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 storage.

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 involve complete loss of power for some consumers and occur when demand for electricity exceeds the available supply. Though rare, even small increases in blackout frequency can impose large social costs because consumers place high value on uninterrupted electricity.[1] 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.[2] Regulation is necessary to fix several 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.[3] 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 via involuntary blackouts that do not reflect consumers' willingness to pay. This rationing can lead to underinvestment in capacity and overreliance on blackouts if firms do not fully capture the value to consumers of avoiding blackouts due to price caps in the wholesale electricity market. These price caps exist to protect consumers from high prices and limit the exercise of market power, a third market failure. Electricity market regulators have introduced various policies to address these market failures individually, such as environmental incentives (carbon taxes, renewable subsidies, etc.) or subsidies to capacity, 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.

[1] For example, the rolling blackouts in Texas in February 2021, caused primarily by a severe winter storm making a large portion of generation capacity unavailable, were estimated to have resulted in very large damages. Golding *et al.* (2021) use a conservative estimate of $4.3 billion for the cost of these rolling blackouts but cite numbers as high as $130 billion.

[2] 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.

[3] Some papers have found that consumers' demand is very inelastic even if they pay real-time electricity prices (Harding & Sexton, 2017; Fabra *et al.*, 2021).

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 that explicitly models blackouts as a market outcome. 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 relevant technologies in which firms can invest (e.g., coal, gas, wind, etc.), resulting in a high-dimensional state space. Finally, electricity markets can be highly concentrated,[4] 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; Fabra *et al.*, 2011), increasing the likelihood of blackouts, 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 firms' forward-looking and strategic behavior in this high-dimensional, nonstationary environment, while remaining computationally tractable. This tractability allows me to explore a wide range of regulatory tools. My primary results study capacity payments and carbon taxes in a particular electricity market. Capacity payments provide firms with subsidies for maintaining capacity, regardless of energy output. These payments are used in many electricity markets to prevent underinvestment and thereby reduce blackouts.[5] Carbon taxes align private and social costs of emissions and shift production and investment toward cleaner technologies. I evaluate how they interact in combination to affect both blackouts and emissions. Some policy combinations can reduce both. These simultaneous reductions are achieved by using capacity payments to incentivize firms to not retire (and potentially invest in) emissions-intensive but reliable technologies, maintaining reliability, while simultaneously shifting production toward cleaner technologies via a carbon tax.

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

[4] In the U.S., for example, several markets (including MISO, PJM, and the Connecticut and Boston zones of the New England ISO) exhibit concentration levels in which 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).

[5] The need for capacity payments is often motivated by wholesale price caps that are lower than consumers' willingness to pay to consume electricity. Joskow & Tirole (2008) show that in a competitive market capacity payments can be used with low price caps to achieve optimal investment (constrained to lacking real-time prices for all consumers), and Fabra (2018) shows how price caps can be useful when market power is present.

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. In the case of insufficient capacity to meet demand, consumers are randomly rationed via blackouts. 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 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. Its electricity market is self-contained and relies on an energy mix of coal, gas, and renewables. During my sample period, there are only three firms that have substantial market shares, ensuring tractability for the dynamic investment game that I estimate.

Using the estimated parameters, I study a rich set of counterfactual policies. In my main set of counterfactuals, I focus on the interaction of capacity payments and carbon taxes. I additionally consider their interaction with the wholesale price cap, which can reduce price spikes but may also weaken incentives to invest. These policies are highly interconnected. For example, carbon taxes raise prices and shift investment toward renewables, which may require more support from capacity payments or higher price caps to maintain reliability.

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. The cost of reduced emissions falls nearly entirely on consumers and is substantial even if carbon tax revenue is rebated back to consumers. Raising price caps can offset the blackout risk of a carbon tax, but at the expense of higher average prices and potentially greater opportunities for firms to exercise market power when making investment decisions. This leads to lower consumer surplus and in some cases can result in lower product market welfare.

When capacity payments and carbon taxes are used together they can reduce both blackouts and emissions. I find that a capacity payment of 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), roughly the size used in Western Australia, reduces blackouts by 97.1% as well as emissions by 38.6%, relative to a world without either policy.[6] Together they can 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. Intuitively, 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 except during times of scarcity when there is insufficient lower-emissions capacity available.

This framework is well-suited for evaluating the effectiveness of alternative policies. In practice, many electricity markets have used renewable subsidies instead of carbon taxes as a means of reducing carbon emissions. I quantify the impact of renewable investment and production subsidies. These 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, however, that for low levels of emissions reductions 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, because they increase the level of investment, which is inefficiently low due to market power. I also quantify the impact of utility-scale storage, equal in capacity to approximately the average hourly load, on investment and reliability. Renewable intermittency can be mitigated by storage, which allows electricity to be stored during times of renewable abundance and used in times of limited availability. Storage of this size does reduce blackouts; however, in part because it reduces incentives to invest in natural gas, this effect is fairly small. This result suggests the size of storage needed to address the

[6] A capacity payment alone would reduce blackouts by a similar amount but *increase* emissions by 11.1%, while a carbon tax alone would decrease emissions by slightly more (46.5%) but *increase* blackouts by 123.7%.

reliability problem caused by renewable intermittency is quite large.

Finally, I explore the distortion to firms' investments caused by market power. I do so by comparing outcomes to a competitive baseline. Firms substantially underinvest in total capacity when they own multiple generators and thus internalize the impact of reduced capacity on the wholesale market price. All generators being owned by independent firms results in a quantity-weighted average price reduction of A$33/MWh compared to the factual ownership of generators.

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, 2014), the impact of adding renewables to the grid (Gowrisankaran *et al.*, 2016; Jha & Leslie, 2025; 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.* (2025), 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 whether they are necessary 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's 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 9 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, the type of market studied in this paper. 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 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.[7] These technologies are therefore 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).

The WEM allows for demand response participants (referred to in the WEM as "demand side programmes"). These participants offer to reduce their contribution to the total electricity load in exchange for a payment. They provide limited short-run elasticity and a mechanism to reduce demand during peak periods without resorting to involuntary blackouts. They have been used only very infrequently in the WEM; however, their availability helps promote reliability by providing a mechanism other than randomly rationing consumers via blackouts to reduce demand in peak periods.

In addition to revenues from wholesale profits, generators receive capacity payments. These are yearly, recurring payments to electricity-generating firms in proportion to their capacities and are not linked to their actual energy output, effectively a subsidy to capacity. In some markets the size of the subsidy, referred to as the "capacity 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.[8]

The capacity price in the WEM is determined three years in advance by a formula that largely depends on the estimated cost of building an open cycle gas turbine in that year. These payments are financed by electricity retailers and ultimately the electricity end-consumers. These consumers typically pay bills with both a fixed component, which recovers fixed costs

[7]Western Australia also has substantial rooftop solar, as described in Jha & Leslie (2025), 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.

[8]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 the capacity auction is competitive, though there is some evidence of market power exercised in these auctions, see, e.g., Teirilä & Ritz (2019)) if trying to maximize welfare. 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.

like the transmission network and these capacity payments, and a variable one that depends on the amount of electricity consumed. Electricity generating firms receive these payments by committing their capacity to be available and receiving a payment that is the size of their committed capacity times the capacity price. Committed capacity that is unavailable is penalized, so in practice very little renewable capacity is committed, while the vast majority of fossil fuel capacity is.

Appendix A.4 provides additional details on these aspects of Western Australia's electricity market.

2.2 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, demand response program availability and dispatch, 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.[9] 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 and temperature data from the Australian Bureau of Meteorology.

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

[9]Some industrial consumers may be at least partially exposed to spot prices, which could complicate calculating the load in this way. However, market customers' bid quantities in the day ahead market suggest there is little price responsiveness, suggesting this is likely not a major concern. Demand can also be reduced via demand response participants, but this change in demand is observed.

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).[10] For my analysis, I use the variable component, as this is the component that enters consumers' consumption decisions.

Generators AEMO provides the identities of each generator, the technology, and the firm that owns the generator. Coal or gas generators often belong to a larger power plant, so there may be multiple generators in a single power plant, and the plant's capacity can be expanded by adding generators or reduced by retiring generators. Generator capacities, however, are fixed.[11] I take as the date of entry and exit the first and final days of production for the generator, 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 or the generator is not present. In those cases, I use the heat rate estimates of Jha & Leslie (2025). 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 not part of a larger power plant are dropped from the analysis, specifically those with a capacity less than 20 MW for renewables and 100 MW for fossil fuel plants, which collectively have a market share of only 3.49%.

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

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

[11]There are two minor exceptions. At the very beginning of my sample Kemerton Power Station (generators KEMERTON_GT11 and KEMERTON_GT12) upgraded its capacity by 15% by installing a wet compression system that helped it operate more efficiently in Western Australia's hot and dry climate. The second is a solar farm (GREENOUGH_RIVER_PV1) that entered in 2011 as a very small 10 MW generator and in 2018 built many additional solar panels, growing to 40 MW. I treat Kemerton Power Station's capacity as the one after its upgrade (since that holds for nearly all of my sample) and treat GREENOUGH_RIVER_PV1's entry as in 2018.

Table 1: Summary Statistics

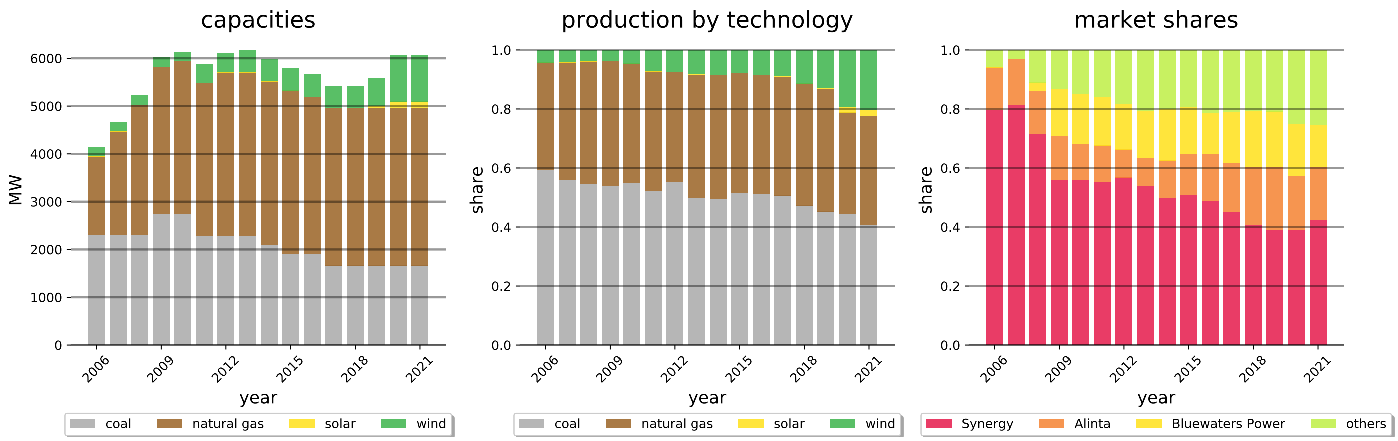
	Mean	Std. Dev.	5th Pctile.	95th Pctile.	Num. Obs.
Half-hourly variables					
price (A$/MWh)	49.51	32.11	21.54	106.99	179 712
total production (MWh)	970.69	199.70	679.75	1 331.95	280 512
load curtailed (MWh)	0.03	2.20	0.00*	340.00*	280 512
demand response dispatched (MWh)	0.01	1.61	0.00*	276.59*	179 712
demand response quantity available (MWh)	296.00	220.22	57.43	560.19	179 712
fraction generated by					
coal (%)	50.99	8.88	35.16	64.62	280 512
natural gas (%)	39.48	8.07	26.36	53.02	280 512
solar (%)	0.37	1.41	0.00	1.94	280 512
wind (%)	9.17	8.28	0.68	26.67	280 512
fraction capacity available					
coal (%)	83.28	34.67	6.62	100.00	3 217 200
natural gas (%)	92.34	24.03	14.40	100.00	5 927 856
solar (%)	13.06	24.40	0.00	81.67	221 040
wind (%)	36.45	29.98	0.00	89.85	1 351 488
Yearly variables					
capacity price (thousand A$/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 (kgCO_2-eq/MWh)	916.47	61.90	850.00	1 028.00	17
natural gas (kgCO_2-eq/MWh)	633.46	82.55	471.60	754.42	23

Note: Values followed by "*" are minimum and maximum values rather than 5th and 95th percentiles. 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 and demand response 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, and the demand response program began on the same day.

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 generators in several coal plants were retired. New investment at the end of the sample has come in the form of renewables, with the construction of new wind farms and—to a much smaller extent—new solar farms.[12] The second subplot depicts production shares over time by technology and more clearly demonstrates the transition to renewables. The share of

[12]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 1: Capacities & Shares over Time



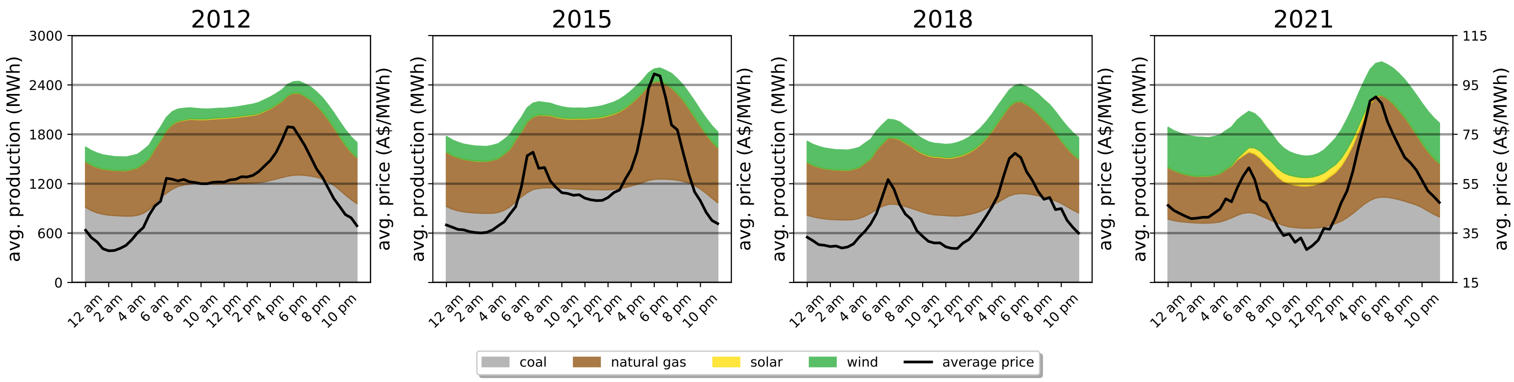
Note: Shares are calculated based on total amount of electricity produced over the year, running from October 1 through September 30 of the following year (consistent with the definition of years used by the WEM for capacity markets). Named firms in the rightmost subplot are those with a market share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

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 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.

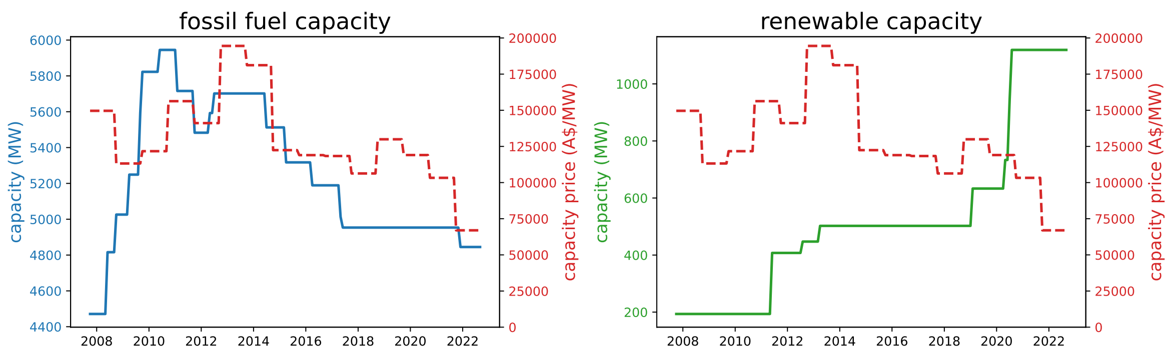
Figure 2: Production Shares throughout the Day and over Time



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 (real-time) markets.

Figure 3 explores the relationship between aggregate capacity (left y-axis) and the capacity price (right y-axis). It is separated by fossil fuels and renewables since fossil fuels receive substantial capacity payments while renewables receive a negligible amount. After an initial ramp up in fossil fuel capacity, aggregate fossil fuel capacity largely follows a similar trajectory as capacity payments. Renewable capacity, meanwhile, is monotonically increasing and does not obviously appear to respond to the capacity price. Table 2 presents results regressing whether a generator is in the market in a given year (i.e., has entered and not retired) on the capacity price. In some specifications, I control for the returns from the wholesale market (using the average wholesale price in a given year) and the costs (using the average fuel costs in that year), as well as a linear time trend in the case of renewables to capture declining renewable investment costs. Fossil fuel generator presence in the market appears to be strongly associated with the capacity price, with an estimated average marginal effect of the capacity price of 18.2 percentage points per A$100 000/MW in the specification that includes wholesale cost and returns controls (specification 4). For renewable generators, meanwhile, the estimated average marginal effect is statistically indistinguishable from zero. These regressions are descriptive and not intended to identify causal effects. They do not capture important features such as forward-looking behavior or multi-generator firm portfolios. In section 3 I explicitly incorporate these features into the structural model. Nevertheless, these regressions help illustrate the variation in capacity prices and generator entry and exit that is leveraged, in part, to estimate the model's parameters.

Figure 3: Capacities & Capacity Prices



Note: The left y-axis (blue/green) of each subplot corresponds to capacity, and the right y-axis (red) corresponds to the capacity price. Fossil fuel capacity is the sum of all coal and gas generators' capacities that have entered the market and not yet exited in each month. Renewable capacity is defined analogously for solar and wind generators.

Table 2: Capacity Price Regressions

	fossil fuels (LPM)	fossil fuels (logit)	fossil fuels (LPM)	fossil fuels (logit)	renew. (LPM)	renew. (logit)	renew. (LPM)	renew. (logit)
cap. price$_t$	0.152	0.155	0.160	0.182	0.090	0.046	0.094	0.047
	(0.034)	(0.031)	(0.038)	(0.033)	(0.050)	(0.064)	(0.047)	(0.064)
avg. price$_t$			-0.000	-0.001			0.001	0.001
			(0.001)	(0.001)			(0.000)	(0.000)
avg. fuel cost$_{gt}$			0.003	0.006				
			(0.003)	(0.004)				
technology f.e.	✓	✓	✓	✓	✓	✓	✓	✓
linear time trend					✓	✓	✓	✓
Num. obs.	640	640	640	640	160	160	160	160

Note: Results obtained by regressing whether a generator is present in the market. Years are capacity years running from October 1 to September 30. Capacity prices are in A\$100 000/MW. Standard errors are clustered by year. Logit specifications report average marginal effects, with logit parameters reported in table 13 in appendix C.1. Average wholesale prices are obtained by averaging half-hourly wholesale prices over the year, and average are fuel costs obtained by taking the average price for coal or natural gas and interacting it with the generator's heat rate. Prices used before July 1, 2012 (the beginning of the balancing market, see note in table 1) are Marginal Cost Administered Prices, which were used prior to the balancing market.

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 are not part of demand response programs 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.[13] 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 $\mathcal{G}_t$. Table 19 at the end of this paper provides a list of all parameters used in this section.

3.1 Short-run: Wholesale Market

Firms enter in a year t a series of half-hourly wholesale markets, each indexed by $h \in \{1, \ldots, H\}$, with a fixed set of generators $\mathcal{G}_t$. At the beginning of the series of intervals, 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 clears the market by assigning production from different generators, reducing load through demand response programs, or implementing rolling blackouts to ration consumers.

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 and across intervals. I refer to δ_{gh} as a generator's capacity factor.[14] Generator $g \in \mathcal{G}_t$ therefore has a maximum production capacity in that half-hour 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 in an hour under ideal circumstances. Available production capacities depend on wind speeds and sun availability for

[13] 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.

[14] Note that sometimes in the energy literature 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, which is much more likely to occur for fossil fuel generators than for zero marginal cost renewables.

renewables, causing them to be able to produce only a fraction of their nameplate capacities. Thermal generators, meanwhile, may also have available capacities less than their nameplate ones due to generator outages.

Production Costs I assume that renewable generators produce at zero marginal cost; however, each gas or coal generator g has a cost in interval h of producing q_{gh}. This cost reflects the purchase of inputs (such as natural gas for a gas generator), the efficiency of the generator, and ramping up generation if the output in the preceding period was low relative to q_{gh}.[15] The cost is given by

$$c_{gh}\left(q_{gh}, q_{g,h-1}\right) = \underbrace{\left(hr_g p^{input}_{s(g),h} + vom_g + \tau e_g\right) q_{gh}}_{\text{constant MC component}} + \underbrace{\frac{r_g}{2}\left(\max\left\{q_{g,h} - q_{g,h-1}, 0\right\}\right)^2}_{\text{ramping component}}, \tag{1}$$

where q_{gh} is the amount (in MWh) generator g produces in interval h, p^{input}_{sh} is the price of the input corresponding to technology s in interval h, vom_g is the variable operations and maintenance cost, and τ is the carbon tax. The second term captures the cost of ramping up a generator if q_{gh} is higher than the previous output, $q_{g,h-1}$, governed by r_g. This cost is quadratic in the increase, which captures that it is costly for a generator to rapidly increase its output.

Demand There are two types of consumers: those on yearly fixed price contracts for whom demand is invariant to the wholesale spot price and those who participate in demand response programs and have contracts to reduce consumption if the wholesale price rises above a certain level.[16]

The total potential demand in interval h is given by $\bar{Q}_h$ MWh of electricity, made up by both types of consumers. It is stochastic and comes from consumers' making consumption decisions. Consumer i in interval h chooses how much electricity to consume, q, based on the end-consumer price they face, P, which for these consumers only varies at an annual frequency since they are on fixed price contracts. Consumer i has an indirect utility in a given interval h of

$$u_{ih}\left(q, P\right) = \frac{\xi_{ih}}{1 - 1/\epsilon} q^{1-1/\epsilon} - Pq, \tag{2}$$

[15] 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.

[16] One could incorporate a third type of consumer that pays the wholesale spot price of electricity. This component of demand would work economically similarly to demand response and be responsive to the wholesale price. In Western Australia demand response capacity is substantially larger than the potential response by consumers exposed to the wholesale price (see footnote 9), so I present the model with simply these two types. Moreover, I treat demand response participants as paying a yearly (rather than hourly) price (but still responsive to the wholesale price through their contract to reduce demand if it rises above a certain level).

where P is the *end-consumer* retail price per unit of electricity consumed (rather than the wholesale price that varies with the interval h). The utility function is scaled such that the marginal utility of money is 1. The parameter ξ_{ih} captures consumer i's value of electricity consumption relative to money and varies across intervals. The parameter ϵ 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[17]

$$q_{ih}^{*}(P) = \left(\frac{\xi_{ih}}{P}\right)^{\epsilon}.$$

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

$$\bar{Q}_h(P) = \int \left(\frac{\xi_{ih}}{P}\right)^{\epsilon} \mathrm{d}i = \frac{\Xi_h}{P^{\epsilon}}, \tag{3}$$

where $\Xi_h = \int \xi_{ih}^{\epsilon}\,\mathrm{d}i$ is an aggregation of consumers' values of electricity in interval h. It varies across intervals, capturing changes in the value of electricity consumption (e.g., people desire more electricity on hot days, during the day vs. at night, etc.).[18]

A subset of consumers, primarily large industrial electricity consumers, belong to the second type and have contracts requiring them to reduce their consumption if the spot price P_h rises above certain levels. Their realized demand is therefore the optimal electricity consumption less any amount they are called on to reduce,

$$q_{ih}^{*}(P) - q_{ih}^{DR}(P_h),$$

where $q_{ih}^{DR}(\cdot)$ represents consumer i's demand response contract. Aggregating across consumers, the aggregate demand response reduction is given by

$$Q_h^{DR}(P_h) = \int q_{ih}^{DR}(P_h)\,\mathrm{d}i.$$

It is (weakly) increasing in P_h.[19]

[17] I am assuming here that consumers respond to the marginal price. While Ito (2014) finds that consumers respond to the average price in California, consumers in Western Australia have very simple bills with a fixed component and a variable one that implies a marginal price that is constant across consumption levels (in contrast to the multiple tiers present in the Californian case).

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

[19] In Western Australia, demand response does not depend directly on the spot price, though effectively it works as if it does. In reality, the system operator instructs demand response participants to curtail demand when it is necessary for system stability when demand is near to exceeding available supply. I therefore treat

The total load for electricity is given by

$$Q_h^{load}(P_t, P_h) = \bar{Q}_h(P_t) - Q_h^{DR}(P_h). \tag{4}$$

Note that, while the total load is responsive to the wholesale spot price due to demand response participants, there is still a region of the demand curve in which the total demand is inelastic. The demand reduction from demand response participants is bounded above; therefore, total load is bounded below, which is why blackouts may be necessary to ration consumers in this region of the demand curve.

Summary of Stochastic Variables 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 these variables and over time, drawn from the following distribution:

$$\boldsymbol{\delta}, \mathbf{p}, \boldsymbol{\Xi} \sim F_t(\mathcal{G}_t). \tag{5}$$

Note that this distribution depends on the generators in the market, $\mathcal{G}_t$ because the first two random variables vary by generator. Also note that this distribution is allowed to vary by year, which captures trends in input prices and changes in demand (captured by $\boldsymbol{\Xi}$) due to residential solar panel adoption, changes in population, electric vehicle adoption, etc.

3.1.2 Market Clearing

Firms submit supply function bids $\mathbf{c}_g^b(\cdot)$ for each of their generators to generate $\mathbf{q}_g$. This bid function maps half-hourly quantities requested by the grid operator to a bid cost for each half-hour interval i.e., $\mathbf{c}_g^b \colon \mathbb{R}^H \to \mathbb{R}^H$. Note that $\mathbf{c}_g^b(\cdot)$ depends on the entire vector of quantities over $\{1, \ldots, H\}$ due to ramping costs, which imply that the cost of production depends on the quantity produced in the previous interval.

The grid operator has three ways it can clear the market so that there is sufficient electricity supplied to meet demand: procuring electricity from generators, reducing demand through demand response participants, and reducing demand by randomly rationing consumers via blackouts. The operator's problem, which I assume is solved with perfect foresight, is therefore

demand from demand response participants as

$$Q_h^{DR}(P_h) = \begin{cases} 0 & \text{if } P_h < \bar{P}_t \\ \bar{Q}_h^{DR} & \text{if } P_h = \bar{P}_t, \end{cases}$$

where $\bar{Q}_h^{DR}$ is the maximum reduction from demand response participants and $\bar{P}_t$ is the price cap. See Appendix A for more details.

given by

$$
\begin{aligned}
\min_{\mathbf{q},\mathbf{q}_{DR},\mathbf{b}} \quad & \left\{ \sum_{h=1}^{H} \left[\sum_{g\in\mathcal{G}_t} c_{gh}^{b}(\mathbf{q}_g) + c_h^{DR}(q_{DR,h}) + c_t^{ration}(b_h) \right] \right\} \\
\text{s.t.} \quad & \sum_{g\in\mathcal{G}_t} q_{gh} \geq \bar{Q}_h(P_t) - q_{DR,h} - b_h \quad \forall h \\
& 0 \leq q_{gh} \leq 0.5\bar{K}_{gh} \quad \forall g \in \mathcal{G}_t, \forall h \\
& 0 \leq q_{DR,h} \leq \bar{Q}_h^{DR} \quad \forall h \\
& 0 \leq b_h \quad \forall h
\end{aligned}
\tag{6}
$$

where $q_{DR,h}$ is the total quantity of demand reduced via demand response participants, $\bar{Q}_h^{DR}$ is the maximum amount that can be reduced via these participants, a reduction of $q_{DR,h}$ comes at a cost

$$
c_h^{DR}\left(q_{DR,h}\right) = \int_0^{q_{DR,h}} Q_h^{DR^{-1}}\left(q\right) \mathrm{d}q,
$$

and b_h is the quantity of demand reduced via blackouts, which occurs at a cost per MWh equal to the price cap $\bar{P}_t$,[20]

$$
c_t^{ration}\left(b_h\right) = \bar{P}_t b_h.
$$

The wholesale market clearing price is the marginal cost of the marginal participant, which is the Lagrange multiplier with respect to the constraint that supply is weakly greater than demand, defined by

$$
P_h = \frac{\partial \text{minimum system total cost}}{\partial \bar{Q}_h}. \tag{7}
$$

Blackouts There are two reasons the wholesale market operations characterized by equation 6 may result in consumers being rationed via blackouts. The first is that there may not be sufficient available generator capacity to meet the realization of demand—even after accounting for demand response participants. The second is that if a generator's bid supply function is above the price cap, the operator will choose to ration consumers at the price cap rather than use a generator at a cost above the price cap.

In either case, the operator will ration consumers via blackouts. These blackouts involve shutting off power to geographic areas, causing everyone within that area to cease to consume electricity from the grid for some period of time, referred to as rolling blackouts. The amount that the operator rations is given by b_h. The grid operator cannot ration by consumers' willingness to pay and so are rationed randomly. That is, for a rolling blackout, with probability $\frac{b_h}{Q_h}$ consumer i consumes 0 and with probability $1 - \frac{b_h}{Q_h}$ they consume $q_{ih}^{*}\left(P\right)$.

[20] Note that this is the cost to the system operator, *not* the social cost of a blackout. This distinction has important welfare implications if the price cap is lower than the amount end-consumers value consuming electricity.

When rationing is necessary, the risk of a systemic blackout, in which the entire grid loses power, grows.[21] When this occurs, the size of the blackout is $\bar{Q}_h$, meaning that no one consumes electricity, and $q_{gh} = 0$ for all generators, meaning that firms receive no profits. Since this is a very rare event, there is little historical evidence to parametrize the exact probability of a systemic blackout, but the power systems engineering literature suggests it is increasing in the size of the necessary rationing (Carreras *et al.*, 2004; Hines *et al.*, 2010). I therefore allow for the possibility of a systemic blackout, with the probability of it occurring equal to the ratio of the size of necessary rationing to demand, $b_h/\bar{Q}_h$. This implies that a small imbalance is unlikely to result in a systemic blackout, while a substantial one has a higher likelihood. The expected size of total rationing, given b_h and $\bar{Q}_h$, is therefore[22]

$$B_h\left(b_h, \bar{Q}_h\right) = \underbrace{\frac{b_h}{\bar{Q}_h}}_{\substack{\text{prob.}\\ \text{systemic}}} \cdot \bar{Q}_h + \underbrace{\left(1 - \frac{b_h}{\bar{Q}_h}\right)}_{\substack{\text{prob.}\\ \text{rolling}}} \cdot b_h. \tag{8}$$

Firm Behavior The amount of electricity that each firm produces depends on its bid costs and those of other firms, as well as the realization of demand and capacity availability. The amount produced by each generator g in an interval h, q_{gh}, is characterized by the solution to the operator's problem (equation 6). The expected profit that each firm receives is therefore given by[23]

$$\pi_{fh}\left(\mathbf{c}^b\right) = \left(1 - \frac{b_h}{\bar{Q}_h}\right) \sum_{g \in \mathcal{G}_{ft}} \left[q_{gh}\left(\mathbf{c}^b\right) P_h\left(\mathbf{c}^b\right) - c_{gh}\left(q_{gh}\left(\mathbf{c}^b\right), q_{g,h-1}\left(\mathbf{c}^b\right)\right)\right]. \tag{9}$$

I assume that firms set their bid costs equal to their true costs, given in equation 1. The assumption of competitive behavior has been commonly used in other papers with models of wholesale electricity markets (Abito *et al.*, 2022; Gowrisankaran *et al.*, 2025). This assumption is in part motivated by forward contracting, the signing of advanced contracts between electricity generating firms and retailers, which 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

[21] An electricity grid must maintain a stable frequency. When demand is greater than supply, the frequency declines, and if it drops too far below some baseline, generators shut off, which can cause cascading failures and a widespread blackout.

[22] Note that I have assumed that a systemic blackout lasts for only one period and do not model the length of time it may take time to restart after a systemic blackout.

[23] I ignore ancillary services (including frequency regulation, spinning reserves, etc.) and assume all revenues come from wholesale energy markets and capacity payments. In my sample period, the share of generators' revenue that comes from ancillary services is just 3.6%.

fraction of electricity is procured via forward contracting. For example, 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). These numbers limited incentives to bid above marginal costs.

An additional 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 utility regulator 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 during a period between 2016 and 2017 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 the long run in their ability to pursue above-marginal cost bidding.[24] 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.

Bid supply functions are therefore given by

$$c_{gh}^{b}\left(q_{gh}, q_{g,h-1}\right) = c_{gh}\left(q_{gh}, q_{g,h-1}\right) \quad \forall q_{g,h}, q_{g,h-1}. \tag{10}$$

3.2 Medium-run: Retail Price Equilibrium

The wholesale market clearing conditions defined by equations 6 and 10 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

[24] Jha & Leslie (2025) document the exercise of market power for gas generators in Western Australia in the period 2014–2018, which overlaps with the period in which Synergy was found to have overstated its costs. I ultimately estimate production costs in section 4, and estimates are robust to dropping the period during which Synergy was founded to have exercised market power, see appendix C.1. 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).

to changes in the distribution of prices.

Equilibrium Consumers buy electricity from intermediaries. These intermediaries charge end-consumers both a fixed component to recover fixed costs (e.g., building the transmission network, paying for capacity payments, etc.) and a variable component based on the amount of electricity consumed. I assume that these intermediaries set the variable component retail price equal to the marginal cost of providing electricity over the year, 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

$$P_t\left(P_t^{avg}\right) = P_t^{avg} + c_{\text{retail}}, \tag{11}$$

where P_t^{avg} is the quantity-weighted average wholesale price and c_{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

$$P_t^{avg} = \frac{\mathbb{E}\left[Q_h P_h\right]}{\mathbb{E}\left[Q_h\right]}. \tag{12}$$

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

$$P_t = \frac{\mathbb{E}\left[Q_h\left(\bar{Q}_h\left(P_t\right), \mathcal{G}_t\right) P_h\left(\bar{Q}_h\left(P_t\right), \mathcal{G}_t\right)\right]}{\mathbb{E}\left[Q_h\left(\bar{Q}_h\left(P_t\right), \mathcal{G}_t\right)\right]} + c_{\text{retail}}, \tag{13}$$

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

We can define the function mapping the set of generators to the retail price, $P_t \colon \Gamma \to \mathbb{R}$, where Γ 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

$$\pi_{fh}\left(\mathcal{G}_t\right) = \pi_{fh}\left(\mathbf{c}^b\left(\mathcal{G}_t\right), \bar{Q}_h\left(P_{t(h)}\left(\mathcal{G}_t\right)\right)\right) \quad \forall f. \tag{14}$$

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 making discrete choices over 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. Many models of oligopolistic industry dynamics consist of firms making simultaneous moves and facing an infinite horizon (e.g., Ericson & Pakes (1995)). I depart from this approach and model investment decisions in a nonstationary, randomly-ordered sequential moves dynamic game with lock-in. In each period, firms sequentially make (dis-)investment decisions, and the order of these moves is random and independent across periods. 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 the rest of time, but that final period stage 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 disk drive industry and features one firm randomly selected to move in each period with a continuation value after a particular end date of 0.

These modeling choices capture firms' dynamic and strategic incentives and are well-suited for considering investment in electricity generators. With sequential moves and a lock-in date that effectively creates a finite horizon from the perspective of investment, the game yields a unique equilibrium that easily and flexibly incorporates nonstationarity. This allows me to incorporate rapidly declining costs of building new renewable generators, which is a first-order concern for modeling investment, and also allows me to simulate nonstationary counterfactual policies (e.g., environmental policies that go into effect only after some date).[25] The game can be solved via backward induction, which makes equilibrium computation straightforward. This computational tractability allows me to consider a rich set of possible policies in order to determine optimal environmental and reliability policy, which would not be feasible in a setting of simultaneous moves and an infinite horizon in which multiple equilibria can arise and equilibrium computation is difficult. In addition to these computational advantages, sequential moves within period is likely to be a better description of reality than one of simultaneous moves because investment decisions are typically made with knowledge of recent actions by competitors who have already made investment plans.[26]

[25] Other sources of nonstationarity 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) as well as coal and gas prices.

[26] Whether moves are sequential or simultaneous may not matter much, as Doraszelski & Judd (2019) find that in a quality ladder model they consider, the equilibria of dynamic games with random, sequential moves

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 14, and is defined as

$$\Pi_{ft}\left(\mathcal{G}_t\right) = \mathbb{E}_{\boldsymbol{\delta},\mathbf{p},\Xi}\left[\sum_h \pi_{fh}\left(\mathcal{G}_t\right)\right] \qquad \forall f. \tag{15}$$

This sums over expected profits from the wholesale market over the year. The expectation is taken over available capacities, input prices, 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.[27] I model these payments in a simple way based on the rules guiding the electricity market in Western Australia. The grid operator chooses a capacity credit price κ_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).[28] Over the year t, a firm f receives a payment $\Upsilon(\cdot)$ based on its set of generators and the capacity credit price. Explicitly,

$$\Upsilon\left(\mathcal{G}_{ft};\kappa_t\right) = \sum_{g\in\mathcal{G}_{ft}} \kappa_t K_g \mathbb{1}\left\{s\left(g\right) \in \left\{\text{coal}, \text{CCGT}, \text{OCGT}\right\}\right\}. \tag{16}$$

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

$$M\left(\mathcal{G}_{ft}\right) = \sum_{g\in\mathcal{G}_{ft}} m_{s(g)} K_g. \tag{17}$$

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

are "practically indistinguishable" from those of simultaneous moves (albeit in an infinite horizon setting rather than one with lock-in).

[27] 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.

[28] 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 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.

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 Ω_t. Firms then sequentially, according to the ordering Ω_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.[29] 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.[30]

Consider a firm's 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 $X \backslash \{f\}$ 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 $\mathcal{F} \backslash X$ still have yet to adjust. This function is given formally below, and a description of the function is given afterward.

$$
\begin{aligned}
V_{ft}^{X}\left(\mathcal{G}_f;\mathcal{G}_{-f}\right) = \quad \max_{\mathcal{G}_f' \in \Gamma_f(\mathcal{G})} \Big\{ \mathbb{E}_{\boldsymbol{\eta}_{\mathcal{F}\backslash X}, \Omega_t | X} \Big[& \Pi_{ft}\left(\mathcal{G}_f'; \mathcal{G}_{X\backslash\{f\}}, \sigma_{\mathcal{F}\backslash X,t}^{\Omega_t}\left(\mathcal{G}_f', \mathcal{G}_{-f}, \boldsymbol{\eta}_{\mathcal{F}\backslash X}\right)\right) \\
& + \Upsilon\left(\mathcal{G}_f'; \kappa_t\right) \\
& - M\left(\mathcal{G}_f'\right) \\
& - \textstyle\sum_{g \in \mathcal{G}_f'} C_{s(g),t} K_g \mathbb{1}\left\{g \notin \mathcal{G}_f\right\} \\
& + \eta_{f,\mathcal{G}_f',t} \\
& + \beta W_{f,t+1}\left(\mathcal{G}_f'; \mathcal{G}_{X\backslash\{f\}}, \sigma_{\mathcal{F}\backslash X,t}^{\Omega_t}\left(\mathcal{G}_f', \mathcal{G}_{-f}, \boldsymbol{\eta}_{\mathcal{F}\backslash X}\right)\right) \Big] \Big\}.
\end{aligned}
\tag{18}
$$

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

[29] 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).

[30] 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.

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 $\sigma^{\Omega_t}_{\mathcal{F}\setminus X,t}\left(\mathcal{G}'_f, \mathcal{G}_{-f}, \boldsymbol{\eta}_{\mathcal{F}\setminus X}\right)$. 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

$$W_{ft}\left(\mathcal{G}_f; \mathcal{G}_{-f}\right) = \mathbb{E}_{\boldsymbol{\eta},\Omega_t}\left[V^{X_f(\Omega_t)}_{ft}\left(\mathcal{G}_f; \sigma^{\Omega_t}_{X_f(\Omega_t)\setminus\{f\},t}\left(\mathcal{G}, \boldsymbol{\eta}_{X_f(\Omega_t)\setminus\{f\}}\right), \mathcal{G}_{\mathcal{F}\setminus X_f(\Omega_t)}\right)\right], \tag{19}$$

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

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

where ω_{nt} is the nth element of Ω_t. This expected value function is the expectation of the value function in equation 18 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.[31] 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.[32]

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

[32] 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,

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. Therefore, the value in year $T+1$ is given by

$$W_{f,T+1}\left(\mathcal{G}_f; \mathcal{G}_{-f}\right) = \sum_{t=T+1}^{\infty} \beta^{t-T-1} \Big(\Pi_{ft}\left(\mathcal{G}_f; \mathcal{G}_{-f}\right) + \Upsilon\left(\mathcal{G}_f; \kappa_t\right) - M\left(\mathcal{G}_f\right) \Big). \tag{20}$$

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

Choice Set Firms can adjust their portfolio of generators only by retiring existing units or building new ones, consistent with how generator portfolios evolve in practice.[33] A firm f has, for each technology s, a portfolio of potential generators $\bar{\mathcal{G}}_{fs}$, of which it operates a subset at time t, denoted $\mathcal{G}_{fst} \subseteq \bar{\mathcal{G}}_{fs}$. The set of potential generators includes all observed generators as well as unobserved ones that could be built. Modeling choices at the level of individual generators allows me to account for within-technology generator heterogeneity like the fact that older generators tend to be less efficient, which is crucial for capturing how policies like carbon taxes affect firms with legacy assets.

Allowing firm f in every period to freely choose *any* subset of generators, i.e.,

$$\bigtimes_{s \in \mathcal{S}} \mathcal{P}\left(\bar{\mathcal{G}}_{fs}\right),$$

where $\mathcal{P}(A)$ is the power set of set A, would result in an intractably large choice set. I therefore impose three restrictions based on how firms adjust generator portfolios in the data. First, generators built or retired together in the data are grouped and treated as a single decision unit. For example, Bluewaters Power built two generators at the same time for their Bluewaters Power Station, and I restrict these generators to be built together. Groupings are provided in Appendix B.1. Second, I restrict a firm to either retire or build generators from *one* grouping per technology at a time. This is motivated by the fact that in practice firms do not build or retire multiple power plants of different technologies at a time.[34] Finally, I

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.

[33] In principle, it is possible to make changes to a generator's nameplate capacity, but in practice this is costly and very rarely done, with almost all adjustments happening via generator entry or exit.

[34] Being able to make adjustments to one plant for each technology may lengthen the amount of time it takes

restrict firms to only operate technologies that they use in the data, so each firm f has a set of technologies $\mathcal{S}_f$.

I assume that all of firm f's generators of a given technology have the same adjustment cost shock conditional on the decision to build or retire (e.g., $\eta_{f,\text{retire coal plant 1},t} = \eta_{f,\text{retire coal plant 2},t}$). This reflects common idiosyncratic costs (e.g., land, labor) across generators belonging to the same firm and technology. This further simplifies the choice set. Under this assumption, firms retire the least profitable or build the most profitable generator within a technology. Profitability primarily depends on a generator's heat rate, which I use, along with observed decisions, as a heuristic to identify the most/least profitable generator grouping, detailed in Appendix B.1.

The choice set for a firm f, given by $\Gamma_f(\mathcal{G})$ in equation 18, is therefore defined as

$$\Gamma_f(\mathcal{G}) = \bigtimes_{s \in \mathcal{S}_f} \Gamma_{fs}(\mathcal{G}_{fs}), \tag{21}$$

where

$$\Gamma_{fs}(\mathcal{G}_{fs}) = \Big\{ \underbrace{\mathcal{G}_{fs} \setminus \mathcal{G}_{fs}^{\text{retire}}(\mathcal{G}_{fs})}_{\text{retire generators}}, \underbrace{\mathcal{G}_{fs}}_{\text{no adjustment}}, \underbrace{\mathcal{G}_{fs} \cup \mathcal{G}_{fs}^{\text{build}}(\mathcal{G}_{fs})}_{\text{build generators}} \Big\}, \tag{22}$$

and $\mathcal{G}_{fs}^{\text{retire}}(\mathcal{G}_{fs})$ is the grouping of generators that would be retired from set $\mathcal{G}_{fs}$ if a firm chose to retire generators, and $\mathcal{G}_{fs}^{\text{build}}(\mathcal{G}_{fs})$ is the grouping of generators that would be built based on the current set $\mathcal{G}_{fs}$ if a firm chose to build new generators.

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 15), which I use in a second stage to estimate the parameters governing firms' investment decisions, which include the sunk costs of investment and fixed maintenance costs. I specify as the large firms those that in the data 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 power plant, and are classified as small firms that can

for a firm to reach its optimal set of generators, but adjustments to generation technologies occur over fairly long time horizons in practice. It is never the case in my data that a firm makes an adjustment to more than one plant of a given technology in a single year.

only operate at most their one plant.[35]

4.1 Wholesale Market Estimation

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

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 so that the fraction of capacity that is used in a given interval is equal to the fraction that could be used.[36]

Demand We can recover electricity consumption valuations Ξ_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 *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 3 provides a possible method of estimating the elasticity ϵ. Taking logs of both sides yields

$$\log\left(\bar{Q}_h\right) = -\epsilon \log\left(P_{t(h)}\right) + \log\left(\Xi_h\right),$$

which would be easily estimable using OLS if Ξ_h and P_t were independent. End-consumer prices reflect demand, however, meaning that estimating ϵ in this way would lead to a biased result. Rather than estimating ϵ 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

[35] I also allow for additional small firms not observed in the data, see appendix B.1.

[36] 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 very small capacity (it would eventually expand, see notes in table 11), so for years prior to 2011, I use solar capacity factor realizations in 2011.

use the period surrounding this change (one month before and one month after). To take into account that there are long-term trends in Ξ_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.[37] 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 3 provides the estimation results as well as more details.

Using this estimate for the elasticity, $\hat{\epsilon}$, we can recover Ξ_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_{retail}. I calibrate c_{retail} by choosing the value that makes the sequence $\{P_t\}_t$ predicted by equation 11 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, variable O&M and ramping costs are not. I assume that marginal O&M costs are the same across technology (i.e., $vom_g = vom_s \, \forall g \in \mathcal{G}_s$) and that marginal ramping costs are inversely proportional to half-hourly capacity within technology (i.e., $r_g = \frac{r_s}{0.5K_g} \, \forall g \in \mathcal{G}_s$). This latter assumption captures that it is cheaper for a large generator to ramp up x MWh from the previous interval than a small one for which it would constitute a higher fraction of its capacity.[38]

[37] Some industrial consumers may be at least partially exposed to spot prices and may reduce load at high prices, although as noted in footnote 9, this effect is likely to be small. Additionally, demand response participants may reduce their contribution to the load in unstable periods, which correspond to times of high prices. Therefore, as a robustness check, I include a specification that drops observations h in which $P_h >$ A\$150/MWh.

[38] This specification imposes a relationship between ramping costs and capacity that is consistent with that found in Gowrisankaran *et al.* (2025) (following Borrero *et al.* (2025)), which estimates ramping costs (with a different specification) in a nonparametric way with respect to both capacity and the size of ramping. They find that the cost of going from 0 to maximum production is strongly increasing in capacity, as is to a lesser degree the cost of ramping by half of capacity. Squaring the ramping in equation 1 imposes that costs of ramping from 0 to maximum production is increasing in capacity, as is by half to a lesser degree. Moreover, imposing $r_g = r_{s(g)}/(0.5K_g)$ makes the relationship between capacity and the total cost of ramping (as a fraction of capacity) linear in the generator's capacity. Without this scaling by the inverse of capacity, the relationship would be strongly convex. This would be at odds with the patterns found in Gowrisankaran *et al.* (2025),

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. The moments that I use to estimate the unobserved costs correspond to the fraction of production from each technology, the average positive rate of increase in generator production for each technology, and the distribution of market clearing wholesale prices. Intuitively, the fraction of production coming from each technology helps to identify relative differences in production costs: high average cost technologies should have smaller average production shares, all else equal. The average positive rate of increase helps to identify ramping costs, as technologies with high ramping costs will adjust production levels more slowly all else equal than those with low ramping costs. Finally, the price distribution helps to identify the level of costs.

I obtain moments by taking draws of sequences of demand $\bar{Q}_h$, capacity factors $\boldsymbol{\delta}$, and input prices $\mathbf{p}$ from the empirical distribution and simulating under candidate parameters the resulting wholesale market equilibria, characterized by equations 6 and 10.[39] The costs for intermittent renewables are assumed to be zero (i.e., $c_{gh} = 0$ for solar and wind). Table 4 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 β. 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

which finds a relationship closer to linear.

[39] Due to the presence of ramping costs, correlation in these variables over time matters for wholesale operations. I therefore take draws of 55 consecutive intervals from the joint empirical distribution, solve for wholesale operations, and drop the final five intervals (since this process imposes an artificial finite horizon). For initial condition production levels (determining ramping costs in the first period), I take production levels in the interval before the first in the drawn sample.

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 in which a portfolio can be adjusted or remain the same, and a single market, for a total sample size of 119), making the precision of the estimates a first order concern. A two-step conditional choice probability estimator (e.g., Bajari *et al.* (2007); Pakes *et al.* (2007); Aguirregabiria & Mira (2007); Pesendorfer & Schmidt-Dengler (2008)) would be infeasible in this setting, as it 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.[40] 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.[41] If it does not invest in a source despite it having a positive return, this similarly implies it is costly to hold the capacity. 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

[40] 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; National Renewable Energy Laboratory, 2023), 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.

[41] 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.

of firms in that year Ω_t is given by

$$\mathcal{L}_{f,t}^{\Omega_t}(\boldsymbol{\theta}) = \prod_{\mathcal{G}' \in \Gamma_f(\mathcal{G}_{t-1})} \Pr\left(\mathcal{G}' = \mathcal{G}_{f,t} \mid \mathcal{G}_{f,t-1}, \mathcal{G}_{X_f(\Omega_t)\setminus\{f\},t}, \mathcal{G}_{\mathcal{F}\setminus X_f(\Omega_t),t-1}, t, \Omega_t\right)^{\mathbb{1}\{\mathcal{G}'=\mathcal{G}_{f,t}\}}. \quad (23)$$

Since the data do not fully reveal the ordering Ω_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

$$\hat{\boldsymbol{\theta}}(\mathcal{G}) = \arg\max_{\theta\in\Theta} \left\{ \sum_{t=1}^{T_{obs}} \sum_{f\in\mathcal{F}} \log\left(\sum_{\Omega_t} \Pr(\Omega_t)\, \mathcal{L}_{f,t}^{\Omega_t}(\boldsymbol{\theta}) \right) \right\}, \quad (24)$$

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 $\boldsymbol{\Pi}_t(\mathcal{G})$ 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 candidate $\boldsymbol{\theta}$. This fact is important for the estimator's computational tractability since the size of the state space is very large.[42] Simulating yearly expected profits involves taking multiday blocks of the stochastic wholesale market variables (since they are correlated over time) and solving for equilibrium profits characterized by equation 14 across many blocks, nested in a fixed point due to the response of demand to average wholesale prices. Details are provided in Appendix B.2.

5 Results

Demand Elasticity Table 3 presents estimates of the demand elasticity. The specifications correspond to the consecutive inclusion of controls. Specifications 1 through 3 correspond to consecutively adding year and month fixed effects, which are used to control for across year and across month differences in demand and are necessary for the identification strategy. Specifications 4 and 5 add additional controls not necessary for the identification strategy but help increase the precision of the estimates using time-of-day dummies and temperature. Specification 6 serves as a robustness exercise, dropping observations with wholesale prices above A$150/MWh, as there may be some elasticity of demand to the wholesale spot price in this region. Specification 5 and 6 are virtually the same, so in later stages I use the estimate in specification 5, which implies an elasticity of -0.111, which is fairly similar to the value of -0.09 found in Deryugina *et al.* (2020) over a six-month horizon of adjustment using data for

[42] The size of the possible combinations of generators is 972 000, and the number of years is 30, for a total size of the state space of 29 160 000.

Illinois.

Table 3: Demand Elasticity Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
Estimates						
$\hat{\epsilon}$	-0.064	0.241	0.094	0.094	0.111	0.117
	(0.024)	(0.097)	(0.101)	(0.047)	(0.047)	(0.047)
Controls						
constant	✓	✓	✓	✓	✓	✓
year effects		✓	✓	✓	✓	✓
month effects			✓	✓	✓	✓
half-hour dummies				✓	✓	✓
temperature					✓	✓
drop high P_h						✓
Num. obs.	12 240	12 240	12 240	12 240	12 225	12 083

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 Ξ_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. Temperature controls include heating degrees ($\max\{\text{temp}_h - 18°\text{C}, 0\}$) and cooling degrees ($\max\{18°\text{C} - \text{temp}_h, 0\}$).

Production Costs Table 4 presents estimates of the variable operations and maintenance cost and ramping cost for each technology as well as a comparison of selected moments from the data and in the simulated equilibria under the parameter estimates. Moments from the simulations under the estimated parameters suggest the model is broadly able to capture the distribution in wholesale market prices, the fraction produced by different technologies, and the degree of ramping by each technology. While the estimated marginal variable O&M costs for OCGT generators is negative, it is statistically indistinguishable from zero, suggesting production costs (apart from ramping, which is also nearly zero) are fully captured by the cost of natural gas inputs. CCGT and especially coal generators, meanwhile, have positive variable O&M costs. Australian regulator reports (e.g., Australian Bureau of Resources and Energy Economics (2012)) suggest variable O&M costs on the scale of a few dollars. While my estimate for variable O&M costs for coal is higher, it is in line with estimates in Gowrisankaran *et al.* (2025). Ramping costs are estimated to be highest for coal and CCGT generators and negligible for OCGT generators, which are designed for flexible peaking operations. My estimate of coal's ramping costs imply it would cost a 400 MW generator approximately A$350 000 to ramp up from zero production to full capacity. This is similar to the estimate for this class of generator in Gowrisankaran *et al.* (2025) (although mine is based on a continuous rather than discrete specification of ramping).

Table 4: Production Cost Estimates

	Coal	OCGT	CCGT
Estimates			
$\widehat{vom}_s$	24.857	-0.477	6.826
	(0.574)	(0.483)	(0.734)
$\hat{r}_s$	3 524.6	114.4	4 004.8
	(2 426.9)	(516.3)	(2 070.1)
Selected Moments		Data	Simulation
avg. price		A$49.51	A$47.73
fraction produced by			
Coal		47.5%	47.9%
OCGT		27.1%	27.0%
CCGT		13.1%	13.2%
avg. increase cap. util. for			
Coal		0.78%	0.60%
OCGT		1.02%	0.83%
CCGT		0.97%	0.77%
Num. obs.		179 711	
Num. simulation draws		5 500	

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.

Wholesale Equilibrium With the demand elasticity and production cost parameter estimates, as well as the empirical distribution of recovered consumption valuations, capacity factors, and input prices (equation 5), I simulate equilibrium profits in each year for each combination of generators $\mathcal{G}$. Table 5 summarizes the relationship between capacity and profits, consumer surplus, and load rationed via blackouts by regressing these annual values on different measures of capacity.

Wholesale profits are on average decreasing in the amount of capacity in the market, but own profits are marginally increasing. Additional capacity lowers average wholesale prices, which determine the retail price consumers pay, resulting in a substantial increase in consumer surplus on average following an increase in aggregate capacity. Blackouts are, unsurprisingly, decreasing in capacity. I split the impact by fossil fuel capacity and renewable capacity, reflecting that renewable intermittency is likely to result in an increase in renewable capacity leading to a lower decrease in blackouts than a similarly sized nameplate capacity increase for fossil fuels. Indeed, a one MW increase in fossil capacity on average lowers the level of blackouts in a year by nearly 200 MWh (about 10% of a single hour's average load), while a one MW increase in renewable capacity on average reduces the level of blackouts by approximately one-third as much.[43]

Table 5: Summary of Wholesale Equilibrium Outcomes across Generator Portfolios

	agg. Π_t (thousand A$)	own Π_t (thousand A$)	CS_t (thousand A$)	B_t (MWh)	B_t (MWh)
agg. capacity (MW)	-114.95		180.52		
	(0.27)		(0.27)		
own capacity (MW)		1.37			
		(0.07)			
other capacity (MW)		-41.25			
		(0.07)			
fossil fuel capacity (MW)				-191.86	
				(0.80)	
renewable capacity (MW)					-67.76
					(0.63)
Num. obs.	972 000	2 916 000	972 000	972 000	972 000

Note: Results are generated by regressing the outcome variable (columns) on various measures of capacity (rows) across all generator portfolios $\mathcal{G}$ in the state space. The outcome variables are yearly measures (e.g., "agg. Π_t" measures the profits *per year*) and capture the expectation over the year over the distribution $F_{2021}(\mathcal{G})$ (see equation 5). These outcome variables consider the case of no carbon tax and are not inclusive of capacity payments. Reported standard errors are heteroskedasticity-robust standard errors.

[43] In the data, 0.003% of load was curtailed over my sample period. The predicted level from the model for the same years and states (i.e., $\sum_{t=2006}^{2021} B_t(\mathcal{G}_t)$ where $\mathcal{G}_t$ is the observed state in year t) is 0.008%, a similar level. It is a little larger, but it also incorporates the possibility of a systemic blackout, which has not occurred in Western Australia.

Investment Decision Table 6 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 for renewables. These values are important for the counterfactual results, as they determine both the likelihood of retirement (to avoid paying the fixed maintenance costs) as well as the likelihood of adoption (as they effectively increase investment costs). While these numbers do not need to align with engineering fixed O&M costs (as they also absorb scrap values, see footnote 41), the estimated values largely align with these costs as reported by the Australian regulator reports.[44] The scale parameter is equivalent in size to roughly one year's worth of average profits (based on the first-stage production cost estimates) for Synergy, the largest firm. This provides firms with some incentive to wait for and choose portfolios with good investment cost shocks. Reported investment costs are not estimated but rather calibrated from engineering estimates.

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 first examine policies aimed at addressing the environmental externality and blackouts, carbon taxes and capacity payments, respectively, as well as their interaction with wholesale spot market price caps. I use these results to examine welfare implications, including distributional burdens of these policies. Next, I examine the impact of renewable subsidies and utility-scale storage. Finally, I explore the influence market power has in this market and on optimal policy. Additional counterfactual results are located in Appendix C.

6.1 Carbon Taxes, Capacity Payments, and Price Caps

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 first 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. Under perfect competition and without environmental

[44] Specifically, Australian Bureau of Resources and Energy Economics (2012) reports costs of A$55/kW for coal, A$17/kW for gas, A$25/kW for solar, and A$40/kW for wind. All estimates are similar to these values except for $\hat{m}_{\text{gas}}$, which may reflect higher scrap values for gas.

Table 6: Investment Model Parameter Estimates and Calibrated Parameters

	Coal	OCGT	CCGT	Solar	Wind
Estimated parameters					
maintenace costs					
$\hat{m}_s$ (A\$/kW)	50.4	70.6		29.3	31.5
	(6.4)	(0.0)		(6.9)	(2.8)
idiosyncratic shock distribution					
$\hat{\sigma}_\eta$ (million A\$)			88.5		
			(0.422)		
Calibrated parameters					
investment costs					
$\hat{C}_{s\,2006}$ (A\$/kW)	3 845.6	905.4	1 450.7	5 512.3	3 373.8
$\hat{C}_{s\,2010}$ (A\$/kW)	3 448.2	811.9	1 300.8	4 942.6	3 025.1
$\hat{C}_{s\,2014}$ (A\$/kW)	3 325.2	765.8	1 127.8	3 222.2	2 358.3
$\hat{C}_{s\,2018}$ (A\$/kW)	3 380.9	812.9	1 182.5	1 515.7	1 834.2
$\hat{C}_{s\,2022}$ (A\$/kW)	3 369.9	819.4	1 213.5	1 047.9	1 619.5
$\hat{C}_{s\,2026}$ (A\$/kW)	3 296.5	788.1	1 167.1	920.2	1 308.7
$\hat{C}_{s\,2030}$ (A\$/kW)	3 223.1	756.8	1 120.7	792.5	1 209.2
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 σ_η 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 18). Standard errors are approximated using the Delta Method. These standard errors do not reflect the uncertainty in the estimates in the first stage.

externalities, capacity payments can be used with low price caps to achieve optimal investment levels (Joskow & Tirole, 2008). I additionally explore carbon taxes and capacity payments under a higher price cap. Price caps limit the returns to investment, potentially increasing blackouts, but also can mitigate market power since large firms may have an incentive to reduce investment and create scarcity conditions in which the price cap binds if there are high returns to doing so. I characterize the welfare impact of each of these policy combinations, along with their distributional implications across consumers, producers, etc. 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 Appendix C.2 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 complementarities between the policies.

Carbon Tax I consider a carbon tax levied on firms based on the emissions rate of each generator, given by table 11 in Appendix A. The value of the carbon tax, τ, enters the cost of each firm as described in equation 1. Figure 4 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 4 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 2020 despite coal making up a majority of production at the start of the sample. Gas generators, which are roughly half as carbon-intensive as coal, do not exhibit the same pattern. Gas investment is non-monotonic in the tax, with carbon taxes of A$100/ton resulting in an *increase* in investment relative to no carbon tax, while at A$200/ton and A$300/ton, there is marginally lower investment. 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 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 at most only about 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, κ, which enters the payment function $\Upsilon_{ft}(\cdot)$, defined in equation 16. Unlike in the sample, in which the value varied over time, I simulate investment and production with a value of κ that is constant for all years. The simulated expected evolution of investment and production is given in figure 5 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 5) 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 remains nearly constant; however, with substantial support from the payments, gas capacity rises substantially over time. 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 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 (though the use of coal versus natural depends strongly on coal and gas prices, which vary from year to year). As the payment size increases, the share of electricity produced by fossil fuels largely increases, and that of renewables declines.

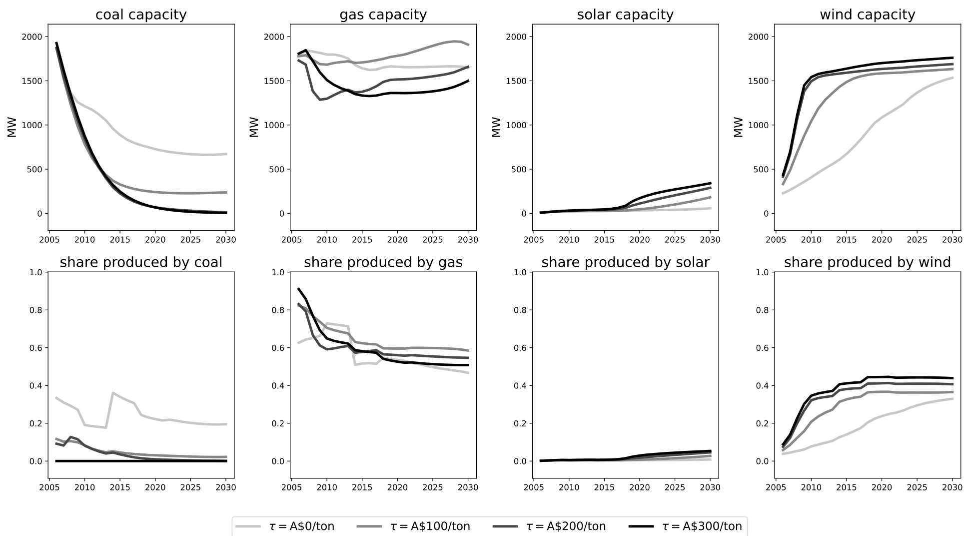
6.1.2 Higher Price Caps

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 marginal 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). Figure 6 depicts investment in the four energy sources over time by price cap and by carbon tax. The relationship between these two variables is nuanced.

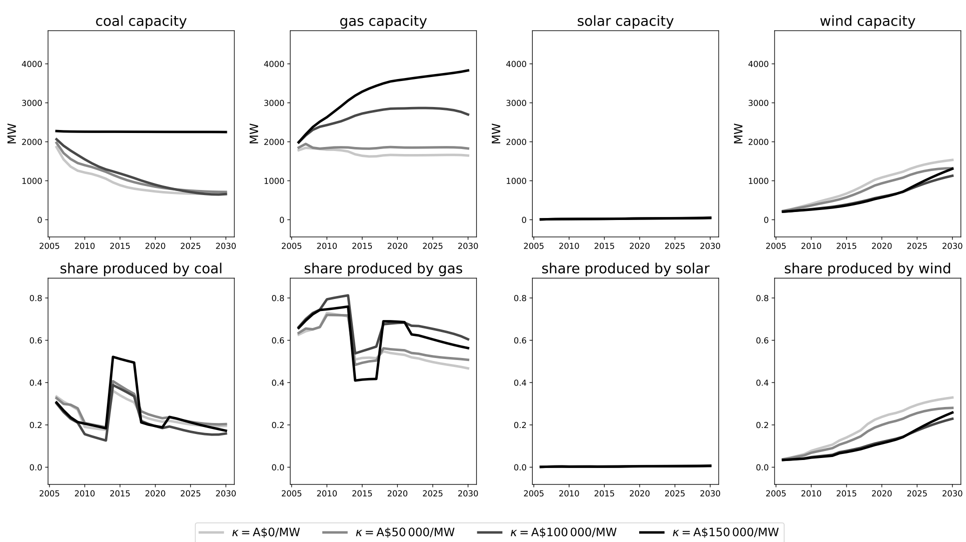
Without a carbon tax, the price cap rarely binds, so a high price cap results in only marginally

Figure 4: 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 across four-year periods.

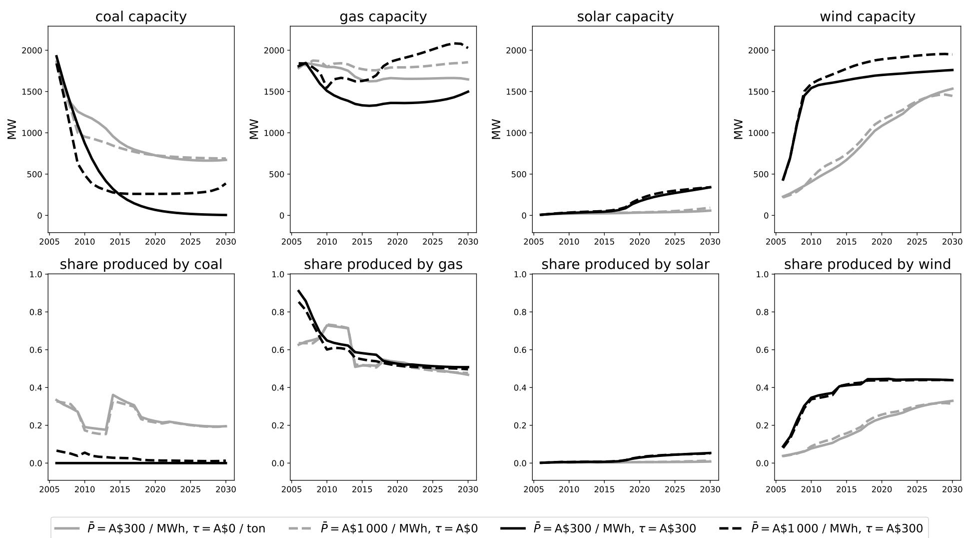
Figure 5: Impact of Capacity Payments on Investment and Production



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 4 apply.

more investment in natural gas.[45] 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. Because price caps typically bind in states of the world with low wind or solar availability, raising the cap has only a modest effect on the marginal return to renewable investment, but it substantially increases investment in fossil fuel generators, especially under a high carbon tax.

Figure 6: 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

[45] 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 η in equation 18) 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 zero even without a carbon tax that substantially raises production costs.

blackouts, which is referred to in the electricity literature as the *value of lost load*.[46]

I consider changes in this welfare function as I change policies, such as a carbon tax or capacity payments. Formally, the change in total surplus going from policy P to policy P' is given by

$$\begin{aligned} \Delta^{P\to P'}W_t\left(\boldsymbol{\Omega},\boldsymbol{\eta}\right) = \quad & \Delta^{P\to P'}\mathrm{CS}_t\left(\boldsymbol{\Omega},\boldsymbol{\eta}\right) \\ & +\Delta^{P\to P'}\textstyle\sum_f \mathrm{PS}_{f,t}\left(\boldsymbol{\Omega},\boldsymbol{\eta}\right) \\ & +\Delta^{P\to P'}\mathrm{T}_t\left(\boldsymbol{\Omega},\boldsymbol{\eta}\right) \\ & +\Delta^{P\to P'}\mathrm{C}_t\left(\boldsymbol{\Omega},\boldsymbol{\eta}\right) \\ & -SCC\times\Delta^{P\to P'}\text{ carbon emissions}_t\left(\boldsymbol{\Omega},\boldsymbol{\eta}\right) \\ & -VOLL\times\Delta^{P\to P'}\text{ MWh experiencing blackout}_t\left(\boldsymbol{\Omega},\boldsymbol{\eta}\right), \end{aligned} \tag{25}$$

where $\mathrm{T}_t(\cdot)$ is the carbon tax revenue, $\mathrm{C}_t(\cdot)$ captures the cost of capacity payments, SCC is the social cost of carbon, and $VOLL$ is the value of lost load.[47] The change in total present discounted expected surplus over the entire time horizon is given by

$$\Delta^{P\to P'}\mathcal{W} = \mathbb{E}_{\boldsymbol{\Omega},\boldsymbol{\eta}}\left[\sum_{t=2006}^{\infty}\beta^{t-2006}\Delta^{P\to P'}W_t\left(\boldsymbol{\Omega},\boldsymbol{\eta}\right)\right]. \tag{26}$$

Table 7 provides consumer surplus, producer surplus, tax revenues, capacity payment costs, emissions, and blackouts (all in expected present discounted values) for a range of values of both the carbon tax τ and the capacity payment size κ, 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

[46]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 2, 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 $\mathrm{CS}_t(\cdot)$ in equation 25, 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.

[47]In terms of total welfare, it does not matter whether consumers ultimately pay for capacity payments (as a fixed cost in their electricity bills, as is the case in Western Australia) or the government finances them (so long as there is no distortionary cost of raising government revenue). Similarly, it does not matter whether carbon tax revenue is rebated back to consumers. In section 6.1.4, I explore welfare specifications that highlight consumer welfare and present results that depend on what is transferred to and financed by consumers.

Table 7: Welfare

		$\Delta\mathbb{E}\left[\sum_{t=0}^{\infty}\beta^t \mathrm{CS}_t\right]$ (billions A$) baseline: –		$\Delta\mathbb{E}\left[\sum_{t=0}^{\infty}\beta^t \mathrm{PS}_t\right]$ (billions A$) baseline: 18.33		$\Delta\mathbb{E}\left[\sum_{t=0}^{\infty}\beta^t \mathrm{T}_t\right]$ (billions A$) baseline: 0.0		$\Delta\mathbb{E}\left[\sum_{t=0}^{\infty}\beta^t \mathrm{C}_t\right]$ (billions A$) baseline: 0.0		$\Delta\mathbb{E}\left[\sum_{t=0}^{\infty}\beta^t \mathrm{E}_t\right]$ (billions kg CO_2-eq) baseline: 184.18		$\Delta\mathbb{E}\left[\sum_{t=0}^{\infty}\beta^t \mathrm{B}_t\right]$ (millions MWh) baseline: 9.5		$\Delta\mathcal{W}$ (billions A$) baseline: –	
τ	κ	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	low price cap	high price cap	low price cap	high price cap
0	0	0.0	-25.89	0.0	23.99	0.0	0.0	0.0	0.0	0.0	-2.06	0.0	-5.56	0.0	4.13
	50 000	1.82	-25.45	1.52	28.11	0.0	0.0	-2.73	-2.72	10.88	12.21	-1.18	-5.37	-0.72	2.5
	100 000	8.98	-22.04	-0.95	28.48	0.0	0.0	-6.79	-5.89	20.83	16.43	-5.15	-5.58	1.6	2.35
	150 000	16.62	-18.15	-1.97	29.03	0.0	0.0	-16.99	-9.68	20.39	21.82	-9.02	-5.98	1.99	2.15
	200 000	17.93	-19.37	3.32	34.39	0.0	0.0	-25.55	-12.92	15.56	18.9	-9.39	-5.7	1.52	3.45
100	0	-18.15	-38.59	4.78	20.4	13.13	13.61	0.0	0.0	-52.83	-48.12	2.53	-6.63	9.39	13.12
	50 000	-15.38	-40.3	3.34	24.46	13.57	13.96	-2.51	-2.49	-48.45	-44.53	-2.96	-6.64	13.12	12.52
	100 000	-13.05	-37.14	4.48	24.7	13.86	13.91	-5.84	-5.17	-45.6	-45.04	-4.93	-6.93	14.87	13.59
	150 000	-4.62	-32.28	3.89	25.83	13.33	15.01	-16.17	-9.67	-50.84	-34.05	-8.44	-7.13	16.56	13.86
	200 000	-2.17	-28.07	8.92	27.78	13.0	14.98	-25.65	-15.77	-54.18	-34.37	-9.46	-7.18	16.03	14.01
200	0	-31.87	-54.77	7.79	24.2	21.4	24.84	0.0	0.0	-77.19	-60.0	6.13	-7.1	8.94	15.17
	50 000	-31.81	-52.77	8.11	25.09	23.51	25.09	-2.57	-2.58	-66.66	-58.75	-1.21	-7.35	13.77	15.69
	100 000	-30.06	-50.47	9.17	26.6	24.59	24.58	-6.87	-5.34	-61.22	-61.27	-5.41	-7.38	16.32	16.84
	150 000	-21.09	-49.31	8.99	30.35	23.11	25.29	-17.69	-9.53	-68.61	-57.73	-9.38	-6.61	18.49	16.69
	200 000	-19.7	-34.6	14.59	27.56	22.83	24.44	-25.69	-20.2	-70.02	-61.98	-9.47	-7.83	17.6	19.3
300	0	-35.74	-76.52	8.7	34.6	25.7	33.4	0.0	0.0	-98.52	-72.87	20.06	-6.82	1.25	15.05
	50 000	-38.21	-73.49	10.11	34.63	28.09	33.58	-2.54	-2.33	-90.55	-72.24	10.97	-7.01	7.3	16.03
	100 000	-41.35	-70.54	12.25	34.76	32.22	33.38	-9.5	-4.99	-76.8	-72.91	-3.52	-7.09	14.79	16.46
	150 000	-36.73	-57.24	14.62	27.89	31.39	34.35	-17.75	-10.91	-79.56	-69.68	-7.57	-8.4	17.4	18.52
	200 000	-35.63	-44.53	20.24	25.11	31.2	32.77	-25.73	-20.86	-80.17	-74.95	-8.76	-9.06	17.28	18.78

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 as well as their investment cost shocks. Baseline values (i.e., the value implied by the *laissez-faire* policy at the low price cap) are provided below each column heading. The values E_t and B_t represent the level of emissions and blackouts, respectively (not inclusive of the SCC or $VOLL$). I construct total welfare using $SCC =$A$230/ton CO_2-eq and $VOLL =$A$1 000/MWh. Consumer surplus and total welfare are only defined in terms of relative changes, so a baseline is not provided. 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 including the final column weighted by the value of lost load, as explained in footnote 46. Consumer surplus inclusive of the blackout cost, as well as several additional measures of welfare, are presented in table 17 in Appendix C.

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 a strong decrease in consumer surplus since consumers face higher prices, and this decrease in consumer surplus is larger with a high price cap for high carbon taxes. The cost of the carbon tax falls almost entirely on consumers, with the average discounted cost to consumers per discounted avoided ton of carbon from a A\$100/ton carbon tax being A\$343.59, while the discounted cost to product market welfare (inclusive of tax revenues) is only A\$4.45. Even if carbon tax revenue is rebated to consumers, this cost is A\$94.98.[48] 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 (especially zero-emitting renewables, which are substantial at high tax rates), this increases producer surplus.

Capacity Payments Capacity payments under a low price cap function as intended at substantially reducing blackouts (almost completely eliminating blackouts for a capacity price of A\$200 000/MW), driven by increased investment in fairly reliable fossil fuel generators. With high price caps, blackouts are lower at baseline and not very 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.

Because capacity payments result in more investment, which lowers average prices, consumer surplus is rising in these payments. In fact, product market welfare (inclusive of tax revenues and capacity payment costs) is also higher, even apart from avoided blackouts, for some values of these payments. This is because strategic firms have an incentive to underinvest to drive up wholesale market prices, as explored in section 6.4. Capacity payments can (partially) mitigate this exercise of market power, much like how a production subsidy generally mitigates the exercise of market power in production. Because of this market power distortion, capacity payments and a low price cap can in some cases achieve higher product market welfare (again,

[48] These numbers are obtained by taking, for $\tau =$ A\$100 and $\kappa =$ A\$0, $\frac{\Delta \text{CS}}{\Delta \text{E}}$, $\frac{\Delta \text{CS}+\Delta \text{T}}{\Delta \text{E}}$, and $\frac{\Delta \text{CS}+\Delta \text{PS}+\Delta \text{T}}{\Delta \text{E}}$, respectively. It does not include the cost of blackouts.

inclusive of tax revenues and capacity payment costs) than a high price cap without capacity payments, highlighting the value of a model that incorporates market power in investment decisions. For example, this value (the sum of the first four columns) under a high price cap without any capacity payments is -1.91 billion A$, while under a low price cap with a capacity price of A$100 000/MW is 1.24 billion A$. Capacity payments and price caps can therefore play a valuable role when market power distorts investment incentives; however, in the next subsection I find that when choosing policies optimally, a high price cap outperforms a low price cap in terms of total welfare.

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 both emissions and blackouts be reduced? And if so, at what cost to product market welfare and government revenues? Table 7 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, firms are incentivized to invest in reliable capacity but also incentivized not to use that emissions-intensive capacity unless necessary. As demonstrated by the final column in table 7, using these tools in combination can increase total welfare. Moreover, whether using a high price cap results in higher welfare than a low one depends on the policy combination, with some combinations under a low price cap outperforming those combinations under a high one.

Optimal Policy 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

Table 8: Total Welfare-Maximizing Policies

		carbon tax alone, low $\bar{P}$		carbon tax alone, high $\bar{P}$		joint policies, low $\bar{P}$			joint policies, high $\bar{P}$		
$VOLL$		τ^*	$\Delta\mathcal{W}$	τ^*	$\Delta\mathcal{W}$	τ^*	κ^*	$\Delta\mathcal{W}$	τ^*	κ^*	$\Delta\mathcal{W}$
1 000		**154.1**	**9.8**	**224.0**	**14.2**	**214.7**	**155 600**	**16.9**	**201.5**	**200 000**	**17.5**
	ΔCS		-23.2		-53.8			-21.1			-31.7
	ΔPS		5.3		23.5			9.3			25.1
	ΔT		16.3		24.5			22.1			22.4
	ΔC		0.0		0.0			-17.0			-18.3
	$-SCC \times \Delta$E		14.2		13.3			14.8			13.0
	$-VOLL \times \Delta$B		-2.8		6.5			8.6			7.1
10 000		**0.0**	**0.0**	**219.8**	**72.6**	**214.7**	**155 600**	**94.6**	**285.0**	**176 200**	**95.3**
	ΔCS		0.0		-53.0			-21.1			-43.5
	ΔPS		0.0		23.2			9.3			22.0
	ΔT		0.0		24.2			22.1			30.4
	ΔC		0.0		0.0			-17.0			-14.1
	$-SCC \times \Delta$E		0.0		13.2			14.8			13.9
	$-VOLL \times \Delta$B		0.0		65.0			86.4			86.4

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. Bold rows show the optimal policy and the difference in welfare compared to the baseline for a given value of the $VOLL$, and the rows below provide a welfare decomposition. I use a SCC of A\$230/ton CO_2-eq. 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 7) and construct a much finer grid to determine optimal policy values by interpolating using bivariate cubic splines.

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 two values. The first is 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). I also consider a larger value of A\$10 000/MWh. Using these values, table 8 provides the optimal policy with a carbon tax alone and when the tax is used jointly with capacity payments, as well as the distributional impact of these optimal policies. Note that, in contrast to table 7, the welfare values are *per customer* for ease of interpretation rather than aggregates.[49]

Using a carbon tax alone and a low price cap, the optimal tax is well below the social cost of carbon. This is driven in part by the fact that blackouts are increasing in the tax. In fact, the marginal increase is high enough that under a high value of lost load, the optimal tax is zero. With a high price cap, however, the level of blackouts is lower and less sensitive to the carbon tax. In this case, the optimal carbon tax is higher, yielding a similar level of emissions and higher total welfare, but at a much greater cost to consumers who pay higher average prices. Optimally choosing a capacity price in addition to the tax substantially increases

[49] There are 1.1 million customers in the WEM.

total welfare (and also reduces the cost to consumers), yielding a similar level of emissions and substantially reduced blackouts.

6.1.4 Alternative Welfare Goals and Alternative Capacity Payment Structures

The results in section 6.1.3 demonstrated that the benefits and costs of reducing carbon emissions via these policy tools are unevenly distributed. In this section I consider alternative welfare goals and characterize optimal policies under these goals. I also consider different capacity payment structures to explore whether these payments can be better targeted and achieve policy goals at a lower cost.

Table 9 presents optimal policies for different welfare goals and for different structures of capacity payments. Each column corresponds to a different welfare goal. The first three seek to minimize emissions subject to not making consumers worse off (column 1), including the cost of blackouts and the cost of providing capacity payments (column 2),[50] and including after rebating carbon tax revenue to consumers (column 3). The fourth maximizes a version of a consumer welfare standard (total welfare not including producer surplus). The final simply maximizes total surplus, as in table 8. Each block of rows corresponds to a different way of structuring capacity payments. The first is a capacity price that applies to all non-intermittent generators, the same as previously considered. The second allows the capacity price to distinguish between coal and gas generators. This structure is motivated by the fact that the two technologies have very different emissions intensities. The final structure ties the capacity price to the quantity-weighted average wholesale spot price, making it inversely proportional to the price so that the higher the price, the lower the capacity payment. This structure reflects that firms may need less of an incentive to invest or delay retirement when wholesale prices are high.

It is feasible to substantially reduce emissions without reducing consumer surplus, captured in the first column. Doing so requires a moderately sized carbon tax coupled with a large capacity payment financed by the government. A capacity price that is tied to the average wholesale spot price achieves the greatest emissions reduction (31%), although only marginally larger than for the other two capacity payment structures. A more holistic description of consumer welfare that includes the cost of blackouts and consumers paying for capacity payments (column 2), however, constrains the maximum emissions reduction to be only about half as large. If carbon tax revenue is rebated back to consumers (column 3), though, the maximum feasible emissions reduction is similar to that attained in the first column.

[50] This specification (including blackout costs and the cost of capacity payments) provides a comprehensive measure of consumer welfare. Blackout costs reflect the welfare loss from unmet demand, and consumers typically pay for capacity payments in most electricity markets that use them.

Table 9: Optimal Policies to Achieve Alternative Welfare Goals

	max $-\Delta$E s.t. ΔCS ≥ 0	max $-\Delta$E s.t. ΔCS + ΔC $-VOLL \times \Delta$B ≥ 0	max $-\Delta$E s.t. ΔCS + ΔT + ΔC $-VOLL \times \Delta$B ≥ 0	max ΔCS + ΔT + ΔC $-SCC \times \Delta$E $-VOLL \times \Delta$B	max $\Delta\mathcal{W}$
			$\kappa_{\text{coal}} = \kappa_{\text{gas}}$		
policy	$\tau^* = 87.1$, $\kappa^* = 200\,000$	$\tau^* = 42.6$, $\kappa^* = 148\,700$	$\tau^* = 128.5$, $\kappa^* = 138\,700$	$\tau^* = 58.9$, $\kappa^* = 153\,200$	$\tau^* = 214.7$, $\kappa^* = 155\,600$
ΔCS	0.0	7.4	-9.5	4.4	-21.1
ΔPS	7.5	-0.3	4.1	0.9	9.3
ΔT	10.7	5.7	14.9	7.8	22.1
ΔC	-23.3	-15.8	-13.0	-16.4	-17.0
ΔE	-52.9 (-29%)	-28.4 (-15%)	-55.2 (-30%)	-40.8 (-22%)	-70.7 (-38%)
ΔB	-9.5 (-99%)	-9.2 (-97%)	-8.4 (-88%)	-9.2 (-97%)	-9.5 (-100%)
$\Delta\mathcal{W}$	14.5	11.3	15.7	13.6	16.9
			separate κ_{coal}, κ_{gas}		
policy	$\tau^* = 88.9$, $\kappa^*_{\text{coal}} = 200\,000$ $\kappa^*_{\text{gas}} = 250\,000$	$\tau^* = 43.5$, $\kappa^*_{\text{coal}} = 151\,400$ $\kappa^*_{\text{gas}} = 142\,900$	$\tau^* = 121.0$, $\kappa^*_{\text{coal}} = 50\,500$ $\kappa^*_{\text{gas}} = 206\,500$	$\tau^* = 67.9$, $\kappa^*_{\text{coal}} = 160\,600$ $\kappa^*_{\text{gas}} = 101\,900$	$\tau^* = 235.7$, $\kappa^*_{\text{coal}} = 24\,400$ $\kappa^*_{\text{gas}} = 192\,400$
ΔCS	0.0	7.2	-7.2	0.2	-23.6
ΔPS	11.2	-0.4	5.5	-0.1	8.7
ΔT	10.8	5.8	13.9	9.3	23.7
ΔC	-27.4	-15.5	-13.8	-11.5	-13.5
ΔE	-53.8 (-29%)	-28.6 (-16%)	-57.4 (-31%)	-42.0 (-23%)	-73.0 (-40%)
ΔB	-9.5 (-100%)	-9.2 (-97%)	-7.9 (-83%)	-8.6 (-90%)	-9.5 (-100%)
$\Delta\mathcal{W}$	14.4	11.4	17.4	14.4	19.2
			$\kappa = \alpha / P_t^{avg}$		
policy	$\tau^* = 94.9$, $\alpha^* = 40\,000\,000$ ($\bar{\kappa} = 407\,500$)	$\tau^* = 35.7$, $\alpha^* = 10\,700\,000$ ($\bar{\kappa} = 154\,500$)	$\tau^* = 106.6$, $\alpha^* = 16\,700\,000$ ($\bar{\kappa} = 151\,800$)	$\tau^* = 91.3$, $\alpha^* = 15\,200\,000$ ($\bar{\kappa} = 145\,300$)	$\tau^* = 223.7$, $\alpha^* = 24\,300\,000$ ($\bar{\kappa} = 140\,700$)
ΔCS	0.0	8.7	-4.1	-2.6	-23.6
ΔPS	34.0	-0.4	3.8	3.0	9.3
ΔT	11.0	5.3	12.6	11.2	23.2
ΔC	-53.2	-16.8	-16.8	-15.1	-15.3
ΔE	-57.1 (-31%)	-19.2 (-10%)	-54.5 (-30%)	-49.5 (-27%)	-70.3 (-38%)
ΔB	-9.5 (-100%)	-8.8 (-93%)	-9.1 (-96%)	-8.7 (-92%)	-9.3 (-98%)
$\Delta\mathcal{W}$	12.4	8.9	15.2	14.7	16.8

Note: The first block of rows corresponds to the case in which the capacity price must be the same for all (non-intermittent) generators. The second block allows for different prices by energy source. The third block sets a capacity price inversely proportional to the quantity-weighted average wholesale spot price. The reported policy for this block includes in parentheses $\bar{\kappa}$, which is the average capacity price as a result of the optimal policy (τ^*, α^*). Welfare values are in thousand A\$ per customer. Each column corresponds to a different policy goal-constraint pair, with the policy achieving the constrained optimum provided in the first set of rows, and the welfare decomposition below. Total welfare values use SCC =A\$230/ton CO_2-eq and $VOLL$ =A\$1 000/MWh. Values are determined via interpolation using cubic splines, see note in table 8. Values in dollar terms (ΔCS, ΔPS, ΔT, ΔC, $\Delta\mathcal{W}$) are in thousand A\$ per customer, while ΔE is in billion kg CO_2-eq and ΔB is in million MWh.

While maximum emissions reductions are similar for the three structures of capacity payments, maximum total welfare (the final column) is more sensitive to the structure. Using separate capacity prices for coal and gas yields a 14% higher expected increase in total welfare than a uniform capacity price. This is achieved by setting a low capacity price for coal and a high one for gas. This structure continues to virtually eliminate blackouts and does so at a smaller cost (given by ΔC). Tying the capacity price to the inverse average wholesale spot price, meanwhile, achieves a similar level of total welfare to that of a uniform capacity price.

6.2 Renewable 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 two types of renewable subsidies. The first type that I consider is a renewable *production* subsidy, which pays renewable generators a fixed amount for each MWh they produce. This subsidy changes renewable generators' marginal cost to $-\varsigma$, where ς is the size of the subsidy (in A\$/MWh). The second type is a renewable *investment* subsidy, which reduces the cost of investment of renewable generators. I structure this subsidy as a fraction of the investment cost (similar to how investment tax credits for renewable energy in the U.S. are structured) and denote the value of this subsidy by s. Under this subsidy, renewable generators only pay a cost to build a new generator of $(1 - s)\, C_{s(g),t}$ per MW (plus the idiosyncratic cost and the yearly maintenance costs).

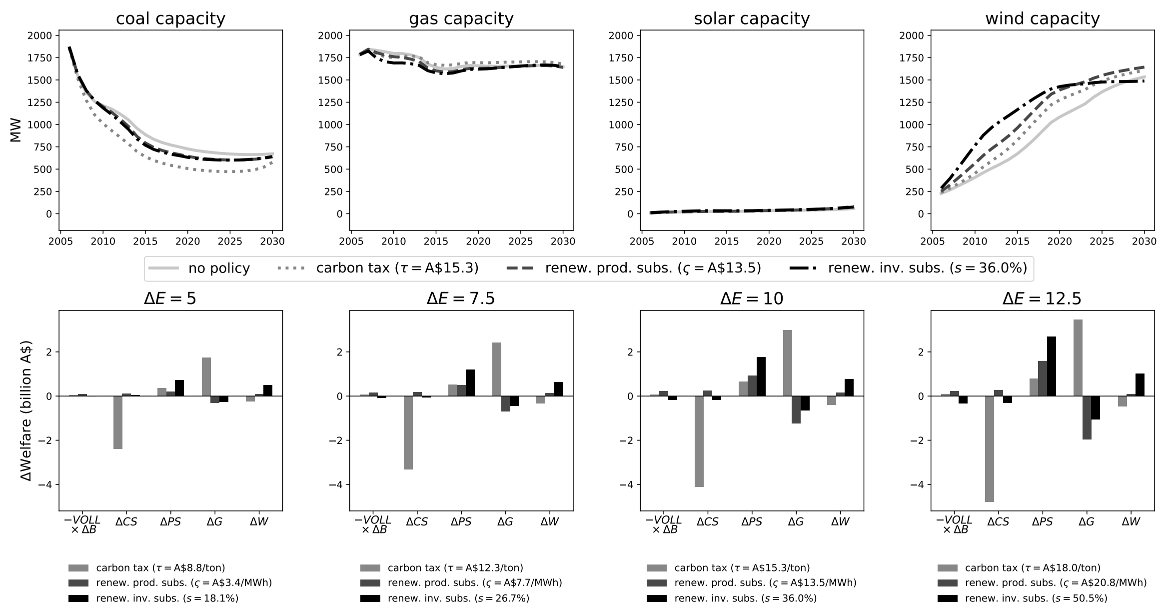
Figure 7 plots expected capacity in each energy source for each type of renewable subsidy and the carbon tax (top row) as well as compares the welfare impact of using each of these policies to obtain a decrease in emissions (bottom row). The value of the subsidy or the tax in the top row is equal to the policy value that yields an expected discounted emissions reduction of 10 million kg CO_2-eq.

Two patterns are readily apparent from figure 7. First, relative to the same emissions reduction achieved using either of the subsidies, carbon taxes reduce coal capacity and increase gas capacity. This is especially apparent from production shares. On average over the plotted years, 16.4% of electricity is produced using coal and 61.2% using gas under a carbon tax, versus 21.7% and 54.5% using a production subsidy (with similar numbers for an investment subsidy). To achieve the same level of an emissions reduction, the production subsidy has higher renewable production (23.9% versus 22.4%).[51]

The second pattern is that a renewable investment subsidy incentivizes earlier investment in renewables than a production subsidy, but ultimately lower investment. The reason for this is

[51] Borenstein & Kellogg (2023) compare carbon taxes to renewable subsidies in the U.S. and find that renewable subsidies can perform surprisingly effectively in part because coal typically has higher marginal production costs than natural gas in the U.S., so renewable subsidies along the transition path to zero emissions disproportionately displace coal rather than natural gas. In Western Australia, coal is typically cheaper than natural gas, resulting in the relatively high reliance on coal in achieving emissions reductions using renewable subsidies.

Figure 7: Comparing Environmental Policies



Note: Depicted in each panel in the top row is the *expectation* for a particular energy source for a particular value of an environmental policy that yields an expected discounted emissions reduction of 5 million kg CO_2-eq. Depicted in each panel in the bottom row is the welfare impact of reducing emissions by a particular amount (given by ΔE, in millions kg CO_2-eq). The value ΔW is defined as the change in total welfare relative to no environmental policy *not* inclusive of the emissions reduction (using $VOLL =$A\$1 000/MWh). Each individual bar corresponds to using a tax, production subsidy, or investment subsidy to achieve the given emissions reduction. The legend below each panel lists the value of the policy that achieves the emissions reduction. 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.

that the investment subsidy is structured as a fraction of the investment cost. Because these costs decline over time, the absolute value of the subsidy is larger in earlier years, creating stronger incentives for early investment. When the subsidy rate is chosen to achieve a given emissions reduction, this declining pattern implies that the effective subsidy is lower in later years relative to the production subsidy, which provides a constant per-MWh incentive over time. As a result, the production subsidy yields weaker incentives early on but supports higher levels of investment later.

Renewable subsidies achieve emissions reductions for small to moderately sized emissions reductions (as displayed in figure 7) with less extreme distributional implications than a carbon tax can. Moreover, despite an inability to finely distinguish between emissions intensities and expanding overall demand rather than contracting it,[52] renewable subsidies achieve these

[52]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.

small to moderate emissions reductions at a lower welfare cost (or even increase welfare). This result has been found before in a different context by Liski & Vehviläinen (2020) studying the Nordic electricity market with substantial storage (from hydro resources). In this setting, market power misaligns firms' investment incentives causing underinvestment (explored in section 6.4), and the subsidy partially mitigates this by incentivizing investment.

6.3 Utility-Scale Storage

In recent years, utility-scale storage has come online in several electricity markets in the form of large lithium-ion batteries.[53] Storage has the potential to reduce the intermittency problem by discharging during periods of low renewable availability. While this reduces the likelihood of blackouts, storage's introduction also changes investment decisions. By smoothing prices over time, it could incentivize or disincentivize renewable investment (Andrés-Cerezo & Fabra, 2025). Additionally, by reducing spikes in the wholesale price, storage could cause fossil fuel generators to retire generators that make most of their profits in these peak demand times. The impact of storage on optimal environmental and reliability policy is therefore an empirical question.

I simulate how investment and optimal policies would respond with the addition of a 2 000 MWh 4-hour storage unit that charges and discharges energy across time, arbitraging price differences. The battery capacity is substantial, approximately the average hourly network load, and corresponds to the amount the Australian government seeks to procure for Western Australia as part of its Capacity Investment Scheme.[54] The storage unit enters the market in 2022, fully anticipated by all firms. It can discharge 2 000 MWh over four hours (500 MWh per hour) with 90% efficiency.[55]

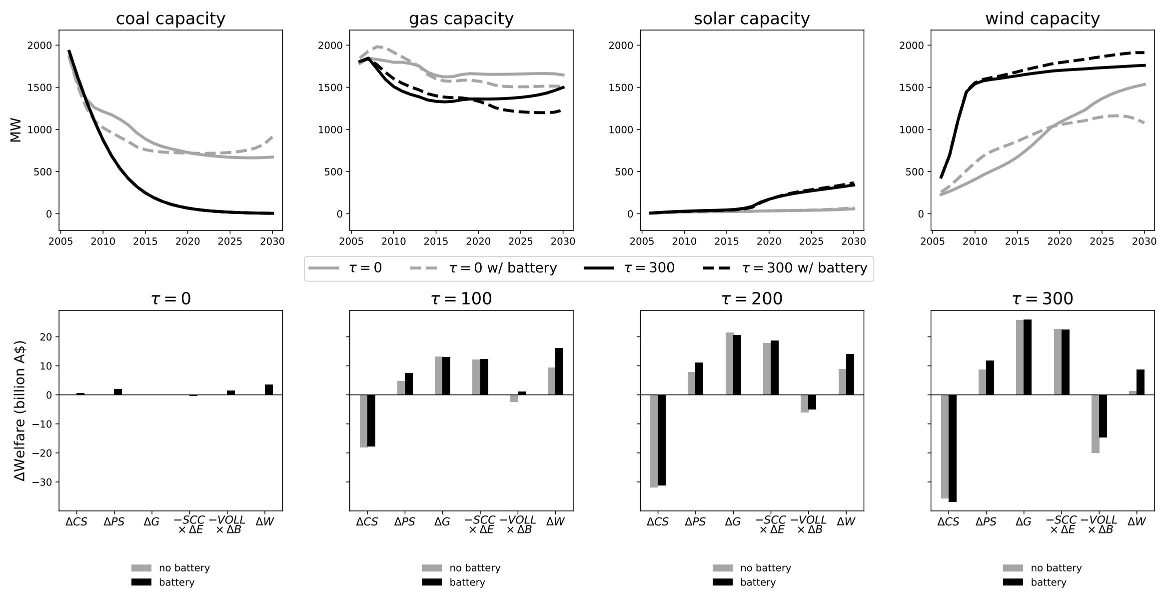
Figure 8 depicts investment patterns both with and without the storage unit's introduction in both the absence and inclusion of a carbon tax (top row) as well as the welfare impact for given levels of a carbon tax (bottom row). At a high carbon tax, the battery's addition leads to higher renewable capacity and lower natural gas capacity. Despite lower natural gas capacity, the battery's inclusion does lead to less blackouts than in a world without the battery. However, the size of this reduction is small relative to the size of the increase in blackouts across tax levels. The implication of this fact is that while this suggests storage does indeed

[53] Some prominent examples include Victorian Big Battery (Australia, 2021, 450 MWh), Dalian Flow Battery Energy Storage Peak-Shaving Power Station (China, 2021, 400 MWh), Sonoran Solar Energy Center (United States, 2024, 1 000 MWh), Bisha Battery Energy Storage System (Saudi Arabia, 2025, 2 000 MWh).

[54] https://aemoservices.com.au/-/media/services/files/cis/cis-t2-wem/cis-t2-tender-guidelines.pdf

[55] To calculate wholesale profits, $\boldsymbol{\Pi}_t(\cdot)$, with the inclusion of the storage unit, for each draw of a series of intervals, I set the storage unit to be half-full in the first interval. I determine equilibrium production, charging, discharging, and prices for each interval. As with the calculation without storage, I drop both the first and last 5 intervals to not bias results by the initial conditions or finite horizon. I assume perfect foresight over demand and generator availability.

Figure 8: Comparing Carbon Taxes with and without Utility-Scale Storage



Note: Depicted in each panel in the top row is the *expectation* for a particular energy source for a particular value of a carbon tax with or without the 2 000 MWh battery. Depicted in each panel in the bottom row is the welfare impact of a carbon tax of a particular size. The value ΔW is defined as the change in total welfare (using SCC =A\$230/ton CO_2-eq and $VOLL$ =A\$1 000/MWh). Each individual bar corresponds to whether a 2 000 MW battery is present. There are no capacity payments.

reduce blackouts, the size of storage necessary to avoid blackouts caused by environmental policies may be much larger than an hour's load. Table 18 in Appendix C provides optimal policies, analogous to table 8, with storage.

6.4 The Role of Market Power

Market power influences both the investment level and type (the technology). In this section, I consider the role market power plays in these decisions as well as in the optimal policy by simulating a market in which every power plant is owned by a separate firm. In other words, there are no large firms (as defined by the model), all firms are small.[56] I refer to this as the competitive framework. A firm therefore does not internalize the impact of its constructing or retiring a generator on other generators' profits.

[56]While all firms are small in this specification, I retain the timing structure from the main model with large firms. In that specification, large firms adjusted first (in random order), followed by small firms. Here, each plant belongs to a separate firm, but I assign adjustment timing based on the plant's original firm type: plants previously associated with large firms adjust first (in random order), followed by those previously associated with small firms (also in random order). This approach makes results comparable and not due to timing differences correlated with firm technology.

Table 10: Comparison between Market Power and Competitive Frameworks

		market power	competitive	market power + opt. tax		competitive + tax		competitive + opt. tax	
VOLL		$\Delta\mathcal{W}$	$\Delta\mathcal{W}$	$\tau^*_{\text{mkt pwr}}$	$\Delta\mathcal{W}$	$\tau^*_{\text{mkt pwr}}$	$\Delta\mathcal{W}$	τ^*_{comp}	$\Delta\mathcal{W}$
1 000		**0.0**	**2.01**	**154.1**	**9.76**	**154.1**	**15.89**	**236.9**	**17.31**
	ΔCS	0.0	9.74		-23.24		-18.29		-30.49
	ΔPS	0.0	-9.21		5.28		-1.85		2.03
	ΔT	0.0	0.0		16.29		18.6		25.85
	$-SCC \times \Delta$E	0.0	-5.48		14.2		10.75		13.42
	$-VOLL \times \Delta$B	0.0	6.96		-2.78		6.69		6.49
10 000		**0.0**	**64.67**	**0.0**	**0.0**	**0.0**	**64.67**	**208.1**	**78.03**
	ΔCS	0.0	9.74		0.0		9.74		-26.42
	ΔPS	0.0	-9.21		0.0		-9.21		0.64
	ΔT	0.0	0.0		0.0		0.0		23.52
	$-SCC \times \Delta$E	0.0	-5.48		0.0		-5.48		12.52
	$-VOLL \times \Delta$B	0.0	69.62		0.0		69.62		67.77

Note: Changes in welfare are with respect to the *laissez-faire* policy ($\tau = 0$) under market power and in expected present discounted terms (using $\beta = 0.95$) in thousand A$ per customer, using a *SCC* of A$230/ton. The value $\tau^*_{\text{mkt pwr}}$ is the carbon tax that maximizes total welfare in a framework in which some firms are large, and the value τ^*_{comp} is the tax that maximizes total welfare in a framework in which all firms are small.

Table 10 compares optimal policies and their distributional impacts under the framework with market power and under the competitive one. Market power leads to reduced investment, as shown in Figure 12 in Appendix C, with an average of 591 MW less capacity under the market power framework (without a carbon tax). All plants being owned by separate firms increases investment, reducing quantity-weighted average prices by A$33/MWh.[57] This leads to higher consumer surplus, fewer blackouts, and higher total surplus despite increased emissions. The size of these differences is quantitatively significant, suggesting that even if there is no market power exercised in wholesale markets, the impact on investment decisions can be meaningful.

A carbon tax changes investment and production patterns, decreasing emissions; however, comparing the third set of results (optimally chosen carbon tax under market power) to the fourth (the same carbon tax but under competitive framework), the reduction in emissions is lower under competition, though total welfare is on net higher. The total welfare-maximizing carbon tax under the competitive framework, meanwhile, is close to the social cost of carbon, resulting in a similar emissions reduction but at a larger cost to consumers than in the market power case (though not if the tax revenue is rebated back to consumers, in which case net consumer surplus is -4.6 in the competitive case versus -6.9 in the market power case, not including the cost of blackouts).

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

[57]These numbers are obtained by taking, in each year, the expected value (over generator portfolios) and averaging over all years up to the year portfolios are “locked in.”

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 strict environmental policies to address the threat of climate change. Changes in technology not studied in this paper—such as real-time pricing, which introduces elasticity to demand, or other production technologies like nuclear energy—may also help to address reliability concerns. However, real-time pricing experiments have highlighted the issue of inattention to price fluctuations, and nuclear power plants have been beset by very large fixed costs. 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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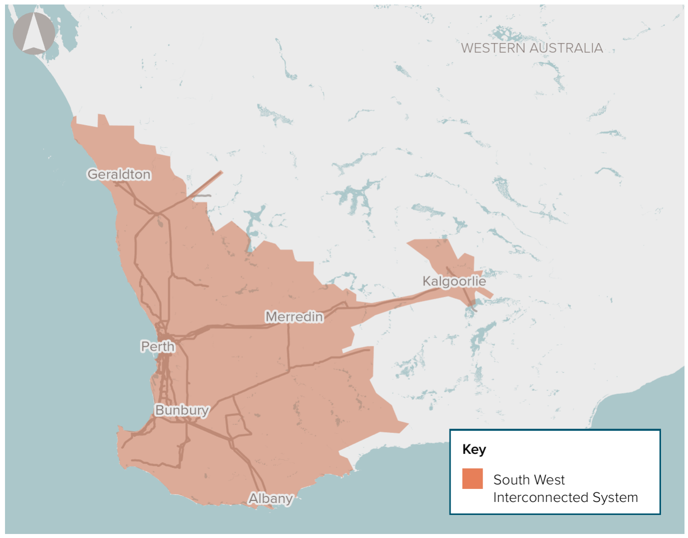
A Additional Industry Details (for Online Publication)

A.1 South West Interconnected System

Figure 9: 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 11 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.[58] 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.1, 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 ranking of different

[58]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, $F_t^{\boldsymbol{\delta},\mathbf{c},\Xi}$. Generators below this cutoff account for just 3.49% of energy produced and 4.36% of fossil fuel capacity.

plants.

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, 2022). The reports are for the years 2010, 2013, 2016, 2019, and 2022. Each report provides capital costs in US$/kW for different generator technologies, including all of those considered in this paper.[59] 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,[60] 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 α_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 2022, I use National Renewable Energy Laboratory (NREL) predictions to discipline the evolution of costs. Specifically, I use the costs predicted by NREL based on their "moderate" scenario for the technology, and scale 2022 Western Australia estimates $\hat{C}_{s,2022}^{WA}$ by the ratio of the NREL prediction for that year to their 2022 cost (National Renewable

[59]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.)

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

Table 11: List of Generators in Data

Generator	Firm	Technology	Capacity (MW)	Heat Rate (GJ/MWh)	Emissions Rate (kgCO$_2$-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 capacity year 2018, 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. ¶Kemerton Power Plant underwent a capacity upgrade of 15% in capacity year 2007, so I use its post-upgrade capacity since that constitutes nearly all of the sample period.

Energy Laboratory, 2023). Explicitly,

$$\hat{C}_{st}^{WA} = \frac{C_{st}^{NREL}}{C_{s,2022}^{NREL}} \hat{C}_{s,2022}^{WA} \quad \forall t > 2022.$$

Calibrated investment costs $\left\{\hat{C}_{st}^{WA}\right\}_{s,t}$ are summarized in table 6.

A.4 WEM Details

Capacity Payments 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. Electricity consumers pay for the cost of these payments as part of the fixed component of their electricity bills,[61] suggesting the size of these payments does not influence how much electricity consumers choose to consume.

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 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. In the model, therefore, I treat only non-intermittent technologies as eligible and do not model penalties and the commitment choice since in practice it results in minimal payments to intermittent technologies and almost full payments to non-intermittent technologies.

Demand Response Participation The WEM allows for the participation of "demand response programmes" that provide some flexibility to the otherwise perfectly inelastic load. These participants receive capacity payments in exchange for agreeing to reduce their contri-

[61] Consumers pay both a fixed fee that does not depend on the amount they consume and a variable fee that does. According to information on network tariffs (Western Power, 2021), "[t]he costs are separated into fixed and variable components and the reference tariffs are similarly split so that fixed costs are recovered by fixed charges and variable costs by variable charges." Capacity payments from the perspective of the retailer (which pays the capacity payments and then passes them along to consumers) are fixed costs, and so paid for ultimately by consumers via the fixed component of their bills.

bution to the demand for electricity in a given interval if called upon by the system operator. Unlike in many electricity markets with demand response participants, they do not receive a payment when they are called upon; instead, they are compensated via a fixed capacity payment (like generators are). The system operator instructs them to curtail demand if the system is at risk of demand exceeding available supply. In practice, this has been extremely rare (see table 1).

The WEM is unusual in compensating participants via a fixed payment rather than payments when load is curtailed based on the market clearing price. In the model (section 3) I allow for demand response that depends on the wholesale market spot price (equation 4), capturing the typical structure of demand that is part of a demand response program. In the empirical application for Western Australia, I treat all demand response load as having a cost equal to the price cap.[62] This ensures that demand response participants are only called upon when necessary to avoid blackouts. The quantity available for demand curtailment from demand response participants (captured by $Q_h^{DR}(\cdot)$) is treated as exogenous, and therefore does not change in the counterfactuals.

B Technical Details (for Online Publication)

B.1 State Space

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 $F_t^{\boldsymbol{\delta},\mathbf{p},\Xi}$, and how many years remain until generator portfolios are locked in). Section 3.3.2 describes how firms' choice sets are constructed, and I provide more detail in this section. Firm's choice sets are potentially multidimensional, with each dimension corresponding to a different technology (e.g., coal, natural gas, etc.). The generator portfolio component of the state space is the cross product of all firms' possible portfolios. Table 12 provides a complete description of the generator portfolio state space.

Dimensions Each firm's component of the state space may include multiple technologies. For each firm f, the set of available technologies, $\mathcal{S}_f$, corresponds to the technologies I observe it using in the data (see section 3.3.2). For WPGENER, which owns many legacy assets, I distinguish between two types of natural gas technologies: modern and old. In the data, WPGENER both retires older generators and builds new ones. I therefore represent its choice set with two separate technology dimensions: "gas (modern)" for newer, more efficient generators and "gas (old)" for less efficient generators it may retire even while continuing to

[62] Technically, I treat their cost as just below the price cap so that curtailing their demand occurs prior to rationing via blackouts in the merit order.

Table 12: Description of Generator Portfolio State Space

Firm	Technology	State	Generators	Total Capacity (MW)
WPGENER	coal	0	∅	0
		1	+ COLLIE_G1	342
		2	+ MUJA_G7, MUJA_G8	796
		3	+ MUJA_G5, MUJA_G6	1 217
		4	+ KWINANA_G5, KWINANA_G6	1 601
		5	+ KWINANA_G1–KWINANA_G4	2 064
	gas (modern)	0	COCKBURN_CCG1	265
		1	+ KWINANA_GT2, KWINANA_GT3	484
		2	+ new natural gas (combined cycle)	884
	gas (old)	0	∅	0
		1	+ KEMERTON_GT11, KEMERTON_GT12	346
		2	+ PINJAR_GT1–PINJAR_GT9	991
		3	+ PPP_KCP_EG1	1 100
		4	+ SWCJV_WORSLEY_COGEN_COG1	1 228
ALINTA	gas	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	0	ALINTA_WWF	88
		1	+ BADGINGARRA_WF1	219
		2	+ YANDIN_WF1	427
		3	+ new wind farm, new wind farm	827
		4	+ new wind farm, new wind farm	1 227
GRIFFINP	coal	0	∅	0
		1	+ BW2_BLUEWATERS_G1, BW1_BLUEWATERS_G2	452
small firms	coal	0	∅	0
		1	+ MUJA_G1–MUJA_G4	236
	gas	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	0	∅	0
		1	+ GREENOUGH_RIVER_PV1	40
		2	+ MERSOLAR_PV1	140
		3	+ new solar pv, new solar pv	540
		4	+ new solar pv, new solar pv	940
	wind	0	ALBANY_WF1, EDWFMAN_WF1	105
		1	+ INVESTEC_COLLGAR_WF1	319
		2	+ MWF_MUMBIDA_WF1	374
		3	+ WARRADARGE_WF1	552
		4	+ new wind farm, new wind farm	952
		5	+ new wind farm, new wind farm	1 352

Note: Rows within a firm-technology category describe a state along that dimension. The states are ordered, so that moving along each state within the firm-technology dimension, adds generators based on the profitability heuristic. For example, for WPGENER-coal, state 3, WPGENER has the following coal generators: COLLIE_G1 and MUJA_G5–MUJA_G8, with a total capacity of 1 217 MW. If it retires generators from state 3, it moves to state 2, retiring MUJA_G5–MUJA_G6, leaving it only with COLLIE_G1 and MUJA_G7–MUJA_G8. If it expands its generator portfolio, it moves to state 4 and adds KWINANA_G5–KWINANA_G6 to its portfolio. 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.

invest in gas. Other firms have newer natural gas plants, so I don't distinguish between the two types. Small firms (with at most one generator) are collapsed into a single dimension per technology. At most one small firm in each technology can adjust per year, similar to large firms' restriction that at most one generator grouping can adjust per year.

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 the distribution of demand as well as 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 of these variables. Doing so would require simulating wholesale markets for every possible combination of plants for every year. 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 is less profitable and 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 retire plant 3 before it would retire plant 4.[63]

New Generators The definition of the state space extends 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 use combined cycle technology, have a heat rate of 8.0 GJ/MWh, an emissions rate of 450 kgCO_2-eq/MWh, and a capacity of 400 MW. New solar and wind generators are assumed to have a capacity of 200 MW and the same capacity factors as existing solar and wind generators.

B.2 Equilibrium Computation Details

The wholesale equilibrium characterized by equation 14 involves a fixed point in the retail price and an expectation over wholesale market stochastic variables. I solve for expectations of wholesale operations by first clustering, for each group of four years (e.g., 2006–2009, 2010–2013, etc.), blocks of 60 wholesale market intervals into 10 groups using a modified version of K-means++ that ensures the highest demand interval is included as a centroid that represents

[63] 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.

the group.[64] This clustering implies weights for each of these groups, and I use these weights in calculating average outcomes for the four-year interval. For each centroid, I solve the wholesale operator's problem (equation 6) using Gurobi. Using this procedure I can calculate the implied quantity-weighted average wholesale prices for a given retail price, and I iterate on the fixed point in the retail price to calculate the equilibrium for a given four year period for a given portfolio. This procedure is given explicitly by Algorithm 1.

Algorithm 1: Wholesale Equilibria Calculation for Year t

Data: $\left\{\{\Xi_h, \mathbf{p}_h, \delta_h\}_{h\in b}\right\}_b$

Cluster Sequences of Intervals using Modified K-means++

- standardize data;
- $k_1 \leftarrow \arg\max_b \{\max_{h\in b}\{\Xi_h\}\}$;
- **for** $i = 2, \ldots K$ **do**
  - select k_i randomly with prob. $\propto$ to Euclidean distance to nearest $k_{i-1}, \ldots, k_1$;
- **for** $b = 1, \ldots, B$ **do**
  - $k(b) \leftarrow \arg\min_k \{\|\textbf{standardized variables}_b - \textbf{standardized variables}_k\|\}$;
- assign weights w_k based on share of b assigned to k;

Solve Wholesale Equilibria

- **for** $\mathcal{G} \in \Gamma$ **do**
  - initialize P^{avg}, P^{diff};
  - **while** $P^{diff} >$ *convergence threshold* **do**
    - **for** $i = 1, \ldots, K$ **do**
      - solve operator's problem (equation 6) for sequence k_i with $\mathcal{G}$ using Gurobi;
    - $P^{new} \leftarrow \dfrac{\sum_{i=1}^{K} w_{k_i} \sum_{h\in k_i} Q_h P_h}{\sum_{i=1}^{K} w_{k_i} \sum_{h\in k_i} Q_h}$;
    - $P^{diff} \leftarrow |P^{new} - P^{avg}|$;
    - $P^{avg} \leftarrow P^{new}$;

C Additional Results (for Online Publication)

C.1 Complete Parameter Values & Robustness Checks

Table 13 presents the parameters of the logit specifications in table 2. Table 14 compares production cost function parameter estimates for the unrestricted sample and for a sample

[64] Blackouts are rare and result from high demand times. It is therefore essential that the time most likely to experience a blackout is included as one of the centroids in the K-means clustering. Therefore, rather than randomly selecting an initial block as the first centroid, as would occur following K-means++, I select as the first centroid the block with the highest demand (and then proceed with the standard K-means++ procedure to choose other centroids based stochastically on their Euclidean distance from the previously selected centroids). This centroid tends to have very low weight because it is atypical compared to the others, but its inclusion is essential to ensure that low probability blackouts are not approximated as zero probability.

that drops the period in which Synergy was found to have overstated its costs, March 31, 2016–July 10, 2017. Results are fairly similar across the two samples.

Table 13: Capacity Price Logit Parameters

	fossil fuels (logit)	fossil fuels (logit)	renew. (logit)	renew. (logit)
intercept	1.076	-1.167	-2.504	-2.995
	(0.223)	(1.627)	(0.476)	(0.391)
cap. price$_t$	1.185	1.400	0.247	0.251
	(0.260)	(0.253)	(0.334)	(0.334)
avg. price$_t$		-0.004		0.007
		(0.005)		(0.003)
avg. fuel cost$_{gt}$		0.046		
		(0.033)		
coal$_g$	-1.972	-0.672		
	(0.481)	(1.303)		
wind$_g$			0.976	0.981
			(0.218)	(0.222)
$t - 2006$			0.247	0.263
			(0.037)	(0.040)
Num. obs.	640	640	160	160

Table 14: Production Cost Estimate Comparison

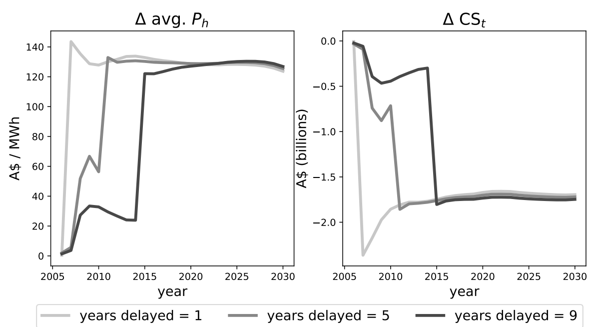
	Coal	OCGT	CCGT
Estimates (full sample)			
$\widehat{vom}_s$	24.857	-0.477	6.826
	(0.614)	(0.517)	(0.784)
$\hat{r}_s$	3 524.6	114.4	4 004.8
	(2 594.1)	(551.9)	(2 212.7)
Estimates (restricted sample)			
$\widehat{vom}_s$	25.263	-0.389	6.754
	(0.687)	(0.417)	(1.119)
$\hat{r}_s$	3 854.7	349.6	4 981.6
	(2 905.2)	(784.0)	(3 088.0)

Note: The sames notes as in table 4 apply.

C.2 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 effectiveness of 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.[65] This delay in the policy's implementation is known to the firms when the policy is announced in 2006.[66]

Figure 10: Impact of Delaying Policy



Note: Displayed is the expectation of the difference in each of the variables for a tax of A$200/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 10 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}.[67] 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-intense) and some coal (which is expensive because of its emissions). When the tax is delayed,

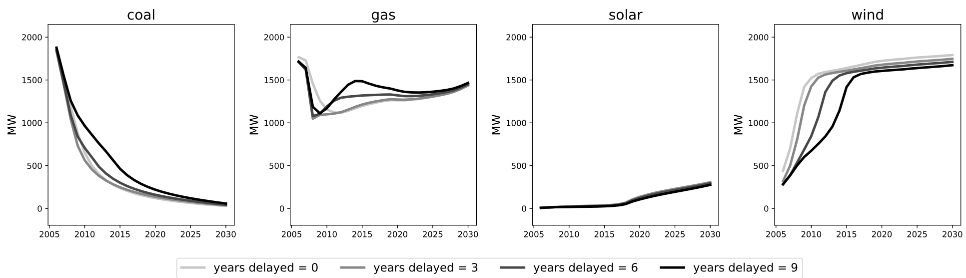
[65] This exercise shares some similarities with the demand-side exercise in Langer & Lemoine (2022), exploring optimal consumer subsidy dynamics to spur residential solar adoption.

[66] As in the counterfactuals in the main text, I assume firms have perfect foresight over future generator costs. This assumption may be particularly consequential in carbon tax delay scenarios, which amplify dynamic tradeoffs.

[67] 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 10) 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.

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 11: Impact of Delaying Policy on Investment



Note: Displayed is the expected investment for each source, summed across firms, for a tax of A$200/ton CO_2-eq and no capacity payment.

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 11 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 15 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).

Ultimately, despite the cost savings delaying a carbon tax can generate, there is little evidence it is worthwhile to delay implementation except for a low social cost of carbon. With a higher

Table 15: Welfare Impact of Delaying Policy

		ΔCS (billions A$)		ΔPS (billions A$)		ΔG (billons A$)		Δ emissions (billions kg CO_2-eq)		Δ blackouts (millions MWh)	
τ	delay	from baseline	from no delay	from baseline	from no delay	from baseline	from no delay	from baseline	from no delay	from baseline	from no delay
100.0	1	-17.04	1.23	3.22	-0.15	12.0	-0.94	-70.31	3.84	0.33	0.0
	5	-12.65	5.63	2.13	-1.24	9.32	-3.63	-53.88	20.27	0.14	-0.19
	9	-11.94	6.34	3.69	0.32	7.41	-5.54	-47.7	26.46	0.12	-0.21
200.0	1	-31.81	2.32	10.43	-0.4	19.17	-1.69	-94.66	4.65	3.34	0.02
	5	-26.88	7.25	10.21	-0.62	14.71	-6.15	-80.88	18.43	3.42	0.09
	9	-22.09	12.05	8.36	-2.47	12.09	-8.76	-63.72	35.59	2.51	-0.82
300.0	1	-36.71	2.97	13.27	-0.51	22.82	-2.16	-114.44	5.91	6.97	-0.01
	5	-29.35	10.33	13.25	-0.53	16.21	-8.76	-101.02	19.33	8.42	1.44
	9	-24.4	15.28	11.16	-2.62	13.52	-11.46	-78.26	42.1	6.64	-0.34

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 as well as their investment cost shocks. Note that values are not necessarily exactly the same as those that would be implied by table 7 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 67. Values "from baseline" compare the welfare measure to no carbon tax, values "from no delay" compare the welfare measure to that tax implemented immediately.

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 about A$116/ton CO_2-eq, the optimal delay is zero years.

Because the environment is non-stationary, the impact of delaying a carbon tax may depend on the year from which the delay is evaluated. To assess this, table 16 reports welfare outcomes when the analysis begins in 2012, so a one-year delay corresponds to a carbon tax's implementation in 2013. The welfare function, analogous to equation 26, is defined as

$$\mathbb{E}_{\mathbf{\Omega},\boldsymbol{\eta}}\left[\sum_{t=2012}^{\infty} \beta^{t-2012} \Delta^{P \to P'} W_t\left(\mathbf{\Omega}, \boldsymbol{\eta}\right)\right].$$

The results in table 16 are broadly consistent with those in table 15 across all carbon tax and delay combinations, suggesting that the conclusions are not sensitive to the initial year from which delay is considered.

C.3 Supplementary Tables and Graphs

This section provides additional results corresponding to the counterfactuals in the main text. Table 17 presents different measures of welfare that combine columns in table 7 in the main text, including broader measures of consumer surplus that include the cost of blackouts and different tax transfers.

Table 16: Welfare Impact of Delaying Policy after 2012

		ΔCS (billions A$)		ΔPS (billions A$)		ΔG (billons A$)		Δ emissions (billions kg CO_2-eq)		Δ blackouts (millions MWh)	
τ	delay	from baseline	from no delay	from baseline	from no delay	from baseline	from no delay	from baseline	from no delay	from baseline	from no delay
100.0	1	-19.59	1.22	5.97	-0.13	11.34	-0.71	-67.58	3.57	1.64	0.01
	5	-16.1	4.71	5.61	-0.5	8.98	-3.07	-56.47	14.68	1.53	-0.1
	9	-10.96	9.85	2.55	-3.55	7.15	-4.9	-42.54	28.61	0.4	-1.23
200.0	1	-32.64	2.38	10.98	-0.43	18.13	-0.91	-85.4	4.48	2.96	0.0
	5	-27.0	8.02	10.13	-1.28	14.96	-4.08	-71.29	18.6	2.85	-0.11
	9	-21.77	13.25	7.96	-3.45	12.52	-6.52	-55.42	34.46	2.06	-0.9
300.0	1	-37.43	3.02	14.31	-0.55	20.15	-0.93	-105.88	5.67	7.71	-0.09
	5	-29.85	10.59	13.84	-1.02	18.42	-2.67	-92.04	19.52	8.62	0.82
	9	-24.99	15.46	11.77	-3.09	15.2	-5.88	-72.51	39.04	6.99	-0.81

Note: Same notes as in table 15 apply. Values are with respect to a starting point of 2012 rather than 2006.

Table 17: Alternative Welfare Measures

		$\Delta\mathbb{E}\left[\sum_{t=0}^{\infty}\beta^t\left(\mathrm{CS}_t - VOLL \times \mathrm{B}_t\right)\right]$ (billions A\$)		$\Delta\mathbb{E}\left[\sum_{t=0}^{\infty}\beta^t\left(\mathrm{CS}_t + C_t - VOLL \times \mathrm{B}_t\right)\right]$ (billions A\$)		$\Delta\mathbb{E}\left[\sum_{t=0}^{\infty}\beta^t\left(\mathrm{CS}_t + \mathrm{T}_t + \mathrm{C}_t - VOLL \times \mathrm{B}_t\right)\right]$ (billions A\$)		$\Delta\mathbb{E}\left[\sum_{t=0}^{\infty}\beta^t\left(\mathrm{CS}_t + \mathrm{T}_t + \mathrm{C}_t - SCC \times \mathrm{E}_t - VOLL \times \mathrm{B}_t\right)\right]$ (billions A\$)	
τ	κ	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	-20.33	0.0	-20.33	0.0	-20.33	0.0	-19.85
	50 000	3.0	-20.09	0.27	-22.81	0.27	-22.81	-2.24	-25.62
	100 000	14.12	-16.46	7.33	-22.35	7.33	-22.35	2.54	-26.13
	150 000	25.64	-12.17	8.65	-21.86	8.65	-21.86	3.96	-26.88
	200 000	27.32	-13.67	1.77	-26.6	1.77	-26.6	-1.8	-30.94
100	0	-20.68	-31.95	-20.68	-31.95	-7.55	-18.35	4.61	-7.28
	50 000	-12.43	-33.66	-14.94	-36.15	-1.36	-22.18	9.78	-11.94
	100 000	-8.12	-30.21	-13.95	-35.39	-0.09	-21.47	10.39	-11.11
	150 000	3.81	-25.15	-12.36	-34.82	0.97	-19.8	12.67	-11.97
	200 000	7.29	-20.89	-18.35	-36.66	-5.35	-21.67	7.11	-13.77
200	0	-38.0	-47.67	-38.0	-47.67	-16.61	-22.83	1.15	-9.03
	50 000	-30.6	-45.43	-33.17	-48.0	-9.67	-22.92	5.66	-9.4
	100 000	-24.65	-43.09	-31.52	-48.43	-6.93	-23.85	7.15	-9.76
	150 000	-11.71	-42.7	-29.4	-52.23	-6.28	-26.94	9.5	-13.66
	200 000	-10.23	-26.76	-35.93	-46.96	-13.09	-22.52	3.01	-8.26
300	0	-55.8	-69.7	-55.8	-69.7	-30.1	-36.31	-7.45	-19.55
	50 000	-49.18	-66.48	-51.72	-68.8	-23.63	-35.22	-2.8	-18.61
	100 000	-37.84	-63.45	-47.34	-68.44	-15.12	-35.06	2.54	-18.29
	150 000	-29.16	-48.84	-46.91	-59.75	-15.53	-25.4	2.77	-9.37
	200 000	-26.87	-35.47	-52.6	-56.33	-21.39	-23.56	-2.95	-6.32

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 as well as their investment cost shocks. Baseline values (i.e., the value implied by the *laissez-faire* policy at the low price cap) are provided below each column heading. I construct welfare measures using $SCC =$A\$230/ton CO_2-eq and $VOLL =$A\$1 000/MWh.

Table 18: Total Welfare-Maximizing Policies with Storage

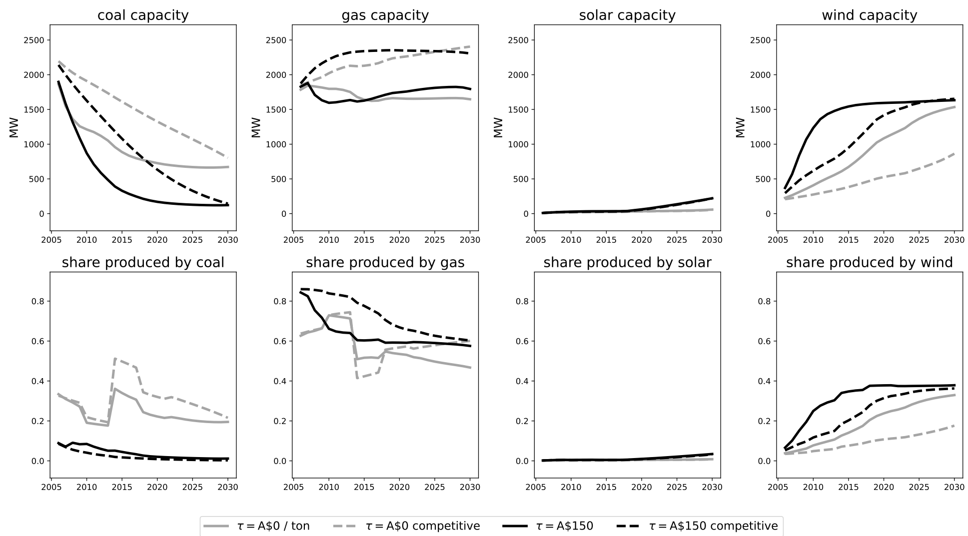
		carbon tax alone, no battery		carbon tax alone, battery		joint policies, no battery			joint policies, battery		
$VOLL$		τ^*	$\Delta\mathcal{W}$	τ^*	$\Delta\mathcal{W}$	τ^*	κ^*	$\Delta\mathcal{W}$	τ^*	κ^*	$\Delta\mathcal{W}$
1 000		**154.1**	**9.8**	**139.6**	**15.6**	**214.7**	**155 600**	**16.9**	**249.5**	**126 300**	**19.7**
	ΔCS		-23.2		-21.0			-21.1			-29.5
	ΔPS		5.3		6.8			9.3			12.0
	ΔG		16.3		15.7			5.2			13.8
	$-SCC \times \Delta$E		14.2		12.8			14.8			15.3
	$-VOLL \times \Delta$B		-2.8		1.4			8.6			8.1
10 000		**0.0**	**0.0**	**129.7**	**29.4**	**214.7**	**155 600**	**94.6**	**212.0**	**157 000**	**97.0**
	ΔCS		0.0		-19.7			-21.1			-19.7
	ΔPS		0.0		6.6			9.3			10.6
	ΔG		0.0		14.8			5.2			4.5
	$-SCC \times \Delta$E		0.0		12.3			14.8			15.2
	$-VOLL \times \Delta$B		0.0		15.3			86.4			86.4

Note: Changes in welfare are with respect to the *laissez-faire* policy ($\tau = 0$, $\kappa = 0$) with no battery and in expected present discounted terms (using $\beta = 0.95$) in thousand A\$ per customer. For all columns, a price cap of $\bar{P} =$ A\$300/MWh is used. Bold rows show the optimal policy and the difference in welfare compared to the baseline for a given value of the $VOLL$, and the rows below provide a welfare decomposition. I use a SCC of A\$230/ton CO_2-eq. I determine optimal policy values by interpolating using bivariate cubic splines, see note in table 8.

Table 18 presents the optimal policy, analogous to table 8 in the main text, when a battery as described in section 6.3 is present and compares the results to when it is not. A battery's presence unsurprisingly increases total attainable welfare, and for the baseline value of lost load achieves this at a higher carbon tax and lower capacity payment support than without a battery.

Figure 12 presents the evolution of expected capacity and production shares by energy source over time under market power and under competition for different levels of a carbon tax. Fossil fuel capacity is higher under competition because fossil fuel generators are disproportionately owned by the largest firms in the data. These firms have an incentive to underinvest in capacity to increase wholesale prices, so when these generators are reallocated to small firms that only own single generators, they invest more. Since under market power wholesale prices are higher due to underinvestment by the largest firms, renewable capacity, which is disproportionately owned by small firms in the data, is actually higher under market power and under competition.

Figure 12: Impact of Market Power vs. Competition on Investment and Production



Note: Depicted in each panel is the *expectation* for a particular energy source summed across all generators of that source for a particular value of a carbon tax under market power or competition.

Table 19: 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)
e_g	emissions rate of generator g (in kg CO_2-eq / MWh)
δ_{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
q_{gh}	quantity produced by generator g in interval h (in MWh)
hr_g	heat rate of generator g (in GJ / MWh)
p_{sh}^{input}	technology-specific input price for technology s in interval h (in A\$ / GJ)
vom_g	(marginal) variable operations and maintenance cost (in A\$ / MWh)
τ	carbon tax (in A\$ / kg of CO_2-eq)
r_g	ramping cost parameter (in A\$ / MWh_+^2)
$\bar{Q}_h$	perfectly inelastic demand in interval h
$u_{ih}(\cdot)$	consumer i's indirect utility function in interval h
P_t	end-consumer price for electricity in year t (in A\$ / MWh)
ξ_{ih}	consumer i's preference parameter for electricity in interval h
ϵ	elasticity of electricity consumption with respect to the end-consumer price
Ξ_h	aggregated preference parameters for electricity in interval h
$Q_h^{DR}(\cdot)$	demand reduction from demand response participants in interval h
$c_{gh}^b(\cdot)$	bid supply function for generator g in interval h
$\bar{P}_t$	price cap in year t (in A\$ / MWh)
$P_h(\cdot)$	wholesale market spot price in interval h (in A\$ / MWh)
$B_h(\cdot)$	expected electricity demand rationed via blackouts in interval h (in MWh)
$\pi_{fh}(\cdot)$	wholesale profit function for firm f in interval h (in A\$)
P_t^{avg}	quantity-weighted average wholesale price in year t (in A\$ / MWh)
c_{retail}	marginal retail cost of delivering electricity (in A\$ / MWh)
$\Pi_{ft}(\cdot)$	yearly expected profit for firm f in year t (in A\$)
κ_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
Ω_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
β	discount rate (at yearly level)
$\sigma_{Yt}^{\Omega}(\cdot)$	policy function for firms in Y in year t under ordering Ω
$X_f(\cdot)$	set of firms that have adjusted prior to f, and including f, under an ordering