except for the BAU scenario when carbon emissions is modeled as a dependent variable. The rejection of the null hypothesis leads us to conclude that there exists a long-run equilibrium relationship among the variables.

The results of the ARDL cointegration tests are further compared with the long-run equilibrium results of the Johansen and Juselius (1990) cointegration test (here we dealt with the ELECP3 scenario only). The results from Table 5 show that there is one cointegrating vector as the null hypothesis of no cointegration at the 5% level can be rejected based on the critical values of the trace statistics and maximum eigenvalue statistics. Thus, the results affirm the presence of a long-run equilibrium relationship between carbon price, carbon emissions, and economic output in Australia. The results from the ARDL tests are not different to the results obtained from the Johansen and Juselius (1990) cointegration test, thereby also asserting the robustness of the results.

Table 4: ARDL Bounds Testing

Estimation Model	Lag Length	F-statistic	Decision
F(CO ₂ output, BAU)	(2, 0, 0)	2.665	No cointegration
F(CO ₂ output, ELECP1)	(4, 6, 0)	4.176*	Cointegration
F(CO ₂ output, ELECP2)	(2, 6, 0)	5.777**	Cointegration
F(CO ₂ output, ELECP3)	(5, 6, 0)	8.688***	Cointegration
Pesaran, Shin, and Smith (2001) critical values		I(0)	I(1)
1% (significance level)	5.15	6.36	
5% (significance level)	3.79	4.85	
10% (significance level)	3.17	4.14	

*** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

Table 5: Cointegration Results from Johansen and Juselius (1990) Test

Hypothesized No. of CE(s)	Trace Statistic	5% Critical Value	Max-Eigenvalue Statistic	5% Critical Value
None*	33.284*	29.797	22.305*	21.132
At most 1	13.344	15.495	9.249	14.265
At most 2	0.251	3.841	0.230	3.841

Note: The * indicates the number of vectors cointegrating at a significant level of 5%.

4.3 ARDL Estimates: Long-run and Short-run

Further estimation involves obtaining long-run and short-run estimates of carbon emission from the electricity price with carbon prices and economic output. The long-run dynamics from the ARDL model with different carbon pricing scenarios are reported in Table 6. The results indicate that the carbon prices in BAU, ELECP1, and ELECP2 scenarios are not statistically significantly associated with carbon emissions. However, in the ELECP3 scenario, the statistical significance of coefficients is indicated by the related p-value, in which elasticities of both independent variables (electricity price with carbon price and economic output) are significant at 1 and 5 % significance levels, respectively. Interestingly, carbon prices are found to be an effective instrument for reducing carbon emissions as a 1% increase in electricity price with carbon price reduces carbon emission by 0.58%, all other things remaining equal. Earlier findings in the Australian context also documented that carbon prices drive emissions reduction (Lin and Jia 2018; Zhou et al. 2011; Yuan et al. 2011; Meng 2012; Meng, Siriwardana, and McNeill 2013; Dwyer et al. 2013; Cao et al. 2019; Diaz, Muñoz, and Moreno 2020). This negative nexus (emissions-electricity price with carbon prices) implies that pricing carbon correctly drives innovation, energy-efficient technology, and the development of renewable generation. However, economic output is positively influenced by carbon emissions. The results obtained from our empirical exercise imply that carbon emissions increase by 0.95% with a 1% increase in economic output.

Table 6: ARDL Long-run Estimation Results

Variable	Scenario			
	BAU	ELECP1	ELECP2	ELECP3
Electricity price with carbon price	-0.638 (-1.334)	0.103 (1.629)	-0.809 (-1.416)	-0.578*** (-3.562)
Economic output	0.937 (1.378)	0.065 (0.449)	0.082* (1.745)	0.948** (2.995)
Constant	0.204 (0.067)	4.265*** (6.298)	0.225 (0.090)	0.010 (0.007)

*** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

Table 7: Results from Short-run Estimation

Dependent Variable	Lag Order					
	0	1	2	3	4	5
<i>Panel I: carbon price (BAU)</i>						
ΔCO_2		-0.247** (-2.043)				
ΔBAU		-0.026 (-0.542)				
ΔGDP	0.010 (0.088)					
ECT_{t-1}	-0.135* (-1.816)					
<i>Panel II: carbon price (CP1)</i>						
ΔCO_2		-0.356** (-2.316)	-0.142 (-0.940)	-0.094 (-0.639)	-0.349** (-2.587)	
ΔELECP1	-1.861 (-0.584)	-1.936 (-0.327)	9.978 (1.458)	-12.752** (-2.101)	1.051 (0.162)	4.095 (1.292)
ΔGDP	0.141 (0.983)					
ECT	-0.108 (0.380)					
<i>Panel III: carbon price (CP2)</i>						
ΔCO_2		-0.198 (-1.548)				
ΔELECP2	-3.118 (-1.048)	-5.436 (-0.939)	4.686 (0.712)	-4.945 (-0.772)	6.331 (0.925)	-0.172 (-0.029)
ΔGDP	-0.691 (-1.085)					
ECT	-0.401*** (-3.627)					
<i>Panel IV: carbon price (CP3)</i>						
ΔCO_2		0.249 (1.487)	0.372** (2.479)	0.496*** (3.342)	0.215 (1.460)	0.488*** (3.283)
ΔELECP3	-0.286 (-0.064)	8.279 (0.819)	-2.760 (-0.285)	-1.391 (-0.147)	8.347 (0.944)	-8.735** (-1.931)
ΔGDP	-0.063 (-0.106)					
ECT	-0.789*** (-4.588)					

*** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

We also estimate the short-run effect on CO₂ emissions of the corresponding variables along with an error correction term (ECT) as specified under Eq. (3). Table 7 provides short-run estimate results. We find that electricity price with carbon prices and economic output do not generate statistically significant effect on CO₂ emissions across all panels (i.e., Panel I, Panel II, and Panel III as reported below) except Panel IV. The wholesale electricity price under a high carbon price generates significantly negative effect on CO₂ emissions. A 1% increase in the wholesale electricity price with high carbon price in the short run is associated with a carbon emissions reduction of 8.74% in Australia. Conversely, the economic output coefficient is negative but no longer statistically significant, indicating no significant impact on emissions. The negative and statistically significant coefficient estimate at the 1% level of significance documents the presence of a long-run equilibrium relationship among the variables taking into account the statistical properties of the lagged error correction term (ECT_{t-1}). Furthermore, the ECT_{t-1} coefficient suggests that short-run deviations from the long-run equilibrium are corrected by about 0.79% in the following quarter, suggesting an oscillating adjustment towards the long-run equilibrium relationship. CO₂ emissions are not influenced by changes in economic output in the short run but the carbon price is a key instrument of emissions reduction.

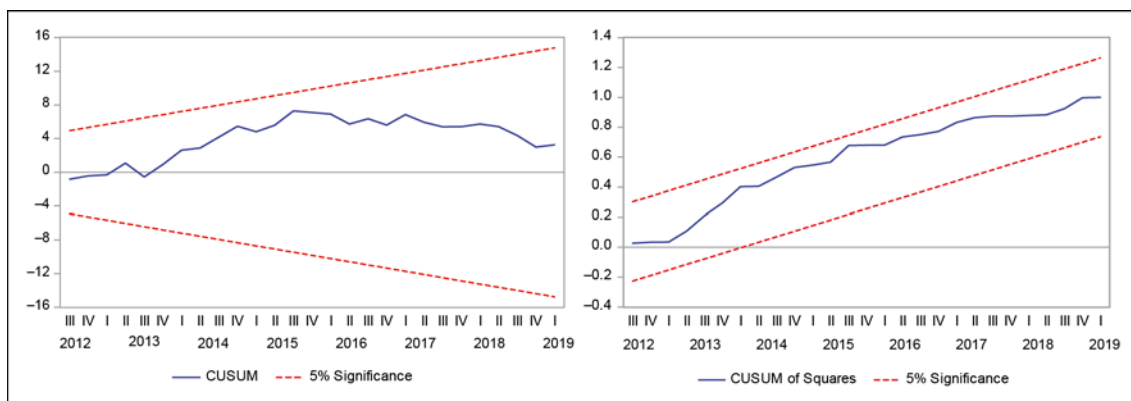
4.4 Model Diagnostic Test Results

We show in this subsection that the ARDL estimated model has survived different diagnostic tests and hence supports the model validity. The goodness of fit of the model specification, ($R^2 = 0.90$) and ($adjR^2 = 0.87$), is near to one, which indicates that the model is favored in econometrics analysis. Table 8 shows the results of several diagnostic tests (we only reported the ELECP3 scenario). The null hypothesis of no serial correlation cannot be rejected at the 5% significance level against the alternative hypothesis of serial correlation as the corresponding p-value is far greater than 0.05. Similarly, the Gaussian residuals assume a normally distributed error term, no functional error, and no autoregressive conditional heteroskedasticity (ARCH). Table 8 correctly specifies all diagnostic tests. Furthermore, we also conduct a model stability test based on cumulative sum (CUSUM) and cumulative sum of square (CUSUMQ) tests as another measure of goodness of fit. The results indicate that the estimated parameters of the model are stable as confirmed by the positioning of the residuals inside the critical bounds at the 5% level of significance.

Table 8: ARDL Model Diagnostic Test Results

	Test Statistics	P-value		Test Statistics	P-value
R-squared		0.904	Adj. R squared		0.867
Serial correlation $\chi^2(1)$	6.04E-06	0.998	Normality		0.114
RESET $\chi^2(1)$	0.013	0.990	Heteroskedasticity $\chi^2(1)$	10.75813	0.869
ARCH $\chi^2(1)$	0.310	0.578	ARCH $\chi^2(2)$	1.357	0.507

Figure 2: Plot of Recursive CUSUM and CUSUMQ



4.5 Results from Granger Causality Test

The presence of cointegration simply confirms the underlying causality among variables and does not specify the direction of actual causal relationships. Engle and Granger (1987) document that the existence of the long-run equilibrium relationship must be held in at least one direction of causality. Therefore, the Granger causality tests are conducted in the VECM to ascertain the direction of causation. Evidence of a long-run equilibrium association among electricity price with carbon price, CO₂ emissions, and economic output provides a clear basis for policymakers to regulate appropriate CO₂ emissions policy, electricity price with carbon prices, and economic output strategies by considering the direction of causation between the variables. The appeal of the VECM-based Granger causality test lies in its endogeneity assumption of variables, which allows a distinction to be made between long-run and short-run causation.

Table 8 reports the results from the VECM Granger causality tests (only considering ELECP3). There are short-run unidirectional Granger causality relationships between CO₂ emissions and electricity price with high carbon price, and electricity price with high carbon price and economic output at the 5% significance level. This implies the following results: (a) a Granger causality relationship spanning from electricity price with high carbon price to CO₂ emissions; (b) a Granger causality relationship running from electricity price with high carbon price to economic output. However, there is no short-run causality relationship between economic output and CO₂ emissions, as was also reported in an earlier study by Salahuddin and Khan (2013) in the case of Australia. The empirical findings are robust to these two alternative estimation techniques.

In the long run, we find that the coefficient of the lagged error correction term (ECT_{t-1}) is negative and statistically significant at the 5% significance level in CO₂ emissions and economic output equations. Thus, there is a bidirectional causality relationship in the long run between economic output and CO₂ emissions with feedback effect. This result corresponds to findings from a previous study by Balaguer and Cantavella (2018) in Australia. Furthermore, the electricity price with high carbon price equation also shows a negative and statistically significant coefficient at the 10% significance level. There is also a bidirectional causality relationship between CO₂ emissions and electricity with high carbon price. The negative significant coefficient of ECT_{t-1} suggests that a long-run equilibrium relationship is achievable as the variables are stable and do not overshoot.

Several conclusions can be drawn from these findings. Both electricity price with high carbon price and economic output are key drivers of CO₂ emissions reduction in Australia. Therefore, any change in one or both of these variables generates an impact on the level of emissions in Australia. Second, electricity price with carbon price is a crucial policy instrument tool that will affect both economic output and emissions in the short and long run. Third, our findings reveal that a feedback relationship effect exists between economic output and emissions, implying that emissions can be reduced by reducing economic output.

Table 9: Results from VECM Granger Causality Test

Dependent Variable	Causality (Short-run)			Causality (Long-run)
	ΔCO_2	ΔGDP	ΔELECP3	ECT
ΔCO_2		1.418 (0.701)	10.423** (0.015)	-0.325** [-2.652]
ΔGDP	2.334 (0.506)		8.071** (0.045)	-0.095** [-2.506]
ΔELECP3	0.789 (0.852)	0.907 (0.824)		-0.005* [-1.946]

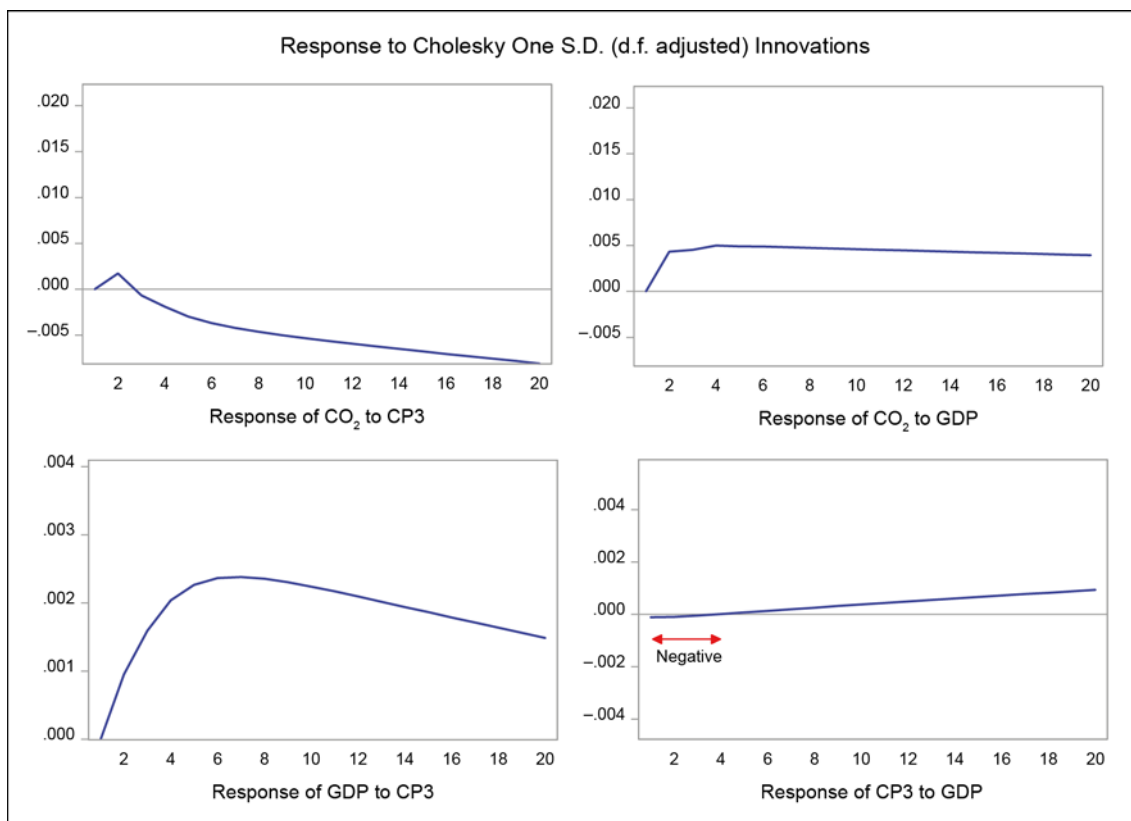
*** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

4.6 Impulse Response Function (IRF) and Variance Decomposition Model (VDM)

The impulse response function (IRF) tests are based on the Cholesky degree of freedom and are calibrated for 20 periods. The IRF analyzes the effect of a random “shock” in the variable itself and in other endogenous variables. The IRF indicates how a random shock in the standard deviation affects the underlying and anticipated values of the endogenous variables. Figure 3 plots the results of the IRF.

Figure 3a reveals that the response of carbon emissions is positive for a very short period but is negative and gradually decreases after the third time horizon after a 1 standard deviation shock from electricity price with high carbon price. This means that an increase in electricity price with a high carbon price gradually reduces emissions. Such a gradual reduction is possibly due to a switch to more renewable electricity generation from nonrenewable electricity generation. Similarly, Figure 3b reveals how a 1 standard deviation shock in economic output affects emissions. Figure 3c shows that the response of economic output is positive but with a sharply declining trend due to electricity price with high carbon price being exposed to a 1 standard deviation shock. This implies that the rise in electricity price due to a high carbon price appears to have impacted energy producers, which would directly affect the manufacturing sector and decrease economic output. Likewise, Figure 3d shows that a 1 standard deviation shock on electricity price gradually increases economic output.

Figure 3: The Impulse Response Function



Note: These graphs consider the response of ELECP3 to CO₂, the response of ELECP3 to GDP, the response of GDP to CO₂, and the response of GDP to ELECP3, but other responses are excluded from the analysis.

We also applied the generalized forecast error variance decomposition method based on VECM specifications to test the magnitude of causal relationships between electricity price under a high carbon price, CO₂ emissions, and economic output in the Australian context. Testing decomposition of the variance not only decomposes the portions of a shift in a variable stemming from own and other variables but also provides information about the degree of causation between the variables (Enders 1995).

Table 10 reports the results from the variance decomposition approach. The results suggest that 54.47% of CO₂ emissions are explained by their innovation shocks, while innovation shocks of electricity price with carbon price and economic output respectively contribute to emissions by 14.29 and 31.24 %. The variance decomposition of economic output suggests that the innovative shocks originating in CO₂ emissions contribute to national economic output by 26%. The contribution of electricity price under a high carbon price to GDP is 16.02% and the remaining is attributed to innovation shocks in GDP.

Overall, our findings show that there is a feedback relationship effect between emissions and economic output in the long run in Australia. There is a unidirectional short-run causality relationship running from electricity price under a high carbon price to emissions and economic output. Overall, our results correspond well to the findings obtained from impulse response function plots.

Table 10: Variance Decomposition Method (VDM)

Period	Variance Decomposition of CO ₂ :			Variance Decomposition of GDP:		
	CO ₂	GDP	CP3	CO ₂	GDP	CP3
1	100.000	0.000	0.000	0.433	99.567	0.000
5	88.611	8.946	2.443	11.382	68.352	20.267
10	67.298	12.941	19.761	16.270	60.444	23.286
15	59.180	14.064	26.756	21.716	58.280	20.004
16	58.035	14.157	27.808	22.767	58.035	19.198
17	57.002	14.219	28.779	23.801	57.813	18.386
18	56.069	14.260	29.672	24.816	57.603	17.581
19	55.228	14.283	30.489	25.813	57.398	16.790
20	54.469	14.291	31.240	26.788	57.191	16.021

Note: Cholesky Ordering: CO₂, GDP.

Standard error: Monte Carlo (EC) method is chosen using 100 repetitions.

5. CONCLUSIONS AND POLICY IMPLICATIONS

This paper, to the best of our knowledge, is possibly the first of its kind in the literature to carry out empirical research on carbon emissions, electricity price incorporating the effects of varying levels of carbon prices, and economic output. We examine the long-run and short-run dynamic relationships between the three variables of electricity price under varying carbon price levels, economic output, and CO₂ emissions based on ARDL and VECM modeling. We assume that different levels of carbon prices in exploring the appropriate carbon price scenario would be effective in reducing carbon emissions and guiding Australian climate policymakers.

Carbon tax is a strategic instrument that plays a pivotal role in curbing carbon emissions and enhancing air quality. However, energy consumption in Australia mostly relies on more than 60% use of nonrenewable energy resources such as coal, lignite, and petroleum products. Fossil fuel electricity generation is one of the major contributors to greenhouse gas emissions and is thus driving climate change in Australia and other global economic regions such as Asia. Australia is one of the world's largest emitters of greenhouse gases (among the top 20 polluters) and therefore merits this study on investigating the impact of carbon prices on carbon emissions and economic output.

Our empirical findings reveal that the variables are cointegrated and thereby implicate the existence of a long-run equilibrium relationship among the different variables. Our findings show that Australia would have achieved a significant carbon reduction in line with the Paris commitments had it priced carbon appropriately since 2001. The European economies, for instance, initiated carbon pricing in the 1990s and they seem quite successful in achieving emissions goals targeted by the UNFCCC by 2030. However, Australia initiated carbon prices in 2012 with lower carbon prices than the EU region. Our BAU scenario incorporated carbon prices after the period 2012–2014, but that did not bring about a significant reduction in carbon emissions. We show that the Australian government would have succeeded in achieving sustainable emissions reduction with high carbon price if correct carbon prices had been implemented from 2001 onwards as per our data and analysis.

This paper recommends that Australia should implement an emissions mitigation scheme that places a high tax rate on carbon emissions from fossil-based electricity generators. This will increase cuts in pollution and impact Australia's economic output only marginally. The government can also allocate a share of the revenue collected from taxing carbon towards encouraging the development of renewable energy sources.

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