An Analysis of Price-Setting Generation Technologies in the Australian National Electricity Market

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Abstract

Being the most competitive energy source in terms of the levelized cost of electricity, and supported by government policies to reduce carbon emissions, variable renewable energy (VRE) penetration is increasing globally, including in the Australian National Electricity Market (NEM). This research tries to analyse the impact of this change on price-setting technologies in the NEM. The main objective of the research is to broaden the knowledge on price-setting dynamics across different Australian regional electricity markets and to provide a full picture of which technologies set market prices during different scenarios. By analysing the 5-minute dispatch period data from 2009-2021 we found that price-setting in the NEM is typically dominated by black coal generators. Hydropower, gas, and brown coal generators also set electricity prices for significant periods, however, contribution of renewable generators (solar, wind) to price-setting is still almost negligible. By conducting a 90-day rolling window analysis we found that the share of black coal to set electricity prices is decreasing, while the share of renewable has been increasing through time. We found that black coal generators are more likely to set electricity prices during off-peak periods, while gas and hydropower generators set electricity prices more frequently during peak periods. Among the renewable generators, solar is more active to set electricity prices in the middle of the day when sunlight is abundant, while wind generators set electricity prices more frequently in the early morning and at midday. Coal generators contributed most to electricity prices during periods of lower demand levels, while at the highest demand quantile, coal, gas, and hydropower generators are more likely to set electricity prices. Peak load generators such as gas and hydropower were also setting negative electricity prices. The start-up cost of those generators is lower, and the ramp-up rate is higher so, setting negative electricity prices by those peak load plants was an anomaly. Our research found some evidence that this anomaly may have resulted from strategic behaviour of these generators. Our logistic regression confirms most of the findings of our factor analysis. In addition, it shows that black and brown coal generators are more likely to set electricity prices in summer, while hydropower and gas generators are more likely to set electricity prices in winter. During the carbon tax period, the probability of renewable generators to set electricity prices was increased, while that of fossil fuel-based generators was decreased. Similarly, over time, black coal is less likely to set any extreme electricity prices, while wind and gas generators have become more likely to set prices during spike periods. At the same time VRE technologies also have a higher probability to set negative prices.

Declaration of Originality

The work contained in this thesis has not been submitted for a higher degree to any university or institution other than Macquarie University.

To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made in the thesis itself.

Also, the thesis is an original piece of research and any help and assistance received in this process have been acknowledged.

Santosh Sapkota
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List of Abbreviations

AEMO	Australian Energy Market Operator
AER	Australian Energy Regulator
GARCH	Generalised autoregressive conditional heteroscedasticity
LCOE	Levelized cost of electricity
NEM	National Electricity Market
NSW	New South Wales
UK	United Kingdom
VRE	Variable renewable energy

Chapter 1: Introduction

Large fluctuations in electricity prices are common in today's liberalised and deregulated electricity markets (Janczura et al., 2013; Reichelstein and Sahoo, 2015; Xiao et al., 2015). Wholesale electricity prices in such markets are determined by an auction mechanism, where generators offer bids to supply a specific amount of electricity at a specific price, giving rise to the supply curve. The dispatch price in a regional market typically represents the marginal value of supply at that location and time. Thus, it will be determined as the price of meeting an incremental change in demand at that location and time, or in other words by the price that is charged by the generator (marginal technology) that supplies the 'final' unit of demand. Note that in most electricity markets around the world, irrespective of their bids, *all* generators that are dispatched at that location and time will then be paid the marginal price for their dispatch volume. For the Australian National Electricity Market (NEM), the spot price is then calculated as the average of the dispatch prices in a respective trading interval. Therefore, the level of wholesale electricity price depends upon which technology remains at the margin. So, the information about marginal technologies (also known as price-setting technologies) plays a pivotal role in spot electricity markets.

It is important to understand that the marginal technology may not remain the same for every trading interval; rather, it heavily depends on the marginal costs of generators as well as electricity demand during that trading period. In the absence of market power, bid prices reflect the marginal costs of generators. Therefore, it is more likely that technologies with marginal costs that fall within the commonly observed range of wholesale electricity prices will set the electricity spot prices. It is only at extremely high or low electricity prices that technologies with high or low marginal costs will provide the marginal price-setting units (Blume-Werry et al., 2018). Similarly, when there is low demand for electricity, low-cost generators such as wind turbines and solar can meet the available load and remain at the margin, while at peak demand, costly generating units will be required to dispatch electricity.

Besides demand and supply (marginal costs of generators), price-setting technologies also depend on the energy generation mix in their respective markets. Electricity markets globally have different electricity generation profiles, referred to as the fuel or generation mix of the market. This generation mix determines the merit order of load management, directly influencing technologies that remain at the margin.

A notable reform in the Australian electricity market relates to the generation mix. The government is promoting investments into renewal energies by offering subsidies. As a result, small-scale renewable energy generation (e.g. wind and solar) is replacing electricity production from carbon-intensive techniques such as coal (Australian Energy Market Operator [AEMO], 2020). The Integrated System Plan recently released by the AEMO states that 80% of energy derived from renewable sources seems to be a feasible projection for 2040. Although the carbon tax imposed in July 2012 was withdrawn in July 2014, there have been recent discussions about reintroducing a tax like mechanism or an emissions trading scheme to better facilitate the transition to carbon-free electricity generation (Shahbazgahrouei et al., 2019). This is expected to accelerate the growth of renewable energy generation in Australia even more.

However, one of the greatest challenges in implementing renewable energy technologies is the disparity between supply and demand. Renewable energy is sourced from natural phenomena that cannot be controlled. For example, wind speed, sunlight and water levels determine the production of electricity from renewable sources, which cannot always be perfectly aligned with electricity demand and may show massive fluctuations over short periods. Therefore, a prerequisite to sustain or further increase contributions from renewable energy are effective storage facilities that can store electricity when demand is low and release it when demand is high.

One of the latest candidates to resolve this issue is represented by the University of Queensland's energy leadership ambitions. The University installed a 1.1 MW / 2.2 MWh Tesla Powerpack battery system, the state’s largest battery storage system, at its St Lucia campus in late 2019. A core function of the project is arbitrage; that is, charging the battery when electricity prices are low and discharging it when electricity prices are high (Wilson et al., 2020). The project generated a net revenue of around $45,000 in 2020, with a 3.21 MWh average daily utilisation rate.[1] The average spread (i.e. the difference between income earned from discharging and the cost of charging) for 2020 was $90.34/MWh (Wilson et al., 2020). The success of this project shows support for the important role of emerging battery storage technologies in increasing the share of intermittent renewable energy sources in the grid (Deloitte Center for Energy Solutions, 2015).

1 There are various ways to measure utilisation rate. The university used the sum of megawatt hours charged and discharged as the utilisation rate (Wilson et al., 2020).

As the most competitive energy source in terms of the levelized cost of electricity (LCOE) and supported by government policies to reduce carbon emissions, variable renewable energy (VRE) penetration is increasing globally, including in the NEM (Graham et al., 2020; Sun Power Corporation, 2008). In the period 2012–2020, almost all investments into electricity generation technologies in the NEM were related to VRE. In contrast, coal and other thermal plants faced significant divestment from 2014 to 2017 (AER, 2020). As a result, the share of renewable energy - wind, solar farms and rooftop solar - in the NEM surged from less than 1% in 2006 to 16% in 2020 (AER, 2020).

The change in the energy generation profile resulting from increasing VRE penetration in the NEM raises several research questions. First, what is the effect of this change in price-setting technologies in Australia's regional electricity markets, and how do these price setting technologies change across days or for intraday scenarios? Second, although it can be hypothesized that the share of renewables on price setting is increasing with an increase in VRE penetration. However, the consequences of this increasing VRE share on price setting in the NEM are still unknown and need to be examined. Third, several researchers (e.g. Zhang et al., 2015; Maenhoudt and Deconinck, 2014; Nappu et al., 2013) have found evidence of generators strategically withholding capacity to manipulate prices. Possibly, information about price-setting technologies will help to further explain the strategic behaviours of generators.

Reichelstein and Sahoo (2015) and Rai and Nunn (2020b) argue that because of the negative correlation between wind output and operational demand and the strong correlation between the energy production of wind generators located in the same geographical area, increasing VRE penetration may increase price volatility and reduce system reliability. Similarly, because of the merit order effect of renewables, electricity prices may have decreased (Huismann et al., 2013, O'Mahoney and Denny, 2011; Sensfuss, 2013). However, Härtel and Korpas (2021) predict that in the long term, the price volatility resulting from the intermittency of VRE generators will be addressed by an increase in cross-sectoral consumers and the cross-border flow of electricity, diminishing the merit order effect. These contrasting arguments lead to further research questions: What are the effects of an increased share of price setting among VREs on price volatility and system reliability? Will the merit order effect of renewables prevail in the NEM?

Despite the importance of the question which technologies determine electricity prices in a market, so far very little research has been conducted on the analysis of price setting technologies. To the best of my knowledge, this is the first study to thoroughly examine price-setting technologies in the Australian electricity market. The few previous studies on price setting in electricity markets focus on European markets (Blume-Werry et. al., 2018; Gissey et. al., 2018; Härtel and Korpas, 2021). Furthermore, these studies do not analyse price setting in electricity markets at the same level of detail or at high frequency. Therefore, using 5-minute dispatch data, this thesis provides a major step forward on examining the behaviour of marginal price setting technologies. Furthermore, there are significant differences in the generation mix between Australia and Europe. For instance, most electricity in Australia comes from coal-fired power plants (AER, 2020), while the United Kingdom's (UK) electricity market is dominated by gas plants (Department for Business, Energy and Industrial Strategy, 2020). Nuclear plants are most common in France, while Scandinavian countries have the highest share of renewables (United Nations, 2018). Further, in European countries characterised by a high level of interconnectivity, price setting is heavily influenced by foreign markets. For instance, foreign power plants set electricity prices in the Dutch market 75% of the time (Gissey et al., 2018). In contrast, Australia's isolated electricity market will not be affected spillover effects from foreign electricity markets. Therefore, findings on the European electricity market may not be applicable to the Australian context. Moreover, while these studies have explored price-setting technologies in the European market, they have not explained the relationship between price-setting technologies and price behaviour.

This thesis responds to these gaps in research. Given the increasing share of renewable energy in overall electricity production in the NEM, this research is aimed at exploring the effect of this change on price setting across various regional markets in Australia. The core objective is to broaden the knowledge of price setting in Australian regional electricity markets and obtain a more nuanced picture of the technologies that determine market prices. In the context of the increasing debate about whether to reintroduce a carbon tax that was withdrawn in July 2014, this research also investigates the effect of carbon prices on price setting in the Australian electricity market.

By analysing price-setting data in the NEM, we found that marginal technologies behave significantly different in response to various peak, off-peak or intraday factors. Although black coal generators continue to dominate price setting in most regional markets (except Tasmania), their contribution to price setting overall is declining. Rather, the contributions of renewable energy generators to electricity prices have risen over time, especially since 2018. In terms of intraday variations, we found that black coal generators were more likely to set electricity prices during off-peak periods, while gas and hydropower generators were more likely to set electricity prices during peak periods. Among the renewable energy generators, wind technologies contributed the most to electricity prices over the entire period of a typical day, while battery storage technologies had little effect in setting electricity prices.

In terms of demand, we found that coal generators contributed most to electricity prices in the lowest demand quantile, but as demand increased, the gap between coal generators and other generators (mainly gas and hydropower) narrowed. In the highest demand quantile, coal, gas and hydropower generators were equally likely to set electricity prices. We also found that the generators that set electricity prices during price spikes also tended to set prices during periods of negative pricing. For technologies such as hydropower and gas, which have high ramp-up rates, setting negative electricity prices is an anomaly. By comparing two extreme price levels (i.e. price spikes and negative prices), we found evidence that information about price-setting technologies can also signals strategic behaviour of generators.

We also applied a logistic regression model, which supported our factor analysis results. In addition, it showed that when the carbon tax was implemented, the probability of renewable energy generators setting electricity prices increased, while that of fossil fuel generators decreased. By using logistic regression, we also found that black and brown coal generators were more likely to set electricity prices during summer, while hydropower and gas technologies were more likely to set electricity prices during winter.

This research provides some unique contributions. First, the findings were generated by analysing every 5-minute dispatch period data over a 12-year period (July 2009–June 2021). To the best of our knowledge, no previous research in this area has used data at this frequency. Second, this research tracked changes across days and intraday for marginal technologies and the role of recent developments such as the increase in renewable energy generation, carbon pricing and battery storage technology in the Australian context. Third, the research explores whether knowledge about price-setting technologies technology signals something about price behaviour and the strategic behaviours of generators.

Our research provides useful insights for consumers, electricity generators, electricity retailers and policymakers because knowledge about price-setting technologies plays an importance role in decision-making. Retail electricity prices are fixed in most regional markets. However, 33% of household electricity costs come from wholesale electricity prices (AER, 2020). Therefore, if spot prices are largely determined by expensive producers such as gas generators, which have high marginal costs, wholesale electricity prices will increase, creating upward pressure on long-term retail prices. Similarly, information about price-setting technologies provides clues to generators on where to invest. If prices are largely determined by low-cost generators such as wind turbines, and solar panels, it may not be profitable to invest in high-cost generators.

If price-setting technologies frequently change, this will create price fluctuations. Such irregular price events and their duration will be potentially harmful to electricity retailers, who must manage the associated price risks (Anderson et al., 2007). Further, information about marginal technologies will be useful for policymakers, who have an incentive to minimise overall electricity prices, reduce price volatility, maintain system reliability, increase the share of renewable resources and reduce carbon emissions.

The remainder of this thesis is structured as follows. Chapter 2 reviews the relevant literature. Chapter 3 provides a brief overview of the NEM, including generation mix profiles across regional markets as well as price-setting mechanisms in Australia. Chapter 4 presents the research methodology and data collection, and Chapter 5 presents the findings of the conducted empirical analysis. Chapter 6 provides a summary and concludes the thesis.

Chapter 2: Literature Review

Levelized cost of electricity LCOE is the tool most widely used to compare the competitiveness of generation technologies. The LCOE measures the total lifecycle cost per megawatt hour of electricity supply of a particular generation technology. Lifecycle cost includes both investment (capital) and operational costs. The US Energy Information Administration (2021) defines LCOE as an estimate of the revenue required to build and operate a generator over a specified cost recovery period.

Some researchers argue that LCOE is a flawed tool to compare the competitiveness of generation technologies, because it treats all forms of generated electricity as a homogenous product governed by a uniform price. In the auction market, the cost of electricity may vary widely across both across days and during intraday intervals. Joskow (2008) found that the difference between the high and low hourly prices can be up to four orders of magnitude. Rai and Nunn (2020a) found that dispatchability premiums (the difference in prices received by dispatchable and non-dispatchable generators) in the NEM have significantly increased Therefore, Joskow (2011) argues that it is important to consider wholesale market price variations when measuring the competitiveness of generators, because hourly output profiles, and the associated market value of electricity supplied by VRE technologies may differ from that of dispatchable technologies.

Reichelstein and Sahoo (2015) argue that the flaws in traditional LCOE can be eliminated by introducing a co-variation coefficient into the analysis that captures synergies (or complementarities) in daily patterns of power generation and pricing. Based on their proposition, generators are competitive only if the product of the electricity price and co-variation coefficient is equal to or higher than the traditional LCOE. The co-variation coefficient for dispatchable generators such as fossil fuel-fired power plants is 1 because energy production can be controlled according to price variations. In terms of solar generation, by using simulated data from the National Renewable Energy Laboratory, Reichelstein and Sahoo (2015) found that there is a significant correlation between high prices and periods of high solar generation. This correlation was higher in summer than in winter for both small and commercial consumers. In contrast, they found a weak association between high prices and periods of high wind generation, especially in summer. During summer, wind generators produced more electricity in the early morning and evening, when prices were generally the lowest. In contrast, in winter, electricity production from wind generators peaked during the day. The co-variation coefficients between price and electricity production for summer and winter were 0.80 and 0.95, respectively. Based on their co-variation coefficients, Reichelstein and Sahoo (2015) concluded that their adjusted LCOE was 10–15% lower than the standard LCOE for solar photovoltaic projects and 10–15% higher for wind projects. Therefore, the unadjusted LCOE undervalues solar photovoltaic generation and overvalues wind energy generation.

While Reichelstein and Sahoo (2015) studied co-variations between prices and electricity output, Rai and Nunn (2020 a) investigated the correlation between electricity generation from wind turbines and electricity demand in the South Australian electricity market. They found a negative correlation between wind output and operational demand but a strong correlation between the energy production of wind firms located in the same geographical area. The negative association between demand and output and the positive association between energy production from different generators means that there is greater aggregate supply available when wind generators are producing electricity, driving down spot prices. Rai and Nunn (2020a) claim that these wind generators receive dispatch-weighted prices, which are lower than firming or time-weighted average prices. The dispatch-weighted price is defined as the price received by generators that meet residual demand (excess demand after the dispatch of VRE generators), while firming prices are the value received by fast-start and flexible generators. The authors conclude that in the NEM, there is a significant and increasing dispatchability premium, defined as the difference in prices received by non-dispatchable plants and either flexible or inflexible dispatchable plants. Using South Australia as an example, they found that this dispatchability premium has been approximately 70% since 2016 and has more than doubled between 2014 and 2019.

On the other hand, Härtel and Korpas (2021) argue that this dispatchability premium will be eliminated in the long run, and price volatility will be well managed by both demand and supply interventions. On the supply side, increasing the flexibility of conventional power plants or detaching electricity from heat production in combined heat and power plants can reduce negative or zero prices. On the demand side, the expansion of storage facilities and the use of hybrid technologies may be options to manage intermittency in supply. Hybrid technologies are technologies that use electricity when excess power is generated by VRE technologies and chemical energy when supply decreases. Another important factor in light of increasing VRE penetration are so-called cross-sectoral technology combinations that exhibit significant efficiency and flexibility, giving greater freedom in planning and operating future energy systems.

To sustain future energy systems dominated by VRE generators, the integration of conventional electricity producers and end users such as buildings, industries and transportation is expected to increase. Similarly, to manage intermittency in VRE, the cross-border supply of electricity is expected to surge. In the context of this expected future trend, Härtel and Korpas (2021) studied the effect of cross-sectoral integration and cross-border supply on market clearing and price-setting behaviours using the cross-sectoral capacity expansion planning model developed by Härtel and Ghosh (2020) and the transmission expansion planning model developed by Härtel (2020). The authors predict that the supply of cross-sectoral energy to meet demand will lead to additional electricity consumption in traditional power sectors in all European markets by 2050. In these markets, in comparison to 2011, the electricity demand is expected to increase by 45% to 138%.To increase the flexibility of generators in low–carbon emission settings, battery storage technologies with a 63.3 GW capacity will play a pivotal role.

The main findings of this paper are that VRE generators, cross-sectoral consumers and cross-border exports and imports will play a vital role in price-setting in the European electricity market. Based on valid opportunity costs, bi- and multivalent electricity consumers will be influential in price setting across the European market. Hybrid price-setting technologies mainly include direct resistive and heat pump heating units, which are at the interface of the power and heat sectors. However, because of high opportunity costs, transport sector technologies will play only a background role in making marginal bids. During this period, the supply side will be dominated by either onshore or offshore VRE generation, mainly from wind and solar photovoltaics.

Similarly, with an increase in cross-border integration, cross-border imports and exports will play a crucial role in price setting; however, this will vary depending on the geographical location of the market Härtel and Korpas (2021). For instance, cross-border electricity flow may have limited influence on price setting in markets such as Finland and Poland because of their geographic isolation. In contrast, electricity imports will occupy a major share in the German and Luxembourg markets, while electricity exports will be crucial in setting market prices in Norway and Sweden. The researchers predict that with an increase in cross-sectoral consumers and the cross-border flow of electricity, cases of zero or negative pricing will decrease. Because the merit order effect will diminish in the long term, refinancing renewable energy sources such as wind and solar may well become possible. Another effect of an increase in the cross-border exchange of electricity is a decrease of the role of generators in price setting.

Härtel and Korpas (2021) studied future price-setting behaviour in Europe based on greenhouse gas emission reductions of 87.5% by 2050. In contrast, Blume-Werry et al. (2018) studied price-setting technologies in current European markets. They tested the conventional claim that gas- and coal-fired power plants set electricity prices in Europe most of the time. In the absence of market power, bid prices reflect the marginal costs of generators. Therefore, it is more likely that technologies with marginal costs that fall within the commonly observed range of wholesale electricity prices will set electricity spot prices. Only at extremely high or low power prices will technologies with high or low marginal costs provide marginal price-setting units. Nuclear power plants and VRE sources often have low marginal costs, while during peak generation, diesel and oil generators have high marginal costs. Therefore, unless electricity prices in any given period are excessively high or low, it may be assumed that gas- or coal-fired power plants set the electricity price.

As expected, Blume-Werry et al. (2018) found that gas- and coal-fired power plants played a crucial role in price setting. However, alongside those technologies, nuclear and VRE technologies provided price-setting units for a significant number of hours in low-demand scenarios. For mid- to high-priced hours, reservoirs and pumped hydropower stations were responsible for price setting for a considerable number of hours. Blume-Werry et al. (2018) also found that price-setting technologies varied significantly across European markets based on the country's generation profile and market connectivity. Large countries significantly influenced price setting in smaller neighbouring countries. Gas-fired power plants were mostly responsible for price setting in southern Europe and the UK, while the northern European market was dominated by hydroelectric storage and pumped hydroelectric plants. The central European market showed the most balanced picture, where price setting reflected the overall generation portfolio.

Blume-Werry et al. (2018) also found that changes in the carbon price did not affect the general price-setting structure. With the introduction of the Dutch carbon price of €18 per tonne of carbon dioxide, carbon dioxide output and electricity production from thermal plants will reduce. This will have a substantial impact on wholesale power prices, fuel switching, carbon emissions and the import–export ratio, while the general structure of price-setting technologies will remain largely the same as that in the reference scenario.

Gissey et al. (2018) largely confirm the findings of Blume-Werry et al. (2018). Studying 6 years of historical data (2012–2017) in European electricity markets, the authors suggest that even though renewable energy generation is on the rise, fossil fuels are still responsible for determining Europe’s electricity prices. These fuels were most influential in setting electricity prices in major European markets such as Germany and the UK, but had limited importance in the French and Norwegian markets. Further, gas-fired plants set electricity prices more frequently in the UK than in any other major European electricity market. The marginal share of gas in the UK was 2–2.5 times higher than that in Spain and Italy and nearly five times higher than that in Germany.

Given that the majority of fossil fuels in the UK are imported, electricity prices depend heavily on exchange rates. Following the European Union referendum, the pound depreciated by 15%, and the UK experienced an 18% rise in its wholesale electricity price and a 6% increase in its retail electricity price. Given its dependence on imported fuels, the UK has suffered increased costs of nearly £1 billion in a single year. The high cost of carbon in the UK is another important factor, putting significant upward pressure on wholesale electricity prices. The price paid for carbon emissions in the UK is much higher than for the rest of Europe, which is leading power inflow into UK with a high marginal share of interconnectors. Thus, it is not surprising that the three interconnections involving the highest electricity prices were those related to the UK. Therefore, Gissey et al. (2018) concluded that the UK’s dependence on fossil fuels has effectively reduced its competitiveness with European countries.

Chapter 3: The Australian National Electricity Market

3.1 Overview

The NEM is the wholesale electricity market of Australia, which commenced operations in December 1998. As one of the world's longest interconnected power systems, the NEM spans five interconnected states in Australia: Tasmania, South Australia, Victoria, Queensland and New South Wales (NSW) (including the Australian Capital Territory). With 40,000 km of transmission lines and cables, the NEM supplies around 200 TWh of electricity to more than 10 million customers each year (AER, 2020).

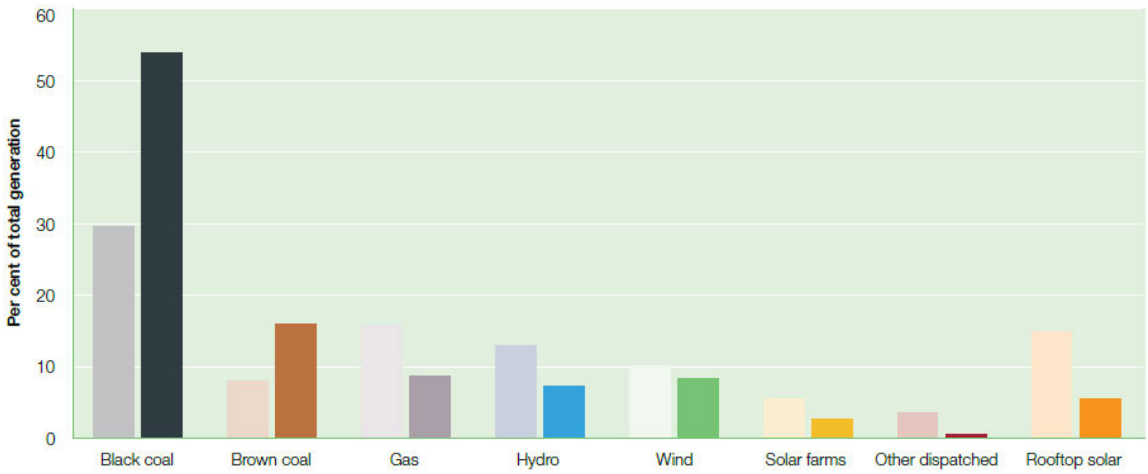
The AEMO is responsible for managing the NEM. It was established in 2009 with the key aim of facilitating the operation of the wholesale electricity market, improving its efficiency and coordinating the interconnected power system. The AEMO is responsible for managing all functions required to maintain the efficiency and reliability of the NEM. To adequately meet supply and demand, it ensures that the right amount of electricity is produced and supplied at the right time. To match real-time demand with supply, the AEMO has implemented sophisticated systems that signal electricity producers about electricity demand every five minutes. In the case of a power shortage, the AEMO issues a notice to electricity generators to increase production or may even directly intervene as a last resort. Similar, on the distribution side, it ensures that transmission structures are sufficiently reliable and efficient to transmit electricity to end users. It monitors electricity frequency and voltage to assure system security. To ensure that the system can accommodate any subsequent losses of generation or transmission capacity, it also monitors the impact of planned power outages.

3.2 Generation Technologies in the National Electricity Market

The AEMO dispatches a diverse range of generators to meet the available demand in the NEM. These generation technologies can be categorised into dispatchable generation technologies and intermittent generation technologies. Conventional technologies such as coal, gas and nuclear are dispatchable generators in which output can be controlled by system operators based on market demand. Market power aside, electricity from these generators is produced when wholesale electricity prices exceed short-term marginal costs (Joskow, 2008). In contrast, the output from intermittent generators is heavily dependent on natural phenomena and is not controllable by system operators. Although the market value of electricity generated by hydropower is higher than the short-term marginal costs, if there are insufficient water levels, electricity cannot be produced. Most renewable generators, such as solar and wind, produce electricity only intermittently and heavily depend on the time of the day, location, season and weather. Most of the electricity in the NEM is supplied by fossil fuel–based dispatchable generation technologies. In 2019, almost 54% of electricity was produced from black coal, 14% was produced from brown coal, and 9% was produced from gas. Only 27% of the remaining electricity was supplied by renewable generators. With respect to renewable technologies, the largest amount of electricity was supplied by wind generators, followed by hydropower, rooftop solar panels and solar farms (see Figure 3.1).

Figure 3.1

Generation Technologies in the National Electricity Market, 2019



Note. Capacity = left column; output = right column. From *State of the Energy Market 2020*, by Australian Energy Regulator (2020)

Each generator type has unique characteristics in terms of initial investment, start-up costs, ramp-up rates, marginal costs, bidding patterns and generation strategies. For instance, coal generators have high investment costs, low variable costs and low ramp-up rates, while gas generators have low investment costs, high variable costs and high ramp-up rates. The fuel costs of hydropower generators are relatively low because they do not directly pay for water; however, they depend on storage capacity and rainfall to replenish storage, making their opportunity costs relatively high. Given their high variable costs, hydropower and gas generators produce electricity when electricity demand and spot electricity prices are high, while coal generators can produce electricity even at lower spot prices.

Table 3.1

Generation technologies and their costs and ramp up rates at NEM

Generation Technology	Investment Costs/ (Per MWh)	Start-up Costs	Marginal Costs	Ramp up rates
Coal generators	High	High	Low	Low
Gas generators	Low	Low	High	High
Hydropower (pump)	High	Low	High	High
Wind generators	Medium	Low	Very low	Very Low
Solar generators	Medium	Low	Very low	Very Low

Source: (Gonzalez et al., 2017)

3.3 Determination of Spot Prices in the National Electricity Market

In the NEM, a typical trading day commences at 4.00 am and ends at 3.59 am the next morning. For each trading day, all generators are required to submit a bid to supply a specific quantity of electricity at a specific price prior to 12.30 pm of the previous day. Each bid must contain a 10-price band with the corresponding quantity. Such bids are categorised as commercial in confidence and represent the base operating level of the energy producer. Bidding prices can fall anywhere between the market floor and market price cap (i.e. the lowest and highest possible bid prices) (Ali et al., 2017). Under the National Electricity Rules, the Australian Energy Market Commission (2020) is required to calculate and publish the market price cap by 28 February each year. The price cap is based on the consumer price index and was fixed at $15,000 in 2020.

Table 3.1 shows a typical example of a bid submitted by a generator to supply electricity. In this case, the generator is ready to supply 100 MWh of electricity with an offer price of $50 or above. Similarly, if the offer price is $20, the generator is willing to supply 50 MWh of electricity.

Table 3.2

Bid Example of a Typical Generator

Band	1	2	3	4	5	6	7	8	9	10
Price (per MWh) (AUD)	−999	−50	2	10	20	50	75	100	200	300
Quantity	0	20	0	0	30	50	0	0	0	0

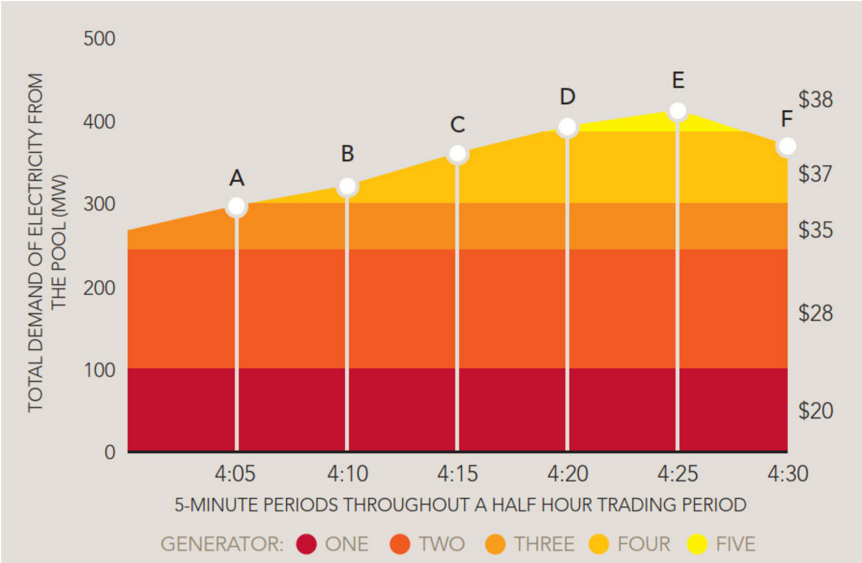
Interestingly, even at the negative price (-50 to 0), the generator is willing to supply 20 MW/h of electricity. The reason for this resides in some unique features of the electricity industry. First, for safe and efficient operations, some electricity generators have minimum on/off time, which cannot be frequently switched on and off within a short period. Second, startup costs are also significant for certain technologies such as nuclear and coal. Third, the limits on ramp rates prevent a generating unit from increasing or decreasing to a specific generation level instantaneously. Finally, even though the bid price is negative, the generator expects the positive settlement price (spot price), determined by the marginal technology.

To determine its production schedule, the AEMO arranges the bids it has received in ascending order for each 5-minute dispatch period, giving rise to the supply curve. Initially, the lowest-cost generators are used to meet the available demand. If these generators are unable to meet the prevailing demand, then higher-cost generators are used. For every dispatch period, the dispatch price is calculated, which is the maximum price offered among dispatched generators. The spot price for the financial settlement is then determined for each trading interval of 30 minutes by taking the average of six dispatch prices (Ali et al., 2017).

Figure 3.2 demonstrates the process of determining the spot price with an example. At 4.05 pm, 300 MW of electricity is in demand. To meet this demand, Generators 1 and 2 (low-cost generators) are dispatched in their full bid capacity, while Generator 3 is partially dispatched. The dispatch price is $35 (the highest offer price among the scheduled generators) and generator 3 is the price setting generator (marginal generator) as it determines the dispatch price at this dispatch period. At 4.10 pm, Generators 1, 2 and 3 are no longer capable of meeting the prevailing demand; thus, Generator 4 is partially dispatched at a dispatch price of $37 and generator 4 is the price setting generator. When demand further increases to 400 MW at 4.20 pm, Generators 1, 2, 3 and 4 are fully dispatched, and Generator 5 is partially dispatched at a dispatch price of $38. Thus, these six dispatch periods are associated with dispatch prices of $35, $37, $37, $38, $38 and $37, respectively.

Figure 3.2

Determination of Spot Price



Note. From AEMO, 2020.

Dispatch prices are determined at 5-minute intervals based on the principle of low cost. Every half hour, the six dispatch prices for that period are averaged to determine the spot price for each trading interval for each region of the NEM. In the above example, the spot price is $37/MWh (i.e. [35 + 37 + 37 + 38 + 38 + 37]/6). This spot price is used for the settlement of financial transactions that took place during this trading interval[2]. The AEMO provides information about predicted load, spot price and available supply along with the other relevant information such as weather and temperature to market participants. Generators may submit their rebids to supply electricity 5 minutes prior to dispatch. While doing so they may change the volume of supply, however they are not permitted to change their offer price.

[2] From 1 October 2021, 5-minute dispatch prices are being used as settlement prices instead of 30-minute spot prices.

Chapter 4: Data and Methodology

4.1 Data Sources

Most of the data for this study were drawn from the AEMO website. The NEM Dispatch Engine provides information about marginal generators in XML files for every 5-minute dispatch period[3]. These data provide information on marginal generators, dispatch prices and corresponding bands for each dispatch period. Similarly, the system load data were downloaded from the Market Management System Data Model database[4].

For analytical purposes, we collected data from a 12-year period (July 2009–June 2021). This sample period was expected to cover most of the recent developments in the NEM, enabling analysing the effects of such developments. For instance, a carbon tax was implemented in 2012 and withdrawn in 2014 (Shahbazgahrouei et al., 2019). Similarly, there was a significant change in the generation mix during this period. As shown in Figure 4.1, from 2014 to 2019, considerable capacity provided by coal-fired generators in various regional markets was replaced by renewable energy, mainly wind and solar plants. More than 2,000 MW of renewable energy capacity (mainly solar) was added to the NSW, Queensland and Victorian markets during this period. As a result, the share of renewable energy increased from 1% in 2006 to 16% in 2019 (see Figure 4.2). Along with this increase in VRE, to maintain a reliable and secure power system in the face of weather-driven volatility, battery storage technology emerged as a prime candidate in the frequency control ancillary services market, pushing gas to the second position (AER, 2020).

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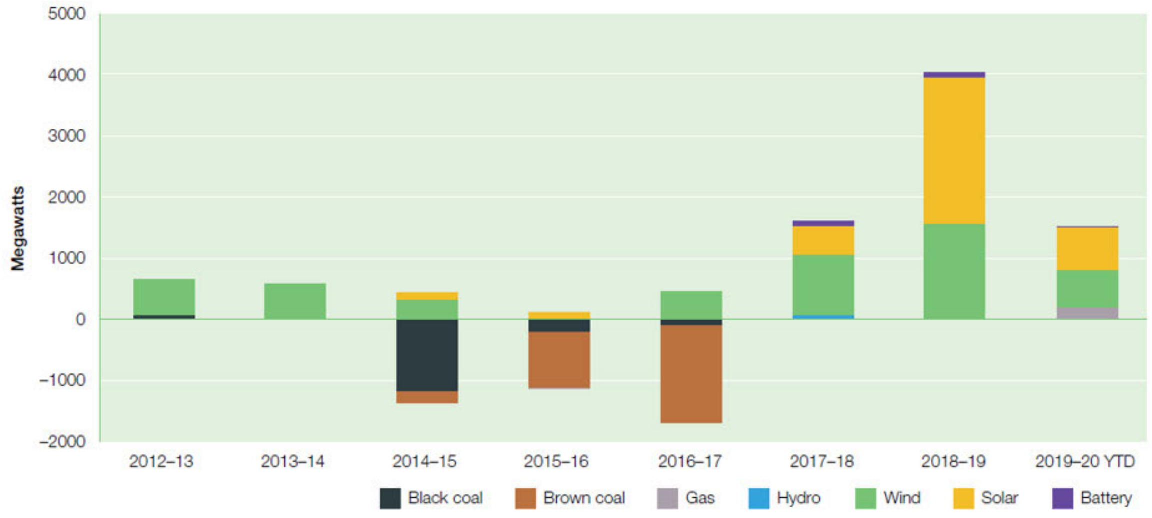
[3] https://visualisations.aemo.com.au/aemo/nemweb/index.html#mms-data-model
[4] https://aemo.com.au/energy-systems/electricity/national-electricity-market-nem/data-nem/market-management-system-mms-data

Figure 4.1

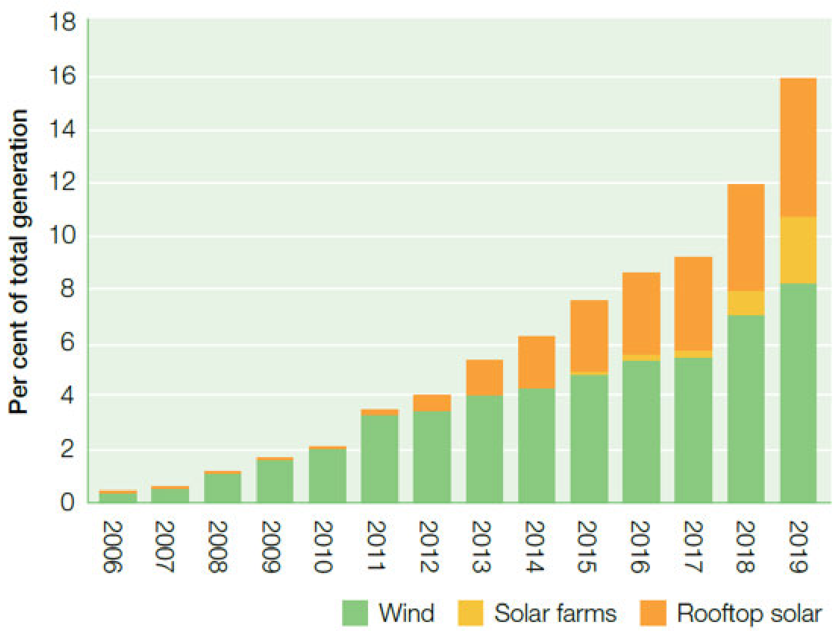
New Generation Investments and Plant Withdrawals



Note. From *State of the Energy Market 2020*, by Australian Energy Regulator (2020)

Figure 4.2

Share of Wind and Solar Energies in Total Electricity Production



Note. From *State of the Energy Market 2020*, by Australian Energy Regulator (2020)

4.2 Analysis of Factors Affecting Price-Setting Technologies

Our analysis will start with an examination of the share of price-setting technologies in the different regional markets for the whole study period. This will help us to understand which technologies remained at the margin for the entire sample period. Thereafter, we will conduct a 90-day rolling window frequency analysis on the share of price-setting technologies, enabling us to understand how those price-setting technologies evolved over the period.

Electricity demand and supply are expected to vary significantly within an intraday period. During peak hours (2.00 pm to 8.00 pm), household electricity demand accelerates. Similar, the supply of electricity, mostly that from renewable generators, is also affected by the time of day. Hourly changes in price-setting technologies were analysed to determine the impact of intraday demand–supply variations on marginal technologies.

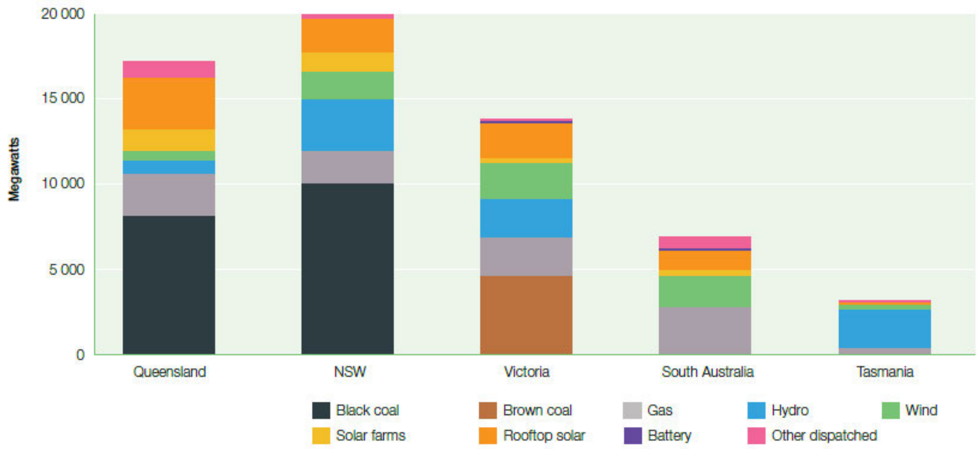
To analyse how price-setting technologies changed at different levels of demand and price, we first derive a load curve for the entire sample period to depict the different levels of demand and the average share of each generation technology at that level of demand. The load curve is derived by plotting the electricity demand of a particular regional market in descending order on the Y axis and the corresponding duration of that load on the X axis. In a similar manner, to determine the effect of price variations on price-setting technologies, a price curve is developed that will allow us to examine the contribution of each technology to price setting.

To determine whether information about marginal technologies may explain the strategic behaviour of generators, we compare the contributions of generators to price setting in negative price situations with those in negative price situations following a price spike at any dispatch period within the same trading interval. This difference in price-setting share may be a result of either a limit in ramp-up rates or the strategic behaviour of generators. When the electricity market experiences a price spike prior to negative prices, peaking generators may be supplying electricity with higher demand or lower supply. Because the price instantly moves from one extreme (price spike) to the another (negative price), those peaking generators may be unable to ramp down their production and are compelled to supply electricity, even at negative prices. By considering generators' ramp-up rates, we aim to explain whether differences in price-setting contributions between negative price situations with no conditions and those with a price spike at any dispatch period during the same trading interval are attributable to generators' ramp-up rates or strategic behaviour.

Our analysis of the factors affecting price-setting technologies has three main objectives: First, the rolling window frequency analysis will help us to identify how price setting has changed over time, expanding our understanding about the trends in price-setting technologies in the NEM in light of the most recent developments on renewable energy, the shutdown of major coal-fired power plants and policy changes. Second, the NEM comprises five heterogeneous markets, each with its own distinct characteristics. Queensland and NSW are dominated by black coal, Victoria is dominated by brown coal, Tasmania is dominated by hydropower, and South Australia has one of the highest VRE penetration rates (see Figure 4.3). Our analysis of factors affecting price-setting technologies will allow us to compare the peculiarities of these regional markets. Finally, little research has been done on identifying the variables affecting price-setting technologies. Our analysis will help to fill this gap in the literature and help us to identify the factors determining marginal technologies.

Figure 4.3

Generation Capacity in the National Electricity Market by Region and Fuel Source, 2019



Note. From *State of the Energy Market 2020*, by Australian Energy Regulator (2020).

4.3 Parametric Analysis

In addition to the more descriptive analysis described in the previous section, we also applied a rolling window logistic regression to analyse how price-setting technologies behave under different circumstances. The dependent variable (marginal technology) is a binary variable that takes on the value of either *yes* or *no* for different generation technologies. Therefore, instead of an ordinary regression analysis, a logit model was chosen. The choice of variables was guided by various studies on modelling electricity prices. For example, Misiorek et al. (2006) included system load, temperature and power plant availability to model electricity prices in the California Power Exchange, using autoregressive, autoregressive-moving average with exogenous terms, threshold autoregressive, threshold autoregressive with exogenous terms, generalised autoregressive conditional heteroscedasticity (GARCH) and regime switching models. Serletis and Shahmoradi (2006) used natural gas as an explanatory variable to model electricity prices in Alberta's power market using the GARCH-in-mean method. Based on this line of thought, we will apply the following model:

$$\ln(P_{it}/1 - P_{it}) = It = \beta_1 + \beta_2 SPD_{\mathrm{t}} + \beta_4 PHD_t + \beta_5 SD + \beta_2 WD_t + \beta_4 NPD_t + \beta_5 PSD$$

where P_{it} is the probability that technology i is setting a price at time t; *SPD* is the shoulder period dummy (7.00 am to 2.00 pm); *PHD* is the peak hour dummy (2.00 pm to 8.00 pm); *SD* denotes a dummy for the summer months; *WD* is a dummy for the winter months; *NPD* is a negative price dummy; *PSD* is a dummy for price spikes; and *CD* is the carbon tax period dummy (July 2012–July 2014). Here, we have defined *price spikes* as all the prices that lie at the upper one percentile in that particular regional market.

Chapter 5: Empirical Results

This chapter is divided into two parts. In the first part, the results from an analysis of the key factors affecting price-setting technologies are presented. We found that price-setting technologies were influenced by a variety of factors such as, e.g., the time of the day, electricity demand and spot electricity prices. We also found that the price-setting share of fossil fuel–based technologies decreased, while that of renewable technologies increased over time. Further, we observed that the contribution of various generators to price setting as well as the effects of factors on price-setting technologies differed significantly across the regional markets.

The second part of this chapter presents results for an applied logistic regression analysis in order to quantify more rigorously the effects of the investigated factors on price-setting technologies. We observed that the time of day (peak or shoulder period), price extremes (lower and upper price levels), seasonal behaviour (winter or summer months) and the carbon tax period (July 2012–July 2014) significantly and strongly affected the price setting of all generation technologies. Similarly, by conducting a 3-years rolling window logistic regression analysis, we found significant changes in the magnitude of these effects on the probability of price setting for different generation technologies through time.

5.1 **Analysis of Factors Affecting Price-Setting Technologies**

In terms of price setting, black coal generators dominated the Australian electricity market throughout the study period (2009–2021). Black coal generators set electricity prices 62% of the time in the Queensland market, 59% of the time in the NSW market, 41% of the time in the Victorian market, 38% of the time in the South Australian market, and only 24% of the time in the Tasmanian market (ranking second after hydropower). Hydropower, gas and brown coal technologies also set electricity prices for significant periods of time. Hydropower generators set electricity prices more than 50% of the time in the Tasmanian market and were the second-highest contributing technology in the other regional markets. Natural gas (which may be combined with diesel or fuel oil) had the third-highest share of price setting, followed by brown coal (see Table 5.1).

Table 5.1

Relative Price-Setting Contribution of Technologies in Regional Markets (July 2009–June 2021)

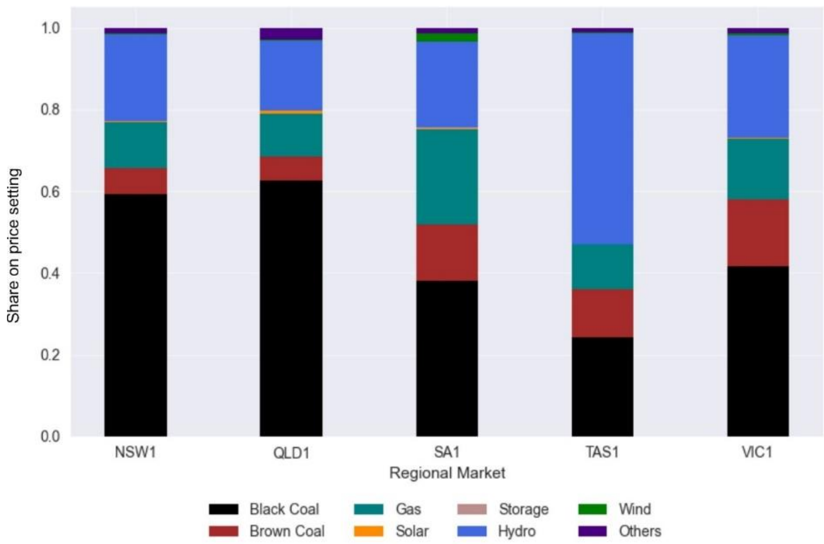
Market	Black coal	Brown coal	Gas	Solar	Storage	Hydro	Wind	Other
New South Wales	58.89%	6.35%	11.42%	1.65%	0.04%	21.30%	0.35%	0.00%
Queensland	62.21%	5.92%	10.67%	3.47%	0.03%	17.36%	0.32%	0.00%
South Australia	37.69%	13.93%	23.52%	1.65%	0.07%	20.89%	2.25%	0.01%
Tasmania	24.15%	11.78%	11.06%	1.19%	0.11%	51.34%	0.37%	0.00%
Victoria	41.23%	16.40%	15.01%	1.60%	0.07%	24.97%	0.72%	0.00%

Note. The number of times that each generator set the electricity price at each 5-minute dispatch interval during the sample period was summed up and is expressed here as a percentage. Other = landfill gas, diesel, waste coalmine gas, coal seam methane, kerosene and wastewater technologies.

Wind and solar generators were less significant in setting electricity prices. While they made minor contributions to price setting in South Australia and Queensland, their contribution to price setting in the other regional markets was very low throughout the sample period (see Figure 5.1).

Figure 5.1

Relative Price-Setting Contribution of Technologies in Regional Markets (July 2009–June 2021)



Note. The number of times that each generator set the electricity price at each 5-minute dispatch interval during the sample period was summed up and is expressed here as a percentage.

5.1.1 Decreasing contribution of black coal to set electricity price

Interestingly, in all regional markets, the contribution of fossil fuel–based technologies to price setting decreased throughout the study period, while that of renewable energy generators (including hydropower) increased. Over the 12-year period, the contribution of black coal to price setting slumped by 10% (from 47% in 2009 to 37% in 2021), brown coal decreased by 3% and gas decreased by 1%. In contrast, a significant increase was seen in the case of renewable generators. The contribution of solar generators increased by 6% (from 0.18% to 6.49%), while that of wind generators and hydropower both increased by 4%. However, the changes in contributions of technologies to price setting over time were not stable. For example, although the share of black coal decreased in most years, it increased in 2011, 2014, 2015 and 2020. Similarly, a significant hike was observed in the contribution of brown coal in 2016. These fluctuations were also observed for other technologies (see Table 5.2).

Table 5.2

Annual contribution of Technologies to Electricity Price Setting in the National Electricity Market for each year 2009-2021

Year	Black coal	Brown coal	Gas	Solar	Storage	Water	Wind	Other
2009	47.51%	12.63%	12.62%	0.18%	0.00%	26.97%	0.10%	0.00%
2010	45.08%	10.74%	11.62%	0.36%	0.00%	32.02%	0.17%	0.01%
2011	45.42%	10.58%	15.44%	0.28%	0.00%	27.98%	0.29%	0.01%
2012	45.30%	10.78%	17.49%	0.46%	0.00%	25.53%	0.43%	0.00%
2013	41.96%	15.57%	12.74%	1.24%	0.00%	27.86%	0.63%	0.00%
2014	45.62%	15.12%	10.59%	2.40%	0.00%	25.56%	0.70%	0.00%
2015	46.72%	14.40%	10.51%	0.96%	0.00%	27.10%	0.31%	0.00%
2016	42.14%	14.95%	14.52%	1.78%	0.00%	26.02%	0.59%	0.00%
2017	41.63%	9.36%	17.79%	1.17%	0.00%	29.92%	0.14%	0.00%
2018	41.22%	6.14%	16.59%	1.57%	0.00%	33.48%	1.01%	0.00%
2019	40.12%	6.17%	17.86%	3.32%	0.14%	31.47%	0.92%	0.00%
2020	42.51%	8.79%	14.67%	4.87%	0.36%	26.67%	2.14%	0.00%
2021	37.65%	9.80%	11.21%	6.49%	0.52%	30.21%	4.11%	0.00%

To identify the changes in price-setting technologies throughout the study period, a rolling window frequency analysis was conducted for each regional market. Based on five-minute dispatch intervals, 90-day moving averages were calculated and plotted to depict these changes. Figures 5.2–5.6 show the changing role of generators in setting electricity prices in each regional market.

Figure 5.2

90-Day Moving Average of Contribution to Price Setting in New South Wales for different technologies

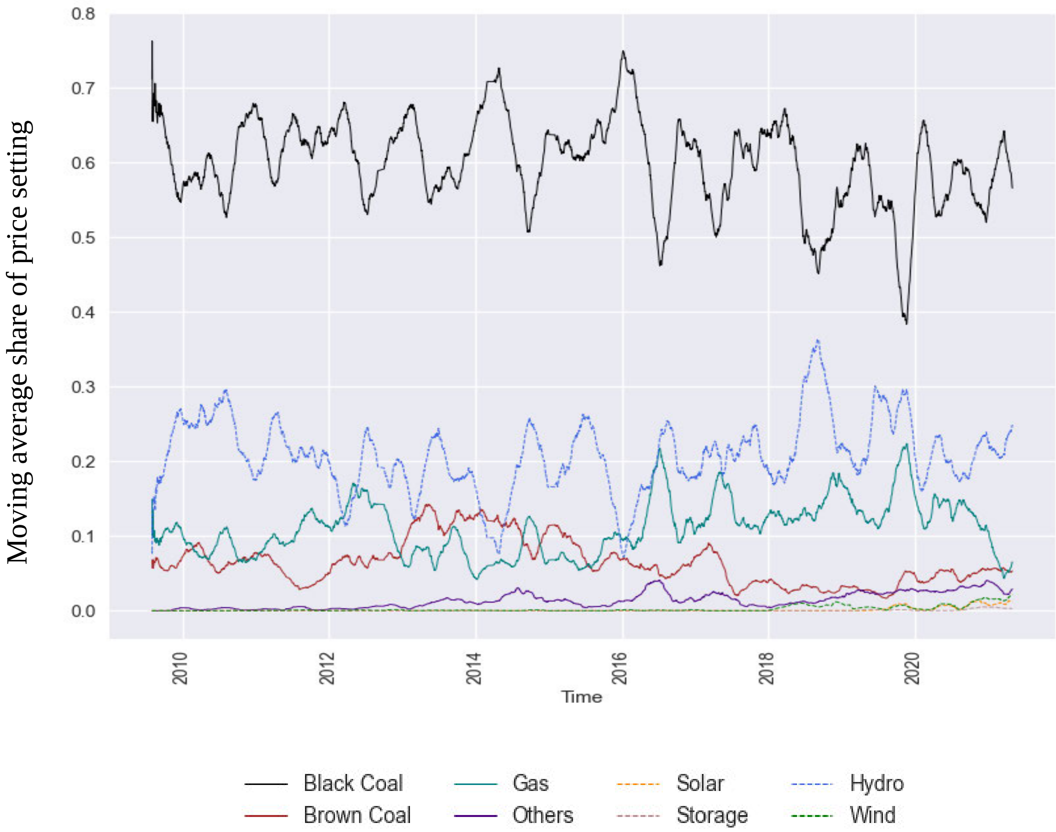


Figure 5.3

90-Day Moving Average of Contribution to Price Setting in Queensland for different technologies

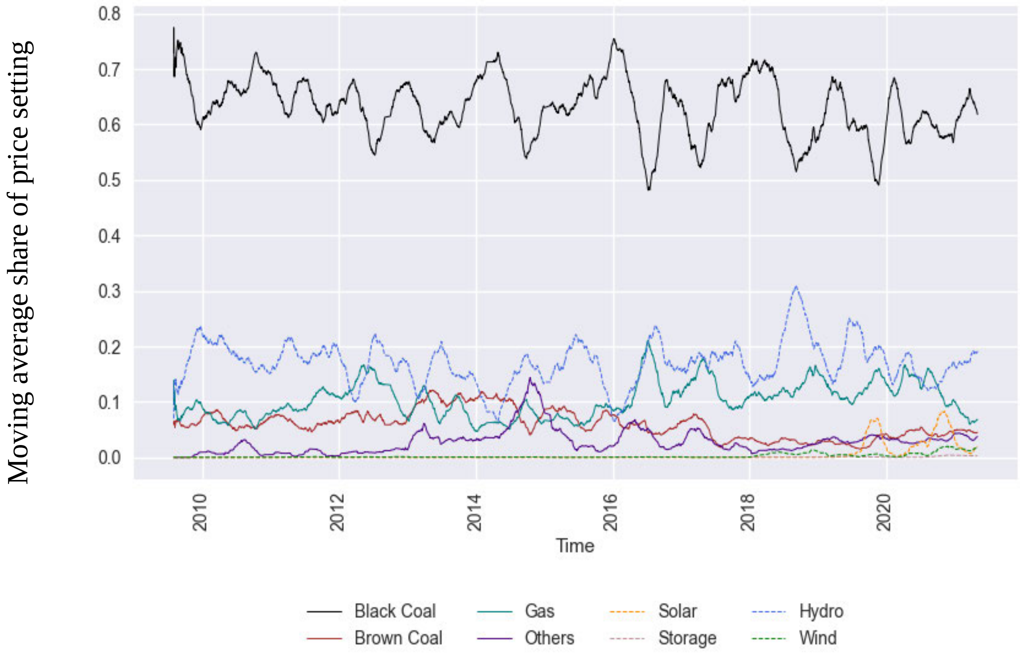


Figure 5.4

90-Day Moving Average of Contribution to Price Setting in South Australia for different technologies

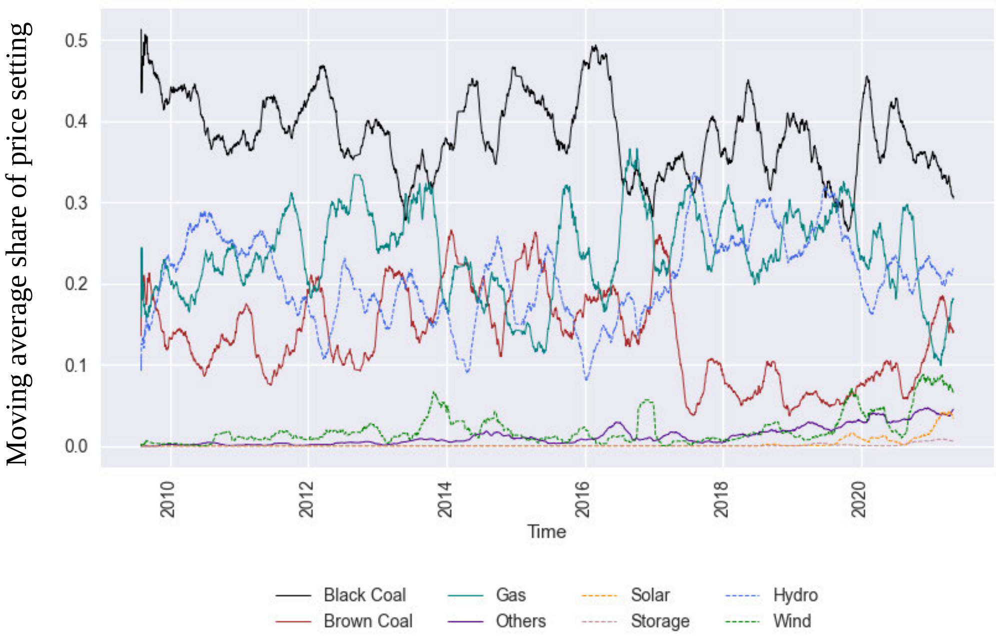


Figure 5.5

90-Day Moving Average of Contribution to Price Setting in Tasmania for different technologies

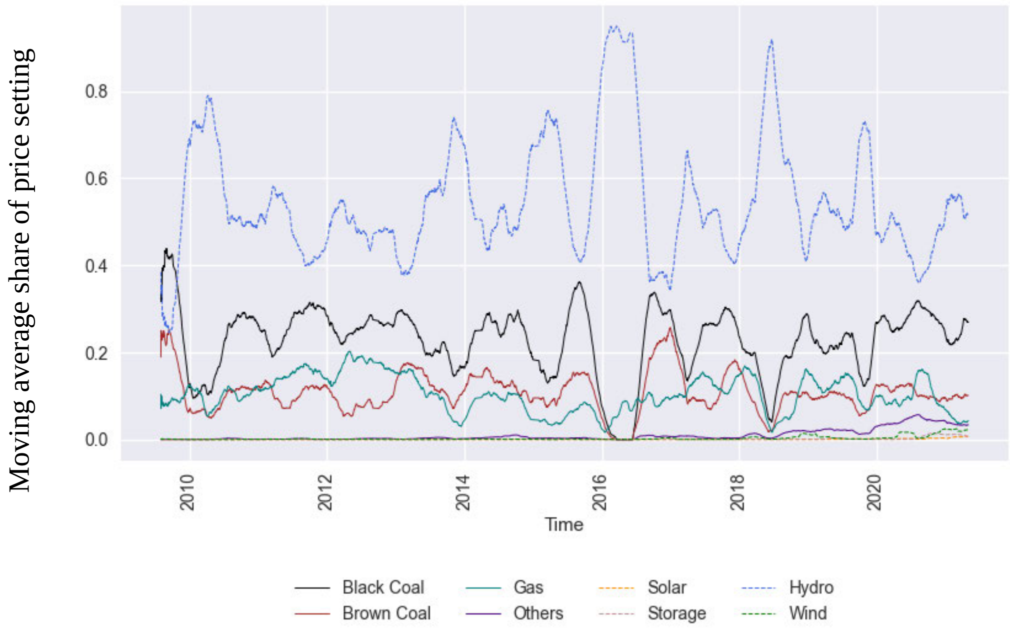
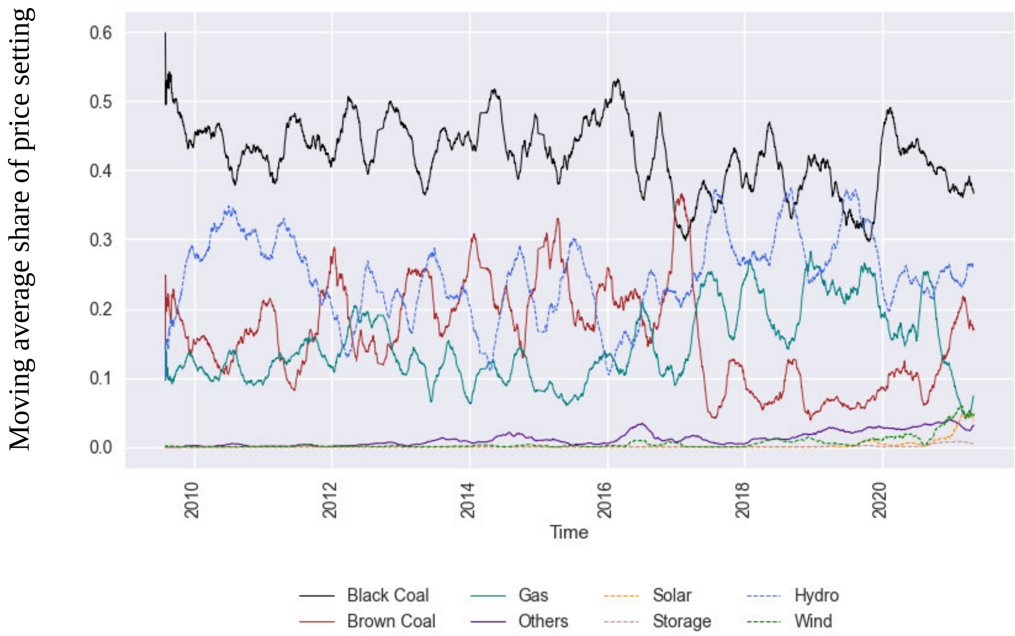


Figure 5.6

90-Day Moving Average of Contribution to Price Setting in Victoria for different technologies



The frequent spikes and slumps over a relatively short period illustrates that the short-term contributions of the generators to price setting were quite volatile. For instance, in the NSW market, black coal technology provided the marginal technology 37–73% of the time. In the Tasmanian market, the contribution of hydropower to price setting swung between 37% and 95%. Similar variations were observed in all regional markets for each generation technology.

Over the long term, the contribution of black coal to electricity price setting showed a decreasing trend. In the NSW market, black coal set electricity prices around 75% of the time at the beginning of the study period, but this had reduced to around 55% by the end of the study period (see Figure 5.2). Similarly, the contribution of black coal to price setting decreased from 60% to 37% in the Victorian market, from 78% to 62% in the Queensland market and from 52% to 30% in the South Australian market.

Although a gap between the price-setting contributions of black coal and those of other generators in the NSW and Queensland markets was evident for the duration of the study period, this gap has narrowed to some extent. This was more apparent in the Victorian and South Australian markets, where between 2016 and 2020, the contribution of hydropower, brown coal and gas technologies to electricity prices was sometimes higher than that of black coal (see Figures 5.4 and 5.6). This trend further confirms that the share of black coal in setting electricity prices is declining.

Notably, Figure 5.4 shows that even though South Australia withdrew all of its coal generators in 2016, both black and brown coal generators are continuing to significantly set electricity prices. Shutdown of the coal plants increases trade dependency of this markets with other regional markets (AER, 2020). Transmission interconnectors link the five regional markets that allow the trade to take place. Through these interconnectors, when the local supply is insufficient to meet demand, South Australia imports electricity from the neighbouring market (Victoria). So, these were the imported coal generators which were setting electricity prices in this market. On the other hand, Tasmania also trades its electricity with other regional markets which is affected by both environmental factors such as local rainfall that affect water storage for hydropower, as well as the market conditions such as Victorian spot prices (AER, 2020). Having coal plants setting the electricity prices in these markets which don’t have their own coal electricity generator indicates that along with local technologies, imported technologies are equally important in setting electricity prices.

Similarly, a massive spike in the contribution of black coal to price setting can be seen at the beginning of 2016, 2018 and 2020 in all regional markets. This almost identical trend across different markets may have been a result of changes in the coal price, electricity demand or seasonal behaviour and requires further investigation.

5.1.2 **Increasing share of renewables to set the electricity prices**

As shown in Figures 5.1–5.6, the contribution of renewable energy generators to price setting was negligible compared with other types of generators. Because these figures are not suitable for observing renewable energy price-setting trends, a separate 90-day rolling window analysis was conducted for renewable generators (solar, wind and storage) (see Figures 5.7–5.11).

Figure 5.7

90-Day Moving Average of the Contributions of Solar, Wind, and the Battery storage to Price Setting in New South Wales

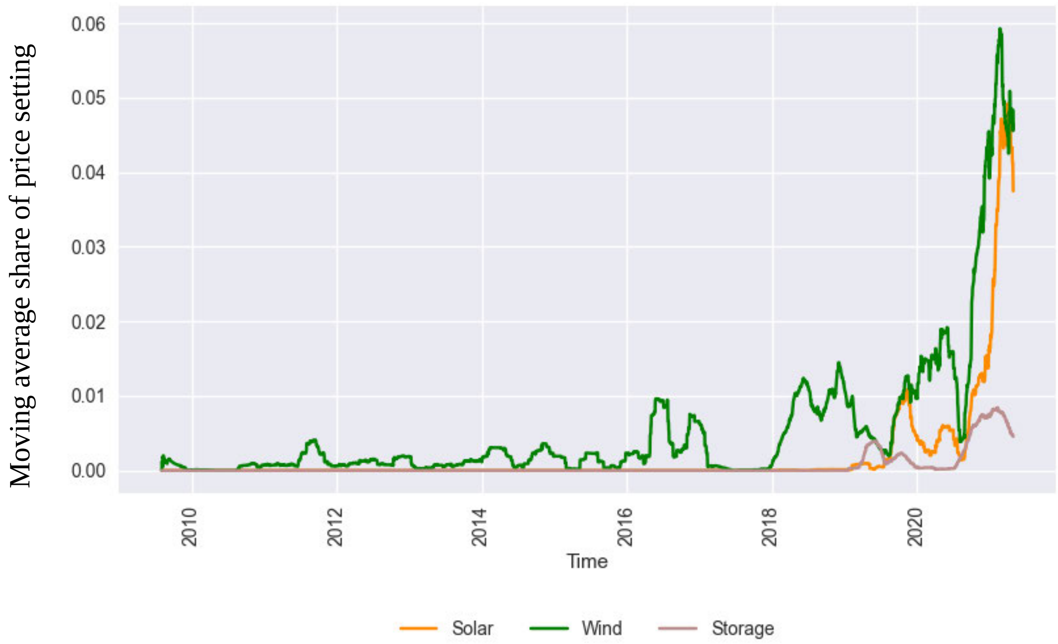


Figure 5.8

90-Day Moving Average of the Contributions of Solar, Wind, and the Battery storage to Price Setting in Queensland

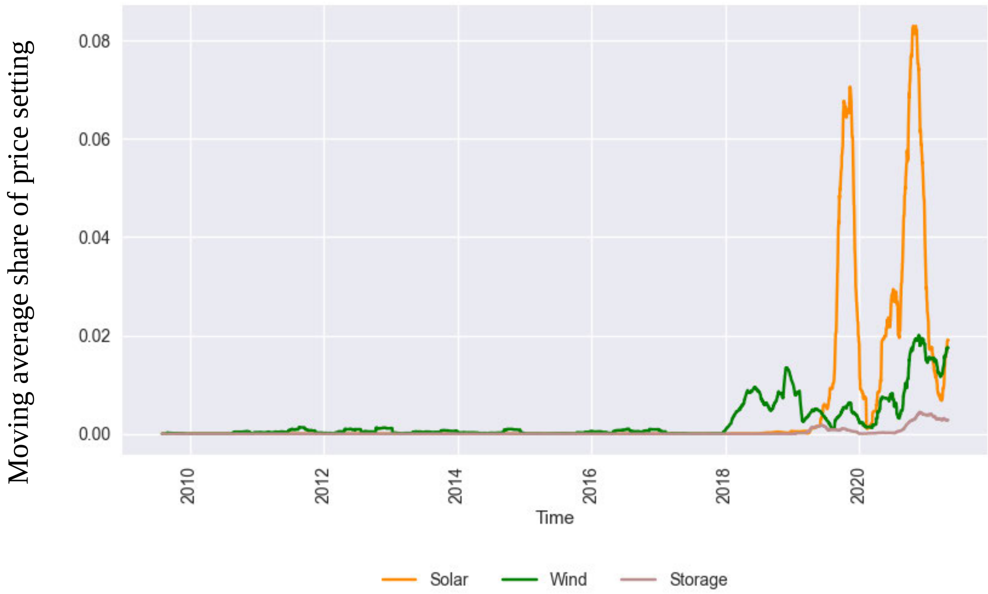


Figure 5.9

90-Day Moving Average of the Contributions of Solar, Wind, and the Battery storage to Price Setting in South Australia

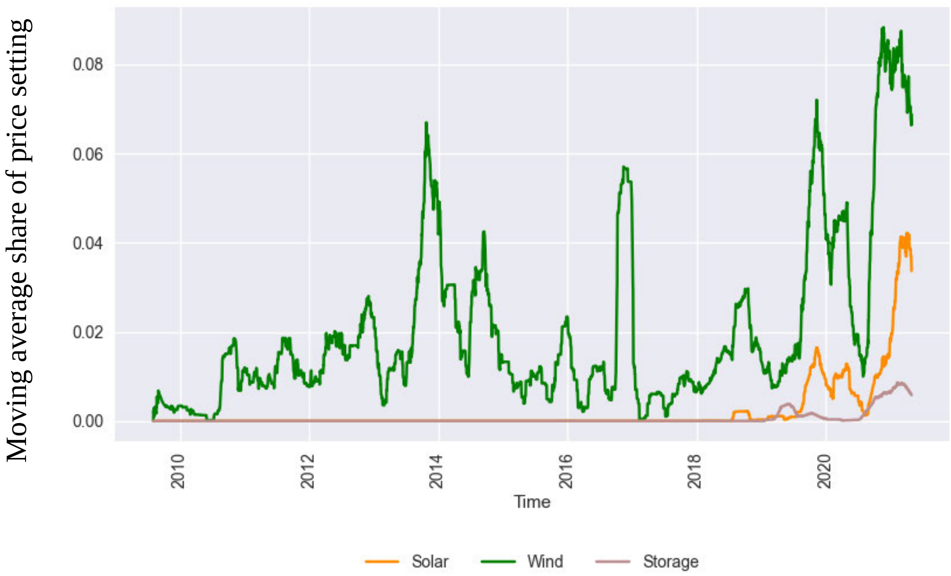


Figure 5.10

90-Day Moving Average of the Contributions of Solar, Wind, and the Battery storage Price Setting in Tasmania

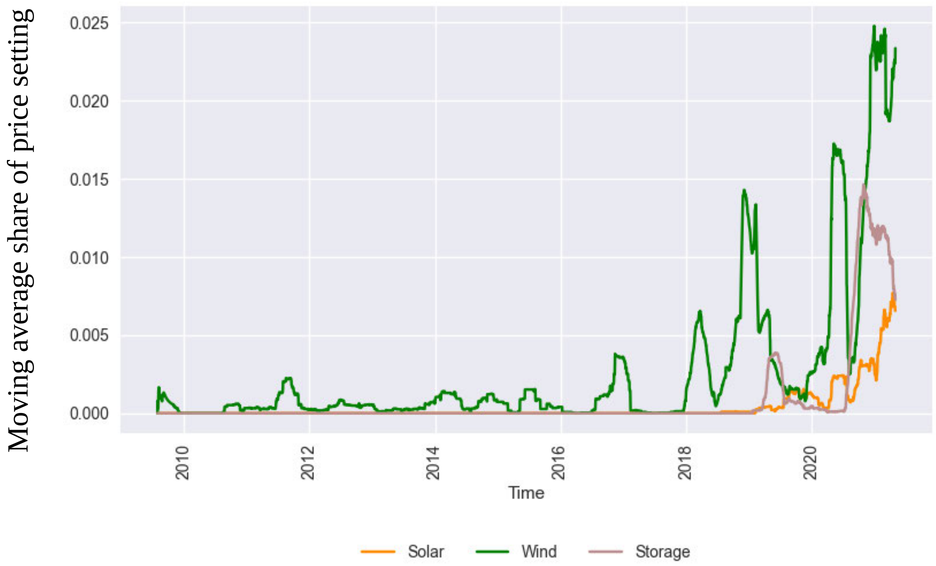
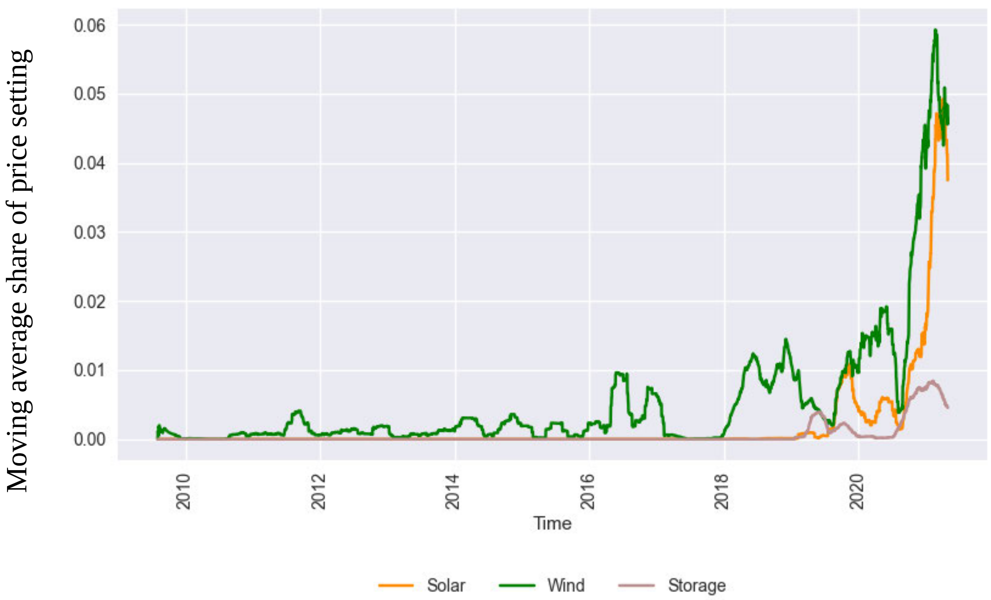


Figure 5.11

90-Day Moving Average of the Contributions of Solar, Wind, and the Battery storage to Price Setting in Victoria



As shown in Figures 5.7–5.11, all regional markets showed a small but gradual increase in wind and solar energy generators setting electricity prices. In most regional markets, wind technologies made greater contributions than did solar and battery storage. However, the

Queensland electricity market showed a distinct picture: not only was the price-setting share of solar the highest of all regional markets, but Queensland was also the only market in which the contribution of solar exceeded that of wind.

As expected, the overall share of renewables to price setting was highest in the South Australian market in compared to other regional market. The negligible contribution of wind generators to price setting at the beginning of 2010 had increased to 7% by the end of the study period. Similarly, the share of solar and storage technologies ramped up after the end of 2018, reaching approximately 4% and 1%, respectively. Although the electricity generation in South Australia is dominated by renewable generators their share on price setting was significantly lower than fossil fuel counterparts. This market is the net importer of the electricity so, these were the imported fossil fuel generators which were setting electricity prices more often than the renewable generators.

Prior to 2018, the contributions of VREs to price setting in all regional markets of the NEM, except South Australia, were below 1%. However, from 2018, the contributions of wind generators began to accelerate, reaching 2.2%, 2%, 2.5% and 5% in NSW, Queensland, Tasmania and Victoria, respectively, by the end of the study period. Similarly, the share of solar generation as price setter surged to 1.3%, 2%, 0.75% and 4% in NSW, Queensland, Tasmania and Victoria, respectively, by the end of the study period. Battery storage remained the least significant in setting electricity prices. Even following a small increase in 2019, the share of battery storage technologies was still lower than 1% for all regional markets.

In all regional markets, the increase in the contributions of renewable energy generators (wind, solar and battery storage) to electricity prices began at almost the same time. The initially negligible contribution of wind generators began to accelerate from the beginning of 2018, while the contributions of solar and battery storage technologies surged from the beginning of 2019. These increases reflect not only the increased investments in VRE generators but also the strong interconnections between the regional electricity markets, given that the price-setting contributions of renewable generators increased at the same time and followed a similar pattern.

5.1.3 Intraday contributions of generators to electricity price setting

As shown in Table 5.3, the contribution of coal to price setting in the NEM differed significantly between peak periods (2.00 pm to 8.00 pm), shoulder periods (7.00 am to 2.00 pm) and off-peak periods. The contribution of coal to price setting decreased dramatically for the entire peak period and the prior three hours of the shoulder period (4.00 am to 7.00 am) but increased during the off-peak period and the remainder of the shoulder period. Conversely, hydropower and gas technologies set electricity prices more frequently during peak periods, while solar was more active in the middle of the day when sunlight is abundant. Similarly, wind generators set electricity prices more frequently in the early morning and at midday.

Figures 5.12–5.16 plot the intraday price-setting trends for each regional market, showing significant variations within a typical day. In all regional markets in the NEM, the contributions of hydropower and gas generators increased during peak hours, while the contributions of coal showed the opposite trend. The contribution of coal technologies to price setting slumped twice a day at around 7.00 am and 6.30 pm, after which it gradually increased, plateauing at the beginning, middle and end of the day. Therefore, in every regional market, the intraday variations in the contributions of coal to price setting generated a W-shaped curve. The intraday contributions of hydropower and gas generators to price setting were the opposite to that of coal generators. Hydropower and gas generators set electricity prices more frequently during peak hours than during off-peak hours, peaking twice a day (at 7.00 am and 6.30 pm, respectively), precisely when coal dropped to its lowest level. Therefore, in contrast to the W-shaped curve for coal generators, hydropower and gas generated an M-shaped curve, illustrating their contrasting roles in electricity generation in the NEM, with hydropower and gas being peak load generators and coal a baseload generator.

Table 5.3

Intraday Variations in Marginal Technologies in the National Electricity Market

Hour	Black coal	Brown coal	Gas	Solar	Storage	Water	Wind	Other
0	48.75%	12.52%	13.63%	1.08%	0.05%	23.57%	0.40%	0.00%
1	49.55%	15.85%	11.12%	1.25%	0.05%	21.59%	0.60%	0.00%
2	51.30%	19.30%	8.04%	1.35%	0.06%	19.11%	0.85%	0.00%
3	51.51%	20.50%	7.01%	1.33%	0.06%	18.55%	1.03%	0.00%
4	51.93%	19.42%	7.14%	1.29%	0.07%	19.12%	1.02%	0.00%
5	49.90%	15.90%	9.14%	1.32%	0.06%	22.80%	0.90%	0.00%
6	43.40%	10.61%	13.42%	1.36%	0.05%	30.44%	0.73%	0.00%
7	40.12%	8.67%	14.57%	1.54%	0.05%	34.40%	0.64%	0.00%
8	41.28%	7.68%	15.74%	1.79%	0.06%	32.78%	0.67%	0.00%
9	42.44%	7.51%	16.17%	1.86%	0.06%	31.19%	0.77%	0.00%
10	43.47%	7.93%	15.64%	2.15%	0.08%	29.76%	0.97%	0.00%
11	43.84%	8.35%	15.17%	2.31%	0.10%	29.16%	1.07%	0.00%
12	44.27%	8.87%	14.92%	2.28%	0.08%	28.47%	1.10%	0.00%
13	44.11%	8.88%	15.08%	2.28%	0.10%	28.41%	1.15%	0.00%
14	43.46%	9.00%	15.49%	2.10%	0.08%	28.77%	1.09%	0.00%
15	42.38%	8.14%	15.92%	2.07%	0.08%	30.49%	0.91%	0.00%
16	38.89%	7.43%	17.47%	2.25%	0.04%	33.23%	0.67%	0.00%
17	34.58%	6.53%	18.03%	2.35%	0.04%	37.92%	0.55%	0.00%
18	33.66%	6.02%	17.32%	2.22%	0.03%	40.21%	0.54%	0.00%
19	36.75%	5.87%	18.56%	2.39%	0.02%	36.01%	0.40%	0.00%
20	40.01%	6.19%	18.08%	2.03%	0.03%	33.28%	0.37%	0.00%
21	42.60%	8.41%	16.63%	1.54%	0.04%	30.39%	0.38%	0.00%
22	44.29%	10.26%	15.93%	1.34%	0.05%	27.68%	0.44%	0.00%
23	48.02%	9.41%	13.42%	1.08%	0.05%	27.52%	0.50%	0.01%

Note. For each hour, the frequency of price setting of each generation technology at each 5-minute dispatch period across the entire sample period was summed up and is expressed in terms of percentage. Other = landfill gas, diesel, waste coalmine gas, coal seam methane, kerosene, and wastewater technologies.

Figure 5.12

Time of the Day and Price Setting in New South Wales

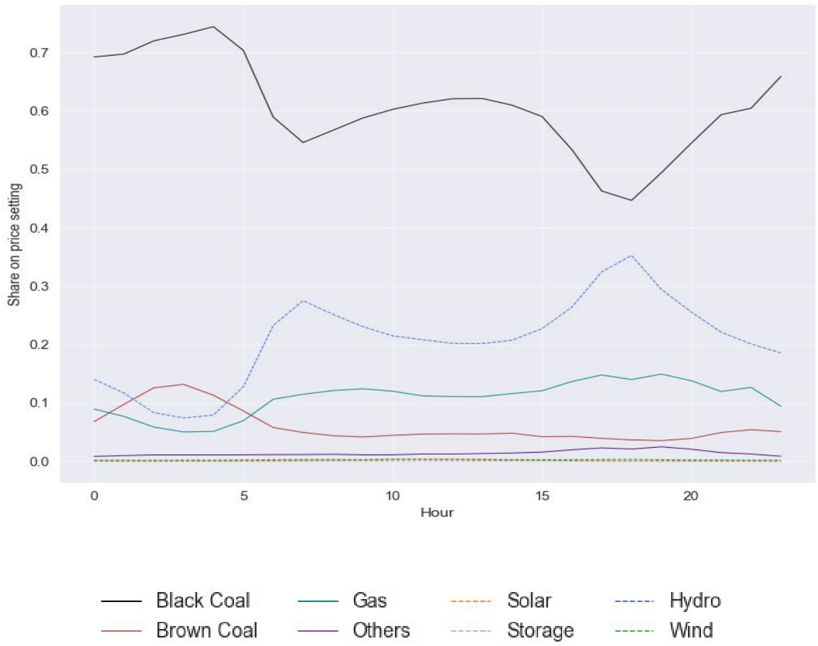


Figure 5.13

Time of the Day and Price Setting in Queensland

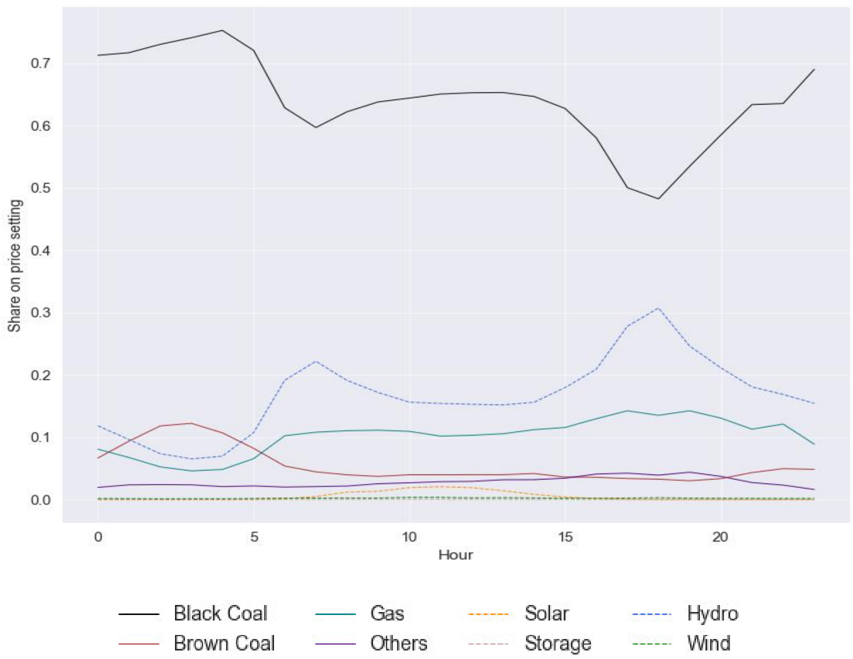


Figure 5.14

Time of the Day and Price Setting in South Australia

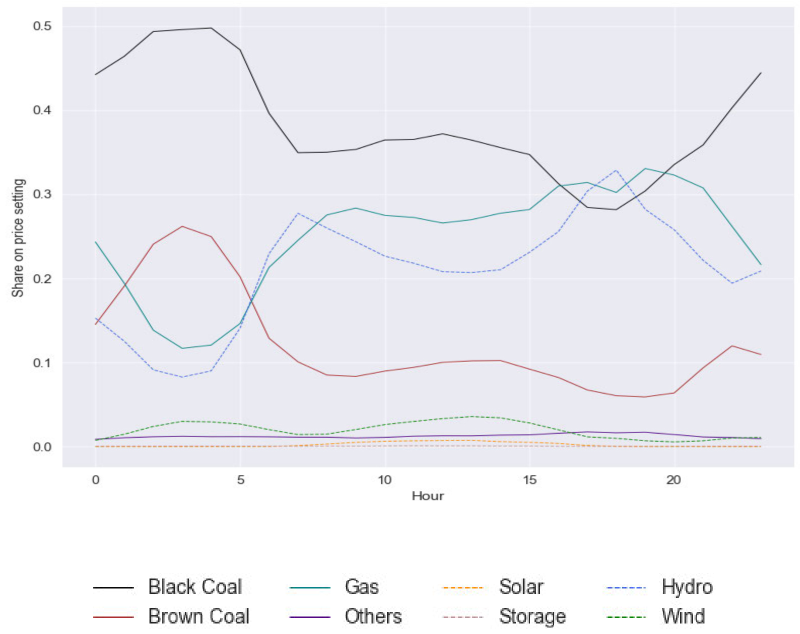


Figure 5.15

Time of the Day and Price Setting in Tasmania

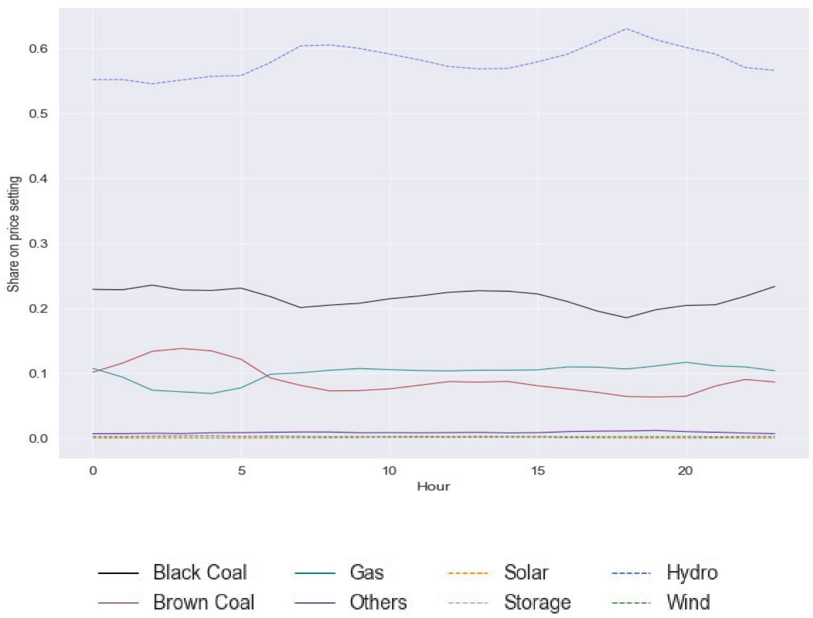
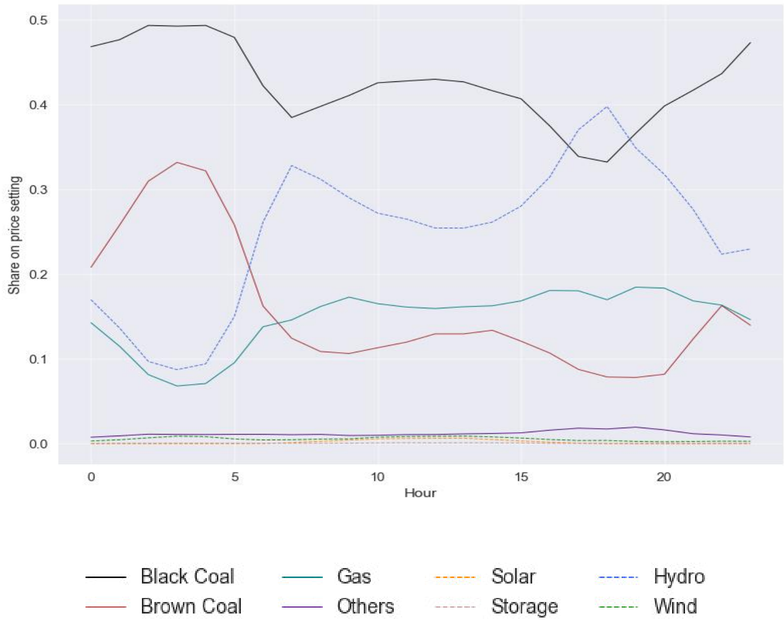


Figure 5.16

Time of the Day and Price Setting in Victoria



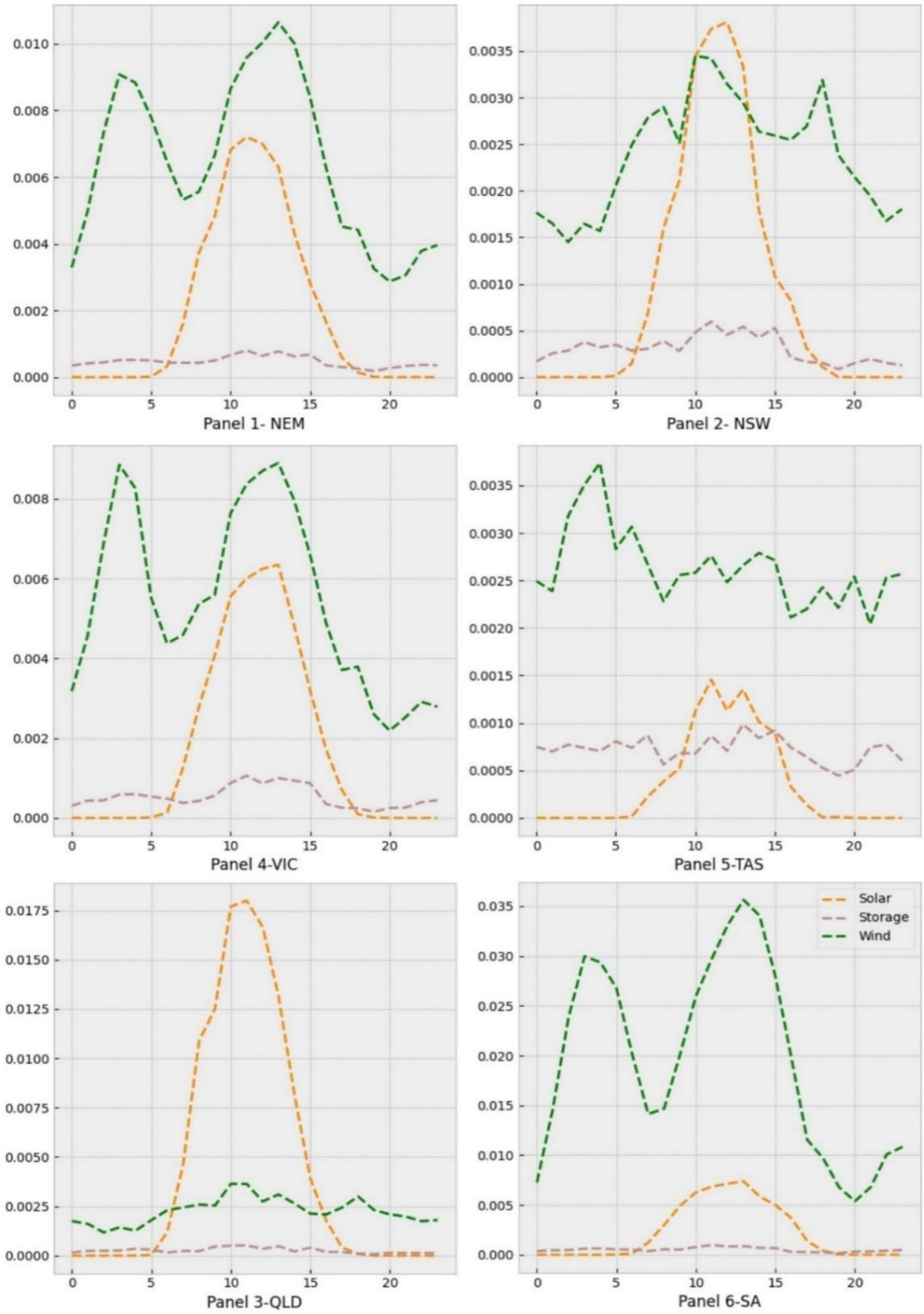
Comparing regional markets in terms of their intraday price-setting variations, a similar pattern was observed for black coal, which set electricity prices most of the time. However, the Tasmanian market was unique in that hydropower was dominant in setting electricity prices over the entire period of a typical day. Similarly, the share of hydropower exceeded that of black coal in setting electricity prices for a short period in the early evening in the South Australian and Victorian markets (see Figures 5.14 and 5.16). During the same hours, gas also surpassed coal in setting electricity prices in the South Australian market.

5.1.4 Intraday contributions of renewable generators to price setting

Figures 5.12–5.16 were unsuitable for analysing intraday variations in the contributions of renewable energies to price setting because these were negligible compared with their dispatchable counterparts. Therefore, the contributions of renewable energies were displayed seperately to show how they behaved during an intraday interval (see Figure 5.17). Panel 1 shows that for the entire NEM, the contribution of wind was higher for the entire period of a typical day, while the contribution of battery storage was negligible.

Figure 5.17

Time of Day and Solar, Wind, and the Battery storage Price Setting in the NEM and the Different Regional Markets



As expected, the contributions of solar generators in a typical day exhibited a bell shape. Before sunrise (5.00 am), solar generators are not active in setting electricity prices because of the absence of sunlight. With the increase in sunlight, their contribution begins to increase, reaching a peak in the middle of the day before rapidly decreasing, with no contributions after 7.00 pm. This bell-shaped pattern for solar generators underneath the wind generator curve was common to almost all regional markets. However, because the capacity of solar generators in Queensland and NSW is higher than that of wind generators (AER, 2020), the contribution of solar to price setting at noon exceeds those of wind in both markets.

Unlike the contributions of solar generators, those of wind generators were not uniform across regional markets. In the South Australian and Victorian markets, the contributions of wind generators fluctuated rapidly, peaking in the early morning and at noon. However, in the other regional markets, the intraday contributions of wind generators to price setting fluctuated. As shown in Figure 5.17, the overall market trend for wind (Panel 1) was driven by the Victorian and South Australian markets, which together possess more than 50% of the total installed capacity of wind generators in the NEM (AER, 2020).

5.1.5 Electricity demand and contributions of generators on electricity price setting

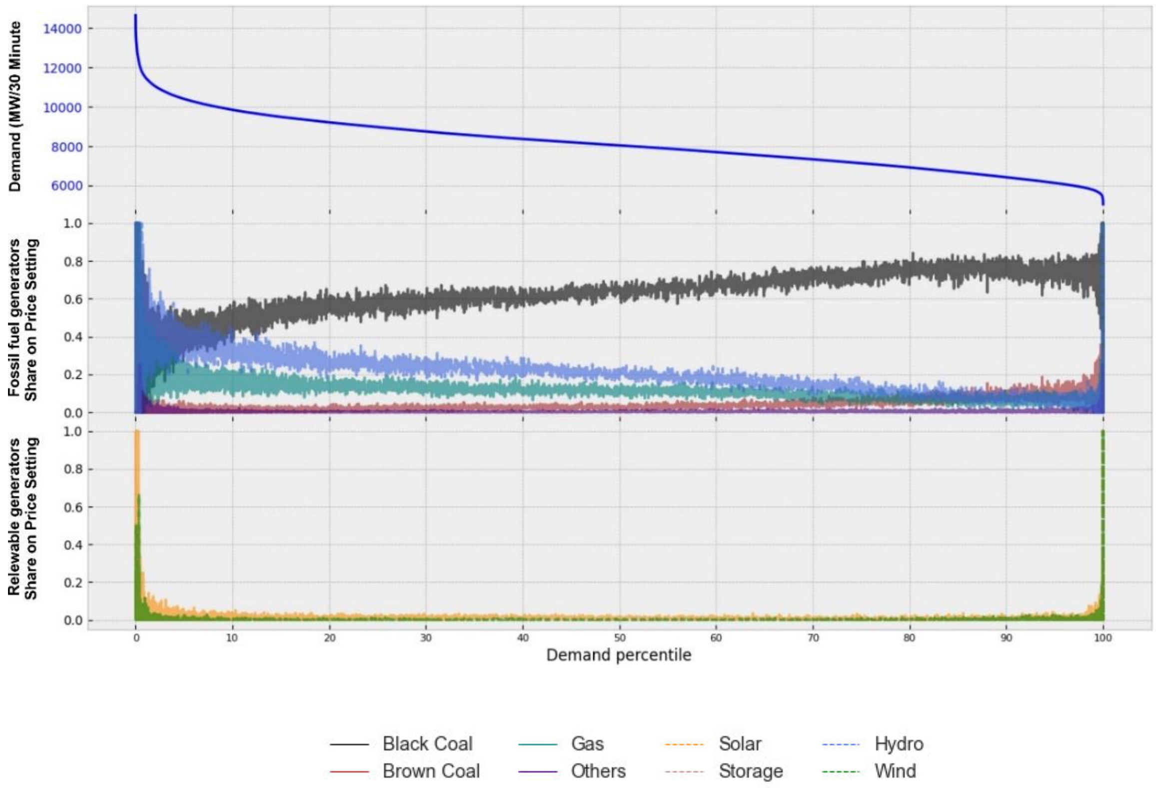
Given their specific characteristics, different generators tend to set electricity prices at different levels of demand. For example, coal-fired plants have high initial investment costs as well as high startup and shutdown costs (because they require a day or more to start up), but once they are built, their variable costs are relatively low (AER, 2020). Their low variable costs and ramp-up rates mean that coal-fired generators represent baseload power plants, which supply electricity and set prices at lower and middle levels of demand. Other generators such as open-cycle gas turbines are cheap to build, but incur relatively high costs to operate. However, their operation is more flexible than that of coal generators, requiring as little as 5 minutes to ramp up their output (AER, 2020). This combination of high flexibility and high operational costs means that gas generators are peaking power plants, which supply electricity and set prices at higher levels of demand. Hydropower generators have relatively low fuel costs because they do not directly pay for the water they use. However, they are constrained by storage capacity and levels of rainfall to replenish storage, making their opportunity costs relatively high. Therefore, similar to gas technologies, they represent peaking plants that supply electricity and set prices at higher levels of demand.

Figures 5.18–5.22 plot the changes in demand across the entire study period and how price-setting technologies responded to different levels of demand. Black coal dominated price setting at lower levels of demand. However, as demand increased, the contribution of black coal to electricity prices decreased, while other generators, mainly hydropower, gas and brown coal, began to increase. At the 95th percentile of demand, all of the above four generation technologies were equally significant in setting electricity prices. Interestingly, for almost all markets, both black coal and brown coal showed parallel downward trends with increasing demand. However, the contributions of renewable energy (solar and wind) to electricity prices were consistent throughout different levels of demand.

In the NSW market, demand exceeded 5,000 MW/30 minutes (approximately) for the entire study period (see Figure 5.18). At that level of demand, black coal was predominant in setting electricity prices for almost 60% of the time. Up to the lower 25th percentile of demand (7,000 MW/30 minutes approximately), the contributions of brown coal, hydropower and gas to price setting were similar; however, as demand increased, the contributions of brown coal decreased, while the contributions of hydropower and gas surged. As shown in Figure 5.18, the hydropower curve is above the gas curve. This indicates that the increasing contributions of hydropower met the decreasing contributions of coal approximately at the 90th percentile of demand, while the increasing contributions of gas met the decreasing contributions of coal approximately at the 95th percentile of demand. At the 98th percentile of demand, the contributions of hydropower and gas to electricity prices were higher than that of coal.

Figure 5.18

Electricity Demand and Generators' Contributions to Electricity Price Setting in New South Wales



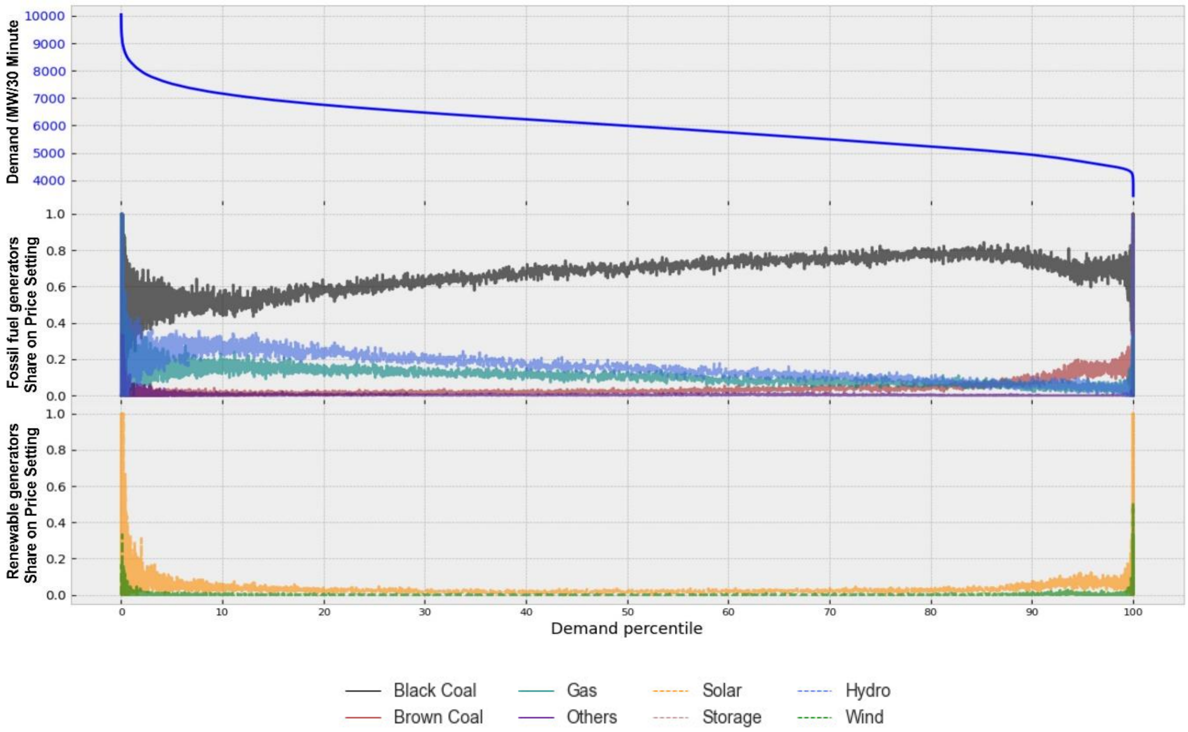
Note. The solid blue line depicts electricity demand. The middle section depicts the contribution of fossil fuel–based and hydropower generators and the lower section depicts the contribution of renewable generators (solar, wind and battery storage) according to demand. For example, demand exceeded 8,000 MW/30 minutes 50% of the time, and black coal was dominant in setting electricity prices for almost 50% of the time at that level of demand.

Similar to the NSW market, the contributions of hydropower were higher than those of gas in both the Queensland and the Victorian markets (see Figures 5.19 and 5.20). However, in the Queensland market, the contributions of hydropower and gas met that of coal at the upper 3rd percentile of demand, whereas in the Victorian market, the contributions of hydropower and coal met at the upper 25th percentile of demand, and the contributions of gas and coal met at the fifth percentile of demand.

Compared with other regional markets, in the Tasmanian market, the contributions of the various generators to electricity prices were more consistent with changing demand. At all levels of demand, hydropower made the greatest contributions, followed by black coal and gas technologies.

Figure 5.19

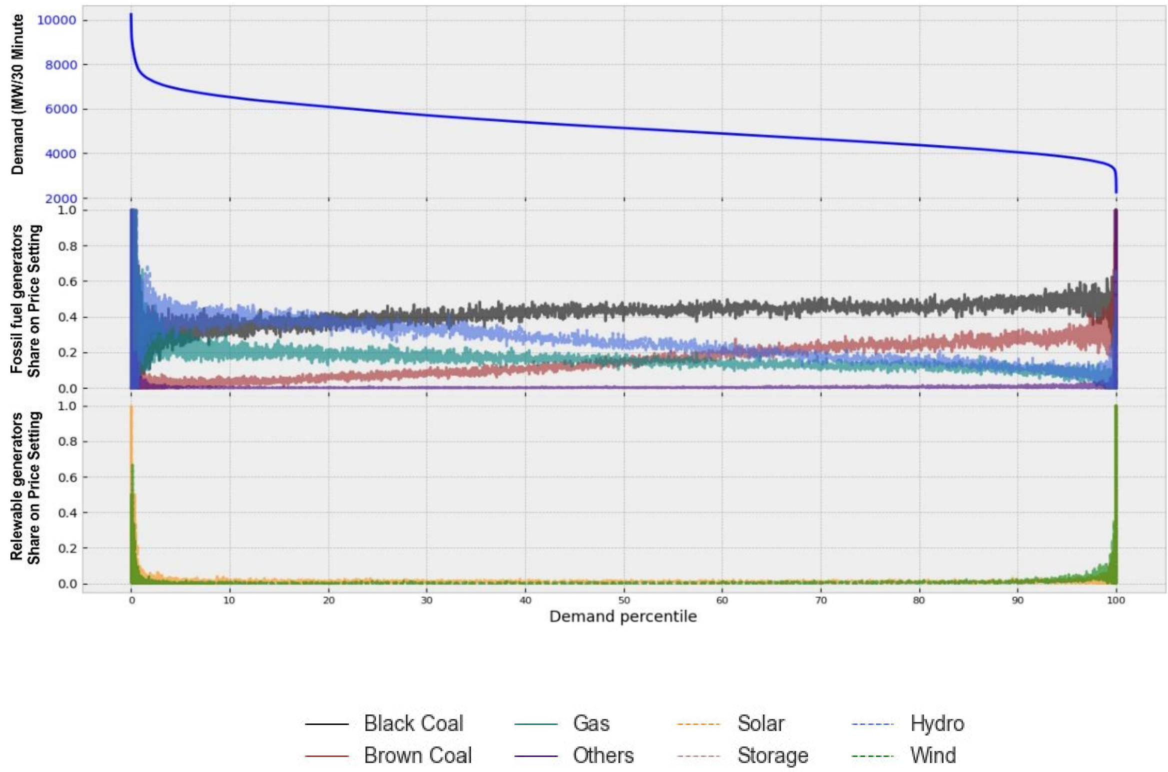
Electricity Demand and Generators' Contributions to Electricity Price Setting in Queensland



Note. The solid blue line depicts electricity demand. The middle section depicts the contribution of fossil fuel–based and hydropower generators and the lower section depicts the contribution of renewable generators (solar, wind and battery storage) according to demand. For example, demand exceeded 6,000 MW/30 minutes 50% of the time, and black coal dominated in setting electricity prices for almost 70% of the time at that level of demand.

Figure 5.20

Electricity Demand and Generators' Contributions to Electricity Price Setting in Victoria



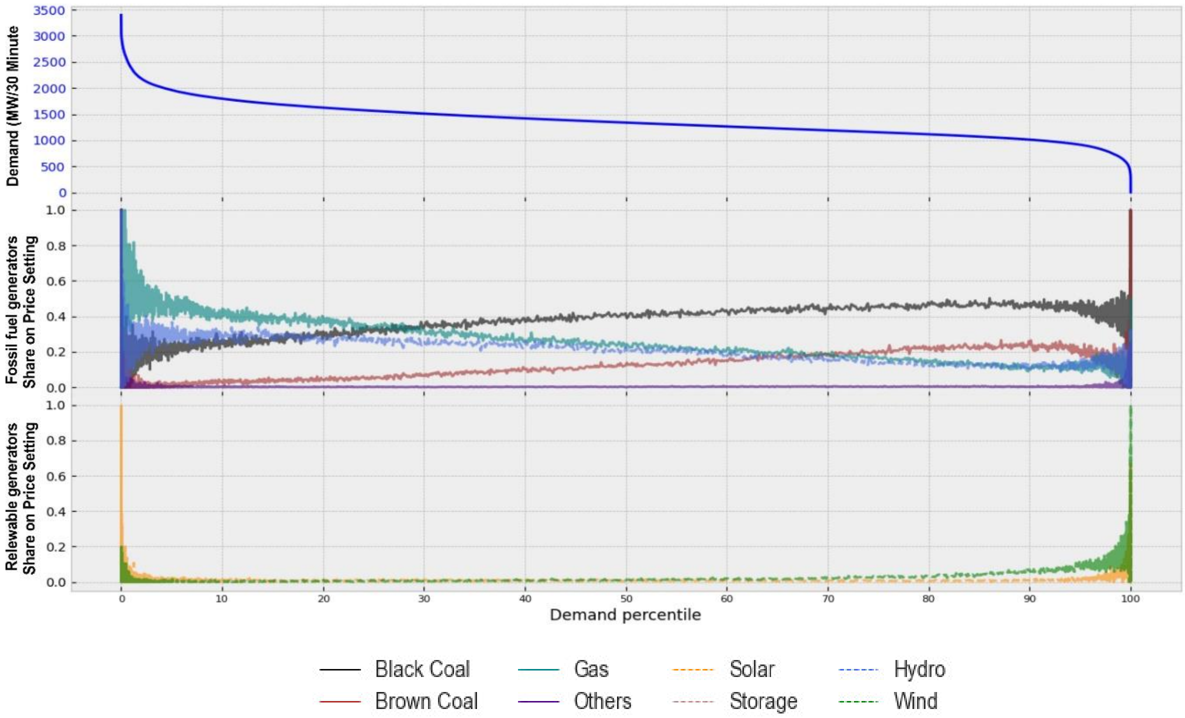
Note. The solid blue line depicts electricity demand. The middle section depicts the contribution of fossil fuel–based and hydropower generators and the lower section depicts the contribution of renewable generators (solar, wind and battery storage) according to demand. For example, demand exceeded 5,500 MW/30 minutes 50% of the time, and black coal dominated in setting electricity prices for almost 40% of the time at that level of demand.

In contrast to the NSW, Queensland and Victorian markets, in South Australia, gas bypassed hydropower in setting electricity prices with rising demand (see Figure 5.21). Similarly, in the highest 15th percentile of demand, gas generators contributed the most to electricity prices, followed by hydropower and black coal.

In almost all regional markets, at both the lowest and highest levels of demand, renewable technologies (wind and solar) set electricity prices more frequently. Apart from the first and 99th percentiles of demand, the contributions of renewable technologies electricity prices were small and consistent. Being intermittent technologies, renewable generators are unable to ramp up their production with increasing demand, unlike hydropower, gas and brown coal, which have much greater control over their production with varying demand. Thus, renewable generators are not able to cash the dispatchability premium (Rai and Nunn, 2020a).

Figure 5.21

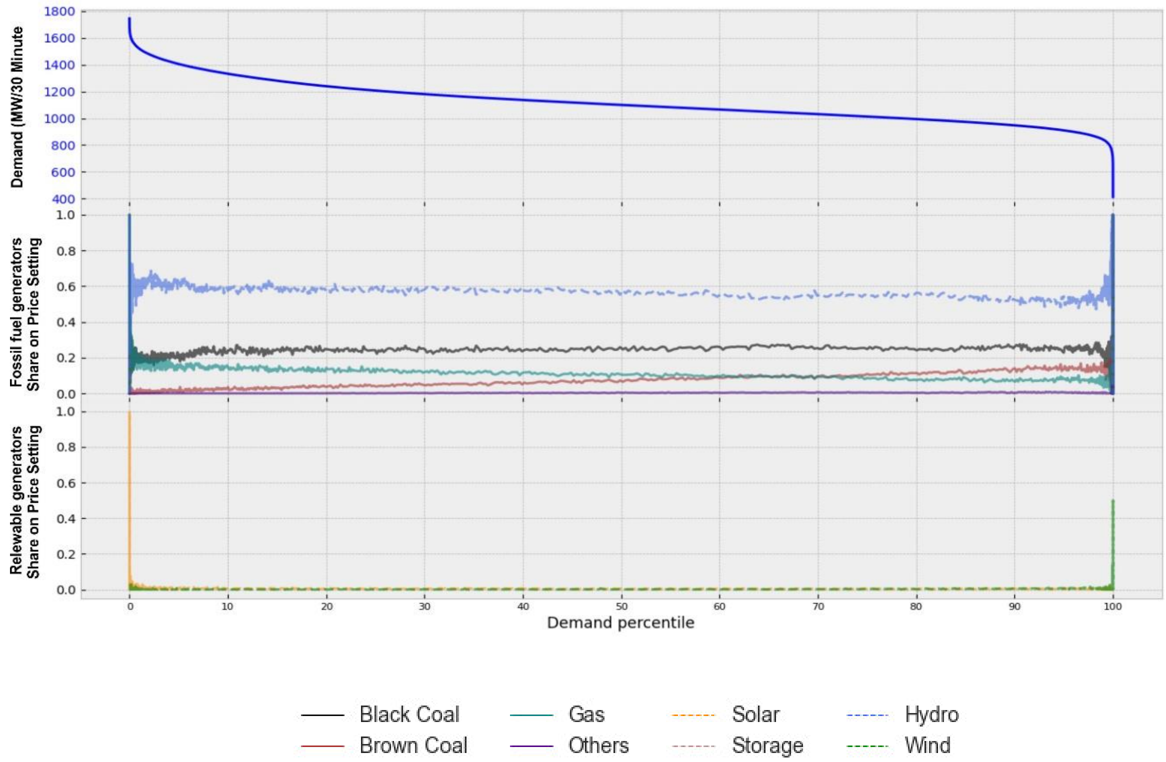
Electricity Demand and Generators' Contributions to Electricity Price Setting in South Australia



Note. The solid blue line depicts electricity demand. The middle section depicts the contribution of fossil fuel–based and hydropower generators and the lower section depicts the contribution of renewable generators (solar, wind and battery storage) according to demand. For example, demand exceeded 1,400 MW/30 minutes 50% of the time, and black coal dominated in setting electricity prices for almost 40% of the time at that level of demand.

Figure 5.22

Electricity Demand and Generators' Contributions to Electricity Price Setting in Tasmania



Note. The solid blue line depicts electricity demand. The middle section depicts the contribution of fossil fuel–based and hydropower generators and the lower section depicts the contribution of renewable generators (solar, wind and battery storage) according to demand. For example, demand exceeded 1,100 MW/30 minutes 50% of the time, and hydropower dominated in setting electricity prices for almost 60% of the time at that level of demand.

5.1.6 Contribution of generators to set electricity prices at different level of prices

To illustrate the changes in marginal technologies with price changes, Figures 5.23–5.27 plot the price curves (top panel) and the average contributions of generators to set electricity prices (bottom panel) for each regional market. Overall, the contributions of black and brown coal generators to electricity prices decreased with an increase in price, while those of hydropower and gas generators increased with an increase in price.

Given that the spot price may be anywhere between the market floor price and market price cap, extreme price cases were seen in every regional market. For illustration purposes, these outliers were treated specifically, enabling us to use the price curve to observe normal price changes as well as extreme price changes. Prices above \$150/MWh were defined as price spikes and the exceedances above \$150 were divided by 100. Similarly, for prices less than –

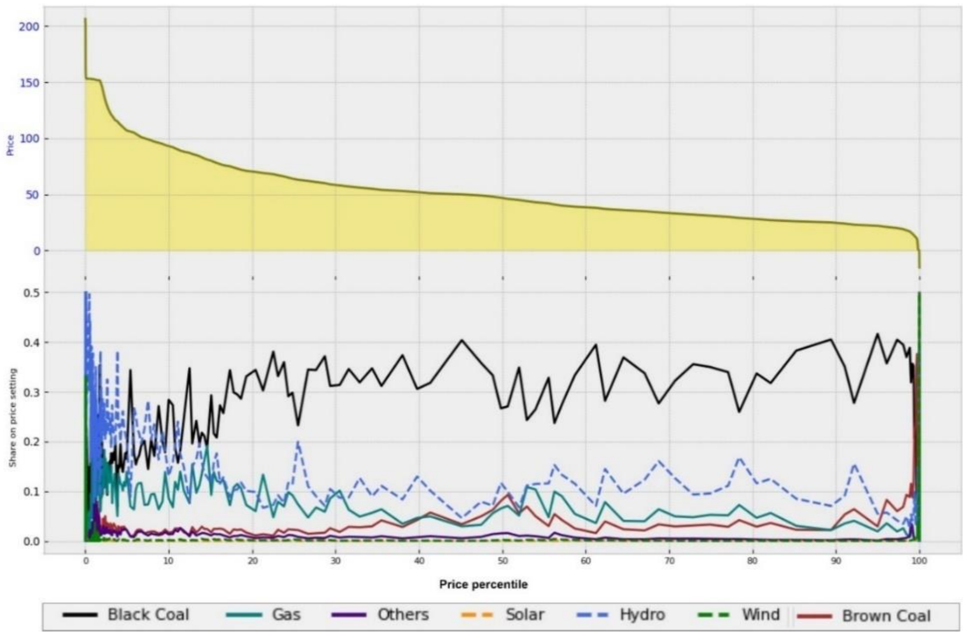
$10, the exceedances below $10 were divided by 10. This normalisation procedure can be written as follows:

- For prices > $150/MWh: Plotted price = $150 + (actual price − 150)/100.
- For prices < −$10/MWh: Plotted price = −10 − (actual price + 10)/10.

This transformation enabled us to display also extreme electricity prices and the generators setting those prices in all markets. As shown in Figures 5.23–5.27, South Australia had more instances of negative prices and price spikes compared with other regional markets. In this market, the price was less than $0 2.5% of the time, when wind generators were dominant in setting the price, and the market experienced price spikes 3.5% of the time, when prices were mostly set by hydropower and gas generators.

Figure 5.23

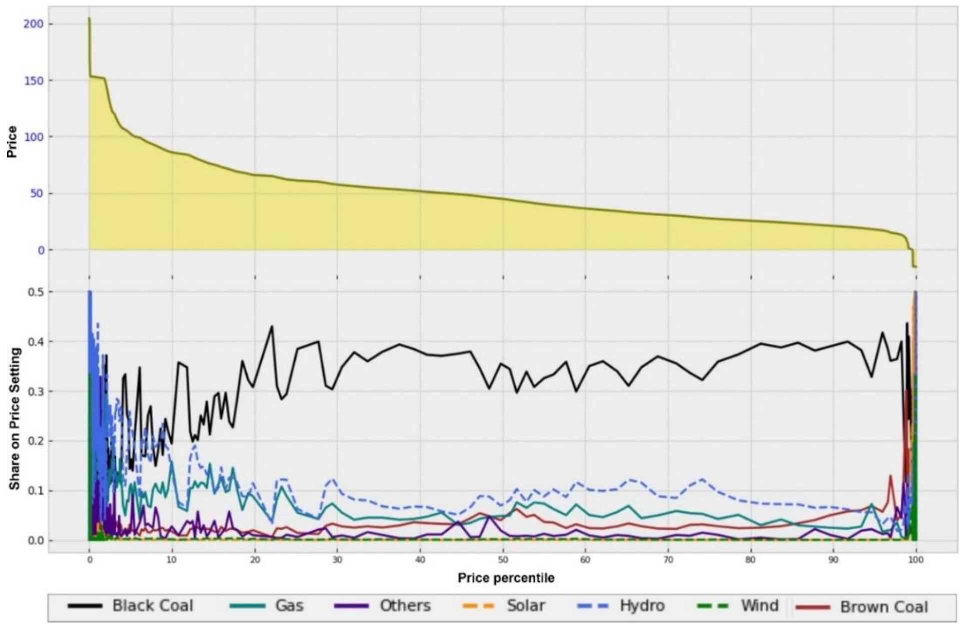
Electricity Prices and Generators' Contributions to Price Setting in New South Wales



Note. The grey line in the upper panel of the figure depicts the price curve at different percentiles. The lower panel depicts the contributions of generators electricity prices according to price. For example, prices exceeded $50/MWh 50% of the time, during which black coal was dominant in setting the price, followed by hydropower, brown coal and gas.

Figure 5.24

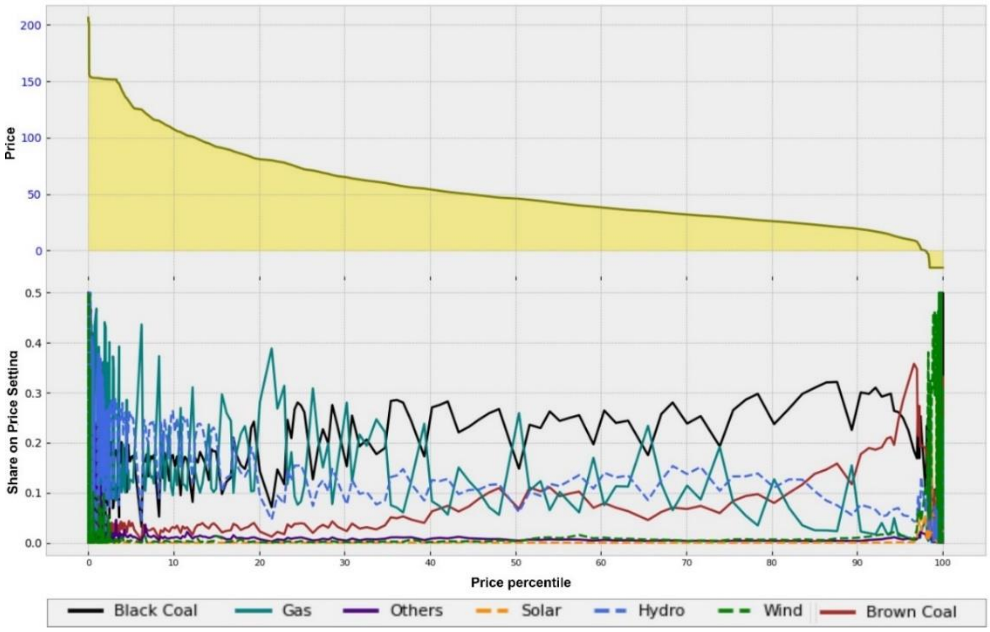
Electricity Prices and Generators' Contributions to Price Setting in Queensland



Note. The grey line in the upper panel of the figure depicts the price curve at different percentiles. The lower panel depicts the contributions of generators electricity prices according to price. For example, prices exceeded $47/MWh 50% of the time, during which black coal was dominant in setting the price, followed by hydropower, gas and brown coal.

Figure 5.25

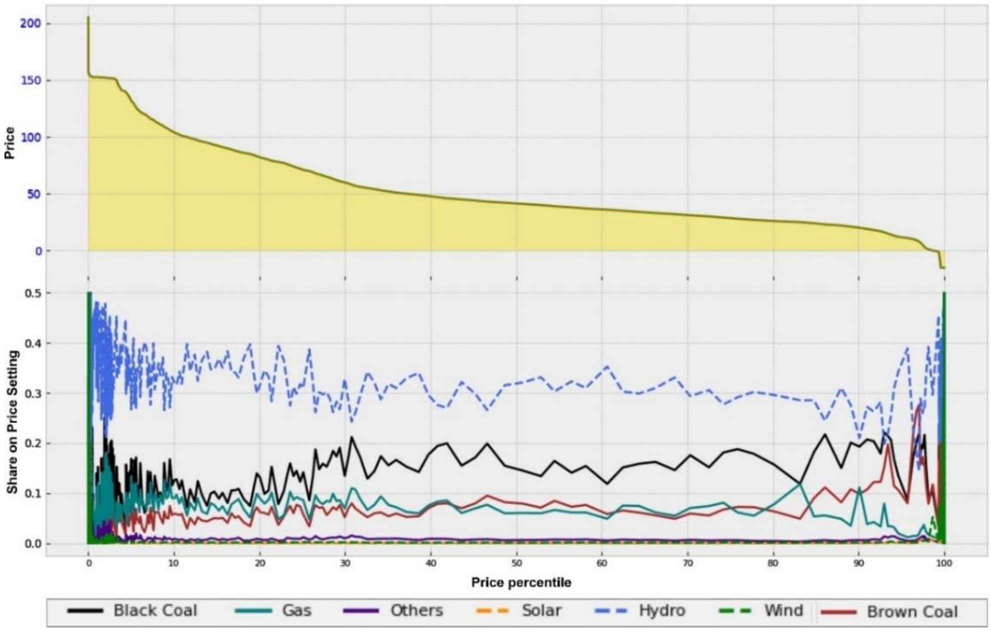
Electricity Prices and Generators' Contributions to Price Setting in South Australia



Note. The grey line in the upper panel of the figure depicts the price curve at different percentiles. The lower panel depicts the contributions of generators electricity prices according to price. For example, prices exceeded $49/MWh 50% of the time, during which black coal was dominant in setting the price, followed by gas, hydropower and brown coal.

Figure 5.26

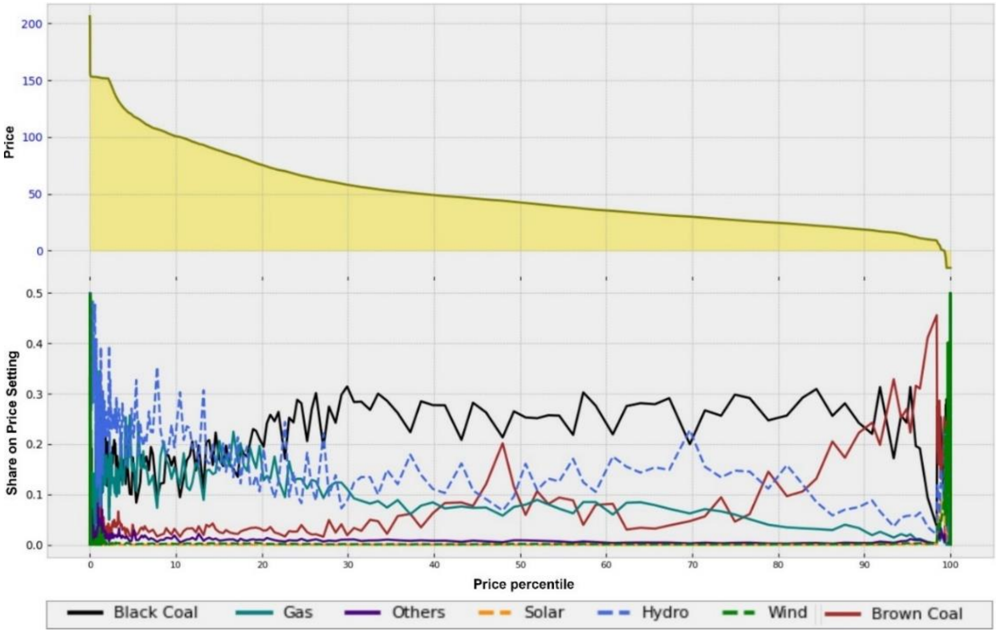
Electricity Prices and Generators' Contributions to Price Setting in Tasmania



Note. The grey line in the upper panel of the figure depicts the price curve at different percentiles. The lower panel depicts the contributions of generators electricity prices according to price. For example, prices exceeded $40/MWh 50% of the time, during which hydropower was dominant in setting the price, followed by black coal, gas and brown coal.

Figure 5.27

Electricity Prices and Generators' Contributions to Price Setting in Victoria



Note. The grey line in the upper panel of the figure depicts the price curve at different percentiles. The lower panel depicts the contributions of generators electricity prices according to price. For example, prices exceeded $40/MWh 50% of the time, during which black coal was dominant in setting the price, followed by hydropower, brown coal and gas.

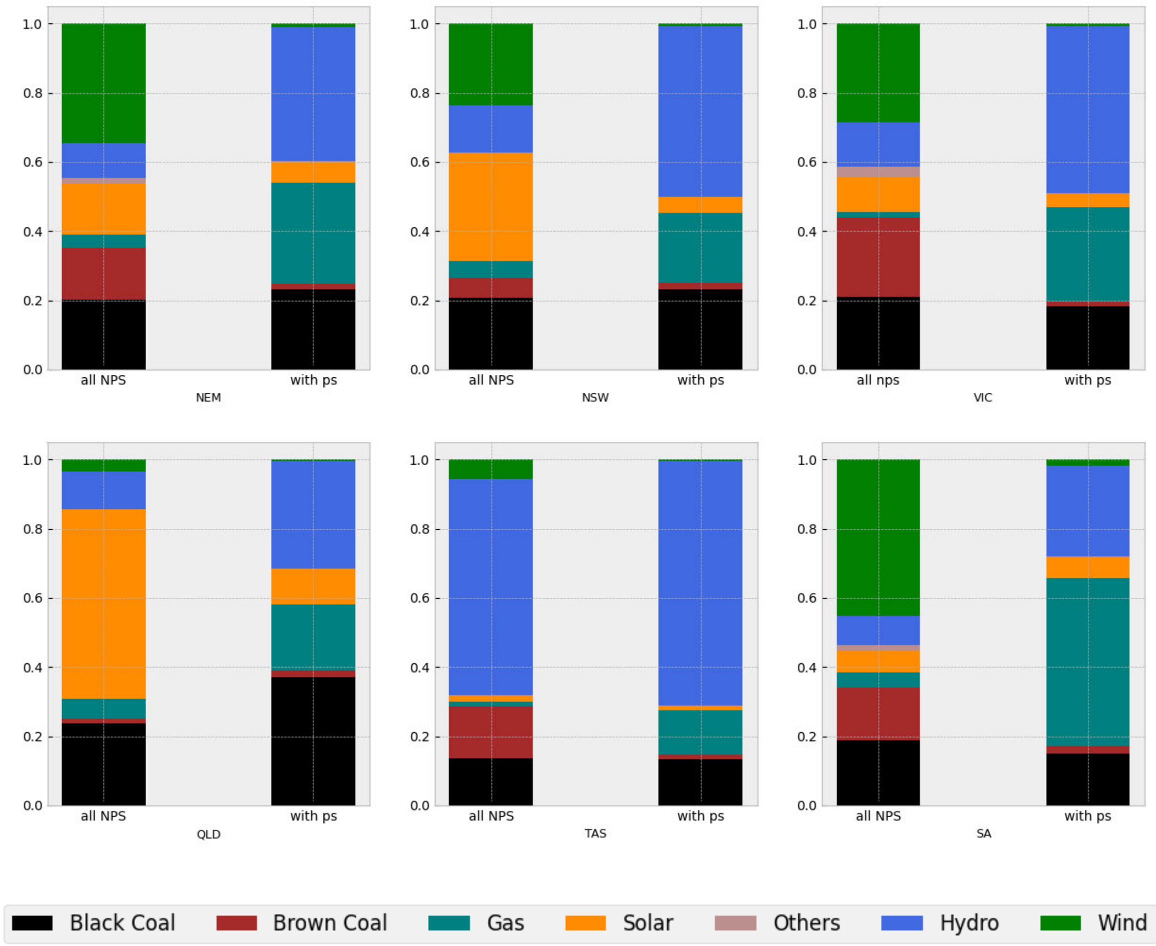
Price outliers were also found in the Tasmanian market. Price spikes were observed 3% of the time, while negative prices were observed 2% of the time. For both of these price extremes, hydropower generators were responsible for setting electricity prices. In Queensland and Victoria, price spikes and negative prices occurred with almost equal frequency (2% and 1%, respectively). The lowest frequency of negative prices occurred in NSW, less than 0.5% of the time, while price spikes were observed less than 2% of the time. During periods of negative prices, solar generators contributed the most to electricity prices in NSW and Queensland, while wind generators contributed the most in Victoria. During periods of price spikes in these markets, gas and hydropower generators contributed most to electricity prices.

For all electricity markets, the generators that set prices at one extreme were the same as those setting prices at the other extreme, which may appear anomalous. According to general convention, during periods of low electricity demand, baseload plants are expected to set electricity prices. On the contrary, during high demand, peaking plants (gas or hydropower generators) are expected to set electricity prices. To examine whether information about price-setting technologies can explain the abovementioned anomaly, the contributions of each generator to negative electricity prices are plotted in Figure 5.28.

The first panel of Figure 5.28 shows the contributions of generators to electricity prices for the whole NEM (excluding Tasmania) during periods of negative prices. Data from Tasmania were not included because the state's generation mix is significantly different to that in the rest of the NEM, and negative prices are more frequent than in other regional markets. Therefore, including Tasmania would have potentially introduced bias into Panel 1 and misrepresented the NEM. As shown in Panel 1, for the NEM overall (excluding Tasmania), the contribution of wind generators to electricity prices was higher than that of other generators during periods of negative prices. This was followed by baseload generators (black and brown coal) and solar plants, with peaking generators (gas and hydropower) making the lowest contributions to electricity prices. However, the figure shows that if a price spike was experienced in any previous dispatch period within the same trading interval, the contributions of peaking generators were substantially higher than those of other generators. In this situation, renewable generators (solar and wind) were negligible in setting electricity prices. Here, the price spike has been defined as all the prices that lies above upper 1 percentile.

Figure 5.28

Price-Setting Generators During Periods of Negative Electricity Prices



Note. The first panel represents the entire National Electricity Market, while the remainder represent the regional markets. All NPS = share of generators to set electricity price at negative price situation; with ps = share of generators to set electricity price at negative price situation, when a (positive) price spikes occurred at any dispatch period of the same trading interval .

One explanation for the association between a previous price spike within the same trading interval and a shift of price-setting contributions from baseload to peaking generators during periods of negative prices may be the limit in ramp-up rates. If an electricity market experienced a price spike just prior to a negative price, it may be that peaking generators were supplying the electricity at the time of the spike. Because the price instantly moves from one extreme (a positive price spike) to the other (a negative price), peaking generators may not be able to ramp down their production and are compelled to supply electricity, even at negative prices. However, hydropower and gas generators can ramp up and ramp down their production within 5 minutes (AER, 2020). This raises the question of why these generators would continue to supply electricity at negative prices.

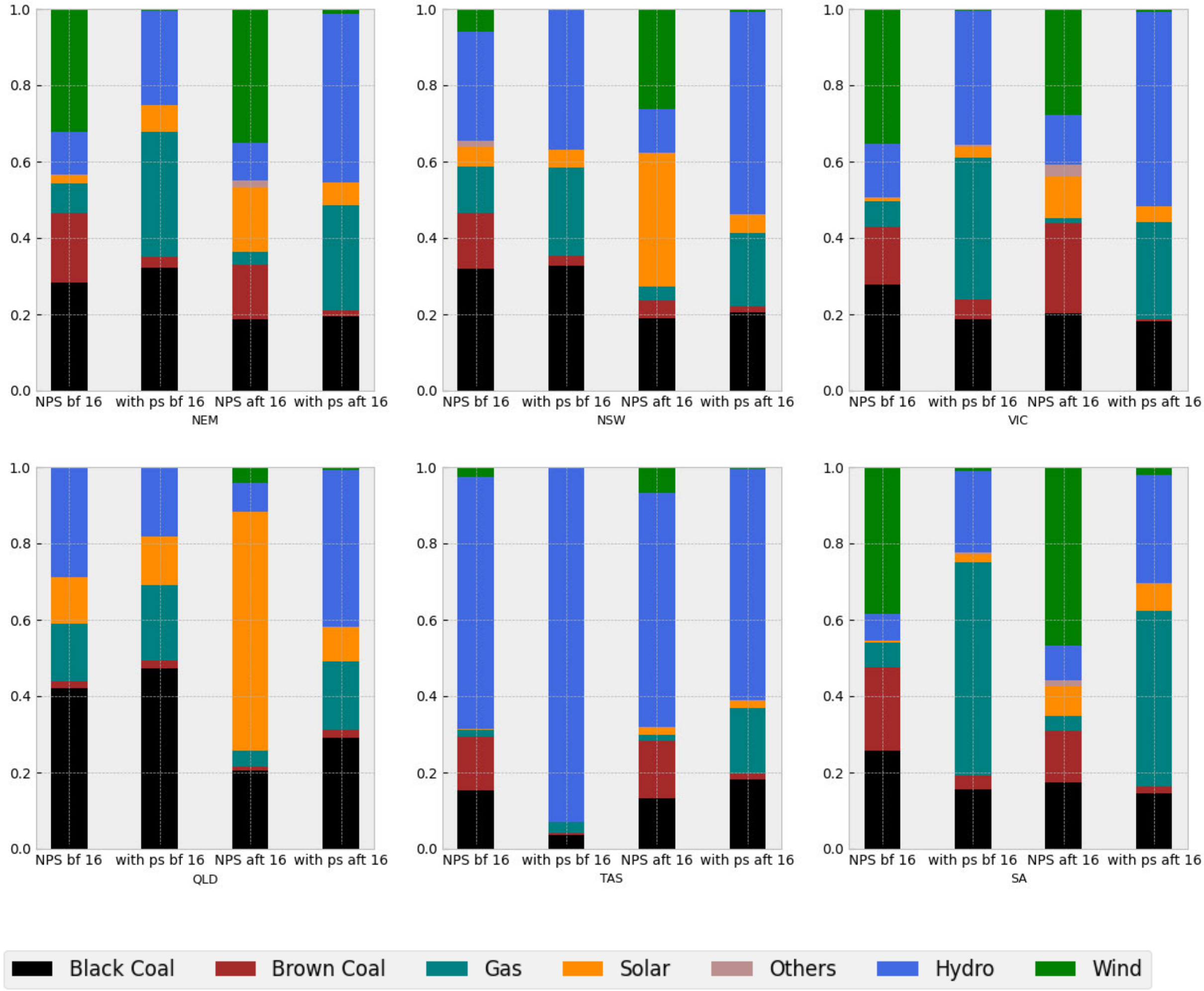
Theoretically, price spikes occur for two main reasons. First, if demand rises to the point of system capacity (e.g. because of extreme hot temperatures), the demand curve will shift upward, leading to an increase in price. Second, if available supply decreases (e.g. because of generation failure), the supply curve also shifts upward, leading to price spikes. However, in the real market, price spikes may also occur as a result of the strategic behaviour of market participants. By intentionally reducing supply capacity (i.e. capacity withholding), generators may increase equilibrium prices over the optimal level (Maenhoudt and Deconinck, 2014; Nappu et al., 2013; Zhang et al., 2015). In this situation, generators withhold supply capacity, initiating a price spike. Given that one price spike is enough to substantially increase the average dispatch price (i.e. spot price), generators may had rebid all of their capacity at a lower price band for the next dispatch period, creating a negative price situation. Clements et al. (2016) studied strategic bidding and rebidding in the Queensland market and found evidence of rebidding following an extreme price spike on 28 August 2013. However, since then, the rules have been tightened (Australian Energy Market Commission, 2015). From 1 July 2016, if a rebid is made during a 30-minute trading interval or less than 15 minutes before the commencement of a trading interval, the generator must make a contemporaneous record setting out the material conditions and circumstances leading to the rebid. This record must be made available to the AER on request (Dungey et al., 2017).

For this reason, Figure 5.29 divides the study period into before and after 1 July 2016. As shown in the first panel, prior to July 2016, during negative price situations, wind generators made the highest contributions to electricity prices, followed by black coal, brown coal, hydropower and gas technologies. The contributions of solar generators were negligible. After July 2016, the contributions of renewable energy generators to electricity prices during negative price situation increased. While wind generators continued to be the highest contributors, solar generators became much more active.

Before July 2016, when a price spike occurred in a previous dispatch period within the same trading interval, black coal and gas were the highest contributors to price, followed by hydropower. However, after July 2016, hydropower became the biggest contributor, followed by gas and coal generators. The contributions of renewable energies were negligible in this case for both study periods. Given that peaking generators set electricity prices equally before and after July 2016, in a negative price situation with a price spike in a previous dispatch period, there was no evidence of a reduction in strategic rebidding following the rule change.

Figure 5.29

Price-Setting Generators During Periods of Negative Electricity Prices Before and After 1 July 2016



Note. The first panel represents the entire NEM, while the remainder represent the regional markets. NPS = negative price situation; ps = price spike; bf 16 = before 1 July 2016; aft 16 = after 1 July 2016.

5.2 Full Sample Logistic Regression

The analysis in the previous sections shows the changes in energy generators' contributions to electricity prices with regards to time, demand and prices. This section presents the analysis of the statistical significance of these factors in explaining the probability of each generation technology setting the electricity price. We first ran a logit model for the entire period to examine the effects of intraday and between day variables on the price setting of electricity prices. In the second stage, we conducted a 3-year rolling window logit regression and plotted the coefficients to observe how they changed over time.

We assumed that the marginal probability of price setting followed a logistic distribution. This can be written as:

$$P_{i,t}\ (Y_{i,t}\ = 1) = \frac{1}{1+\exp\left(-\alpha-\beta x_{i,t}\right)},$$

where $Y_{i,t}$ is an indicator that equals 1 if technology i sets the electricity price at period t, and 0 otherwise. Furthermore, $x_{i,t}$ is a vector of explanatory variables at period t, which includes the shoulder period dummy (*SPD*) (7.00 am to 2.00 pm), peak hour dummy (*PHD*) (2.00 pm to 8.00 pm), summer dummy (*SD*), winter dummy (*WD*), lower price dummy (*NPD*) (which equals 1 if the electricity price lies below the first percentile and 0 otherwise), price spike dummy (*PSD*) (which equals 1 if the electricity price lies above the 99th percentile and 0 otherwise) and a carbon tax period dummy (*CD*) (July 2012–July 2014). A higher value for $\alpha + \beta x_{i,t}$ implies a higher probability of the generator setting the electricity price.

Tables 5.4 and 5.5 show the logit regression results for the entire sample period for fossil fuel–based technologies and renewable technologies, respectively. Almost all seven variables included in the model were highly statistically significant for all generation technologies and regional markets.

Table 5.4

Logistic Regression Results for Fossil Fuel–Based Generation Technologies (July 2009–June 2021)

	NEM	New South Wales	Victoria	Queensland	South Australia	Tasmania
Black coal						
Constant	0.352 (0.002) ***	0.9 (0.004) ***	0.223 (0.003) ***	1.085 (0.004) ***	0.27 (0.003) ***	−0.577 (0.003) ***
CD	0.02 (0.002) ***	0.094 (0.006) ***	0.024 (0.005) ***	0.001 (0.006)	−0.315 (0.005) ***	0.227 (0.005) ***
SPD	−0.052 (0.002) ***	−0.075 (0.004) ***	−0.038 (0.004) ***	0.027 (0.004) ***	−0.088 (0.004) ***	−0.058 (0.004) ***
PHD	−0.379 (0.002) ***	−0.517 (0.005) ***	−0.33 (0.005) ***	−0.456 (0.005) ***	−0.524 (0.005) ***	−0.185 (0.005) ***
SD	0.078 (0.002) ***	0.248 (0.005) ***	0.019 (0.004) ***	0.158 (0.005) ***	0.076 (0.004) ***	−0.067 (0.004) ***
WD	0.013 (0.002) ***	−0.087 (0.004) ***	−0.077 (0.004) ***	−0.089 (0.005) ***	−0.15 (0.004) ***	0.45 (0.004) ***
NPD	−0.601 (0.007) ***	−0.273 (0.015) ***	−0.465 (0.018) ***	−2.006 (0.026) ***	−0.966 (0.012) ***	−0.611 (0.015) ***
PSD	−1.494 (0.009) ***	−2.122 (0.021) ***	−1.416 (0.021) ***	−1.499 (0.018) ***	−1.776 (0.024) ***	−1.395 (0.025) ***
Pseudo-R^2	0.009	0.018	0.007	0.017	0.018	0.013
Brown coal						
Constant	−1.749 (0.002) ***	−2.582 (0.006) ***	−1.251 (0.004) ***	−2.538 (0.006) ***	−1.403 (0.004) ***	−1.477 (0.004) ***
CD	0.412 (0.003) ***	0.828 (0.008) ***	0.334 (0.006) ***	0.692 (0.008) ***	0.275 (0.006) ***	0.309 (0.006) ***
SPD	−0.148 (0.002) ***	−0.166 (0.007) ***	−0.164 (0.005) ***	−0.227 (0.007) ***	−0.142 (0.005) ***	−0.098 (0.005) ***
PHD	−0.505 (0.003) ***	−0.404 (0.01) ***	−0.603 (0.006) ***	−0.552 (0.01) ***	−0.653 (0.007) ***	−0.349 (0.006) ***
SD	0.199 (0.003) ***	0.059 (0.008) ***	0.307 (0.005) ***	0.076 (0.008) ***	0.313 (0.005) ***	0.074 (0.005) ***
WD	−0.065 (0.003) ***	−0.227 (0.009) ***	−0.138 (0.005) ***	−0.228 (0.009) ***	−0.122 (0.006) ***	0.173 (0.005) ***
NPD	1.293 (0.007) ***	1.65 (0.016) ***	0.557 (0.02) ***	−0.007 (0.051)	0.222 (0.013) ***	0.281 (0.016) ***
PSD	−1.17 (0.018) ***	−0.366 (0.041) ***	−1.808 (0.047) ***	−0.591 (0.048) ***	−1.899 (0.05) ***	−1.094 (0.033) ***
Pseudo-R^2	0.015	0.029	0.016	0.016	0.016	0.007

	NEM	New South Wales	Victoria	Queensland	South Australia	Tasmania
Gas						
Constant	−1.58 (0.002) ***	−1.896 (0.005) ***	−1.522 (0.004) ***	−2.03 (0.005) ***	−0.945 (0.004) ***	−1.715 (0.005) ***
CD	−0.109 (0.003) ***	−0.478 (0.009) ***	−0.382 (0.007) ***	−0.311 (0.008) ***	0.026 (0.006) ***	0.288 (0.006) ***
SPD	−0.017 (0.002) ***	0.011 (0.006) *	0.021 (0.005) ***	0.006 (0.006)	−0.004 (0.004)	−0.069 (0.005) ***
PHD	0.233 (0.003) ***	0.313 (0.007) ***	0.258 (0.006) ***	0.345 (0.007) ***	0.302 (0.005) ***	0.04 (0.006) ***
SD	−0.099 (0.003) ***	−0.204 (0.007) ***	−0.084 (0.006) ***	−0.103 (0.007) ***	−0.154 (0.005) ***	0.049 (0.006) ***
WD	0.155 (0.002) ***	0.078 (0.006) ***	0.149 (0.005) ***	0.052 (0.006) ***	0.206 (0.005) ***	0.237 (0.006) ***
NPD	−0.938 (0.013) ***	−1.505 (0.041) ***	−1.96 (0.052) ***	−0.549 (0.044) ***	−1.669 (0.02) ***	−1.92 (0.04) ***
PSD	0.503 (0.008) ***	−0.258 (0.026) ***	0.015 (0.021)	0.377 (0.023) ***	1.149 (0.018) ***	−0.53 (0.028) ***
Pseudo-R^2	0.005	0.009	0.007	0.005	0.015	0.008

Note. NEM: National Electricity Market; **Table 5.4** *CD*: carbon tax period dummy; *SPD*: shoulder period dummy; *PHD*: peak hour dummy; *SD*: summer dummy; *WD*: winter dummy; *NPD*: negative price dummy (below the first percentile); *PSD*: price spike dummy (above the 99th percentile). *** p = .001, ** p = .005, * p = .01. Standard errors are presented in parentheses.

Table 5.5

Logistic Regression Results for Renewable Energy Generation Technologies (July 2009–June 2021)

	NEM	New South Wales	Victoria	Queensland	South Australia	Tasmania
Hydropower						
Constant	−0.639 (0.002) ***	−1.26 (0.004) ***	−0.976 (0.004) ***	−1.509 (0.004) ***	−1.092 (0.004) ***	1.377 (0.004) ***
CD	−0.166 (0.002) ***	−0.375 (0.006) ***	−0.355 (0.006) ***	−0.278 (0.007) ***	−0.463 (0.006) ***	0.372 (0.007) ***
SPD	0.125 (0.002) ***	0.177 (0.005) ***	0.23 (0.004) ***	0.093 (0.005) ***	0.221 (0.004) ***	0.093 (0.005) ***
PHD	0.396 (0.002) ***	0.572 (0.005) ***	0.613 (0.005) ***	0.556 (0.006) ***	0.533 (0.005) ***	0.12 (0.006) ***
SD	−0.17 (0.002) ***	−0.323 (0.005) ***	−0.246 (0.005) ***	−0.278 (0.006) ***	−0.229 (0.005) ***	−0.024 (0.005) ***
WD	0.023 (0.002) ***	0.096 (0.005) ***	0.166 (0.004) ***	0.115 (0.005) ***	0.129 (0.005) ***	−0.443 (0.005) ***
NPD	0.11 (0.007) ***	−1.425 (0.029) ***	−0.554 (0.022) ***	−0.616 (0.035) ***	−1.034 (0.016) ***	0.89 (0.022) ***
PSD	0.967 (0.008) ***	2.349 (0.02) ***	1.632 (0.019) ***	1.391 (0.017) ***	0.096 (0.019) ***	1.928 (0.044) ***
Pseudo-R^2	0.007	0.029	0.021	0.017	0.016	0.012
Solar						
Constant	−3.904 (0.005) ***	−4.098 (0.013) ***	−4.099 (0.013) ***	−3.514 (0.01) ***	−4.051 (0.012) ***	−4.032 (0.013) ***
CD	−0.51 (0.009) ***	−0.368 (0.021) ***	−0.666 (0.024) ***	0.099 (0.013) ***	−0.964 (0.027) ***	−1.397 (0.032) ***
SPD	0.309 (0.006) ***	0.177 (0.015) ***	0.292 (0.014) ***	0.236 (0.011) ***	0.303 (0.014) ***	0.14 (0.014) ***
PHD	0.447 (0.007) ***	0.553 (0.016) ***	0.457 (0.017) ***	0.492 (0.012) ***	0.421 (0.016) ***	0.156 (0.017) ***
SD	−0.014 (0.006) ***	−0.149 (0.016) ***	0.006 (0.015)	−0.02 (0.011) *	0.092 (0.014) ***	0.127 (0.015) ***
WD	−0.041 (0.006) ***	−0.084 (0.015) ***	−0.087 (0.015) ***	−0.022 (0.011) **	−0.172 (0.015) ***	0.183 (0.015) ***
NPD	1.376 (0.013) ***	1.804 (0.025) ***	2.463 (0.024) ***	4.341 (0.027) ***	1.862 (0.017) ***	0.683 (0.034) ***
PSD	0.994 (0.015) ***	0.332 (0.05) ***	0.971 (0.038) ***	0.796 (0.031) ***	1.702 (0.029) ***	0.075 (0.056)
Pseudo-R^2	0.013	0.018	0.035	0.067	0.05	0.014

	NEM	New South Wales	Victoria	Queensland	South Australia	Tasmania
Wind						
Constant	−4.911 (0.008) ***	−5.728 (0.028) ***	−5.04 (0.02) ***	−5.411 (0.027) ***	−4.318 (0.013) ***	−5.136 (0.022) ***
CD	−0.365 (0.013) ***	−1.89 (0.091) ***	−1.551 (0.061) ***	−2.266 (0.108) ***	0.863 (0.015) ***	−2.045 (0.084) ***
SPD	0.547 (0.009) ***	0.604 (0.031) ***	0.304 (0.022) ***	0.342 (0.031) ***	0.306 (0.013) ***	0.066 (0.025) ***
PHD	0.436 (0.011) ***	0.709 (0.038) ***	0.208 (0.027) ***	0.298 (0.038) ***	0.204 (0.016) ***	−0.139 (0.032) ***
SD	−0.193 (0.009) ***	−0.752 (0.036) ***	−0.099 (0.022) ***	−0.617 (0.038) ***	−0.281 (0.014) ***	0.1 (0.026) ***
WD	−0.227 (0.009) ***	−0.401 (0.033) ***	−0.296 (0.025) ***	−0.304 (0.032) ***	−0.004 (0.014)	−0.39 (0.03) ***
NPD	3.518 (0.009) ***	3.136 (0.032) ***	4.718 (0.022) ***	2.177 (0.057) ***	4.55 (0.013) ***	2.713 (0.028) ***
PSD	0.199 (0.035) ***	0.878 (0.089) ***	0.471 (0.083) ***	0.369 (0.114) ***	0.46 (0.055) ***	0.095 (0.104)
Pseudo-R^2	0.107	0.094	0.241	0.034	0.3	0.07

Note. NEM: National Electricity Market; *CD*: carbon tax period dummy; *SPD*: shoulder period dummy; *PHD*: peak hour dummy; *SD*: summer dummy; *WD*: winter dummy; *NPD*: negative price dummy (below the first percentile); *PSD*: price spike dummy (above the 99th percentile). *** $p = .001$, ** $p = .005$, * $p = .01$. Standard errors are presented in parentheses.

As shown in Table 5.4, for most regional markets, black coal generators were less likely to set electricity prices during peak and shoulder periods and at both lower and upper price extremes and more likely to set electricity prices during summer and winter. Similarly, brown coal generators were less likely to set electricity prices during shoulder and peak periods and more likely to set electricity prices during summer and in lower price situations. However, in contrast to black coal generators, they were less likely to set electricity prices during winter. Gas generators were more likely to set electricity prices during peak hour periods, in winter and during price spikes and less likely to set electricity prices during shoulder periods, in summer and at lower prices.

As shown in Table 5.5, the likelihood of hydropower setting the electricity price was higher for both upper and lower price extremes. The likelihood also increased during periods of high demand such as the peak and shoulder periods and in winter. Hydropower was less likely to set electricity prices in summer. Solar and wind technologies were more likely to set electricity prices during shoulder and peak hour periods and at both upper and lower price extremes and less likely in both summer and winter.

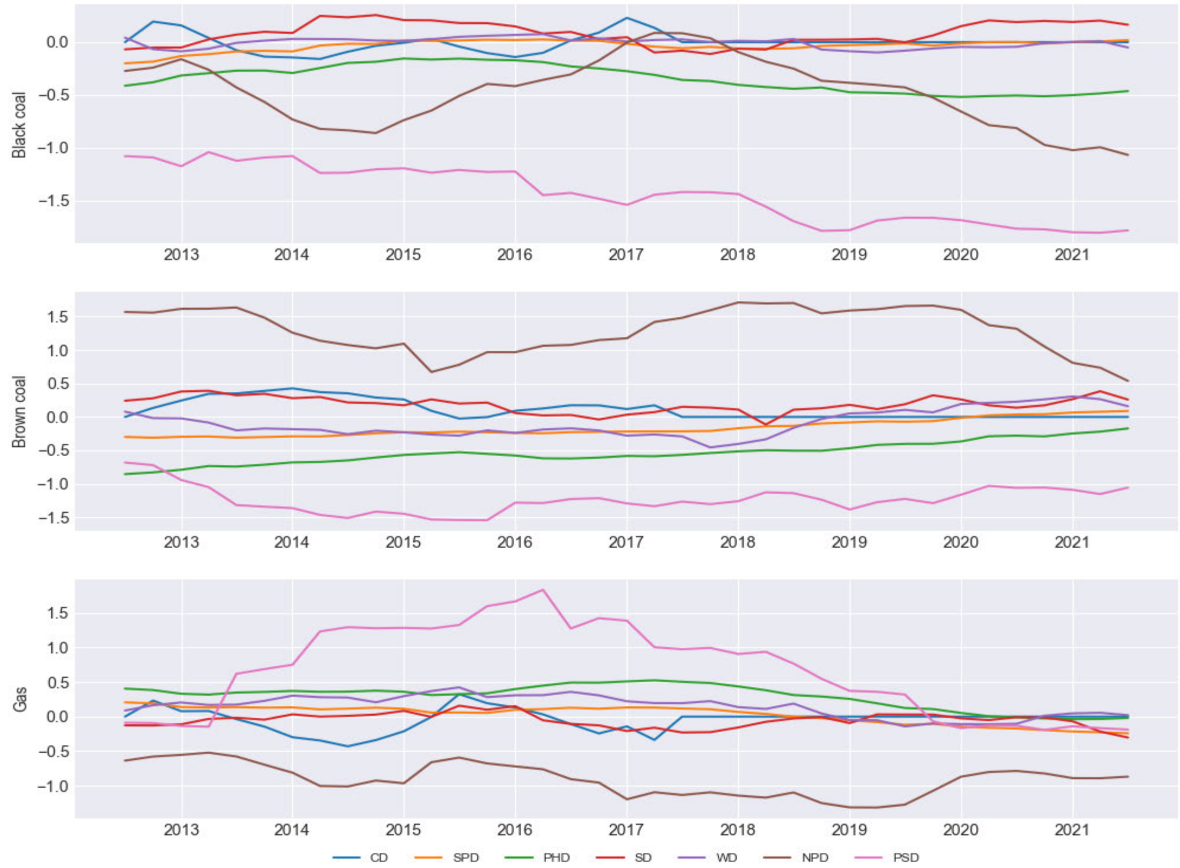
During the carbon tax period (July 2012–July 2014), the probability of coal generators setting electricity prices was higher than that of other generators, including renewable energy technologies. Given that this period was dominated by coal technologies, and the share of renewable energies was negligible, this result may be explained by supply rather than the carbon tax policy.

5.3 Rolling Window Logistic Regression

To examine the change in the likelihood of energy generators setting electricity prices throughout the study period, 3-year rolling window logistic regressions were conducted and the coefficients plotted in Figures 5.30 and 5.31. These graphs illustrate the logistic regression coefficient results for fossil fuel and renewable generators, respectively, in the NEM (see Appendices 2–6 for the coefficient plots of the individual regional markets).

Figure 5.30

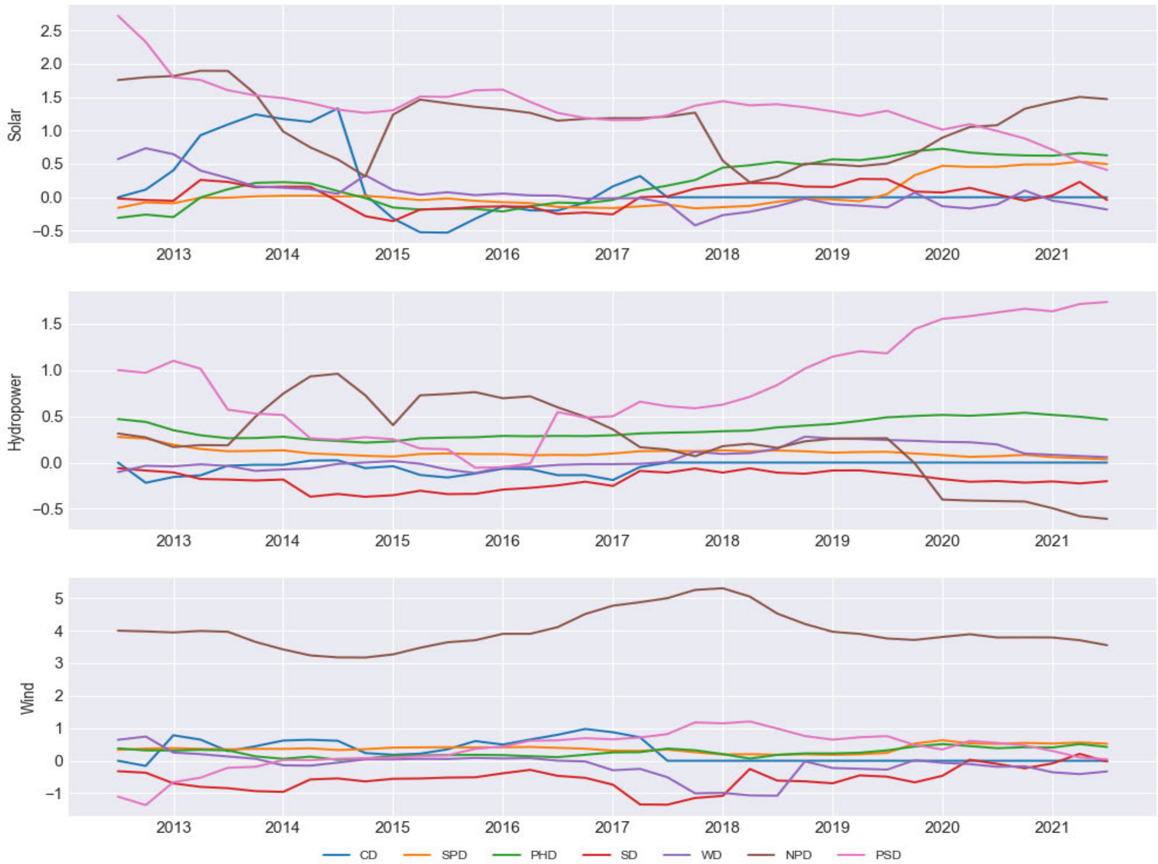
Three-Year Rolling Window Logistic Regression Coefficient Plots for Fossil Fuel Generators in the National Electricity Market



Note. *CD*: carbon tax period dummy; *SPD*: shoulder period dummy; *PHD*: peak hour dummy; *SD*: summer dummy; *WD*: winter dummy; *NPD*: Lower price dummy (below the first percentile); *PSD*: price spike dummy (above the 99th percentile). All coefficients were statistically significant at the 1% level.

Figure 5.31

Three-Year Rolling Window Logistic Regression Coefficient Plots for Renewable Energy Generators in the National Electricity Market



Note. *CD*: carbon tax period dummy; *SPD*: shoulder period dummy; *PHD*: peak hour dummy; *SD*: summer dummy; *WD*: winter dummy; *NPD*: negative price dummy (below the first percentile); *PSD*: price spike dummy (above the 99th percentile). All coefficients were statistically significant at the 1% level.

As shown in Figure 5.30, for black coal generators, the coefficient for the price spike dummy (*PSD*) was negative (less than −1) throughout the study period and followed a declining trend. The coefficient for the lower price dummy (*NPD*) was also negative and showed a declining trend for most of the study period (apart from a gradual increase from 2015 to 2017). Similarly, the coefficient for the peak hour dummy (*PHD*) was negative and decreased throughout the period. Therefore, black coal generators had a low probability of setting electricity prices during peak hours and periods of extreme price levels, and this inverse relationship became stronger over time. While the coefficient for the summer dummy (*SD*) for black coal generators was negative from mid-2016 to mid-2019, it was positive for the rest of the period. Therefore, most of the time, there was a positive association between the probability of black coal generators setting the electricity price and the summer season. In the case of winter, this relationship fluctuated.

For the brown coal generators, the lower price dummy (*NPD*) was positive throughout the period but followed a declining trend. However, the price spike dummy (*PSD*) was negative and gradually increased from 2015. Therefore, the probability of brown coal generators setting the electricity price was higher during periods of negative prices and lower during periods of price spikes. Both of these relationships weakened over time. Initially, the coefficients for the peak hour dummy (*PHD*) and shoulder period dummy (*SPD*) were negative; however, a gradual increase was observed over time. Although *PHD* remained negative, *SPD* became positive after 2020. Therefore, for brown coal generators, the negative association between the probability of setting electricity prices and the peak and shoulder periods weakened over time. Similarly, although the coefficient for the winter dummy (*WD*) slowly declined up until 2018, this negative association reversed after 2019. In the case of the summer dummy (*SD*), the coefficient was positive and steady throughout the study period.

For the gas generators, despite a dramatic increase in the coefficient for the price spike dummy (*PSD*) after 2013, a massive slump was observed after 2016. Although the coefficient was positive for most of the period, the relationship was weaker in the later stages than in the early stages of the study period. As expected, the coefficient for the lower price dummy (*NPD*) was negative throughout the study period, implying that gas technologies are less likely to set electricity prices during periods of lower prices. Similarly, until 2018, the coefficients for the peak hour (*PHD*) and shoulder period dummies (*SPD*) were positive and stable. However, after 2018, both of these coefficients began to fall. Hence, the probability of gas generators setting electricity prices during peak hours was lower in the later stages of the study period compared with the early stages. For most of the study period, the coefficient for summer was negative, while the coefficient for winter was positive, indicating that gas technologies are more likely to set electricity prices during winter.

As shown in Figure 5.31, for hydropower generators, all coefficients apart from those for price extremes were almost consistent with the usual signs throughout the study period. Despite its massive slump in 2013, the coefficient for the price spike dummy rose dramatically after 2016 and remained positive. However, from mid-2014, the coefficient for the negative price dummy declined consistently, becoming negative from mid-2019. Therefore, over time, hydropower was more likely to set electricity prices during price spikes and less likely to set electricity prices during negative prices. The coefficients for peak and shoulder periods were positive and consistent throughout the period, while the coefficient for the summer dummy was negative for most of the period. Therefore, as a peaking plant, hydropower had a higher probability of setting electricity prices during peak periods and a lower probability of setting electricity prices in summer.

Most of the coefficients for solar power fluctuated significantly during the initial years of the study period. The coefficient for price spikes gradually decreased over time. However, all coefficients gradually increased after 2016, with the coefficient for the negative price dummy increasing after mid-2018. Therefore, apart from during price spikes, the probability of solar generators setting electricity prices was higher in the later stages of the study period.

For wind generators, the coefficient of the negative price dummy was strong and positive throughout the study period, implying that wind generators have a high probability of setting electricity prices in lower price situations. From 2015, the coefficient for price spikes was positive, although it declined after 2018. Therefore, there is a high probability of wind generators setting electricity prices during price extremes. The coefficients for the peak and shoulder period dummies were consistently positive throughout the study period, while the coefficient for summer was negative. This indicates that wind generators have a high likelihood of setting electricity prices during peak hours and a low likelihood of setting electricity prices during summer.

As expected, for most of the study period, the coefficients for the carbon tax dummy (*CPD*) were negative for most fossil fuel–based generators (except brown coal) and positive for renewable generators (wind and solar). This indicates that during the carbon tax period, the probability of renewables setting electricity prices had increased , while the probability for fossil fuel–based generators had decreased.

5.4 **Summary of Logistic Regression**

Our regression analysis confirms the results of our initial more descriptive examination. For instance, the finding that black coal generators are less likely and hydropower more likely to set electricity prices during shoulder and peak hours is consistent with our previous findings (see Section 4.4). Similarly, based on our findings presented in Sections 4.6 and 4.7, the contributions of coal generators to electricity price setting during periods of high demand and high electricity prices were lower, while the contributions of hydropower and gas were higher.

This is further confirmed by the regression analysis, because the coefficients for the price spike dummy were negative for coal generators and positive for hydropower and gas.

The regression analysis provides some additional insights. In particular, it expands our understanding of how price-setting technologies behave in different seasons of the year. Our results indicate that black and brown coal are more likely to set electricity prices in summer, while hydropower and gas generators are more likely to set electricity prices in winter. Similarly, during the carbon tax period, the likelihood of renewable energy generators setting electricity prices was higher, while that of fossil fuel–based generators was lower.

Chapter 6: Conclusion and Discussion

This study conducts a detailed analysis of the price setting generation technologies in the Australian NEM for the sample period from 1 July 2009 to 30 June 2021. The main objective of the study is to broaden the knowledge about the price setting generation (marginal) technologies in the NEM and to provide a full picture of which technology sets market prices under different circumstances. The thesis aims to make three specific contributions to the literature. First, it aims to analyse the variation in price setting technologies across days and intraday and to identify the factors that initiate such variation across different regional markets in Australia. Second, the research attempts to analyse the impacts of the recent changes, such as the increasing share of renewable generators, the 2012-2014 carbon tax, and the introduction of battery storage technologies, on the marginal technologies. Third, the research also tries to explain the strategic behavior of market participants based on information on marginal price setting technologies.

By analyzing 5-minute dispatch data for the entire sample period we found that black coal generators set the electricity prices most frequently, followed by hydropower and gas technologies in most of the regional markets, except for Tasmania. As a result of the distinct generation profile of the Tasmanian regional market, hydropower was more likely to set the electricity price there, however, black coal was still significant in setting electricity prices also in Tasmania. These findings are quite different from those of Blume-Werry et al. (2018) who found that gas generators, followed by hydropower and coal technologies, set electricity prices for most of the hours in European markets. The quite different findings of this thesis might be the result of a very distinct generation mix for Australia in comparison to European markets. We also found renewable generators (wind and solar generators), as well as battery storage technologies only very rarely, act as price-setting technologies, although their share has been increasing in recent years. However, in comparison to other fossil fuel technologies, apart from a minor contribution to setting electricity prices in the South Australian market, they were barely setting electricity prices for the rest of the regional markets.

To examine how price-setting generation technologies were changing throughout the study period, a 90-day rolling window analysis was conducted. Based on this rolling window analysis we found that the shares of generators to set the electricity price fluctuate substantially through time. The analysis showed that the share of fossil fuel-based generation technologies to set electricity prices is decreasing throughout the sample period, while the share of renewable generators including hydropower has been increasing. Although black coal was still dominating electricity price setting, during later phases of the study period, the gap between the share of black coal generators and other generators (mainly hydro and gas) to set electricity prices has narrowed.

In terms of renewable energy, gradual but small increments in the share of wind and solar generation technologies to set electricity prices could be witnessed at the beginning of the sample period. Although this growth was accelerated after 2018 in all regional markets, the share of renewable to set electricity prices is still meagre. This finding was consistent with Gissey et. al. (2018) who suggest that even though renewable generation is on the rise, fossil fuels are still responsible for determining EU electricity prices. Among the renewable generators, for most of the time, wind generators were much more active as price setters than solar generators in all regional markets except Queensland. The share of battery storage technologies as price setters was less than 1% in all regional markets. This indicates a potential need for further investment in battery storage technologies to manage the intermittency of renewable generators and sustain their growth.

In terms of variation across days, coal generators were more active to set electricity prices during off-peak periods while hydropower and gas technologies were setting electricity prices more frequently during peak periods. The contribution of coal technologies to price setting slumped twice a day at around 7.00 am and 6.30 pm, after which it gradually increased, plateauing at the beginning, middle and end of the day. Therefore, in every regional market, the intraday variations in the contributions of coal to price setting generated a W-shaped curve. Hydropower and gas generators set electricity prices more frequently during peak hours than during off-peak hours, peaking twice a day (at 7.00 am and 6.30 pm, respectively), precisely when coal dropped to its lowest level. Therefore, in contrast to the W-shaped curve for coal generators, hydropower and gas generated an M-shaped curve.

Among the renewable generators, solar generators are more active to set electricity prices in the middle of the day when sunlight is abundant while wind generators set electricity prices more frequently in the early morning and at midday. For the entire hours of a typical day, the contribution of wind generators to setting electricity prices was higher than solar and battery storage technologies in most of the regional market. However, for Queensland and NSW the contributions of solar generators to price setting exceeds those of wind generators around midday.

The thesis also examined the relationship between electricity market demand and price setting technologies. For all regional markets (except Tasmania), black coal dominated price setting at lower levels of demand. However, as demand increased, the contribution of black coal to set electricity prices decreased, while other generators, mainly hydropower, gas and brown coal, began to increase. At upper quantiles of demand, the shares of hydropower and gas in price setting were even higher than those of black coal generators. However, this upper quantile where share of gas and hydropower exceeded black coal generators varied significantly across the regional markets. Along with the rising demand, the contribution of gas increased rapidly in South Australia compared to other regional markets. In the South Australian market, the share of gas technologies to set electricity prices was higher than the share of black coal for the entire upper quartile of demand. Likewise, the pace of increment of hydropower contribution in price setting was higher in the Victorian market in comparison to other regional markets. For Victoria, the contribution of hydropower was higher than black coal for the entire upper demand quintile.

As expected, being intermittent technologies, renewable generators were unable to ramp up their production along with increasing demand. For most demand percentiles, the contribution of renewable technologies to set electricity prices was consistently small. Thus, as stated by Rai and Nunn (2020a) renewable generators were not able to obtain a dispatchability premium.

Examining the relationship between price levels and price setting technologies, this study found that the contribution of black coal to set electricity prices decreases along with higher price levels. At the same time, the contribution of hydropower and gas technologies showed an inverse trend, i.e. those technologies were more likely to be at the margin for higher price levels. These results were consistent with Blume-Werry et. al., (2018) who found that for mid- to high-price hours, reservoirs and pumped-hydro power stations were responsible for price setting for considerable hours. Examining negative prices, the study found that throughout the considered sample period wind generators were most likely to be the price-setting technology followed by black coal, brown coal, and solar generators. Peak load generators such as hydropower and gas were not active to set electricity prices during negative price scenarios. However, if a price spike occurred in any of the five-minute dispatch periods of a 30-minute trading interval, the shares of peak load plants were higher than the base load plants to set negative electricity prices.

Because of their high ramp rate and lower start-up cost, peak load plants like gas and hydropower would normally not be expected to play a role in setting prices during negative price scenarios. The finding that there were still a number of occurrences of price setting during trading intervals with initial price spikes followed by negative prices may be a result of capacity withholding rather than higher demand or lower supply. Given that one price spike is enough to substantially increase the average dispatch price (i.e. spot price), in such a scenario generators may rebid all of their capacity at a lower price band for the next dispatch period, creating negative prices. Such cases of strategic re-bidding were also found by Clements et al. (2016).

In the light of tighter re-bidding rule enforced by July 2016, we also examined whether the price setting behaviour during negative price scenarios was different after the rule change. Before July 1, 2016, during negative price situations, wind generators made the highest contributions to electricity prices, followed by black coal, brown coal, hydropower, and gas technologies. The contributions of solar generators were negligible. However, after 2016, solar generators became much more active to set negative electricity prices, ranked in second position after wind generators. Meanwhile, if the price spikes were observed in the previous dispatch period of the same trading interval, peaking generators (hydropower and gas) were dominating to set negative electricity prices both before and after July 1, 2016. Hence, no evidence of a reduction in strategic rebidding was found following the rule change.

Our logistic regression during the full sample period conformed to most of our findings from the conducted descriptive analysis. In addition, we found that black coal and brown coal were more likely to set electricity prices during summer, while gas and hydropower were more likely to set electricity prices during the winter season. Similarly, based on a rolling window logistic regression analysis we found that throughout our sample period, overall, the probability of black coal generators setting electricity prices during extreme price scenarios such as price spikes and negative prices were increasing. At the same time, hydro generators became less likely to set lower electricity prices but more likely to be the price-setting technology during price spikes. On the contrary, gas generators were less likely to set price spikes in later stages than in the early stages of the study period. Wind and solar generators were equally active to set extreme electricity prices, however, over time their probability to set price spikes were low.

Based on applied logistic regression, we found that the probability for renewable generators to set electricity prices was increased during the carbon tax period, while fossil fuel-based generators' (except brown coal) were less likely to set electricity prices.

Lastly, our research showed that different generation technologies set electricity prices at different levels, which may have a direct influence on the profitability of the generators. So, in future research, it will be interesting to investigate the impact of changes in marginal technologies on the profitability of the generators. Similarly, our findings also suggest that the share of renewables in price setting is increasing while the share of fossil fuel-based generators is decreasing. Because of the intermittence in electricity production, renewable generators are often regarded as less reliable (Rai and Nunn, 2020b). Further analysis may be conducted to explore if this shift in price-setting technologies creates any reliability issues in the Australian electricity market.

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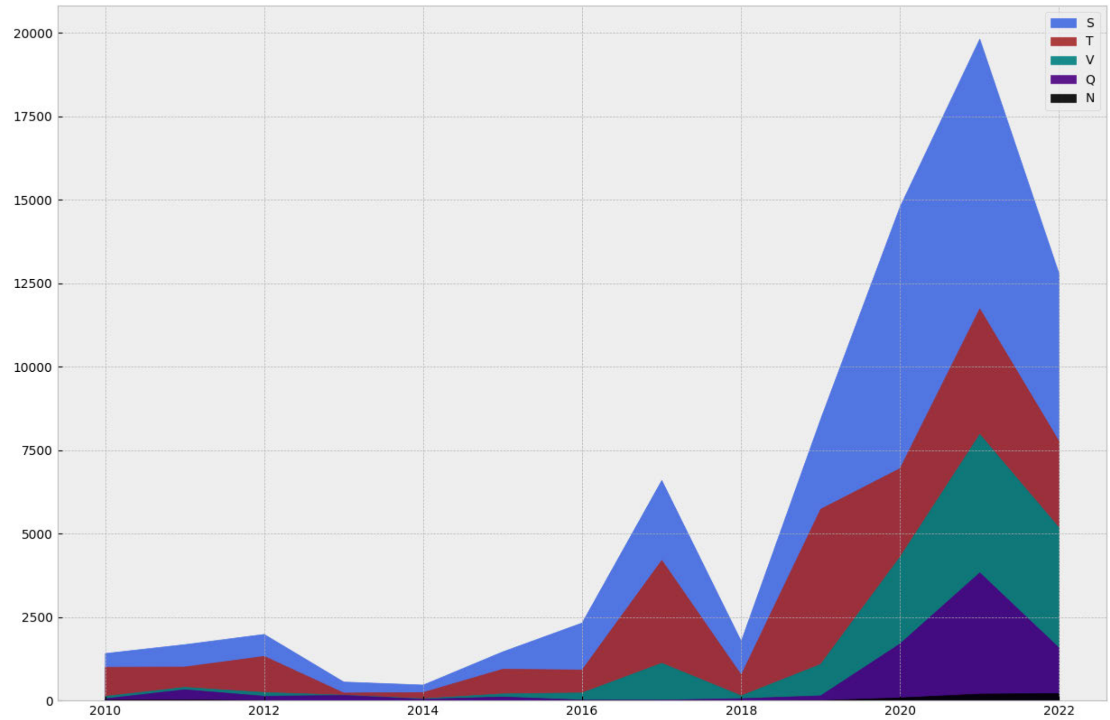
Appendices

Appendix 1

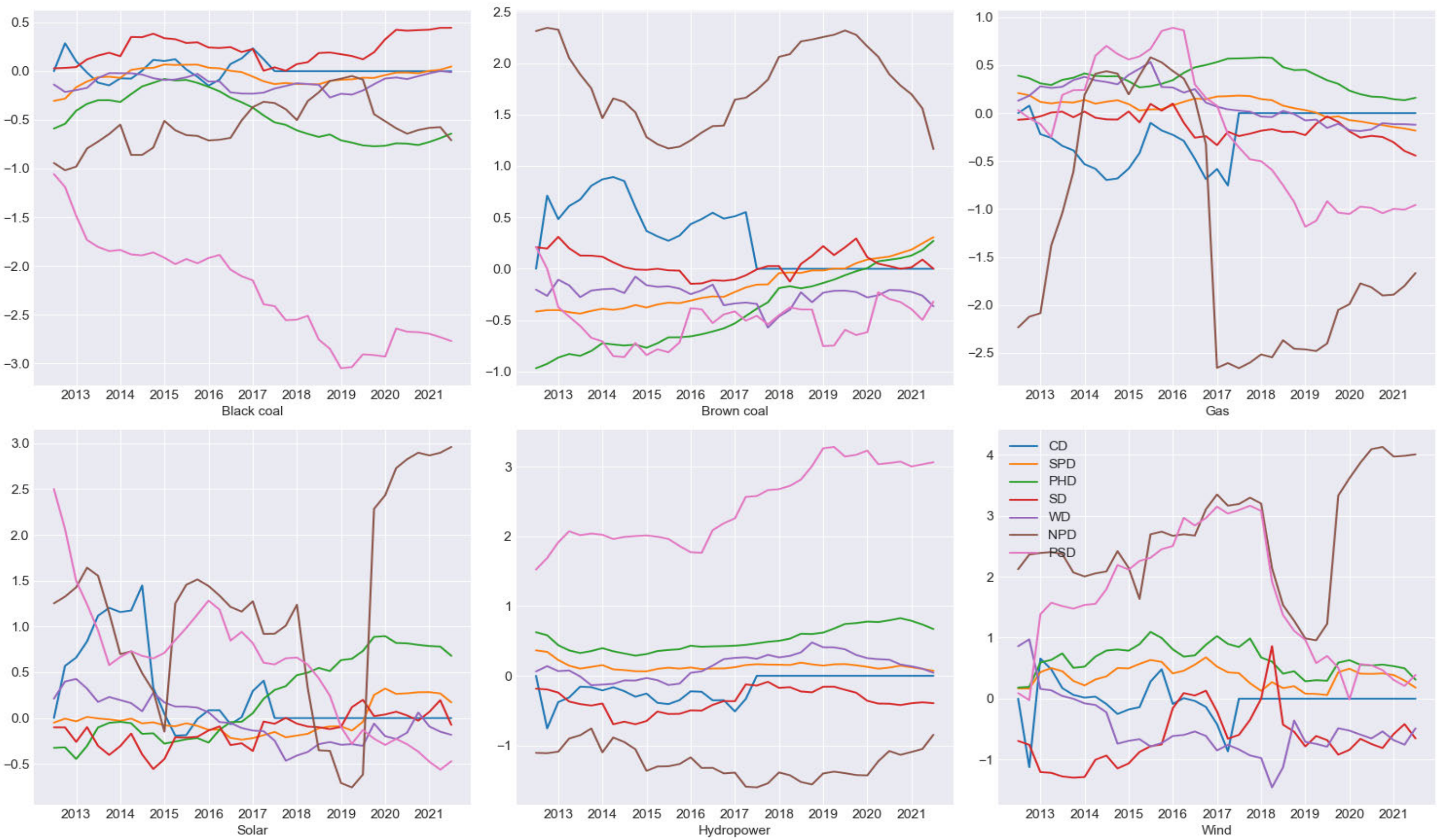
The stack plot of the negative electricity prices in NEM (July 2009–June 2021)



Note. S: South Australia; T: Tasmania; V: Victoria; Q: Queensland; N: New South Weals. The figure shows the annual frequency of negative electricity price cases in NEM. Each colour represents the contribution of corresponding regional markets.

Appendix 2

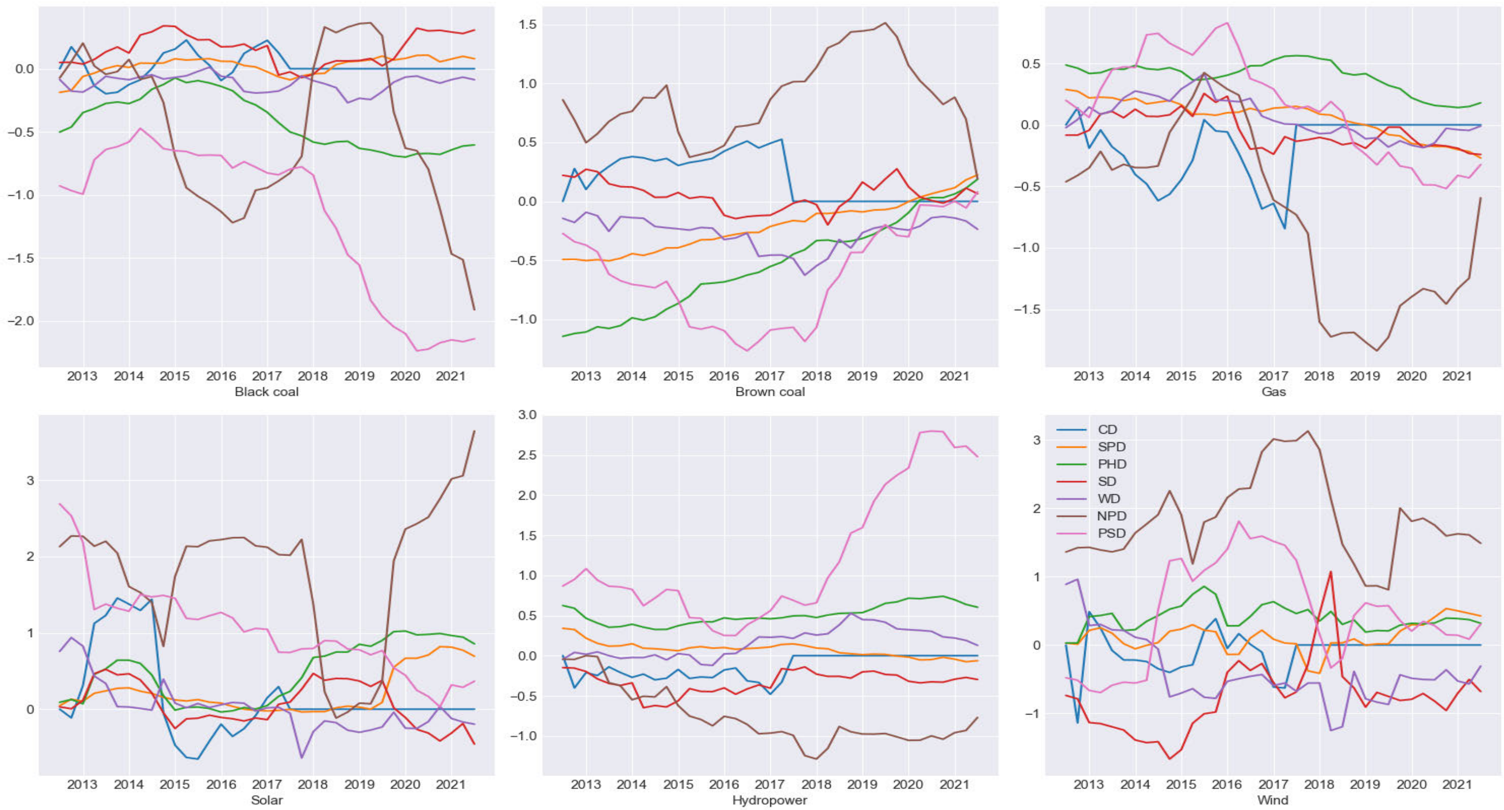
Three-Year Rolling Window Logistic Regression Coefficient Plots for Electricity Generators in the New South Wealth Market



Note. *CD*: carbon tax period dummy; *SPD*: shoulder period dummy; *PHD*: peak hour dummy; *SD*: summer dummy; *WD*: winter dummy; *NPD*: Lower price dummy (below the first percentile); *PSD*: price spike dummy (above the 99th percentile). All coefficients were statistically significant at the 1% level except SPD coefficient of gas technologies was significant at 10% level.

Appendix 3

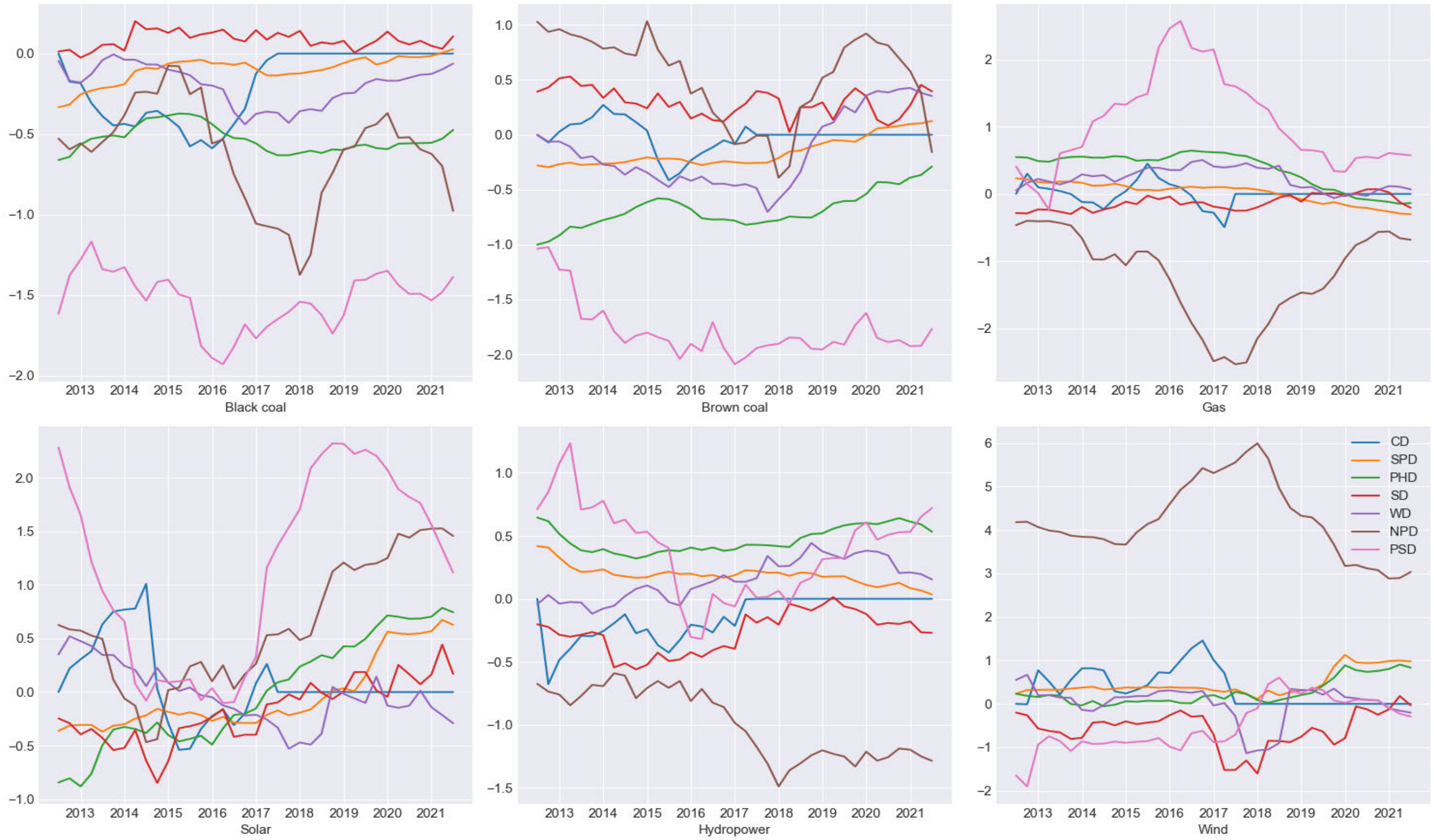
Three-Year Rolling Window Logistic Regression Coefficient Plots for Electricity Generators in the Queensland Market



Note. *CD*: carbon tax period dummy; *SPD*: shoulder period dummy; *PHD*: peak hour dummy; *SD*: summer dummy; *WD*: winter dummy; *NPD*: Lower price dummy (below the first percentile); *PSD*: price spike dummy (above the 99th percentile). All coefficients were statistically significant at the 1% level except SD coefficient of solar generators was significant at the 10% level, WD coefficient of solar generators was significant at the 5% level while CD coefficient of black coal generators, NPD coefficient of brown coal generators and SPD coefficient of gas generators were not statistically significant.

Appendix 4

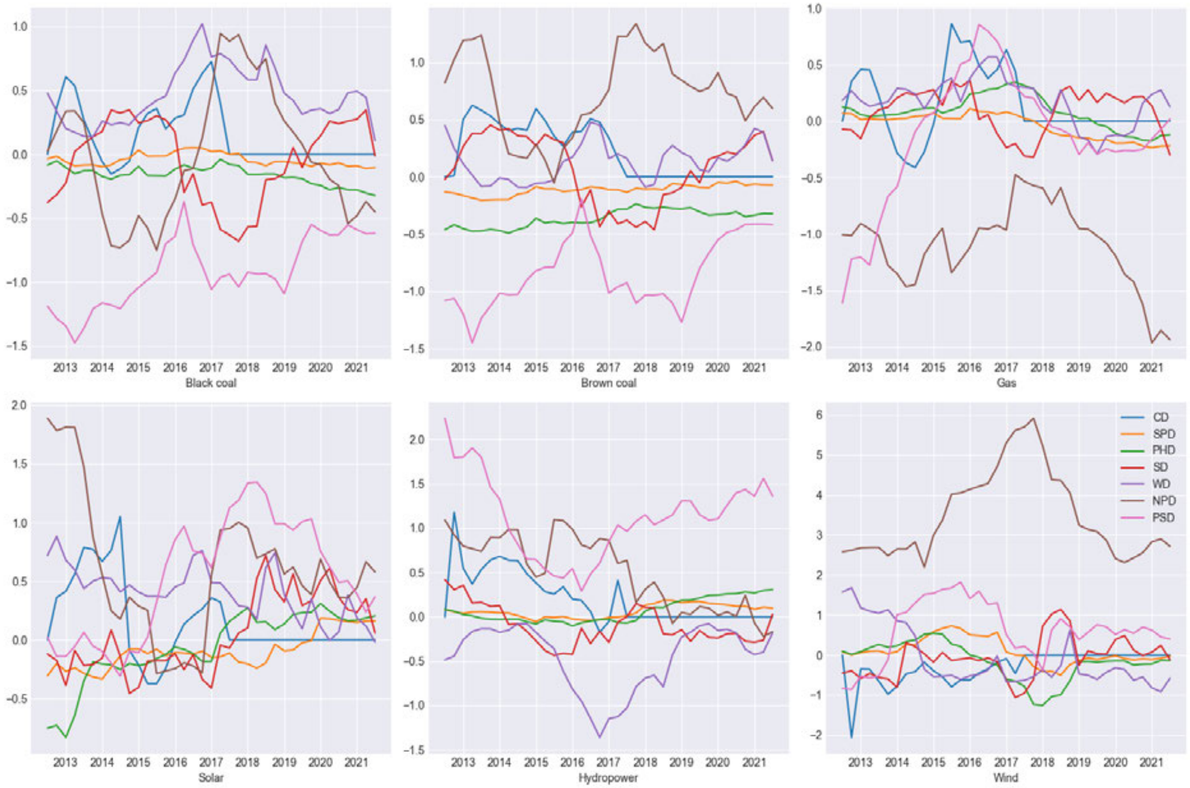
Three-Year Rolling Window Logistic Regression Coefficient Plots for Electricity Generators in the South Australian Market



Note. CD: carbon tax period dummy; SPD: shoulder period dummy; PHD: peak hour dummy; SD: summer dummy; WD: winter dummy; NPD: Lower price dummy (below the first percentile); PSD: price spike dummy (above the 99th percentile). All coefficients were statistically significant at the 1% level except SPD coefficient of gas generators and WD coefficient of wind generators.

Appendix 5

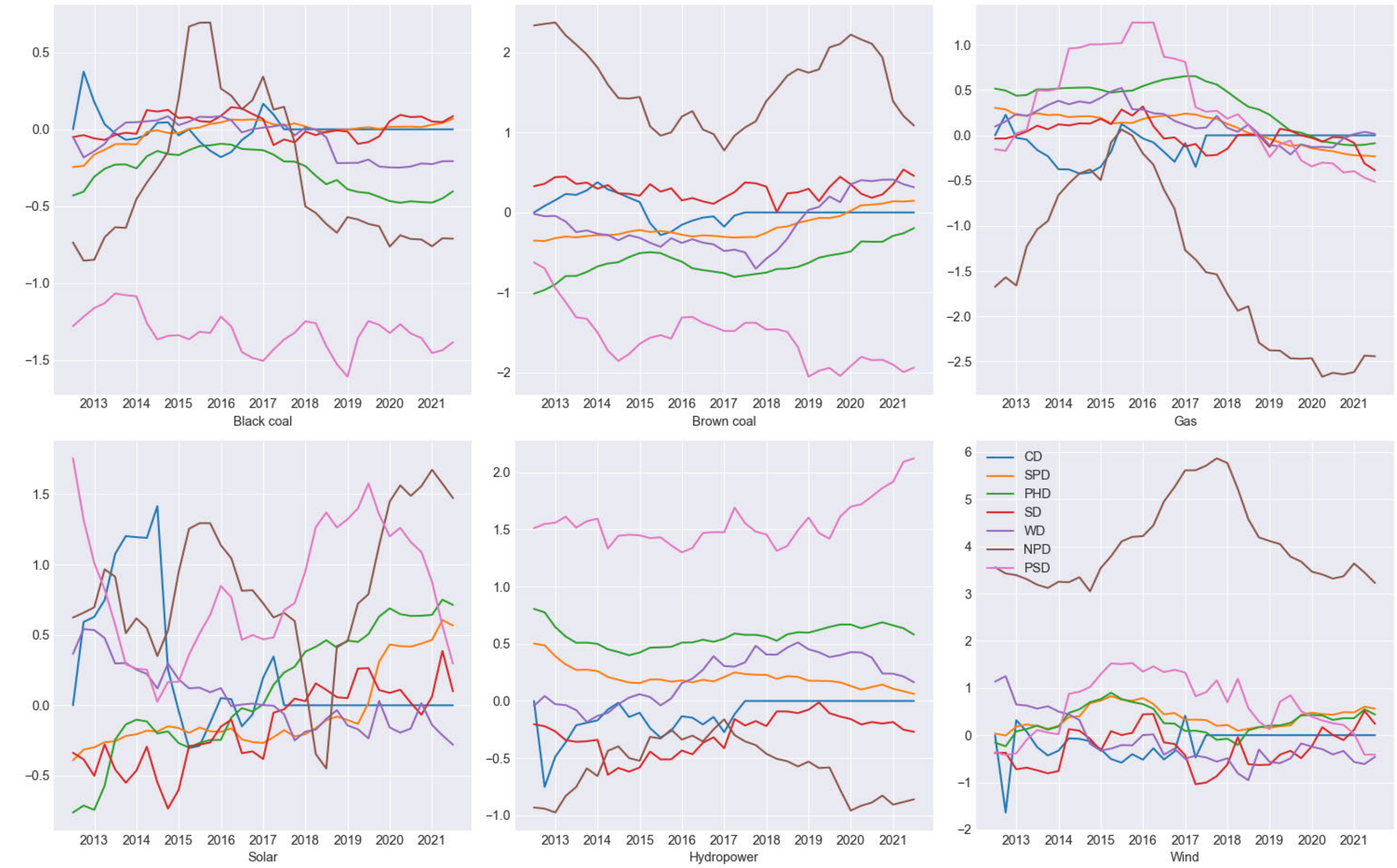
Three-Year Rolling Window Logistic Regression Coefficient Plots for Electricity Generators in the Tasmanian Market



Note. CD: carbon tax period dummy; SPD: shoulder period dummy; PHD: peak hour dummy; SD: summer dummy; WD: winter dummy; NPD: Lower price dummy (below the first percentile); PSD: price spike dummy (above the 99th percentile). All coefficients were statistically significant at the 1% level.

Appendix 6

Three-Year Rolling Window Logistic Regression Coefficient Plots for Electricity Generators in the Victorian Market



Note. CD: carbon tax period dummy; SPD: shoulder period dummy; PHD: peak hour dummy; SD: summer dummy; WD: winter dummy; NPD: Lower price dummy (below the first percentile); PSD: price spike dummy (above the 99th percentile). All coefficients were statistically significant at the 1% level except SD coefficient of solar generators.