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Keywords

electricity markets, price caps, fuel price

JEL Classification

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Fuel Price Caps in the Australian National Wholesale Electricity Market

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Abstract

Fuel price caps are one of the potential regulatory tools for controlling wholesale electricity prices when fuel prices are volatile. In this paper, we introduce a theoretical model to study the effects of such caps on firms' bidding behavior and clearing prices in spot market auctions. We then use data from the Australian National Electricity Market (NEM), which recently implemented such caps, to empirically test and compare their effectiveness in three different states. Our theoretical findings suggest that fuel price caps can be binding, especially when electricity demand is lower and competition among generators is higher. When demand is high, alternative policy tools, such as market price caps, may be more effective in controlling auction prices. Our empirical analysis employs various techniques, such as Generalized Additive Models (GAM) and machine learning algorithms, to test the effectiveness of price caps in the NEM. We find mixed results regarding the effectiveness of fuel price caps in different states. Specifically, fuel price caps reduced wholesale electricity prices in Queensland and New South Wales, while they were not effective in controlling wholesale prices in Victoria.

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1 Introduction

The prices for fuel such as natural gas and coal skyrocketed in the aftermath of the 2022 war between Russia and Ukraine causing a crisis among wholesale electricity markets such as the Australian National Electricity Market (NEM) dominantly powered by fossil fuels. In 2021 alone, fossil fuels contributed to 71% of total electricity generation in the NEM consisting of coal (51%), gas (18%) and oil (2%). Therefore, since late 2022, several countries including Australia have imposed general fuel price caps as a market correction mechanism to protect the businesses and households from instances of excessively high gas and coal prices. Australia's Commonwealth Government imposed fixed price caps of $125 per tonne (t) and $12 per giga joule (GJ) for coal and gas respectively in late 2022 (Simshauser, 2023). The European Union also agreed on a "dynamic" gas price cap to be triggered for inframarginal electricity producers excluding hydro at 180 euros per megawatt hours (Council Regulation EU, Benjamin, 2022).[1] Interestingly, in Australia, the price cap on natural gas may become permanent to ensure that domestic industry remains viable while consumers have access to affordable energy (Australian Government, 2022).[2]

In liberalized wholesale electricity markets such as the NEM, increases in gas prices have been passed on to the wholesale electricity markets, as gas-fired generation often sets market prices. This has led to electricity prices that are well above their historical average (Fabra, 2022). Consequently, the rational economic expectation is that fuel price caps, if implemented appropriately, will lower the auctioned wholesale electricity price and ultimately result in lower prices for consumers and households. However, to date, no empirical evidence exists to document the effectiveness of the imposed price caps in Australia. The primary question this study seeks to answer is whether price caps have successfully lowered wholesale electricity prices by suppressing the auction price of wholesale electricity. We aim to address this question by first proposing a theoretical framework that investigates how price caps on fuels might affect bidding behaviour and auction prices in a wholesale market. Subsequently, we use data from the NEM to test how the implemented caps influenced spot market prices in three major states in Australia.

Our theoretical analysis reveals that fuel price caps may help in reducing the auction clearing prices, particularly under conditions of lower electricity demand. Nevertheless, these price caps do not significantly impact auction prices when the price increase is driven by higher demand. Under such circumstances, market price caps become crucial in controlling inflated prices due to demand. Therefore, the effectiveness of fuel price caps is context-dependent, working effectively in some scenarios and proving less useful in others. Our empirical investigation leverages three forecasting methodologies - simple linear regression, non-linear regression via Generalized Additive Models (GAM), and machine learning

[1] The price cap will be automatically activated if the month-ahead Title Transfer Facility (TTF) price exceeds €180/MWh for 3 working days and if the TTF price is €35 higher than a reference price for liquefied natural gas (LNG) on global markets for the same 3 working days.

[2] `https://treasury.gov.au/sites/default/files/2022-12/c2022-343998-cp_2.pdf`.

models. The findings suggest a mixed effectiveness of the fuel price cap policy across different regions. For Queensland, the policy appears successful, as actual prices were lower than the predicted ones. In New South Wales, the impact of the policy was less clear, showing some effectiveness but not producing very significant outcomes. In Victoria, the results were statistically insignificant, indicating that the policy was ineffective in reducing electricity prices.

Our study is one of the few studies globally, and certainly the first in the Australian context, to directly examine the effectiveness of fuel price caps on auctioned wholesale electricity prices. This study is both timely and relevant, as the Australian government has proposed permanent price controls in the form of a 'reasonable pricing provision', considering that Australia exports most of its natural gas.[3] Therefore, the extremely high international prices, caused by market disruptions in Europe, are leading to high domestic prices in Australia, against which Australian consumers need to be safeguarded.[4]

The economics of implementing price caps as a credible regulatory instrument to establish market stability is, however, debated. Nonetheless, an observable or unobservable price cap has always existed for a vital commodity or service such as electricity that is motivated by political economy factors (Jamasb et al., 2023). Moreover, price caps are generally driven by distributional and equity concerns, although they incur some efficiency losses. Gas price caps, for example, have been demonstrated to hinder long-term investment in Australia by sending negative signals for exploration and development of gas resources, gas storage economics in Victoria, and the viability of LNG imports on the east coast.[5] Reducing long-term investment incentives is detrimental to achieving resource adequacy inviting future supply shortages. Price caps will certainly lower Australian gas production and reduces the value of Australia's gas resources (i.e., resource wealth).[6] Gas price caps can also delay the progress towards global emissions reduction and renewable energy transition. A better economic approach would be to let the market maximise the value of the resource and then to choose a tax policy such as a tax on windfall profits that does not affect investment (Pollitt et al., 2022). A recent modelling study by Roeger and Welfens (2022) in the context of the Russia-Ukraine War captured the impacts of gas price caps on electricity production effects. Their results favour a combination of gas price caps targeted at the electricity market rather than a general price cap and transfers over a tax on windfall profits in generating positive macroeconomic effects as well as a positive welfare effect on

[3]Natural Gas Price Caps in Australia are Poor Policy and may be Permanent:[https://www.iaee.org/en/publications/newsletterdl.aspx?id=1063]

[4]It is important to note that the 2023 Gas Mandatory Code of Conduct allows companies that satisfy the Australian Competition and Consumer Commission (ACCC) with "court-enforceable supply commitments" to become exempt from the cap. See, The Australian Government, Department of Climate Change, Energy, the Environment and Water:[https://www.dcceew.gov.au/]. Furthermore, the gas price caps are not binding to small producers that direct their supply solely to the domestic market.

[5]See, The Australian Petroleum Production & Exploration Association (APPEA):[https://www.appea.com.au/wp-content/uploads/2022/12/221201-EnergyQuest-APPEA-Price-Cap-Report.pdf]

[6]https://www.iaee.org/en/publications/newsletterdl.aspx?id=1063

households through lower electricity prices.

The NEM provides an intriguing case study to investigate the impacts of gas price caps. The government has opted to extend the price cap on wholesale gas prices until at least mid-2025 with the aim of curbing escalating energy costs. The NEM, operational as a wholesale spot market for electricity since December 1998, is composed of five interconnected states that also function as price regions: Queensland (QLD), New South Wales (NSW) (inclusive of the Australian Capital Territory (ACT)), South Australia (SA), Victoria (VIC), and Tasmania (TAS). The NEM operates as an energy-only market, where the wholesale electricity price is determined based on offers made by generators to supply specific volumes of electricity to the market at specified prices and times, and according to the prevailing demand. Price volatility is inevitable in an energy-only market and therefore NEM has a market price cap of $15,500/MWh and a market price floor of -$1000/MWh. In addition to the marker price cap, the NEM has built-in price caps which are automatically triggered if wholesale prices are persistently too high. The regulator imposes a $300/MWh price if cumulative wholesale spot prices total approximately $1.4m in any state on a seven-day rolling.

The market clearing rule in the NEM is based on a uniform-price auction.[7] Numerous studies have analysed various aspects of the uniform-price auction in wholesale electricity markets. For instance, Fabra et al. (2006) compares the uniform-price auction with the discriminatory auction in a paper motivated by the electricity market in England and Wales. They show that the uniform-price auction results in higher prices, but the overall efficiency ranking of the two auctions remains ambiguous. In the Australian context, Khezr and Nepal (2021) previously studied uniform-price auctions in a wholesale electricity market where firms have diminishing marginal values. They argue that if marginal cost regulation is not properly designed, firms cannot generate a positive profit in the auction. Consequently, capacity payments are necessary to guarantee the long-term operation of the generators. However, in this paper, our primary focus is on fuel price caps in an energy-only market, where we aim to show how these price caps could influence bidding behavior and under what conditions the caps are effective.

The contributions of the paper are twofold. From the empirical point of view, this is the first paper in the Australian context to empirically examine the impacts of fuel price caps on wholesale electricity prices by price zones under different conditions. We employ Random Forest and Boosting algorithms to identify significant variables and analyze the impact of coal/gas caps on electricity prices. These algorithms excel in capturing non-linear relationships, extracting hidden insights, and improving predictive performance. Additionally, their robustness against outliers minimizes their influence on the analysis.[8] For forecasting, we

[7] Given that electricity is a homogeneous product, the literature on multi-unit auctions involving homogeneous goods is most relevant to this context. See Khezr and Cumpston (2022) for a survey.

[8] Capturing intricate patterns and interactions that may not be easily captured by traditional time series models. This flexibility allows for the extraction of hidden insights and enhances overall predictive

utilize the GAM due to its flexibility in capturing complex relationships, and handling non-linearity, interactions, and non-parametric components. GAMs adapt to changing trends and capture time-varying effects, enhancing forecasting accuracy. Furthermore, GAMs exhibit robustness against outliers, making them resilient to extreme values in the time series data (For more details about the application of GAM in forecasting, see Serinaldi (2011), Meier et al. (2020), and Matsumoto et al. (2022).[9] The second contribution of the paper is the theoretical analysis of fuel price caps in wholesale electricity auctions. This study is the first of its kind that investigates such interventions and using auction theory shows under what circumstances these price caps can reduce the auction clearing price. The findings of our study is significant to policymaking and would shed light on the important issue of the design of effective price caps on fuels in the wholesale electricity market.

The rest of this paper is organized as follows. Section 2 presents a fundamental model of the spot market incorporating fuel price caps. In Section 3, we outline the empirical analysis and methodology employed to investigate the NEM both before and after the introduction of price caps. The empirical findings are presented in Section 4. Lastly, Section 5 concludes the paper by offering final remarks.

2 Theoretical model

Suppose there are two firms in a wholesale electricity market that collectively produce the entire supply of the market. Each firm $i \in 1, 2$ has a marginal cost of $c_i > 0$ for producing electricity. Without loss of generality, we assume $c_1 < c_2$. We attribute the marginal cost of producing electricity solely to fuel costs. Hence, the two firms use different technologies, each with varying levels of fuel efficiency. One can consider generators that use different fossil fuels, such as natural gas or coal, to produce electricity. The marginal costs are random realizations from two different distributions: $C_1(.)$ on $[\underline{c}_1, \bar{c}_1]$ and $C_2(.)$ on $[\underline{c}_2, \bar{c}_2]$ with $\bar{c}_1 < \underline{c}_2$.

Each firm i has a maximum capacity, denoted by λ_i, to produce electricity at their fixed marginal cost. Market demand for electricity is represented by θ, which is unknown at the time of production. Firms are only aware that θ is independently distributed according to some distribution function $D(.)$ with density $d < \infty$ on $[0, \bar{\theta}]$. We allow the possibility of demand exceeding the supply, that is, $\lambda = \sum \lambda_i < \bar{\theta}$.

Firms compete to sell electricity in a spot market using a uniform-price auction. The stages of the game are as follows: First, the marginal costs are realized by all parties. Then both firms submit bid prices, indicating the minimum price they are willing to accept to

performance. Further, employing Random Forest and Boosting algorithms effectively minimize the influence of outliers, unlike certain time series models that may be more susceptible to outliers and require additional preprocessing steps.

[9] Some recent studies about electricity price forecasting relied on time-series modelling and agent-based simulation techniques (Lehna et al., 2022; Naeem et al., 2022; Apergis et al., 2023).

sell their supply of electricity. Finally, the system operator begins with the lowest bid and continues to clear the market until supply meets demand. The price for all units supplied is set at the intersection of supply and demand. Let $\bar{p}$ denote the maximum price (market price cap) that is allowed for electricity in the wholesale market. Consequently, the price paid to the generators is the minimum of the auction clearing price and $\bar{p}$.

In this paper, we investigate two scenarios: In the first, fuel prices are not regulated, and marginal prices can assume any value within their defined intervals. In the second, we consider a case where the regulator imposes a cap on fuel prices, which is binding and less than the highest possible fuel prices. We seek to understand how such fuel price regulation influences the bidding behavior of firms in the spot market and, ultimately, how it impacts wholesale electricity prices.

2.1 Bidding in a spot market

We start by exploring a case where firms bid to sell electricity in a spot market with no control over the fuel prices. At this stage we assume the marginal costs can take any value within their interval. Given that the demand is not known at the time of bidding we abstract to a case where each firm submit a bid price for their total capacity. Therefore firms cannot withhold capacity to increase the auction clearing price.

Proposition 1. *The equilibrium auction clearing price is set as follows depending on the demand:*

- *If $\theta \leq \lambda_1$ then the auction clearing price is equal to* $\min\{c_2, \bar{p}\}$.
- *If $\lambda_1 < \theta \leq \lambda$ then the auction clearing price is equal to $\bar{p}$.*
- *If $\lambda \leq \theta$ then the auction clearing price is equal to $\bar{p}$.*

Proof. (i) Suppose $\theta \leq \lambda_1$. In this case, demand is lower or equal to the production capacity of Firm 1. As Firm 1 is the more cost-efficient firm, it will be able to supply all the electricity needed at its marginal cost c_1. However, since the auction clearing price is set by the highest accepted bid, and Firm 2 will bid no less than its own marginal cost c_2, the auction clearing price will be equal to c_2 if Firm 2's supply is needed to meet the demand. This results in the price being set to c_2. If Firm 1 bids any amount above c_2, then Firm 2 can underbid it and win the auction. Therefore any bid above c_2 by Firm 1 cannot be an equilibrium.

(ii) If $\lambda_1 < \theta \leq \lambda$: In this case, demand exceeds the capacity of Firm 1 but is lower or equal to the total capacity available from both firms λ. Therefore, both firms' supplies are needed to meet the demand. As the auction price is set by the highest accepted bid, bidding equal to c_2 guarantees the dispatch of Firm 1's entire capacity. Firm 2's best response is to bid equal to $\bar{p}$ and sell an amount equal to the remaining demand at the highest possible price.

(iii) When $\lambda \leq \theta$, the demand is too high and above the total capacity to supply. In this case, the demand for electricity exceeds the total capacity available from both firms. Here, every unit of capacity from both firms will be used to meet the demand. In this high demand scenario, the firms have the incentive to bid high, and considering the price cap, they will bid at $\bar{p}$. Hence, the auction clearing price will be equal to $\bar{p}$.

$\square$

The analysis above suggests that marginal costs and market price caps play a critical role in determining the auction clearing price. In our basic model, where there are only two firms, the significance of price caps is heightened as firms possess greater market power. They can easily exploit this power during the bidding process to drive prices to their maximum level. However, even with only two firms, there are instances where the marginal cost of firm 2 sets the auction clearing price. Therefore, a price cap on marginal costs implies that, on average, we observe lower auction clearing prices.

Moreover, the results of Proposition 1 underscore the importance of market price caps in the spot market and their potential impact on setting wholesale electricity prices. If the caps are too high, they will become non-binding, and we can expect to see higher prices on average. If the price caps are seen too low, they may fall below marginal (fuel) costs and result in negative profits for electricity generators. Consequently, in an environment fraught with multiple uncertainties, selecting an appropriate price cap becomes a challenging task.

2.2 Bidding with fuel price caps

Suppose the regulator imposes two binding price caps on fuel prices. Specifically, we denote $\kappa_1 < \bar{c}_1$ and $\kappa_2 < \bar{c}_2$ as the two price caps. In situations where the fuel price exceeds these caps, the regulator enforces the hard cap either through subsidies or other regulatory methods. It is reasonable to assume that these price caps are lower than the market price cap, $\bar{p}$. The reasoning is if a fuel price cap exceeds the market price cap, $\bar{p}$, it essentially becomes non-binding as the price can never surpass $\bar{p}$. The following proposition examines various scenarios concerning the demand and firms' capacities.

Proposition 2. *When there are price caps on fuel prices, the equilibrium auction clearing price is set as follows depending on the demand:*

- *If $\theta \leq \lambda_1$ then the auction clearing price is equal to $\min\{c_2, \kappa_2\}$.*
- *If $\lambda_1 < \theta \leq \lambda$ then the auction clearing price is equal to $\bar{p}$.*
- *If $\lambda \leq \theta$ then the auction clearing price is equal to $\bar{p}$.*

Proof. (i) If $\theta \leq \lambda_1$: In this case, demand is lower or equal to the production capacity of Firm 1. As before, Firm 1 can meet all the electricity demand. Hence the auction clearing price will be set by Firm 1's bid based on the uniform price auction rules defined before. Similar to the proof of Proposition 1, one can show that bidding equal to c_2 is the best response of Firm 1. However in this case, because there is a cap on fuel prices, c_2 cannot go beyond κ_2. Therefore the auction clearing price is the minimum of the two.

The rest of the proof is similar to the proof of Proposition 1.

□

The above result suggests that when demand is too low, the fuel price cap could play a role in setting the auction clearing price. However, similar to the case without fuel price caps, with average to high demand the price can only be controlled with the market price cap. Thus fuel price caps are only effective for a particular case; where the demand is low and fuel price is high. Later in subsection 2.4 we discuss the effectiveness of the two different price regulations in more detail.

2.3 Multiple electricity generators

We now extend our basic model to a case where there are multiple generators of each type. Suppose there are $n > 1$ firms with a marginal cost equal to c_1 and there are $m > 1$ firms with a marginal cost equal to c_2. Denote λ_n and λ_m as the total capacity of type 1 and 2 firms respectively. For tractability, we assume firms in each type are identical.

When there are multiple firms that generate electricity, the market power of firms declines relative to the benchmark case with only two firms. Therefore, we expect that in more instances we observe prices that are below the market cap. However, one concern is that with multiple firms, a pure strategy Nash equilibrium may not exist. The next proposition characterises the results in such scenarios.

Proposition 3. *With multiple firms and fuel price caps, the equilibrium auction clearing price is set as follows depending on the demand:*

- *If $\theta \leq \lambda_n$ then the only pure strategy equilibrium price is* $\min\{c_1, \kappa_1\}$.
- *If $\lambda_n < \theta \leq \lambda_n + \lambda_m$ then the only pure strategy equilibrium price is* $\min\{c_2, \kappa_2\}$.
- *If $\lambda_n + \lambda_m \leq \theta$ then the auction clearing price is equal to $\bar{p}$.*

Proof. If $\theta \leq \lambda_n$: In this case, the market demand θ is less than or equal to the total capacity of firms with marginal cost c_1. All demand can be met by these low cost firms. If all type one firms place bids equal to c_2 they are not guaranteed to dispatch their capacity as the demand is less or equal to the sum of their capacities. In fact, any price above c_1 cannot characterize an equilibrium as type 1 firms would have incentives to undercut this price marginally and sell their total capacity. The only price that can be an equilibrium is c_1 which gives all type one firms zero profit. Type two firms are indifferent between placing any bid equal to or above c_2. The auction clearing price is therefore determined by the bids of type one firms and the price cap imposed by the regulator, which is $\min c_1, \kappa_1$.

If $\lambda_n < \theta \leq \lambda$: Suppose type one firms submit a bid price equal to c_2. We first show there is no equilibrium with a clearing price above c_2. To have such equilibrium at least one type 2 firms must bid above c_2. Given that in this scenario the total demand is less than the supply, any firms with not dispatched remaining capacity would have incentives to marginally bid below a price that is above c_2 to increase their payoff. Therefore a price above c_2 cannot characterize a pure strategy equilibrium.

If $\lambda \leq \theta$: In this scenario, the total market demand exceeds the total capacity of all firms. The market is short on supply. Therefore, similar to the previous proposition the price cap $\bar{p}$ becomes the equilibrium price. □

The above result suggests that, with more producers, there's a higher chance that prices become lower. It is intuitive as more firms mean less market power and higher competition. The implication of this result for the caps we study is that, when we extend our model to a more realistic situation with multiple firms, then there is a lower chance that the auction clearing price becomes equal to the market cap. Therefore, market caps will become less important. Although the results cannot confirm the importance of marginal prices in determining the auction clearing price, it is reasonable to conclude that now with multiple firms the marginal price caps may become more important than the market price cap. While there is no pure strategy equilibrium when the market demand is between $\lambda_n < \theta \leq \lambda$, one can still argue marginal costs are important determinant of firms' bidding functions as they are the lowest price that firms accept to produce electricity.

2.4 Market price cap versus fuel caps

In this subsection, we discuss the distinctions between market price caps and fuel caps from a regulatory perspective. The analysis conducted so far in this section provides us with a deeper understanding of how firms react to each of these regulatory frameworks. Subsequently, we highlight the advantages and disadvantages of each method from a theoretical viewpoint.

One crucial point to note is that when high demand drives prices up, fuel price caps have no role in determining wholesale electricity prices. In such circumstances, the market price cap $\bar{p}$ is the only mechanism available to prevent high electricity prices. Our benchmark results suggest two main bidding strategies. The first is competitive bidding, where firms reduce their bids to match their marginal costs. This is the scenario where fuel price caps can influence electricity prices. The second strategy involves firms pushing the price up to the market price cap. In such circumstances, fuel price caps have no influence on the auction clearing price.

When we expand the benchmark model to include multiple firms of each type producing electricity, the reduction in market power results in fewer instances where the auction clearing price equals the price cap. Under these circumstances, we expect bidding strategies to fall somewhere between the two extreme scenarios outlined above. Consequently, the significance of fuel price caps increases relative to a situation with high market power and a low number of firms.

In conclusion, both fuel price caps and market price caps are effective regulatory tools for controlling prices in a wholesale electricity spot market. As competition among firms increases, we anticipate fuel price caps to play a more substantial role in controlling market prices. When competition is low or demand is high, fuel price caps are not an effective way of controlling prices. In such cases, the market price cap plays a more crucial role in controlling wholesale electricity prices.

3 Empirical analysis

In this section, we aim to comprehensively examine the impact of the gas cap policy in Australia. Our analysis focuses on three crucial regions located in the eastern part of the country, namely Queensland, New South Wales, and Victoria. These regions are of particular interest as they encompass a substantial portion of the NEM[10] and collectively caters to a considerable number of energy consumers, estimated to be in the range of millions. Figure 1 shows NEM network regions on the east coast of Australia[11].

To investigate the effects of the Gas cap policy, we employ a range of analytical methods and techniques. To gain a deeper understanding of how the policy influences the electricity market and its implications for the mentioned regions. We aim to provide valuable insights and shed light on the potential consequences and outcomes associated with the market capitalization policy. The selected regions, hold significant importance within the NEM framework. Queensland, located in the northeastern part of Australia, is renowned for its abundant natural resources, particularly coal and gas reserves. New South Wales, situated to the south of Queensland, is also rich in coal resources and plays a crucial role in the country's energy landscape. Victoria, located in the southeastern part of Australia, has diverse energy sources, including coal, natural gas, and renewable energy.

When comparing the Australian electricity market to other markets, distinct features emerge. On the demand side, electricity is traded almost in real-time, with prices settled

[10] According to the Australian Energy Market Operator (AEMO), which operates the NEM, the market serves over 9 million customers in the eastern and southern states. However, this figure represents the total number of customers rather than households specifically. It includes residential, commercial, and industrial customers, both small and large.

[11] Source: Australian Energy Market Operator

just five minutes ahead. In contrast, European markets settle electricity prices one day in advance. On the supply side, Australia relies more heavily on high running cost fossil fuel power stations, whereas the American and European markets have a larger share of nuclear or hydraulic power generation. Therefore, a modelling approach is needed that can accommodate the unique characteristics of each market and be easily applied to electricity prices across different regions. So in order to analyze the impact of the gas cap on electricity prices, we adopt a systematic approach consisting of three distinct steps. Firstly, we employ linear regression models to assess the relationship between the gas cap and electricity prices. Secondly, we utilize a generalized additive model, which is a nonlinear model, to further investigate this association. Lastly, we incorporate machine learning techniques, specifically Support Vector Machines (SVM) and Random Forests, to enhance our understanding of the complex dynamics between the gas cap and electricity prices.[12]

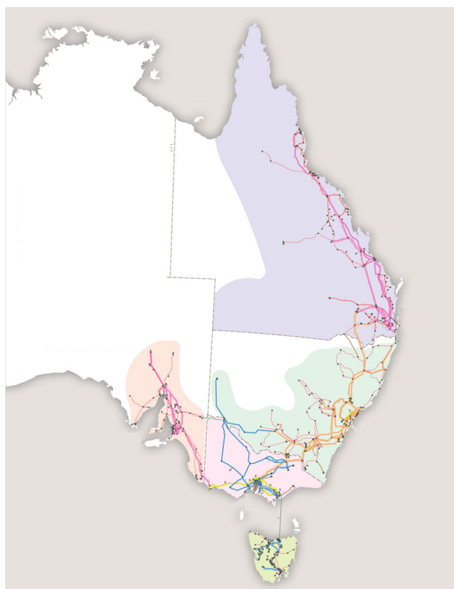


Figure 1: The National Electricity Market encompasses five interconnected regions situated along the east coast of Australia, encompassing Queensland, New South Wales, Victoria, Tasmania, and South Australia.

[12]In the NEM, wholesale prices can range from the floor price of -1000 AUD/MWh to the cap price of 14200 AUD/MWh.

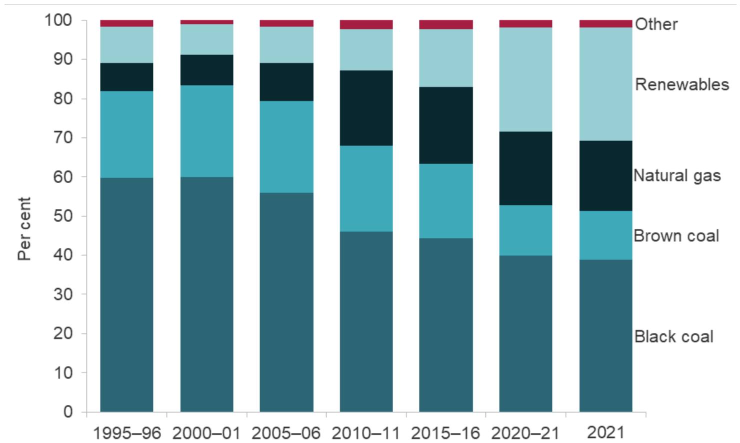


Figure 2: Australian electricity generation by fuel mix.

3.1 Data and Setting

The data set in this study contains the following; (a) five minutes of electricity (price and demand) data sourced from each state of Australia, (b) temperature data set records in Melbourne airport, NSW airport and Brisbane airport,[13] (c) we consider calendar effects such as holidays, weekdays and trend as well which we will explain them further in the model.

The selection of states is based on their significant installation capacities and unique characteristics within the electricity market. NSW possesses an installed generation capacity of approximately 18,000 MW, with a diverse mix of generation sources including coal-fired power plants, gas-fired plants, and renewable energy installations. In contrast, QLD boasts a higher installed generation capacity of around 20,000 MW, derived from a variety of sources such as coal, gas, and renewables. VIC, on the other hand, has a relatively lower installed generation capacity of approximately 9,500 MW. While VIC relies heavily on brown coal for electricity generation, it also utilizes gas-fired power plants and is experiencing growth in its renewable energy sector. NSW has historically experienced higher prices compared to other states. This can be attributed to factors such as network infrastructure costs, the generation mix, and demand-supply dynamics. However, prices in NSW are subject to variation based on factors such as wholesale market conditions and regulatory influences. In contrast, QLD has generally enjoyed lower electricity prices compared to NSW and VIC. This can be partially attributed to the state's abundant coal resources, which provide a cost-effective source of generation. Nevertheless, variations in prices can still occur in QLD due to factors such as network costs and demand patterns. In VIC, elec-

[13]We use daily temperature and maximum temperate data records via The Bureau of Meteorology in Australia.

tricity prices have shown fluctuating behavior influenced by elements like fuel costs, network tariffs, and market dynamics. The state's reliance on brown coal, which is becoming less cost-competitive compared to renewable sources, contributes to price fluctuations.[14]

The datasets utilized in this study encompass a duration of 2 years, specifically ranging from 01 September 2021 to 30 April 2023, resulting in a total of 166,176 five-minute observations. It should be noted that for analytical purposes, the data has been transformed into 578 daily observations. This decision is primarily motivated by the central objective of this research, which aims to analyze the impact of coal and gas caps on electricity prices. By aggregating the data into daily observations, the potential for biased outcomes arising from forecasting errors is significantly reduced, thereby minimizing the risk of spurious results. Additionally, the conversion to daily data facilitates synchronization with weather records, as they are available at a comparable frequency. This transformation to daily data was also influenced by limitations in the available dataset, which necessitated the consideration of daily observations.

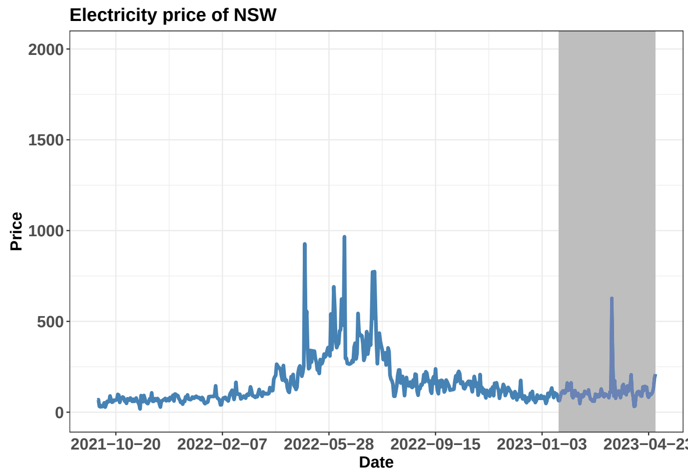
The Australian Energy Market Operator (AEMO) serves as the primary data source for this information.[15] Additionally, we incorporate temperature data obtained from records at Melbourne Airport, NSW Airport, and Brisbane Airport. We specifically utilize daily temperature records and maximum temperature values for these locations. The Bureau of Meteorology in Australia provides the dataset utilized for this purpose.[16] Furthermore, we consider calendar effects in our analysis, including holidays, weekdays, and trends. These factors are essential in capturing temporal variations that may influence electricity prices. A detailed explanation of these calendar effects and their incorporation into the model will be provided further in the subsequent sections.

Figure 3 presents the historical prices observed in the three distinct regions, namely NSW, QLD, and VIC. The shaded portion corresponds to the duration when the market cap policy was implemented. Table 1 demonstrates descriptive statistics of data for each region which in terms of the price range, NSW exhibits prices ranging from 17.91 to 966.19, QLD's prices span from -63.40 to 1933.65, and VIC's prices vary between -50.03 and 797.55. Skewness values indicate the distribution's asymmetry, with NSW and VIC showing positive skewness of 2.61 and 2.23, respectively, while QLD demonstrates a highly positively skewed distribution with a skewness of 4.78. It indicates a tendency towards higher price spikes or extreme positive price movements. Kurtosis values reflect the tail heaviness of the distributions, with NSW having a relatively high kurtosis of 9.32, QLD showing high

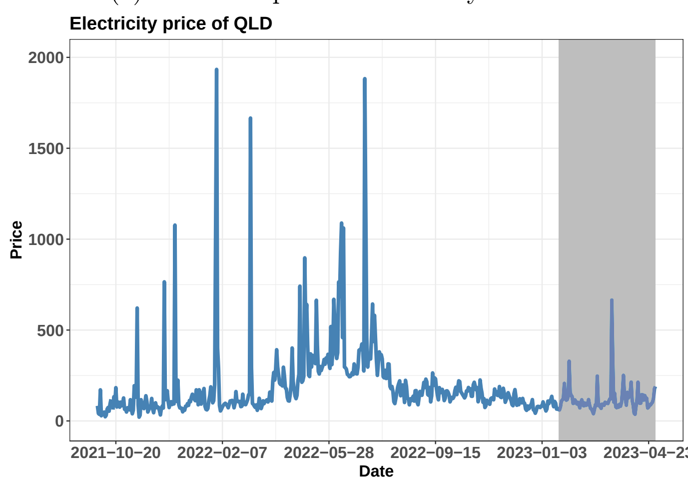
[14]In NSW, there are over 4 million electricity customers, with an estimated 2.7 million households using electricity. Moving to QLD, approximately 2.6 million customers are served by the electricity network, with around 1.9 million households utilizing electricity. Similarly, in VIC, the number of electricity customers is approximately 2.6 million, aligning with the figure in QLD. VIC also has an estimated 2.6 million households using electricity. These numbers highlight the substantial consumer base and high demand for electricity in these states.

[15]AEMO:[https://aemo.com.au/]

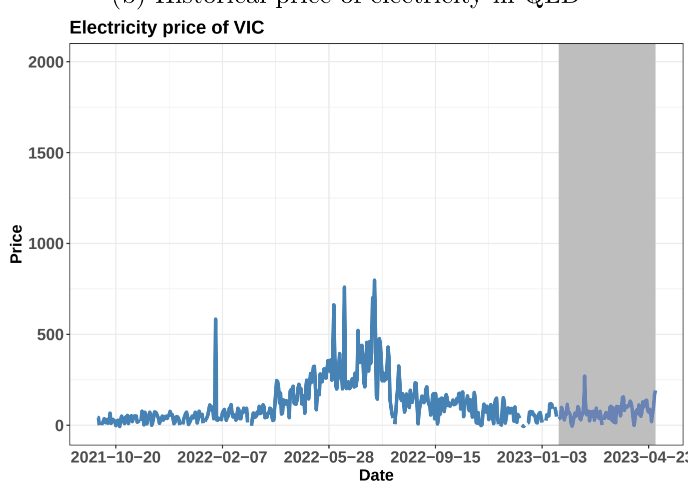
[16]The Bureau of Meteorology in Australia



(a) Historical price of electricity in NSW



(b) Historical price of electricity in QLD



(c) Historical price of electricity in VIC

Figure 3: Historical price of electricity in each state.

leptokurtosis with 31.66, and VIC exhibiting moderate kurtosis at 6.98.

		Min	Max	Std	Skew	Kurtosis	Obs
NSW	Price	17.91	966.19	122.80	2.61	9.32	578
	Demand	7034.35	2791932.00	247547.90	-0.63	8.74	578
QLD	Price	-63.40	1933.65	192.55	4.78	31.66	578
	Demand	5593.44	2247101.00	163527.30	-1.70	21.70	578
VIC	Price	-50.03	797.55	114.06	2.23	6.98	578
	Demand	4705.95	1803686.00	182128.30	-0.25	4.41	578

Table 1: Descriptive statistics of the dataset for both price and demand.

3.2 Model specification

In the primary analysis, our investigation incorporates four distinct categories of variables, namely "recent demand," "temperature," "policy," and "calendar" variables. The model is defined as follows:

$$P_t = f_1(D_t) + f_2(T_t) + f_3(MaxT_t) + B_0 h_{d(t)} + \sum_{j=1}^{7} B_j w^j_{d(t)} + f_4(L((d-1)+t)). \tag{1}$$

In Equation (1), P represents the grid price in megawatts of the d^{th} day in the dataset. The functions f_1, f_2, f_3, and f_4 are assumed to be smooth and will be estimated using a cubic regression spline. It is worth noting that different knot positions and various numbers of knots need to be considered for this purpose.[17]

The holiday effect is denoted by $h_{d(t)}$ and takes a value of 1 if it corresponds to a public holiday, and 0 otherwise. The variable $w^j d(t)$ is equal to 1 if $d(t)$ represents the j^{th} day of the week. The coefficients $B1, ..., B_7$ are unknown parameters associated with the weekdays.

Furthermore, the "time of year" effect is captured using a half-hourly timescale spanning the first to the last hour of the calendar year, with the function defined as $L((d-1)+t)$. Inputs are repeated annually to account for the recurring trend.

In this model, T_t represents all temperature variables available at the time of forecast, while $MaxT_t$ represents the maximum monthly temperature. The smooth function $L_t(d)$ captures the repeating trend of the data over each year.

It is important to note that the non-linear function f_i for $i = 1, 2, 3, 4$ can be estimated using a penalized regression approach with a spline basis. Each function can be expressed

[17] In this part it needs to consider different knot positions and different numbers of knots.

as:

$$f_i(x) = \sum_{j=1}^{k} \gamma_{i,j} \psi_j^i(x),$$

Here, k represents the dimension of the spline basis function, and ψ_j^i corresponds to the corresponding spline function. A common approach to estimate these smooth functions is by employing penalized regression methods such as ridge regression. The minimization objective is defined as follows:

$$\sum_{k=1}^{n} \left(P_k - \sum_{i=1}^{s} f_i(x_k) \right)^2 + \sum_{i=1}^{s} \lambda_i \int ||f_i''(x)||^2 dx,$$

In the above equation, the penalty terms $\Lambda_=(\lambda_1, \cdots, \lambda_s)$ need to be optimized. It should be noted that Λ controls the level of smoothness, with larger values of λ_s resulting in smoother functions. To estimate these smooth functions, we will utilize the R package mgcv Wood (2001), which implements this method.

4 Empirical results

In the first step, we fit GAM model based constant coefficients which will be a simple regression model. Results of modelling reports on Table 2 show that in NSW, electricity prices are significantly impacted by variables such as electricity demand (coefficient: 0.0001, $p < 0.001$), temperature (coefficient: 1.5766, $p = 0.0794$), and temperatureMax (coefficient: -6.0776, $p < 0.0001$). This indicates that these factors play a crucial role in determining electricity prices in NSW. Conversely, variables trend, weekdays, and CPI are found to be statistically insignificant. Notably, the variables gas and coal have a significant influence on electricity prices in NSW, while the policy does not exhibit a significant effect. In the QLD model, the primary variables influencing electricity prices are electricity demand (coefficient: 0.0005, p<0.001), temperature (coefficient: 1.4070, p=0.5938), and temperatureMax (coefficient: -25.4200, p<0.001). These findings suggest that electricity prices in QLD are predominantly driven by electricity demand and maximum temperature, with temperature exerting a stronger impact compared to NSW. Significantly, the cap policy variable (CPol) demonstrates expected significance ($p < 0.0139$) and plays a notable role in determining electricity prices in QLD. In terms of the Victoria model, the significant variables affecting electricity prices are electricity demand (coefficient: 0.0002, $p < 0.001$), temperature (coefficient: 0.5433, p=0.4175), and temperatureMax (coefficient: -5.7210, $p < 0.001$). This implies that electricity prices in Victoria are influenced by electricity demand and maximum temperature, although the impact of temperature is less pronounced compared to NSW and QLD. Furthermore, the cap policy variable (CPol) is found to be statistically insignificant in Victoria, aligning with the expected result.

In order to gain a more comprehensive understanding of the independent variables, we have employed a non-linear modelling approach known as GAM. The results of the GAM analysis can be found in Tables 3 to 5. Table 3, reveals that the parametric coefficients indicate that the intercept term has a significant positive impact on electricity prices (Estimate = 104.6916, $p < 0.001$), while the CPol variable has a significant negative effect (Estimate = -16.7562, p = 0.0268). Moreover, the Coal variable shows a significant positive association with electricity prices (Estimate = 0.1769, $p < 0.001$). The table also provides approximate significance for smooth terms, indicating that the interaction between WDN and demand, as well as the relationship between temperature and Trend, have significant effects on electricity prices. Additionally, the smooth terms for temperatureMax and Gas show a significant relationship with electricity prices. For NSW, this cap policy is significant at the level of 10%.
In terms of results for QLD, Table 4c, the parametric coefficients indicate that the intercept term has a significant positive impact on electricity prices (Estimate = 137.4739, $p < 0.0001$). The CPol variable is found to have a significant negative effect on electricity prices (Estimate = -47.8780, $p = 0.0006$), while the Coal variable shows a significant positive association (Estimate = 0.1856, $p = 0.0411$). The table also presents approximate significance for the smooth terms, indicating that the interaction between WDN (Weekday name) and demand, as well as the relationship between temperature and Trend, have significant effects on electricity prices. Additionally, the smooth term for temperatureMax shows a significant relationship. The smooth term for Gas has a lower significance ($p = 0.0178$). Importantly, the cap policy for QLD as we expected is highly significant ($p < 0.0006$).
Finally, in terms of VIC, Table 4, shows that the intercept term has a significant positive impact on electricity prices (Estimate = 94.8439, $p < 0.001$). However, the CPol variable (Estimate = -0.7896, $p = 0.9120$) and the Coal variable (Estimate = 0.0505, $p = 0.3400$) do not exhibit significant associations. The table also provides information on the significance of smooth terms. The interaction between WDN and demand ($p < 0.0001$) and the relationship between temperature and Trend ($p = 0.0184$) are significant factors impacting electricity prices. Additionally, the smooth term for temperatureMax ($p = 0.0055$) and Gas ($p = 0.0033$) show significant relationships.

Figures 4-6 display the smooth functions associated with each dataset, providing insights into observed patterns. In Figure 4, distinct variations arise in the behaviours of variables, such as demand and weekdays, across states. Specifically, the effects of weekdays in NSW and VIC exhibit similarities, while demonstrating significant differences in QLD. Notably, in NSW, the weekdays consistently exhibit high values throughout the work days of the week, whereas in QLD, the early days of the week exhibit maximum values.[18] Regarding

[18]One possible reason for this pattern in NSW would be related to its larger population and concentra-

Coefficients:	Estimate	Std.Error	t value	Pr(>|t|)	
			NSW		
demand	0.0001	0.0000	8.2440	0.0000	***
temperature	1.5766	0.8970	1.7580	0.0794	.
temperatureMax	-6.0776	0.7115	-8.5420	0.0000	***
Trend	-8.1553	10.3531	-0.7880	0.4312	
WDN	-1.3229	1.4782	-0.8950	0.3712	
CPI	0.6570	1.3997	0.4690	0.6390	
CPol	7.9474	8.6248	0.9210	0.3572	
Gas	4.9024	0.4885	10.0350	0.0000	***
Coal	0.1343	0.0407	3.2980	0.0010	**
Multiple R-squared: 0.8732, Adjusted R-squared: 0.8712					
F-statistic: 434.8, p-value: < 2.2e-16					
			QLD		
demand	0.0005	0.0001	9.1240	0.0000	***
temperature	1.4070	2.6370	0.5340	0.5938	
temperatureMax	-25.4200	3.6710	-6.9230	0.0000	***
Trend	1.3000	23.5600	0.0550	0.9560	
WDN	-2.3220	3.3670	-0.6900	0.4907	
CPI	6.3630	2.9880	2.1290	0.0336	*
CPol	-46.6100	18.9000	-2.4660	0.0139	*
Gas	3.7880	0.9594	3.9490	0.0001	***
Coal	0.1025	0.0831	1.2340	0.2179	
Multiple R-squared: 0.6599, Adjusted R-squared: 0.6545					
F-statistic: 122.5, p-value: < 2.2e-16					
			Victoria		
demand	0.0002	0.0000	10.6370	0.0000	***
temperature	0.5433	0.6697	0.8110	0.4175	
temperatureMax	-5.7210	0.5341	-10.7120	0.0000	***
Trend	-14.3700	9.6930	-1.4820	0.1388	
WDN	-0.3666	1.4080	-0.2600	0.7947	
CPI	5.2420	1.4380	3.6470	0.0003	***
CPol	4.1410	7.8160	0.5300	0.5964	
Gas	4.0820	0.4524	9.0230	0.0000	***
Coal	-0.0897	0.0410	-2.1900	0.0289	*
Multiple R-squared: 0.8337, Adjusted R-squared: 0.831					
F-statistic: 316.3, p-value: < 2.2e-16					
Note: Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1					

Table 2: Regression model for three states.

Figure5, considering the trend value of 1/365 on the first day of January and 1 on the last day of December, a peak is observed around the mid-year (approximately 0.5 of the trend value). In NSW and QLD, this peak is evident for both low and high temperatures, whereas in VIC, it is primarily associated with low temperatures, in June and July, which corresponds to the winter season. The contour plots indicate slightly higher demand in QLD, as evidenced by the pink areas above and below the plot. This disparity can be attributed to the broader geographic area of NSW, encompassing both coastal and inland regions with varying climate patterns. Urban centres like Sydney may experience higher demand for air conditioning and cooling systems compared to more temperate regions. Energy-efficient building practices and regulatory measures further contribute to a comparatively smaller impact of temperature on electricity consumption in NSW. Conversely, VIC displays more blue areas on the plot, indicating a more temperate climate. Although summers in VIC can still be warm, they generally do not reach the extreme heat levels observed in QLD and certain parts of NSW. Consequently, the influence of temperature on electricity consumption in VIC is somewhat less pronounced.

In Figure 6, which pertains to the gas cap policy, the effect of gas price cap policy during the first half of January is not significant across all three regions. Subsequently, the effect reaches its maximum in February before gradually declining in March and April. One possible reason for this decline could be the decreasing demand for electricity observed in all regions during this period.

Parametric coefficients					
	Estimate	Std.Error	tvalue	Pr(>|t|)	
(Intercept)	104.6916	15.5251	6.7430	0.0000	***
CPol	-16.7562	7.5471	-2.2200	0.0268	*
Coal	0.1769	0.0511	3.4610	0.0006	***
Approximate significance of smooth terms:					
	edf	Ref.df	F	p-value	
te(WDN,demand)	3.9300	4.7580	7.1550	0.0000	***
te(temperature,Trend)	20.6740	24.9300	9.3180	0.0000	***
s(temperatureMax)	2.9290	3.0000	12.9640	0.0000	***
s(Gas)	1.8720	2.0000	13.2430	0.0000	***
R-sq.(adj) = 0.74 Deviance explained = 75.4%					
GCV = 4159.7 Scale est. = 3926.1 n = 577					

Table 3: GAM model estimation for NSW

tion of commercial and financial activities in Sydney, which may demonstrate higher weekday electricity demand. The densely populated metropolitan areas, along with manufacturing and service industries, can significantly impact electricity consumption on weekdays.

Parametric coefficients					
	Estimate	Std.Error	tvalue	Pr(>|t|)	
(Intercept)	137.4739	27.7583	4.9530	0.0000	***
CPol	-47.8780	13.9196	-3.4400	0.0006	***
Coal	0.1856	0.0906	2.0480	0.0411	*
Approximate significance of smooth terms:					
	edf	Ref.df	F	p-value	
te(WDN,demand)	43.9060	50.4000	7.0530	0.0000	***
te(temperature,Trend)	49.7190	52.0700	6.5460	0.0000	***
s(temperatureMax)	1.0000	1.0000	12.4000	0.0005	***
s(Gas)	1.4620	3.0000	1.8100	0.0178	*
R-sq.(adj) = 0.714 Deviance explained = 76.3%					
GCV = 12804 Scale est. = 10605 n = 577					

Table 4: GAM model estimation for QLD

To gain a deeper understanding of the key variables influencing electricity prices, we employ the machine learning techniques random forest (RF) and Gradient Boosted (GB) models, (both explained briefly in Appendix A). These models, widely used for classification and regression tasks, offer valuable insights into variable importance. The GB model, in particular, is an ensemble method that combines multiple weaker models to form a robust model Natekin and Knoll (2013).[19] In our study, we utilize both RF and GB models, which are trained with hyperparameters such as a learning rate of $\lambda = 0.1$, 500 trees, and a tree depth of 8. It is worth noting that the results are not significantly affected by these specific parameter choices. The summary of the model fitting, showcasing the important variables and their effects, is depicted in Figure 7. Generally, we can see there is consistency between both results with different approaches.

In the final phase of our analysis, we employ forecasting techniques under specific conditions to gain deeper insights into a particular scenario by ignoring market caps for both gas and coal. Given that we possess information about all other variables in equation (1), this approach enables us to examine the potential outcomes for prices. Moreover, this approach would allow us to analyze the average policy effect by comparing the changes in the outcome variable (electricity price) during the last few months after the policy's introduction to the changes in the outcome variable before the policy caps were imposed over the same period.

[19]Note that random forest regression models differ from simple regression models in their approach to estimating coefficients. While simple linear regression estimates coefficients for the linear equation linking the response variable to predictors, random forest regression models consist of a collection of decision trees, each constructed using a random subset of predictors. As a result, instead of estimating a single set of coefficients, random forest regression models assign weights to each predictor, indicating their significance in the model. This approach reduces the risk of overfitting and enhances robustness against outliers.

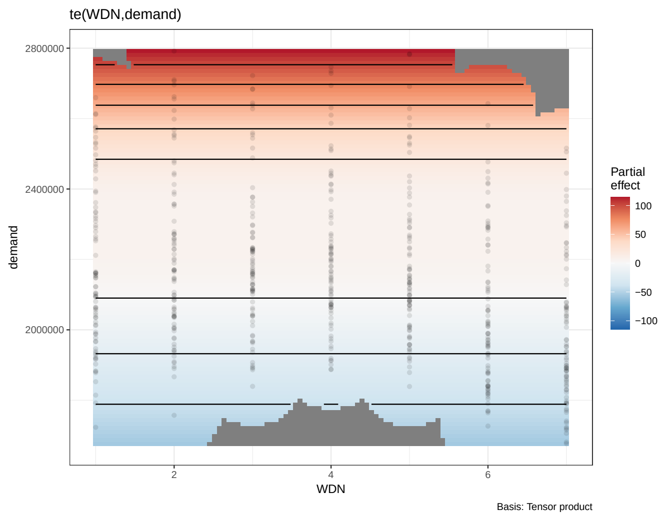
Parametric coefficients					
	Estimate	Std.Error	tvalue	Pr(>|t|)	
(Intercept)	94.8439	16.1519	5.8720	0.0000	***
CPol	-0.7896	7.1473	-0.1100	0.9120	
Coal	0.0505	0.0529	0.9540	0.3400	
Approximate significance of smooth terms:					
	edf	Ref.df	F	p-value	
te(WDN,demand)	17.7270	22.4200	7.5010	0.0000	***
te(temperature,Trend)	14.6570	19.7100	1.7880	0.0184	*
s(temperatureMax)	8.9290	9.5800	2.8910	0.0055	**
s(Gas)	2.5550	3.0000	3.7780	0.0033	**
R-sq.(adj) = 0.753 Deviance explained = 77.3%					
GCV = 3498.9 Scale est. = 3214.7 n = 577					

Table 5: GAM model estimation for VIC

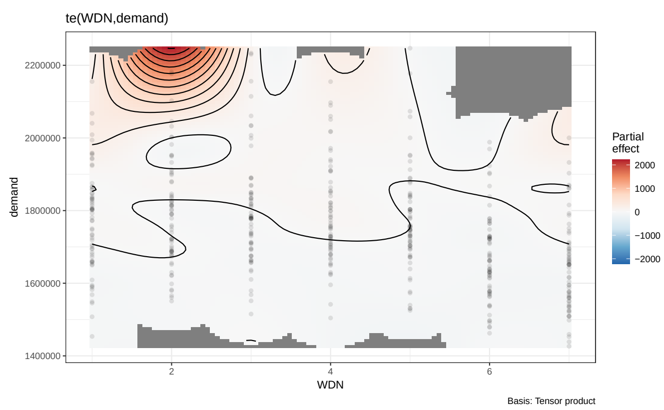
Our objective is to minimize forecasting bias, which in turn enables us to determine whether the current real price is lower than the price forecast. If the current price is indeed lower than the forecast values, it can be inferred that the market cap is functioning effectively, leading to a decrease in prices.[20]

To conduct this analysis, we utilized a dataset spanning from September 2021 to the end of December 2022 as our in-sample data. The remaining portion of the dataset was set aside for out-of-sample analysis. This division enables us to evaluate the reliability of our forecasting model and its ability to accurately predict future prices. Figure 4 illustrates the outcomes of the forecasting process conducted for the three aforementioned states. It is evident from the results that the projected price values exceed the actual values in over 70% of cases for QLD. In contrast, the proportions of overestimated values for NSW and VIC are relatively lower, approximately 60% and 49% respectively. Additionally, the root mean square errors (RMSE) associated with the forecasting models are found to be 139.04, 64.31, and 41.86 for QLD, NSW, and VIC correspondingly.

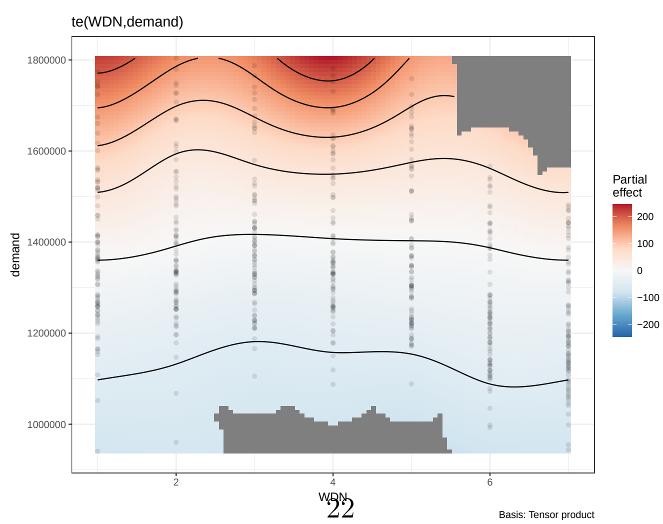
[20]It is important to note that, in the absence of the policy, the trends in the price of electricity before and after introducing the policy would have followed parallel paths over time.



(a) Contour plot of WDN & demand for NSW

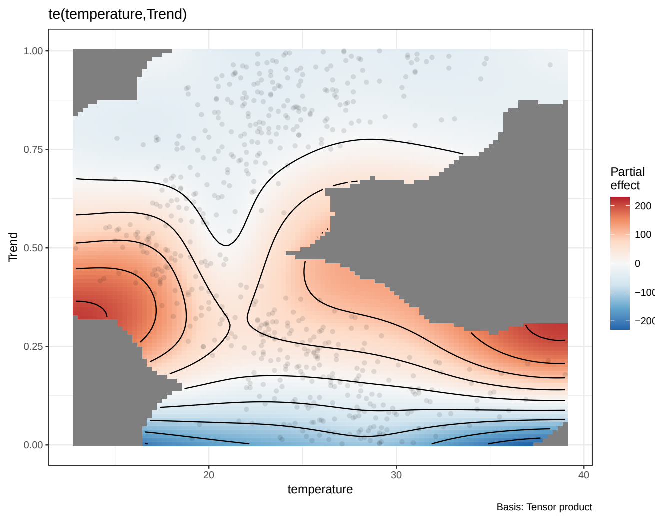


(b) Contour plot of WDN & demand for QLD

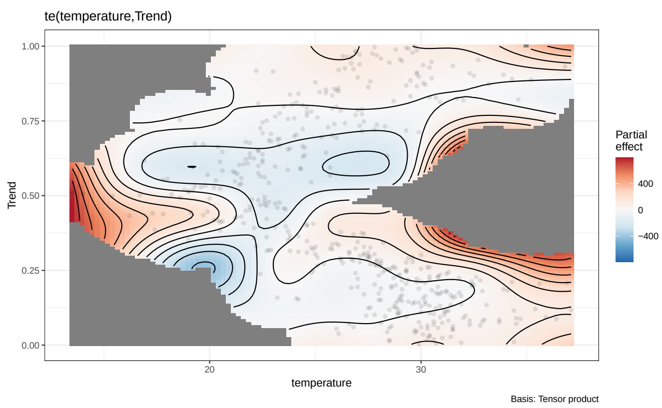


(c) Contour plot of WDN & demand for VIC

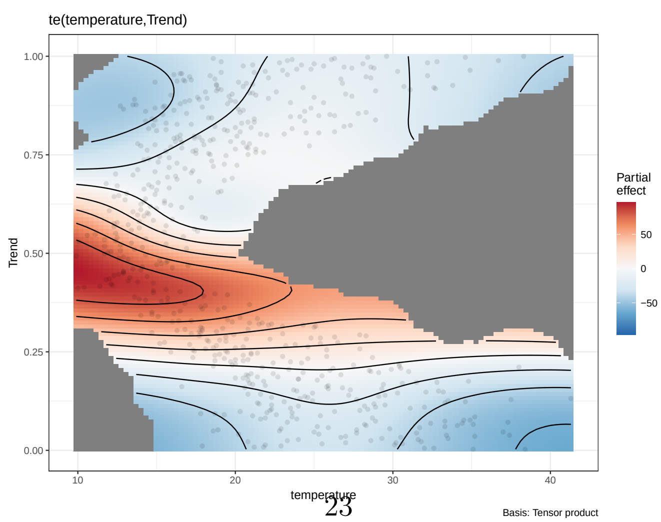
Figure 4: Smooth functions of models for each state based on GAM for all three states. The first row showcases contour plots specifically for NSW, while the second and last rows correspond to QLD and VIC, respectively.



(a) Contour plot of temp&trend for NSW

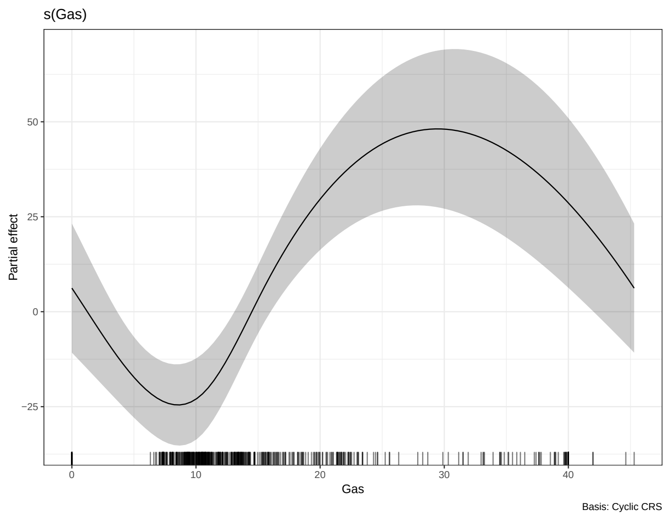


(b) Contour plot of temp&trend for QLD

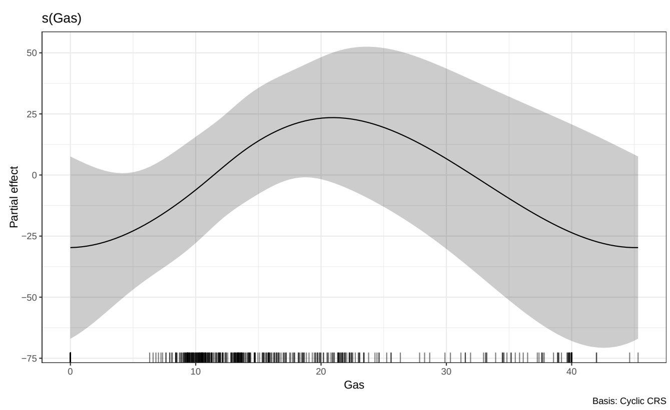


(c) Contour plot of temp&trend for VIC

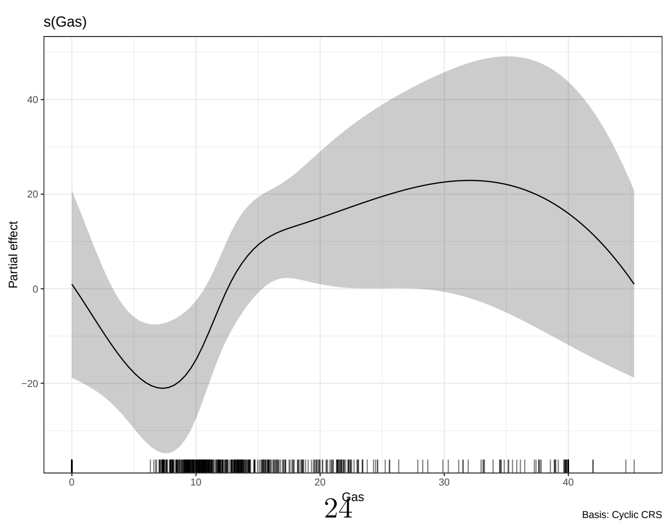
Figure 5: Smooth functions of models for each state based on GAM for all three states. The first row showcases contour plots specifically for NSW, while the second and last rows correspond to QLD and VIC, respectively.



(a) Smooth function for Gas effect NSW

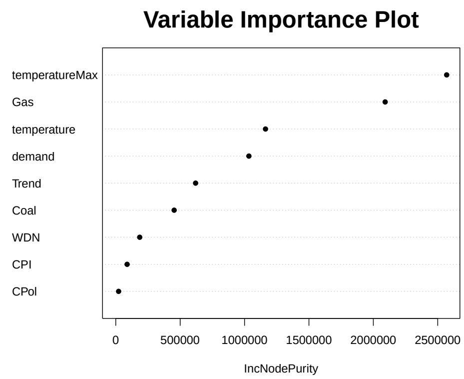


(b) Smooth function for Gas effect QLD

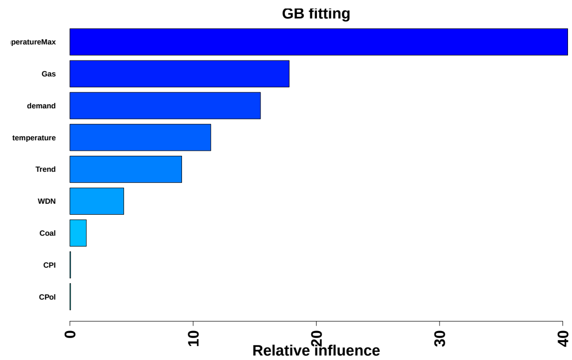


(c) Smooth function for Gas effect VIC

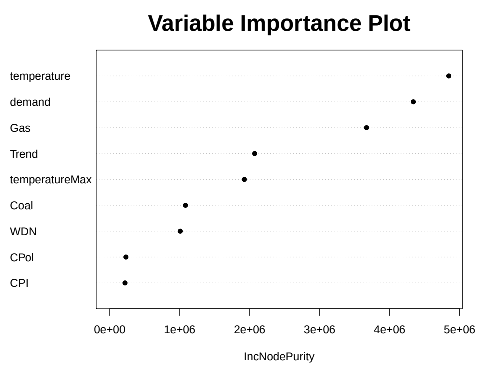
Figure 6: Smooth functions of models for each state based on GAM for all three states. The first row showcases contour plots specifically for NSW, while the second and last rows correspond to QLD and VIC, respectively.



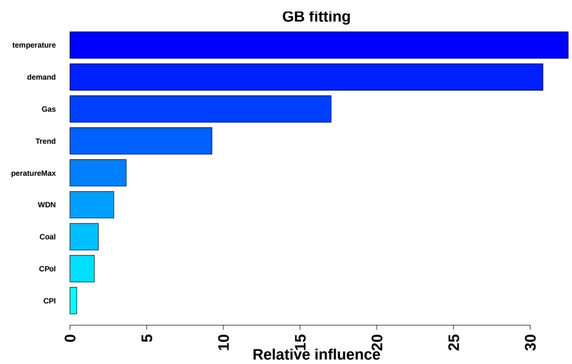
(a) important variable for NSW based on RF



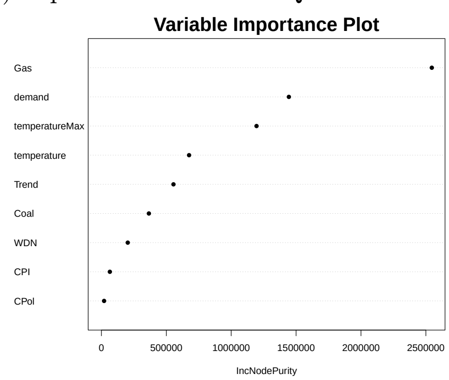
(b) important variable for NSW based on GB



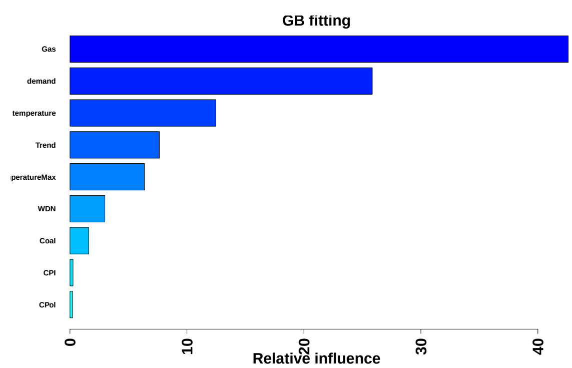
(c) important variable for QLD based on RF



(d) important variable for QLD based on GB

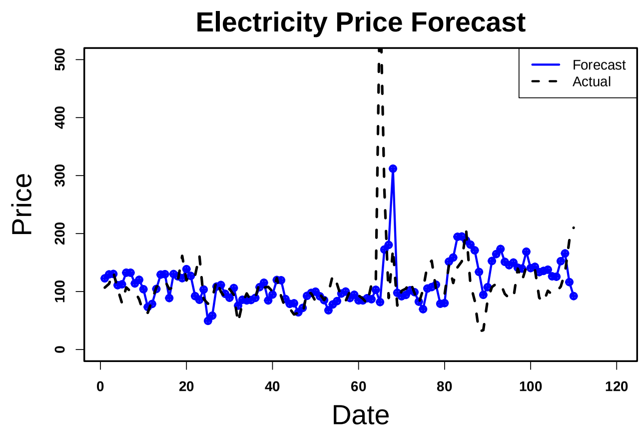


(e) important variable for VIC based on RF

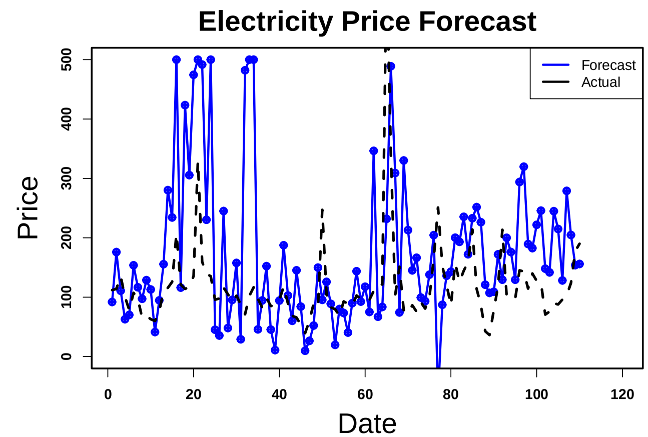


(f) important variable for VIC based on GB

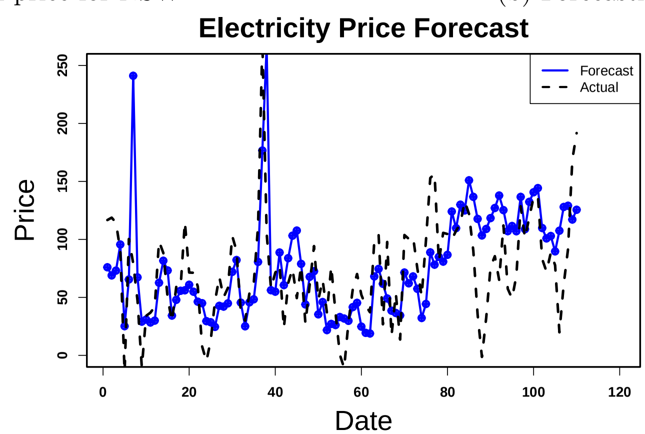
Figure 7: Important variables were identified using Random Forest (RF) and Boosting algorithm (GB) for each state. Node purity, a stopping criterion in decision trees, including Random Forest, measures the extent to which the samples within a node belong to a single class.



(a) Forecasting of price for NSW



(b) Forecasting of price for QLD



(c) Forecasting of price for VIC

Figure 8: Forecasting of price based on GAM models for each state.

5 Concluding remarks

This paper investigates the effectiveness of fuel price caps in controlling wholesale electricity prices. As demonstrated in our theoretical analysis, fuel price caps do not consistently prove effective, rather, their effectiveness depends on the drivers of market conditions and competition. Therefore, they may or may not be binding under different circumstances. Considering the varying dynamics of electricity markets, we propose a two-pronged approach, suggesting a combination of fuel price caps and market price caps, as the ideal solution to address all sources of price volatility in a spot market. It is important to note that a single market price cap may not achieve the same objectives as a fuel price cap, as a single market price cap is primarily effective when high prices are driven by high demand.

Our empirical analysis provides further insight into the effectiveness of fuel price caps. While our findings reveal a mixed impact across different zones, it is imperative to interpret this variability within the context of the region's unique market characteristics, including factors like demand elasticity, fuel availability, and market competition level.

Furthermore, our research opens the avenue for additional work on optimizing price cap policies. Policymakers could explore adaptive, region-specific approaches that account for these varying market conditions and other external factors weather and regulatory changes. By combining theoretical and empirical analyses, this study has advanced our understanding of how fuel price caps influence electricity markets and underscored the importance of further research to enhance their effectiveness in designing electricity markets and regulating electricity prices.

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Appendices

A Machine learning approaches

Random Forest and Gradient Boosting Machines (GBMs) are ensemble learning techniques that harness the combined power of multiple models to achieve accurate predictions. Random Forest excels in creating a diverse set of decision trees and consolidating their predictions. In contrast, GBMs employ an iterative optimization process that minimizes loss gradients to continually enhance the ensemble. In the subsequent sections, we will provide concise explanations of each technique.

A.1 Random Forest algorithm (RF)

Random Forest is an ensemble learning algorithm that combines the predictions of multiple decision trees to make accurate predictions. The algorithm operates by constructing a forest of decision trees during the training phase. Each tree is trained on a randomly selected subset of the training data, as well as a random subset of features. This randomness helps to create diversity among the trees and reduces overfitting. The final prediction of the Random Forest is obtained by aggregating the predictions of all the individual trees. For a classification task, let's consider a Random Forest ensemble with T decision trees. Each tree is denoted as $T_t(x)$, where x represents the input features. The prediction of the Random Forest ensemble for a given input x is obtained through majority voting:

$$\hat{y} = arg\, max_y \sum_{T}^{t=1} I(T_t(x) - y),$$

where $\hat{y}$ is the predicted class label, $I(.)$ is the indicator function that returns 1 if the condition is true and 0 otherwise, and y represents the class label, (for more information see Biau and Scornet (2016))

A.2 Gradient Boosting algorithm (GB)

Gradient Boosting algorithm (GB) is a powerful machine learning technique that is widely used for regression and classification tasks. The main idea behind GB is to iteratively build an ensemble of weak prediction models, such as decision trees, and combine their predictions to form a strong overall prediction. At each iteration, the algorithm tries to fit the negative gradient of a loss function associated with the data, effectively minimizing the residuals. This is done by training a new weak model on the negative gradient values, and then adding it to the ensemble. The final prediction is obtained by summing the predictions of all the weak models. Mathematically, the prediction at each iteration can be represented as follows:

$$F_{m+1}(x) = F_m(x) + \nu h_{m+1}(x),$$

where $F_{m+1}(x)$ represents the overall prediction at iteration m, $F_m(x)$ is the prediction from the previous iteration, ν is the learning rate that controls the contribution of each weak model, and $h_m(x)$ represents the prediction of the new weak model trained on the negative gradient. The learning rate is typically set to a small value to prevent overfitting. By iteratively adding weak models that focus on the residual errors of the previous models, GB is able to gradually improve the overall prediction accuracy, (for more detail see Natekin and Knoll (2013)).