CATÓLICA
CEGE · CENTRO DE ESTUDOS
EM GESTÃO E ECONOMIA
PORTO

The price impacts of the exit of the Hazelwood coal power plant

Ricardo Gonçalves
Flávio Menezes

CEGE WORKING PAPER SERIES WP22.06
October 2022

fct Fundação para a Ciência e a Tecnologia
This work was supported by Fundação para a Ciência e Tecnologia (through project UIDB/00731/2020).

The price impacts of the exit of the Hazelwood coal power plant*

Ricardo Gonçalves†
Católica Porto Business School and CEGE, Universidade Católica Portuguesa

Flávio Menezes‡
School of Economics, The University of Queensland

October 2022

Abstract

This paper estimates the price impacts of the unanticipated closure of Hazelwood, a large brown coal power plant (1600 MW) in Victoria, Australia. We measure the total impact of the closure on prices in Australia's National Electricity Market for each half-hour interval and for each state 3 months, 6 months, and 12 months from closure. We also break down the impact into direct and indirect effects. We find that the total impact of the closure on prices varies considerably across half-hours. The results vary not only in magnitude and across time, but also in statistical significance. Our estimates suggest an upper bound for the impact on the average half-hourly price of $18.90/MW 12 months from closure, with a total market impact of $4,287.7 million. When we break down the total impact into direct and indirect effects, we find the latter to be the main driver of our results. In particular, we find that the reduction in the prices because of increased wind generation in a given half hour – the merit-order effect – has decreased markedly following the closure, and this largely explains the observed price increases post-closure.

JEL Classification: D4, L94

Keywords: electricity markets; market impacts; closure of coal power plant.

---

*We would like to thank Vasilis Sarafidis for extremely useful comments on an earlier draft. Financial support from Fundação para a Ciência e Tecnologia through project UIDB/GES/00731/2020 is gratefully acknowledged.

†Postal address: Católica Porto Business School, Universidade Católica Portuguesa, Rua Diogo Botelho, 1327, 4169-005 Porto, Portugal. E-mail: rlgoncalves@ucp.pt.

‡Postal address: School of Economics, University of Queensland, Brisbane 4072, Australia. E-mail: f.menezes@uq.edu.au.

1 Introduction

The energy transition around the world is happening at a much faster pace than most had anticipated (IEA, 2021a). This faster transition requires regulators to encourage investment by providing regulatory certainty and managing energy systems with an ever-increasing penetration of variable renewable energy.[1] This paper provides a measure of the economic cost of regulators' failure to anticipate the impact of the energy transition. We estimate the price impacts of the closure of Hazelwood, a large brown coal power plant (1600 MW) in Victoria, one of the states in Australia's National Electricity Market (NEM). Hazelwood, with an approximate 20% market share in the Victorian NEM region, ceased operating in April 2017; the owners provided less than 5 months' notice. The unanticipated closure exposed the lack of a regulatory framework to govern the exit of coal power plants.

The notion that the increased penetration of renewables would adversely impact the economics of coal power generation has been well estabished for quite some time. This occurs mostly through the combination of declining spot market revenues and rising costs because of reduced availability and utilisation. Our main contribution is to provide an econometric estimate of the impact of Hazelwood's exit on wholesale prices for each half-hour of the day.

We estimate the impact of the closure using two complementary approaches. First, we take the standard approach of measuring the total impact by adding a dummy variable to our price regression that captures the price changes that occurred in the NEM during each half-hour interval for each state (once all other explanatory factors are considered) over the 3 months, 6 months, and 12 months after the closure. Our second approach entails breaking down the total impact into direct and indirect effects. The indirect effect refers to whether the impact of additional solar or wind production on NEM prices changed after the closure. That is, the indirect effect measures any change in the magnitude of the merit-order effect as a result of the closure. The direct impact is measured by a dummy variable that reflects the impact 12 months after the closure, controlling for the indirect effect.

Our novel approach of estimating total, direct, and indirect impacts yields some interesting insights. First, and perhaps not surprisingly, the total impact of Hazelwood's closure on prices varies considerably across half-hours. The results vary not only in magnitude but also in statistical significance, and clearly point to a positive and significant (in the sense that it contributes to wholesale price increases) or statistically insignificant effect (depending on the half-hours we look at). Clearly, our results suggest caution in using changes in average daily prices to measure the

[1] Recognition of the role of regulators in the energy transition is made visible, for example, by the recent launch of the Regulatory Energy Transition Accelerator (RETA). This is a global initiative that brings energy regulators together to discuss the challenges they face and share best practices. In addition to the IEA, the RETA includes the UK's Office of Gas and Electricity Markets (Ofgem), the International Renewable Energy Agency (IRENA), and the World Bank (IEA, 2021b).

impact of the closure.

Second, we find that the total impact is larger than the direct impact (which in fact is estimated to be negative), which suggests that the indirect effect must have induced an increase in wholesale prices. In particular, the closure reduced the magnitude of the merit-order effect of wind generation. That is, additional wind generation in a particular half-hour leads to a smaller reduction in NEM prices for that half-hour after the closure than it would have had there been no exit. This is a counterintuitive result, since the closure of a low (private) marginal cost generator means that additional wind generation in a particular half-hour replaces a higher cost generator, and, everything else the same, should result in a larger – rather than smaller – merit-order effect.

Our estimates also allow us to measure the costs, in terms of the accumulated increase in prices multiplied by the respective quantities, of the failure of regulators to have an exit mechanism in place prior to the closure. We can then compare the impact on prices with the amount that was required for Hazelwood to remain operational. We note, however, that our cost estimates only capture the impact on spot market prices and ignore the impact in other markets. The closure has certainly impacted forward contract prices, and likely impacted the market prices of ancillary services and may have led to a larger number of costly interventions by the market operator to ensure resources adequacy.

We also note that the emissions intensity of a brown coal generator such as Hazelwood was very high, and therefore its exit had significant environmental benefits. While the purpose of our paper is not to carry out a fully fledged cost-benefit analysis of the Hazelwood plant closure, Section 6 provides an estimate of the net impact on emissions. Our calculations suggest a market value of reduced emissions that is far smaller than the impact of the exit on market prices.

Understanding the market impact of the exit of large coal power plants throughout the day is also important from the perspective of investors and the market operator. Moreover, the more significant increase in solar generation from 2018 has further undermined the economics of coal generation (see Gonçalves and Menezes, 2022), which raises questions about the effectiveness of the 3-year closure rule. The Energy Security Board is currently working to ensure resources adequacy, given that coal will exit the market faster than anticipated (ESB, 2021). There have also been more recent announcements of the early closure of other coal power plants.[2]

The paper is organized as follows. Section 2 provides a brief background of the NEM and the Hazelwood power plant; Section 3 contains a short review of the literature; Section 4 describes the data used, and Section 5 describes our empirical approach; Section 6 presents the results, and Section 7 concludes.

[2]See https://www.abc.net.au/news/2022-02-17/origin-to-shut-eraring-power-station-early/100838474.

2 Background

The NEM, which started operations in December 1990, is one of the world's longest interconnected power systems. It encompasses around 150 large power stations (and approximately 240 plant units in total). The transmission network comprises around 40 thousand km of high voltage power lines, and transports electricity to large energy users and distribution networks. A competitive retail market services approximately 10 million residential, commercial, and industrial energy users.[3]

The NEM is an energy-only gross pool – that is, all electricity is traded on the spot market. Prices and the quantity dispatched by each generator are determined through the interaction of the bids made by generators and system demand (total demand net of household PV generation). A dispatch price for each of the NEM regions[4] is set every 5 minutes and is equal to the bid of the marginal generator. Until October 2021, six dispatch prices were averaged every half hour to determine the spot price for each trading interval. System demand can be met within one region or across regions. Interconnectors deliver energy from lower-price regions to higher-price regions, thus linking prices across regions. However, when interconnectors are constrained, electricity continues to be transported from a lower-price region and sold in a higher-price region up to the capacity of the interconnector, but prices are no longer codetermined.[5] The wholesale market is complemented by a sophisticated derivative market that connects the economics of the physical power system to investment and resource adequacy.

Arguably, the NEM has been successful in promoting allocative and dynamic efficiency.[6] In particular, the NEM's very high market price cap (currently at A$15,100/MWh) has ensured that the "missing money" problem that prevailed in many electricity markets around the world did not manifest itself in the NEM.[7] This success, however, has ended for a number of reasons, including the uncoordinated exit of a large coal power plant, climate change policy uncertainty, and the discontinuity of the carbon price in 2014, with consequential developments in the gas market.[8] Out-of-market mechanisms, such as renewable certificates, severed the link between NEM prices, investment requirements, and system operations.[9]

These severed links, and the increased penetration of renewables, undermined the economics of coal power stations. The resulting declining spot market revenues and rising costs, because of

[3] See, for example, Australian Energy Regulator (2018a), Chapter 2.

[4] There are five regions in the NEM: New South Wales, Queensland, South Australia, Tasmania, and Victoria.

[5] Detailed information on the least-cost, security-constrained dispatch process followed by the market operator can be found at https://aemo.com.au/en/energy-systems/electricity/national-electricity-market-nem/system-operations/dispatch-information.

[6] See, for example, Simshauser (2019c).

[7] The missing money problem refers to the fact that imperfections in wholesale energy-only electricity markets, such as market price caps, result in generators' not earning net revenues that are sufficient to support investment in a least-cost portfolio of generating capacity and to satisfy consumer preferences for reliability. See, for example, Joskow (2007) and Joskow and Tirole (2007).

[8] See, for example, Simshauser (2019a).

[9] See, for example, Simshauser (2019b) and Gonçalves and Menezes (2022).

reduced availability and utilisation, led to the closure of the 540 MW Northern Power Station in mid-2016. Two months later, the 1600 MW Hazelwood Power Station in the adjacent VIC region (with a 20% market share) announced it would close on 01 April 2017. Hazelwood was a brown coal-fuelled thermal power station in the Latrobe Valley of Victoria, Australia. It was a subcritical pulverized coal-fired boiler and supplied a substantial amount of baseload power.

The closure of Hazelwood was driven by mounting capital reinvestment requirements ($400 million) related to plant safety, and it had a significant impact on market prices.[10] As pointed out by Simhauser (2019c), "... annual wholesale spot market turnover rose from $7.7 billion to $17.2 billion either side of the Hazelwood exit." Following Hazelwood's exit, regulators introduced a legal requirement for the continuous disclosure of plant exit timing (referred to as the 3-year closure rule).

The Australian Energy Regulator (2018b) investigated the market impact of the closure of Hazelwood and concluded:

> Our key finding is that the exit of Hazelwood removed a significant low fuel cost generator, which was largely replaced by higher cost black coal and gas plant – at a time when the input costs of black coal and gas plant were increasing. These factors, in turn, drove significant increases in wholesale electricity prices. We found no evidence to suggest that prices were being driven by rebidding close to dispatch, or physical or economic withholding – behaviours more usually associated with the exercise of market power.

Our approach allows us not only to measure the total impact on prices for each half-hour that is solely attributable to the closure, but also to explore whether the closure has had an impact on the magnitude of the merit-order effect – i.e., the reduction in prices in a particular half-hour associated with increased production of renewables in that half-hour. Understanding such a relationship will be even more important in designing regulatory practices to address the exit of coal from the NEM at a much faster rate than originally anticipated in the context of a much higher penetration of renewables.

3 Relation to the literature

Competitive wholesale electricity markets, in which prices are determined by the interaction of supply and demand, are pervasive around the world. It is well understood that in such markets, the presence of zero-marginal-cost renewable generators will tend to reduce the wholesale price at the time of generation, this is the merit-order effect.

[10] See Simhauser (2019c).

Early literature on the contemporaneous merit-order effect includes (among several others) Azofra et al. (2014); Clò et al. (2015); Cludius et al. (2014); Gelabert et al. (2011); Ketterer (2014); and Woo et al. (2011). Specifically for the NEM, Bell et al. (2017); Csereklyei et al. (2019); Cutler et al. (2011); Forrest and McGill (2013); Gonçalves and Menezes (2022); McConnell et al. (2013); and Simshauser (2018) have provided support for the merit-order effect, albeit using markedly different methodologies. The papers that are methodologically closest to ours are Csereklyei et al. (2019); Clò et al. (2015); Cludius et al. (2014); and Gonçalves and Menezes (2022).

Csereklyei et al. (2019) analyse the merit-order effect of solar and wind production in the NEM between 2011 and 2018, and whether its magnitude has changed over time with the increased market shares of solar relative to wind generation. Their empirical strategy uses both half-hourly and daily price data in an autoregressive distributed lag (ARDL) model that controls for other relevant explanatory factors of price – namely, the price of natural gas – in their daily price regressions. The results are suggestive of a strong contemporaneous merit-order effect, for both wind and solar production.

The econometric approach to estimating the contemporaneous merit-order effect followed by Csereklyei et al. (2019) is somewhat different from ours: the dependent variable is the half-hourly price observed in each state, and explanatory factors include (i) solar and (ii) wind production in each half-hourly interval, as well as (iii) total demand, and (iv) half-hourly, weekday, and month fixed effects; an annual time trend; and state fixed effects (Tasmania is excluded from the analysis). Because of the estimation methodology adopted – ARDL – two lags of half-hourly (v) prices and (vi) total demand are also included to address autocorrelation issues. Under this approach, all observations are pooled and (implicitly) specific half-hourly time slots are assumed (all else equal) to induce a level change in prices. In other words, what is estimated is an average merit-order effect across half-hourly intervals throughout the day. By contrast, we estimate the merit-order effect (separately) for each of the 48 half-hourly intervals in the day. Our approach explicitly recognises that the impact of solar or wind production on prices (as well as that of other explanatory variables) may differ significantly across half-hourly slots, since the marginal generator is likely to be different.

In addition, different from Csereklyei et al. (2019), we consider the integrated nature of the NEM: Whereas Csereklyei et al. (2019) use solar, wind, and total demand in each state (and in each half-hour) as explanatory variables, we consider solar, wind, and total generation (in each half-hour) across states, and we include an 'excess demand' variable to account for state-specific imbalances between generation and supply.

Moreover, Csereklyei et al. (2019) only include other explanatory factors for prices, such as the wholesale price of natural gas, in the regression that has as the dependent variable the (average) daily price of electricity. Instead, for each half-hourly slot, we consider factors that may affect the mix of electricity generation in that half-hour – namely, natural gas prices or average rainfall. We also include rooftop PV generation in our regression (while Csereklyei et al., 2019, do not). Finally, we address possible serial correlation issues as well as possible dependence across the cross-sections (that is, between the time series of the various states) by reporting Driscoll-Kraay standard errors (for each half-hour).

Because of the close association between Csereklyei et al.'s (2019) methodology and ours, in our robustness checks section we conduct a reconciliation exercise that shows that the main effects of the Hazelwood closure we are picking up in our half-hourly regressions also emerge when we apply Csereklyei et al.'s (2019) estimation approach.

Clò et al. (2015) examine the merit-order effect for solar and wind generation in the day-ahead Italian wholesale market from 2005 to 2013. Although they have access to hourly price data, they chose instead to use as the dependent variable the average of hourly prices throughout each day. As explanatory variables they use, as we do, solar and wind production as well as total (national) demand; they also include natural gas prices and weekday, month, and year fixed effects. However, the 'quantity' variables (solar, wind, and total demand) are the daily average of hourly quantities. Therefore, albeit for reasons different from those of Csereklyei et al. (2019), Clò et al. (2015) do not shed light on merit-order effects within each day (that is, for each hourly interval).

Cludius et al. (2014) follow an approach similar to Csereklyei et al. (2019) and regress hourly day-ahead price data (2008-2016) from the European Power Exchange for wind, solar, and total demand, including hourly, daily, monthly, and yearly fixed effects. As with Csereklyei et al. (2019), this regression methodology estimates an average merit-order effect across all hourly slots and does not shed light on possible within-day variations of such an effect.

Gonçalves and Menezes (2022) follow an approach similar to ours, insofar as they examine the price-setting process within the NEM for each half-hour over a long period of time (2009-2020). Their goal, however, is to understand the medium-run impact of renewable generation, and therefore, instead of looking at the contemporaneous merit-order effect (the impact of half-hourly renewable production on prices), they analyse the impact of total daily renewable production on half-hourly prices. Among other explanatory factors, they control for the Hazelwood power plant closure and find that it had a positive and significant effect on market prices in most half-hourly slots throughout the day, with a notable exception being the time period from 16h30-19h30. In this paper, we zero in on the impact of the exit of Hazelwood on wholesale prices

4 Data description

In our analysis, we use half-hourly data for the full year before the Hazelwood plant closure and the full year immediately after the closure. Therefore, our data include the period from 1 April 2016 until 30 March 2018. When we refer to the period 'before (after) Hazelwood closure', we are referring to the full year before (after) the closure. The reason for focusing on a 1-year period before and after the closure is straightforward: Considering a period shorter than one year would not allow us to properly control for seasonality, especially that associated with months within the year (and which would capture summer vs. winter effects); had we considered a period longer than 1 year, there would be an increased likelihood that factors other than the ones we consider to be the main price drivers could affect the results. For instance, Gonçalves and Menezes (2022) found that the market impact of solar production depends to a significant degree on the evolutionary stage of solar penetration. Looking at a 1-year period before and after closure seems to strike a reasonable compromise.

Figure 1 displays the average weight of each of the main types of electricity production in each half-hour before and after the plant closure. Naturally, a sharp drop – of around 5 percentage points – is observed for brown coal production in the NEM, and this is rather evenly spread across half-hourly slots. This drop in the weight of brown coal production was compensated for by an increase of black coal production (around 3 percentage points) and natural gas production (around 2 percentage points). Again, these 'compensations' were fairly evenly spread throughout the half-hourly slots during the day. Changes in the weights of solar, wind, and hydro production were fairly modest (less than 1 percentage point). In particular, solar production during this period had a very low weight in price formation in the NEM. Gonçalves and Menezes (2022) show that the impact of daily solar production on prices changed substantially from the second half of 2018, with the addition of significant solar capacity to the NEM.

Figure 2 displays the average price in each of the five states for each half hour slot, before and after the plant closure. QLD and NSW register (on average) price increases, but the most significant price changes were observed in VIC and TAS, where prices increased significantly – in VIC, across all half-hour slots, and in TAS mainly during the afternoon and night.

Figure 3 provides a more dynamic perspective on changes in the weight of each type of electricity production. It depicts the monthly average weight of each type of electricity production in the 12 months before and 12 months after the plant closure (which occurred in April). The weight of brown coal production drops markedly in April 2017 (top left panel); the second largest drop occurs much later in the year, in the months of September-December. The weight of black coal increases more markedly in July and then in October-December (top right panel). The weight of natural gas production increases through the rest of the months of 2017, until December (middle left panel). Solar and wind production do not display unidirectional changes in their weight in total production: In some months their weight increases and in others it decreases (middle right and bottom left panels). Generally, the average weight of solar and wind production before and after the plant closure is largely unchanged. Finally, hydro also displays some volatility and, on average, approximately a 1 percentage point drop in its weight in total production (bottom right panel).

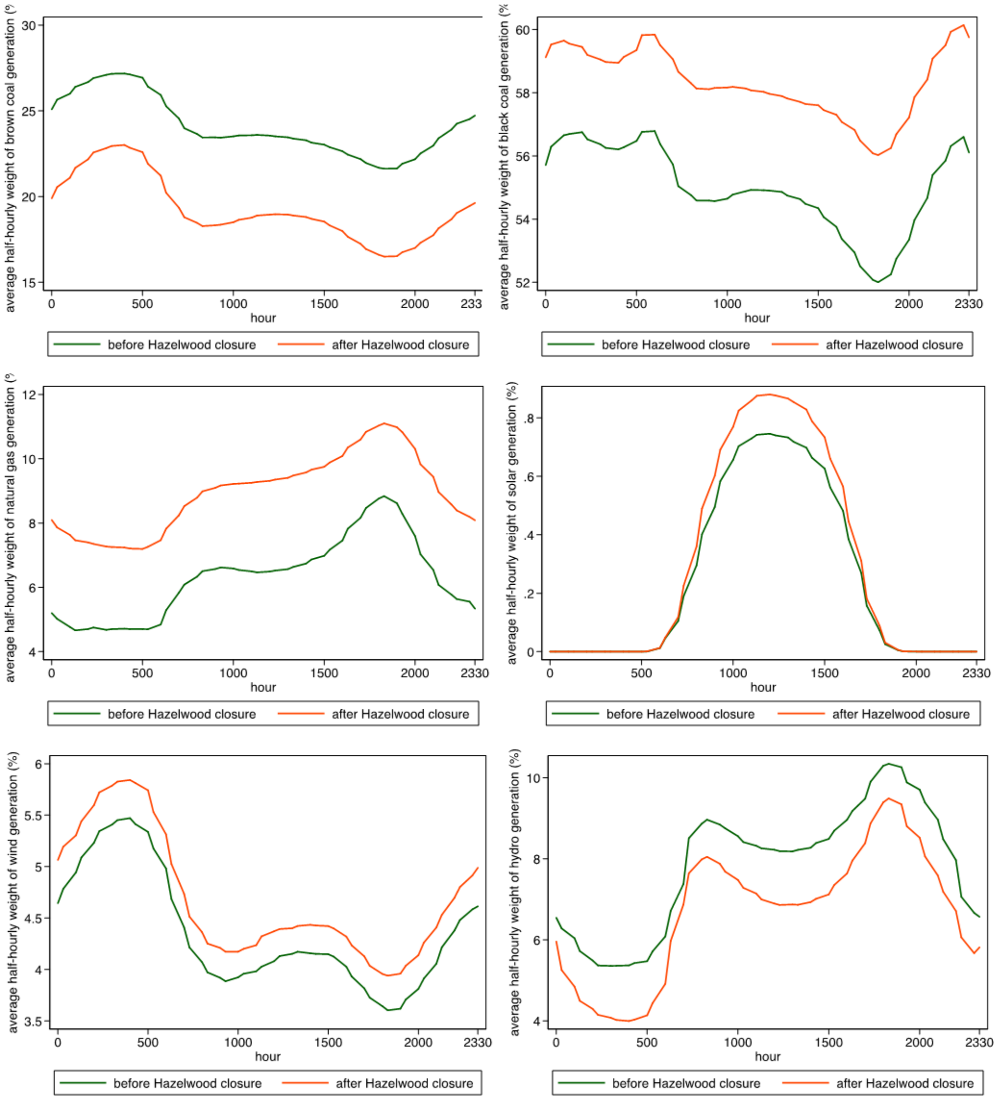

Figure 1: Weight of each type of electricity production, before and after closure, by half-hourly slots

5 Empirical approach

Our goal is to assess the impact of the Hazelwood power plant closure on within-day electricity prices (that is, for every half-hour of the day). As such, we exploit the half-hourly nature of wholesale price setting in the NEM.

We adopt a widely used methodology, especially in the field of finance: an event study (see Campbell et al., 1997, or Kothari and Warner, 2007). We start by defining a model that explains NEM prices unconditional on the Hazelwood closure. We then calculate the price impact of the closure as the difference between observed prices post-closure and predicted prices had the closure not occurred.

Figure 2: Average wholesale prices in each state, before and after closure, by half-hourly slots

We proceed in two different (but complementary) ways: First, we estimate the total impact of the closure on NEM prices. Since this impact may have been different in the months following the closure, we estimate the impact on prices in the 3, 6, and 12 months following the closure. This 'dynamic' perspective allows us to understand at which point in time subsequent to the closure the impacts were larger (or smaller). Second, we put forward the idea that this total impact is in fact a combination of two effects: a direct effect, whereby the plant closure's impact on prices is due to changes in the industry supply curve that follows from the exit of a competitor and/or any changes in bidding behaviour that reflect possible changes in generators' market power; and an indirect effect, whereby the closure of a coal power plant may affect the magnitude of the merit-order effect. As is well known in the contemporaneous merit-order literature referred to above, solar and wind production typically drive down wholesale electricity prices because their low marginal production

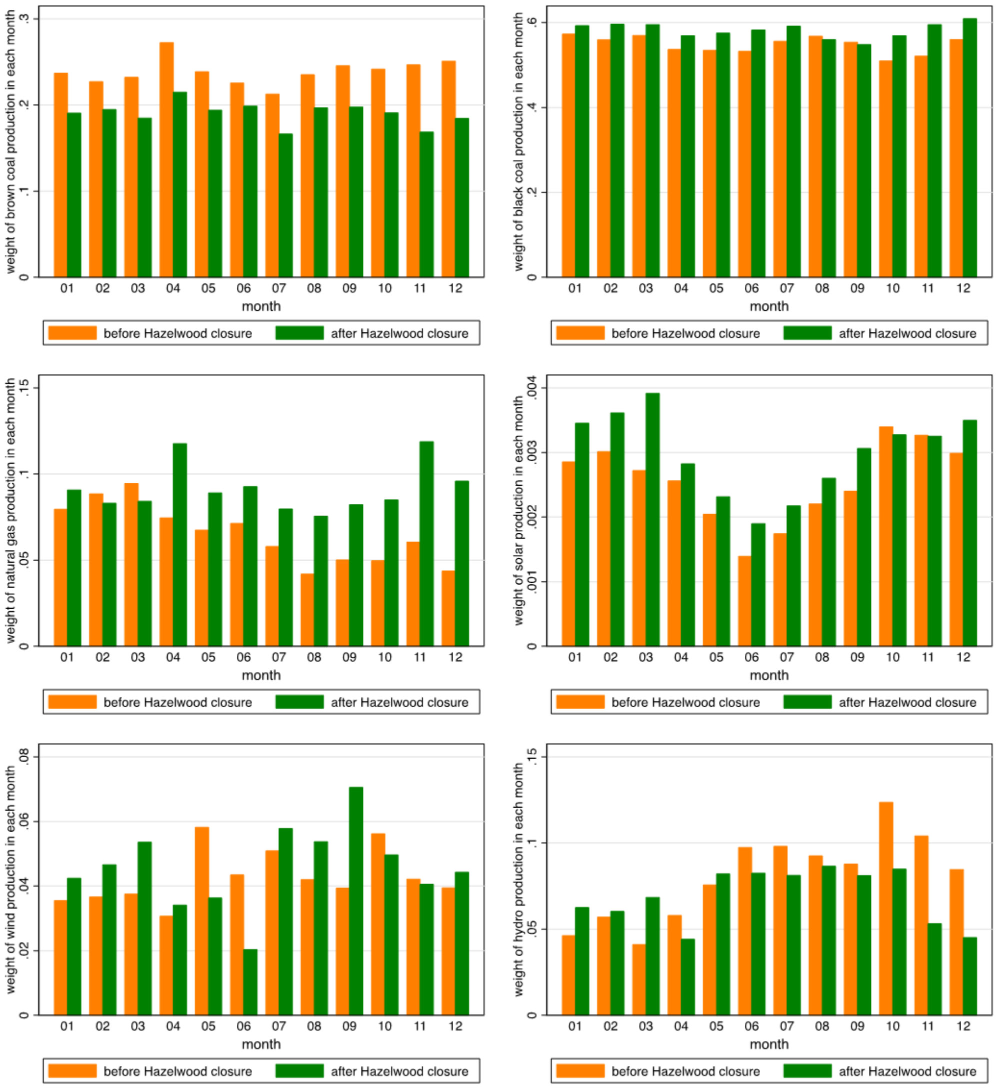

Figure 3: Average monthly weight of each type of electricity production, before and after closure

costs replace higher-cost technologies. We propose that the unexpected and uncoordinated closure of a such a large coal power plant (which could have been used to offset renewable fluctuations) may affect the relationship between renewable production and wholesale prices. This could be especially true where Hazelwood's output could be counted on during the late afternoon, as solar production comes to an end. Broadly speaking, the total impact would be the sum of the direct and indirect effects.

To estimate the total impact, we proceed as follows. In the NEM and the period under analysis, prices are established on a half-hourly basis for each state. For every half-hour of each day (which we define as 'hh') from 1 April 2016 to 30 March 2018, the dataset contains wholesale prices for each state s. That is, we have a panel dataset: For each of the five states, we have a time series of half-hourly prices. Let $t = 1$ day (this will be used to denote the lagged variables; see below).

In this context, as our baseline regression, we estimate a (state) fixed effects model separately for every half-hour of the day:

$$
\begin{aligned}
P_{hh,s} \quad = \quad & \beta_{hh}^{Hazelwood\_3}.Hazelwood\_3 + \beta_{hh}^{Hazelwood\_6}.Hazelwood\_6 + \beta_{hh}^{Hazelwood\_12}.Hazelwood\_12 + \\
& +\alpha_{hh,s} + \beta_{hh}^{solar}.Solar_{hh} + \beta_{hh}^{wind}.Wind_{hh} + \beta_{hh}^{ngas}.NaturalGas_{hh} + \\
& +\beta_{hh}^{rainNSW}.RainNSW_d + \beta_{hh}^{rainNSW}.RainTAS_d + \beta_{hh}^{householdPV}.HouseholdPV_{hh} + \\
& + \sum_{t=1}^{6} \theta_{hh,t}.P_{hh-t,s} + \boldsymbol{\gamma}_{hh}.\mathbf{X}_{hh,s} + \varepsilon_{hh,s}
\end{aligned}
\tag{1}
$$

$Hazelwood\_3$, $Hazelwood\_6$ and $Hazelwood\_12$ are dummy variables that take the value of 1 for the period 3, 6, and 12 months (respectively) after the closure. These are the main variables of interest. Their coefficients provide an estimate of the price changes that occurred in the NEM for each half-hour interval in each state that can be attributed to the closure (once all other explanatory factors are taken into account). As we outline above, the estimated coefficients for these dummy variables are an indicator of the total impact of the closure.

The variable $\alpha_{hh,s}$ is a dummy variable for each state and captures possible state-specific (fixed) effects on prices. As other explanatory factors, we include in our regression $Solar_{hh}$ and $Wind_{hh}$, which correspond to the total (across states) solar and wind-based (respectively) electricity inserted into the NEM in each half-hour hh of the sample period. $Naturalgas$ is the price of natural gas, captured by the Declared Wholesale Gas Market (DWGM) price, which is available on an intra-day basis in 5 schedule intervals. The price of each schedule interval for each day was matched with the appropriate half-hour/day in our dataset. $RainNSW$ and $RainTAS$ contain the daily rainfall in two locations in New South Wales and Tasmania that are close to major hydroelectric plants in Australia. Including them in the regression allows us to control for periods of heavier rainfall and potentially lower (opportunity) cost of water. We note, however, that around a third of Australia's hydroelectric capacity is pumped hydro; therefore, rainfall matters less for supply availability. Finally, we also include in our regression total PV electricity generation by households ($HouseholdPV$). These data are available in half-hourly intervals in each of the five states, and were provided by the Australian Energy Market Commission. As we have done with solar and wind production, this variable aggregates total household PV generation in each half-hour across all five states.

Note that we have deliberately excluded coal prices as a possible explanatory variable. This is in line with the findings of Gonçalves and Menezes (2022), who report a negative impact of the daily price of coal on electricity prices – a counterintuitive result. This could be due to a strategic effect, since many coal generators are not subject to coal prices because they either own or have long-term contracts with nearby coal mines: When coal plants are called to generate during peak hours, they can shadow price gas generators to ensure dispatch, and thus lower wholesale prices. Therefore, that variable does not appear to be a good proxy for coal plants' costs, and we have chosen not to include it in our regression.

The vector $\mathbf{X}_{hh,s}$ encompasses a range of additional relevant explanatory variables: $XD_{hh,s}$ is the excess demand for electricity in half-hour hh in state s and is the difference, in that half-hour, between state s's total demand and its own electricity production. A positive value of $XD_{hh,s}$ implies that state s in half-hour hh 'imports' electricity generated by other states via the interconnectors. Therefore, this variable attempts to capture the potential price impacts of interconnection capacity constraints. TG_{hh} measures the total electricity production in half-hour hh across all states and captures long term-trends in demand. As we outline below, we include three lags of this variable in the regression; that is, the total electricity produced in the same half-hour hh in the previous three days. Finally, the dummy variables *weekday* and *month* capture weekday or month fixed effects.

As usual in this type of approach (e.g., Clò et al., 2015; Cludius et al., 2014; Csereklyei et al., 2019; Gelabert et al., 2011; Ketterer, 2014; or Woo et al., 2011), we tested our state-level time series for unit roots. Carrying out this type of regression with nonstationary variables could lead to spurious results (Davidson and MacKinnon, 2004). We employed the Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979), and the Phillips-Perron test (Phillips and Perron, 1988). In both cases, we conducted a prior analysis of how many lags to consider in the test by examining the Schwarz information criterion (SIC) and Akaike's information criterion (AIC) for each state-level half-hourly time series. The null hypothesis of a unit root (nonstationarity) could be rejected at the 10% significance level (and the vast majority at 5%) for all state-level half-hourly time series. Therefore, the nonstationarity of the variables does not appear to be a problem.

However, we did find significant autoregressive processes in most of the state-level time series. This has led us to include lags of the electricity price (dependent variable) and of the total half-hourly electricity generated – an approach that was also followed by Csereklyei et al. (2019). In particular, we based our decision on the number of lags in the SIC and the AIC. For the electricity price, we introduced six lags and for total generation we included three lags. Given that each state-level time series is half-hourly, this means that we included in the regression the observed price in the same half-hour in the previous week (6 days) – this is captured by coefficients $\theta_{hh,t}$, with $t = 1, ..., 6$ – and the observed electricity generation in the same half-hour of the previous 3 days.

To break down this total impact into a direct and indirect effect, we proceed as follows: We create two variables that interact the dummy variable $Hazelwood\_12$ with solar and wind production. The purpose is to understand whether the impact of additional solar or wind production in the NEM had an impact after the closure that differs from the one it had before the closure. In other words, the estimated coefficients for these two interaction variables provide us with an indication of any material changes in the merit-order effects that existed before the closure – that is, the indirect effect we discuss above. We focused only on the interaction with the $Hazelwood\_12$ variable (although we also could have considered shorter-term changes in the merit-order effect). At the same time, the $Hazelwood\_12$ dummy variable included in the regression provides us with an indication of the direct impact of the closure on wholesale electricity prices. The regression we estimated is as follows:

$$
\begin{aligned}
P_{hh,s} \quad = \quad & \beta_{hh}^{Hazelwood\_12}.Hazelwood\_12 + \alpha_{hh,s} + \\
& + \beta_{hh}^{solar}.Solar_{hh} + \beta_{hh}^{Hazelwood\_12Xsolar}.Hazelwood\_12.Solar_{hh} \\
& + \beta_{hh}^{wind}.Wind_{hh} + \beta_{hh}^{Hazelwood\_12Xwind}.Hazelwood\_12.Wind_{hh} + \\
& + \beta_{hh}^{ngas}.NaturalGas_{hh} + \beta_{hh}^{rainNSW}.RainNSW_{d} + \beta_{hh}^{rainNSW}.RainTAS_{d} + \\
& + \beta_{hh}^{householdPV}.HouseholdPV_{hh} + \sum_{t=1}^{6}\theta_{hh,t}.P_{hh-t,s} + \boldsymbol{\gamma}_{hh}.\mathbf{X}_{hh,s} + \varepsilon_{hh,s}
\end{aligned}
\tag{2}
$$

Given the nature of our panel data, it is possible that there may be correlation across states (dependence across the cross section; see, for instance, Sarafidis and Wansbeek, 2012, or Wansbeek and Sarafidis, 2021) and over time within each state (autocorrelation). We address autocorrelation by including lags of the dependent variable, as well as lags of one of the explanatory variables (total electricity generation). To deal with possible correlation between states' time series, we use a state-specific variable: excess demand. As observed earlier, prices are determined simultaneously to match supply and demand across the five states for each half-hour, taking technical constraints into account. It follows that the excess demand variable is likely a main driver of a possible correlation across states. We also report Driscoll and Kraay (1998) standard errors, which are heteroskedasticity- and autocorrelation-consistent, as well as robust to general forms of spatial and temporal dependence.

Finally, we highlight an important methodological point. The estimated β and γ coefficients in equations (1) and (2) are often called short-run effects: They give us an estimate of the immediate effect on prices of a unit change in the associated explanatory variable. However, due to the presumed autoregressive nature of prices, any immediate changes in prices will also have an effect on subsequent days. Therefore, the long-run effect of a unit change in an explanatory variable is the cumulative effect on prices. For an explanatory variable i that is not lagged in equations (1) and (2), this long-run effect is given by $\beta^{i}/(1-\sum_{t=1}^{6}\theta_{hh,t})$.[11] We are mainly interested in these long-run estimates, and throughout the paper this is what we will be referring to.

[11] For the lagged explanatory variable – total electricity generation – the long-run effect is given by $\left(\sum_{t=0}^{3}\gamma_{hh,t}^{TG}\right)/(1-\sum_{t=1}^{6}\theta_{hh,t})$, where $\gamma_{hh,0}^{TG}$ is the coefficient of the original variable (electricity generation in half-hour hh) and $t=1,...3$ represents electricity generation in the same half-hour hh in the previous t days.

6 Results

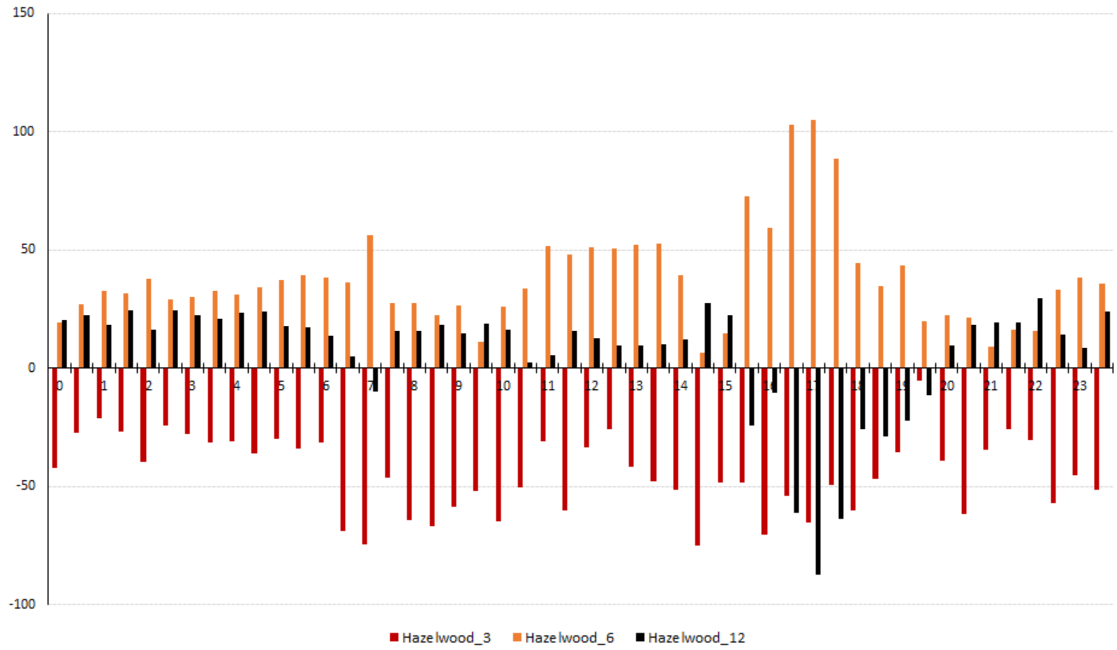

Figure 4: Total impact of the Hazelwood power plant closure

Figure 4 provides long-run estimates associated with $\beta_{hh}^{Hazelwood\_3}$, $\beta_{hh}^{Hazelwood\_6}$, and $\beta_{hh}^{Hazelwood\_12}$ for each half-hour of the day. Overall, the effect on prices in the first 3 months subsequent to the closure (that is, until 30 June 2017) was largely negative – that is, once all other factors are controlled for, the closure can be associated with a significant decrease in wholesale prices. This drop in prices simply reflects the fall in the demand for electricity as a very hot summer came to an end.

By contrast, the effect on prices in the 6 months subsequent to the closure (that is, from 1 April to 30 September 2017) was largely positive. This means that the impact on prices between July and September was very significant, so much so that the negative effect of the first 3 months was more than overcome. These months broadly correspond to winter in Australia, and therefore during this period the closure was more significantly felt in terms of wholesale prices in the NEM.

The results for the full 12-month period subsequent to the closure are more mixed, and depend on the half-hourly slots we consider. During the night, from 20h00 onward, the effect is positive and statistically significant (except for 23h); in the 6h30 and 7h half-hourly slots, it becomes insignificant; it is again positive and significant between 7h30 and 10h, and 11h30-12h and 14h-14h30. For all other half-hourly slots, the long-run estimate is not statistically significant. Therefore, whenever it is significant, the long-run estimate is positive and this occurs during the night and during several daily periods in the morning and early afternoon.

Once we carry out the second regression, breaking down the total impact into direct and indirect

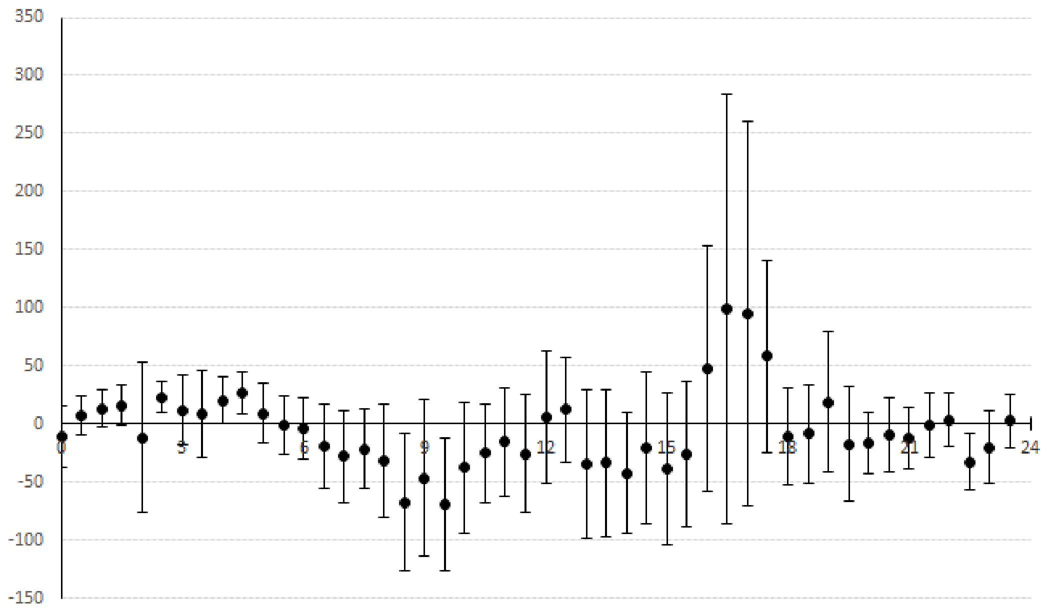

Figure 5: Direct effect of the Hazelwood power plant closure

effects, we obtain the following results. Figure 5 displays the long-run estimates associated with $\beta_{hh}^{Hazelwood\_12}$ – the direct effect. By and large, the estimated long-run coefficients are lower than those of Figure 4: Under the first approach, the average total impact on prices during the day is \$6.16/MW, while the second approach suggests an average direct effect of -\$5.37/MW – that is, a negative direct effect. However, many of the estimated coefficients are not statistically significant. If we consider only the half-hourly slots for which the coefficient estimate is statistically significant (at the 10% level), the average total impact is \$18.90/MW, while the average direct impact is -\$8.86/MW.[12]

Since the direct effect estimate is negative, this suggests that the closure must have had an indirect effect that clearly contributed to an increase in prices. Figure 6 displays the impact of solar production on NEM prices (the long run coefficient estimates of β_{hh}^{solar}, before and after the closure). On average, unit increases in half-hourly (daylight) solar production before the closure induced price increases (on average, \$0.01/MW), while after the closure the effect was in line with the merit-order literature: decreases of \$0.09/MW. In that sense, it appears that the closure is associated with the emergence (on average) of a merit-order effect for solar production that did not exist before. The case of wind is the reverse (Figure 7): The closure appears to have contributed to a reduction of the existing merit-order effect. Before the closure, unit increases in wind production led (on average) to price decreases of \$0.039/MW; after the closure, an equivalent unit increase in wind production only led to a \$0.021/MW price reduction. Since wind has a larger weight in total

[12] If instead we consider only the coefficient estimates that are significant at the 5% level, the average total impact is \$19.57/MW, while the direct impact is -\$24.05/MW.

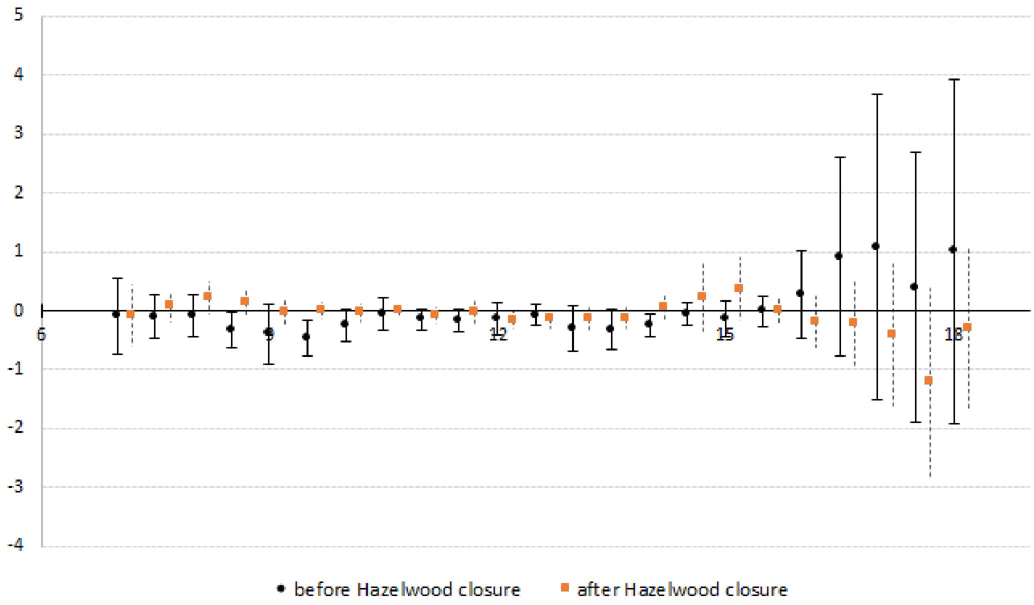

Figure 6: Indirect effect of the Hazelwood power plant closure: solar production

production in the NEM during this period, the latter is the dominant indirect effect, which thus contributes to an overall increase in prices.

6.1 The impact of other variables of interest

In this section, we consider the impact of other variables of interest in our first approach (equation (1)). Figure 8 displays the impact on wholesale prices of an increase in the natural gas price. Unsurprisingly, the coefficient estimates are almost always positive, although not always statistically significant – for instance, in the period between 04h30 and 07h00 or 15h00 and 17h30. The impact is largest between 9h and 10h and around 18h30. Prices in the NEM are often set by gas plants, which are typically required to meet demand at peak hours.[13] Therefore, increases in natural gas prices are expected to be associated with increased wholesale electricity prices.

Also, Figure 9 shows that state excess demand plays an important role in the observed prices in each state, especially late in the afternoon (17h-17h30). For all half-hourly slots, the coefficient estimates are positive and statistically significant, which suggests that an imbalance between a state's total demand and its own electricity production leads to price increases, especially in the late afternoon period.

6.2 An estimate of the market impact of the Hazelwood plant closure

In this subsection we provide an estimate of the market impact of the Hazelwood power plant closure in the 12 subsequent months. We proceed as follows: We consider the 48 half-hourly long-

[13] See https://aemo.com.au/-/media/files/major-publications/qed/2021/q1-report.pdf?la=en.

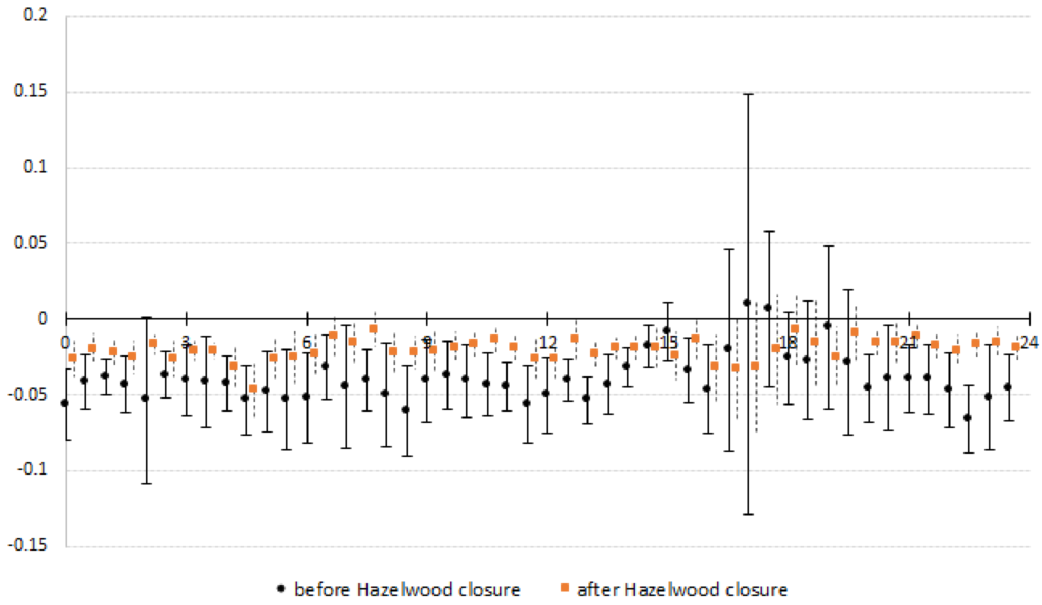

Figure 7: Indirect effect of the Hazelwood power plant closure: wind production

run estimates of the total impact of the closure ($\beta_{hh}^{Hazelwood\_12}$, displayed in Figure 4). Broadly speaking, these estimates correspond to the price differential in the 12 months post-closure that cannot be explained by any of the other variables in our regression and can therefore be associated with the closure. Each of the 48 coefficients provides an estimate of the price differential or total impact in a given half-hourly slot. As we state above, this total impact is (on average across half-hourly slots) \$6.16/MW. However, some of these coefficient estimates are not statistically significant – a point we also note in our discussion above. If we only consider coefficient estimates that are significant at the 10% level, the average (across hourly slots) total impact is \$18.90/MW, as we state above. We therefore use these total impact estimates under two approaches: In approach (i), we use all 48 half-hourly coefficient estimates of the total price impact of the closure; in approach (ii), we only use the 30 half-hourly coefficient estimates that are statistically significant at the 10% level (and consider the total impact in all other half-hourly slots to be equal to zero).

We then consider the electricity that was traded in the NEM in each half-hourly slot for the 12-month period after the closure. By multiplying the total impact estimate by the electricity that was traded in each half-hourly slot, we are able to calculate the total market impact of the closure. Under approach (i), this estimate is \$1830.1 million; under approach (ii), it is \$4,287.7 million. We can then compare these estimates of the market impact of the closure with the capital reinvestment requirements of \$400 million related to plant safety. Under our preferred approach of only considering statistically significant coefficients, there is an (almost) 11-to-1 ratio between the market impacts of the closure and the private cost for Hazelwood to remain in operation longer.

Our analysis, however, only provides a partial picture of the full impact of the closure. As we

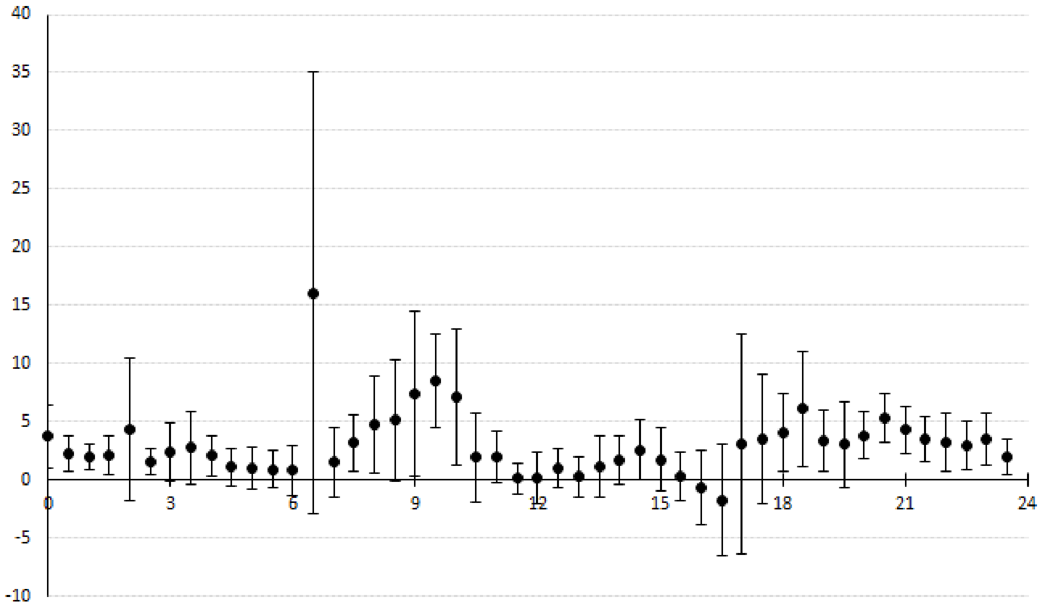

Figure 8: Coefficient estimates of the marginal effect of natural gas prices

discussed earlier, it may also have had repercussions in other markets (e.g., the forward market or the market for ancillary services). At the same time, the exit generated direct and indirect regulatory costs, such as increased use by the market operator of the off-market Reliability and Emergency Reserve Trader (RERT) mechanism. On the other hand, the closure of a brown coal power plant has had a significantly positive environmental effect in terms of lower emissions, as we describe in Section 2.

We note that the purpose of our paper is not to carry out a fully fledged cost-benefit analysis of the Hazelwood plant closure. While such an analysis may be of interest, our purpose is to better understand the impact of the closure of a large coal power plant on market dynamics. Better understanding of the market impact may help regulators and policy makers to more effectively manage the unavoidable exit of coal power plants.

Despite this, we believe it is useful to provide an estimate of the market value of the environmental benefit associated with Hazelwood's closure – namely, due to lower CO2 emissions. Based on Green Energy Markets (2018), we estimate total Hazelwood generation in the year before closure to be 9300 GWh,[14] and Environment Victoria (2017) suggests Hazelwood's CO2 emissions were 1.56 tonnes per MWh. This implies that total Hazelwood emissions in the 12 months before closure may have totalled 14.5 million tonnes of CO2.

Hazelwood's electricity production in the year before closure will have been substituted by other sources in the year after closure. So we use our dataset to calculate the mix of energy sources in

[14] Green Energy Markets (2018) points to the 8509 GWh generated in the 11 months up to February 2017 and 9200 GWh in 2016, its last full year of operation.

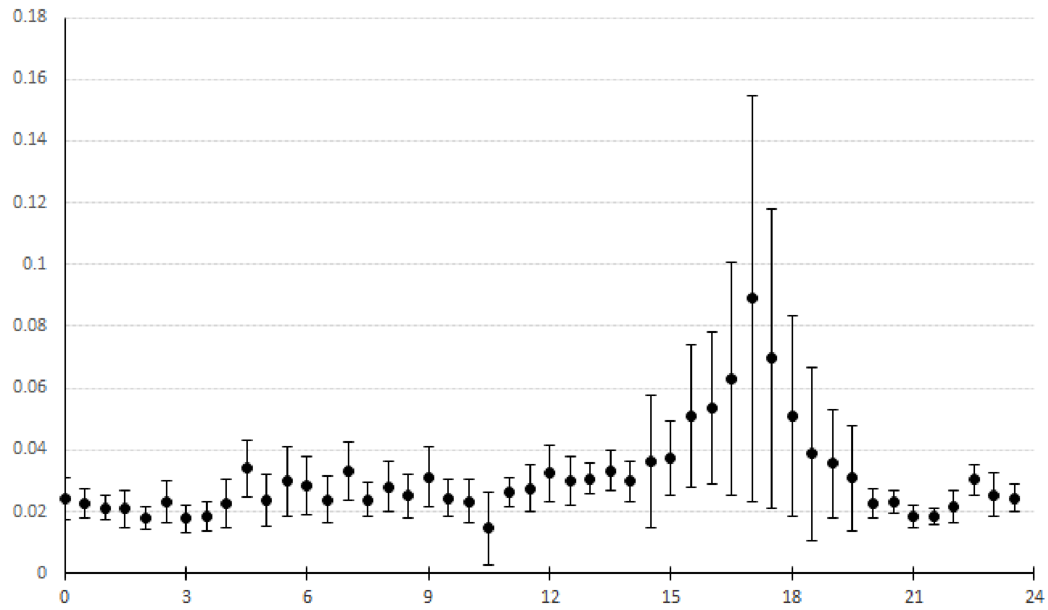

Figure 9: Coefficient estimates of the marginal effects of state excess demand

the post-closure period: black coal (58%), brown coal (19%), natural gas (9%), hydro (7%), and wind (5%) were the main electricity generation sources. Using this mix, we calculate how the 9300 GWh Hazelwood generated in the year before closure (assuming its production in the year after closure would have remained constant) will have been substituted by other energy sources. We then use the emissions-intensity figures of Menezes et al. (2009) to calculate the CO2 emissions of those substitute energy sources:[15] approximately 8.3 million tonnes of CO2. This suggests that Hazelwood's closure will have reduced CO2 emissions by around 6.2 million tonnes.

Using price data for the Australian Carbon Credit Unit (ACCU) in 2018 (with an average price of $13.87/tonne of CO2) yields a market value of reduced emissions of $86.5 million.[16] An alternative would be to use the longer established carbon price in the EU ETS, which was on average around €15.67/tonne of CO2 in 2018.[17] Using the 2018 average exchange rate of €0.63/$ results in a market value of reduced emissions of $155.1 million. The bottom line is that our estimates suggest that the benefits of closure, in the form of reduced investment and emissions, are likely to have been substantially smaller than the costs in terms of its market impact. At minimum, this analysis suggests that the failure of regulators to match the pace of transformation of the electricity sector may incur very high costs.

[15] The intensities used were: 1.3 tonnes/MWh for brown coal, 1 tonne/MWh for black coal, 0.55 tonnes/MWh for natural gas (an average of open-cycle and closed-cycle gas turbines' intensities), and 0.55 tonnes/MWh for other fossil-based fuel sources (e.g., kerosene, diesel, natural gas diesel, natural gas fuel oil) (Menezes et al., 2009).

[16] http://www.cleanenergyregulator.gov.au/ERF/auctions-results/december-2018.

[17] https://icapcarbonaction.com/en/ets-prices.

6.3 Robustness checks

	(1)		(2)	
	Coefficient (std. error)	p-value	Coefficient (std. error)	p-value
state fixed effects	yes		yes	
half-hour fixed effects	yes		yes	
day of w eek fixed effects	yes		yes	
month fixed effects	yes		yes	
half-hourly state solar production	-0.05	0.00	-0.06	0.00
	(0.01)		(0.01)	
half-hourly state w ind production	-0.03	0.00	-0.03	0.00
	(0)		(0)	
half-hourly state demand	0.07	0.00	0.07	0.00
	(0.01)		(0.01)	
half-hourly state demand (t-1)	-0.07	0.00	-0.07	0.00
	(0.01)		(0.01)	
half-hourly state demand (t-2)	0.02	0.00	0.02	0.00
	(0.01)		(0.01)	
half-hourly price (t-1)	0.55	0.00	0.55	0.00
	(0)		(0)	
half-hourly price (t-2)	0.06	0.00	0.06	0.00
	(0)		(0)	
natural gas price			1.32	0.00
			(0.16)	
rainfall NSW			0.11	0.10
			(0.07)	
rainfall TAS			-0.03	0.57
			(0.06)	
half-hourly household PV			0.01	0.00
			(0)	
post-Hazelw ood (3 months)	-7.46	0.00	-12.55	0.00
	(2.17)		(2.23)	
post-Hazelw ood (6 months)	12.97	0.00	11.34	0.00
	(1.86)		(1.88)	
post-Hazelw ood (12 months)	0.90	0.40	1.89	0.08
	(1.08)		(1.09)	
constant	-75.65	0.00	-85.49	0.00
	(5.97)		(6.08)	
Number of observations	175190		175190	
F test	1361.0		1296.4	
R^2	0.38		0.38	

Table 1: Coefficient estimates of a reconciliation exercise using the methodology of Csereklyei et al. (2019)

To check whether our results are affected by our regression approach, we sought to conduct a reconciliation exercise using the methodology of Csereklyei et al. (2019). As we briefly described in Section 3, their approach relies on a fixed-effects regression (including all half-hourly observations across all states) in which half-hourly prices are explained by (1) half-hourly solar dispatch, (2) half-hourly wind dispatch, (3) half-hourly demand, (4) half-hour dummies, (5) days of week dummies (working days, weekends, public holidays), (6) month fixed effects, (7) annual time trend, and (8) state fixed effects. In addition, to account for possible autocorrelation issues, they include two half-hourly lags of state-level prices and demand.

Our approach includes other controls – natural gas price, rainfall, and household PV – which

Csereklyei et al. (2019) do not include in their main regression. Therefore, in our reconciliation exercise with their methodology, we seek to understand whether such differences in control variables are likely to influence the results. In doing so, we kept our day of week dummies (rather than using a dummy for working days/weekends/public holidays, as Csereklyei et al., 2019, do). In addition, we do not use an annual time trend, since our time horizon is much shorter.

Our first approach – model (1) in Table 1 – replicates Csereklyei et al.'s (2019) approach: We do not include our controls. In our second approach – model (2) – we add our controls (natural gas price, rainfall, and household PV) to Csereklyei et al.'s (2019) regression.

Our results show a negative effect on prices in the 3 months following the closure and a 6-month positive effect. This is true across both models, and the coefficient is statistically significant. Therefore, for these two time periods, the results are fully consistent with those we report for each half-hour (Figure 4). The 12-month effect is less clear-cut across models: Using Csereklyei et al.'s (2019) approach, the effect is positive but statistically insignificant. However, when we include our controls – model (2) –, the effect is positive and significant, and this is broadly consistent with the average positive effect we find across all half-hours.[18]

7 Discussion and conclusion

This paper estimates the price impacts of the closure of the Hazelwood power station on Australia's National Electricity Market. We measure the total impact of the closure on prices for each half-hour interval and for each state 3 months, 6 months, and 12 months after closure. We also break down the impact into two effects and measure the indirect impact of the closure on the magnitude of the merit-order effect, as well as its direct impact on prices after 12 months.

The total impact of the closure on prices varies considerably across half-hours. The results vary not only in magnitude and across time, but also in statistical significance. In particular, averaging each of the 48 coefficients results in a total average price impact of \$6.16/MW 12 months after the closure. However, if we only consider the coefficient estimates that are significant at the 10% level, the total average price impact is estimated at \$18.90/MW 12 months after the closure. These different average estimates suggest two very different values for the total market impact (that is, prices multiplied by quantites): \$1830.1 million and \$4,287.7 million, respectively.

When we break down the total impact into direct and indirect effects, we obtain an estimate of average direct impact that is negative. Therefore, in order for the total impact to be positive, it must be that the closure had an indirect effect, which clearly contributed to an increase in prices. The implication is that the magnitude of the merit-order effect – the reduction in the price in a half-hour because of increased renewable generation in that half hour – must have decreased

[18] Note that Csereklyei et al. (2019) do not report long-run estimates. Instead, they report only the short-run coefficients. We followed the same procedure in this reconciliation exercise to allow for comparisons with Csereklyei et al.'s results.

following the closure. We show that this is indeed the case, but only for wind; during this period, solar generation was in its very early stages and its weight in the NEM was very low.

The reduction in the merit-order effect is perhaps our most significant result, beyond demonstrating the high costs of the regulatory failure associated with the lack of a mechanism to manage the exit of coal from the NEM. As predicted by AEMO (2021), coal power plants are likely to exit the NEM three times faster than originally anticipated, and the renewables' share of total generation is increasing at unprecedented rates. It follows that it will be increasingly important to fully understand the mechanism through which the exit of coal power plants impacts the reduction in the merit-order effect. This will require close examination of bidding behavior in the NEM, and regulators are well advised to undertake such scrutiny as part of the process of designing better rules to manage the energy transition.

References

[1] Allaz, B. & Vila, J.L. (1993). Cournot competition, forward markets and efficiency. *Journal of Economic Theory,* 53(1), pp. 1-16.

[2] Australian Energy Market Commission (2021), Draft 2022 Integrated System Plan. Available at https://aemo.com.au/-/media/files/major-publications/isp/2022/draft-2022-integrated-system-plan.pdf?la=en.

[3] Australian Energy Regulator (2018a), State of the Energy Market 2018. Available at https://www.aer.gov.au/publications/state-of-the-energy-market-reports/state-of-the-energy-market-2018.

[4] Australian Energy Regulator (2018b). AER electricity wholesale performance monitoring - Hazelwood advice. Available at https://www.aer.gov.au/wholesale-markets/performance-reporting/aer-electricity-wholesale-performance-monitoring-hazelwood-advice-march-2018.

[5] Australian Energy Regulator (2021). State of the Energy Market: 2021. Available at https://www.aer.gov.au/publications/state-of-the-energy-market-reports/state-of-the-energy-market-2021.

[6] Azofra, D., Jiménez, E., Martínez, E., Blanco, J., & Saenz-Díez, J. C. (2014). Wind power merit-order and feed-in-tariffs effect: a variability analysis of the Spanish electricity market. *Energy Conversion and Management*, 83, pp. 19-27.

[7] Bell, W., Wild, P., Foster, J., & Hewson, M. (2017). Revitalising the wind power induced merit order effect to reduce wholesale and retail electricity prices in Australia. *Energy Economics*, 67, pp- 224-241.

[8] Bushnell, J. & Novan, K. (2021). Setting with the Sun: the impacts of renewable energy on conventional generation. *Journal of the Association of Environmental and Resource Economists*, 8 (4), pp. 759-796.

[9] Campbell, J. Y., Lo., A. W., & MacKinlay, A. C. (1997). Event-Study Analysis. In J. Campbell, A. Lo & A. MacKinlay (Eds.), *The Econometrics of Financial Markets* (ch. 4, pp. 149-180). Princeton University Press.

[10] Clò, S., Cataldi, A., & Zoppoli, P. (2015). The merit-order effect in the Italian power market: the impact of solar and wind generation on national wholesale electricity prices. *Energy Policy*, 77, pp. 79-88.

[11] Cludius, J., Hermann, H., Matthes, F., & Graichen, V. (2014). The merit order effect of wind and photovoltaic electricity generation in Germany 2008-2016: estimation and distributional assumptions. *Energy Economics*, 44, pp. 302-313.

[12] Csereklyei, Z., Qu, S., & Ancev, T. (2019). The effect of wind and solar power generation on wholesale electricity prices in Australia. *Energy Policy*, 131, pp. 358-369.

[13] Cutler, N.J., Boerema, N.D., MacGill, I.F., Outhred, H.R. (2011). High penetration wind generation impacts on spot prices in the Australian national electricity market. *Energy Policy*, 39, 5939–5949.

[14] Davidson, R. & MacKinnon, J. (2004). *Econometric Theory and Methods*. New York: Oxford University Press.

[15] Dickey, D. A. & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, 74, 427-431.

[16] Driscoll, J. C., & Kraay, A. C. (1998). Consistent covariance matrix estimation with spatially dependent panel data. *Review of Economics and Statistics*, 80(4), 549-560.

[17] Elliston, B., Riesz, J., & MacGill, I. (2016). What cost for more renewables? The incremental cost of renewable generation – An Australian National Electricity Market case study. *Renewable Energy*, 95, pp. 127-139.

[18] Energy Security Board (ESB) (2021). Delivering adequate power supplies right now and into the future. Available at https://esb-post2025-market-design.aemc.gov.au/resource-adequacy-mechanisms-and-ageing-thermal-retirement.

[19] Environment Victoria (2017). Media backgrounder: Hazelwood closure, available at https://environmentvictoria.org.au/hazelwood-faqs/.

[20] Forrest, S., & MacGill, I. (2013). Assessing the impact of wind generation on wholesale prices and generator dispatch in the Australian National Electricity Market. *Energy Policy*, 59, pp. 120-132.

[21] Gelabert, L., Labandeira, X., & Linares, P. (2011). An ex-post analysis of the effect of renewables and cogeneration on Spanish electricity prices. *Energy Economics*, 33, pp. S59-S65.

[22] Gilmore, J., Riesz, J., Rose, I., & Vanderwaal, B. (2015). Integration of solar generation into electricity markets: an Australian National Electricity Market case study. *IET Renewable Power Generation*, 9 (1), pp. 46-56.

[23] Gonçalves, R., & Menezes, F. (2022). Market-wide impact of renewables on electricity prices in Australia. *Economic Record*, 98 (320), 1-21.

[24] Green Energy Markets (2018). Hazelwood's closure in review: what happened 12 months on? Report for Environment Victoria, available at https://environmentvictoria.org.au/2018/03/29/hazelwood-closure-cuts-victorias-greenhouse-pollution-10-percent-new-report-shows/.

[25] International Energy Agency (IEA) (2021a). Renewables 2021: Analysis and Forecasts to 2026. Available at https://www.iea.org/reports/renewables-2021.

[26] International Energy Agency (IEA) (2021b, 3 November). Regulatory Energy Transition Accelerator launched at COP26 by IEA, Ofgem, IRENA and the World Bank. https://www.iea.org/news/regulatory-energy-transition-accelerator-launched-at-cop26-by-iea-ofgem-irena-and-the-world-bank.

[27] Joskow, P.L. (2007). Competitive Electricity Markets and Investment in New Generating Capacity. In D. Helm (Ed.), *The New Energy Paradigm*. Oxford University Press.

[28] Joskow, P.L. & Tirole, J. (2007). Reliability and Competitive Electricity Markets. *RAND Journal of Economics*, 38(1), pp. 60-84.

[29] Ketterer, J. (2014). The impact of wind power generation on the electricity price in Germany. *Energy Economics*, 44, pp. 270-280.

[30] Kothari, S. P. & Warner, J. B. (2007). Econometrics of event studies. In B. E. Eckbo (Ed.), *Handbook of Corporate Finance*, vol 1 (ch. 1, pp. 3-36). Elsevier.

[31] McConnell, D., Hearps, P., Eales, D., Sandiford, M., Dunn, R., Wright, M., Bateman, L. (2013). Retrospective modeling of the merit-order effect on wholesale electricity prices from distributed photovoltaic generation in the Australian National Electricity Market. *Energy Policy*, 58, 17–27.

[32] McConnell, D., & Sandiford, M. (2020). Impacts of LNG export and market power on Australian electricity market dynamics, 2016-2019. *Current Sustainable/Renewable Energy reports*, 7, pp. 176-185.

[33] Menezes, F. M. & Monteiro, P. K. (2008). *An Introduction to Auction Theory*. Oxford University Press.

[34] Menezes, F. M., Quiggin, J., & Wagner, L. (2009). Grandfathering and Greenhouse: The Role of Compensation and Adjustment Assistance in the Introduction of a Carbon Emissions Trading Scheme for Australia. *Economic Papers*, 28 (2), 82-92.

[35] Phillips, P. & Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika*, 75 (2), 335-346.

[36] Sarafidis, V., & Wansbeek, T. (2012). Cross-sectional dependence in panel data analysis. *Econometric Reviews*, 31 (5), 483-531.

[37] Sensfuß, F., Ragwitz, M. and Genoese, M. (2008). The merit-order effect: A detailed analysis of the price effect of renewable electricity generation on spot market prices in Germany. *Energy Policy*, 36 (8), pp. 3086-3094.

[38] Simhauser, P. (2018). On intermittent renewable generation & the stability of Australia'sNational Electricity Market. *Energy Economics*, 72, 1–19.

[39] Simshauser, P. (2019a). Missing money, missing policy and resource adequacy in Australia's National Electricity Market. *Utilities Policy*, 60, 100936.

[40] Simshauser, P. (2019b). On the stability of energy-only markets with government-initiated Contracts-for-Differences. *Energies*, 12 (13), 2566.

[41] Simshauser, P. (2019c). Lessons from Australia's National Electricity Market 1998-2018: the strengths and weaknesses of the reform experience. Cambridge Working Papers in Economics 1972, Faculty of Economics, University of Cambridge.

[42] Simshauser, P. (2020). Merchant renewables and the valuation of peaking plant in energy-only markets. *Energy Economics*, 91, 104888.

[43] Wansbeek, T., & Sarafidis, V. (2021). Celebrating 40 years of panel data analysis: Past, present and future. *Journal of Econometrics*, 220 (2), 215-226.

[44] Ward, J., & Power, M. (2015). Cleaning up Victoria's Power Sector: the full social cost of Hazelwood power station. Harvard Kennedy School of Government. Available at https://environmentvictoria.org.au/wp-content/uploads/2016/06/Hazelwood-Report-Social-cost-of-carbon.pdf.

[45] Woo, C. K., Horowitz, I., Moore, J., & Pacheco, A. (2011). The impact of wind generation on the electricity spot-market price level and variance: The Texas experience. *Energy Policy*, 39 (7), pp. 3939-3944.

[46] Woo, C. K. (2012). Blowing in the Wind: Vanishing Payoffs of a Tolling Agreement for Natural-gas-fired Generation of Electricity in Texas. *Energy Journal*, 33 (1), pp. 207-229.

[47] Woo, C. K., Zarnikau, J., Kadish, J., Horowitz, I., Wang, J., & Olson, A. (2013). The Impact of Wind Generation on Wholesale Electricity Prices in the Hydro-Rich Pacific Northwest. *IEEE Transactions On Power Systems*, 28 (4), pp. 4245-4253.

[48] Woo, C. K., Moore, J., Schneiderman, B., Ho, T., Olson, A., Alagappan, L., Chawla, K., Toyama, N. & Zarnikau, J. (2016). Merit-order effects of renewable energy and price divergence in California's day-ahead and real-time electricity markets. *Energy Policy*, 92, pp. 299-312.