# Investment, Emissions, and Reliability in Electricity Markets*

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**Abstract**

This paper explores how to reduce emissions from electricity generation while preventing blackouts. Zero-emissions wind and solar are intermittent, which can lead to blackouts if the entry of renewables causes more reliable power plants to retire. I build a structural dynamic oligopoly model of investment in generators of different energy sources. Using data from Western Australia I show that a combination of carbon taxes and capacity subsidies substantially reduces emissions while keeping reliable generators from retiring, thereby maintaining a low risk of blackouts. I also explore the impact of renewable subsidies and delaying an environmental policy's implementation.

**Keywords:** electricity, renewable energy, dynamic oligopoly, market structure, investment, carbon tax, capacity payments, greenhouse gas emissions, blackouts

**JEL Classification:** L11, L13, L94, Q41, Q52

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# 1 Introduction

The electricity industry emits more greenhouse gases than any other industry and accounts for approximately a quarter of total global emissions (IPCC, 2014). Given the industry's outsized impact, environmental regulation of electricity markets is a key component of climate policy. Renewable energy sources, such as solar and wind, provide a way to produce electricity without emitting greenhouse gases; however, they are intermittent. This intermittency matters because a critical concern when designing regulations in these markets is the risk of extremely costly blackouts, which occur when demand for electricity exceeds the available supply. The inclusion of renewables can exacerbate blackouts if they replace dirty but more reliable sources since their supply is more variable.

This paper studies how we should regulate restructured electricity markets given the intermittency of clean energy sources.[1] Regulation is necessary to fix two major market failures. First, firms fail to internalize the environmental cost of their emissions and therefore rely excessively on dirty energy sources such as coal. Second, consumers do not respond to short-term fluctuations in the wholesale spot price of electricity because, rather than the spot price, they pay a price for electricity that is fixed in the short run. Therefore, if their demand in a given moment exceeds the maximum amount of electricity that can be produced in that moment, some consumers must be rationed randomly via blackouts rather than by willingness to pay. This rationing can lead to underinvestment in capacity if firms do not fully capture the value to consumers of avoiding blackouts (due to, e.g., price caps in the wholesale electricity market). Electricity market regulators have introduced various policies to address these market failures individually, but these issues are interdependent. Since it is the clean energy sources that are less reliable, policies that aim to reduce emissions can increase blackouts, and those that aim to reduce blackouts can increase emissions.

Determining the impact that policies would have on blackouts and emissions requires a framework that endogenizes not only production but also investment. Investment determines the capacity in the market, which influences whether or not blackouts occur, as well as the feasible generation mix, which influences emissions. In this paper, I develop a structural dynamic oligopoly model of investment and production in restructured electricity markets. Modeling investment in this industry is challenging for several reasons. First, investment is dynamic, and the environment is nonstationary due primarily to rapidly declining renewable investment costs. Second, there are many technologies in which firms can invest and that are relevant to the question explored in this paper (e.g., coal, gas, wind, etc.), resulting in a high-dimensional

[1] Restructured electricity markets are those in which independent generators sell electricity. This market structure stands in contrast to vertically integrated markets. Many electricity markets were restructured in the 1990s, and these are the markets that I focus on in this paper. See Borenstein & Bushnell (2015) for a history and evaluation of restructuring.

state space. Finally, electricity markets can be highly concentrated,[2] leading to concerns about market power in these investment decisions. Market power can lead to underinvestment in capacity (Kreps & Sheinkman, 1983; von der Fehr & Harbord, 1997), and it can also bias investment in favor of higher marginal cost technologies in order to raise wholesale prices (Bushnell & Ishii, 2007; Myatt, 2017).

The framework that I develop in this paper captures both the non-stationary dynamic incentives firms face in investing in many possible technologies and also their strategic incentives, while remaining computationally feasible. This computational feasibility allows me to explore a rich set of policies and determine taxes and subsidies that achieve the dual policy goals of emissions reductions and blackout avoidance. These simultaneous reductions are achieved by incentivizing firms to not retire (and potentially invest in) relatively emissions-intensive but reliable technologies while at the same time incentivizing the least emissions intensive technologies that are available to be used to meet demand.

In the first part of this paper I develop the dynamic oligopoly model that links short-run production and long-run investment. Firms supply electricity in repeated wholesale spot markets. In each spot market, the firms use their portfolio of generators, consisting of coal plants, natural gas plants (both peaker and combined cycle), wind farms, and solar farms, to satisfy the demand for electricity. Demand is stochastic and inelastic in the short-run, though it responds to retail electricity prices, which depend on average wholesale prices in the long-run. Firms submit bids for providing electricity from each of their generators, which have different production costs and stochastic capacities, reflecting power plant outages and fluctuations in wind and sunlight. The demand and bids determine the wholesale market price and result in a stream of profits, which is a function of the portfolio of generators in the market.

Over time, the firms periodically decide whether to adjust their generator portfolios by building new generators or retiring existing ones to reduce the cost of maintaining generators. They trade off the cost of this decision with the discounted flow of wholesale spot market profits, which depends on other firms' generator portfolios. Declining renewable investment costs provide an incentive for firms to wait to invest in new generators—even if it would be profitable to do so today—since they could increase their net profits by waiting for the cost to decline further. In order to address the challenges accompanied by a high-dimensional non-stationary dynamic game, I make timing assumptions similar to those of Igami & Uetake (2020) that make the game solvable using backward induction. Specifically, firms are assumed to make their generator portfolio decisions sequentially, the order of which is random and changes each

[2] In U.S. markets, for example, in MISO, PJM, and the Connecticut and Boston zones of the New England ISO, the top three suppliers own at least 30% of total capacity (Caplan, 2020). In Great Britain, the top three own over 40% of total capacity (Mettrick, 2021).

year. Additionally, I impose that at some point in the future, firms will no longer be able to adjust their generator portfolios. I refer to this setup as a non-stationary, randomly-ordered sequential moves dynamic game with lock-in.

In the second part of this paper I estimate the model's parameters using data from Western Australia and simulate counterfactual policies. Western Australia is an ideal case study for studying environmental and reliability policies. It relies on an energy mix of coal, gas, and renewables. While every electricity system has a different feasible set of sources (e.g., some have hydropower resources), these energy sources are available nearly everywhere. Additionally, Western Australia is a tractable setting for modeling how production and investment decisions respond to different policies. It is a relatively small market (compared to, e.g., PJM or CAISO), so it is feasible to capture the generators in the state without the state becoming intractably large. Moreover, the system's isolation precludes trading electricity with other markets. Modeling investment would be difficult with trade since investment decisions would depend on both the state in the market as well as in connected markets.

I study two policy tools in my main set of counterfactuals. The first is a commonly-used tool (including in Western Australia) called capacity payments, which are essentially subsidies to capacity and are not linked to energy output. These aim to reduce blackouts by providing an incentive for firms to maintain extra capacity. The second type is a carbon tax levied on firms in proportion to the amount of carbon emitted. I also explore the interaction of these policy tools with wholesale price caps, which can reduce investment incentives.

In the absence of a carbon tax, capacity payments decrease blackouts but increase emissions. They make it profitable for coal plants to remain in the market, reducing the number that retire, and also increase the number of natural gas plants. In equilibrium this causes investment in renewables to decline. Carbon taxes, meanwhile, exhibit the opposite pattern: they decrease emissions but increase blackouts. A higher tax induces quick retirement of coal plants and more (and earlier) investment in renewable generators. Higher price caps can prevent the increase in blackouts as a carbon tax increases; however, this comes at the cost of a greater exercise of market power in firms' investment decisions, which can result in lower product market welfare for some values of the carbon tax.

When these tools are used together they can reduce both emissions and blackouts. I find that a capacity payment of the size used in Western Australia (about 150 000 Australian dollars (A$) per MW per year, or—dividing by the number of hours in a year—A$17.12 per hour per MW) and a carbon tax equal to the social cost of carbon proposed by the U.S. Environmental Protection Agency (US$190/ton of $CO_2$) reduces blackouts by 47.4% as well as emissions by 41.1%, relative to a world without either policy.[3] Together they can

[3] A capacity payment alone would reduce blackouts by 53.2% and increase emissions by 15.5%, while a

achieve both reliability and environmental goals because blackouts and emissions depend on different margins. The level of blackouts depends on the level of investment of different types of generators. Emissions, however, depend on which of those generators are used to produce electricity. Firms keep existing fossil fuel plants online while investing in renewables because the payments cover the cost of maintaining generators, but the tax makes it unprofitable for emissions-intensive generators to produce unless there is insufficient low-emissions capacity available.

In practice, many electricity markets have adopted alternative environmental policy tools to reduce emissions. I quantify the impact of two commonly-used alternative policies, namely renewable investment and production subsidies. Renewable subsidies do not distinguish between emissions intensities of different types of generators. Since coal is roughly twice as emissions-intensive as natural gas, one may expect that renewable subsidies are less efficient at reducing emissions than a carbon tax. I find that for low levels of emissions reductions, however, both types of renewable subsidies result in a lower cost of reducing emissions than a carbon tax, measured in the distortion to product market welfare and government revenues. This result is because these subsidies counteract the exercise of market power. Renewable subsidies, however, cannot achieve as deep of emissions reductions, especially investment subsidies, which target the investment margin rather than the production margin that determines emissions.

Many environmental policies, such as clean vehicle standards or the EPA's proposed power plant regulations, have a delay between announcement and implementation to allow firms time to respond. My model can handle nonstationary costs and also nonstationary policies. It is therefore well-suited for analyzing the timing of a policy's implementation. I study the impact of delaying the implementation of a carbon tax following its announcement. By delaying implementation, firms have time to respond to the new environment by investing in renewables (as well as less emissions-intensive natural gas). This time to respond can yield cost savings, as firms can avoid using high marginal cost generators when their set of generators is high-emitting while they adjust their generator portfolios. I find that delaying the policy does indeed yield cost savings, but firms simply delay their investments in renewables. Therefore, delaying the policy also substantially increases emissions levels in both the medium- and (to a lesser extent) even the long-run. Ultimately, I find that total welfare cannot be increased by delaying implementation.

**Related Literature** This paper contributes to three main literatures. First, it contributes to an empirical literature on electricity markets. This literature has primarily focused on the short-run functioning of wholesale electricity markets, studying market design (Reguant,

carbon tax alone would decrease emissions by 45.3% and increase blackouts by 89.7%.

2014), the impact of adding renewables to the grid (Gowrisankaran *et al.*, 2016; Jha & Leslie, 2023; Karaduman, 2020b), the addition of utility-scale batteries (Karaduman, 2020a), and power plant closures (Davis & Hausman, 2016; Kim, 2020). While this paper is related to these papers, its focus is on investment. Most papers studying investment use a two-stage entry model in which electricity-generating firms set capacity and then compete (Borenstein, 2005; Borenstein & Holland, 2005; Castro-Rodriguez *et al.*, 2009; Allcott, 2013; Linn & McCormack, 2019; Holland *et al.*, 2022). These two-stage entry models are meant to simulate long-run investment decisions but are unable to capture the transition period following a policy's implementation or the decline in the cost of renewable generators. The cost of renewables is a key determinant to the emissions output of the industry, and retirements and entry in the transition period are a key determinant of the likelihood of blackouts, necessitating the fully dynamic approach that I take. My approach is therefore closely related to Butters *et al.* (2021), Abito *et al.* (2022), and Gowrisankaran *et al.* (2022), which develop dynamic models of investment in a limited set of technologies.

This paper also contributes to and connects the literatures on environmental policies and capacity payments. Several papers and reports (Larsen *et al.*, 2020; Phadke *et al.*, 2020; Stock & Stuart, 2021) have characterized the costs and effectiveness of different environmental policy tools using cost-minimizing capacity expansion models. These models, however, do not capture three features captured in this paper's framework that are important for understanding how environmental regulation impacts reliability: market power, response of demand over the long run, and (since these models determine the least cost way to meet demand) blackouts. Capacity payments, meanwhile, have been the topic of considerable debate about their necessity for avoiding underinvestment (Hogan, 2005; Joskow & Tirole, 2008; Joskow, 2008; Bushnell *et al.*, 2017; Fabra, 2018), their impact on renewable investment (Llobet & Padilla, 2018; Mays *et al.*, 2019), and their interaction with strategic behavior (Teirilä & Ritz, 2019; McRae & Wolak, 2020). This paper speaks to these debates by quantifying the reduction in blackouts that the policy yields, the distortions they cause, and the impact on renewable investment in an imperfectly competitive environment. This paper combines these literatures on environmental and reliability policies by studying the interdependence between the two policies, finding that there are important complementarities.

Finally, this paper contributes to a literature studying environmental regulation in imperfectly competitive environments (Buchanan, 1969). Two closely related papers are Ryan (2012) and Fowlie *et al.* (2016), which empirically study the cement industry and also endogenize investment and emissions. The electricity industry differs from that of cement because there are many technologies in which to invest (e.g., coal, gas, wind, solar) and investment costs are nonstationary. Moreover, because I observe a single market, the two-step conditional choice probability estimator based on Bajari *et al.* (2007) used by the aforementioned papers would be infeasible. I therefore adopt a different modeling and estimation strategy, similar to Igami & Uetake (2020), which also studies a non-stationary environment and observes only a single market (mergers in the hard disk drive industry).

**Outline** The paper is organized as follows. Section 2 provides institutional details on the Western Australia electricity market, describes the data, and presents descriptive statistics about the electricity market. Section 3 presents the structural model, section 4 the estimation method, and section 5 the estimation results. In section 6 I describe and present the counterfactuals. Finally, section 7 concludes.

# 2 Institutional Details and Data

## 2.1 Western Australia Electricity Market

Western Australia's Wholesale Electricity Market (WEM) supplies electricity to southwestern Australia via the South West Interconnected System electricity grid, which includes the city of Perth and the surrounding area. The grid is unconnected with the grid in the eastern part of the country, meaning trade cannot occur between the WEM and other markets. Figure 8 in Appendix A.1 provides a map of this grid. As of 2023, the WEM serves approximately 1.1 million customers, supplying roughly 17 terawatt hours of electricity every year (WEM, 2023).

In September 2006, the Western Australian electricity industry went through a restructuring, moving from a vertically-integrated utility company that generated, distributed, and sold electricity to a "restructured" market with independent generators selling electricity. This resulted in the creation of the WEM, which is operated by the Australian Energy Market Operator. Following the restructuring, independent generators sell electricity to retailers. This can either happen through bilateral contracts or through auctions, both day-ahead and real-time (the latter of which began on July 1, 2012). The auctions determine production in half-hour intervals and result in a market clearing price for every half hour. In addition to these revenues from producing electricity, generators also receive yearly capacity payments, described in detail in the following section.

In the WEM, almost all utility-scale electricity is generated by one of five technologies: coal, open cycle gas turbines (OCGT), combined cycle gas turbines (CCGT), solar, and wind, collectively making up 99.4% of all electricity generated.[4] These technologies will therefore

[4]Western Australia also has substantial rooftop solar, as described in Jha & Leslie (2023), but I focus on utility-scale generation. In the model developed in this paper, the adoption of rooftop solar is captured by changes in the distribution in *net* demand (i.e., electricity demand less that which is supplied by rooftop solar) over time.

be the focus of this paper, abstracting away from less-used technologies in Western Australia (e.g., oil or biomass) as well as technologies not currently used in Western Australia (e.g., nuclear or hydropower).

### 2.2 Capacity Payments: Background & Implementation

Capacity payments are yearly, recurring payments to electricity-generating firms in proportion to their capacities and are not (typically) linked to their actual energy output. These payments are therefore effectively a subsidy to capacity. The size of this subsidy, the *capacity price* (in $/MW), usually varies from year to year. In some markets this price is determined by the market operator, and firms are free to choose the amount of capacity that they commit. In other markets, the grid operator chooses the amount of capacity and runs an auction to determine the price. The WEM falls in the former group.[5]

Since the start of electricity market "restructurings," when electricity generation was separated from transmission and distribution in many markets, electricity grid operators have been concerned that independent generators might underinvest in capacity. This underinvestment results in blackouts, which is a form of rationing during high demand periods.[6] Many electricity markets use capacity payments with the aim to prevent this underinvestment.

The WEM has used capacity payments since its commencement. The market uses a system of allocating capacity credits called the "Reserve Capacity Mechanism." A capacity credit corresponds to a megawatt (MW) of certified electricity generation capacity that a firm commits to make available in the wholesale market. The WEM chooses the price of a capacity credit for a year, and firms choose a level of capacity for which to receive capacity credits. This process occurs three years prior to when firms will receive payments (e.g., the capacity price for 2020 is announced in 2017), allowing time for firms to build or retire capacity. The price is based on a formula that depends in large part on the cost in that year of building an open cycle gas turbine generator. Firms are then contractually obliged in the year of the capacity payments to make available at least as much electricity as they have capacity credits or otherwise pay a penalty.[7]

[5]It is more common to use the latter system; however, the optimal capacity prices that are determined in this paper's counterfactuals are informative for these systems too. These values suggest the level of monetary support capacity auctions should yield if trying to maximize welfare (the exact form is provided in section 6). If, instead, the exercise was to determine the optimal level of capacity (the choice variable of the grid operator in the latter system), it is reasonable that this value would be more specific to a particular context and not as generalizable to other markets.

[6]Rationing is necessary since electricity end-consumers do not pay the wholesale spot market price but rather an average price charged by an electricity retailer. Demand is therefore unresponsive to the spot price, so prices cannot be used to ration short-run demand for electricity. Instead, grid operators typically ration electricity by geography in rolling blackouts.

[7]Making electricity "available" is not the same as actually producing that level of electricity. In practice, firms bid quantities and prices in an auction with a price cap. Firms are required to bid at least as much

## 2.3 Data

The data used in this paper primarily come from the Australia Energy Market Operator (AEMO), which publishes data on the wholesale electricity markets, capacity payments, and generator characteristics. I use data from October 1, 2006 through September 30, 2022. In addition to the data published by the market operator, I use supplementary data on generator characteristics, input prices, and other variables detailed below.

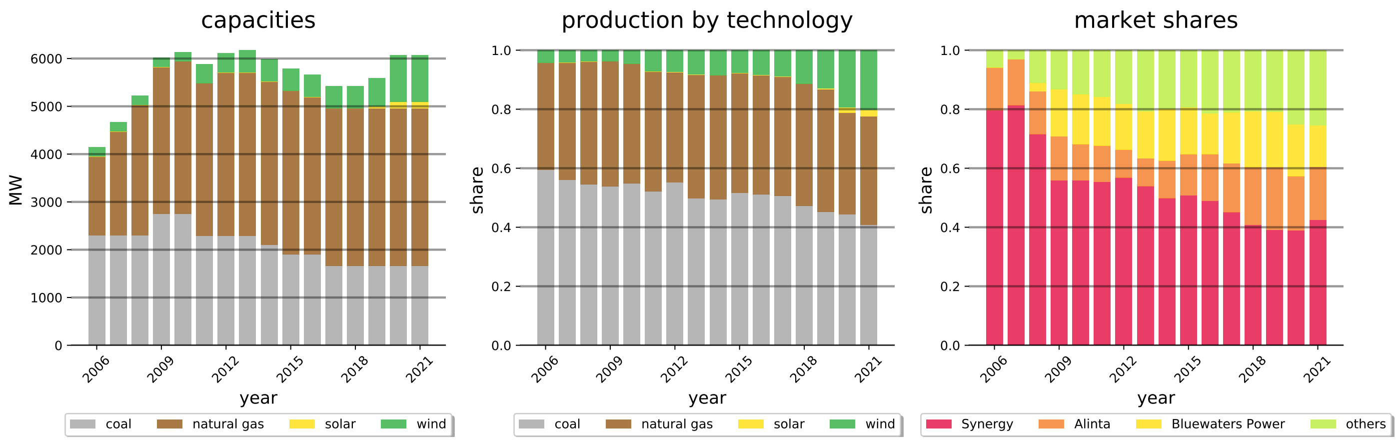
**Half-Hourly Wholesale Market Data** The data provided by AEMO on wholesale markets are at a half-hourly interval and include generator-level production, market clearing prices in the auctions, load curtailed, and generator outages. Since demand is virtually inelastic, I use as the demand for electricity in that interval the sum of the production from each generator plus the load that is curtailed. For each interval, there are two market clearing prices, one from the day-ahead auction (called the "short-term energy market") and the other from the real-time auction (called the "balancing market"). For the analysis in this paper, I use the market clearing prices from the balancing market. Generator outages are a measure of the capacity unavailable to each generator in an interval. Two measures of outages are reported: an *ex ante* level and an *ex post* level. I use the *ex post* measure of generator outages. In addition to the wholesale market data provided by AEMO, I collect the history of prices of coal and natural gas in Western Australia from the Western Australian Department of Mines, Industry Regulation, and Safety's 2022 Major Commodities Resources dataset.

**Yearly Market Data** Capacity payments, price caps, and retail electricity prices all vary at a yearly frequency. Capacity payments are composed of a capacity price and the commitments of each generator, both of which are reported by AEMO. These payments correspond to a year running from October 1 through September 30 of the following calendar year. I adopt the same year naming convention in this paper (e.g., intervals in January 2020 will correspond to the year 2019 for the purposes of estimation and counterfactuals). Price caps limit the maximum bids of firms in the wholesale auctions. Retail electricity prices correspond to the prices paid by residential consumers for electricity. These prices are regulated and change on July 1 of each year and correspond to a fixed and variable component. I hand collect these prices from yearly reports from Western Power (the entity responsible for operating the network).[8] For my analysis, I use the variable component, as this is the component that enters consumers' consumption decisions.

electricity as they have capacity credits, with no limit on the prices other than a universal price cap. Renewables are allowed to receive capacity payments; however, they typically commit only a small fraction of their nameplate capacities, and so in the model I treat only non-intermittent technologies as eligible.

[8] The specific tariff that I collect is Reference Tariff 1, which is for residential consumers.

Figure 1: Capacities & Shares over Time




*Note*: Shares are calculated based on total amount of electricity produced over the year, running from October 1 through September 30 of the following year (consistent with the definition of years used by the WEM for capacity markets). Named firms in the rightmost subplot are those with a market share of at least 10% over the course of the sample. All others are aggregated into "others."

**Generators** AEMO provides the identities of each generator, the technology, and the firm that owns the generator. I take as the date of entry and exit the first and final days of production, respectively. I infer capacities from production in the wholesale market, using the maximum amount of electricity I ever observe a generator produce in the sample. To capture a generator's production costs, I require a measure of the generator's heat rate (the amount of energy needed to produce a MWh of electricity). Heat rates and (closely related) greenhouse gas emissions rates are not provided by AEMO. Instead, I use SKM (2014), an engineering report that included the heat and emissions rates of many of the WEM's generators. For a few generators, the heat rates in the report are withheld for confidentiality reasons. In those cases, I use the heat rate estimates of Jha & Leslie (2023). A list of all generators used in this paper's analysis can be found in Appendix A.2. As explained in that section, some small generators are dropped from the analysis, specifically those with a capacity less than 20 MW for renewables and 100 MW for fossil fuel plants.

Table 1 summarizes the data described above.

**Data Patterns** Figure 1 depicts the evolution of several key variables across time. The first subplot depicts capacities across time by technology. The period following the restructuring of Western Australia's electricity market witnessed new investment in fossil fuels, including both natural gas and coal. Following 2010, however, there was no new investment in coal, and several coal plants were retired. New investment at the end of the sample has come

Table 1: Summary Statistics

| | Mean | Std. Dev. | 5th Pctile. | 95th Pctile. | Num. Obs. |
|---|---|---|---|---|---|
| *Half-hourly variables* | | | | | |
| price (A$/MWh) | 49.51 | 32.11 | 21.54 | 106.99 | 179 712 |
| total production (MWh) | 970.69 | 199.70 | 679.75 | 1 331.95 | 280 512 |
| load curtailed (MWh) | 0.03 | 2.20 | 0.00 | 0.00 | 280 512 |
| fraction generated by | | | | | |
| coal (%) | 50.99 | 8.88 | 35.16 | 64.62 | 280 512 |
| natural gas (%) | 39.48 | 8.07 | 26.36 | 53.02 | 280 512 |
| solar (%) | 0.37 | 1.41 | 0.00 | 1.94 | 280 512 |
| wind (%) | 9.17 | 8.28 | 0.68 | 26.67 | 280 512 |
| fraction capacity available | | | | | |
| coal (%) | 83.28 | 34.67 | 6.62 | 100.00 | 3 217 200 |
| natural gas (%) | 92.34 | 24.03 | 14.40 | 100.00 | 5 927 856 |
| solar (%) | 13.06 | 24.40 | 0.00 | 81.67 | 221 040 |
| wind (%) | 36.45 | 29.98 | 0.00 | 89.85 | 1 351 488 |
| *Yearly variables* | | | | | |
| capacity price (thousand A$/MW) | 125.68 | 32.68 | 71.85 | 183.17 | 18 |
| price cap (A$/MWh) | 277.85 | 49.20 | 214.60 | 350.41 | 16 |
| retail price variable component (A$/MWh) | 81.26 | 12.22 | 59.82 | 97.07 | 15 |
| *Generator variables* | | | | | |
| capacity | | | | | |
| coal (MW) | 161.83 | 79.17 | 58.37 | 251.14 | 17 |
| natural gas (MW) | 148.40 | 97.64 | 42.28 | 345.22 | 23 |
| solar (MW) | 69.98 | 30.18 | 42.82 | 97.14 | 2 |
| wind (MW) | 122.40 | 67.25 | 33.58 | 211.92 | 8 |
| heat rate | | | | | |
| coal (GJ/MWh) | 10.75 | 0.81 | 9.70 | 11.70 | 17 |
| natural gas (GJ/MWh) | 11.70 | 1.65 | 9.00 | 13.50 | 23 |
| $CO_2$ emissions rate | | | | | |
| coal (kg$CO_2$-eq/MWh) | 916.47 | 61.90 | 850.00 | 1 028.00 | 17 |
| natural gas (kg$CO_2$-eq/MWh) | 633.46 | 82.55 | 471.60 | 754.42 | 23 |

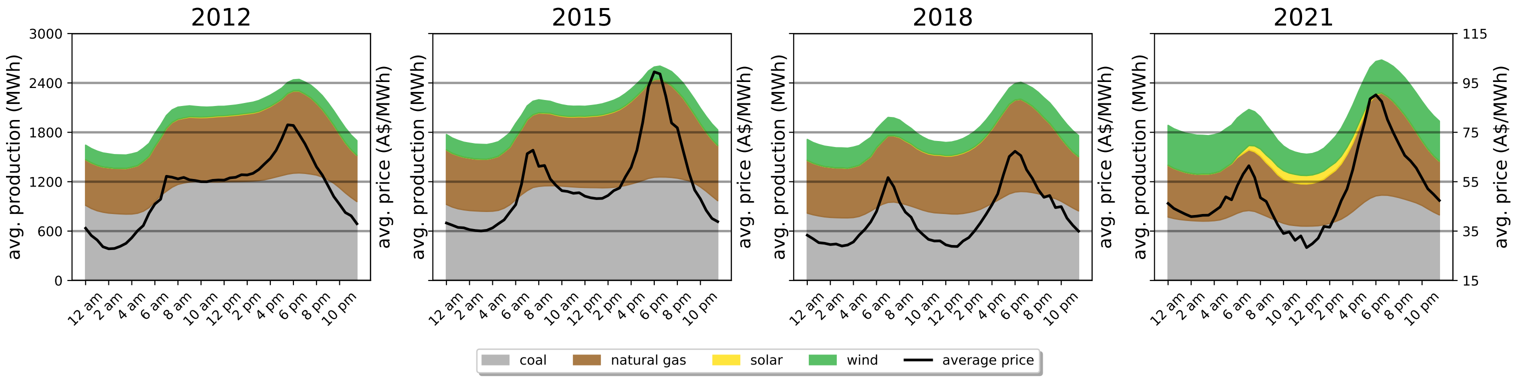
*Note*: All prices in this table and presented in this paper are in 2015 A$. Prices are converted to 2015 A$ using the consumer price index from the Australian Bureau of Statistics. The number of observations for prices is smaller than that for other half-hourly variables because the prices used come from the balancing market, which only began on July 1, 2012.

in the form of renewables, both wind and—to a much smaller extent—solar.[9] The second subplot depicts production shares over time by technology and more clearly demonstrates the transition to renewables. The share of electricity produced using coal has declined almost every year, while renewables have made up an increasing share, making up over 20% in 2021.

The production of electricity in Western Australia is quite concentrated, although it has become less so over the sample, as depicted in the third subplot. Following the restructuring of Western Australia's electricity market, the firm Synergy became the owner of the vast majority of electricity generators in the market and therefore also the main producer of electricity. In

[9]Capacities and production shares in figure 1 depict utility-scale capacities and production. Western Australia has recently experienced substantial adoption of rootop solar, which impacts the net load on the grid but is not captured by any of the variables depicted in figure 1.

Figure 2: Production Shares throughout the Day and over Time




*Note*: Average hourly production across the course of the day is depicted in each subplot, which corresponds to a year running from October 1 to September 30 of the following year (consistent with the definition of years used by the WEM for capacity markets). Prices (right y-axis) are averages across the year for that interval in the day, unweighted by the production in that interval. The first year depicted is 2012, the first complete year following the start of the balancing markets.

the years following the restructuring, Synergy's market share has declined substantially from a very high initial share. While the market share of the next largest firm, Alinta, has grown moderately in the final years of the sample, the majority of the decline in Synergy's share has come from the entry of the third largest firm, Bluewaters Power, and from other smaller firms.

Figure 2 depicts the evolution of the share of electricity produced by different sources and average wholesale electricity prices over the course of the day. The distribution of demand has changed over time, and toward the end of the sample is lowest precisely when solar is available (a phenomenon observed recently in many markets with substantial rooftop solar adoption, called the "duck curve"). Prices are also particularly low during this time. This figure highlights the importance of capturing in the structural model how these variables evolve over time and the correlation among them. For example, the negative correlation between demand and solar availability that arises at the end of the sample leads to low wholesale prices, reducing the incentives for investment in solar.

## 3 Model

In order to predict the impact of electricity market policies, I develop a model of electricity production and investment in electricity generators. The model captures short-run electricity production, how the distribution of demand responds to wholesale market prices, and long-run investment. In the short-run wholesale market, firms use a fixed set of generators to produce electricity to supply the demand for electricity in a given interval. Since end-consumers who determine the demand pay an *average* price for electricity rather than the *wholesale spot* *market* price, this demand is perfectly inelastic with respect to the spot market price. In the long-run, these firms can make costly adjustments to that set of generators. Since the distribution of the demand for electricity *does* respond to the average wholesale price, the level of investment also impacts the distribution of demand.

Before introducing each component of the model in detail, I provide some notation that is common to all components. Generators are indexed by $g$, and each generator belongs to a firm $f$. A firm can be large, in which case it has the ability to own many power plants, or small, in which case it can only own a single power plant.[10] Generators vary in several other dimensions, including the production technology $s(g) \in$ {coal, natural gas open cycle, natural gas combined cycle, wind, solar}, the capacity $K_g$, the heat rate $hr_g$, and the carbon emissions rates $e_g$. Wholesale markets occur in intervals at the half-hourly level, indexed by $h$, and each interval $h$ belongs to a year $t(h)$. In a year $t$, there is a set of generators in the market $\mathcal{G}_t$ and a distribution of demand $\mathcal{Q}_t$. Table 11 at the end of this paper provides a list of all parameters used in this section.

## 3.1 Short-run: Wholesale Market

Firms enter a wholesale market in a half-hour interval $h$ with a fixed set of generators $\mathcal{G}_{t(h)}$. At the beginning of the interval, several time-varying variables are realized: the effective capacities of each generator (after accounting for generator outages and intermittency of renewables), the costs of producing electricity, and the demand for electricity. Firms then choose bids for each of their generators, and the grid operator determines the price that clears the market. If no such price exists (i.e., demand exceeds the available capacity), then some consumers are rationed up to the point that there exists a market-clearing price.

### 3.1.1 Model Primitives

**Available Capacities** The fractions of generators' capacities that are available in interval $h$ is given by $\boldsymbol{\delta}_h$, which is stochastic and potentially correlated across generators. I refer to $\delta_{gh}$ as a generator's capacity factor.[11] Generator $g \in \mathcal{G}_{t(h)}$ therefore has a maximum production capacity in that interval of $\bar{K}_{gh} = \delta_{gh} K_g$, where $\delta_{gh} \in [0, 1]$. The available capacity $\bar{K}_{gh} \leq K_g$ reflects that a generator cannot always produce at its nameplate capacity $K_g$, which is the maximum level of production possible under ideal circumstances. Available production capacities depend on wind speeds and sun availability for renewables, causing them to be able to produce only a fraction of their nameplate capacities. Thermal generators,

[10] Power plants are made up of potentially multiple generators, so a small firm may have multiple generators, but those generators all belong to a single power plant.

[11] Note that sometimes the term *capacity factor* is used to refer to the fraction of nameplate capacity used for production. I use the term in this paper to refer to the fraction of nameplate capacity that is available, but production may be lower than that if a generator does not produce in some intervals.

meanwhile, may also have available capacities less than their nameplate ones due to generator outages.

**Production Costs** Each generator $g$ has a constant marginal cost (in A\$ / MWh) of producing in interval $h$, which is stochastic and given by $c_{gh}$. This cost reflects the purchase of inputs (such as natural gas for a gas generator) and the efficiency of generation (which can vary across generators and also over time based on factors such as the temperature).[12] The marginal cost is given by

$$c_{gh} = hr_g p^{input}_{s(g),h} + \tau_{t(h)} e_g + \varepsilon_{gh}, \tag{1}$$

where $p^{input}_{sh}$ is the price of the input corresponding to technology $s$ in interval $h$, $\tau_t$ is the carbon tax in year $t$, and $\varepsilon_{gh}$ is a generator $g$-specific cost shock. The cost shock captures idiosyncratic factors. These could arise due to prices in firms' natural gas or coal contracts deviating from the spot price captured by $p^{input}_{sh}$, for example, or from unmodeled features that influence production decisions such as forward contracts, transmission constraints, minimum operating capacities, or start up and ramping costs. Some of these features have been modeled explicitly by other papers (e.g., start up and ramping costs in Reguant (2014) or transmission constraints in Gonzales *et al.* (2023)) but would be very difficult to include within a dynamic model of investment that requires simulating wholesale markets an extremely large number of times. The cost shocks provide a way to capture these features, albeit in a reduced form way, which is why they are included even though most papers simply use "engineering costs" (i.e., the components in equation 1 other than the cost shock). Since the distribution of these cost shocks for each generator technology is assumed to be invariant to policies, I am assuming that any unmodeled cost components captured by these shocks are constant as the mix of generators in the market changes.

**Demand** Consumers in interval $h$ demand $\bar{Q}_h$ MWh of electricity, which is stochastic and invariant to the wholesale spot market price in interval $h$ since consumers do not pay real-time prices. This quantity comes from consumers' making consumption decisions, described in more detail in section 3.2, with a price for electricity that does not depend on any particular realization of the stochastic elements described above.

The stochastic variables described in this section may be correlated not only across generators but also across these variables. For example, weather can impact available capacities and also the demand for electricity. I allow for correlation among all these variables, drawn from the

[12] Generators also have fixed costs, reflecting labor and other components that do not vary with the quantity produced. These costs are introduced in the long-run component of the model and do not affect firms' bidding decisions.

following distribution:

$$\boldsymbol{\delta}_h, \mathbf{c}_h, \bar{Q}_h \sim F_{t(h)}^{\boldsymbol{\delta},\mathbf{c},\bar{Q}}.$$

This distribution is allowed to vary by year in order to capture trends in input prices and changes in demand due to residential solar panel adoption, changes in population, electric vehicle adoption, etc.

#### 3.1.2 Market Clearing

Firms submit a bid $b_{gh}$ in each interval for each of their generators. In order to clear the market, the grid operator finds the lowest price such that the sum of the available capacities of the generators with bids below that price exceed demand for electricity. This is simply the price at which supply meets demand, given by the following formula

$$P_h\left(\mathbf{b}, \bar{Q}_h\right) = \min\left\{\min_{P:\ \sum_{g:b_{gh}\leq P}\bar{K}_{gh}\geq\bar{Q}_h}\left\{P\right\}, \bar{P}_{t(h)}\right\}. \tag{2}$$

There are two deviations in equation 2 from the market clearing price $P_h$ being *any* price that compels firms to produce the *full* demand realization. The first is that the price is constrained to be less than a price cap $\bar{P}_{t(h)}$, captured by the outer minimum function. Second, there may not be sufficient available capacity to meet the realization of demand. In that case, there will be rationing—some consumers experience a blackout—and the price defaults to the price cap since there is no price that induces sufficient production (the feasibility constraint in the inner minimum function). Both of these deviations are described in more detail below.

**Price Caps** Virtually all restructured electricity markets utilize price caps, which prevent the wholesale market price from rising above some threshold. These price caps imply that the relevant available capacity is not necessarily the sum of generators' available capacities but rather the sum of available capacities with bids below the price cap. This is imposed in the market clearing condition (equation 2) by the outer minimum, which ensures that the wholesale price $P_h$ is below the price cap in that year.

**Insufficient Capacity** Because demand is invariant to the spot price and the capacity available has a hard cap, if demand exceeds the capacity available, consumers will need to be rationed. This rationing is captured by the function $Q_h\left(\mathbf{b}, \bar{Q}_h\right)$, the demand satisfied, defined as

$$Q_h\left(\mathbf{b}, \bar{Q}_h\right) = \min\left\{\bar{Q}_h, \sum_{g:b_{gh}\leq\bar{P}_{t(h)}}\bar{K}_{gh}\right\}. \tag{3}$$

If there is sufficient available capacity with bids lower than the price cap, the market will be able to satisfy all demand $\bar{Q}_h$; otherwise, it satisfies only a fraction of that demand, and

$$B_h\left(\mathbf{b},\bar{Q}_h\right)=\bar{Q}_h-Q_h\left(\mathbf{b},\bar{Q}_h\right) \tag{4}$$

will be rationed via blackouts, and the affected consumers will not be able to consume any electricity.

**Firm Behavior** The amount of electricity that each firm produces depends on its bid and those of other firms, as well as the realization of demand. Explicitly, the amount produced by generator $g$ in interval $h$, $q_{gh}$, is given by

$$q_{gh}\left(\mathbf{b},P_h,\bar{Q}_h\right)=\begin{cases}\bar{K}_{gh} & \text{if } b_{gh}<P_h\\ \frac{Q_h\left(\mathbf{b},\bar{Q}_h\right)-\sum_{g:b_{gh}<\bar{P}_{t(h)}}\bar{K}_{gh}}{\sum_{g:b_{gh}=\bar{P}_{t(h)}}\bar{K}_{gh}}\bar{K}_{gh} & \text{if } b_{gh}=P_h\\ 0 & \text{if } b_{gh}>P_h.\end{cases} \tag{5}$$

The first case captures inframarginal generators with bids below the wholesale spot price, which provide all of their available capacity. The second case captures marginal generators with bids that set the spot price; they produce a fraction of their available capacity, proportional to the fraction of electricity supplied by the marginal generators. The last case captures generators with bids above the spot price, which do not produce any electricity in interval $h$. The profit that each firm receives is therefore given by

$$\pi_{fh}\left(\mathbf{b}_h,\bar{Q}_h\right)=\sum_{g\in\mathcal{G}_{f,t(h)}}q_{gh}\left(\mathbf{b},P_h\left(\mathbf{b}_h,\bar{Q}_h\right),\bar{Q}_h\right)\left(P_h\left(\mathbf{b}_h,\bar{Q}_h\right)-c_{gh}\right). \tag{6}$$

I assume that firms set their bids equal to each generator's marginal cost of production. This assumption that firms bid competitively is motivated by three facts. First, in restructured electricity markets, firms can bid supply (step-)functions. Theoretically, the resulting supply function equilibrium is bounded between the competitive and Cournot equilibria (Klemperer & Meyer, 1989). The supply function equilibrium is generally computationally intractable (and can have a multiplicity of equilibria), but the competitive equilibrium is likely to be a good approximation for this type of equilibrium. This is because whether the supply function equilibrium more resembles the competitive or the Cournot equilibrium depends on the steepness of the supply function bids. The supply function bids in the data tend to be quite flat, suggesting that the equilibrium is close to the competitive one.[13] The assumption of compet-

[13]Taking for each facility and each generator or firm (depending on whether the firm bids at the generator- or firm-level) the difference between the highest bid under the price cap and the lowest and dividing by the total quantity of electricity bid yields an average slope of A$0.31/MWh.

itive behavior has been commonly used in other papers with models of wholesale electricity markets (e.g., Abito *et al.* (2022) and Gowrisankaran *et al.* (2022)).

Second, forward contracting—the signing of advanced contracts between electricity generating firms and retailers—limits the incentive to exercise market power. Because firms precommit to prices for some of the electricity they produce, this limits the quantity subject to the wholesale price they can potentially influence in their bidding decisions. Their incentive to raise prices in the wholesale market is therefore reduced. A large fraction of electricity is procured via forward contracting (Reguant (2014) estimates about 85% of the quantity that is sold in the day-ahead market is forwarded in Spain, and Wolak (2007) finds about 88% is in the National Electricity Market in Australia in the eastern part of the country), suggesting limited incentives to bid above margainal costs.

The third reason that the competitive bidding assumption should well-approximate equilibrium behavior is because the grid operator can punish firms for above marginal cost bidding. Because marginal costs depend mostly on heat rates and input prices, grid operators have a strong signal about generators' marginal costs. In Western Australia, the grid operator can fine firms that they demonstrate have bids above their marginal costs. For example, in 2019 the Economic Regulation Authority found that Synergy overstated its costs and required it to pay a substantial fine. While this example may suggest that historically firms have attempted to exercise market power, the example also demonstrates that these regulations are utilized and firms are constrained in their ability to pursue above-marginal cost bidding.[14] Grid operators do not, in contrast, generally have the ability to punish firms for exercising market power in their investment decisions, which is why the model of investment presented later in this section allows for strategic behavior at that stage.

Bids are therefore given by[15]

$$b_{gh}^{*} = c_{gh}. \tag{7}$$

[14] There is a literature that looks at strategic behavior in wholesale market bidding. While some of these papers have found a significant impact on prices from the exercise of market power (Wolfram, 1999; Borenstein *et al.*, 2002; Sweeting, 2007; Bushnell *et al.*, 2008), these papers have tended to study settings early after restructuring, during which mechanisms limiting the exercise of market power were not employed (e.g., lack of forward contracting in California).

[15] One may be concerned that if a generator has the highest marginal cost in the market, it will be unable to recover its fixed costs under the assumption of competitive bidding. In that case, a firm would be unwilling to invest in the generator. However, every generator achieves strictly positive profits in expectation—even without capacity payments—for two reasons. First, the cost shocks ensure that in some intervals the generator will be inframarginal with a marginal cost less than the market clearing price. Second, when demand exceeds the available capacity, the market clearing price is the price cap.

### 3.2 Medium-run: Retail Price Equilibrium

The wholesale market clearing conditions defined by equations 2 and 7 yield a distribution of wholesale market spot prices since the prices depend on available capacities, production costs, and demand, which are all stochastic. While the realized demand is inelastic with respect to the spot price, demand does respond over the long run to wholesale prices since they ultimately enter the end-consumer retail prices that consumers pay for electricity. More precisely, these end-consumer prices are based on the *average* wholesale price, which impacts the *distribution* of possible demand realizations. This means that consumers do not respond in their consumption choices to the spot price in a particular interval, but they do respond to changes in the distribution of prices.

**Consumer's Problem** Each consumer $i$ in interval $h$ chooses how much electricity to consume, $q$, based on the end-consumer price they face. Consumer $i$ has an indirect utility in a given interval $h$ of

$$u_{ih}\left(q, P_{t(h)}\right) = \frac{\xi_{ih}}{1-1/\epsilon} q^{1-1/\epsilon} - P_{t(h)} q, \tag{8}$$

where $P_{t(h)}$ is the *end-consumer* retail price per unit of electricity consumed (rather than the wholesale price that varies with the interval $h$). It is constant over the course of a year. The utility function is scaled such that the marginal utility of money is 1. The parameter $\xi_{ih}$ captures consumer $i$'s value of electricity consumption relative to money and varies across intervals. The parameter $\epsilon$ controls the concavity of the utility function with respect to electricity consumption $q$.

The consumers' first order conditions imply that the optimal electricity consumption is

$$q^*_{ih}\left(P_{t(h)}\right) = \left(\frac{\xi_{ih}}{P_{t(h)}}\right)^{\epsilon}.$$

Aggregating across consumers, the aggregate demand for electricity is given by

$$\bar{Q}_h\left(P_{t(h)}\right) = \int \left(\frac{\xi_{ih}}{P_{t(h)}}\right)^{\epsilon} di = \frac{\Xi_h}{P^{\epsilon}_{t(h)}}, \tag{9}$$

where $\Xi_h = \int \xi^{\epsilon}_{ih} di$ is an aggregation of consumers' values of electricity in interval $h$. It varies across intervals, capturing changes in the value of electricity consumption across intervals (e.g., people desire more electricity on hot days, during the day vs. at night, etc.).[16]

[16]Note that it is not necessary to take a stance on the distribution of $\xi_{ih}$ and the degree of correlation across individuals. What matters for the distribution of demand is the distribution of $\Xi_h$, not $\xi_{ih}$. This is also true for determining consumer surplus and the cost of blackouts. In the case of blackouts, the exact distribution of $\xi_{ih}$ does not matter apart from yielding $\Xi_h$ because consumers are rationed randomly and not by how much they value electricity.

**Equilibrium** Consumers buy electricity from intermediaries. I assume that these intermediaries set retail prices equal to the marginal cost of providing electricity over the long-run, averaging over the prices in the wholesale markets. This assumption is motivated by the fact that in Western Australia residential consumers buy electricity at regulated retail electricity prices. Retail prices are therefore given by

$$P_t\left(P_t^{avg}\right) = P_t^{avg} + c_{\text{retail}}, \tag{10}$$

where $P_t^{avg}$ is the quantity-weighted average wholesale price and $c_{\text{retail}}$ is the marginal retail cost of delivering electricity (e.g., providing customer services, using the network to deliver electricity, etc.). The quantity-weighted average wholesale price is given by

$$P_t^{avg} = \frac{\mathbb{E}\left[Q_h P_h\right]}{\mathbb{E}\left[Q_h\right]}. \tag{11}$$

The average wholesale price depends on demand, and demand depends on the average wholesale price. The equilibrium with respect to retail prices is defined as a price $P_t$ such that

$$P_t = \frac{\mathbb{E}\left[Q_h\left(\bar{Q}_h\left(P_t\right), \mathcal{G}_t\right) P_h\left(\bar{Q}_h\left(P_t\right), \mathcal{G}_t\right)\right]}{\mathbb{E}\left[Q_h\left(\bar{Q}_h\left(P_t\right), \mathcal{G}_t\right)\right]} + c_{\text{retail}}, \tag{12}$$

where we have made explicit the dependence of satisfied demand and wholesale prices on $P_t$ as well as the generators in the market $\mathcal{G}_t$.

We can define the function mapping the set of generators to the retail price, $P_t \colon \Gamma \to \mathbb{R}$, where $\Gamma$ is the set of all possible generator combinations. Additionally, we can define a similar mapping of generators to profits that takes into account the equilibrium end-consumer prices (and therefore demand), $\boldsymbol{\pi}_h \colon \Gamma \to \mathbb{R}^F$, as

$$\pi_{fh}\left(\mathcal{G}_t\right) = \pi_{fh}\left(\mathbf{b}_h^*\left(\mathcal{G}_t\right), \bar{Q}_h\left(P_{t(h)}\left(\mathcal{G}_t\right)\right)\right) \qquad \forall f. \tag{13}$$

### 3.3 Long-run: Generator Investment

Each year $t$, firms enter with a set of generators inherited from the previous year $\mathcal{G}_{t-1}$. The firms can choose to make costly adjustments to their sets of generators by adding new ones and/or retiring existing generators. After (dis-)investment decisions are made, the newly updated set of generators, $\mathcal{G}_t$, is used in a series of many wholesale electricity markets (one for each half-hour), providing firms with a stream of profits. This chosen set of generators impacts the profits that firms receive, as well as the levels of emissions and the frequency of blackouts.

Firms are forward-looking as they make investment decisions, and they are strategic in these decisions, taking into account the impact their decisions have on the market. The standard empirical model of oligopolistic industry dynamics is Ericson & Pakes (1995), which is a stochastic dynamic game in which firms make simultaneous moves and face an infinite horizon. I do not adopt an Ericson & Pakes (1995)-type modeling approach to the investment game for a few reasons. First, this model can yield multiple equilibria, coming from nonuniqueness of the stage game or through expectations over future values. Many papers have been able to empirically analyze industry dynamics even in the presence of this multiplicity. This feature is particularly problematic for my setting, however, since data limitations prevent me from taking a non-parametric two-step estimator approach (discussed in more detail in section 4.2), as is common for estimating this style of dynamic games. Second, estimation is difficult with the standard modeling approach to dynamic games when the setting exhibits nonstationarity.[17] Rapidly declining costs of building new renewable generators introduce a source of nonstationarity that is a first-order concern for modeling investment.[18]

The modeling approach that I take to investment decisions is that of a nonstationary, randomly-ordered sequential moves dynamic game with lock-in. Firms make (dis-)investment decisions sequentially in each period, and the order of these moves is random and independent across periods.[19] After some specified length of time, firms decisions are locked in. After that lock-in period, firms cease to be able to adjust their sets of generators. They continue to receive profits from those generators for all eternity, but that game is effectively a static one without dynamic considerations. These modeling assumptions are similar to and inspired by those of the model in Igami & Uetake (2020), which studies endogenous mergers in the hard drive disk industry. In that model, one firm is randomly selected to move in each period, and the continuation value after a particular end date is 0 (because the hard drive disk industry will cease to exist).

These modeling choices capture firms' dynamic and strategic incentives and also have some advantages that make it well-suited for considering investment in electricity generators. First, with sequential moves and a lock-in date that effectively creates a finite horizon, the investment game yields a unique equilibrium. Second, the game easily incorporates nonstationarity (and is, in fact, by definition nonstationary because there is a lock-in date), allowing me to incorporate nonstationary generator costs and also simulate nonstationary counterfactual

[17] For two-step estimation approaches, estimation would require estimating choice probabilities in each period that exhibits nonstationarity, which is not feasible in my setting.

[18] Other sources of nonstationary present in this setting include the distribution of demand (due, in particular, to the rapid rise in rooftop solar, resulting in low net demand during the middle of sunny days).

[19] While one may worry that a model of random, sequential moves may imply significantly different behavior from one of simultaneous moves, Doraszelski & Judd (2019) find that in a quality ladder model they consider, the equilibria of dynamic games with random, sequential moves are "practically indistinguishable" from those of simultaneous moves (albeit in an infinite horizon setting rather than one with lock-in).

policies (e.g., environmental policies that go into effect only after some date). Third, the game can be solved via backward induction, which makes equilibrium computation relatively easy. This computational tractability allows me to consider a rich set of possible policies in order to determine optimal environmental and reliability policy. It also makes estimation via maximum likelihood feasible.[20]

### 3.3.1 Per-Period Model Components

Conditional on a set of generators $\mathcal{G}_t$ in the market, firms receive a stream of profits from the wholesale markets over the course of the year. The function mapping $\mathcal{G}_t$ to yearly expected profits, $\mathbf{\Pi}_t \colon \Gamma \to \mathbb{R}^F$, is based on the wholesale profit function $\boldsymbol{\pi}_h(\cdot)$ defined in equation 13, and is defined as

$$\Pi_{ft}(\mathcal{G}_t) = \mathbb{E}_{\boldsymbol{\delta},\mathbf{c},\Xi}\left[\sum_{h=1}^{H} \pi_{fh}(\mathcal{G}_t)\right] \qquad \forall f. \tag{14}$$

This sums over expected profits from the wholesale market over the year.The expectation is taken over available capacities, production costs, and demand, which all vary with $h$.

In addition to wholesale profits, firms receive capacity payments over a year as a function of their generators' capacities.[21] I model these payments in a simple way based based on the rules guiding the electricity market in Western Australia. The grid operator chooses a capacity credit price $\kappa_t$ for year $t$, which is in A\$ / MW. Firms receive payments based on this price in proportion to the amount of *dispatchable* capacity they own (that is, coal and gas plants).[22] Over the year $t$, a firm $f$ receives a payment $\Upsilon(\cdot)$ based on its set of generators and the capacity credit price. Explicitly,

$$\Upsilon(\mathcal{G}_{ft}; \kappa_t) = \sum_{g \in \mathcal{G}_{ft}} \kappa_t K_g \mathbb{1}\left\{g \in \{\text{coal}, \text{CCGT}, \text{OCGT}\}\right\}. \tag{15}$$

[20] The model in Igami & Uetake (2020) with similar timing and horizon assumptions yields the same properties, and the authors make these modeling choices for similar reasons as me, facing the same data limitations and a nonstationary setting.

[21] That the payments depend on *capacity* rather than *production* follows the capacity payment rules adopted by the WEM. Subsidizing capacity but not mandating production is extremely common in markets that use capacity payments. There are electricity markets that have experimented with policies that more strongly incentivize production, such as that of Colombia, which is studied in detail by McRae & Wolak (2020). How to design capacity payments to incentivize production is an interesting question; however, I do not study it in this paper.

[22] The WEM allows all generators to participate in its capacity market and choose how many capacity credits to receive; however, there are penalties for being unavailable. Coal and gas plants are very rarely unavailable, while renewable sources are. Coal and gas plants therefore tend to commit all of their capacity and rarely have to pay penalties, while renewable generators tend to commit very little of their capacity. I therefore take a simplified approach to modeling capacity payments that corresponds very closely to the result of the WEM's rules by assuming coal and gas plants receive capacity credits for *all* of their generators' capacities (and do not have to pay unavailability penalties), while renewable plants do not receive capacity credits for *any* of their generators' capacities.

Finally, firm $f$ must pay a cost for maintaining its generators, given by

$$M\left(\mathcal{G}_{ft}\right) = \sum_{g \in \mathcal{G}_{ft}} m_{s(g)} K_g. \tag{16}$$

This cost is technology-specific and in proportion to a generator's capacity. It captures costs related to generators that are fixed with respect to the amount of electricity produced over the course of the year. It therefore does not depend on generators' levels of production and makes unused capacity costly.

### 3.3.2 Investment Decisions

At the beginning of each year $t \leq T$, where $T+1$ is the year the set of generators is locked in, Nature randomly selects an ordering of firms $\Omega_t$. Firms then sequentially, according to the ordering $\Omega_t$, adjust their sets of generators and receive profits and payments from the new set, which then carries over into the next period. Large firms (those that can have multiple power plants) move first, though in a random order, followed by small firms (those that can only have at most one), again in a random order.[23] All orderings with this structure have an equal probability of occurring. When a firm is selected to move, it knows which firms moved before it and what adjustments they made; however, it does not know the order of the firms that move after it, only which firms still have yet to move.[24]

We will introduce firms' investment decisions using the value function at a particular point in this ordering. Denote by $X$ the set of firms that have already adjusted *and* the firm now able to adjust, $f$. The firm $f$ is therefore the $|X|$th firm to adjust. Firm $f$'s expected value function when $X \setminus \{f\}$ have already adjusted and it is able to adjust is denoted by $V_{ft}^{X}\left(\mathcal{G}_f; \mathcal{G}_{-f}\right)$, where $\mathcal{G}_{-f}$ reflects the adjustments already made. Firms $\mathcal{F} \setminus X$ still have yet to adjust. This function

[23]Explicitly, $\Omega_t \in \mathfrak{S}_{\mathcal{F}_L} \times \mathfrak{S}_{\mathcal{F}_S}$, where $\mathfrak{S}_A$ is the symmetric group on $A$ (i.e., all permutations of the elements in $A$).

[24]This modeling choice is made for two reasons. First, it captures that in reality while investment decisions are often made in sequence (not simultaneously), firms are unlikely to know which other firms will make decisions immediately following them (i.e., they do not know the specific ordering). Second, this modeling choice is computationally more tractable, as we only need to compute choice probabilities for each state conditional on the set of firms $X$ still needing to move rather than choice probabilities for every permutation of $X$. At the estimated parameters, the model generates extremely similar choice probabilities under the alternative assumption that firms know the ordering of the firms that move after them within a year.

is given formally below, and a description of the function is given afterward.

$$
\begin{aligned}
V_{ft}^{X}\left(\mathcal{G}_f;\mathcal{G}_{-f}\right)= \quad \max_{\mathcal{G}_f'\in\Gamma_f(\mathcal{G})}\Big\{\mathbb{E}_{\boldsymbol{\eta}_{\mathcal{F}\setminus X},\Omega_t\mid X}\Big[&\Pi_{ft}\left(\mathcal{G}_f';\mathcal{G}_{X\setminus\{f\}},\sigma_{\mathcal{F}\setminus X,t}^{\Omega_t}\left(\mathcal{G}_f',\mathcal{G}_{-f},\boldsymbol{\eta}_{\mathcal{F}\setminus X}\right)\right)\\
&+\Upsilon\left(\mathcal{G}_f';\kappa_t\right)\\
&-M\left(\mathcal{G}_f'\right)\\
&-\textstyle\sum_{g\in\mathcal{G}_f'}C_{s(g),t}K_g\mathbb{1}\left\{g\notin\mathcal{G}_f\right\}\\
&+\eta_{f,\mathcal{G}_f',t}\\
&+\beta W_{f,t+1}\left(\mathcal{G}_f';\mathcal{G}_{X\setminus\{f\}},\sigma_{\mathcal{F}\setminus X,t}^{\Omega_t}\left(\mathcal{G}_f',\mathcal{G}_{-f},\boldsymbol{\eta}_{\mathcal{F}\setminus X}\right)\right)\Big]\Big\}.
\end{aligned} \tag{17}
$$

When firm $f$ is selected to adjust, it knows the firms in $X$ other than it have already adjusted, and it chooses any new set of generators within its feasible set $\Gamma_f(\mathcal{G})$ (described in detail later) to maximize its expected value. The firm takes an expectation over both the order of the firms that have yet to adjust ($\Omega_t \mid X$) as well as private information shocks to their adjustment costs ($\boldsymbol{\eta}_{\mathcal{F}\setminus X}$). The firm receives expected profits from the wholesale markets ($\Pi_{ft}(\cdot)$), in which it is subject to its new, adjusted set of generators. Firms $\mathcal{F}\setminus X$ still will adjust before the wholesale markets begin, so firm $f$ takes an expectation over what set of generators they will choose, given by the policy function for the firms $\sigma_{\mathcal{F}\setminus X,t}^{\Omega_t}\left(\mathcal{G}_f',\mathcal{G}_{-f},\boldsymbol{\eta}_{\mathcal{F}\setminus X}\right)$. The second term is the net capacity payment that the firm receives with its adjusted set of generators. The third term is the cost of maintaining its adjusted set of generators. The fourth and fifth terms represent the adjustment cost. The fourth term captures the cost of building new generators, where $C_{st}$ is the cost (per MW) of construction of technology $s$ in year $t$, and it scales with the size of an increase in capacity. The fifth term is a private information, idiosyncratic cost shock. It represents land acquisition costs, permitting, interconnection, and anything else that is difficult for firms to predict. The final term is the continuation value, carrying the set of generators over to the next period.

The value $W_{ft}(\cdot)$ in the continuation value is the value function *prior to the realization of the ordering*. It is given for a firm $f$ by

$$
W_{ft}\left(\mathcal{G}_f;\mathcal{G}_{-f}\right)=\mathbb{E}_{\boldsymbol{\eta},\Omega_t}\left[V_{ft}^{X_f(\Omega_t)}\left(\mathcal{G}_f;\sigma_{X_f(\Omega_t)\setminus\{f\},t}^{\Omega_t}\left(\mathcal{G},\boldsymbol{\eta}_{X_f(\Omega_t)\setminus\{f\}}\right),\mathcal{G}_{\mathcal{F}\setminus X_f(\Omega_t)}\right)\right], \tag{18}
$$

where $X_f(\Omega_t)$ is the set of firms that have adjusted prior to $f$ (and including $f$) under ordering $\Omega_t$, i.e.

$$
X_f(\Omega_t)=\left\{\, f'\in\Omega_t : f'\in\left\{\,\omega_{1t},\omega_{2t},\ldots,f\,\right\}\right\},
$$

where $\omega_{nt}$ is the $n$th element of $\Omega_t$. This expected value function is the expectation of the value function in equation 17 with respect to the ordering and cost shocks.

Note that the adjustment to the set of generators is immediate; when a firm adjusts its generators at the beginning of the year, it is able to use that adjusted capacity for all of the wholesale markets in that year. This timing assumption is motivated by when capacity prices are announced in Western Australia and how long it takes to build power plants. Capacity prices are announced three years prior to when they take effect.[25] The choice of three years notice is partially to give firms time to build new generators in response to the capacity price. While different technologies take different amounts of time to build, three years is approximately sufficient for a firm to make adjustments. By allowing generators to come online in the same year that a capacity price goes into effect, I am capturing the effect of pre-announced capacity prices and time-to-build.[26]

Regarding firms' beliefs, I assume that firms have perfect foresight over the path of future generator costs, the path of the distribution $F_t$ (which includes input prices, capacity factors, and demand shocks), and capacity prices. Since there is no uncertainty in these variables, they are simply included in the time dimension of the state.

**Final Period of Adjustment** Firms adjust their sets of generators for the final time in year $T$. In all periods $t > T$, firms continue to compete in wholesale electricity markets with the set of generators $\mathcal{G}_T$ chosen in year $T$. This is simply a static game repeated over time. Therefore, the value in year $T+1$ is given by

$$W_{f,T+1}\left(\mathcal{G}_f; \mathcal{G}_{-f}\right) = \sum_{t=T+1}^{\infty} \beta^{t-T-1} \Big( \Pi_{ft}\left(\mathcal{G}_f; \mathcal{G}_{-f}\right) + \Upsilon\left(\mathcal{G}_f; \kappa_t\right) - M\left(\mathcal{G}_f\right) \Big). \tag{19}$$

Given the final period defined above, we can solve for the (unique) equilibrium of this game using backward induction.

**Choice Set** The choice set for a firm $f$ depends on its current set of generators, given by $\Gamma_f\left(\mathcal{G}\right)$ in equation 17. For each of its technologies, a firm is assumed to be able to make an adjustment of either building or retiring (depending on the technology) *one* power plant.[27] Technologies are either expandable or retirable. Existing coal and open cycle natural gas can be retired ("retirable"), while combined cycle natural gas, new open cycle natural gas, wind,

[25] Other electricity markets that use capacity payments have similar lags in the determination of capacity prices and when they take effect.

[26] A slightly more realistic model may have a state space that keeps track of this year's capacity price as well as the next three, as well as this year's generators and those that will come online in the next few years. I do not adopt this modeling choice because it would be computationally intractable to use such a large state space, and differences in time-to-build across different technologies are unlikely to have a meaningful impact on the results since the time-to-build of the technologies used in Western Australia are not dramatically different.

[27] An alternative way of modeling investment would be as a continuous capacity decision rather than discrete power plants. I opt to model power plants discretely in order to account for the fact that there is heterogeneity in generators (e.g., older generators tend to be less efficient). This is important for capturing the impact that a carbon tax would have since it would not impact all generators of a given technology the same way if there are a substantial number of legacy power plants, as there is in Western Australia and most markets.

and solar can be built ("expandable").[28] For example, if a firm uses both coal (retirable) and combined cycle natural gas (expandable), it can either (1) do nothing, (2) retire a coal plant and keep natural gas the same, (3) keep coal the same and build a gas plant, or (4) retire a coal plant and build the gas plant. The firm cannot, however, retire two coal plants or build two gas plants in a given year, since it can only adjust one plant for each technology in a given year.[29]

In addition to whether to adjust a technology, the firm decides *which* of the plants to adjust. I assume that all of firm $f$'s plants of a given technology have the same adjustment cost shock conditional on an adjustment decision (i.e., $\eta_{f,\text{retire coal plant 1},t} = \eta_{f,\text{retire coal plant 2},t}$). The idea behind this assumption is that the idiosyncratic component of the cost (e.g., labor cost shock of decommisioning the coal plant, land acquisition cost shock for a wind farm, etc.) is the same cost regardless of which plant of the same technology it is applied to. This simplifies the choice set considerably. Combined with the assumption that a firm can only make an adjustment to one plant for each technology in a given year, conditional on adjusting the technology, the firm will either build the most profitable one (in the case of an expandable technology) or retire the least profitable one (in the case of a retirable technolgy). We therefore only need to select which is the most (least) profitable. A plant's profitability compared to others within a technology primarily depends on its heat rate. I use heat rates as well as observed decisions as a heuristic to identify the plant. See appendix B for more details, as well as an explicit definition of the choice set for each firm.

For small firms with at most one plant, the choice set depends on which other small firms of the same technology have already entered (or exited, in the case of a retirable technology). I assume that only one small firm of a given technology may enter (exit) in a given year. I additionally assume that each of the small firms within the same technology have the same idiosyncratic adjustment cost shock. These assumptions mean, just as described in the within-firm case above, that for each technology only the most profitable small firm (if the technology is expandable) or the least profitable small firm (if retirable) will adjust. There are, therefore, only as many small firms making decisions in a given year as there are technologies.

[28] I make the distinction that *old* open cycle natural gas plants are retirable, while *new* ones are expandable because I observe both retirements and construction of this technology. See appendix B for more details.

[29] The main purpose of this assumption is for computational tractability. This limits the number of choices that the firm can to make. This restriction in choices is unlikely to have a significant impact on the model's predictions, however. Being able to make adjustments to one plant for each technology may lengthen the amount of time it takes for a firm to reach its optimal set of generators, but adjustments to generation technologies occur over fairly long time horizons in practice. Moreover, it is never the case in the data that a firm makes an adjustment to more than one plant of a given technology in a single year.

## 4 Estimation and Identification

In the following section I lay out a strategy for estimating the parameters of the model described in section 3. I estimate the model parameters in two stages. In a first stage I estimate the parameters governing the wholesale market. I then use these first-stage estimates to construct the expected yearly profit function (equation 14), which I use in a second stage to estimate the parameters governing firms' investment decisions, including the sunk costs of investment and fixed maintenance costs. I specify as the large firms those that in the data that own more than one power plant. This results in two firms; however, I additionally include another firm, GRIFFINP, which only has one power plant but the plant is very large, yielding a market share for this firm of greater than 10% in the sample. All other firms have market shares less than 10%, own only one other power plant, and are classified as small firms that can only operate at most their one power plant.[30]

### 4.1 Wholesale Market Estimation

In the first stage I estimate the joint distribution of wholesale market variables: generators' production costs, capacity factors, and demand shocks, $F_t^{\boldsymbol{\delta},\mathbf{c},\Xi}$. Some of these variables are observed directly in the data (capacity factors $\boldsymbol{\delta}$), some can be backed out from observed data (electricity consumption valuations $\Xi$), and some need to be estimated to recover the full distribution (production costs $\mathbf{c}$).

**Capacity Factors** Capacity factors $\boldsymbol{\delta}$ are observed in the data. For coal and natural gas plants, plant outages are reported to the grid operator. For intermittent renewables, outages are not sufficient for capturing the capacity factor since they depend on sun/wind availability. I take the fraction of nameplate generator capacity that is produced in a given interval as the capacity factor for solar and wind generators. By doing so, I am implicitly assuming that all available wind and solar capacity clears the auction.[31]

**Demand** We can recover electricity consumption valuations $\Xi_h$ given the demand for electricity and the elasticity of demand with respect to end-consumer prices. The demand for electricity ($\bar{Q}_h$) is simply the sum of demand satisfied ($Q_h$) and the load that is curtailed, which is estimated and reported by the grid operator. The elasticity of demand for electricity is a value of general interest, and there exists a large literature that has sought to estimate this value (Jessoe & Rapson, 2014; Harding & Sexton, 2017; Deryugina *et al.*, 2020; Fabra

[30] I also allow for additional small firms not observed in the data, see appendix B.

[31] Prior to 2011, there are no solar generators, meaning there are no realizations of solar capacity factors from which to sample in those years. In 2011 GREENOUGH_RIVER_PV1 entered with a small capacity (it would eventually expand, see notes in table 9), so for years prior to 2011, I use solar capacity factor realizations in 2011.

*et al.*, 2021). While the estimates from this literature provide a range of plausible values of this elasticity, given the wide range of elasticities estimated in different markets, I choose to estimate the elasticity for the Western Australian market.

Equation 9 provides a possible method of estimating the elasticity $\epsilon$. Taking logs of both sides yields

$$\log\Big(\underbrace{\bar{Q}_h}_{=Q_h+Q^{\text{load curtailed}}}\Big) = -\epsilon\log\left(P_{t(h)}\right) + \log\left(\Xi_h\right),$$

which would be easily estimable using OLS if $\Xi_h$ and $P_t$ were independent. End-consumer prices reflect demand, however, meaning that estimating $\epsilon$ in this way would lead to a biased result. Rather than estimating $\epsilon$ off the full sample of intervals, therefore, I utilize that retail prices change at particular intervals. Specifically, prices change on July 1 of each year. I use the period surrounding this change (one month before and one month after). To take into account that there are long-term trends in $\Xi_h$ (e.g., population growth, rooftop solar adoption), I use year fixed effects. Furthermore, to control for the fact that demand may be different in June than in July (e.g., due to temperature differences), I use month fixed effects. The identifying assumption is that, after controlling for average (log) demand in June and July of that year and average (log) demand for the months of June and July, (log) retail prices are independent of demand shocks. This assumption is reasonable since retail prices only depend on demand realizations over the long run, not hourly or daily fluctuations. Under this assumption, we can attribute changes in demand (after controlling for year and month average demand) to changes in the retail price consumers face. For retail prices, I use the variable component of residential electricity tariffs. Table 2 provides the estimation results as well as more details.

Using this estimate for the elasticity, $\hat{\epsilon}$, we can recover $\Xi_h$ in each interval using:

$$\hat{\Xi}_h = \bar{Q}_h P_t^{\hat{\epsilon}}.$$

While $P_t$ is observed in the data, in order to determine $P_t$ when there are different sets of generators in the market, I also need a value of $c_{\text{retail}}$. I calibrate $c_{\text{retail}}$ by choosing the value that makes the sequence $\left\{P_{t(h)}\right\}_h$ predicted by equation 10 on average equal to the residential tariffs observed in the data.

**Generator Production Costs** While some components of the cost function (equation 1) are observed, such as generator heat rates and the input prices, the cost shocks are not. While wholesale market bidding data may present a possible method of recovering these cost shocks, this is complicated by the fact that in Western Australia some firms bid not at the *generator* level but rather the *firm* level, making it difficult to associate shocks to particular generators or technologies.

Rather than using the bidding data, I use production and price data to form moments about the wholesale market and use simulated method of moments to estimate the distribution of cost shocks. I assume that this distribution follows a skew multivariate normal distribution, which generalizes the multivariate normal distribution to allow for skewness. Allowing for skewness is useful because cost shocks, which capture transportation costs, transmission constraints, ramping, and forward contracts, may not be symmetric.[32] Moreover, using a multivariate distribution that allows for correlation in the cost shocks is important because many of these circumstances the cost shocks are meant to capture are likely to be similar across generators within an interval. Specifically, I assume $\boldsymbol{\varepsilon}_h \sim \mathcal{SN}(\boldsymbol{\xi}, \boldsymbol{\Sigma}, \boldsymbol{\alpha})$, where $\boldsymbol{\xi}$ captures the location, $\boldsymbol{\Sigma}$ the covariance, and $\boldsymbol{\alpha}$ the shape. These parameters vary only at the technology-level (e.g., $\xi_g = \xi_{s(g)}$), and the covariance $\boldsymbol{\Sigma}$ is given by

$$\boldsymbol{\Sigma} = \begin{bmatrix} \sigma_1^2 & \rho_{1,2}\sigma_1\sigma_2 & \cdots & \rho_{1,G}\sigma_1\sigma_G \\ \rho_{2,1}\sigma_2\sigma_1 & \sigma_2^2 & & \\ \vdots & & \ddots & \\ \rho_{G,1}\sigma_G\sigma_1 & & & \sigma_G^2 \end{bmatrix}.$$

The value $\rho_{g,g'}$ captures the correlation between the cost shocks of generators $g$ and $g'$ and also varies only at the technology level (i.e., $\rho_{g,g'} = \rho_{s(g),s(g')}$). While the parameters of the cost shock distribution only vary at the technology-level, note that there is still heterogeneity in average costs across generators within the same technologies due to differences in heat rates, which is the primary reason we would expect cost differences to arise.

The moments that I use to estimate the cost shock distribution correspond to the distribution of market clearing wholesale prices, the fraction of production from each technology, the covariance among these technology production fractions, and the covariance between these fractions and the prices. Intuitively, the fraction of production coming from each technology helps to identify relative differences in average production costs: high average cost technologies should have smaller average production shares, all else equal. The variance in the fraction produced by each technology helps to identify the variance in the cost shocks: technologies with a high variance in cost shocks, all else equal, will have a higher variance in production shares. Covariances help to identify the degree of correlation in the cost shocks. Finally, the price distribution helps to identify the level of cost shocks as well as their skewness.

[32] For example, if a firm does not produce in an interval, despite a high wholesale price due to a transmission constraint, this may need to be rationalized by the possibility of a large cost shock. Since generators have more flexibility *not* to produce, the cost shock distribution may not need to allow for similarly low cost shocks, as a symmetric distribution would impose.

I obtain moments as a function of the distribution parameters by taking draws of the cost shocks (as well as draws from the joint empirical distribution of demand $\bar{Q}_h$, capacity factors $\boldsymbol{\delta}$, and input prices $\mathbf{p}^{input}$) and simulating the resulting wholesale market equilibria, characterized by equations 2 and 5. The costs for intermittent renewables are assumed to be zero (i.e., $c_{gh} = 0$ for solar and wind). Table 3 provides estimates as well as a comparison for selected moments used in the estimation procedure between those in the data and those simulated under the parameter estimates.

### 4.2 Investment Decision Estimation

With the cost and demand distributions estimated as described in section 4.1, the remaining parameters of the model are those that enter the long-run stage of the model. These include maintenance costs $\{m_s\}_s$, the variable cost of investment $\{C_{st}\}_{s,t}$, the distribution of the idiosyncratic shocks $\boldsymbol{\eta}$, and the discount factor $\beta$. As is common in the discrete choice literature, I assume that the idiosyncratic shocks are i.i.d. Type I Extreme Value, yielding closed form choice probabilities. Estimating the distribution of the idiosyncratic shocks thus reduces to estimating the variance of these shocks. I additionally set $\beta = 0.95$, which is common in the dynamic discrete choice literature given the difficulty in estimating discount factors (Magnac & Thesmar, 2002).

I use a full-information maximum likelihood approach to estimate these parameters in the style of Rust (1987). This is the same approach taken by Igami & Uetake (2020), which uses similar timing and horizon assumptions in modeling the dynamic game. The full-information approach, in which I compute the equilibrium of the model for every guess of the parameters, is feasible because the equilibrium is unique and relatively straightforward to compute using backward induction. Moreover, this method allows me to incorporate nonstationary investment costs and provides precise estimates because it uses the full structure of the model. The latter point is important because I have limited data corresponding to investment (17 years, 7 decisions per year, and a single market, for a total sample size of 119), making the precision of the estimates a primary concern. The approaches common in the dynamic games estimation literature (e.g., Bajari *et al.* (2007); Pakes *et al.* (2007); Aguirregabiria & Mira (2007); Pesendorfer & Schmidt-Dengler (2008)), which are two-step procedures, would therefore be infeasible in this setting, as they would require precise first stage estimates of choice probabilities in *every* year (due to the nonstationarity of the setting).

Since investment costs are nonstationary (due primarily to rapidly declining renewable costs) and I observe only one market, it is infeasible to estimate these time-varying costs. Instead, I use engineering estimates to construct the path of new generator costs in each year for each energy source.[33] While there exists a general concern that accounting or engineering costs may neglect some components of costs important to firm decisions, that is unlikely to be a major concern in this case. The cost of generator construction is likely to constitute the vast majority of the cost of an adjustment.

I estimate the maintenance costs and the variance of the idiosyncratic shocks using firms' investment and retirement decisions. Maintenance costs are identified by the level of capacity that firms maintain conditional on profits and investment costs. For example, if a firm retires a particular energy source (such as the coal retirements observed in the data), that implies it is costly to maintain that source relative to the profits it receives for it.[34] The variance of the idiosyncratic shocks is identified (in part) by the covariance between investment decisions and profitability. If investment and profitability are highly correlated, that suggests idiosyncratic shocks play a minor role in investment decisions, and the variance is small. Conversely, if they are weakly correlated, that suggests the shocks are large relative to the profitability of an investment.

The likelihood function for a firm $f$ in year $t$ implied by the model conditional on an ordering of firms in that year $\Omega_t$ is given by

$$\mathcal{L}_{f,t}^{\Omega_t}\left(\boldsymbol{\theta}\right) = \prod_{\mathcal{G}' \in \Gamma_f} \Pr\left(\mathcal{G}' = \mathcal{G}_{f,t} \mid \mathcal{G}_{f,t-1}, \mathcal{G}_{X_f(\Omega_t)\setminus\{f\},t}, \mathcal{G}_{\mathcal{F}\setminus X_f(\Omega_t),t-1}, t, \Omega_t\right)^{\mathbb{1}\left\{\mathcal{G}'=\mathcal{G}_{f,t}\right\}}. \tag{20}$$

Since the data do not fully reveal the ordering $\Omega_t$ in which a decision is made (because in the case on non-adjustment, it is unclear when a firm moved), the maximum likelihood estimator therefore integrates over the ordering and is given by

$$\hat{\boldsymbol{\theta}}\left(\mathcal{G}\right) = \arg\max_{\theta\in\Theta}\left\{\sum_{t=1}^{T_{obs}}\sum_{f\in\mathcal{F}}\log\left(\sum_{\Omega_t}\Pr\left(\Omega_t\right)\mathcal{L}_{f,t}^{\Omega_t}\left(\boldsymbol{\theta}\right)\right)\right\}, \tag{21}$$

where $T_{obs}$ is the number of observed periods, which is 17 years in my sample. I set the last year before lock-in (year $T$) to be 30 years after the start of the sample in order to give firms a long time period to adjust. I use the same value for $T$ in my counterfactuals.

Note that $\boldsymbol{\Pi}_t\left(\mathcal{G}\right)$ depends only on parameters estimated in the previous stage. I can therefore pre-compute this function for each $\mathcal{G} \in \Gamma$ and $t \leq T$, which remains the same for each

[33] Specifically, I use engineering cost estimates from Western Australia (Australian Bureau of Resources and Energy Economics, 2012), which provide a snapshot of costs in a particular year, and from the U.S. (U.S. Energy Information Administration, 2010, 2013, 2016, 2020), which provide a time series of costs for each energy source. Appendix A.3 provides a description of these data sources and the assumptions made to obtain the full sequence of costs over time for Western Australia.

[34] I am assuming here that scrap values are equal to 0. Maintenance costs and scrap values are not separately identified, so I make the assumption that scrap values are equal to 0 and estimate the maintenance costs.

candidate $\boldsymbol{\theta}$. This fact is important for the estimator's computational tractability since the size of the state space is very large,[35] and for each $(\mathcal{G}, t)$, I solve the wholesale market equilibrium 1 000 times to compute expected profits, nested in a fixed point due to the response of demand to average wholesale prices (equation 12), upon which I iterate until convergence.

# 5 Results

**Demand Elasticity** Table 2 presents estimates of the demand elasticity. The three specifications correspond to whether year and month fixed effects are used to to control for across year and across month differences in demand. The preferred specification (and the one used in later stages) is the final one, which implies an elasticity of -0.094. While the demand elasticity is imprecisely estimated, this value is very similar to the value of -0.09 found in Deryugina *et al.* (2020) over a six-month horizon of adjustment using data for Illinois.

Table 2: Demand Elasticity Estimates

| | (1) | (2) | (3) |
|---|---|---|---|
| *Estimates* | | | |
| $\hat{\epsilon}$ | -0.064 | 0.241 | 0.094 |
| | (0.024) | (0.097) | (0.101) |
| *Controls* | | | |
| constant | ✓ | ✓ | ✓ |
| year effects | | ✓ | ✓ |
| month effects | | | ✓ |
| *Num. obs.* | | 12 240 | |

*Note*: Reported standard errors are heteroskedasticity-robust standard errors. The sample period is constructed by using years after 2014, within 30 days of July 1, but not within 15 days. The buffer of 15 days surrounding July 1 is chosen to give consumers some time to respond to the new prices they face. The choice of using years after 2014 is to avoid Australia's carbon tax (repealed in 2014). The carbon tax is a potential confounder because it impacts prices $P_t$ as well as electricity consumption valuations $\Xi_h$ (e.g., switching heating to electricity to reduce carbon tax burden). This would be a violation of the identifying assumption, and thus the years before 2014 are dropped from the sample.

**Production Cost Shocks** Table 3 presents estimates of the distribution of production cost shocks as well as a comparison of selected moments from the data and in the simulated equilibria under the parameter estimates. For all three technologies, the estimated parameters imply cost shocks have a positive mean, nontrivial variance, and are positively skewed.[36] Cost

[35] The size of the possible combinations of generators is 810 000, and the number of years is 30, for a total size of the state space of 24 300 000.

[36] Note that $\xi_s$, $\sigma_s$, and $\alpha_s$ are the location, scale, and shape parameters of the multivariate skew normal distribution but are not direct measures of the distribution's mean, variance, and skewness.

shocks are positively correlated among one another, and the correlation within a technology is greater than across technologies. Moments from the simulations under the estimated parameters suggest the model is broadly able to capture the distribution in wholesale market prices and the fraction produced by different technologies.

Table 3: Production Cost Shock Estimates

| | Coal | OCGT | CCGT |
|---|---|---|---|
| *Estimates* | | | |
| $\hat{\xi}_s$ | 8.553 | 10.114 | 3.382 |
| | (0.290) | (0.352) | (1.334) |
| $\hat{\sigma}_s$ | 23.017 | 25.364 | 42.482 |
| | (0.209) | (0.248) | (1.158) |
| $\hat{\alpha}_s$ | -0.200 | 6.679 | 2.582 |
| | (0.427) | (0.892) | (0.472) |
| $\hat{\rho}_{s,\text{Coal}}$ | 0.333 | 0.333 | 0.025 |
| | (0.016) | (0.011) | (0.015) |
| $\hat{\rho}_{s,\text{OCGT}}$ | 0.333 | 0.333 | 0.148 |
| | (0.011) | (0.010) | (0.017) |
| $\hat{\rho}_{s,\text{CCGT}}$ | 0.025 | 0.148 | 0.167 |
| | (0.015) | (0.017) | (0.018) |
| *Selected Moments* | | Data | Simulation |
| fraction intervals | | | |
| $P_h \leq 25$ AUD | | 5.9% | 4.2% |
| $P_h \leq 38$ AUD | | 29.6% | 20.8% |
| $P_h \leq 50$ AUD | | 64.4% | 49.7% |
| $P_h \leq 62$ AUD | | 77.2% | 76.3% |
| $P_h \leq 75$ AUD | | 85.3% | 91.9% |
| fraction produced by | | | |
| Coal | | 54.5% | 56.1% |
| OCGT | | 14.0% | 14.1% |
| CCGT | | 16.6% | 14.8% |
| *Num. obs.* | | 174 708 | |
| *Num. simulation draws* | | 50 000 | |

*Note*: The weighting matrix used in obtaining these estimates is the inverse of the sample covariance matrix of the moments, which is an efficient weighting matrix. Selected moments are not an exhaustive list of those used for estimation. Section 4.1 describes all of the moments used. For moments calculated in the data, only intervals with nonnegative wholesale prices and after the beginning of the real-time market on July 1, 2012 are used. Draws from the multivariate skew normal distribution are obtained using the procedure proposed by Azzalini & Capitanio (1999). Rather than searching over the correlation parameters ($\rho_{s,s'}$) directly (for which it can be difficult to maintain positive definiteness for the covariance matrix), I search over the inverse tangent transform of the Cholesky factor of the correlation matrix, which ensures that the correlation matrix implied by the parameters is a proper correlation matrix. Standard errors for these parameters are approximated using the Delta Method.

With estimates of the demand elasticity, production cost shocks, as well as the empirical distribution of consumption valuations, capacity factors, and input prices, I can simulate equilibrium profits in each year for each combination of generators $\mathcal{G}$. This estimate of yearly expected profits $\hat{\mathbf{\Pi}}_t(\mathcal{G})$ can then be used in the second stage of estimation.

**Investment Decision** Table 4 presents parameter estimates for the investment stage of the model. Maintenance costs are positive for all energy sources, suggesting it is costly to hold idle capacity, and they are larger (in per MW terms) for fossil fuel generators than renewables. Standard errors are larger for renewable generators, however, driven in part because there are fewer observations in which a firm adjusts its set of renewable generators. Idiosyncratic investment cost shocks appear to be nontrivial in size. The scale parameter is equivalent in size to between approximately one-third and one-half of the profits the largest firm received in the sample period (based on the first-stage production cost estimates). This provides firms with an incentive to wait for and choose portfolios with good investment cost shocks.

Table 4: Investment Model Parameter Estimates

| | Coal | OCGT | CCGT | Solar | Wind |
|---|---|---|---|---|---|
| *Estimates* | | | | | |
| maintenace costs | | | | | |
| $\hat{m}_s$ (A\$/kW) | 143.5 | 151.6 | | 70.0 | 29.4 |
| | (31.5) | (8.5) | | (58.1) | (20.1) |
| average investment costs | | | | | |
| $\hat{C}_{s\,2007}$ (A\$/kW) | 3 766.7 | 886.8 | 1 420.9 | 5 399.1 | 3 304.5 |
| $\hat{C}_{s\,2011}$ (A\$/kW) | 3 357.7 | 783.8 | 1 230.1 | 4 478.1 | 2 831.6 |
| $\hat{C}_{s\,2015}$ (A\$/kW) | 3 401.8 | 786.1 | 1 135.1 | 2 760.8 | 2 199.4 |
| $\hat{C}_{s\,2019}$ (A\$/kW) | 3 340.0 | 817.3 | 1 203.1 | 1 138.9 | 1 736.5 |
| idiosyncratic shock distribution | | | | | |
| $\hat{\sigma}_\eta$ (million A\$) | | | 119.4 | | |
| | | | (7.575) | | |
| *Num. obs.* | | | 119 | | |

*Note*: Maintenance costs for OCGT and CCGT are imposed to be the same and are hence grouped in the table. Investment costs are reported for a subset of years and lack standard errors because they are not estimated and come from engineering estimates (see Appendix A.3). To make the likelihood convex, rather than searching for the scale of the idiosyncratic shock $\sigma_\eta$ directly, I make the standard normalization to the scale (such that $\sigma_\eta = 1$ and the variance is equal to $\pi^2/6$) and allow profits and investment costs to be scaled by a parameter in the search. In the results presented in this table, I scale the results back so that they are in terms of dollars (the form presented in equation 17). Standard errors are approximated using the Delta Method. These standard errors do not reflect the uncertainty in the estimates in the first stage.

# 6 Counterfactuals

In this section, I consider the impact that counterfactual policies have in equilibrium on investment, production, greenhouse gas emissions, and blackouts. The estimates of firms' costs, capacity factors, and electricity demand provided in section 5 allow me to predict the path of investment and production that firms undertake in equilibrium under counterfactual policies. I study carbon taxes and capacity payments, which aim to address the environmental externality and blackouts, respectively, as well as alternative environmental policies that are widely used in practice.

### 6.1 Electricity Market Policies

In this section I consider policies that are intended to address a specific market failure, both in isolation and as a policy bundle. In particular, I consider two policy tools, carbon taxes and capacity payments. Carbon taxes address the environmental externality by making electricity production using carbon-intensive technologies more costly, and, in the absence of other market failures (such as market power, price caps, or lack of real-time pricing), they can achieve the social optimum. Capacity payments address blackouts by subsidizing capacity, increasing the returns to investment. Since price caps limit the returns to investment, potentially increasing blackouts, I also explore the welfare impact of these policies under a higher price cap. Each of the policies are static, in the sense that they do not vary over time, and this is known by the firms at all points in time. In Section 6.3 I consider time-varying policies. I simulate the market forward from the same state starting in year 2006 as that observed in the data and obtain the distribution of firms' investment decisions.

#### 6.1.1 Policies in Isolation

First, I consider each of the policy tools in isolation. For each policy tool that I consider, I set the other tool to a value of 0. Price caps are set to A\$300/MWh, approximately the same as the average price cap historically in Western Australia. I predict the impact of a carbon tax in the absence of capacity payments, and I consider capacity payments in the absence of a carbon tax. The goal of this exercise is to isolate the impact of each tool separately. In section 6.1.3 I consider complimentarities between the policies.

**Carbon Tax** I consider a carbon tax levied on firms based on the emissions rate of each generator, given by table 9 in Appendix A. The value of the carbon tax, $\tau$, enters the cost of each firm as described in equation 1. Figure 3 presents the evolution over time of the expectation of aggregate capacities by energy source and share of production for that energy source for four different values of the carbon tax.

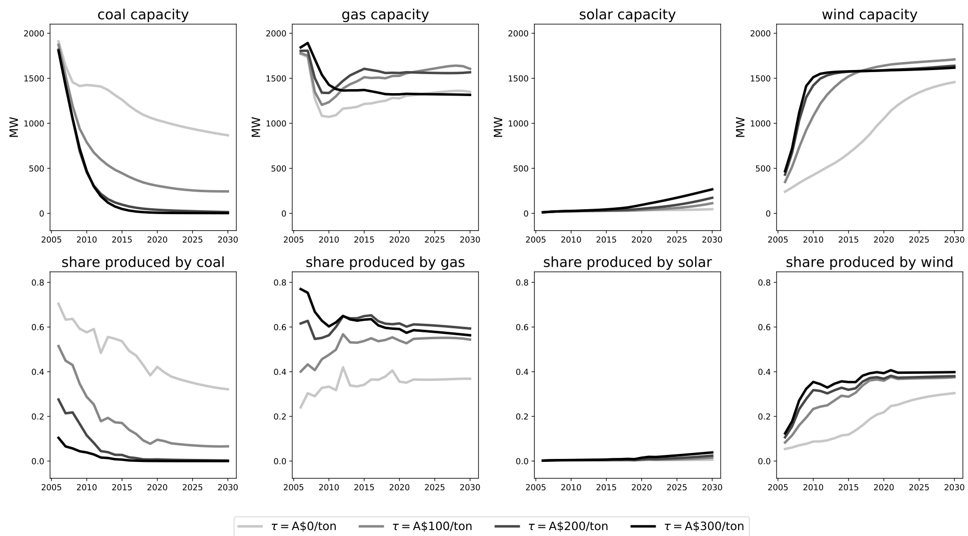
The top of figure 3 captures substitution along the extensive (investment) margin. A carbon tax results in a decline in coal generators due to coal being the most carbon-intensive technology and having a high estimated maintenance cost, making it costly to hold idle coal capacity. A carbon tax of A\$200/ton results in nearly complete retirement of coal capacity by 2015 despite coal making up a majority of production at the start of the sample less than 10 years earlier. Gas generators, which are roughly half as carbon-intensive as coal, do not exhibit the same pattern. Gas investment has a non-monotonic pattern, with carbon taxes of A\$100/ton or A\$200/ton resulting in an *increase* in investment relative to no carbon tax, while at A$300/ton, there is marginally lower investment by 2030. This relationship reflects gas being an energy source that is less carbon intensive than coal and not intermittent, resulting in gas replacing coal; however, at high carbon taxes, there is less investment in this technology. Wind and solar, which emit zero $CO_2$, experience a substantial increase in capacity as the carbon tax rises; firms adopt more renewable generators, and they adopt them earlier. Most of this investment is in wind, however, reflecting higher estimated solar maintenance costs and low net demand in the middle of the day (due to rooftop solar) when solar is available.

The bottom row of the figure captures substitution along the intensive (production) margin, which reflects the investment decisions described above as well as the relative production costs of each energy source. In early years, when there exists significant coal capacity and little renewable capacity due to high investment costs, as the carbon tax increases, so too does the share produced by gas, while the share produced by coal declines. Since there does not yet exist significant renewable capacity, electricity demand must be satisfied by either coal or gas. Since gas is the less carbon-intensive technology of the two, as the carbon tax rises, a higher fraction of gas capacity is used, while the reverse is true for coal. Over time, firms invest in renewable generators; however, even at the highest carbon tax, they make up less than half of total production. In intervals in which there is little sun or wind, natural gas is used to meet demand.

**Capacity Payments** I next consider the impact of capacity payments by varying the value of the payment, $\kappa$, which enters the payment function $\Upsilon_{ft}(\cdot)$, defined in equation 15. Unlike in the sample, in which the value varied over time, I simulate investment and production with a value of $\kappa$ that is constant for all years. The simulated expected evolution of investment and production is given in figure 4 for four different values of the payments.

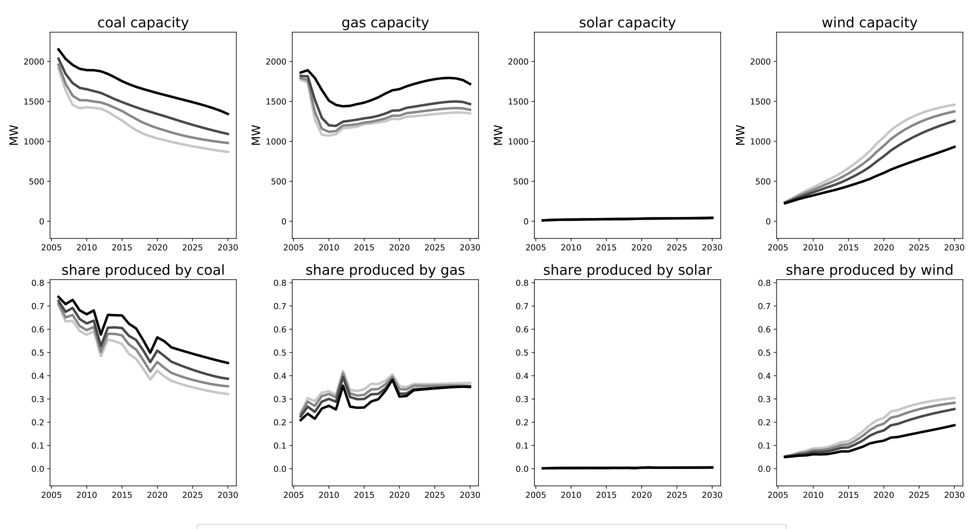
The results suggest that the high levels of payments observed in the data (on average around A$125 000/MW during the sample period, which would be between the third and fourth lines in figure 4) are what have kept coal capacity at a relatively slow decline in Western Australia. Gas capacity is also very responsive to the size of the capacity payments. Without capacity payments, expected gas capacity experiences a small decline comparing 2030 and 2006; however, with the payments, gas is roughly the same in those two years (with a small dip in the intermediate period as less efficient gas plants are retired and more efficient ones built). An active policy question regarding capacity payments is their impact on renewables. The results suggest that capacity payments have a negative impact on renewable capacity, most pronounced for wind since solar capacity without a carbon tax is negligible. Increasing the size of capacity payments decreases the incentive to invest in wind because the payments promote fossil fuel investment, increasing the number of these generators, which lowers the

Figure 3: Impact of Carbon Tax on Investment and Production




*Note*: Depicted in each panel is the *expectation* for a particular energy source summed across all strategic firms and the competitive fringe for a particular value of a carbon tax. The top row predicts levels of capacity in each year ($x$-axis) for each energy source (columns), and the bottom row presents the same but for shares of production. Note that production shares are less smooth than investment because of variation in coal and gas prices as well as the distribution of demand from year-to-year.

Figure 4: Impact of Capacity Payments on Investment and Production




*Note*: Depicted in each panel is the *expectation* for a particular energy source summed across all strategic firms and the competitive fringe for a particular value of a capacity payment. The same notes as in figure 3 apply.

average wholesale price of electricity.

Lacking a carbon tax or any policy affecting the production margin, production follows a similar pattern to that of capacity. As the payment size increases, the share of electricity produced by coal rises with the associated capacity. Gas experiences a more nuanced pattern. While there is substantial investment in gas capacity because the investment costs of these generators are relatively cheap, gas is not as competitive as coal in the wholesale markets, so the share produced by gas actually goes *down* in most years as we increase the size of the payments since coal capacity is increasing.

### 6.1.2 Higher Price Caps

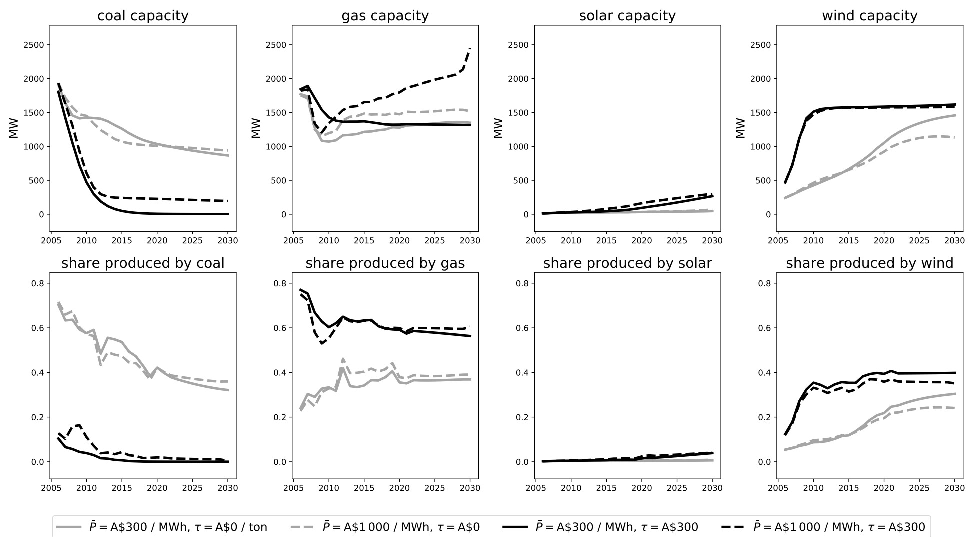
Price caps limit the maximum attainable market-clearing wholesale spot price. These can contribute to blackouts via two mechanisms. First, a low price cap can cause some generators to not participate in the wholesale market because their production costs exceed the cap (especially if the carbon tax is sufficiently high). Second, by limiting the maximum price, caps dampen the returns to investment, generating less investment in generation capacity.

In this subsection, I explore the impact of price caps on investment by simulating a higher price cap of A$1 000/MWh (rather than A$300/MWh). In the following subsection (6.1.3) I explore their impact on welfare. Figure 5 depicts investment in the four energy sources over time by price cap and by carbon tax. The relationship between these two variables is nuanced.

Without a carbon tax, the price cap rarely binds, so a high price cap results in only marginally more investment in natural gas and less in wind.[37] A high carbon tax, however, raises production costs, leading to the low price cap binding more frequently. The price cap therefore has a larger impact in this case. Conditional on generator portfolios, prices are higher on average with a higher price cap, raising the returns to investment. Renewable investment is nearly completely unaffected by the price cap; however, fossil fuel generators—especially natural gas—receive substantially more investment with a higher price cap. Price caps typically bind in the states of the world with low wind or sun availability, so the marginal return to renewable investment does not increase by very much when the price cap rises.

[37] Note that while the low price cap is rarely binding for most states of the world, for states of the world with low investment levels, the price cap matters because it is the wholesale price when blackouts result. Given investment cost shocks (captured by $\eta$ in equation 17) with full support along the real line, there is some probability of ending up in these states, and this probability is reflected in the expectation, which is why the impact of the price cap, while not large, is also not trivial even without a carbon tax that substantially raises production costs.

Figure 5: Impact of Carbon Taxes and Price Caps on Investment




*Note*: Depicted in each panel is the *expectation* for a particular energy source summed across all strategic firms and the competitive fringe for a particular value of a carbon tax (given by how dark the line is) and price cap (given by whether the line is solid or dashed).

### 6.1.3 Welfare Impact

In this section, I consider the impact of the policies introduced in the previous section on welfare. I use a welfare function that includes a carbon externality, which is the sum of carbon emitted to produce electricity times the social cost of carbon. It also includes a blackout cost, which is the expected Megawatt-hours of electricity experiencing a blackout due to demand exceeding available supply times consumers' willingness to pay to avoid a Megawatt-hour of blackouts, which is referred to in the electricity literature as the *value of lost load*.[38,39]

I consider changes in this welfare function as I change policies, such as a carbon tax or capacity

[38] I assume that blackouts are rolling and the grid operator can perfectly ration a fraction of consumers to equate demand with the maximum available supply. For example, if consumers demand 1 000 MWh in a given interval, but the available supply is only 900 MWh, then 100 MWh are randomly rationed. The consumers who are rationed receive zero electricity.

[39] In theory, the blackout cost is a part of consumer surplus, but the utility specification I use is meant to capture changes in prices and is not well-suited for considering the cost to consumers of zero electricity provided. In fact, using the utility specification in equation 8, the marginal utility at zero electricity for a consumer is infinite. Instead, I opt to separate the consumer surplus that reflects prices and quantity of *satisfied demand* and the cost of blackouts from *unsatisfied demand* separately. Consumer surplus, captured by $CS_t(\cdot)$ in equation 22, is measured only for consumers not experiencing a blackout. For those experiencing a blackout, I use the cost of a blackout (the value of lost load) multiplied by the amount of unsatisfied demand. This is equivalent to the specification in equation 8 with the marginal willingness to pay capped so that this willingness does not exceed the value of lost load.

payments. Formally, the change in total surplus going from policy $P$ to policy $P'$ is given by

$$\begin{aligned} \Delta^{P\to P'} W_t(\boldsymbol{\Omega},\boldsymbol{\eta}) = \quad & \Delta^{P\to P'} CS_t(\boldsymbol{\Omega},\boldsymbol{\eta}) \\ & + \Delta^{P\to P'} \textstyle\sum_f PS_{f,t}(\boldsymbol{\Omega},\boldsymbol{\eta}) \\ & + \Delta^{P\to P'} G_t(\boldsymbol{\Omega},\boldsymbol{\eta}) \\ & - SCC \times \Delta^{P\to P'} \text{ carbon emissions}_t(\boldsymbol{\Omega},\boldsymbol{\eta}) \\ & - VOLL \times \Delta^{P\to P'} \text{ MWh experiencing blackout}_t(\boldsymbol{\Omega},\boldsymbol{\eta}), \end{aligned} \tag{22}$$

where $SCC$ and $VOLL$ are the social cost of carbon and the value of lost load, respectively. The change in total present discounted expected surplus over the entire time horizon is given by

$$\Delta^{P\to P'}\mathcal{W} = \mathbb{E}_{\boldsymbol{\Omega},\boldsymbol{\eta}}\left[\sum_{t=0}^{\infty}\beta^t \Delta^{P\to P'} W_t(\boldsymbol{\Omega},\boldsymbol{\eta})\right]. \tag{23}$$

Table 5 provides consumer surplus, producer surplus, government revenues, emissions, and blackouts for a range of values of both the carbon tax $\tau$ and the capacity payment size $\kappa$, for both a low and a high price cap. I first consider the welfare impacts of carbon taxes and capacity payments separately and then complementarities between the two policy tools.

**Carbon Taxes** A carbon tax decreases emissions as intended. As the carbon tax increases, however, the marginal reduction in emissions declines. For low levels of a tax, the decrease in emissions is similar for both a low and a high price cap; however, at higher levels, there is relatively more investment in fossil fuels with high price caps, resulting in less of a decline in emissions than with a low price cap. Blackouts, meanwhile, are increasing in the size of the tax for low price caps. The tax causes coal capacity to decline, and gas capacity does not change substantially to make up the difference. For high price caps, however, there is more investment in gas (and not complete retirement of coal), so the level of blackouts is basically invariant to the size of the tax.

A carbon tax increases the production costs of carbon-intensive technologies. As the tax increases, this results in decreased consumer surplus since consumers face higher prices, and this decrease in consumer surplus is larger with a high price cap. Interestingly, producer surplus does not decrease but rather *increases* as the tax increases. This pattern is driven by two factors. First, demand is highly inelastic, so most of the increased cost in producing electricity is passed on to consumers (consistent with Fabra & Reguant (2014) in the case of Spain and Nazifi *et al.* (2021) in the case of the eastern portion of Australia). Second, the wholesale price is set by the marginal generator. Since a fossil fuel generator is typically the marginal generator (even at high tax levels with substantial renewable investment), a higher tax increases the market price. With lower emissions-intensity inframarginal generators

Table 5: Welfare

| | | ΔCS (billions A\$) | | ΔPS (billions A\$) | | ΔG (billons A\$) | | Δ emissions (billions kg $CO_2$-eq) | | Δ blackouts (millions MWh) | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $\tau$ | $\kappa$ | low price cap | high price cap | low price cap | high price cap | low price cap | high price cap | low price cap | high price cap | low price cap | high price cap |
| 0 | 0 | 0.0 | -24.67 | 0.0 | 29.13 | 0.0 | 0.0 | 0.0 | 1.65 | 0.0 | -3.34 |
| | 50 000 | 1.79 | -23.2 | 1.0 | 30.74 | -2.51 | -2.55 | 7.71 | 6.56 | -1.36 | -3.49 |
| | 100 000 | 3.85 | -21.19 | 2.04 | 31.78 | -5.35 | -5.24 | 16.22 | 10.03 | -2.72 | -3.76 |
| | 150 000 | 7.37 | -18.95 | 2.17 | 32.68 | -9.19 | -8.12 | 30.32 | 13.78 | -4.73 | -4.06 |
| | 200 000 | 13.22 | -17.44 | 2.65 | 34.11 | -18.05 | -11.05 | 43.92 | 15.84 | -6.7 | -4.34 |
| 100 | 0 | -18.79 | -36.16 | 4.31 | 19.78 | 13.53 | 15.17 | -60.47 | -44.03 | 4.77 | -4.59 |
| | 50 000 | -16.64 | -35.84 | 3.42 | 22.67 | 11.49 | 13.04 | -59.47 | -40.91 | 0.95 | -4.49 |
| | 100 000 | -13.69 | -32.82 | 2.09 | 22.29 | 9.4 | 10.27 | -52.83 | -43.21 | -3.31 | -5.1 |
| | 150 000 | -10.49 | -31.39 | 2.07 | 23.45 | 5.81 | 7.62 | -48.89 | -43.49 | -6.38 | -5.36 |
| | 200 000 | -5.86 | -32.61 | 3.48 | 26.75 | -3.69 | 4.93 | -43.52 | -41.24 | -7.61 | -5.09 |
| 200 | 0 | -31.87 | -52.45 | 5.91 | 22.0 | 21.41 | 24.57 | -88.71 | -72.88 | 7.98 | -4.83 |
| | 50 000 | -31.46 | -49.42 | 6.7 | 21.75 | 19.99 | 22.18 | -85.82 | -72.91 | 4.09 | -5.42 |
| | 100 000 | -30.84 | -46.81 | 7.78 | 22.12 | 18.14 | 19.58 | -83.02 | -73.11 | 0.6 | -5.86 |
| | 150 000 | -28.67 | -43.75 | 8.01 | 22.15 | 14.77 | 16.77 | -80.53 | -72.18 | -4.22 | -6.4 |
| | 200 000 | -23.79 | -37.98 | 8.74 | 20.33 | 4.54 | 11.84 | -81.27 | -73.72 | -7.46 | -7.15 |
| 300 | 0 | -39.87 | -75.73 | 8.86 | 34.93 | 26.25 | 33.41 | -108.24 | -84.4 | 21.83 | -3.11 |
| | 50 000 | -40.88 | -70.64 | 10.24 | 30.52 | 25.36 | 31.57 | -105.12 | -82.91 | 17.21 | -4.75 |
| | 100 000 | -42.34 | -64.99 | 11.3 | 27.62 | 24.51 | 28.57 | -99.29 | -84.37 | 8.56 | -5.85 |
| | 150 000 | -41.94 | -66.0 | 11.05 | 31.71 | 20.64 | 26.32 | -92.98 | -83.3 | -4.8 | -5.48 |
| | 200 000 | -38.38 | -58.18 | 13.21 | 28.86 | 8.13 | 21.25 | -93.24 | -84.8 | -8.66 | -6.83 |

*Note*: Changes are with respect to the *laissez-faire* policy ($\tau = 0$, $\kappa = 0$) at the low price cap ($\bar{P} =$ A\$300). The high price cap is the same as that used in section 6.1.2, A\$1 000/MWh. All values are in expected present discounted terms, using the same discount factor as that used by the firms, $\beta = 0.95$, with the expectation taken with respect to both the ordering of firms' decisions and well as their investment cost shocks. Note that consumer surplus is the surplus for consumers who do not experience a blackout, and the full consumer surplus (which includes the cost of blackouts) is captured by the final column weighted by the value of lost load, as explained in footnote 39.

(especially zero-emitting renewables, which are substantial at high tax rates), this increases producer surplus.

**Capacity Payments** Capacity payments function as intended at reducing blackouts, driven by increased investment in fairly reliable fossil fuel generators. With low price caps the decrease is substantial, while with high price caps blackouts are only marginally sensitive to the size of the payments. Because in equilibrium firms invest less in renewables as the size of these payments increases, the share of electricity produced by fossil fuels is increasing and the share of renewables is declining. This drives a significant increase in emissions.

**Joint Policies** Given that carbon taxes reduce emissions but increase blackouts, and capacity payments reduce blackouts while increasing emissions, it is worth considering complementarities between these two policy tools. By using both policy tools, can we reduce both emissions and blackouts? And if so, at what cost to product market welfare and government revenues? Table 5 provides the welfare impact for combinations of these two tools. The pattern of blackouts increasing with the size of the carbon tax weakens significantly when capacity payments are introduced in addition to the tax. Additionally, the pattern between emissions and the size of the capacity payments weakens when a carbon tax is also introduced. With a sufficiently high carbon tax, emissions can be reduced regardless of the capacity payment, and with a sufficiently high capacity payment size, blackouts can be reduced regardless of the carbon tax.

Both blackouts and emissions can be substantially reduced due to the fact that these variables are a function of different margins. Emissions are a function of the production margin (which sources are used to produce electricity), and blackouts are a function of the investment margin (how much effective capacity is there in the market). While these two margins are linked (investment is a function of production, and vice versa), subsidizing reliable capacity reduces blackouts, and a carbon tax incentivizes firms to reduce the fraction of capacity they use from emissions-intensive sources. By using both a carbon tax and capacity payments, therefore, we can incentivize firms to invest in reliable capacity but also incentivize them not to use that emissions-intensive capacity unless necessary.

Table 5 also provides the impact a policy has on product market welfare and government revenues. A carbon tax has a significant negative impact on consumer surplus, even if the tax revenue raised (given in the column ΔG) is rebated back to consumers, which may explain the political opposition to a carbon tax. Capacity payments, however, can marginally increase product market welfare and government revenues even apart from their impact on blackouts (for example, $\Delta CS + \Delta PS + \Delta G$ is higher under $\kappa =$ A\$150 000/MW than $\kappa =$ A\$0/MW). Strategic firms have an incentive to underinvest to drive up wholesale market prices. Capacity

Table 6: Welfare-Maximizing Policies for Particular $SCC$ and $VOLL$

| carbon tax alone, low $\bar{P}$ | | carbon tax alone, high $\bar{P}$ | | joint policies, low $\bar{P}$ | | | joint policies, high $\bar{P}$ | | |
|---|---|---|---|---|---|---|---|---|---|
| $\tau^*$ | $\Delta\mathcal{W}$ | $\tau^*$ | $\Delta\mathcal{W}$ | $\tau^*$ | $\kappa^*$ | $\Delta\mathcal{W}$ | $\tau^*$ | $\kappa^*$ | $\Delta\mathcal{W}$ |
| 152.3 | 8.94 | 207.8 | 7.6 | 215.0 | 168 400 | 15.71 | 230.9 | 181 200 | 16.98 |

*Note*: Changes in welfare are with respect to the *laissez-faire* policy ($\tau = 0$, $\kappa = 0$) with a low price cap ($\bar{P} =$ A\$300) and in expected present discounted terms (using $\beta = 0.95$) in thousand A\$ per customer. I use a $SCC$ of 230/ton $CO_2$-eq and a $VOLL$ of 1 000/MWh. Since computing the equilibrium given a policy is computationally intensive, I calculate equilibria for a relatively sparse grid (seven equally spaced points for the carbon tax and five equally spaced points for the capacity payments, with the same end points as shown in table 5) and construct a much finer grid to determine optimal policy values by interpolating using bivariate cubic splines.

payments can (partially) mitigate this exercise of market power, much like how a production subsidy generally mitigates the exercise of market power in production.

Characterizing optimal policy requires taking a stance on the values of both the social cost of carbon and the value of lost load. Both of these values are subject to significant debate, and there remains considerable uncertainty about them. The goal of this paper is not to take a strong stance on either of these values; however, I use particular baseline values to illustrate how optimal policy responds to using certain policy tools. For the social cost of carbon, I use the value proposed by the U.S. Environmental Protection Agency, which is US\$190/ton $CO_2$-eq (equal to approximately A\$230/ton $CO_2$-eq in 2015 A\$). For the value of lost load, I use a relatively small value of A\$1 000/MWh, in line with some estimates of the value for residential consumers (London Economics International LLC, 2013). This value is the same as the price cap in the high price cap simulation. In the absence of market power or the environmental externality, and constrained to no real-time pricing, setting the price cap to the value of lost load would achieve the (constrained) first best (Bushnell *et al.*, 2017). Using these values, table 6 provides the optimal policy with a carbon tax alone and when the tax is used jointly with capacity payments, as well as the change in welfare that these optimal policies yield.

Using a carbon tax alone, the optimal tax is well below the social cost of carbon. The tax causes an increase in blackouts and can also exacerbate the exercise of market power. The optimal tax is higher under a high price cap than a low one but generates a smaller increase in welfare. With optimally-set capacity payments, however, the tax is closer to the social cost of carbon, reflecting the role of capacity payments in preventing the increase in blackouts that results from a carbon tax. This pattern holds regardless of whether a low or a high price cap is used. In this case, a high price cap generates a larger increase in welfare, and the tax is nearly equivalent to the social cost of carbon under the high price cap.

### 6.2 Carbon Taxes vs. Renewable Investment Subsidies

Many electricity markets that have adopted environmental policies to reduce emissions have used policies other than a carbon tax. In this section, I consider the impact on investment, production, and welfare-relevant variables of renewable subsidies, which are alternative environmental policies that have been widely used in practice. The first type of renewable subsidy I consider is a renewable *production* subsidy, which pays renewable generators a fixed amount for each MWh they produce. I will denote the value of this subsidy (in A\$/MWh) by $\varsigma$. This subsidy changes a generator's production cost (equation 1) to $c_{gh} + \varsigma \mathbb{1}\left\{s\left(g\right) \in \mathcal{S}_{\text{renewable}}\right\}$. The second type is a renewable *investment* subsidy, which reduces the cost of investment of renewable generators. I will denote the value of this subsidy by $s$. Under this subsidy, generators pay a cost to build a new generator of $\left(1 - s\mathbb{1}\left\{s\left(g\right) \in \mathcal{S}_{\text{renewable}}\right\}\right) C_{s(g),t}$ per MW. A renewable generator therefore only pays $(1-s) \times 100\%$ of the cost of a new generator (plus the idiosyncratic cost and the yearly maintenance costs). Figures 9 and 10 in Appendix C display analogous results to those in figures 3 and 4.

Table 7 compares the welfare impact of these three policy tools in isolation without any capacity payments and a low price cap. For each level of emissions reduction, this table provides the policy value that attains that reduction and the changes in blackouts, consumer surplus, producer surplus, and government revenues that result. Renewable investment subsidies, widely used in practice, are not very effective at reducing emissions, as demonstrated by the fact that no subsidy $s \leq 100\%$ can yield a substantial emissions reduction. A renewable investment subsidy yields a low reduction in emissions because it does not incentivize emissions reduction during production, and it also results in less investment in renewable capacity (see figure 9 in Appendix C), reflecting that high estimated renewable maintenance costs cause firms to not invest even if their sunk investments are largely subsidized.

A renewable production subsidy, meanwhile, can obtain larger emissions reductions than an investment subsidy. This subsidy better incentivizes emissions-reducing production decisions in the wholesale market; however, it is unable to distinguish between the emissions intensities of the fossil fuel generators, which are significant (and therefore the maximum emissions reduction it can attain is lower than that of a carbon tax). Despite this inability to finely distinguish between emissions intensities, for a given emissions reduction, this subsidy actually achieves the reduction at a lower cost to product market welfare and government revenues. This result is perhaps surprising since, in addition to only coarsely distinguishing emissions intensities, it lowers production costs, which expands demand rather than contracts it.[40] Market power misaligns firms' investment incentives, and the subsidy partially mitigates this.

[40]This is the standard reason why, in the case of two production technologies, a "green" subsidy cannot achieve the first best while a "dirty" tax can.

Table 7: Comparing Environmental Policies

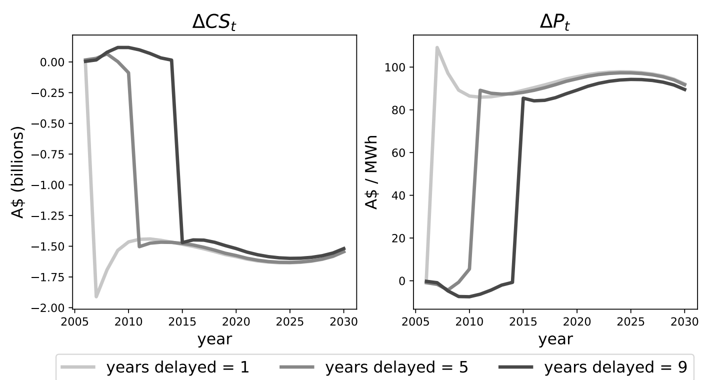
| $\Delta$emissions (billions kg$CO_2$-eq) | policy | policy value | $\Delta$blackouts (millions MWh) | $\Delta$CS (billions A$) | $\Delta$PS (billions A$) | $\Delta$G (billions AUD) | $\Delta$ (CS + PS + G) (billions A$) |
|---|---|---|---|---|---|---|---|
| 0 | carbon tax | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| | renew. prod. subs. | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| | renew. inv. subs. | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| 5 | carbon tax | 10.7 | -0.5 | -1.6 | -1.1 | 2.4 | -0.3 |
| | renew. prod. subs. | 2.3 | -0.1 | 0.2 | -0.1 | -0.1 | -0.0 |
| | renew. inv. subs. | 23.5 | -0.1 | 0.4 | 0.5 | -0.5 | 0.4 |
| 10 | carbon tax | 19.6 | -0.8 | -3.0 | -1.7 | 4.2 | -0.5 |
| | renew. prod. subs. | 10.9 | -0.3 | 0.8 | -0.2 | -0.7 | -0.1 |
| | renew. inv. subs. | 48.3 | -0.1 | 0.7 | 1.5 | -1.2 | 0.9 |
| 15 | carbon tax | 27.1 | -0.9 | -4.2 | -2.0 | 5.5 | -0.7 |
| | renew. prod. subs. | 23.6 | -0.5 | 1.6 | 0.0 | -1.7 | -0.1 |
| | renew. inv. subs. | 77.7 | -0.2 | 1.0 | 3.0 | -2.4 | 1.6 |
| 20 | carbon tax | 33.2 | -1.0 | -5.3 | -2.2 | 6.5 | -0.9 |
| | renew. prod. subs. | 38.6 | -0.6 | 2.1 | 0.7 | -3.1 | -0.2 |
| | renew. inv. subs. | - | - | - | - | - | - |
| 25 | carbon tax | 38.5 | -1.0 | -6.2 | -2.2 | 7.3 | -1.0 |
| | renew. prod. subs. | 53.9 | -0.6 | 2.6 | 1.7 | -4.7 | -0.4 |
| | renew. inv. subs. | - | - | - | - | - | - |
| 30 | carbon tax | 43.0 | -1.0 | -7.0 | -2.1 | 8.0 | -1.1 |
| | renew. prod. subs. | 79.0 | -0.7 | 3.0 | 3.6 | -7.4 | -0.8 |
| | renew. inv. subs. | - | - | - | - | - | - |
| 35 | carbon tax | 47.2 | -1.0 | -7.8 | -2.0 | 8.6 | -1.2 |
| | renew. prod. subs. | - | - | - | - | - | - |
| | renew. inv. subs. | - | - | - | - | - | - |

*Note*: Changes in emissions, blackouts, and welfare variables are all in presented expected discounted values, which are the relevant values for evaluating the welfare function given in equation 23. Since simulated values are along a discrete grid, to back out the policy value that yields a given change in emissions, I interpolate values using cubic splines. I then use the interpolation to determine the policy value yielding the given change in emissions. For blackouts and welfare variables, I also use cubic spline interpolation, taking the implied policy value and determining the corresponding interpolated blackout or welfare variable value. For some of the higher levels of emissions reductions, there does not exist a renewable investment subsidy that would yield that level of an emissions reduction. In this case, the values in the corresponding columns are replaced with "-". Carbon tax values are in A$/ton $CO_2$-eq, renewable production subsidy values are in A$/MWh, and renewable investment subsidy values are in percentage points.

## 6.3 Policy Timing

Policies that induce large investments are often delayed to allow firms time to adjust to the policy. In this section, I explore the returns to delaying the implementation of a carbon tax in order to allow firms to first adjust their generator portfolios. This highlights one of the advantages of my framework using a non-stationary, randomly-ordered sequential moves dynamic game with lock in: it allows for non-stationary policy environments in addition to non-stationary costs and demand. Delaying a policy results in cost savings since firms have time to react and invest in low emissions generators, but the delay also reduces the mechanism that reduces emissions. I predict investment and production with the carbon tax *announced* in 2006 but not actually implemented until $T_{delay}$ years later.[41] This delay in the policy's implementation is known to the firms when the policy is announced in 2006.

Figure 6: Impact of Delaying Policy




*Note*: Displayed is the expectation of the difference in each of the variables for a tax of A\$150/ton $CO_2$-eq and a capacity payment of A\$100 000/MW relative to no tax (but maintaining the capacity payment). The capacity payment is implemented immediately, but the carbon tax's implementation is delayed based on the line.

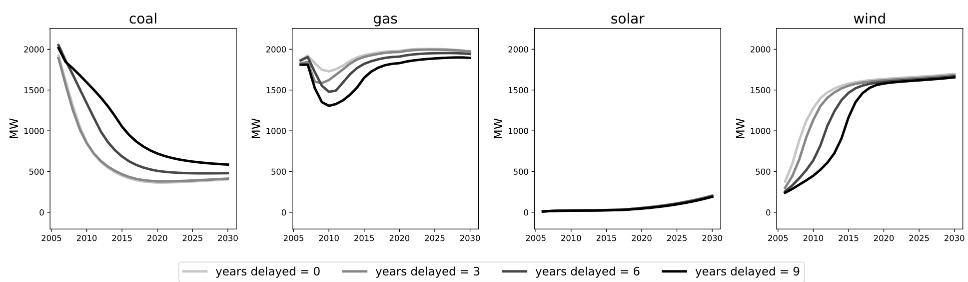
Figure 6 displays the change in consumer surplus and quantity-weighted average wholesale prices in each year relative to those without a carbon tax for three different values of $T_{delay}$.[42] In the year that the carbon tax becomes implemented, consumer surplus drops since the tax raises the price of electricity (depicted in the second panel). As the policy is delayed, however, the drop in consumer surplus decreases. This decrease is a result of firm investment. If the carbon tax becomes implemented without a delay, firms have almost no emissions-free renewable capacity and instead use a high fraction of gas capacity (since it is less emissions-

[41]This exercise shares some similarities with the demand-side exercise in Langer & Lemoine (2022), exploring optimal consumer subsidy dynamics to spur residential solar adoption.

[42]Rather than use the estimated profit function for each year, $\hat{\mathbf{\Pi}}_t(\cdot)$, in this exercise I use the profit function for a particular year (2015) in each year, i.e. $\hat{\mathbf{\Pi}}_{2015}(\cdot)$. This is because each year's profit function depends on the distribution of demand shocks and input prices for that year, which makes changes in prices and consumer surplus relative to no carbon tax (depicted in figure 6) that result from delaying a carbon tax difficult to separate from changes due to different distributions of demand shocks and input prices in each year.

intense) and some coal (which is expensive because of its emissions). When the tax is delayed, firms can respond in the years leading up to the implementation by investing in renewables and some in less emissions-intensive natural gas. Ultimately, this results in less of a spike in prices, and therefore a smaller reduction in consumer surplus.

Figure 7: Impact of Delaying Policy on Investment




*Note*: Displayed is the expected investment for each source, summed across firms, for a tax of A\$150/ton $CO_2$-eq and a capacity payment of A\$100 000/MW. The capacity payment is implemented immediately, but the carbon tax's implementation is delayed based on the line.

While the delay in the implementation of the carbon tax can increase product market welfare, it also results in time during which firms do not have as strong of an incentive to reduce emissions. This lack of emissions-reducing incentives is especially true at the production margin (e.g., there is no incentive to favor gas over coal), but also at the investment margin. While it could be possible that, since the firms anticipate the tax, investment in renewables is similar regardless of the delay, figure 7 shows that without a near immediate tax, firms choose to delay investment in renewables (particularly wind since there is virtually no solar investment early on). Firms have a strong incentive to delay investment, even though that means they may not receive good adjustment cost shocks before the tax's implementation, because the cost of building new renewable generators is declining so much over time.

Given that delaying the policy can increase product market welfare but does not result in the same level of an emissions decline during the delayed years, the impact on total welfare of delaying the policy is ambiguous. Table 8 provides the impact of delaying the policy for different values of the tax on the welfare-relevant variables. Since firms significantly delay changing their generator portfolios when a carbon tax is delayed, the impact of delaying a tax on emissions is substantial. The impact on consumer surplus and government revenues is also large, while producer surplus is relatively unaffected by delaying. One might think that delaying the tax's implementation could alleviate blackouts that occur in the transition to a long-run set of generator portfolios; however, blackouts are nearly unaffected by the delay, driven primarily by the fact that delaying implementation results in more coal and less natural gas capacity, even in the long run (which contributes to higher emissions levels).

Table 8: Welfare Impact of Delaying Policy

| $\tau$ | delay | $\Delta$CS (billions A$) | $\Delta$PS (billions A$) | $\Delta$G (billons A$) | $\Delta$ emissions (billions kg $CO_2$-eq) | $\Delta$ blackouts (millions MWh) |
|---|---|---|---|---|---|---|
| 100 | 1 | -16.95 | -3.78 | 16.67 | -56.05 | -2.05 |
| | 5 | -13.11 | -3.52 | 12.9 | -45.03 | -1.98 |
| | 9 | -10.53 | -2.95 | 10.17 | -34.79 | -1.9 |
| 200 | 1 | -35.46 | 2.56 | 25.77 | -95.38 | 3.11 |
| | 5 | -29.03 | 3.17 | 20.13 | -79.99 | 3.48 |
| | 9 | -24.26 | 3.49 | 16.03 | -65.08 | 3.1 |
| 300 | 1 | -45.63 | 3.57 | 31.84 | -114.34 | 6.82 |
| | 5 | -35.18 | 3.48 | 24.78 | -95.47 | 10.5 |
| | 9 | -29.13 | 3.73 | 19.81 | -78.02 | 9.75 |

*Note*: Changes are with respect to a policy environment with no carbon tax (i.e., $\tau = 0$) in all years. Capacity payments are set equal to A$100 000/MW and the price cap to A$300/MWh. All values are in expected present discounted terms, using the same discount factor as that used by the firms, $\beta = 0.95$, with the expectation taken with respect to both the ordering of firms' decisions and well as their investment cost shocks. Note that values are not necessarily the same as those that would be implied by table 5 because rather than using the estimated profit functions for each year ($\hat{\mathbf{\Pi}}_t(\cdot)$), I use the same profit function in each year ($\hat{\mathbf{\Pi}}(\cdot)$) in this exercise, for the reason described in footnote 42.

Ultimately, despite the cost savings delaying a carbon tax can generate, there is little evidence it is worthwhile to delay implementation, regardless of the precise value of the social cost of carbon. With a higher social cost of carbon, emissions are more costly. With a higher tax, the cost savings of delaying implementation are higher; however, so too is the cost of increased emissions. If a policy maker can simultaneously choose a carbon tax and a number of years to delay, I find that for any social cost of carbon greater than A$30/ton $CO_2$-eq, the optimal delay is zero years.[43]

# 7 Conclusion

Declining costs of renewables and the urgent need to reduce emissions have created a need to understand the impact electricity market regulations have on production and investment. This paper provides a framework that links the two in the setting of restructured electricity markets. This framework allows for the relevant margins of adjustment—production and investment—in all relevant energy sources, which is a necessary component for understanding the impact on emissions and reliability that play a key role in this paper.

Using this framework, I show that without both environmental and reliability policy tools, there are tradeoffs between emissions and blackouts. Using both tools, we can simultaneously reduce emissions and blackouts, highlighting the need for joint regulation as the world adopts

[43] For very small values of the social cost of carbon, the optimal tax is small, and it is possible to increase welfare a little by delaying its implementation. However, most estimates of the social cost of carbon are well above A$30/ton $CO_2$-eq.

strict environmental policies to address the threat of climate change. Changes in technology not studied in this paper—such as utility-scale batteries, which are in their infancy but starting to be adopted, or real-time pricing, which introduce elasticity to demand—may also help to address reliability concerns. However, batteries are still extremely expensive and also have capacities that limit their ability to fill long-term gaps in available capacity, while real-time pricing experiments have highlighted the issue of inattention to fluctuations in prices. This means that reliability concerns and the policy tools studied in this paper are likely to be relevant well into the future.

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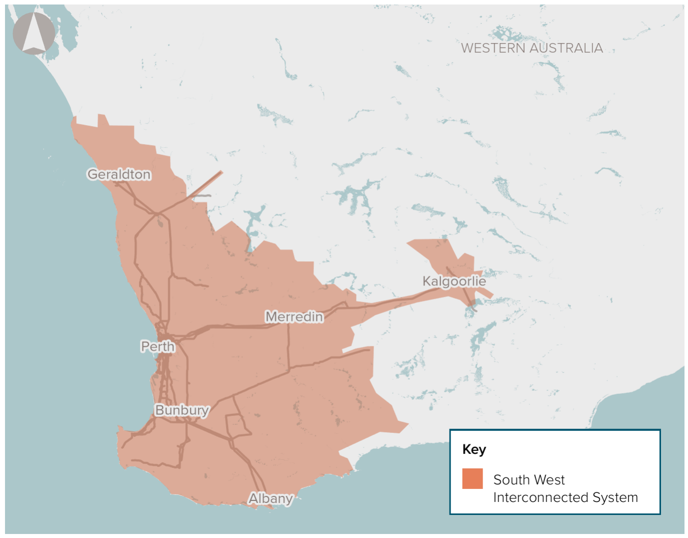
# A Additional Industry Details (for Online Publication)

## A.1 South West Interconnected System

Figure 8: Map of South West Interconnected System




*Source*:
https://www.infrastructureaustralia.gov.au/map/south-west-interconnected-system-transformation

## A.2 Generators in Western Australian Electricity Market

Table 9 lists all generators observed in the market during the data sample that use a technology considered in this paper (namely, coal, combined cycle natural gas (CCGT), open cycle natural gas (OCGT), wind, or solar) and have a non-trivial capacity. Capacity cutoffs are based on a *plant*'s capacity (rather than a generator's) since some plants (e.g., PINJAR) have several small generators. These cutoffs are 20 MW for solar and wind and 100 MW for coal and gas plants. Generators below this threshold are excluded from estimating production costs and investment decisions.[44] This capacity threshold for inclusion in investment decisions serves two purposes. First, not allowing small changes in capacity to alter the state reduces the size of the state space. Including all changes in the set of generators that result from small generators entering or exiting would make the state space intractably large. Second, as described in section B, the generators that enter or exit when a firm adjusts its set of generators are identified using a heuristic of profitability. This heuristic does not take into account capacity. By only focusing on large generators, there is less dispersion in capacities, meaning the heuristic is a better approximation of the true profitability of different plants.

[44]Since small generators are excluded from this analysis, I adjust the total demand for electricity in an interval downward by the amount produced by the generators not included in the analysis when estimating the distribution of wholesale market variables, $F_t^{\boldsymbol{\delta},\mathbf{c},\Xi}$.

Table 9: List of Generators in Data

| Generator | Firm | Technology | Capacity (MW) | Heat Rate (GJ/MWh) | Emissions Rate (kg$CO_2$-eq/MWh) | Entered Year | Exit Year |
|---|---|---|---|---|---|---|---|
| ALBANY_WF1 | ALBGRAS | wind farm | 22 | – | 0.0 | – | – |
| ALINTA_PNJ_U1 | ALINTA | OCGT | 157 | 12.0 | 627.0 | – | – |
| ALINTA_PNJ_U2 | ALINTA | OCGT | 151 | 12.0 | 627.0 | – | – |
| ALINTA_WGP_GT | ALINTA | OCGT | 371 | 11.5 | 601.0 | 2007‡ | – |
| ALINTA_WGP_U2 | ALINTA | OCGT | 210 | 11.5 | 601.0 | 2007‡ | – |
| ALINTA_WWF | ALINTA | wind farm | 88 | – | 0.0 | – | – |
| BADGINGARRA_WF1 | ALINTA | wind farm | 131 | – | 0.0 | 2018 | – |
| BW1_BLUEWATERS_G2 | GRIFFINP | coal | 223 | 9.8 | 908.0 | 2008 | – |
| BW2_BLUEWATERS_G1 | GRIFFINP | coal | 229 | 9.8 | 908.0 | 2008 | – |
| COCKBURN_CCG1 | WPGENER | CCGT | 265 | 9.0 | 470.0 | – | – |
| COLLIE_G1 | WPGENER | coal | 342 | 9.5 | 884.0 | – | – |
| EDWFMAN_WF1 | EDWFMAN | wind farm | 83 | – | 0.0 | – | – |
| GREENOUGH_RIVER_PV1 | GRENOUGH | solar pv | 40 | – | 0.0 | 2018§ | – |
| INVESTEC_COLLGAR_WF1 | COLLGAR | wind farm | 214 | – | 0.0 | 2010 | – |
| KEMERTON_GT11 | WPGENER | OCGT | 173 | 12.2 | 638.0 | – | – |
| KEMERTON_GT12 | WPGENER | OCGT | 173 | 12.2 | 638.0 | – | – |
| KWINANA_G1 | WPGENER | coal* | 116 | 11.7† | 850.0† | – | 2010 |
| KWINANA_G2 | WPGENER | coal* | 117 | 11.7† | 850.0† | – | 2010 |
| KWINANA_G3 | WPGENER | coal* | 113 | 11.7† | 850.0† | – | 2010 |
| KWINANA_G4 | WPGENER | coal* | 117 | 11.7† | 850.0† | – | 2010 |
| KWINANA_G5 | WPGENER | coal* | 189 | 11.7 | 850.0 | – | 2014‡ |
| KWINANA_G6 | WPGENER | coal* | 195 | 11.7 | 850.0 | – | 2014‡ |
| KWINANA_GT2 | WPGENER | OCGT | 109 | 9.3 | 486.0 | 2011 | – |
| KWINANA_GT3 | WPGENER | OCGT | 110 | 9.3 | 486.0 | 2011 | – |
| MERSOLAR_PV1 | SUNAUST22 | solar pv | 100 | – | 0.0 | 2019 | – |
| MUJA_G1 | VINALCO | coal | 58 | 10.4† | 972.5† | – | 2016 |
| MUJA_G2 | VINALCO | coal | 58 | 10.4† | 972.5† | – | 2016 |
| MUJA_G3 | VINALCO | coal | 59 | 10.4† | 972.5† | – | 2016 |
| MUJA_G4 | VINALCO | coal | 60 | 10.4† | 972.5† | – | 2016 |
| MUJA_G5 | WPGENER | coal | 214 | 11.0 | 1 028.0 | – | 2022‡ |
| MUJA_G6 | WPGENER | coal | 207 | 11.0 | 1 028.0 | – | 2022‡ |
| MUJA_G7 | WPGENER | coal | 228 | 9.8 | 917.0 | – | – |
| MUJA_G8 | WPGENER | coal | 226 | 9.8 | 917.0 | – | – |
| MWF_MUMBIDA_WF1 | MUMBIDA | wind farm | 55 | – | 0.0 | 2012 | – |
| NEWGEN_KWINANA_CCG1 | NEWGEN | CCGT | 345 | 7.9 | 759.8 | 2007 | – |
| NEWGEN_NEERABUP_GT1 | NGENEERP | OCGT | 345 | 11.1 | 659.7 | 2008 | – |
| PERTHENERGY_KWINANA_GT1 | WENERGY | OCGT | 122 | 14.1 | 763.0 | 2009 | – |
| PINJAR_GT1 | WPGENER | OCGT | 43 | 13.5 | 706.0 | – | – |
| PINJAR_GT10 | WPGENER | OCGT | 122 | 12.1 | 653.0 | – | – |
| PINJAR_GT11 | WPGENER | OCGT | 138 | 12.0 | 638.0 | – | – |
| PINJAR_GT2 | WPGENER | OCGT | 42 | 13.5 | 706.0 | – | – |
| PINJAR_GT3 | WPGENER | OCGT | 43 | 13.2 | 690.0 | – | – |
| PINJAR_GT4 | WPGENER | OCGT | 43 | 13.2 | 690.0 | – | – |
| PINJAR_GT5 | WPGENER | OCGT | 45 | 13.2 | 690.0 | – | – |
| PINJAR_GT7 | WPGENER | OCGT | 41 | 13.2 | 690.0 | – | – |
| PINJAR_GT9 | WPGENER | OCGT | 128 | 12.1 | 653.0 | – | – |
| PPP_KCP_EG1 | WPGENER | OCGT | 108 | 9.0 | 470.0 | – | 2021 |
| SWCJV_WORSLEY_COGEN_COG1 | WPGENER | OCGT | 128 | 12.0 | 627.0 | – | 2015 |
| WARRADARGE_WF1 | WARADGE | wind farm | 178 | – | 0.0 | 2019 | – |
| YANDIN_WF1 | ALINTA | wind farm | 208 | – | 0.0 | 2019 | – |

Entry and exit years are based on the calendar used by the WEM, which runs from October 1 through September 30 of the next year. If a generator first began producing in January of 2015, therefore, its entry year is 2014 (corresponding to the year beginning in October 2014. An entry year of "–" means the generator entered before the sample period. Firm names are provided using the names reported by AEMO; for the three largest firms, WPGENER is commonly known as "Synergy," ALINTA as "Alinta," and GRIFFINP as "Bluewaters Power." *These generators are capable of using coal, natural gas, or distillate and have historically used all three. During the sample period they mostly used coal (Global Energy Monitor, 2023). They are therefore classified as coal plants. †The data sources used for heat rates and emissions rates did not include data for these generators. The values used are therefore an average of either the other generators within a power plant for which data is available or, lacking that, an average of others with the same technology. ‡These entry/exit years have been adjusted by at most a year so that generators part of the same plant that enter/exit around the same time have the same entry/exit year (since they presumably were part of a single decision by the firm). §GREENOUGH_RIVER_PV1 was first constructed as a 10 MW facility in 2011; however, in 2018 (using the year naming convention described), it was expanded by 30 MW, so this facility is classified as entering in 2018 since that is when most of its capacity was installed.

## A.3 Capacity Costs

Generator cost data comes from two different sources. The first source is a series of reports produced by the U.S. Energy Information Administration (EIA) on capital costs of electricity generators (U.S. Energy Information Administration, 2010, 2013, 2016, 2020). The reports are for the years 2010, 2013, 2016, and 2019. Each report provides capital costs in US$/kW for different generator technologies, including all of those considered in this paper.[45] The second source is the 2012 Australian Energy Technology Assessment (Australian Bureau of Resources and Energy Economics, 2012), which I shall refer to as AETA. While this report only provides a snapshot in time, unlike the series of EIA reports that construct a panel, AETA does helpfully provide cost estimates specific to the South West Interconnected System in Western Australia that I study in this paper.

I use the EIA reports to construct a time series for each technology and AETA to convert the time series based on U.S. estimates to those for the electricity market in Western Australia. In order to construct a complete time series of generator costs over time for Western Australia, I first interpolate the time series provided by the EIA report. For each energy source, I linearly interpolate values in years not covered by an EIA report,[46] providing me with $\hat{C}_{st}^{EIA}$. Next, I convert the interpolated EIA estimates to those for Western Australia. To do so, I assume that Western Australia costs are a source-specific proportion $\alpha_s$ of the EIA costs, common over time. Explicitly, I assume

$$C_{st}^{WA} = \alpha_s C_{st}^{EIA}.$$

Since I have cost estimates for Western Australia in 2012, I can recover $\{\alpha_s\}_s$:

$$\hat{\alpha}_s = \frac{C_{s,2012}^{WA}}{\hat{C}_{s,2012}^{EIA}}.$$

For years past 2019, I assume costs remain the same as those in 2019, i.e. $\hat{C}_{st}^{WA} = \hat{C}_{s,2019}^{WA}$ for all $t > 2019$. Calibrated investment costs $\left\{\hat{C}_{st}^{WA}\right\}_{s,t}$ are summarized in table 4.

# B State Space Details (for Online Publication)

The state space is defined by which generators are in the market and the year (which captures the investment costs, the distribution of wholesale market variables $F_t^{\boldsymbol{\delta},\mathbf{c},\Xi}$, and how many years remain until generator portfolios are locked in). Section 3.3.2 describes at a high

[45] In some cases the technologies provided are more narrowly defined than in this paper. For coal, I use the capital costs of ultra-supercritical coal plants without carbon capture; for wind, onshore wind with a small footprint in coastal regions; and for solar, solar PV with single tracking. (For natural gas plants, the technologies are defined at the same level as used in this paper, CCGT and OCGT.)

[46] The sample covers a years before 2010. For these years, I use the earliest values in the EIA reports.

level how firms' choice sets are constructed. Firm's choice sets are potentially multidimensional, with each dimension corresponding to a different technology (e.g., coal, CCGT, etc.) and whether the technology is expandable or retirable. Expandable dimensions mean new generators of that technology can be built, while retirable dimensions mean that generators can be removed from the portfolio. The generator portfolio component of the state space is the cross product of all firms' possible portfolios. The following paragraphs explain further details about how the state space is constructed, and table 10 provides a complete description of the generator portfolio state space.

**Dimensions** In each firm's component of the state space, there are potentially multiple technologies. I assume that firms are able to include in their portfolios only the technologies I observe them use in the data. This restriction keeps the size of the state space tractable and is consistent with observed firm behavior, as I never observe firms make a substantial investment in a new technology.

For each type of technology, I classify it as expandable (can build new plants) or retirable (can only shut down existing plants). I classify renewables as expandable. Coal plants are classified as retirable; however, I observe in the data one introduction of a new coal plant by Bluewaters Power, so coal is expandable for Bluewaters Power's generator portfolio. Natural gas can be expandable or retirable. Natural gas plants that I observe enter are classified as expandable, while those that I observe being retired are classified as retirable. I classify open cycle gas plants that are not retired in the data as retirable, while combined cycle gas plants are classified as expandable.

**Profitability Heuristic** Along each dimension, firms choose which plants to adjust. Since I assume that all options within a dimension have the same idiosyncratic cost shock (see section 3.3.2), the order in which a firm would adjust along a dimension depends on the profitability of adjusting each plant. This profitability ordering depends on three characteristics of the generators: heat rates, capacities, and emissions rates (when the carbon tax is nonzero). It would be infeasible to determine a profitability ordering taking into account all three of these characteristics. Doing so would require simulating wholesale markets for every possible combination of plants. Instead, I use as a heuristic the order I observe in the data and, where that is uninformative, the heat rate.

Specifically, if I observe in the data a firm retire plant 1 and several years later plant 2, I assume plant 1 will always be retired before plant 2. Since not all plants are adjusted, if I do not observe an adjustment, I order the plants by heat rates. For example, suppose the firm in the example also has plants 3 and 4 of the same technology. If plant 3 has a higher heat rate than plant 4 (meaning a higher marginal cost of production), I assume the firm would

Table 10: Description of Generator Portfolio State Space

| Firm | Technology | Expand / Retire | State | Generators | Total Capacity (MW) |
|---|---|---|---|---|---|
| WPGENER | coal | retire | 5 | ∅ | 0 |
| | | | 4 | COLLIE_G1 | 342 |
| | | | 3 | MUJA_G7, MUJA_G8 | 796 |
| | | | 2 | MUJA_G5, MUJA_G6 | 1 217 |
| | | | 1 | KWINANA_G5, KWINANA_G6 | 1 601 |
| | | | 0 | KWINANA_G1–KWINANA_G4 | 2 064 |
| | gas | expand | 0 | COCKBURN_CCG1 | 265 |
| | | | 1 | KWINANA_GT2, KWINANA_GT3 | 484 |
| | | | 2 | new natural gas (combined cycle) | 884 |
| | gas | retire | 4 | ∅ | 0 |
| | | | 3 | KEMERTON_GT11, KEMERTON_GT12 | 346 |
| | | | 2 | PINJAR_GT1–PINJAR_GT9 | 991 |
| | | | 1 | PPP_KCP_EG1 | 1 100 |
| | | | 0 | SWCJV_WORSLEY_COGEN_COG1 | 1 228 |
| ALINTA | gas | expand | 0 | ALINTA_PNJ_U1, ALINTA_PNJ_U2 | 308 |
| | | | 1 | ALINTA_WGP_GT, ALINTA_WGP_U2 | 889 |
| | | | 2 | new natural gas (combined cycle) | 1 289 |
| | wind | expand | 0 | ALINTA_WWF | 88 |
| | | | 1 | BADGINGARRA_WF1 | 219 |
| | | | 2 | YANDIN_WF1 | 427 |
| | | | 3 | new wind farm | 827 |
| | | | 4 | new wind farm | 1 227 |
| GRIFFINP | coal | expand | 0 | ∅ | 0 |
| | | | 1 | BW2_BLUEWATERS_G1, BW1_BLUEWATERS_G2 | 452 |
| small firms | coal | retire | 1 | ∅ | 0 |
| | | | 0 | MUJA_G1–MUJA_G4 | 236 |
| | gas | expand | 0 | ∅ | 0 |
| | | | 1 | NEWGEN_KWINANA_CCG1 | 345 |
| | | | 2 | NEWGEN_NEERABUP_GT1 | 690 |
| | | | 3 | PERTHENERGY_KWINANA_GT1 | 812 |
| | | | 4 | new natural gas (combined cycle) | 1 212 |
| | | | 5 | new natural gas (combined cycle) | 1 612 |
| | solar | expand | 0 | ∅ | 0 |
| | | | 1 | GREENOUGH_RIVER_PV1 | 40 |
| | | | 2 | MERSOLAR_PV1 | 140 |
| | | | 3 | new solar pv | 540 |
| | | | 4 | new solar pv | 940 |
| | wind | expand | 0 | ALBANY_WF1, EDWFMAN_WF1 | 105 |
| | | | 1 | INVESTEC_COLLGAR_WF1 | 319 |
| | | | 2 | MWF_MUMBIDA_WF1 | 374 |
| | | | 3 | WARRADARGE_WF1 | 552 |
| | | | 4 | new wind farm | 952 |
| | | | 5 | new wind farm | 1 352 |

*Note*: Rows within a firm-technology category describe a state along that dimension. The dimension could include expandable plants (those that firms can choose to build) or retirable plants (those that firms can choose to retire). If the category corresponds to expandable plants, movements along that dimension (building additional plants) are in descending order. If it corresponds to retirable plants, movements along that dimension (retiring additional existing plants) are in ascending order. An implication of this ordering is that for a particular row, the state in that dimension includes all generators listed in that row as well as those above in the same firm-technology category. The final column lists the total capacity in that state for all of the generators within that firm-technology category that are in the market in that state. For example, for WPGENER-coal, state 2, WPGENER has the following coal generators: COLLIE_G1 and MUJA_G5–MUJA_G8, with a total capacity of 1 217 MW. It can choose to move from state 2 to state 3, retiring the generators MUJA_G5–MUJA_G6, leaving it only with MUJA_G7–MUJA_G8 and COLLIE_G1.

retire plant 3 before it would retire plant 4.[47]

**New Generators** The definition of the state space expands beyond just those generators that have been observed in the data. It also includes the possibility of building additional natural gas, solar, and wind generators. I assume that new natural gas plants have a heat rate of 8.0 GJ/MWh and an emissions rate of 450 kg$CO_2$-eq/MWh. All new generators are assumed to have a capacity of 400 MW.

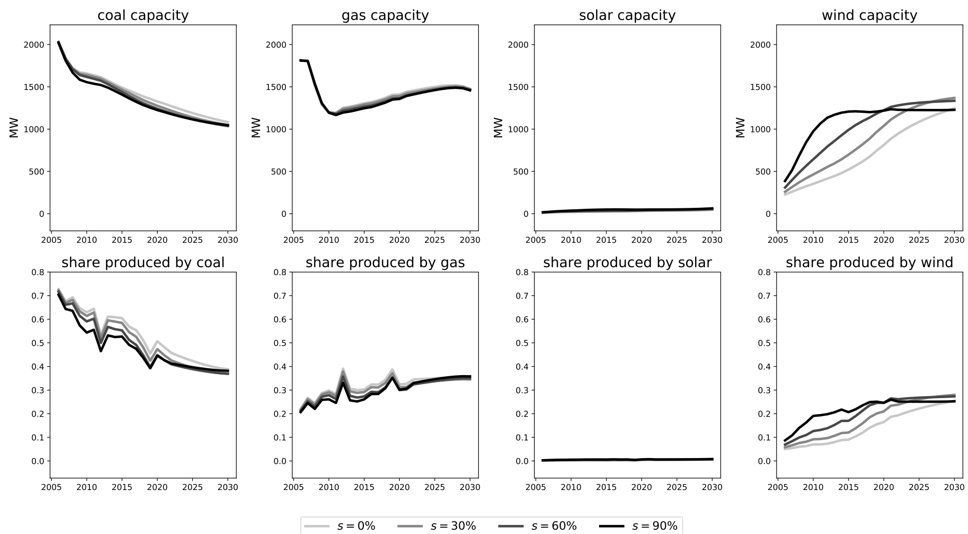
# C Additional Results (for Online Publication)

## C.1 Welfare

Figures 9 and 10 display the impact of renewable subsidies on capacity and production.

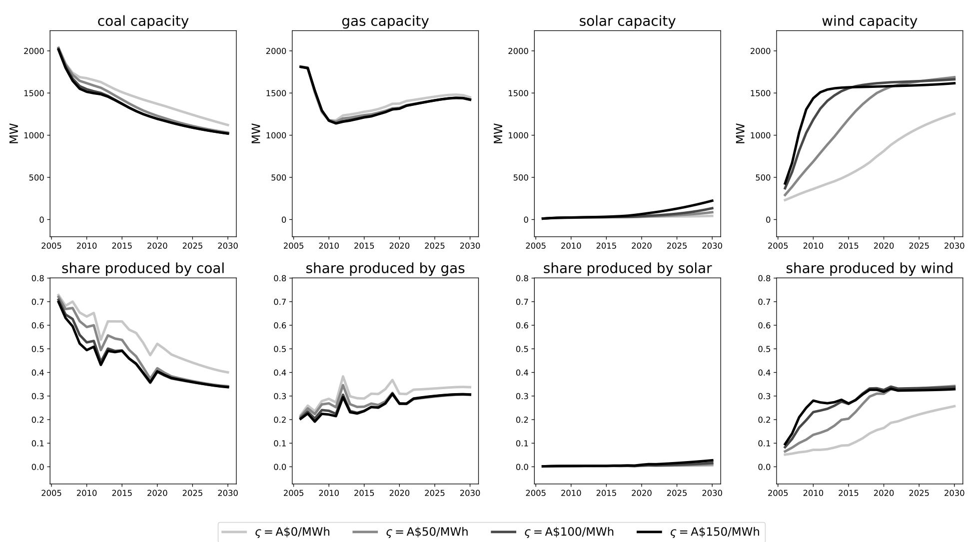
[47] One may be concerned that when a carbon tax is introduced, the emissions rate matters for profitability, potentially changing the profitability ordering. Emissions rates, conditional on a technology, depend primarily on a generator's heat rate, however. Profitability orderings are therefore unlikely to change in response to a carbon tax, meaning we can use the same orderings in the counterfactuals.

Figure 9: Impact of Renewable Investment Subsidy on Investment and Production




*Note*: Depicted in each panel is the *expectation* for a particular energy source summed across all strategic firms and the competitive fringe for a particular value of a renewable investment subsidy.

Figure 10: Impact of Renewable Production Subsidy on Investment and Production




*Note*: Depicted in each panel is the *expectation* for a particular energy source summed across all strategic firms and the competitive fringe for a particular value of a renewable production subsidy.

Table 11: Notation

| Symbol | Description |
|---|---|
| $t$ | indexes years (going from October 1 – September 30) |
| $h$ | indexes wholesale half-hourly intervals, which belong to a particular year $t$ |
| $f$ | indexes all firms |
| $\mathcal{F}$ | set of firms |
| $\mathcal{F}_L$ | set of large firms |
| $\mathcal{F}_S$ | set of small firms |
| $\mathcal{G}_t$ | set of generators in year $t$ |
| $g$ | indexes generators |
| $s(\cdot)$ | returns the technology of a generator |
| $K_g$ | nameplate capacity of generator $g$ (in MW) |
| $hr_g$ | heat rate of generator $g$ (in GJ / MWh) |
| $e_g$ | emissions rate of generator $g$ (in kg $CO_2$-eq / MWh) |
| $\mathcal{Q}_t$ | distribution of demand in year $t$ |
| $\delta_{gh}$ | capacity factor for generator $g$ in interval $h$ |
| $\bar{K}_{gh}$ | available capacity for generator $g$ in interval $h$ (in MW) |
| $c_{gh}$ | production cost for generator $g$ in interval $h$ |
| $p_{sh}^{input}$ | technology-specific input price for technology $s$ in interval $h$ (in A\$ / GJ) |
| $\tau_t$ | carbon tax in year $t$ (in A\$ / kg of $CO_2$-eq) |
| $\varepsilon_{gh}$ | idiosyncratic production cost shock for generator $g$ in interval $h$ |
| $\bar{Q}_h$ | perfectly inelastic demand in interval $h$ |
| $b_{gh}$ | generator $g$'s bid in interval $h$ |
| $\bar{P}_t$ | price cap in year $t$ (in A\$ / MWh) |
| $Q_h(\cdot)$ | demand satisfied in interval $h$ (in MWh) |
| $P_h(\cdot)$ | wholesale market spot price in interval $h$ (in A\$ / MWh) |
| $B_h(\cdot)$ | electricity demand rationed via blackouts in interval $h$ (in MWh) |
| $q_{gh}(\cdot)$ | quantity produced by generator $g$ in interval $h$ (in MWh) |
| $\pi_{fh}(\cdot)$ | wholesale profit function for firm $f$ in interval $h$ (in A\$) |
| $u_{ih}(\cdot)$ | consumer $i$'s indirect utility function in interval $h$ |
| $P_t$ | end-consumer price for electricity in year $t$ (in A\$ / MWh) |
| $\xi_{ih}$ | consumer $i$'s preference parameter for electricity in interval $h$ |
| $\epsilon$ | elasticity of electricity consumption with respect to the end-consumer price |
| $\Xi_h$ | aggregated preference parameters for electricity in interval $h$ |
| $P_t^{avg}$ | quantity-weighted average wholesale price in year $t$ (in A\$ / MWh) |
| $c_{\text{retail}}$ | marginal retail cost of delivering electricity (in A\$ / MWh) |
| $\Pi_{ft}(\cdot)$ | yearly expected profit for firm $f$ in year $t$ (in A\$) |
| $\kappa_t$ | capacity price in year $t$ (in A\$ / MW) |
| $\Upsilon(\cdot)$ | capacity payment (in A\$) |
| $m_s$ | cost of maintaining a MW of capacity of a generator of technology $s$ (in A\$ / MW) |
| $M(\cdot)$ | yearly capacity maintenance cost (in A\$) |
| $T$ | final year in which possible to adjust set of generators |
| $\Omega_t$ | order in which firms can move in year $t$ |
| $X$ | the set of firms that have already moved or are now able to move |
| $\Gamma_f(\cdot)$ | set of possible combinations of generators to which firm $f$ can adjust |
| $C_{st}$ | cost of new generator capacity of technology $s$ in year $t$ (in A\$ / MW) |
| $\eta_{f,\mathcal{G},t}$ | idiosyncratic adjustment cost shock for firm $f$, adjustment decision $\mathcal{G}$, in year $t$ |
| $\beta$ | discount rate (at yearly level) |
| $\sigma_{Yt}^{\Omega}(\cdot)$ | policy function for firms in $Y$ in year $t$ under ordering $\Omega$ |
| $X_f(\cdot)$ | set of firms that have adjusted prior to $f$, and including $f$, under an ordering |