



# Assessing the Effects of Solar and Wind Prices on the Australia Electricity Spot and Options Markets using a Vector Autoregression Analysis

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## ABSTRACT

This paper examines the impact of solar and wind prices on the Australian electricity spot and options markets for the period January 2006-March 2018. Using a vector autoregression analysis, we examine both the direction of influence and influence absorption through Granger causality testing, the impulse response function, and forecast error variance decompositions. We identify a unidirectional Granger causal relationship between the solar and wind electricity prices and the spot prices in New South Wales, Queensland, Victoria, and South Australia. The forecast results suggest that the solar and wind electricity prices reduce the spot and options electricity market prices. These results are important for energy policymakers and government organizations that support renewables, as their use not only decreases the wholesale spot prices, but also encourages initiatives to explore and switch to alternative energy sources, which tend to be more cost effective and environmentally friendly.

**Keywords:** Electricity Pricing, Renewable Energy, Vector Autoregression Model

**JEL Classifications:** C32, Q41, Q42

## 1. INTRODUCTION

Electricity represents one of the most important resources of every national economy, as it plays an essential role in both economic production and life more generally. In recent years, the share of solar and wind power has increased worldwide, which has resulted in these renewable power sources having an increasing impact on electricity system prices and costs. The direct effect of solar and wind power on the electricity spot and options markets is typically adverse, since renewables allow for the generation of power at very low or even zero marginal cost and hence displace more costly means of generation. Solar and wind power can also indirectly decrease the electricity spot and options prices by lowering the power of the market in systems in which generators bid strategically.

Electricity prices are among the most important contemporary policy issues in Australia, and they represent a critical component of current discussions concerning energy and climate change policies. Several attempts to move forward with energy and climate change policies have been stymied by concerns about potential additional increases in electricity prices. Within this policy debate in Australia, renewable electricity generation is considered to be a fundamental factor influencing electricity prices. Due to the increasing penetration of wind and solar power generation in Australia coinciding with increasing wholesale and retail electricity prices, there is now a widely held belief that the wholesale electricity price increases are related to the increased penetration of renewables.

The aim of the present study is to investigate the nature and influence of solar and wind prices on the electricity spot and

options markets for a number of Australian states. The study will be conducted a multivariate analysis to examine the causal nature of the market, particularly the relationship that may exist between solar and wind pricing and the electricity spot and options prices in each of the investigated states. Increased information concerning the dynamics of the electricity, solar, and wind prices will allow for a better understanding of the flow of pricing information among the markets. To achieve this, a vector autoregression (VAR) model will be used to examine the extent of the dynamic interactions that occur between the solar and wind prices and the electricity spot and options valuations.

Moreover, Granger causality (GC) tests will be applied to investigate the Granger-type causal linkages between solar and wind pricing and the spot and options electricity markets. Additionally, the use of the impulse response analysis (IRA) will allow for the measurement of the duration and speed of the interactions that exist between solar and wind pricing and the electricity spot and options markets. Further, forecast error variance decomposition (FEVD) will also be applied so as to determine the extent to which the forecast error variances of the solar, wind, spot, and options prices are influenced by one another.

The present study considers quantitative data regarding the electricity markets in five Australian states, namely New South Wales (NSW), Queensland (QLD), South Australia (SA), Victoria (VIC), and Tasmania (TAS). The time series data concerning each state involves four variables, that is, the wind, solar, spot, and options prices (as expressed in Australian dollars per megawatt hour [\$/MWh]). In this study, the dataset consists of monthly observations, while the sample covers the period from January 2006 to March 2018.

This study makes two significant contributions to the literature. First, it helps to explain the relationships between the pricing of renewables, such as solar and wind power, and the electricity markets. The effects of solar and wind power on electricity prices are of great concern, not only to participants in the energy market, for example, risk managers, who must have a clear understanding of price dynamics, but also to policymakers, who need to adjust the market design based on new challenges so as to improve market efficiency and, thus, social welfare. Second, the study adds to the limited body of literature analysing the relationships between solar and wind prices and the spot and options electricity markets using multivariate models such as VAR. This study will fill a gap in the prior literature by disentangling the differential effects of solar and wind prices on the Australian spot and options electricity markets.

The remainder of this paper is organized as follows. Section 2 introduces the relevant literature and situates the present paper in relation to it. Section 3 outlines the methodology employed in the study, while section 4 describes the data sources. Section 5 presents the empirical results, while section 6 discusses the findings and offers a conclusion to the study.

## 2. LITERATURE REVIEW

The relationships between green energy alternatives and the electricity markets have been studied in many different countries

and areas (Badyda and Dylík, 2017; Csereklyei et al., 2019; Forrest and MacGill, 2013; Gürtler and Paulsen, 2018; Odeh and Watts, 2019; Sorknæs et al., 2019; Winkler et al., 2016; Worthington and Higgs, 2017). Further, the number of studies evaluating the relationships between green alternatives, such as wind and solar power, and the wholesale electricity prices in deregulated or liberalized electricity markets has grown steadily in recent years. These prior studies have mainly been based on econometric models using real historical data (Würzburg et al., 2013).

The investigation of the associations and linear relationships between the proportion of renewable energy sources within the generation mix and the wholesale price of electricity began with the seminal work of Jensen and Skytte (2003). Their findings showed that a greater share of renewable energy within the total electricity generation mix can result in a decrease in the wholesale electricity price. In a European case study, Clò et al. (2015) applied a multivariate regression model to investigate the impact of solar and wind power generation on electricity market prices in the Italian power market using hourly data from January 01, 2005 to October 31, 2013. Their major conclusion was that one GWh generated from solar and wind sources (hourly average) reduces prices by 2.3€/MWh and 4.2€/MWh, respectively.

With regard to the specific case of the Australian electricity market, Forrest and MacGill (2013) investigated the impact of wind power generation on electricity prices in the Australian market using half-hourly data from March 01, 2009 to February 28, 2011. They applied econometric analysis techniques to estimate the impact of the wind output on prices based on empirical data. Their results showed that wind power caused a drop in the spot market price to \$8.05/MWh for SA and \$2.73/MWh for VIC. Yet, they also showed how a greater drop in the spot market energy price, as caused by the higher integration of wind power, actually limited its development.

Worthington and Higgs (2017) examined the impact of the generation mix, encompassing both fossil fuels (black and brown coal and natural gas) and renewables (hydropower and wind power), on the daily spot electricity prices in the Australian National Energy Market (ANEM) from January 01, 2006 to September 06, 2012. Using least squares and quantile regressions, they evaluated the emergent effects of government policy and industry developments regarding the generation choice on the wholesale electricity prices. Their results showed that changing the generation mix used for the production of electricity exerts a strong influence on wholesale prices.

Recently, Csereklyei et al. (2019) used autoregressive distributed lag (ARDL) models to decompose the merit-order effect of wind and utility-scale solar photovoltaic (PV) generation on the wholesale electricity prices in Australia from 2010 to 2018. Their results showed that an extra GW of dispatched wind capacity decreases the wholesale electricity price by 11 AUD/MWh at the time of generation, while an extra GW of dispatched solar capacity results in a decrease of 14 AUD/MWh.

A few studies have considered Granger causal modelling in relation to the electricity markets and solar and wind power (Ata,

2018; Kyritsis et al., 2017). For example, Kyritsis et al. (2017) investigated the GC from solar power generation, wind power generation, and the total electricity load to the day-ahead electricity prices in the German electricity market. They found that solar power generation, wind power generation, and the total electricity load all Granger-cause the electricity prices at the 1% significance level.

Ata (2018) estimated the causal relationship between renewable energy consumption and electricity prices using data from 1990 to 2012 for three case study countries, namely the United Kingdom, Turkey, and Nigeria. The study found that (a) there is unidirectional causality running from electricity prices to renewable energy consumption for Turkey; (b) there is a unidirectional causal link between renewable energy consumption and electricity prices for Nigeria; and (c) there is bidirectional causality in the relationship between renewable energy consumption and electricity prices for the United Kingdom.

Moreover, several studies have examined the relationships between different energy prices (i.e., crude oil prices, coal prices, uranium prices, and natural gas prices) and the electricity markets (Bernal et al., 2019; Ferkingstad et al., 2011; Furio and Poblacion, 2018; Mjelde and Bessler, 2009). For example, Bernal et al. (2019) analysed the relationships between Mexican electricity prices and the fossil fuel, crude oil, natural gas, and coal prices for the period from January 2006 to January 2016. They used an unrestricted vector autoregressive model and reported that, in the short term, the crude oil, natural gas, and coal prices have a significant positive impact on electricity prices. In the long term, they found that the crude oil and natural gas prices also have a significant positive impact on electricity prices as well as on commercial and industrial electricity rates.

This section has provided an overview of the major studies to have examined the nature and effects of green alternatives on the electricity markets and, in particular, on the spot and options pricing. In the main, the previous studies have shown solar and wind generation, rather than pricing, to be generally and consistently associated with reduced electricity prices. Work on the effects of pricing remains to be done in terms of the spot and options prices. Additionally, the above review showed that multivariate models can be used to decipher the dynamic relationships that may exist between the wholesale electricity spot prices and the prices of renewables based on the fact that the fuel sources for electricity generation have previously been studied using the VAR, ARDL, and vector error correction model (VECM) approaches.

### 3. METHODOLOGY

The present study examines the nature and influence of solar and wind prices in relation to the electricity spot and options markets of the ANEM within the context of a VAR analysis (Sims, 1980). As previously stated, the study investigates the extent, speed, and duration of the interactions among the markets based on GC, impulse response, and variance decomposition analyses.

#### 3.1. VAR Model

The VAR model is a standard tool for econometrics and multivariate time series analysis. The endogenous variables,  $x_t$ ,

and the exogenous variables,  $z_t$ , are observed as random vectors depending on the (time)  $= 1, 2, \dots$ . The basic idea behind the VAR model is that the endogenous variables depend linearly on their  $k$  previous values, as well as on the current values of the exogenous variables, so that

$$x_t = \mu + \sum_{\tau=1}^k M_{\tau} x_{t-\tau} + \gamma z_t + e_t, \tag{1}$$

Where  $M_{\tau}$  and  $\gamma$  are the coefficient matrices of the sizes  $n \times n$  and  $n \times d$ , respectively,  $n$  is the number of endogenous variables, and  $d$  is the number of exogenous variables. Further,  $\mu$  is a constant vector and  $e_t$  is a vector of residuals (innovations).

All the variables must have the same order of integration. If all the variables are stationary,  $I(0)$ , we have the standard case of a VAR model, but if all the variables are non-stationary,  $I(d)$ ,  $d > 1$ , we have two possibilities. First, if the variables are not cointegrated, then they must be differenced  $d$  times in order to obtain a VAR. Second, if the variables are cointegrated, a VECM may be used.

#### 3.2. Stationarity and Stability

We assume two basic conditions regarding the data,  $X_t$ , and its associated VAR[p] model, namely stationarity and stability. A stochastic process  $X$  is weakly stationary (or wide-sense stationary [WSS]) if its first and second moments (mean and covariance) do not change over time. In other words,  $E(x_t) = \mu$  for all  $t$  and

$$E[(x_t - \mu)(x_{t-h} - \mu)'] = \Gamma(h) = \Gamma(-h) \tag{2}$$

For all  $t$  and  $h=0, 1, 2, \dots$  where  $E$  denotes the expected value. A VAR[p] process is considered to be stable if its reverse characteristic polynomial has no roots in or on the complex unit circle. Formally,  $x_t$  is stable if

$$\det(I_{MP} - A_Z) \neq 0 \text{ for } |Z| \leq 1 \text{ where} \tag{3}$$

$$A = \begin{bmatrix} A_1 & A_2 & \dots & A_p \\ I_M & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & I_M & 0 \end{bmatrix} \\ (M_p \times M_p)$$

Equivalently,  $x_t$  is stable if all the eigenvalues of  $A$  have a modulus of  $<1$  (Lütkepohl, 2006). A stable process is one that will not diverge to infinity (“blow up”). It is important to recognize that stability implies stationarity; thus, it is sufficient to test for stability when seeking to ensure that a VAR[p] process is both stable and stationary.

#### 3.3. GC Analysis

A key element of employing a VAR model concerns its use in forecasting. Its structure provides information regarding the ability of variables or variable groups to forecast other variables. Granger (1969) introduced this intuitive notion of a variable’s ability to forecast. If a  $Y_1$  variable or variable group was to prove

instrumental in another  $Y_2$  variable's or variable group's prediction, then the  $Y_1$  variable Granger-causes the  $Y_2$  variable. In the opposite case,  $Y_1$  does not Granger-cause  $Y_2$  if, for all  $s > 0$ , the mean squared error of a forecast of  $Y_{2,t}$  based on  $(Y_{2,t}, Y_{2,t-1})$  is the same as the mean squared error of a forecast of  $Y_{2,t+s}$  based on  $(Y_{2,t}, Y_{2,t-1})$  and  $(Y_{1,t}, Y_{2,t-1})$ . It is worth noting that Granger's causality notion only suggests the ability to forecast.

A VAR (p) bivariate model for  $Y_t = (Y_{1,t}, Y_{2,t})'$  sees the failure of  $Y_2$  to Granger-cause  $Y_1$ , given that all the p VAR matrices of the coefficients are lower triangular. The Wald statistic can test the p linear restrictions on the coefficients. The coefficient matrices of the VAR are diagonal in the event that both  $Y_2$  and  $Y_1$  fail to Granger-cause each other. It is important to note that GC is rather useful in the field of finance and that it continues to be extensively used because it shows the bidirectional as well as unidirectional causality of the time series data. In essence, how and in what ways the other variables contribute to the prediction process of a given variable – that is, which variables (or which information in terms of the variables) are crucial for the prediction process – contribute significantly to the forecasting of a given variable.

### 3.4. IRA Analysis

The IRA is considered in terms of the standard deviation shocks that occur during the studied period. It shows how the variables respond to those shocks and how their responses affect the other variables. In this study, the IRA measures the durations and effects of the spot electricity price, the options electricity price, the solar price, and the wind price from one variable to another by tracing the effects of a shock to one endogenous variable on the other variables within the VAR structure.

The processes of vector moving averages (VMA) can be used to represent the VAR (p) model as follows:

$$Y_t = \mu + u_t + \zeta_1 u_{t-1} + \zeta_2 u_{t-2} + \dots + \zeta_s u_{t-s} \quad (4)$$

$$Y_t = \mu + \sum_{i=0}^s \zeta_i u_{t-i}$$

Where the moving average matrices  $\zeta_s$  are of the  $(k \times k)$  matrix type. The coefficient matrix elements then represent the shock effects on  $Y_t$ . Based on this, an impulse response in the following form can be determined:

$$\frac{\partial Y_{i,t+s}}{\partial u_{j,t-s}} = \frac{\partial Y_{i,t}}{\partial u_{j,t-s}} = \zeta_{ij}^s \quad (5)$$

Where the coefficient sets  $\zeta_{ij}(s) = \zeta_{ij}^s$  represent the impulse response functions and where  $i, j = 1, \dots, T$ .

### 3.5. FEVD Analysis

In econometrics and other applications of the multivariate time series analysis, a variance decomposition or FEVD is used to aid in the interpretation of a VAR model once it has been fitted (Lütkepohl, 2005). Variance decomposition concerns the decomposition of the variance in a given dataset so as to show the changes in a variable that are brought about by its own innovation or due to some other variable. To examine how the spot electricity

price, options electricity price, solar price, and wind price variable affects the other variables, a variance decomposition analysis within the context of a VAR will be conducted. In general, we consider a k-dimension vector autoregressive model denoted as VAR (p):

$$Y_t = \sum_{i=1}^p \theta_i Y_{t-i} + \varepsilon_t \quad (6)$$

Where  $\varepsilon_t$  is an independent and identical distributed error term with a zero mean and the covariance matrix  $\Sigma$ . If we assume weak stationary,  $Y_t$  will obtain a moving average order that can be represented as,

$$Y_t = \sum_{j=0}^{\infty} A_j \varepsilon_{t-j} \quad (7)$$

Suitable restrictions are available such that  $\Sigma$  can be represented as PP, while  $\varepsilon_t = P^{-1} \varepsilon_t$  is the orthogonalized error with the identity covariance matrix.

## 4. DATA SOURCES

In the present study, the dataset consists of monthly observations, while the sample covers the period from January 2006 to March 2018. The variables included in the estimations are the spot, options, solar, and wind electricity prices (as expressed in \$/MWh) from five Australian electricity markets, namely the NSW, QLD, SA, TAS, and VIC markets (save for the options electricity prices in the case of TAS). The choice of study period was constrained by the availability of time series data concerning the solar and wind electricity prices.

The time series data concerning the spot electricity prices were collected on a monthly basis from the Australian Energy Market Operator (AEMO). The AEMO collates and reports the average daily, monthly, and annual observations for each price for the five market regions within the ANEM. The data concerning the options prices (closing prices) were collected from among the ASX Energy daily market data and then converted into monthly terms (January 2006 to March 2018). All the utilized data include only those options contracts with non-zero trading volumes.

The MAC Global Solar Energy Index and the ISE Global Wind Energy Index were used as the solar and wind electricity price proxy variables, respectively. Time series data concerning the two indices were collected on a monthly basis from Bloomberg.

## 5. RESULTS

### 5.1. Vector Autoregressive System Stationarity and Stability

One formal test of the stability of a VAR involves examining the (inverse) roots of the autoregressive characteristic polynomial of the VAR. When all the inverse roots are within a unit circle (i.e., all the eigenvalues have a modulus of <1), then the VAR is said to be stable (Lütkepohl, 2006). As establishing the stability of a time series implies that the series is also stationary, the

stability condition is sometimes referred to in the literature as the stationarity condition (Kammerdiner, 2008). However, it is important to remember that the two conditions are not equivalent. In fact, although a stable vector autoregressive series is always stationary, the reverse is not true, that is, an unstable time series is not necessarily non-stationary.

As shown in Table 1, the specified models were stable (i.e. all the VAR values were <1). This means that the modulus latent root was both <1 and a non-singular polynomial with a non-zero determinant. Further, it means that the system was a stationary stochastic process that can reach convergence.

### 5.2. Vector Autoregressive Order Selection Criteria (Lag Selection)

Prior to estimating the VAR, the optimum lag is determined based on the results of the Schwarz’s Bayesian information criterion (SBIC) test. Selecting the optimal lag before constructing the VAR is important, as a trade-off is involved in the selection of the number of lags. According to Kireyev (2000), excessively short lags may fail to capture a system’s dynamics, thereby leading to the omission of certain variables, coefficient biases, and serial correlation-based errors, while lag lengths that are excessively long cause the rapid loss of the degree of freedom and over-parameterisation. In other words, the estimation of an appropriate lag length avoids the over-parameterisation of the model. The order of the VAR model was determined according to the information criteria: Akaike information criterion (AIC), Schwarz information criterion (SC), sequential modified likelihood

ratio test statistic (LR), and final prediction error (FPE) (Lütkepohl, 2005). The number of lags that minimized the value of each of the above-mentioned criteria was chosen as the appropriate VAR order. Thus, a lag order selection test was performed and, based on several of the four criteria, a lag order of two was indicated. The lag length selection table is presented in Table 2, which shows a significant lag length (two) for the NSW, QLD, VIC, SA, and TAS set variables.

### 5.3. Testing the Adequacy of the Vector Autoregressive Model

The Lagrange multiplier test is used to check for the presence of autocorrelation within the residuals. The null hypothesis is that there is no autocorrelation up to the specified lag for the variables, while the alternative hypothesis is that there is autocorrelation up to the specified lag for the variables. The Lagrange multiplier test results, as presented in Table 3, show that all the p-values are higher than the critical value (5%). Based on this finding, the null hypothesis of no serial autocorrelation within the residuals cannot be rejected for lag order *h*, which in this case is lag two. The VAR of the spot, options, solar, and wind electricity prices and the combined trait models can be considered both representative and stable.

### 5.4. Vector Autoregressive Estimation Model

Table 4 presents the results of the VAR analysis. As shown in the table, some of the variables used in the VAR framework have significant coefficients. Hence, significant interdependence exists among certain of the variables, that is, either as a variable influencing another variable or as a variable that is influenced.

**Table 1: VAR stability condition roots of characteristics polynomials**

Root	Modulus	Root	Modulus
<b>NSW</b>		<b>QLD</b>	
0.966227	0.966227	0.958898-0.075513i	0.961866
0.926792-0.072548i	0.929627	0.958898+0.075513i	0.961866
0.926792+0.072548i	0.929627	0.959900	0.959900
0.505895	0.505895	0.397502-0.132467i	0.418993
0.261254	0.261254	0.397502+0.132467i	0.418993
0.049756-0.115689i	0.125934	-0.092651-0.152693i	0.178604
0.049756+0.115689i	0.125934	-0.092651+0.152693i	0.178604
0.008560	0.008560	0.128222	0.128222
<b>VIC</b>		<b>SA</b>	
0.964308	0.964308	0.968637	0.968637
0.940158-0.070187i	0.942774	0.903933-0.020487i	0.904165
0.940158+0.070187i	0.942774	0.903933+0.020487i	0.904165
0.608949	0.608949	0.411944	0.411944
0.421076	0.421076	0.262662-0.206804i	0.334304
0.231144	0.231144	0.262662+0.206804i	0.334304
-0.229707	0.229707	-0.183765	0.183765
-0.029544	0.029544	-0.081277	0.081277
<b>TAS</b>			
0.965889-0.013243i	0.965980		
0.965889+0.013243i	0.965980		
0.526198	0.526198		
0.320651	0.320651		
-0.078019	0.078019		
0.064342	0.064342		
0.965889-0.013243i	0.965980		
0.965889+0.013243i	0.965980		

All the eigenvalues lie inside the unit circle. VAR satisfies the stability condition. NSW: New South Wales, QLD: Queensland, SA: South Australia, VIC: Victoria, TAS: Tasmania, VAR: Vector autoregression

**Table 2: Results of the criteria for spot, option, solar and wind electricity prices**

Lag	LL	LR	FPE	AIC	SC
<b>NSW</b>					
0	-2824.686		1.79e+12	39.56204	39.64491
1	-2178.285	1247.598	2.65e+08	30.74525	31.15963*
2	-2148.794	55.26972*	2.19e+08*	30.55656*	31.30245
3	-2138.118	19.41074	2.37e+08	30.63103	31.70842
4	-2129.676	14.87799	2.64e+08	30.73672	32.14563
<b>QLD</b>					
0	-2868.387		3.29e+12	40.17324	40.25612
1	-2202.636	1284.945	3.72e+08	31.08582	31.50020*
2	-2183.352	36.14037	3.56e+08*	31.03989*	31.78578
3	-2167.411	28.98416*	3.56e+08	31.04071	32.11811
4	-2160.194	12.71708	4.04e+08	31.16356	32.57246
<b>VIC</b>					
0	-2822.787		1.74e+12	39.53548	39.61836
1	-2158.431	1282.253	2.00e+08	30.46756	30.88195*
2	-2130.895	51.60590*	1.71e+08*	30.30622*	31.05211
3	-2121.002	17.98777	1.86e+08	30.39163	31.46903
4	-2111.933	15.98063	2.06e+08	30.48858	31.89748
<b>SA</b>					
0	-2871.576		4.57e+12	40.50108	40.58434
1	-2262.410	1175.434	1.07e+09	32.14661	32.56293*
2	-2245.761	31.18747*	1.07e+09*	32.13747*	32.88684
3	-2235.358	18.90021	1.15e+09	32.21631	33.29873
4	-2226.583	15.44918	1.28e+09	32.31807	33.73354
<b>TAS</b>					
0	-2475.430		2.27e+11	34.66335	34.72551
1	-2009.979	904.8630	3.84e+08	28.27942	28.52805*
2	-1999.274	20.36195*	3.75e+08*	28.25557*	28.69068
3	-1995.306	7.380546	4.02e+08	28.32596	28.94753
4	-1987.565	14.07406	4.10e+08	28.34357	29.15162

\*indicates lag order selected by the criterion, AIC: Akaike information criterion, SC: Schwarz information criterion, LR: Likelihood ratio, FPE: Final prediction error, VAR: Vector autoregression

**Table 3: Lagrange-multiplier test**

States	Lag	Chi-square	Prob.>Chi-square
NSW	1	19.53	0.24
	2	23.01	0.11
QLD	1	26.05	0.53
	2	30.68	0.14
VIC	1	11.6	0.77
	2	21.2	0.17
SA	1	18.85	0.27
	2	23.04	0.11
TAS	1	5.23	0.81
	2	9.97	0.35

Null hypothesis: no autocorrelation at lag order. NSW: New South Wales, QLD: Queensland, SA: South Australia, VIC: Victoria, TAS: Tasmania, VAR: Vector autoregression

The VAR results show that the spot price lag one had a significant positive impact on the spot price in each state, while lag two was not significant because the probability value was more than the critical value of 5%. In addition, the results suggest that the options price (lags 1 and 2) had strong positive and negative effects due to the lags of the options prices in NSW, QLD, VIC, and SA. Further, the results indicate that the solar and wind prices strongly impacted each other in both the positive and negative directions.

Moreover, the VAR results suggest that the independent variable, that is, the options price (lags 1 and 2), is a significant variable (<5%

and 10%) in terms of explaining the dependent variable, namely the spot price, in NSW and QLD. Further, the wind price (lag 2) variable is statistically significant at the 5% level and, therefore, it may be able to explain the options prices in NSW, VIC, and SA.

**5.5. Forecasting Performance**

A key advantage of the VAR model concerns its potential for use in forecasting. Its structure provides information regarding the ability of the variables or variable groups to forecast other variables. The VAR has a multivariate advantage, as the developed forecasts can be made conditional on the potential future trends in the other given variables. This study forecasts the spot, options, solar, and wind electricity prices using a VAR model with a 2-year horizon (i.e., April 2018 to March 2020).

Using Equations 7, 8, 9, and 10, the forecast results for the spot, options, solar, and wind electricity prices in NSW (Figure 1a) show negative growth rates of around 10.87%, 19.78%, 18.93%, and 26.50%, respectively. The results also suggest that the future values of the spot, options, solar, and wind electricity prices in QLD can be predicted using Equations 11, 12, 13, and 14. Figure 1b shows that the electricity spot, options, and wind prices are expected to decrease by an average of 11.21%, 4.25%, and 24.84%, respectively, over the next 2 years. However, the forecast results concerning the solar electricity price in QLD show positive growth rates of around 51.31%.

**Table 4: VAR coefficients**

Region	Variable	Spot		Option		Solar		Wind	
		Coef.	P-value	Coef.	P-value	Coef.	P-value	Coef.	P-value
NSW	Spot (-1)	0.249	0.002	0.002	0.440	0.132	0.634	0.081	0.045
	Spot (-2)	0.017	0.834	0.002	0.393	-0.070	0.800	-0.018	0.660
	Option (-1)	6.943	0.001	1.277	0.000	13.160	0.070	0.690	0.513
	Option (-2)	-6.746	0.001	-0.388	0.000	-13.543	0.051	-1.496	0.138
	Solar (-1)	-0.021	0.531	0.000	0.940	0.711	0.000	-0.053	0.002
	Solar (-2)	-0.024	0.487	-0.001	0.352	0.233	0.054	0.044	0.013
	Wind (-1)	0.079	0.725	-0.009	0.252	2.465	0.002	1.459	0.000
	Wind (-2)	0.131	0.131	0.017	0.053	-2.290	0.006	-0.434	0.000
	C	14.285	0.026	0.110	0.639	-15.946	0.475	4.093	0.208
	QLD	Spot (-1)	0.304	0.000	0.001	0.639	0.139	0.542	0.056
Spot (-2)		0.036	0.658	0.001	0.743	-0.014	0.951	0.024	0.481
Option (-1)		5.973	0.024	1.198	0.000	9.554	0.201	-0.529	0.629
Option (-2)		-6.153	0.018	-0.271	0.001	-7.617	0.299	-0.106	0.921
Solar (-1)		-0.079	0.060	0.001	0.461	0.679	0.000	-0.049	0.005
Solar (-2)		0.033	0.432	-0.001	0.258	0.278	0.020	0.047	0.007
Wind (-1)		0.265	0.352	-0.010	0.270	2.873	0.000	1.434	0.000
Wind (-2)		-0.064	0.824	0.014	0.109	-2.767	0.001	-0.442	0.000
C		18.016	0.043	0.087	0.750	-35.163	0.162	4.344	0.238
VIC		Spot (-1)	0.363	0.000	0.004	0.233	-0.378	0.270	-0.013
	Spot (-2)	0.150	0.067	0.000	0.975	0.317	0.355	0.046	0.362
	Option (-1)	-0.953	0.561	1.340	0.000	10.196	0.137	0.322	0.751
	Option (-2)	1.145	0.475	-0.426	0.000	-9.654	0.149	-0.959	0.333
	Solar (-1)	-0.031	0.258	0.001	0.443	0.697	0.000	-0.050	0.004
	Solar (-2)	0.000	0.991	-0.002	0.145	0.246	0.039	0.041	0.021
	Wind (-1)	0.255	0.172	-0.016	0.067	2.653	0.001	1.446	0.000
	Wind (-2)	-0.098	0.607	0.021	0.018	-2.467	0.002	-0.427	0.000
	C	5.537	0.336	0.261	0.322	-20.864	0.386	5.650	0.113
	SA	Spot (-1)	0.204	0.016	0.003	0.354	-0.127	0.505	0.007
Spot (-2)		0.041	0.624	0.002	0.481	0.177	0.348	0.035	0.203
Option (-1)		-1.487	0.544	1.094	0.000	3.435	0.533	-0.394	0.628
Option (-2)		2.771	0.226	-0.254	0.001	-4.086	0.428	-0.250	0.743
Solar (-1)		-0.094	0.070	0.000	0.874	0.678	0.000	-0.055	0.002
Solar (-2)		0.062	0.259	-0.003	0.086	0.251	0.043	0.040	0.029
Wind (-1)		0.397	0.250	-0.013	0.257	2.613	0.001	1.472	0.000
Wind (-2)		-0.209	0.573	0.029	0.016	-2.352	0.005	-0.426	0.001
C		9.974	0.277	0.054	0.857	-21.131	0.306	2.195	0.472
TAS		Spot (-1)	0.560	0.000			-0.180	0.494	0.003
	Spot (-2)	0.012	0.890			-0.132	0.620	0.006	0.881
	Solar (-1)	-0.021	0.564			0.654	0.000	-0.059	0.001
	Solar (-2)	-0.013	0.716			0.256	0.023	0.054	0.001
	Wind (-1)	0.138	0.548			2.832	0.000	1.551	0.000
	Wind (-2)	0.030	0.897			-2.464	0.001	-0.550	0.000
	C	6.388	0.310			-20.255	0.310	1.077	0.720

No options electricity prices in the case of TAS. NSW: New South Wales, QLD: Queensland, SA: South Australia, VIC: Victoria, TAS: Tasmania, VAR: Vector autoregression

Relying on Equations 15, 16, 17, and 18, Figure 2c shows the spot, options, solar, and wind electricity price forecasts for VIC from April 2018 to March 2020. The results suggest decreasing growth rates of around 23.67% for the spot price, 13.51% for the options price, and 23.55% for the wind price. Further, Figure 2d shows predicted decreases in the spot, options, and solar electricity prices in SA of around 43%, 8.84%, and 11.05%, respectively, using Equations 19, 20, and 21. Additionally, using Equation 23, Figure 2e shows that the spot electricity price in TAS is predicted to decrease by 8.27% in March 2020 when compared to the prices in March 2018.

The equations for NSW are:

$$Spot_t = 14.28 + 0.24Spot_{t-1} + 0.01Spot_{t-2} + 6.94Option_{t-1} - 6.74Option_{t-2} - 0.02Solar_{t-1} - 0.02Solar_{t-2} + 0.07Wind_{t-1} + 0.13Wind_{t-2} + u_t \tag{7}$$

$$Option_t = 0.10 + 0.002Spot_{t-1} + 0.002Spot_{t-2} + 1.27Option_{t-1} - 0.38Option_{t-2} - 0.00Solar_{t-1} - 0.001Solar_{t-2} - 0.009Wind_{t-1} + 0.016Wind_{t-2} + u_t \tag{8}$$

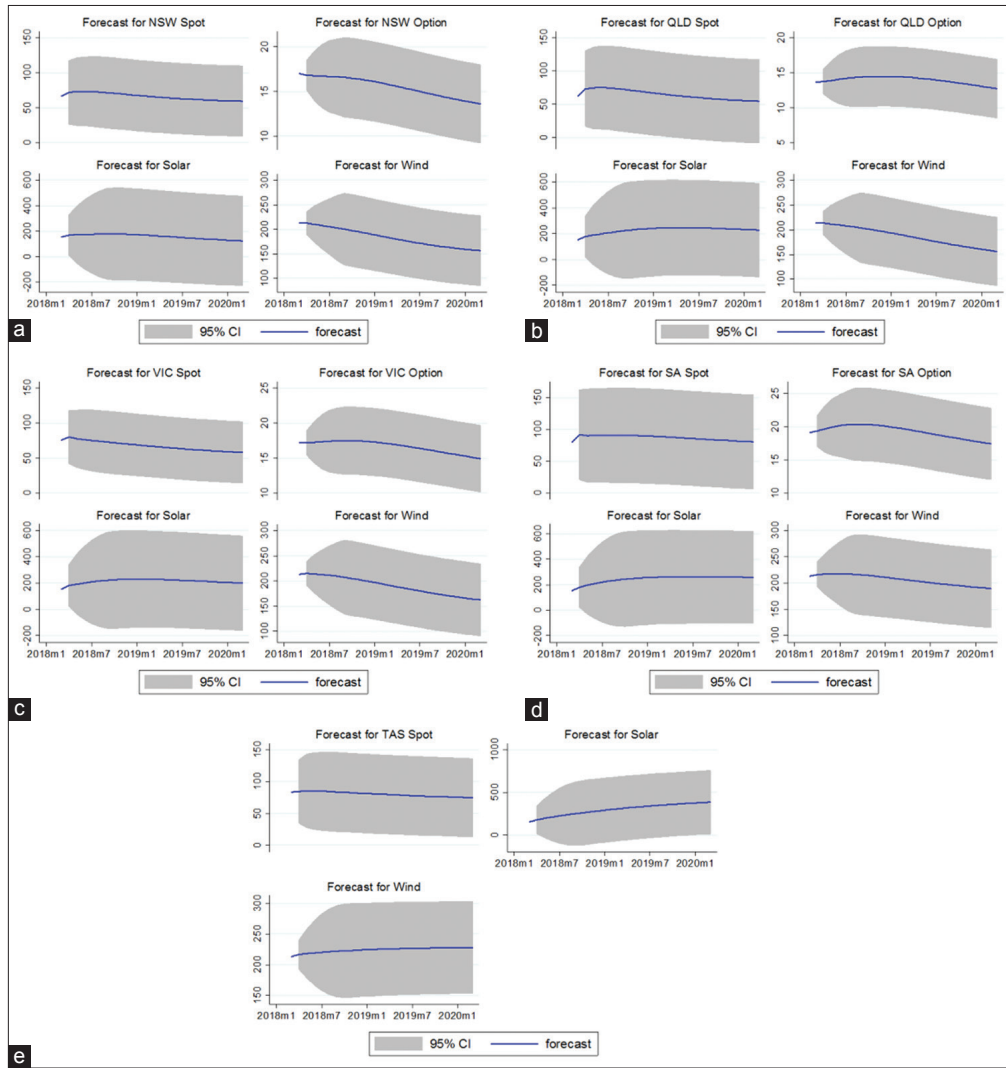
$$Solar_t = -15.94 + 0.13Spot_{t-1} - 0.07Spot_{t-2} + 13.16Option_{t-1} - 13.54Option_{t-2} + 0.71Solar_{t-1} + 0.23Solar_{t-2} + 2.46Wind_{t-1} - 2.29Wind_{t-2} + u_t \tag{9}$$

$$Wind_t = 4.09 + 0.08Spot_{t-1} - 0.01Spot_{t-2} + 0.68Option_{t-1} - 1.49Option_{t-2} - 0.05Solar_{t-1} + 0.04Solar_{t-2} + 1.45Wind_{t-1} - 0.43Wind_{t-2} + u_t \tag{10}$$

The equations for QLD are:

$$Spot_t = 18.01 + 0.30Spot_{t-1} + 0.03Spot_{t-2} + 5.97Option_{t-1} - 6.15Option_{t-2} - 0.07Solar_{t-1} + 0.03Solar_{t-2} + 0.26Wind_{t-1} - 0.06Wind_{t-2} + u_t \tag{11}$$

**Figure 1:** Vector autoregression (VAR) time-series forecasts (a) New South Wales VAR time-series forecasts, (b) Queensland VAR time-series forecasts, (c) Victoria VAR time-series forecasts, (d) South Australia VAR time-series forecasts, (e) Tasmania VAR time-series forecasts



$$\begin{aligned}
 Option_t = & 0.08 + 0.001Spot_{t-1} + 0.0008Spot_{t-2} + 1.19Option_{t-1} \\
 & - 0.27Option_{t-2} + 0.00Solar_{t-1} - 0.001Solar_{t-2} \\
 & - 0.009Wind_{t-1} + 0.014Wind_{t-2} + u_t
 \end{aligned} \tag{12}$$

$$\begin{aligned}
 Solar_t = & -35.16 + 0.13Spot_{t-1} - 0.01Spot_{t-2} + 9.55Option_{t-1} \\
 & - 7.61Option_{t-2} + 0.67Solar_{t-1} + 0.27Solar_{t-2} \\
 & + 2.87Wind_{t-1} - 2.76Wind_{t-2} + u_t
 \end{aligned} \tag{13}$$

$$\begin{aligned}
 Wind_t = & 4.34 + 0.05Spot_{t-1} + 0.02Spot_{t-2} - 0.52Option_{t-1} \\
 & - 0.10Option_{t-2} - 0.04Solar_{t-1} + 0.04Solar_{t-2} \\
 & + 1.43Wind_{t-1} - 0.44Wind_{t-2} + u_t
 \end{aligned} \tag{14}$$

The equations for VIC are:

$$\begin{aligned}
 Spot_t = & 5.53 + 0.36Spot_{t-1} + 0.14Spot_{t-2} - 0.95Option_{t-1} \\
 & + 1.14Option_{t-2} - 0.03Solar_{t-1} + 0.00Solar_{t-2} \\
 & + 0.25Wind_{t-1} - 0.09Wind_{t-2} + u_t
 \end{aligned} \tag{15}$$

$$\begin{aligned}
 Option_t = & 0.26 + 0.004Spot_{t-1} - 0.0001Spot_{t-2} + 1.34Option_{t-1} \\
 & - 0.42Option_{t-2} + 0.00Solar_{t-1} - 0.001Solar_{t-2} \\
 & - 0.01Wind_{t-1} + 0.02Wind_{t-2} + u_t
 \end{aligned} \tag{16}$$

$$\begin{aligned}
 Solar_t = & -20.86 - 0.37Spot_{t-1} + 0.31Spot_{t-2} + 10.19Option_{t-1} \\
 & - 9.65Option_{t-2} + 0.69Solar_{t-1} + 0.24Solar_{t-2} \\
 & + 2.65Wind_{t-1} - 2.46Wind_{t-2} + u_t
 \end{aligned} \tag{17}$$

$$\begin{aligned}
 Wind_t = & 5.65 - 0.13Spot_{t-1} + 0.04Spot_{t-2} + 0.32Option_{t-1} \\
 & - 0.95Option_{t-2} - 0.04Solar_{t-1} + 0.04Solar_{t-2} \\
 & + 1.44Wind_{t-1} - 0.42Wind_{t-2} + u_t
 \end{aligned} \tag{18}$$

The equations for SA are:

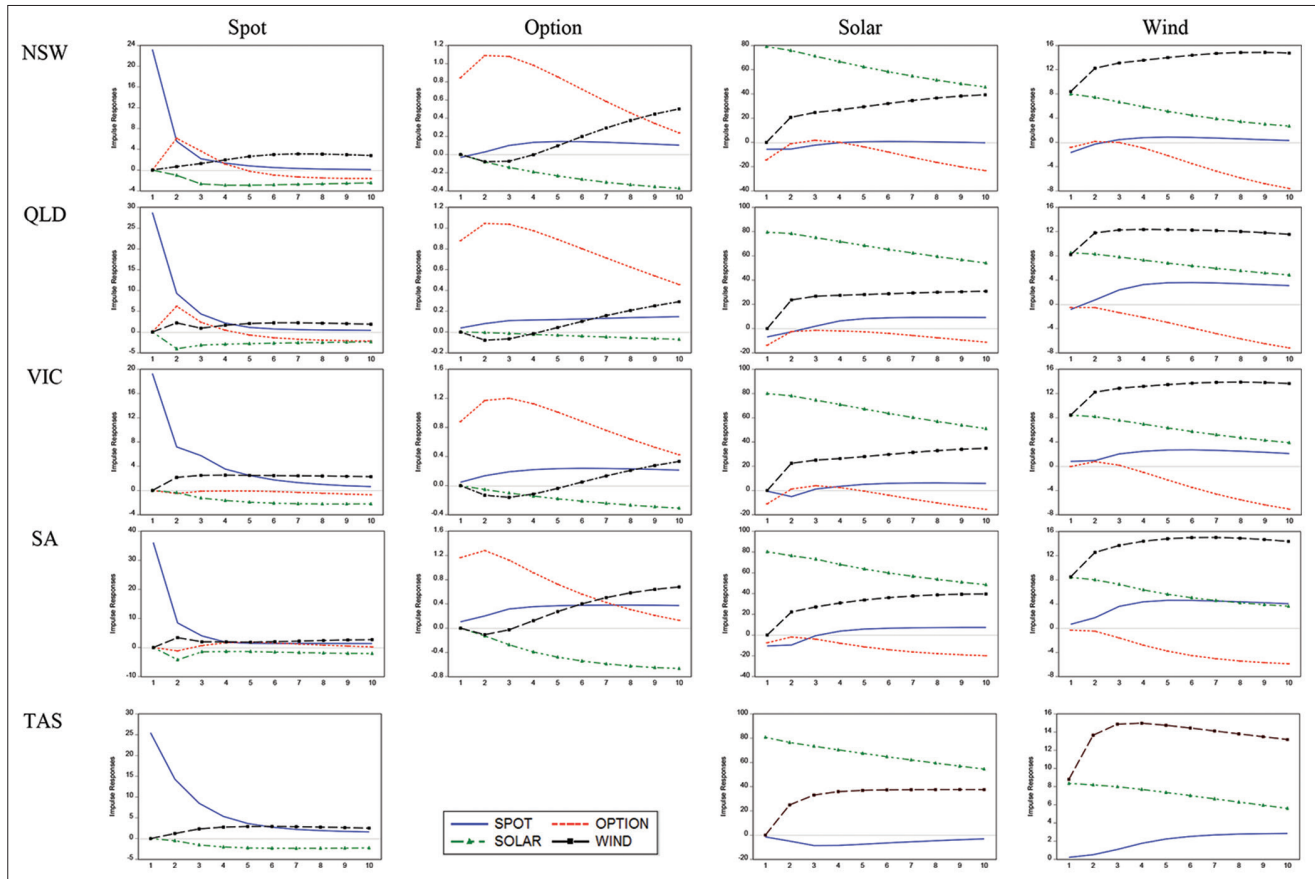
$$\begin{aligned}
 Spot_t = & 9.97 + 0.20Spot_{t-1} + 0.04Spot_{t-2} - 1.48Option_{t-1} \\
 & + 2.77Option_{t-2} - 0.09Solar_{t-1} + 0.06Solar_{t-2} \\
 & + 0.39Wind_{t-1} - 0.20Wind_{t-2} + u_t
 \end{aligned} \tag{19}$$

$$\begin{aligned}
 Option_t = & 0.05 - 0.002Spot_{t-1} + 0.0001Spot_{t-2} + 1.09Option_{t-1} \\
 & - 0.25Option_{t-2} - 0.00Solar_{t-1} - 0.003Solar_{t-2} \\
 & - 0.01Wind_{t-1} + 0.02Wind_{t-2} + u_t
 \end{aligned} \tag{20}$$

$$\begin{aligned}
 Solar_t = & -21.13 - 0.12Spot_{t-1} + 0.17Spot_{t-2} + 3.43Option_{t-1} \\
 & - 4.08Option_{t-2} + 0.67Solar_{t-1} + 0.25Solar_{t-2} \\
 & + 2.61Wind_{t-1} - 2.35Wind_{t-2} + u_t
 \end{aligned} \tag{21}$$



Figure 2: Impulse response graphs



$$\begin{aligned}
 Wind_t = & 2.19 + 0.006Spot_{t-1} + 0.03Spot_{t-2} - 0.39Option_{t-1} \\
 & - 0.24Option_{t-2} + 0.05Solar_{t-1} + 0.03Solar_{t-2} \\
 & + 1.47Wind_{t-1} - 0.42Wind_{t-2} + u_t
 \end{aligned} \tag{22}$$

The equations for TAS are:

$$\begin{aligned}
 Spot_t = & 6.38 + 0.55Spot_{t-1} + 0.01Spot_{t-2} - 0.02Solar_{t-1} \\
 & - 0.01Solar_{t-2} + 0.13Wind_{t-1} + 0.02Wind_{t-2} + u_t
 \end{aligned} \tag{23}$$

$$\begin{aligned}
 Solar_t = & -20.25 - 0.18Spot_{t-1} - 0.13Spot_{t-2} + 0.65Solar_{t-1} \\
 & + 0.25Solar_{t-2} + 2.83Wind_{t-1} - 2.46Wind_{t-2} + u_t
 \end{aligned} \tag{24}$$

$$\begin{aligned}
 Wind_t = & 1.07 + 0.003Spot_{t-1} + 0.005Spot_{t-2} - 0.05Solar_{t-1} \\
 & + 0.05Solar_{t-2} + 1.55Wind_{t-1} - 0.55Wind_{t-2} + u_t
 \end{aligned} \tag{25}$$

**5.6. GC Test Results**

An additional advantage offered by the VAR model concerns its ability to perform GC testing in order to examine the directions of causality among the variables. The GC test is used to check the lead lag, or Granger causal relationship, between the variables. If a variable, for example, *X* is found to be helpful with regard to predicting another variable, for example, *Y*, then *X* is said to Granger-cause *Y*. The methodological structure of the model allows for GC tests to be conducted so as to indicate whether there is one- or two-way GC between the four variables, namely the spot, options, solar, and wind electricity prices.

The GC tests were performed to test the VAR model of the ANEM, as well as to determine whether or not each variable plays a

significant role in each of the equations. The results of the short-run GC tests are presented in Table 5.

In the case of NSW, the GC tests show that a significant Granger causal effect exists from the options, solar, and wind electricity prices to the spot price at a significance level of <1%. In addition, unidirectional GC from the solar and wind electricity prices to the options price exists at a significance level of <5%. Further, the results suggest that there is significant GC between the solar and wind prices, whereby each variable Granger-causes the other at less than the 1% significance level.

In terms of QLD, the GC tests show that there is unidirectional GC running from the solar and wind electricity prices to the spot electricity price at the 1% (high) level of significance. Similarly, there is unidirectional short-run GC running from the options price to the spot electricity price at the 10% (low) level of significance. Moreover, bidirectional GC exists between the options and wind prices at the 5% (medium) level of significance and from the options price to the wind price at the 10% (low) level of significance.

With regard to the situation in VIC, no causality is noted from the options electricity price to the spot electricity price. The results also suggest that there is one-way GC from the solar price to the spot electricity price (at the 1% significance level) and the options electricity price (at the 10% significance level). However, the GC tests show that there is a two-way Granger causal effect from

**Table 5: Granger causality Wald tests for spot, option, solar and wind electricity prices**

Equation	Excluded	Chi-square	df	P-value	Equation	Excluded	Chi-square	df	P-value
<b>NSW</b>					<b>QLD</b>				
<i>Spot</i>	<i>Option</i>	11.523	3	0.003	<i>Spot</i>	<i>Option</i>	5.6013	3	0.061
<i>Spot</i>	<i>Solar</i>	13.629	3	0.001	<i>Spot</i>	<i>Solar</i>	14.346	3	0.001
<i>Spot</i>	<i>Wind</i>	12.055	3	0.002	<i>Spot</i>	<i>Wind</i>	10.128	3	0.006
<i>Spot</i>	ALL	47.282	9	0.000	<i>Spot</i>	ALL	47.282	9	0.000
<i>Option</i>	<i>Spot</i>	1.8729	3	0.392	<i>Option</i>	<i>Spot</i>	0.47599	3	0.788
<i>Option</i>	<i>Solar</i>	8.0838	3	0.018	<i>Option</i>	<i>Solar</i>	2.5081	3	0.285
<i>Option</i>	<i>Wind</i>	11.761	3	0.003	<i>Option</i>	<i>Wind</i>	6.7346	3	0.034
<i>Option</i>	ALL	126.24	9	0.000	<i>Option</i>	ALL	126.24	9	0.000
<i>Solar</i>	<i>Spot</i>	0.24048	3	0.887	<i>Solar</i>	<i>Spot</i>	0.3926	3	0.822
<i>Solar</i>	<i>Option</i>	3.8357	3	0.147	<i>Solar</i>	<i>Option</i>	2.2567	3	0.324
<i>Solar</i>	<i>Wind</i>	11.19	3	0.004	<i>Solar</i>	<i>Wind</i>	12.949	3	0.002
<i>Solar</i>	ALL	126.24	9	0.000	<i>Solar</i>	ALL	126.24	9	0.000
<i>Wind</i>	<i>Spot</i>	4.0539	3	0.132	<i>Wind</i>	<i>Spot</i>	4.5786	3	0.101
<i>Wind</i>	<i>Option</i>	8.4026	3	0.015	<i>Wind</i>	<i>Option</i>	5.2738	3	0.072
<i>Wind</i>	<i>Solar</i>	11.951	3	0.003	<i>Wind</i>	<i>Solar</i>	7.9221	3	0.019
<i>Wind</i>	ALL	126.24	9	0.000	<i>Wind</i>	ALL	126.24	9	0.000
<b>VIC</b>					<b>SA</b>				
<i>Spot</i>	<i>Option</i>	0.67602	3	0.713	<i>Spot</i>	<i>Option</i>	3.4282	3	0.180
<i>Spot</i>	<i>Solar</i>	11.378	3	0.003	<i>Spot</i>	<i>Solar</i>	4.9153	3	0.086
<i>Spot</i>	<i>Wind</i>	12.697	3	0.002	<i>Spot</i>	<i>Wind</i>	4.6221	3	0.099
<i>Spot</i>	ALL	47.282	9	0.000	<i>Spot</i>	ALL	47.282	9	0.000
<i>Option</i>	<i>Spot</i>	1.7324	3	0.421	<i>Option</i>	<i>Spot</i>	1.6948	3	0.429
<i>Option</i>	<i>Solar</i>	5.4878	3	0.064	<i>Option</i>	<i>Solar</i>	20.802	3	0.000
<i>Option</i>	<i>Wind</i>	8.9984	3	0.011	<i>Option</i>	<i>Wind</i>	21.621	3	0.000
<i>Option</i>	ALL	126.24	9	0.000	<i>Option</i>	ALL	126.24	9	0.000
<i>Solar</i>	<i>Spot</i>	1.4519	3	0.484	<i>Solar</i>	<i>Spot</i>	1.1154	3	0.573
<i>Solar</i>	<i>Option</i>	2.2128	3	0.331	<i>Solar</i>	<i>Option</i>	0.72397	3	0.696
<i>Solar</i>	<i>Wind</i>	12.341	3	0.002	<i>Solar</i>	<i>Wind</i>	13.068	3	0.001
<i>Solar</i>	ALL	126.24	9	0.000	<i>Solar</i>	ALL	126.24	9	0.000
<i>Wind</i>	<i>Spot</i>	0.85627	3	0.652	<i>Wind</i>	<i>Spot</i>	1.8782	3	0.391
<i>Wind</i>	<i>Option</i>	6.3063	3	0.043	<i>Wind</i>	<i>Option</i>	4.6745	3	0.097
<i>Wind</i>	<i>Solar</i>	10.079	3	0.006	<i>Wind</i>	<i>Solar</i>	12.776	3	0.002
<i>Wind</i>	ALL	126.24	9	0.000	<i>Wind</i>	ALL	126.24	9	0.000
<b>TAS</b>									
<i>Spot</i>	<i>Solar</i>	8.5692	3	0.014					
<i>Spot</i>	<i>Wind</i>	8.6469	3	0.013					
<i>Spot</i>	ALL	47.282	9	0.000					
<i>Solar</i>	<i>Spot</i>	1.5881	3	0.452					
<i>Solar</i>	<i>Wind</i>	17.505	3	0.000					
<i>Solar</i>	ALL	126.24	9	0.000					
<i>Wind</i>	<i>Spot</i>	0.06329	3	0.969					
<i>Wind</i>	<i>Solar</i>	11.968	3	0.003					
<i>Wind</i>	ALL	126.24	9	0.000					

Null hypothesis was rejected when the probability value was <0.05. NSW: New South Wales, QLD: Queensland, SA: South Australia, VIC: Victoria, TAS: Tasmania, VAR: Vector autoregression

the wind price to the options electricity price at less than the 5% significance level. Further, there is a one-way Granger causal effect from the wind price to the spot electricity price at the 1% significance level.

In relation to SA, the GC tests show that the solar and wind prices Granger-cause the spot electricity price at less than the 10% significance level; however, the reverse is not true for both variables. The results also show that the GC was at the 1% (high) level of significance from the solar price to the options electricity price. In addition, the GC between the wind price and the options electricity price was significant in both directions at the 1% (high) significance level from the wind price to the options price and at the 10% (low) significance level from the options price to the wind price.

In the case of TAS, the GC result indicates that the solar and wind prices Granger-cause the spot electricity price at the 1% (high) level of significance. However, no GC is noted from the spot electricity price to the solar and wind prices.

### 5.7. Impulse Response Test Results

This study conducted an IRA to determine the speed and duration of the interactions among the spot, options, solar, and wind electricity prices in the ANEM. The IRA was performed based on the generalized method established by Pesaran and Shin (1998). This technique avoids variations in the results due to the ordering of variables, which is a problem that occurs when using the Cholesky decomposition method. The results of the generalized IRA are presented as figures showing the impulse responses for the spot, options, solar, and wind electricity prices, with the responses being plotted between  $1 \leq t \leq 10$ .

The IRA was performed on the NSW variables, and the effects are shown in Figure 2. However, relative to the impact of the wind price shock, the spot price first decreased and then increased rapidly at  $t = 3$  before tending toward zero at  $t = 10$ . In response to the wind price shock, the options price did not move markedly in a positive direction and, in fact, moved in a negative direction after  $t = 2$ . As a result of a single shock to the wind price, the solar price first increased and then decreased rapidly after  $t = 2$ . Further, in response to a spot price shock, the options price moved markedly in a positive direction after  $t = 1$ , thereafter exhibiting an increasing trend toward zero between  $5 \leq t \leq 10$ . In addition, Figure 2 shows that the options price did not markedly affect the spot, solar, and wind prices.

For QLD, relative to the impact of a solar price shock, the spot price first decreased and then moved markedly in a positive direction. In contrast, in response to a solar price shock, the options price moved markedly in a negative direction. As a result of a wind price shock, the spot price initially became negative and then became positive. Further, in response to a wind price shock, the variable options price decreased sharply after  $t = 2$ . Figure 2 shows that a unit shock to the spot price caused the options price to become positive and then to decrease sharply after  $t = 3$  so as to become negative. However, the options price shock did not noticeably affect the other variables.

In the case of VIC, as a result of a solar price shock, the spot price initially became negative and then became positive after  $t = 2$ . Moreover, the variable options price oscillated in response to a solar price shock, that is, the options price first decreased and then became positive and continually decreased from  $t = 5$  onwards so as to be negative. In response to a wind price shock, the spot price increased after  $t = 2$ , while the options price decreased sharply after  $t = 4$ . Further, the spot price variable was not significantly affected by the options price and, similarly, the options price variable was not significantly affected by the spot price.

With regard to SA, relative to the impact of a solar price shock, the spot price first decreased and then moved markedly in a positive direction after  $t = 3$ . In response to a solar price shock, the options price moved in a negative direction. Yet, the response of the wind price to a shock in the spot price was positive and extended in an upward direction, while the options price response was negative and extended in a downward direction. Further, in response to a spot price shock, the options price first decreased and then increased rapidly at  $t = 3$  before tending toward zero at  $t = 8$ .

In terms of TAS, the response of the solar price to a shock in the spot price was negative and exhibited a downward direction, while the response of the wind price to a shock in the spot price was positive and exhibited an upward direction.

### 5.8. Variance Decomposition Test Results

Another important aspect of a VAR analysis concerns the ability to see how an innovation from one variable affects both itself and other variables. This can be achieved by applying the FEVD. The theory behind the FEVD is straightforward. First, it is necessary to forecast the VAR model. Then, the error and variance of the

forecast error in any h-step forecast are calculated. During this step, the variance of the forecast error is the sum of all the portions of all the shocks. Finally, the FEVD is calculated by dividing the portions of each shock to the compound variance. If the innovation of one variable accounts for a large part of the total variance in itself or in another variable in the h-step forecast, we can say that the former variable has an important effect on itself or on the latter variable.

This study's analyses applied FEVD to investigate the relationships between the spot, options, solar, and wind electricity prices in the ANEM, as well as to gauge the influences that the variables exert on each other. Table 6 presents the results of the variance decomposition. The reported numbers indicate the percentage of the forecast error in each variable that can be attributed to innovations in the other variables at ten different horizons: from 1 to 10 months ahead (short-run to long-run).

With regard to the situation in NSW, the variance decomposition of the spot prices reveals that the major changes in the spot price are attributable to its own innovation. Further, the contribution of the options price is 8.21%, the solar price is 8.03%, and the wind price is 7.57% over the 10-month period. The results also show that 79.72% of the options price is explained by its own innovative shocks. The contributions of the spot, solar, and wind prices to the options price are 1.68%, 8.81%, and 9.76%, respectively.

In relation to QLD, the results of the variance decomposition approach show that 84.52% of the electricity spot price is explained by its own innovative shocks, whereas the contributions of the options, solar, and wind prices to the spot electricity price are equal to 5.65%, 6.74%, and 3.07%, respectively. The results also show that 94.38% of the options electricity price is explained by its own innovative shocks. The spot electricity price's contribution to the options price is 1.99%, the solar price contributes to the options price to only a very negligible extent (0.25%), and the wind price's contribution to the options price is 3.35%.

In terms of VIC, the forecast error variance of the spot electricity price is explained by its innovation as well as by the options, solar, and wind electricity prices in the final period with a distribution of 84.95%, 0.26%, 5.70%, and 9.07%, respectively. For the options electricity price, at the end of the tenth period, 87.51% of the variance decomposition is explained by options electricity price itself. The roles of the spot, solar, and wind electricity price shocks are almost equally important, and they can each explain about 12% of the variance decomposition in the options electricity price at the end of the tenth period.

In the case of SA, the variance decomposition of the spot electricity price shows that the main change in this variable results from its own innovation. The contributions of the options, solar, and wind electricity prices to the spot electricity price are 0.84%, 2.71%, and 3.39%, respectively. For the options electricity price, the contribution of the solar price is the most important, accounting for about 21%, while the contribution of the wind price is the second most important, accounting for roughly 15%, and the spot electricity prices accounts for about 10%.

Table 6: Variance decomposition for spot, option, solar and wind electricity prices

Region	Step	VDA (Spot)			VDA (Option)			VDA (Solar)			VDA (Wind)						
		Spot	Option	Solar	Spot	Option	Solar	Spot	Option	Solar	Spot	Option	Solar				
NSW	1	100.00	0.00	0.00	0.13	99.86	0.00	0.00	0.00	0.00	0.50	3.21	96.27	0.00	2.03	46.25	51.20
	2	93.63	6.127	0.167	0.09	99.22	0.35	0.32	0.32	0.32	0.49	1.65	94.48	3.36	0.84	34.67	64.27
	3	90.42	7.966	1.290	0.37	98.37	0.86	0.37	0.37	0.37	0.37	1.16	92.83	5.63	0.55	29.18	70.12
	4	88.53	7.983	2.579	0.71	97.45	1.54	0.28	0.28	0.28	0.29	0.90	91.34	7.46	0.47	25.35	73.96
	5	86.48	7.798	3.790	1.05	96.16	2.40	0.42	0.42	0.42	0.24	0.79	89.70	9.25	0.44	22.22	76.69
	6	84.22	7.724	4.874	1.24	94.22	3.46	1.06	1.06	1.06	0.21	0.88	87.78	11.12	0.40	19.54	78.54
	7	81.93	7.767	5.827	1.42	91.52	4.68	2.36	2.36	2.36	0.18	1.19	85.58	13.03	0.37	17.24	79.61
	8	79.79	7.886	6.661	1.55	88.09	6.02	4.31	4.31	4.31	0.16	1.72	83.16	14.93	0.33	15.29	80.06
	9	77.86	8.044	7.391	1.64	84.09	7.42	6.84	6.84	6.84	0.15	2.46	80.62	16.76	0.30	13.67	80.02
	10	76.17	8.220	8.032	1.68	79.72	8.81	9.76	9.76	9.76	0.14	3.35	78.04	18.45	0.26	12.32	79.64
QLD	1	100.000	0.000	0.000	0.00	99.80	0.00	0.00	0.00	0.00	0.72	2.89	96.37	0.00	0.51	51.23	48.05
	2	93.880	3.950	1.68	0.42	99.23	0.001	0.33	0.33	0.41	1.47	93.90	4.20	0.35	0.16	40.31	59.16
	3	92.468	4.359	2.61	0.67	98.95	0.007	0.35	0.35	0.30	1.01	92.21	6.47	1.20	0.43	35.49	62.85
	4	91.470	4.306	3.42	0.84	98.85	0.01	0.27	0.27	0.38	0.79	90.91	7.90	2.21	0.90	32.29	64.58
	5	90.367	4.300	4.14	1.19	98.68	0.03	0.26	0.26	0.53	0.67	89.75	9.03	2.98	1.60	29.83	65.56
	6	89.164	4.425	4.77	1.63	98.333	0.06	0.42	0.42	0.67	0.62	88.68	10.02	3.51	2.57	27.79	66.11
	7	87.932	4.653	5.34	2.06	97.740	0.09	0.80	0.80	0.79	0.62	87.63	10.93	3.83	3.80	26.01	66.33
	8	86.732	4.949	5.86	2.45	96.88	0.13	1.41	1.41	0.90	0.69	86.60	11.80	4.02	5.26	24.43	66.27
	9	85.591	5.288	6.32	2.79	95.76	0.19	2.27	2.27	0.99	0.81	85.55	12.63	4.11	6.89	23.008	65.97
	10	84.524	5.655	6.74	3.07	94.38	0.25	3.35	3.35	1.07	0.98	84.50	13.42	4.14	8.65	21.72	65.47
VIC	1	100.00	0.00	0.00	0.28	99.71	0.00	0.00	0.00	0.004	1.85	98.13	0.00	0.44	0.001	49.52	50.02
	2	98.82	0.06	0.03	1.08	98.12	0.13	0.79	0.79	0.19	0.93	95.03	3.82	0.41	0.15	38.16	61.25
	3	97.28	0.05	0.35	2.30	96.92	0.36	1.18	1.18	0.14	0.71	93.30	5.84	0.96	0.10	33.17	65.75
	4	95.54	0.05	0.90	3.49	96.09	0.68	1.13	1.13	0.15	0.57	92.004	7.26	1.44	0.19	29.76	68.59
	5	93.71	0.05	1.61	4.60	95.35	1.09	0.95	0.95	0.21	0.47	90.74	8.56	1.80	0.65	26.92	70.61
	6	91.86	0.06	2.42	5.64	94.45	1.61	0.86	0.86	0.28	0.44	89.41	9.85	2.04	1.47	24.45	72.02
	7	90.04	0.07	3.26	6.60	93.24	2.22	1.01	1.01	0.34	0.52	87.96	11.16	2.16	2.61	22.28	72.93
	8	88.27	0.11	4.11	7.50	91.68	2.94	1.47	1.47	0.39	0.71	86.41	12.47	2.20	3.97	20.38	73.44
	9	86.57	0.17	4.92	8.32	89.76	3.74	2.25	2.25	0.43	1.004	84.80	13.75	2.18	5.47	18.72	73.60
	10	84.95	0.26	5.70	9.07	87.51	4.60	3.34	3.34	0.46	1.38	83.16	14.98	2.13	7.04	17.29	73.51
SA	1	100.00	0.00	0.00	0.81	99.18	0.00	0.00	0.00	1.65	0.83	97.51	0.00	0.30	0.06	49.14	50.48
	2	97.82	0.09	1.26	1.69	97.39	0.53	0.37	0.37	1.54	0.44	94.19	3.81	0.94	0.09	36.55	62.40
	3	97.40	0.12	1.39	3.36	94.32	2.03	0.27	0.27	1.05	0.38	92.14	6.42	2.65	0.46	30.02	66.85
	4	96.84	0.32	1.51	4.92	90.21	4.36	0.48	0.48	0.87	0.54	89.77	8.81	3.97	1.20	25.31	69.50
	5	96.26	0.54	1.63	6.28	84.98	7.19	1.54	1.54	0.82	0.87	87.25	11.04	4.81	2.12	21.85	71.21
	6	95.68	0.71	1.79	7.40	78.86	10.23	3.49	3.49	0.83	1.31	84.72	13.12	5.29	3.08	19.25	72.36
	7	95.07	0.80	1.98	8.30	72.33	13.23	6.11	6.11	0.85	1.81	82.29	15.04	5.56	4.01	17.26	73.16
	8	94.43	0.84	2.21	8.99	65.89	16.02	9.08	9.08	0.87	2.33	80.004	16.79	5.71	4.87	15.70	73.70
	9	93.74	0.85	2.45	9.48	59.87	18.51	12.12	12.12	0.90	2.85	77.88	18.36	5.78	5.67	14.46	74.06
	10	93.03	0.84	2.71	9.80	54.49	20.66	15.02	15.02	0.92	3.35	75.92	19.78	5.81	6.41	13.47	74.29
TAS	1	100.00	0.00	0.00	0.00	99.96	0.00	0.00	0.00	0.03	0.03	99.96	0.00	0.07	47.38	52.58	
	2	99.79	0.03	0.03	0.17	99.71	0.00	0.17	0.17	0.20	0.20	95.01	4.77	0.03	0.03	34.11	65.80
	3	98.98	0.28	0.28	0.72	98.71	0.00	0.72	0.72	0.51	0.51	90.71	8.77	0.21	0.21	29.18	70.60
	4	97.82	0.69	0.69	1.47	97.82	0.00	1.47	1.47	0.67	0.67	87.71	11.61	0.47	0.47	26.66	72.86
	5	96.53	1.18	1.18	2.28	96.53	0.00	2.28	2.28	0.72	0.72	85.55	13.71	0.76	0.76	25.09	74.13
	6	95.23	1.69	1.69	3.06	95.23	0.00	3.06	3.06	0.72	0.72	83.89	15.37	1.05	1.05	23.96	74.98
	7	94.008	2.20	2.20	3.78	94.008	0.00	3.78	3.78	0.71	0.71	82.52	16.76	1.31	1.31	23.06	75.62
	8	92.87	2.68	2.68	4.44	92.87	0.00	4.44	4.44	0.68	0.68	81.33	17.98	1.54	1.54	22.29	76.15
	9	91.83	3.14	3.14	5.02	91.83	0.00	5.02	5.02	0.64	0.64	80.27	19.08	1.74	1.74	21.63	76.62
	10	90.88	3.56	3.56	5.54	90.88	0.00	5.54	5.54	0.61	0.61	79.29	20.09	1.92	1.92	21.03	77.04

No options electricity prices in the case of TA.

With regard to TAS, the variance decomposition reveals that the forecast error variance of the spot electricity price is completely explained by itself during the first period. At the end of the tenth period, 5.54% of the forecast error variance of the spot electricity price is explained by the wind price, while the contribution of the solar price is 3.56%. The results show that the most important variable in terms of explaining the solar price is the solar price itself during all the investigated months. In addition, the contribution of the spot electricity price is 0.61%, while that of the wind price is 20%, over the 10-month period. Further, the variance decomposition of the wind price reveals that the major changes in it are attributable to its own innovation. The contribution made by the spot electricity price is 1.92%, while that made by the solar price is 21%.

## 6. DISCUSSION AND CONCLUSION

The aim of this study was to examine the nature and influence of solar and wind prices on the electricity spot and options prices for the ANEM. To this end, we applied a VAR model with which we could obtain GC, IRF, and FEVD results for interpretation. To the best of our knowledge, the present results are not directly comparable to the results of any other study due to the methodology used, the variables included in the model, and the aim of the analysis.

Generally speaking, the VAR results for the selected time series indicated that the spot and options electricity prices were strongly influenced by themselves in the ANEM. Further, the VAR results showed that the options electricity price had a strong influence on the spot electricity price in NSW and QLD. Furthermore, the wind electricity price had a medium-to-strong influence on the options price in NSW, VIC, and SA.

This study's analyses applied FEVD to investigate the relationships among the spot, options, solar, and wind electricity prices in the ANEM, as well as to gauge the influences of the variables upon one another. The FEVD results indicated that the contribution of the solar electricity price to the spot electricity price in NSW, QLD, VIC, SA, and TAS was 8.03%, 6.74%, 5.70%, 2.71%, and 3.56%, respectively. The results of the FEVD analysis also showed that the contribution of the wind electricity price to the spot electricity price was 7.57% in NSW, 3.07% in QLD, 9.07% in VIC, 3.39% in SA, and 3.56% in TAS. However, the FEVD results suggested that the spot and options electricity price shocks were mostly caused by their own innovations.

These findings are not surprising for Australia, where fossil fuel sources contributed some 212,066 GWh (81%) to the total Australia electricity generation in 2018. In fact, coal accounted for the majority of the electricity generation (60%) in 2018. Renewable sources contributed some 49,339 GWh (19%) to the total electricity generation, with the largest source of renewable generation being hydro (7% of the total generation), followed by wind (6%) and solar (5%) in 2018 (Commonwealth of Australia Department of Environment and the Energy, 2019).

GC provides the justification for the predictive causal ability of models based on the available information criteria. The GC

analysis indicated that there was a significant unidirectional Granger causal relationship from the solar and wind electricity prices to the spot price in NSW, QLD, VIC, and TAS at the 1% significance level, while in the case of SA the relationship was significant at less than the 10% level. In addition, there was one-way GC from the solar electricity price to the options price in NSW (at the 5% significance level), VIC (at the 10% significance level), and SA (at the 1% significance level). However, the VAR model revealed bidirectional Granger causal relationships from the wind electricity price in NSW and VIC (at the 5% significance level) as well as in QLD and SA (at the 10% significance level).

This finding is consistent with the prior literature concerning the relationship between the electricity price and renewable energy consumption (Ata, 2018; Kyritsis et al., 2017). The results of Kyritsis et al. (2017) showed that there is statistically significant evidence of GC from solar power generation and wind power generation to the electricity prices.

Finally, this study attempted to forecast the spot, options, solar, and wind prices in the ANEM using the VAR model with a 2-year horizon. The forecast results concerning the spot electricity price suggested that price decreases for NSW (10.87%), QLD (11.21%), VIC (23.67%), SA (43%), and TAS (8.27%). Similarly, the forecast results concerning the options electricity price indicated price decreases for NSW (19.78%), QLD (4.25%), VIC (13.51%), and SA (8.84%).

These findings are similar to those of certain prior studies (Bell et al., 2017; Csereklyei et al., 2019). For instance, Bell et al. (2017) found that increasing wind power penetration decreased the wholesale spot prices, although retail prices increased for many Australian states. Csereklyei et al. (2019) found that an extra GW of wind capacity decreased the wholesale electricity price by 11 \$/MWh, while an extra GW of solar capacity decreased the wholesale electricity price by 14 \$/MWh, in the ANEM.

In summary, the VAR models applied in this study helped to provide a better understanding of the overall nature of the relationships that exist between the spot, options, solar, and wind electricity prices in the ANEM. The analyses showed that the relationships between the four variables were discernible using the times series methodology. The results of this study are hence of value to energy analysts, government organizations, and policymakers in terms of the Granger causalities, forecast variances, and impulse responses. The results support the notion that energy policies in Australia should continue to support wind and solar electricity generation because such an approach leads to higher spot and options electricity prices. On the contrary, energy policies that support the further penetration of renewables are likely to create effects that decrease the wholesale electricity prices. In addition, energy policies that support renewables are in line with medium- and long-term aims regarding the reduction of greenhouse gas emissions, such as the aim for zero net emissions by 2050 (Office of Environment and Heritage, 2015) or Australia's 2030 climate change targets (Commonwealth of Australia, 2019).

Future studies should aim to extend the present findings by further investigating this matter in Australia by using a multivariate time

series analysis. It would be useful to further study the effects of the cost and generation of wind and solar power on retail electricity prices in Australia as well as other electricity derivatives markets, such as futures and forwards. Furthermore, comparing the interdependence of electricity pricing in Australia, Europe, and the USA would help to develop a solid foundation upon which a number of implications and recommendations can be drawn regarding the nature of the associated trends, autocorrelations, Granger causalities, variance decompositions, and impulse responses.

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