Investment, Emissions, and Reliability in Electricity Markets*

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Abstract

This paper studies how to design electricity markets to reduce emissions and prevent blackouts. Zero-emission renewable energy sources, such as wind and solar, are intermittent, which can lead to blackouts if the addition of renewables causes more reliable power plants to retire. To quantify the impact of electricity market policies, I build a structural equilibrium model of investment and dis-investment in generators of different energy sources. Oligopolistic firms make dynamic decisions to build or retire generators based on the profits they receive from wholesale electricity markets, which respond to the composition of generators supplying electricity. Using data from the electricity market in Western Australia, I estimate this model and use it to simulate investment and production under counterfactual policies. Carbon taxes reduce emissions but, for certain values, can result in an increase in blackouts by causing retirement of coal and gas plants. Subsidizing capacity prevents this from occurring, but at the expense of higher emissions. Using both policies together, however, keeps reliable, emissions-intensive generators in the market and prevents them from being used unless necessary, substantially lowering emissions while keeping the likelihood of blackouts low. I also explore alternative environmental policies, which are less effective at reducing emissions but have a lower cost to consumers.

Keywords: electricity, renewable energy, market structure, investment, capacity payments, greenhouse gas emissions

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

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1 Introduction

The electricity industry emits more greenhouse gases than any other industry, accounting for 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. A critical concern when designing regulations in these markets is the risk of blackouts, which occur when demand for electricity exceeds the available supply. Zero-emission renewable energy sources are intermittent. Their inclusion can exacerbate blackouts if they replace dirty but more reliable sources.

This paper studies how we should regulate electricity markets given the intermittency of clean energy sources. Regulation is necessary to fix two major market failures. First, firms fail to internalize the environmental cost of their emissions, leading to excessive reliance on dirty energy sources such as coal. Second, consumers must be rationed via blackouts when demand exceeds supply because consumers do not respond to short-term fluctuations in the wholesale spot price of electricity. Firms do not fully capture the value to consumers of avoiding rationing when they add capacity, so they underinvest in aggregate capacity. Electricity market regulators have introduced policies to address these market failures individually, but these issues are interdependent. Since it is the clean energy sources that are less reliable, policies that aim to reduce emissions can increase blackouts, and those that aim to reduce blackouts can increase emissions.

I develop a dynamic equilibrium framework to quantify how electricity market policies impact investment and production. The framework builds on models previously developed in the literature in three ways in order to quantify the impact a policy has on emissions and reliability.[1] First, it endogenizes investment and production in all energy sources (in my application, coal, natural gas, and wind), which depend on production, maintenance, and investment costs. Second, it incorporates generators' stochastic capacity constraints that lead to blackouts. Lastly, following a wide literature documenting the presence of market power in electricity markets (Borenstein *et al.* , 2002; Sweeting, 2007; Bushnell *et al.* , 2008), it includes market power, which influences firms' investment and production decisions.

I use production and investment data from the electricity market in Western Australia to estimate the production, maintenance, and investment costs that determine firms' production and investment decisions. Using the estimated model, I study two policy tools in my main set

[1] The framework is specifically for "restructured" electricity markets in which independent generators sell electricity to the grid. This type of market stands in contrast to vertically integrated markets in which the grid operator also owns the generators. Many electricity markets were restructured in the 1990's, and these are the markets that I focus on in this paper. See Borenstein & Bushnell (2015) for a history and evaluation of restructuring. Although this review of restructuring is specific to the US, restructuring has happened across the globe, including in the electricity market that I study, Western Australia.

of counterfactuals. The first is a commonly-used tool (including in Western Australia) called capacity payments, which are essentially subsidies to capacity and are not linked to energy output. These aim to reduce the probability of blackouts by increasing grid capacity. The second type is a carbon tax levied on firms in proportion to the amount of carbon emitted. Capacity payments reduce blackouts but increase emissions. A carbon tax reduces emissions but, for certain values, increases blackouts. Used together, I find that capacity payments and a carbon tax used jointly can achieve both reliability and environmental goals. These policies induce substantial renewable investment and keep the reliable, high carbon-emitting generators in the market, while inducing them to act mostly as backups.

The model developed in this paper links short run production in wholesale electricity markets and long run investment. Firms produce electricity in repeated wholesale spot markets. In each spot market, the firms use their portfolio of generators, consisting of coal plants, natural gas plants, and wind farms, to satisfy the demand for electricity, resulting in a stream of profits. These profits depend on each firm's investment level in different energy sources. Over time, the firms periodically decide whether to adjust their generator portfolios by building new generators or retiring existing ones.

The wholesale market model captures how the level of investment determines wholesale market prices. For a realization of demand, firms choose how much electricity to supply from each of their generators. Production costs vary by energy source, and each generator is limited in its production by its capacity constraint, which varies over time due to power plant outages or variation in wind speeds. These costs and constraints determine how much electricity is produced by coal, natural gas, and wind. As firms add new generators, they decrease the cost to a firm of producing a given level of electricity and increase the maximum amount they can produce. Lower costs lead to lower wholesale market prices. Higher maximum levels of production allow firms to produce more electricity and also decrease the extent of blackouts, but firms do not fully internalize the value of reduced blackouts.

Generator portfolio decisions depend on this relationship between investment levels and wholesale market prices. Firms add and retire coal, gas, and wind generators based on the marginal profits of the generators, as well as the costs of building and maintaining them. Maintenance costs are particularly important for retirements. If the cost of maintaining a generator is high relative to the profits it yields, the firm will retire the generator. Investment decisions depend on these costs as well as both the present and future costs of building generators. Future generator construction costs are an important component of investment decisions because the costs of renewable generators have experienced a tremendous decline over the sample period. Declining 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.

Incorporating dynamic decisions among strategic firms introduces a challenge for estimation and counterfactuals. The dynamic investment game is nonstationary due to declining renewable costs. With just a single market, nonstationarity means that there is at most only one observation for each state. The typical approach to estimation in dynamic oligopoly settings relies on estimating choice probabilities in each state, which would be infeasible with at most one observation. I use stochastic alternating moves and a final period of investment, similarly to Igami & Uetake (2020), to simplify computation and ensure uniqueness of the equilibrium. This modeling approach captures the dynamic and strategic features that are important to this setting. Firms are forward looking and strategic. They anticipate future generator costs and also other firms' responses to their own investment decisions. Moreover, with a unique and computable equilibrium, I can take a full-information approach to estimation and also predict production and investment for a rich set of counterfactual policies.

I estimate the model parameters in two stages using data from the Western Australian electricity market. Western Australia is an ideal case study because the issues of reliability and emissions are particularly salient in this market. Western Australia is geographically isolated from the rest of the country and therefore lacks a grid connection to other electricity markets with which it could trade during times of high demand. This market also has a particularly heavy reliance on emissions-intensive coal, which made up 54% of electricity production in 2007.

In the first stage, I estimate the distribution of demand and wholesale production costs for each energy source using generators' first order conditions. Since generators may be constrained in their production, first order conditions may imply only a bound on their marginal costs, so I employ a Tobit-like strategy to accommodate these capacity constraints. Generators' costs vary over time, and I allow them to be correlated with one another. I estimate a high degree of correlation in costs across generators, which limits the returns to investing in an extra generator, as its costs are likely to be similar to other generators' costs. I then use these estimates to construct the stream of profits as a function of generator portfolios.

In a second stage, I estimate fixed generator costs. Firms have two types of fixed costs: the cost of building new generators and the cost of maintaining them. Because the cost of building new generators is nonstationary, rather than estimating these for each year I use yearly engineering estimates. I estimate maintenance costs based on firms' investment and retirement decisions using a full-information maximum likelihood approach. The modeling approach that I take to the investment game makes it possible to compute the equilibrium for every guess of the maintenance costs because the equilibrium is unique and computationally feasible. The estimates suggest that wind and coal are more expensive to maintain per MW of capacity than natural gas, which is consistent with engineering estimates.

Using the estimated model, I study the impact different regulatory tools have on emissions, blackouts, and product market welfare by solving for the equilibrium of the investment game. I use the state of the industry in 2007, the first year of my sample, and simulate the distribution of investment and production for future years. In a first set of counterfactuals, I study the interaction between environmental and reliability policies using a carbon tax and capacity payments. The carbon tax is levied on generators in proportion to their emissions, making natural gas and especially coal more expensive to produce. Capacity payments, which are widely used in electricity markets to prevent underinvestment including in Western Australia, provide generators with a payment in proportion to their capacities regardless of whether or not the generator ultimately uses that capacity to produce electricity. The payments provide an incentive for firms to maintain extra capacity.

In the absence of a carbon tax, capacity payments make it profitable for coal plants to remain in the market, reducing the number that retire, and the payments also increase the number of natural gas plants by increasing the returns to investment. In equilibrium this causes a significant decrease in blackouts but also causes investment in renewables to decline and emissions to increase. For example, a yearly capacity payment equal to the average of the payments used in Western Australia, ∼150 000 Australian dollars (AUD) per MW (or 17.12 AUD per hour), virtually eliminates blackouts (by over 99%) but increases emissions by 11%. Carbon taxes result in significantly higher and earlier investment in renewable generators, but without capacity payments, the tax induces quick retirement of coal plants. A carbon tax of 50 AUD per tonne of CO_2 decreases emissions by 37% but increases blackouts by 10%. Used together, a carbon tax and capacity payments significantly reduce both emissions and blackouts. The same capacity payment and carbon tax reduce blackouts by 98% and emissions by 36%. Together they can achieve both reliability and environmental goals because blackouts and emissions depend on different margins. The frequency of blackouts depends on the total level of investment and which types of generators receive that investment. Emissions, however, depend on which of those generators are used to produce electricity. Firms keep coal plants online because the payments cover the cost of maintaining generators, and they also increase the number of natural gas generators, but the tax makes it unprofitable for emissions-intensive generators to produce unless there is insufficient low-emission capacity available.

I use this exercise to determine optimal carbon taxes and capacity payments as a function of the social cost of carbon. I find that when the policy tools are used separately, they reflect the trade-off between emissions reductions and blackout reductions. Used together, the optimal carbon tax is very similar to the social cost of carbon, and the optimal size of capacity payments is roughly constant.

In practice, many electricity markets have adopted alternative environmental policy tools to reduce emissions. I quantify the impact of two commonly-used alternative policies, namely renewable investment and production subsidies. These renewable subsidies are not as effective at reducing emissions as a carbon tax. Coal is roughly twice as emissions-intensive as natural gas, but these subsidies do not distinguish between their emissions intensities. Moreover, the subsidy to investment, which is commonly used in practice, is particularly ineffective at reducing emssions because it targets the investment margin rather than the production margin that determines emissions. Both of these policies, however, result in a lower cost to consumers than does a carbon tax even if the carbon tax is rebated back to consumers.

Many environmental policies, such as clean vehicle standards or the Obama Administration's Clean Power Plan, have a delay between announcement and implementation to allow firms time to respond. My model can handle nonstationary costs and also nonstationary policies. It is therefore well-suited for analyzing the optimal timing for a policy's implementation. I determine the optimal delay in the implementation of a carbon tax following its announcement. By delaying implementation, firms have time to respond to the new environment by investing in natural gas and renewables. This time to respond can yield cost savings, as firms can avoid using expensive generators when their set of generators is high-emitting. I find that delaying the policy does indeed yield cost savings. Despite these cost savings, however, for most values of the social cost of carbon, the optimal delay is only one year, as the increased emissions outweigh the cost savings from delayed implementation.

Related Literature Equilibrium investment levels depend on the wholesale profits firms receive for a given set of generators. The modeling of wholesale markets used in this paper is influenced by an extensive literature that studies competition in electricity markets. This literature goes back to the early days of restructured electricity markets, measuring markups in wholesale markets due to imperfect competition (Wolfram, 1999; Borenstein & Bushnell, 1999; Bushnell *et al.* , 2008), and more recently using bidding data from wholesale auctions to study strategic behavior (Hortaçsu & Puller, 2008) and also estimate production costs (Wolak, 2007; Reguant, 2014). This paper uses similar methods as some of the aforementioned papers (particularly Bushnell *et al.* (2008)) to characterize market power in wholesale electricity markets, varying the capacity available in the market. This paper is therefore related to papers studying the equilibrium impact on wholesale markets, including the impact of adding renewables to the grid (Gowrisankaran *et al.* , 2016; Jha & Leslie, 2019; Karaduman, 2020b), the addition of utility-scale batteries (Karaduman, 2020a), and power plant closures (Davis & Hausman, 2016; Kim, 2020).

The model of wholesale profits is nested into a model of generator investment. To the best of my knowledge, this is the first paper to model dynamic oligopolistic equilibrium investment in electricity generators. Several papers consider two-stage entry models in which electricity-generating firms set capacity and then compete (Borenstein, 2005; Borenstein & Holland, 2005; Castro-Rodriguez *et al.* , 2009; Linn & McCormack, 2019). Allcott (2013) also uses such a model and studies similar capacity policies to those that I do (like capacity payments), but the focus of that paper is on real-time pricing. These two-stage entry models are meant to simulate long-run investment decisions. Such long-run investment models 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), which develops a fully dynamic investment model in batteries. They study investment in utility-scale batteries in which the cost of batteries declines over time, but this paper differs from Butters *et al.* (2021) in two key ways that allow me to consider different policies. First, I endogenize the investment of all energy sources in the market (rather than just batteries).[2] Second, I study investment with firms that have market power rather than competitive firms.

In order to study the impact of policies on oligopolistic firms' investment and production decisions, I adopt techniques developed in the empirical dynamic games literature. Two closely related papers are Ryan (2012) and Fowlie *et al.* (2016), which also study environmental regulation in imperfectly competitive markets, but in the cement industry. Similarly to these papers, I consider dynamic investment decisions among oligopolistic firms and the impact of environmental policy on equilibrium investments and emissions. Unlike these papers, I find that the optimal price of carbon under imperfect competition is only slightly below the social cost of carbon rather than substantially below, as in Fowlie *et al.* (2016). Additionally, the electricity market differs from that of cement because investment is in multiple different technologies (e.g., coal, gas, wind), and the market is nonstationary (due to declining costs of renewable generators). That latter point is what causes me to adopt a different modeling and estimation strategy, instead following Igami & Uetake (2020). Igami & Uetake (2020) study mergers in the hard disk drive industry, and, similarly to this paper, observe a single market in a nonstationary environment, which rules out the ability to employ the two-step conditional choice probability estimator based on Bajari *et al.* (2007) used by the aforementioned papers. Igami & Uetake (2020) make restrictions to the timing of the game that makes a full-information solution tractable, and I follow by making similar restrictions, detailed in section 3.

[2]There are no utility-scale batteries in the Western Australia market during the timeline I study. Since I do not study the impact of batteries, my model of wholesale market operations also differs significantly from that employed by Butters *et al.* (2021).

This paper is also related to 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 power sector models. These models contain very rich engineering details of electricity markets, but the model in this paper captures two features not included in these models that are important for understanding how environmental regulation impacts reliability: market power and underinvestment in capacity. Capacity payments have been the topic of considerable debate about their necessity for avoiding underinvestment (Hogan, 2005; Joskow & Tirole, 2008; Joskow, 2008; Bushnell *et al.* , 2017; Fabra, 2018), their impact on renewable investment (Llobet & Padilla, 2018; Mays *et al.* , 2019), and their interaction with strategic behavior (Teirilä & Ritz, 2019; McRae & Wolak, 2020). This paper speaks to these debates by quantifying the reduction in blackouts that the policy yields and the impact on renewable investment in an imperfectly competitive environment. I find that the blackout reduction that results is large, but whether to use these payments depends on the value of avoiding blackouts and whether environmental policies are also used. I also find that these payments depress renewable investment, though the quantitative impact is small and largely disappears when used jointly with a carbon tax. This paper combines the literatures on environmental and reliability policies by studying the interdependence between the two policies and is therefore related to Wolak (2021), which considers how increasing intermittent renewables affect how electricity markets should compensate reliability. This paper considers this question in a model of investment while also considering how these policies choices impact greenhouse gas emissions.

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

2 Institutional Details and Data

2.1 Western Australia Electricity Market

Western Australia's Wholesale Electricity Market (WEM) supplies electricity to southwestern Australia via the South West Interconnected System electricity grid, which includes the city of Perth and the surrounding area. Figure 11 in Appendix A.1 presents a map of this electricity grid. The WEM serves over one million customers and supplies roughly 18 terawatt hours of electricity every year. The South West Interconnected System is geographically isolated and therefore not connected with other grids in the country, preventing the WEM from trading electricity with other markets.

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 market with independent generators selling electricity to the grid (now owned by a separate state-owned company). 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 a day-ahead auction. Generators also receive capacity payments, described in detail in the following section.

The data begin with the commencement of this restructured market and are described in detail in section 2.3. Throughout the sample period, almost all electricity sold on the grid has been generated by one of three sources: coal, natural gas, and wind, collectively making up 98.5% of all electricity generated.[3] These energy sources will therefore be the focus of this paper.

2.2 Capacity Payments

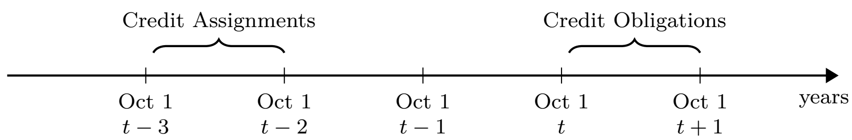
Capacity payments are yearly, recurring payments to electricity-generating firms in proportion to their capacities and are not linked to their actual energy output. These payments are typically structured with a *capacity price* (in $ / MW) that varies each year. In some markets this price is determined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

Since the start of electricity market "restructuring," when electricity generation was separated from transmission and distribution in many markets, electricity grid operators have been concerned that independent generators might underinvest in capacity. This underinvestment results in blackouts, which is a form of rationing during high demand periods.[4] Advocates of capacity payments argue the payments prevent this underinvestment, which could occur

[3]Western Australia also has substantial rooftop solar, as described in Jha & Leslie (2019), but I focus on utility-scale generation, of which solar makes up only 0.9% of generation.

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

Figure 1: Timeline of capacity credit for capacity year t to $t+1$



for two reasons (Fabra, 2018). First, firms may underinvest due to market operator-imposed price caps meant to limit market power. Limiting rents during times of high demand reduces the returns to investment, depressing the capacity in the market. Second, firms do not receive the value additional capacity creates for consumers by reducing blackouts, resulting in underinvestment.

The WEM has used capacity payments since its commencement. The market uses a system of allocating capacity credits called the Reserve Capacity Mechanism. A capacity credit corresponds to a megawatt (MW) of certified electricity generation capacity that a firm commits to make available in the wholesale market. The WEM chooses the price of a capacity credit for a year, and firms choose a level of capacity for which to receive capacity credits. Firms are then contractually obliged to make available at least as much electricity as they have capacity credits or otherwise pay a penalty.[5]

At the beginning of a capacity year (which runs from October 1 to September 30), the grid operator announces a capacity credit price. These credits are valid for the capacity year three years following. For example, if on October 1, 2010 the grid operator announces a capacity credit price, then these credits commit a firm to produce in the year from October 1, 2013 through September 30, 2014. In the same year as the price is announced, firms decide whether to request capacity credits, and credit allocations are finalized by the end of the first capacity year.[6] Once the fourth capacity year begins, firms are under their availability obligations according to the number of capacity credits they hold for that year. Wholesale markets occur in half-hour intervals, and firms pay a penalty if they fail to make their committed capacity available in an interval. Figure 1 depicts the timeline described above.

[5] 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. Failures to make electricity available are mostly due to generator outages.

[6] If the operator fails to reach a sufficient level of credit assignments, it can run a capacity auction for the remaining amount of desired capacity. Such an auction has never been necessary.

2.3 Data

The data come from the Wholesale Electricity Market and are provided by the Australia Energy Market Operator (AEMO). The data include information on the wholesale market, including short-term energy market prices, quantities supplied by each generator, and generator outages at half-hourly intervals. These data are complemented by data from AEMO on capacity payments (both capacity prices as well as capacity credit allocations by generator) and generator investment decisions (including dates of entry or retirement, energy source that powers the generator, and generator owner).[7] Table 1 summarizes the data described above.

Table 1: Summary Statistics

	Mean	**Std. Dev.**	**Min.**	**Max.**	**Num. Obs.**
Half-hourly data					
Price (AUD / MW)	\$48.87	\$33.98	-\$68.03	\$498.0	258 576
Quantity (aggregate) (MWh)	1 004.72	200.26	476.04	2 002.95	258 576
Quantity (generator-level) (MWh)	3.92	29.57	0.0	859.04	66 195 456
Fraction capacity produced	0.26	0.29	0.0	1.0	66 195 456
Fraction capacity experiencing outage	0.06	0.23	0.0	1.0	4 137 216
Generator data					
Capacity (coal) (MW)	161.83	79.17	58.15	341.51	17
Capacity (natural gas) (MW)	95.37	85.78	10.8	344.79	20
Capacity (wind) (MW)	59.42	75.54	0.95	206.53	16
Capacity price data					
Capacity price (AUD / MW)	\$130 725.56	\$24 025.49	\$97 834.89	\$186 001.04	14

Note: Prices are in 2015 AUD.

The production of electricity in Western Australia is very concentrated, although it has become less so over the sample. 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. Table 2 provides the market shares of Synergy, the next two largest firms, and the aggregated market share of all of the other electricity-generating firms in the market, each of which constitutes a market share of less than 10%. 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.

[7] Capacity investment decisions are observed for most firms. For the facilities without capacity data, I infer capacities from quantities in the wholesale market. These imputed capacities are based on the maximum observed electricity produced in a half-hour interval by a generator. An analysis of the validity of these imputations can be found in Appendix E.1.

Table 2: Market Shares

Year	Synergy	Alinta	Bluewaters Power	Others
2007	79.83%	15.06%	0.00%	5.11%
2011	55.29%	12.09%	16.22%	16.40%
2015	50.12%	13.86%	15.61%	20.41%
2019	38.67%	20.90%	18.64%	21.79%

Note: Shares are calculated based on total amount of electricity produced over the year. Named firms are those with $\geq 10\%$ market shares. All others are aggregated into "Others."

Table 3: Source Shares

Year	Coal	Natural Gas	Wind
2007	54.24%	41.68%	4.08%
2011	51.26%	41.44%	7.29%
2015	50.90%	42.05%	7.05%
2019	44.74%	43.04%	12.21%

Not only has the distribution of market shares evolved substantially in the years following the restructuring, but so too have the energy sources producing the electricity. Table 3 provides energy source shares over time, which documents a decline in the share of electricity produced using coal, a small increase in the share using natural gas, and a larger increase in the share using wind. Changes in generation capacity reflect similar trends. Figure 2 plots changes in capacity by each energy source. Over the course of the sample, coal has experienced a small but notable decline after an initial increase (the entry of Bluewaters Power, which exclusively uses coal power plants). Coal generators have been replaced primarily by new wind generators.

Capacity prices in Western Australia have varied substantially over time. Figure 3 displays the evolution of the capacity price. The capacity credit price mostly increased in the years

Figure 2: Capacity Evolution over Time

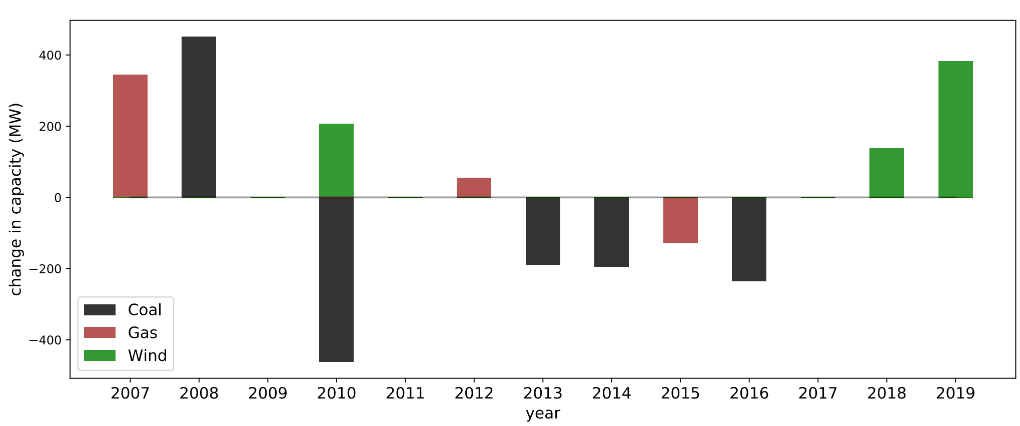
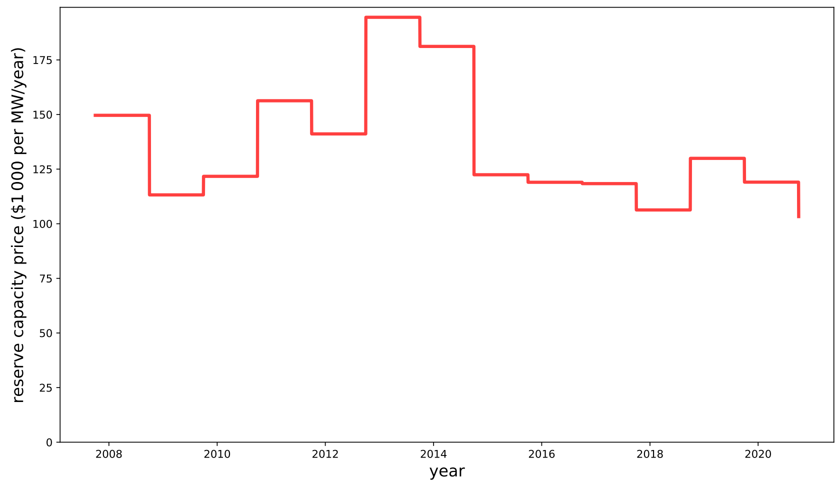


Figure 3: Capacity Price



Note: Prices are in 2015 AUD.

leading up to 2014, after which it experienced a steep decrease before stabilizing.

3 Model

In order to predict the impact of electricity market policies, I develop in this section a dynamic oligopolistic model of electricity production and investment in electricity generators. I combine a model of short-run wholesale electricity markets with a model of long-run investment. In the short-run wholesale market, firms use a fixed set of generators to produce electricity, and in the long-run, they can make costly adjustments to that set of generators. The short-run component of the model determines the returns to investment in a generator, and the long-run component models the trade-off firms make in that investment.

In the short-run wholesale market component, firms compete oligopolistically à la Cournot to supply the demand for electricity, determining the wholesale spot market price for electricity. Since end-consumers who determine the demand pay an *average* price for electricity rather than the *wholesale spot market* price, this demand is perfectly inelastic with respect to the spot market price determined by competition among the firms.

The short-run wholesale market component provides the basis for the three market failures that characterize this market. First, the environmental externality is a result of the fact that generators emit greenhouse gases when they produce electricity. Second, blackouts are a result of the fact that demand is unresponsive to the spot market price. Finally, firms have market power, creating a wedge between the private and social returns to production.

Over the long-run, firms make decisions about whether to retire or add generators. These generators are then used in the wholesale market and carry over to future periods. The firms' investment decisions determine the level of investment in each energy source, emissions, prices, and blackout frequencies. 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. The investment decisions therefore determine the size of the welfare cost of the market failures in the wholesale market.

Before introducing each component of the model in detail, I will introduce some notation that is common to both components. I index firms by f. A firm can be either a part of a fixed set of strategic firms $\{1, \ldots, n, \ldots, N\}$ or belong to a competitive fringe c. The difference between the strategic firms and the competitive fringe is whether they take into account the impact their decisions have on the market price. The set of generators is given by $\mathcal{G}$. A generator $g \in \mathcal{G}$ varies in three ways: the firm to which it belongs, $f(g)$; its capacity, K_g; and its energy source, $s(g) \in \mathcal{S} = \{\text{coal}, \text{gas}, \text{wind}\}$. Wholesale markets occur in intervals at the half-hourly level, indexed by h, and each interval h belongs to a year $t(h)$. Finally, the distribution of demand is given by $\mathcal{Q}$. 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 a wholesale market in interval h with a fixed set of generators $\mathcal{G}_{t(h)}$. At the beginning of the interval, several time-varying variables are realized: the effective capacities of each generator (after accounting for generator outages and intermittency in renewables), the costs of producing electricity, and the demand for electricity. Firms then make static production decisions for each of their generators and compete in quantities (à la Cournot) to maximize their profits. Appendix B.1 provides a description of how this model of the wholesale market compares to other papers in the literature and the implications of these differences.

3.1.1 Model Primitives

The fractions of generators' capacities that are usable is given by $\boldsymbol{\delta}_h$. Generator $g \in \mathcal{G}_{t(h)}$ therefore has a maximum production capacity in interval h of $\bar{K}_{g,h} = \delta_{g,h} K_g$, where $\delta_{g,h} \in [0, 1]$. The effective capacity $\bar{K}_{g,h} \leq K_g$ reflects that generators cannot always produce at their nameplate capacities $\mathbf{K}$, which are the maximum levels of production possible under ideal circumstances. Generator outages occur for all types of generators. Moreover, intermittent renewables are constrained by the shining of the sun or the blowing of the wind and therefore sometimes can only produce at a fraction of their nameplate capacities.

Each generator g has a cost of producing $q_{g,h}$ Megawatt-hours of electricity, $c_{g,h}(q_{g,h})$. This cost reflects the purchase of inputs (such as natural gas for a gas generator), the efficiency of generation (which can vary, for example, with the temperature), and the fraction of a generator's capacity used. Generators also have a fixed cost, reflecting labor and other components that do not vary with the short-run quantity produced $q_{g,h}$. That cost is included in the long-run component of the model and does not affect the firms' short-run production decisions.

Explicitly, the variable cost function is given by

$$c_{g,h}(q_{g,h}) = \left(\zeta_{1,g,h} + \tau_{t(h)} r_{s(g)}\right) q_{g,h} + \zeta_{2,s(g)} \left(\frac{q_{g,h}}{K_g}\right)^2, \tag{1}$$

where $q_{g,h}$ is the amount of electricity produced by generator g in interval h. The linear parameter $\zeta_{1,g,h}$ reflects the component of marginal costs that are constant across quantities, such as the per-unit costs of coal or natural gas. It is generator- and time-varying because commodity prices vary over time and generators may face different costs or have different dynamic considerations not modeled here. The parameter τ_t is a carbon tax and r_s captures the rate of emissions per Megawatt-hour of electricity produced by a generator of source s.[8] The quadratic parameter $\zeta_{2,s}$ captures costs associated with using a large fraction of available capacity. I parameterize the linear parameter $\zeta_{1,g,h}$ by

$$\zeta_{1,g,h} = \mathbf{x}'_{g,h} \boldsymbol{\beta}_{s(g)} + \varepsilon_{g,h}, \tag{2}$$

where $\mathbf{x}_{g,h}$ is a vector of potentially generator- and time-varying covariates that affect the marginal cost of production, and $\varepsilon_{g,h}$ is a common-knowledge shock to marginal costs, possibly correlated with other such shocks.

The functional form chosen in equation 1 is influenced by, but differs in a key way from, other papers in the electricity literature estimating generator costs, primarily Wolak (2007) and Reguant (2014). Specifically, I follow the cost function of the cited papers in using a quadratic form, but equation 1 lacks the start-up and ramping costs that those papers incorporate. I do not include these costs in order to keep the model of the wholesale market static. As discussed earlier, the decision to model the wholesale market as static allows me

[8]See Appendix A.4 for a list of these emissions rates.

to tractably simulate the wholesale market an extremely large number of times in order to incorporate it into a larger model of generator investment. To the extent that there are dynamic costs not explicitly incorporated into this model, they will be absorbed in estimation into the distribution of $\boldsymbol{\zeta}_1$. If, for example, demand rapidly increases, necessitating many firms to incur ramp-up costs, we will estimate a distribution of costs $\boldsymbol{\zeta}_1$ that have occasionally large shocks, correlated with one another, possibly correlated with demand.

Demand for electricity $\bar{Q}_h$ is realized at the beginning of the interval, drawn from the distribution $\mathcal{Q}_{t(h)}$, which is exogenous in the short-run and potentially correlated with the other stochastic variables also realized in an interval h. Consumers do not pay the wholesale spot market prices and are therefore perfectly inelastic with respect to the short-run fluctuations in the wholesale price of electricity, so $\bar{Q}_h$ does not respond to the wholesale market price. In equilibrium, conditional on there being sufficient capacity to satisfy demand, $\sum_{g\in\mathcal{G}_{t(h)}} q_{g,h} = \bar{Q}_h$. If, however, there is insufficient capacity, i.e., $\sum_{g\in\mathcal{G}_{t(h)}} \bar{K}_{g,h} < \bar{Q}_h$, a blackout results.

3.1.2 Firm Competition

Generators belong either to a strategic firm or to the competitive fringe. Generators in the competitive fringe take prices as given, yielding a generator supply curve given by

$$Q_{c,h}\left(P_h\right) = \sum_{g\in\mathcal{G}_{c,t(h)}} q^*_{g,h}\left(P_h\right),$$

where $q^*_{g,h}\left(P_h\right)$ for $g \in \mathcal{G}_{c,t(h)}$ is the quantity yielding a marginal cost of P_h (or the generator's constraints), i.e.

$$q^*_{g,h}\left(P_h\right) = \max\left\{\underline{K}_{s(g)}, \min\left\{\bar{K}_{g,h}, \frac{P_h - \zeta_{1,g,h}}{2\zeta_{2,s(g)}/K_g^2}\right\}\right\},$$

where $\underline{K}_g$ is the minimum production level of a generator of source s. Note that the second term in the minimum operator (the quantity yielding a marginal cost of P_h) comes from equation 1, the generator's cost function.

While consumers' demand for electricity in interval h is perfectly inelastic, strategic firms face a downward-sloping residual demand curve because generators belonging to the competitive fringe of producers respond to the market price. In equilibrium, demand equals supply. If the strategic firms' supply falls short of demand, the fringe's supply makes up the difference, which determines the market price.

The inverse residual demand curve that the strategic firms face is therefore given by

$$P_h\left(Q_{s,h}\right) = Q_{c,h}^{-1}\left(\bar{Q}_h - Q_{s,h}\right), \tag{3}$$

where $Q_{s,h}$ is the quantity of electricity produced by the strategic firms.

Using equation 3, the profit function of a strategic firm $f \in \{1, \ldots, N\}$ is

$$\pi_{f,h}\left(\mathbf{q}_{f,h}; \mathbf{q}_{-f,h}\right) = P_h\left(\mathbf{q}_h\right) \sum_{g \in \mathcal{G}_{f,t(h)}} q_{g,h} - \sum_{g \in \mathcal{G}_{f,t(h)}} c_{g,h}\left(q_{g,h}\right), \tag{4}$$

and the total profit of the competitive fringe is

$$\pi_{c,h}\left(\mathbf{q}_{s,h}\right) = P_h\left(\mathbf{q}_{s,h}\right) \sum_{g \in \mathcal{G}_{c,t(h)}} q_{g,h}^*\left(P_h\left(Q_{s,h}\right)\right) - \sum_{g \in \mathcal{G}_{c,t(h)}} c_{g,h}\left(P_h\left(Q_{s,h}\right)\right).$$

With the defined profit functions, the strategic firms play a Cournot game in quantities, constrained by the generators' constraints. Explicitly, for a strategic firm f,

$$\mathbf{q}_{f,h}^*\left(\mathbf{q}_{-f,h}\right) = \arg \max_{\underline{\mathbf{K}}_f \leq \mathbf{q}_{g,h} \leq \bar{\mathbf{K}}_{f,h}} \left\{\pi_{f,h}\left(\mathbf{q}_{f,h}, \mathbf{q}_{-f,h}\right)\right\}. \tag{5}$$

These best response functions characterize the wholesale market equilibrium. The equilibrium quantities in h are given by the vector of strategic quantities $\mathbf{q}_{s,h}^*$ such that for each strategic firm f, $\mathbf{q}_{f,h}^* = \mathbf{q}_{f,h}^*\left(\mathbf{q}_{-f,h}^*\right)$. The quantities of the generators in the competitive fringe are given by $\mathbf{q}_{c,h}^*\left(P_h\left(Q_{s,h}^*\right)\right)$. Due to market power and production capacity constraints, solving for the vector of equilibrium quantities $\mathbf{q}_h^*$ is difficult.[9] Appendix C.1 provides a detailed description of how to solve for $\mathbf{q}_h^*$.

Using the wholesale equilibrium quantities, we can define the function mapping the set of generators to profits in the interval, $\boldsymbol{\pi}_h : \Gamma \to \mathbb{R}^{N+1}$, where Γ is the set of all possible generator combinations, as

$$\pi_{f,h}\left(\mathcal{G}_t\right) = \pi_{f,h}\left(\mathbf{q}_h^*\left(\mathcal{G}_t\right)\right) \qquad \forall f \in \{1, \ldots, N, c\}. \tag{6}$$

[9]The wedge between private and social benefits of production that results from market power means that which generators' capacity constraints bind is a function of residual demand curves, and residual demand curves are a function of which generators' capacity constraints bind. In contrast, in the competitive case, which generators' capacity constraints bind is a function of the market demand, but the market demand does not depend on which generators' capacity constraints bind.

3.2 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 adjust their sets of generators by adding new ones and/or retiring existing generators. After (dis-)investment decisions are made, the newly updated set of generators, $\mathcal{G}_t$, is used in a series of many wholesale electricity markets, providing firms with a stream of profits. This chosen set of generators impacts the profits the firms receive—both through the changes induced by the choice in generators in costs and in competition—as well as the levels of emissions and the frequency of blackouts.

Investment decisions are dynamic and firms are strategic. The standard empirical model of oligopolistic industry dynamics is Ericson & Pakes (1995) (henceforth, EP), which is a stochastic dynamic game in which firms make simultaneous moves and face an infinite horizon. This model can yield multiple equilibria, coming from nonuniqueness of the stage game or through expectations over future values. While many papers have been able to analyze industry dynamics even in the presence of this multiplicity, this feature is particularly problematic for my setting. As will be discussed in more detail in the estimation section (section 4.2), data limitations prevent me from taking a non-parametric two-step estimator approach (such as Bajari *et al.* (2007)), as is common in the literature on estimating dynamic games.

In order to facilitate estimation through a maximum likelihood approach, as well as incorporate the non-stationarity of the cost of new generators (in particular wind), I define an equilibrium that removes both sources capable of generating multiple equilibria: the simultaneity of decisions and the infinite horizon. This modeling approach was developed and used by Igami & Uetake (2020) (henceforth, IU) in order to study endogenous mergers in the hard-drive disk industry. IU faced similar data limitations as I do and introduced to the EP framework sequential decisions within a period and a final period after which the game ends.[10]

I make similar modeling decisions as those in IU. First, in each year one randomly-selected strategic firm is allowed to adjust its set of generators, and all other strategic firms keep their current sets of generators. This assumption is consistent with the data, in which at most one strategic firm adjusts its set of generators. After the strategic firm decides, the competitive fringe responds.[11]

[10]IU assume that one firm is selected to move in each period and that the continuiation value after a particular end date is 0 (because the hard-drive disk industry will cease to exist). While I also introduce sequential moves and a final period, I differ from IU in both assumptions.

[11]While one may worry that the introduction of random, sequential moves may bias the model in some significant way, Doraszelski & Judd (2019) find that in a quality ladder model they consider, the equilibria of dynamic games with random, sequential moves are "practically indistinguishable" from those of simultaneous moves (albeit in an infinite horizon setting).

Second, I impose a finite horizon for the investment game in electricity generators. Specifically, I assume that in some final year, firms will cease to continue to be able to adjust their sets of generators. They will continue to receive profits from those generators for all eternity, but that game is effectively a static one without dynamic considerations. This assumption allows firms to backward induct, yielding a unique equilibrium in investment decisions. The assumption of a year after which firms can no longer invest is a strong one; however, by choosing a date far in the future, I allow the industry to reach a steady state hopefully well-approximated by the repeated static game without investment. Additionally, I perform robustness checks, varying the date at which this occurs, the results of which can be found in section 5.2.

Beyond making a maximum likelihood estimator tractable, this definition of the investment game has some additional advantages that make it well-suited for considering investment in electricity generators. First, the game easily incorporates non-stationarity (and is, in fact, by definition non-stationary because there is a final end date). Many changes in electricity markets that I consider are non-stationary. The cost of new wind generators, for example, is non-stationary and has fallen precipitously over the course of the time period I consider. Any analysis of this market must, therefore, incorporate this non-stationary. Additionally, the ability to solve the investment game via backward induction makes equilibrium computation relatively easy. This computational tractability allows me to consider a rich set of possible policies in order to determine optimal environmental and reliability policy.

With the aforementioned modeling assumptions, within-period timing is therefore as follows. Nature chooses a strategic firm to (potentially) make a costly adjustment to its set of generators. The competitive fringe observes this decision and responds. Firms then receive yearly profits as well as a capacity payment. The firms then all carry their generators over into the next period. After the last period of the game, firms can no longer adjust their sets of generators and must continue using them in all future periods.

3.2.1 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, $\mathbf{\Pi}_t : \Gamma \to \mathbb{R}^{N+1}$, is based on the wholesale profit function $\boldsymbol{\pi}_h$ defined in equation 6, and is defined as

$$\Pi_{f,t}\left(\mathcal{G}_t\right) = \underbrace{\sum_h \mathbb{E}_{\bar{Q}_h\left(\bar{P}_t(\mathcal{G}_t)\right),\boldsymbol{\eta},\boldsymbol{\delta}}\left[\pi_{f,h}\left(\mathcal{G}_t\right)\right]}_{\text{wholesale market profits}} - \underbrace{\sum_{g\in\mathcal{G}_{f,t}} M_{s(g)}K_g}_{\text{maintenance costs}} \qquad \forall f \in \{1,\ldots,N,c\}\,. \tag{7}$$

The first term of the above equation captures the total expected profits from the wholesale market over the year.[12] The expectation is taken over demand shocks ($\bar{Q}$), cost shocks ($\boldsymbol{\varepsilon}$), and production capacity shocks ($\boldsymbol{\delta}$), which all vary with h. The second term captures the cost of maintaining generators, where the cost for each generator is source-specific and in proportion to its capacity. This maintenance cost captures costs related to generators that are fixed with respect to the amount of electricity produced over the course of the year and therefore does not depend on generators' levels of production. This cost makes unused capacity costly.

While demand is perfectly inelastic in the short term, the distribution of inelastic demand shocks responds to the price level, which is captured in equation 7 by the dependency of $\bar{Q}_h$ on the quantity-weighted average wholesale price $\bar{P}_{t(h)}$. The details of this function can be found in Appendix B.3, which microfounds electricity demand.

Since wholesale market prices depend on the set of generators in the market, the distribution of demand indirectly depends on the set of generators. The quantity-weighted average wholesale price $\bar{P}_t$ is defined implicitly as a function of the generators $\mathcal{G}_t$ as follows:

$$\bar{P}_t = \frac{\mathbb{E}\left[\bar{Q}_h\left(\bar{P}_t\right)P_h^*\left(\mathcal{G}_t\right)\right]}{\mathbb{E}\left[\bar{Q}_h\left(\bar{P}_t\right)\right]}, \tag{8}$$

where $P_h^*\left(\mathcal{G}_t\right)$ is the wholesale market price in interval h with the set of generators $\mathcal{G}_t$. Equation 8 requires that $\bar{P}_t$ equals the quantity-weighted average wholesale price under the distribution of demand implied by $\bar{P}_t$. The long-run distribution of demand therefore responds to the set of generators in the market, and the strategic firms anticipate this when making investment decisions.

In addition to wholesale profits, firms can receive capacity payments over a year as a function of generator capacities. I model these payments based on the rules guiding the electricity market in Western Australia. The grid operator chooses a capacity credit price κ_t in year t. Each firm chooses a number of capacity credits to receive, modeled as the fraction of each of its generators' capacities to commit, γ_g. In each wholesale market, if a firm fails to have sufficient capacity to meet its commitment, then it must pay a penalty $\psi_{f,h}\left(\cdot\right)$. Such a penalty could occur due to an outage causing effective capacity $\bar{K}_{g,h}$ to fall below $\gamma_g K_g$, but *not* because the firm chooses to produce $q_{g,h}^* < \gamma_g K_g$.[13]

[12] Intervals take place every half-hour, and the summation is with respect to all intervals in a year, so there are 17 520 intervals.

[13] That the penalty depends on available *capacity* rather than *production* follows the capacity payment rules adopted by the WEM. Some electricity markets have adopted policies that more strongly incentivize production, such as that of Colombia, studied in detail by McRae & Wolak (2020). How to design capacity payments to incentivize efficient production is an interesting question that I do not examine in this paper, relying instead of the structure used by the WEM.

Over the year t, a firm f receives a net payment $\Upsilon_{f,t}(\cdot)$ based on its set of generators and the capacity credit price. Explicitly,

$$\Upsilon_{f,t}\left(\mathcal{G}_{f,t};\kappa_t\right) = \max_{\gamma \in [0,1]^{G_{f,t}}} \left\{ \sum_{g \in \mathcal{G}_{f,t}} \gamma_g K_g \kappa_t - \mathbb{E}\left[\sum_h \psi_{f,h}\left(\gamma;\kappa_t,\mathcal{G}_{f,t}\right) \right] \right\}. \tag{9}$$

The first term captures the gross capacity payment (before paying any penalties). The second term captures the total penalty the firm expects to pay over the year. The function $\psi_{f,h}(\cdot)$ returns the penalty firm f must pay in interval h if it fails to have sufficient capacity to meet its obligation, defined as

$$\psi_{f,h}\left(\gamma;\kappa_t,\mathcal{G}_{f,t}\right) = \sum_{g \in \mathcal{G}_{f,t}} \lambda_{s(g)} \max\left\{\left(\gamma_g - \delta_{g,h}\right) K_g, 0\right\} \kappa_t,$$

where $\lambda_{s(g)}$ is a source-specific refund factor, which is multiplied by the committed capacity unavailable, scaled by the capacity price. A more detailed description of the capacity payment mechanism used by the WEM is given in Appendix A.

3.2.2 Strategic Firms

At the beginning of each year, a strategic firm $f \in \{1, \ldots, N\}$ is randomly selected to adjust its set of generators. Each strategic firm has an equal probability of being selected, $\frac{1}{N}$. Firm f's value function *prior to the strategic firm selection* is given by

$$W_{f,t}\left(\mathcal{G}_f;\mathcal{G}_{-f},\mathcal{G}_c\right) = \sum_{m=1}^{N} \frac{1}{N} V_{f,t}^{m}\left(\mathcal{G}_f;\mathcal{G}_{-f},\mathcal{G}_c\right), \tag{10}$$

where $V_{f,t}^{m}(\cdot)$ is firm f's value function in the state of the world in which firm m is selected. If $m = f$, then the firm can adjust its own set of generators. Therefore, $V_{f,t}^{f}(\cdot)$ is the expected present-discounted value of firm f when it can optimally adjust its generators in the present year, other strategic firms cannot, and the competitive fringe responds. In the case where $m \neq f$, then a different firm can adjust its generators, and firm f remains with its current set. In this case, $V_{f,t}^{m}(\cdot)$ is the expected present-discounted value of firm f with its current set of generators, firm m optimally adjusting, other strategic firms keeping their current generators, and the competitive fringe responding.

The function $V^m_{f,t}(\cdot)$ is given formally below. A description of the function is given afterward.

$$V^m_{f,t}\left(\mathcal{G}_f;\mathcal{G}_{-f},\mathcal{G}_c\right)=\begin{cases}\max_{\mathcal{G}'_f\in\Gamma_f}\Big\{\mathbb{E}_{\boldsymbol{\eta}_c}\Big[\Pi_{f,t}\left(\mathcal{G}'_f;\mathcal{G}_{-f},\sigma_{c,t}\left(\mathcal{G}',\boldsymbol{\eta}_c\right)\right) \\ \qquad\qquad\qquad\qquad +\Upsilon_{f,t}\left(\mathcal{G}'_f;\kappa_t\right) \\ \qquad\qquad\qquad\qquad -\sum_{g\in\mathcal{G}'_f}C_{s,t}K_g\mathbb{1}\left\{g\notin\mathcal{G}_f\right\} \\ \qquad\qquad\qquad\qquad +\eta_{f,\mathcal{G}'_f,t} \\ \qquad\qquad\qquad\qquad +\beta\mathbb{E}\left[W_{f,t+1}\left(\mathcal{G}'_f;\mathcal{G}_{-f},\sigma_c\left(\mathcal{G}',\boldsymbol{\eta}_c\right)\right)\right]\Big]\Big\} & \text{if } m=f \\ \mathbb{E}_{\boldsymbol{\eta}_{m,c}}\Big[\Pi_{f,t}\left(\mathcal{G}_f;\mathcal{G}_{-f,-m},\sigma_{m,t}\left(\mathcal{G},\boldsymbol{\eta}_m\right),\sigma_{c,t}\left(\mathcal{G}_{-m},\sigma_{m,t}\left(\mathcal{G},\boldsymbol{\eta}_m\right),\boldsymbol{\eta}_c\right)\right) \\ \qquad +\Upsilon_{f,t}\left(\mathcal{G}_f;\kappa_t\right) \\ \qquad +\eta_{f,\mathcal{G}_f,t} \\ \qquad +\beta\mathbb{E}\left[W_{f,t+1}\left(\mathcal{G}_f;\mathcal{G}_{-f,-m},\sigma_{m,t}\left(\mathcal{G},\boldsymbol{\eta}_m\right),\sigma_{c,t}\left(\mathcal{G}_{-m},\sigma_{m,t}\left(\mathcal{G},\boldsymbol{\eta}_m\right),\boldsymbol{\eta}_c\right)\right)\right]\Big] & \text{if } m\neq f.\end{cases} \tag{11}$$

In the first case ($m=f$), firm f can adjust its generators. It can choose any set of generators in the set of possible sets of generators for the sources it uses, Γ_f. The firm then receives expected profits from the wholesale markets ($\Pi_{f,t}(\cdot)$), in which it is subject to its new, adjusted set of generators. While the other strategic firms do not adjust their generators, the competitive fringe can, so firm f takes an expectation over wholesale profits with respect to the competitive fringe's adjusted set of generators, given by $\sigma_{c,t}\left(\mathcal{G}',\boldsymbol{\eta}_c\right)$. The second term is the net capacity payment that the firm receives with its adjusted set of generators. The third and fourth terms represent the adjustment cost. The third term captures the cost of building new generators, and scales with the size of an increase in capacity. The fourth term is an idiosyncratic cost shock and represents transmission line expansions, permitting, and land acquisition. The final term is the continuation value, carrying the set of generators over to the next period.

In the second case ($m\neq f$), firm f cannot adjust its generators. Its value in this period is therefore the sum of its expected wholesale profits (term 1), its net capacity payments (term 2), any idiosyncratic costs (term 3), and its continuation value (term 4). Firm f takes an expectation over its wholesale profits with respect to the adjustment of the adjusting firm (firm m) and the competitive fringe.

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 (see Figure 1). The choice of three years notice is partially to give firms time to build new generators in response to the capacity price. While different energy sources 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.[14]

3.2.3 Competitive Fringe

The competitive fringe enters a year observing the adjusted set of generators of the strategic firms from the earlier stage $\mathcal{G}_{-c}$.[15] The competitive fringe is made up of many generators that make separate entry decisions. Generators that have not entered may choose to enter or to remain out of the market and wait to potentially enter in a future period. Generators that have already entered may choose to remain in the market or to retire the generator. After retirement, a generator may re-enter, but it must pay the investment cost again.[16]

A competitive generator g's value function is given below. The value function is denoted by $v_{g,t}(\cdot)$, where the lower script denotes that it is a competitive single generator (rather than one of the strategic firms with multiple generators, which use an upper case V). The function takes as arguments whether a generator has already entered the market (given by $e \in \{\text{in}, \text{out}\}$), as well as the set of competitive and strategic generators *before* competitive

[14] 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. I do not believe that differences in time-to-build across different technologies will have a meaningful impact on the results.

[15] Note that this vector may be different from the set of generators the strategic firms observe when they make decisions. If a firm chooses to adjust, then the set of generators *after adjustment* is what the competitive fringe observes.

[16] The decision to allow generators to re-enter is made to match the modeling of strategic firms, which can retire a generator and then build it anew. Since investment costs are substantial and maintenance costs do not fluctuate over time, this modeling assumption should not ultimately matter. While any such investment decision has positive probability (since the idiosyncratic shocks have full support along the real line), there is no strong incentive to retire a generator and then build it again.

generators make entry decisions in this period.

$$v_{g,t}\left(e,\mathcal{G}_c,\mathcal{G}_s\right)=\begin{cases}\max\limits_{\text{in / out}}\Big\{\Pi_{g,t}\left(\mathcal{G}_t^*\left(\mathcal{G},\boldsymbol{\eta}_c\right)\right) \\ \qquad +\Upsilon_{g,t}\left(\{g\};\kappa_t\right) \\ \qquad -C_{s(g),t}K_g \\ \qquad +\eta_{g,e,t} \\ \qquad +\beta\mathbb{E}_{\boldsymbol{\eta}_{-c}}\left[\frac{1}{N}\sum_{m=1}^{N}v_{g,t+1}\left(\text{in},\mathcal{G}_{c,t}^*\left(\mathcal{G},\boldsymbol{\eta}_c\right),\mathcal{G}_{-c,-m},\sigma_{m,t+1}\left(\mathcal{G}_t^*\left(\mathcal{G}\right),\boldsymbol{\eta}_m\right)\right)\right], \\ \quad \eta_{g,e,t} \\ \qquad +\beta\mathbb{E}_{\boldsymbol{\eta}_{-c}}\left[\frac{1}{N}\sum_{m=1}^{N}v_{g,t+1}\left(\text{out},\mathcal{G}_{c,t}^*\left(\mathcal{G},\boldsymbol{\eta}_c\right),\mathcal{G}_{-c,-m},\sigma_{m,t+1}\left(\mathcal{G}_t^*\left(\mathcal{G}\right),\boldsymbol{\eta}_m\right)\right)\right]\Big\} & \text{if } e=\text{out} \\ \max\limits_{\text{in / out}}\Big\{\Pi_{g,t}\left(\mathcal{G}_t^*\left(\mathcal{G},\boldsymbol{\eta}_c\right)\right) \\ \qquad +\Upsilon_{g,t}\left(\{g\};\kappa_t\right) \\ \qquad +\eta_{g,e,t} \\ \qquad +\beta\mathbb{E}_{\boldsymbol{\eta}_{-c}}\left[\frac{1}{N}\sum_{m=1}^{N}v_{g,t+1}\left(\text{in},\mathcal{G}_{c,t}^*\left(\mathcal{G},\boldsymbol{\eta}_c\right),\mathcal{G}_{-c,-m},\sigma_{m,t+1}\left(\mathcal{G}_t^*\left(\mathcal{G}\right),\boldsymbol{\eta}_m\right)\right)\right], \\ \quad \eta_{g,e,t} \\ \qquad +\beta\mathbb{E}_{\boldsymbol{\eta}_{-c}}\left[\frac{1}{N}\sum_{m=1}^{N}v_{g,t+1}\left(\text{out},\mathcal{G}_{c,t}^*\left(\mathcal{G},\boldsymbol{\eta}_c\right),\mathcal{G}_{-c,-m},\sigma_{m,t+1}\left(\mathcal{G}_t^*\left(\mathcal{G}\right),\boldsymbol{\eta}_m\right)\right)\right]\Big\} & \text{if } e=\text{in}.\end{cases} \tag{12}$$

A generator enters a year t as either not having already entered the market (the first case in equation 12) or having entered it (the second case). If it has not entered the market, then it can either pay the cost of investment (analogous to that of strategic firms) and enter the market (receiving wholesale profits and capacity payments), or it can not enter and potentially enter in a future year. If the generator has already entered the market, it can either continue existing, and receive profits and capacity payments, or it can retire (but potentially re-enter in a future year).

The generator set $\mathcal{G}_t^*(\cdot)$ is the equilibrium set of competitive generators in year t. It takes as an input the set of strategic generators (after making adjustment decisions in that year) and the incumbent competitive generators. This set is determined by a free entry condition: generators enter (or retire) up to the point that entering is not profitable. Appendix C.5 includes more details about how this set is determined.

3.2.4 Final Period of Adjustment

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

is given by

$$W_{f,T+1}\left(\mathcal{G}_f;\mathcal{G}_{-f}\right)=\sum_{t=T+1}^{\infty}\beta^{t-T-1}\mathbb{E}\left[\Pi_{f,t}\left(\mathcal{G}_f;\mathcal{G}_{-f}\right)+\Upsilon_{f,t}\left(\mathcal{G}_f;\kappa_t\right)+\eta_{f,\mathcal{G}_f,t}\right]. \tag{13}$$

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

4 Estimation and Identification

In the following section I lay out a strategy for estimating the model described in section 3. I estimate this model in two stages. In a first stage I estimate the parameters governing the wholesale market, including production costs and the distribution of demand. I then use these first-stage estimates to construct the expected yearly profit function (equation 7), which I use to estimate the parameters governing firms' investment decisions, including the sunk costs of investment and fixed maintenance costs. I specify the three largest firms in the market, which are the three with market shares $\geq 10\%$ listed in section 2.3, as the strategic firms and assume that all other generators belong to the competitive fringe. These three firms are substantially larger than the next largest firm, creating a natural cutoff point between strategic firms and the fringe.

4.1 Wholesale Market Estimation

In the first stage, I need to estimate the joint distribution of generator costs, capacity factors, and demand shocks. Capacity factors and demand are both observed in the data. I recover capacity factors using detailed outage data provided by the grid operator that reports the size of outages for each generator. Short-run demand is perfectly inelastic, and therefore the quantity of electricity provided in a given interval is simply the quantity supplied by generators during that time, which is observed (conditional on no blackouts occurring, which is a rare event).[17]

Generator costs, in contrast, are not directly observed in the data. For each generator, I observe the quantity of electricity produced, but not the cost of producing it. I can, however, use the firms' first order conditions associated with equation 5 to recover marginal costs. The

[17] Like many electricity markets, there do exist so-called demand-response participants, which participate in the wholesale market auctions with a bid to *decrease consumption*. While their existence means that demand is not truly *perfectly* inelastic, the reduction in demand from these participants constitutes an extremely small fraction of total market demand, and I therefore ignore them.

model provides an inversion between the prices and quantities observed and unconstrained generators' marginal costs. Generators, however, frequently produce zero electricity or their full capacity. For generators that are constrained in an interval at either their lower production limit $\underline{K}_g$ or their upper one $\bar{K}_{g,h}$, the first order conditions do not hold exactly but do imply a bound on marginal costs. I use both the recovered marginal costs as well as those bounds to estimate the distribution of marginal costs via maximum likelihood with a Tobit-like likelihood.

Separate identification of the component of cost that depends on the fraction of capacity used ($\boldsymbol{\zeta}_2$) from the constant component ($\boldsymbol{\zeta}_1$) comes from the covariance between price and capacity utilizations (i.e., the fraction of capacity used). If capacity utilizations and prices are highly positively correlated (capacity utilizations are high when prices are high, and they are low when prices are low), ζ_2 is large relative to the variance of the cost shocks $\boldsymbol{\varepsilon}$. If it is expensive to use a large fraction of capacity (high ζ_2), then when $\bar{Q}_h$ is high, necessitating a high capacity utilization, prices will rise. If, in contrast, capacity utilizations and prices are weakly correlated, then ζ_2 is small relative to the variance of the cost shocks. In that case, most of the difference in costs comes from shocks to ζ_1, and high prices come from expensive generators needing to run rather than needing to use high fractions of generators' capacities. This correlation determines the relative scale of these parameters to one another, and the level is determined by the range of prices observed.

The identification argument described above is nonparametric, but I impose a parametric distribution on the cost shocks $\boldsymbol{\varepsilon}$ for the sake of tractability. Specifically, I assume that

$$\boldsymbol{\varepsilon}_h \sim \mathcal{N}\left(\mathbf{0}, \boldsymbol{\Sigma}_{\varepsilon}\right).$$

There are two ways in which this parametric distribution makes estimation more tractable, both related to allowing correlation among generators' cost shocks within an interval. It is important to allow for this correlation since it impacts the profits firms expect when they choose to add or retire generators.[18] First, the Tobit likelihood combines the unconstrained generators' cost shocks likelihood with the likelihood that the constrained generators' cost shocks exceed some bounds. With correlation among cost shocks, as I explain in the following section, we must condition the constrained generators' likelihood on the unconstrained cost shocks. Generally speaking, solving for the conditional probability $F\left(X_2 \middle| X_1 = x_1\right)$ of an arbitrary distribution F can be difficult, but the conditional distribution of a multivariate normal is a multivariate normal, making computation relatively easy. Second, with many generators, the dependence among cost shocks is extremely high-dimensional, requiring an

[18] Indeed, I find that the correlation across generators' cost shocks is very high (see table 4 in section 5).

enormous data requirement beyond even the hundreds of thousands of wholesale markets I observe. The multivariate normal puts structure on the correlation, which reduces the dimension of the object I estimate, thereby making the estimation problem tractable.

4.1.1 Generator Costs

Generators' costs are specified in equation 1, provided again below for convenience:

$$c_{g,h}\left(q_{g,h}\right) = \left(\zeta_{1,g,h} - \tau_{t(h)} r_{s(g)}\right) q_{g,h} + \zeta_{2,s(g)} \left(\frac{q_{g,h}}{K_g}\right)^2, \tag{1 revisited}$$

where

$$\zeta_{1,g,h} = \mathbf{x}'_{g,h} \boldsymbol{\beta}_{s(g)} + \varepsilon_{g,h}. \tag{2 revisited}$$

Wind generators have zero marginal costs, so I do not need to estimate the distribution of wind generators' costs. I use $\tilde{\mathcal{G}}$ to denote only the set of thermal generators (i.e., coal and gas generators, excluding wind). I further partition the set of generators by whether or not the generator is (optimally) operating at a constraint in a given interval h based on the quantity $q_{g,h}$ I observe in the data. Let $\tilde{\mathcal{G}}_h^u$ denote the set of generators unconstrained in interval h, i.e., $q_{g,h} \in \left(\underline{K}_{s(g)}, \bar{K}_{g,h}\right)$; $\tilde{\mathcal{G}}_h^-$ the generators constrained from below, i.e., $q_{g,h} \leq \underline{K}_g$; and $\tilde{\mathcal{G}}_h^+$ the generators constrained from above, i.e., $q_{g,h} = \bar{K}_{g,h}$.[19] The set $\tilde{\mathcal{G}}_h^{-u} = \tilde{\mathcal{G}}_h^- \cup \tilde{\mathcal{G}}_h^+$ denotes those that are constrained from any direction. Superscripts on generator-level variables (such as $\mathbf{q}$ or $\boldsymbol{\varepsilon}$) similarly denote the subset of that variable for which the corresponding generators belong to the set of thermal generators with the same superscript (e.g., $\mathbf{q}_h^+$ is the quantities in interval h produced by the generators in $\tilde{\mathcal{G}}_h^+$).

Unconstrained Generators The idea behind the estimation procedure is to use the generators' production first order conditions associated with equation 5, given below, to back out the distribution of costs:

$$\begin{aligned} P_h &= \boldsymbol{\beta}'_{s(g)} \mathbf{x}_{g,h} + 2\zeta_{2,s(g)} \tfrac{q_{g,h}}{K_g^2} + \varepsilon_{g,h} \qquad \forall g \in \tilde{\mathcal{G}}_{c,h}^u \\ MR_{g,h} &= \boldsymbol{\beta}'_{s(g)} \mathbf{x}_{g,h} + 2\zeta_{2,s(g)} \tfrac{q_{g,h}}{K_g^2} + \varepsilon_{g,h} \qquad \forall g \in \tilde{\mathcal{G}}_{s,h}^u. \end{aligned} \tag{14}$$

Note that the marginal revenue of strategic generators, $MR_{g,h}$, is a function of the competitive supply curve and the other strategic firms' production decisions.

[19] The relation between $q_{g,h}$ and $\underline{K}_g$ is an inequality rather than an equality because $\underline{K}_g$ is not necessarily zero. Coal generators, for example, have a minimum production level of approximately $\frac{1}{2} K_g$. If a generator fails to produce at least $\underline{K}_g$, then it simply shuts down and produces 0.

Since $q_{g,h}$ is a function of each generator's cost shock $\varepsilon_{g,h}$, I cannot solve for $\boldsymbol{\varepsilon}_h^u$ by simply subtracting the first two terms on the right hand side of equation 14 from the left hand side. While this would yield $\boldsymbol{\varepsilon}_h^u$ at the true cost parameters $(\boldsymbol{\beta}, \boldsymbol{\zeta}_2)$, solving for $\boldsymbol{\varepsilon}_h^u$ in this way will lead to an inconsistent estimator for these parameters because $\mathbf{q}_h^u$ is a function of $\boldsymbol{\varepsilon}_h^u$. Instead, I solve for the equilibrium prices and quantities as a function of the cost shocks, and then invert the observed prices and quantities to obtain the cost shocks, accounting for the endogeneity of $\mathbf{q}_h^u$. I denote this mapping by $\boldsymbol{\phi}_h(\cdot)$.[20] Conditional on the cost parameters $(\boldsymbol{\beta}, \boldsymbol{\zeta}_2)$, I recover the unconstrained cost shocks as follows:

$$\boldsymbol{\varepsilon}_h^u(\boldsymbol{\beta}, \boldsymbol{\zeta}_2) = \boldsymbol{\phi}_h^{-1}(\mathbf{q}_h^u, P_h; \boldsymbol{\beta}, \boldsymbol{\zeta}_2).$$

Constrained Generators The above method recovers the cost shocks for $g \in \tilde{\mathcal{G}}_h^u$, and I now describe how I bound the cost shocks for $g \in \tilde{\mathcal{G}}_h^{-u}$. As with the unconstrained generators, the first order conditions in equation 14 provide information relevant to the realizations of $\boldsymbol{\varepsilon}_h$. I can replace the equalities in equation 14 with inequalities, as follows:[21]

$$\begin{array}{rcll} P_h & \leq & \boldsymbol{\beta}'_{s(g)}\mathbf{x}_{g,h} + 2\zeta_{2,s(g)}\frac{K_g}{\bar{K}_g^2} + \varepsilon_{g,h} & \forall g \in \tilde{\mathcal{G}}_{c,h}^{-} \\ P_h & \geq & \boldsymbol{\beta}'_{s(g)}\mathbf{x}_{g,h} + 2\zeta_{2,s(g)}\frac{\bar{K}_{g,h}}{\bar{K}_g^2} + \varepsilon_{g,h} & \forall g \in \tilde{\mathcal{G}}_{c,h}^{+} \\ MR_{g,h} & \leq & \boldsymbol{\beta}'_{s(g)}\mathbf{x}_{g,h} + 2\zeta_{2,s(g)}\frac{K_g}{\bar{K}_g^2} + \varepsilon_{g,h} & \forall g \in \tilde{\mathcal{G}}_{s,h}^{-} \\ MR_{g,h} & \geq & \boldsymbol{\beta}'_{s(g)}\mathbf{x}_{g,h} + 2\zeta_{2,s(g)}\frac{\bar{K}_{g,h}}{\bar{K}_g^2} + \varepsilon_{g,h} & \forall g \in \tilde{\mathcal{G}}_{s,h}^{+}. \end{array} \tag{15}$$

Unlike in equation 14 for the unconstrained generators, $\mathbf{q}_h^{-u}$ does not enter the right hand side of the inequalities in equation 15. I therefore do not have the same endogeneity problem with the quantities, and the inversion is easier. I can simply subtract the first two terms of the right hand side of each inequality from the left hand side and obtain bounds on $\boldsymbol{\varepsilon}_h^{-u}$.

These bounds depend on the marginal revenue for the strategic, constrained generators, which are a function of the residual demand that the strategic firms face. Using $\boldsymbol{\varepsilon}_h^u(\boldsymbol{\beta}, \boldsymbol{\zeta}_2)$, we can

[20]The first order conditions in equation 14 provide this mapping from $\boldsymbol{\varepsilon}_h^u$ to $(\mathbf{q}_h^u, P_h)$. Appendix C.2 provides a closed form solution to this system of equations (equations 42 and 43) and shows that it is injective. Because $\boldsymbol{\phi}_h(\cdot)$ is injective, it is invertible, and Appendix C.2 provides a closed form (equation 44) of the inversion from $(\mathbf{q}_h^u, P_h)$ to $\boldsymbol{\varepsilon}_h^u$, $\boldsymbol{\phi}_h^{-1}(\cdot)$.

[21]I am using here that $\zeta_{2,s} > 0$ for all s.

trace out locally the supply curve for competitive firms, which Appendix B.2 shows is linear:[22]

$$Q_{c,h}\left(P_h;\boldsymbol{\beta},\boldsymbol{\zeta}_2\right)=\underbrace{\sum_{g\in\mathcal{G}^+_{c,h}}\bar{K}_{g,h}}_{\substack{\text{constrained}\\\text{generators}}}+\underbrace{\alpha_h\left(\boldsymbol{\varepsilon}^u_h\left(\boldsymbol{\beta},\boldsymbol{\zeta}_2\right)\right)+\beta_h\left(\boldsymbol{\varepsilon}^u_h\left(\boldsymbol{\beta},\boldsymbol{\zeta}_2\right)\right)P_h}_{\substack{\text{unconstrained}\\\text{generators}}}.$$

The residual demand curve that the strategic firms face is therefore

$$P_h\left(\mathbf{q}_h;\boldsymbol{\beta},\boldsymbol{\zeta}_2\right)=\frac{\bar{Q}_h-Q^{\text{wind}}_h-\sum_{g\in\mathcal{G}^+_{c,h}}\bar{K}_{g,h}-\alpha_h\left(\boldsymbol{\varepsilon}^u_h\left(\boldsymbol{\beta},\boldsymbol{\zeta}_2\right)\right)-\sum_{g\in\mathcal{G}_s}q_{g,h}}{\beta_h\left(\boldsymbol{\varepsilon}^u_h\left(\boldsymbol{\beta},\boldsymbol{\zeta}_2\right)\right)},$$

which we can rewrite as

$$P_h\left(\mathbf{q}_{s,h};\boldsymbol{\beta},\boldsymbol{\zeta}_2\right)=a_h\left(\boldsymbol{\beta},\boldsymbol{\zeta}_2\right)-b_h\left(\boldsymbol{\beta},\boldsymbol{\zeta}_2\right)\sum_{g\in\mathcal{G}_s}q_{g,h}.$$

The marginal revenue $MR_{g,h}$ for the strategic generators is therefore given by

$$MR_{g,h}\left(\boldsymbol{\beta},\boldsymbol{\zeta}_2\right)=a_h\left(\boldsymbol{\beta},\boldsymbol{\zeta}_2\right)-b_h\left(\boldsymbol{\beta},\boldsymbol{\zeta}_2\right)\sum_{\substack{g'\in\tilde{\mathcal{G}}_s:\\ f(g')\neq f(g)}}q_{g',h}-2b_h\left(\boldsymbol{\beta},\boldsymbol{\zeta}_2\right)\sum_{\substack{g'\in\tilde{\mathcal{G}}_s:\\ f(g')=f(g)}}q_{g',h}.$$

Likelihood With the ability to back out the cost shocks for unconstrained generators and bounds for the constrained ones, I can construct a Tobit-like estimator that combines the density function of $\boldsymbol{\varepsilon}_h$ with the c.d.f. to estimate the model's parameters. With a univariate Tobit, each draw is independent, so we do not need to condition one draw on another's outcome. In my case, I have dependent cost draws across generators within an interval, meaning that the cost shock realization I back out for unconstrained generators is informative about the likelihood of the realizations I cannot back out and must bound. In order to calculate the joint likelihood in an interval, which I denote $\tilde{f}_h(\cdot)$, I break the likelihood into the marginal density of the unconstrained generators and the conditional probability of the constrained firms:

$$\tilde{f}_h\left(\boldsymbol{\varepsilon}_h\right)=f_h\left(\boldsymbol{\varepsilon}^u_h\right)F_h\left(\boldsymbol{\varepsilon}^{-u}_h\middle|\,\boldsymbol{\varepsilon}^u_h\right).$$

[22] Note that the supply curve here is the *local* supply curve. As P_h increases, generators' capacity constraints will bind and the constraints of generators constrained from below will cease to bind, giving a different (but still linear) function. I am only interested in the supply function in order to construct strategic generators' marginal revenues at the quantity $\mathbf{q}_{s,h}$ observed in the data, however. The local supply curve is all that matters for this calculation. Therefore, to calculate strategic generators' marginal revenues at $\mathbf{q}_{s,h}$, I can ignore the fact that competitive generators' capacity constraints will bind (or cease to) at points outside of a neighborhood around $\mathbf{q}_{s,h}$.

I use this likelihood function to estimate the cost distribution parameters via maximum likelihood.

I assume that the generator cost shocks are jointly realized in each interval (allowing for correlation) and are normally distributed $\boldsymbol{\varepsilon}_h \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma}_\varepsilon)$, where $\boldsymbol{\Sigma}_\varepsilon$ is the covariance matrix, given by

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

Values vary only at the energy source-level (*i.e.*, $\sigma_g = \sigma_{s(g)}$, $\rho_{g,g'} = \rho_{s(g),s(g')}$). The value $\rho_{s,s'}$ captures the correlation between energy sources s and s'. This restriction reduces the number of correlation parameters we need to estimate and makes likelihood computations much simpler.

For notational convenience, I combine both competitive and strategic generator inversions implied by equation 15. Let

$$\nu_{g,h}(\boldsymbol{\beta}, \boldsymbol{\zeta_2}) = \begin{cases} P_h - \boldsymbol{\beta}'_{s(g)}\mathbf{x}_{g,h} - 2\zeta_{2,s(g)}\frac{q_{g,h}}{K_g^2} & \text{if } g \in \mathcal{G}_c \\ MR_{g,h}(\boldsymbol{\beta}, \boldsymbol{\zeta_2}) - \boldsymbol{\beta}'_{s(g)}\mathbf{x}_{g,h} - 2\zeta_{2,s(g)}\frac{q_{g,h}}{K_g^2} & \text{if } g \in \mathcal{G}_s. \end{cases}$$

The log-likelihood of observations is given by[23]

$$\begin{aligned} \ell(\boldsymbol{\beta}, \boldsymbol{\zeta}_2, \boldsymbol{\Sigma}_\varepsilon) \quad &= \textstyle\sum_h \log\left(\phi_{G_h^u}\left(\boldsymbol{\varepsilon}_h^u(\boldsymbol{\beta}, \boldsymbol{\zeta_2}); \boldsymbol{\Sigma}_\varepsilon\right)\right) \\ &\quad + \log\left(\Pr\left(\boldsymbol{\varepsilon}_h^+ \le \boldsymbol{\nu}_h^+(\boldsymbol{\beta}, \boldsymbol{\zeta_2}) \text{ and } \boldsymbol{\varepsilon}_h^- \ge \boldsymbol{\nu}_h^-(\boldsymbol{\beta}, \boldsymbol{\zeta_2}) \middle| \boldsymbol{\varepsilon}_h^u = \boldsymbol{\varepsilon}_h^u(\boldsymbol{\beta}, \boldsymbol{\zeta_2}); \boldsymbol{\Sigma}_\varepsilon\right)\right). \end{aligned} \tag{16}$$

4.1.2 Other Wholesale Market Parameters

In addition to cost shocks, each interval in the wholesale market contains demand shocks $\bar{Q}_h$ and effective capacity shocks $\boldsymbol{\delta}_h$. I assume that demand shocks are log-normally distributed and allow for these shocks to be correlated with the available wind capacity.

Wind capacity factors $\boldsymbol{\delta}_h^{\text{wind}}$ lie in the interval $(0,1)^{G_{\text{wind},h}}$. I flexibly capture correlation among these nonzero capacity factor shocks and with demand shocks by assuming that a random variable $\mathbf{x}_h$ is drawn from a multivariate normal distribution, and $\delta_{g,h} = f(x_{g,h})$, where $f : \mathbb{R} \to (0,1)$ is the standard logistic function $f(x) = \frac{\exp(x)}{1+\exp(x)}$.

[23]See Appendix C.3 for details on computing the second term in equation 16.

Explicity, I denote the joint vector of transformed demand shocks and wind capacity factors as $\boldsymbol{\omega}_h$, which is distributed

$$\underbrace{\begin{bmatrix} \log\left(\bar{Q}_h\right) \\ \log\left(\frac{\boldsymbol{\delta}_h^{\text{wind}}}{1-\boldsymbol{\delta}_h^{\text{wind}}}\right) \end{bmatrix}}_{=:\boldsymbol{\omega}_h} \sim \mathcal{N}\left(\boldsymbol{\mu}_{\boldsymbol{\omega}}, \boldsymbol{\Sigma}_{\boldsymbol{\omega}}\right). \tag{17}$$

The correlation matrix $\boldsymbol{\Sigma}_{\boldsymbol{\omega}}$ is given by

$$\boldsymbol{\Sigma}_{\boldsymbol{\omega}} = \begin{bmatrix} \sigma_{\bar{Q}}^2 & \rho_{\bar{Q},\delta}\sigma_{\bar{Q}}\sigma_\delta & \cdots & \rho_{\bar{Q},\delta}\sigma_{\bar{Q}}\sigma_\delta \\ \rho_{\bar{Q},\delta}\sigma_{\bar{Q}}\sigma_\delta & \sigma_\delta^2 & \cdots & \rho_{\delta,\delta}\sigma_\delta^2 \\ \vdots & \vdots & \ddots & \\ \rho_{\bar{Q},\delta}\sigma_\delta\sigma_{\bar{Q}} & \rho_{\delta,\delta}\sigma_\delta^2 & \cdots & \sigma_\delta^2 \end{bmatrix}.$$

The correlation parameters $\rho_{\bar{Q},\delta}$ and $\rho_{\delta,\delta}$ capture the correlation between demand shocks and wind capacity factors and within capacity factors, respectively.

Coal and gas capacity factors have a different support than do wind capacity factors. Unlike wind, for which capacity factors capture the extent to which the wind blows, coal and gas capacity factors capture whether a generator is experiencing an outage. These factors therefore have the support $\{0, 1\}$. I assume that $\boldsymbol{\delta}_h^{-\text{wind}}$ are independent and distributed as follows. For each $g \in \tilde{\mathcal{G}}$,

$$\delta_{g,h} = \begin{cases} 1 & \text{with probability } p_{s(g)} \\ 0 & \text{with probability } 1 - p_{s(g)}. \end{cases}$$

Cost shocks, demand shocks and wind capacity factors, and thermal generator capacity factors are independent across these groups.[24] The log-likelihood function therefore is given by

$$\begin{aligned} \ell\left(\boldsymbol{\beta}, \boldsymbol{\zeta}_2, \boldsymbol{\Sigma}_{\varepsilon}, \boldsymbol{\mu}_{\boldsymbol{\omega}}, \boldsymbol{\Sigma}_{\boldsymbol{\omega}}, \mathbf{p}\right) &= \textstyle\sum_h \log\left(\phi_{G_h^u}\left(\boldsymbol{\varepsilon}_h^u\left(\boldsymbol{\beta}, \boldsymbol{\zeta_2}\right); \boldsymbol{\Sigma}_{\varepsilon}\right)\right) \\ &\quad + \log\left(\Pr\left(\boldsymbol{\varepsilon}_h^+ \leq \boldsymbol{\nu}_h^+\left(\boldsymbol{\beta}, \boldsymbol{\zeta_2}\right) \text{ and } \boldsymbol{\varepsilon}_h^- \geq \boldsymbol{\nu}_h^-\left(\boldsymbol{\beta}, \boldsymbol{\zeta_2}\right) \middle| \boldsymbol{\varepsilon}_h^u = \boldsymbol{\varepsilon}_h^u\left(\boldsymbol{\beta}, \boldsymbol{\zeta_2}\right); \boldsymbol{\Sigma}_{\varepsilon}\right)\right) \\ &+ \log\left(\phi\left(\boldsymbol{\omega}_h; \boldsymbol{\mu}_{\boldsymbol{\omega}}\boldsymbol{\Sigma}_{\boldsymbol{\omega}}\right)\right) \\ &+ \textstyle\sum_{g\in\tilde{\mathcal{G}}}\left(\delta_{g,h}\log\left(p_{s(g)}\right) + \left(1-\delta_{g,h}\right)\log\left(1-p_{s(g)}\right)\right). \end{aligned} \tag{18}$$

The first line captures the likelihood of the unconstrained cost shocks and the second line the constrained cost shocks. The third line captures the likelihood of the demand shocks and wind capacity factors. Finally, the last line captures the likelihood of the thermal generator capacity factors.

[24] In theory, I could also allow for correlation across these groups of shocks. In practice, to reduce the dimension of the parameter space, I assume that these groups are independent. Demand shocks and thermal generator capacity factors, both of which I observe, are virtually uncorrelated in the data.

I can therefore estimate the cost distribution via maximum likelihood:

$$\hat{\boldsymbol{\beta}}, \hat{\boldsymbol{\zeta}}_2, \hat{\boldsymbol{\Sigma}}_{\varepsilon}, \hat{\boldsymbol{\mu}}_{\boldsymbol{\omega}}, \hat{\boldsymbol{\Sigma}}_{\boldsymbol{\omega}}, \hat{\mathbf{p}} = \arg\max \left\{ \ell \left(\boldsymbol{\beta}, \boldsymbol{\zeta}_2, \boldsymbol{\Sigma}_{\varepsilon}, \boldsymbol{\mu}_{\boldsymbol{\omega}}, \boldsymbol{\Sigma}_{\boldsymbol{\omega}}, \mathbf{p} \right) \right\}.$$

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 $\{M_s\}_{s\in\mathcal{S}}$, the variable cost of investment $\{C_{s,t}\}_{s,t}$, the distribution of the idiosyncratic shocks $\boldsymbol{\varepsilon}$, and the discount factor β. As is common in the discrete choice literature, I assume that the idiosyncratic shocks are 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.

Following Igami & Uetake (2020), I use a full-information maximum likelihood approach to estimate these parameters in the style of Rust (1987). 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 simple to compute using backward induction. Moreover, this method allows me to incorporate nonstationary investment costs and provides precise estimates because it uses the full structure of the model. The latter point is important because I have limited data corresponding to investment (only 14 years and a single market), making the precision of the estimates a primary concern. The approaches common in the dynamic games estimation literature, which are two-step procedures, would therefore be infeasible in this setting.[25]

Since the variable cost component of investment is non-stationary 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.[26] I assume that firms have perfect foresight over the path of future generator costs. Since there is no uncertainty in future costs, generator costs are simply included in the time dimension of the state.

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

[25] These procedures include Bajari *et al.* (2007); Pakes *et al.* (2007); Aguirregabiria & Mira (2007); Pesendorfer & Schmidt-Dengler (2008).

[26] Specifically, I use engineering cost estimates from Western Australia (Australian Bureau of Resources and Energy Economics, 2012), which provides a snapshot of costs in a particular year and from the U.S. (U.S. Energy Information Administration, 2010, 2013, 2016, 2020), which provides 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.

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. The variance of the idiosyncratic shocks is identified 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 is given by

$$\mathcal{L}_{f,t}(\boldsymbol{\theta}) = \Pr\left(f \in \chi_t; \mathcal{G}_t, \mathcal{G}_{t-1}\right) \times \prod_{\mathcal{G}' \in \Gamma_f} \Pr\left(\mathcal{G}' = \mathcal{G}_{f,t} \middle| \mathcal{G}_{-f,t}, \mathcal{G}_{t-1}, t\right)^{\mathbb{1}\left\{\mathcal{G}' = \mathcal{G}_{f,t}\right\}}, \qquad (19)$$

where χ_t is the set of firms selected to move in year t. I can determine $\Pr\left(f \in \chi_t\right)$ based on generator investment decisions. If a strategic firm adjusts its set of generators in one year, then it must be the case that it was the firm selected to adjust, and this probability is zero for all other firms. Note that it is never the case in the sample that multiple strategic firms adjusted their generators in the same years. This probability is therefore

$$\Pr\left(f \in \chi_t; \mathcal{G}_t, \mathcal{G}_{t-1}\right) = \begin{cases} 1 & \text{if } f = c \\ 1 & \text{if } f \neq c \text{ and } \mathcal{G}_{f,t} \neq \mathcal{G}_{f,t-1} \\ 0 & \text{if } f \neq c \text{ and } \exists f' \in \{1, \ldots, N\} \setminus \{f\} \text{ s.t. } \mathcal{G}_{f',t} \neq \mathcal{G}_{f',t-1} \\ \frac{1}{N} & \text{if } f \neq c \text{ and } \forall f' \in \{1, \ldots, N\}, \mathcal{G}_{f',t} = \mathcal{G}_{f',t-1}. \end{cases}$$

The maximum likelihood estimator is therefore given by

$$\hat{\boldsymbol{\theta}}(\mathcal{G}) = \arg\max_{\theta \in \Theta} \left\{ \frac{1}{2} \frac{1}{T_{obs}} \sum_{t=1}^{T_{obs}} \log\left(\sum_f \mathcal{L}_{i,t}(\boldsymbol{\theta}) \right) \right\}, \qquad (20)$$

where T_{obs} is the number of observed periods. This reflects the fact that there are only two firms that are able to adjust in each period. Appendix C.4 provides details about the choice of Γ, the possible generator combinations for each firm.[27]

[27] 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 $\mathcal{G} \in \Gamma$ (which is computationally difficult, see appendix C.1.2), which then remain the same for each candidate $\boldsymbol{\theta}$.

Table 4: Wholesale Market Estimates

(a) Cost Distribution Estimates

	(1)	(2)
Capacity utilization costs		
$\hat{\zeta}_{2,\text{coal}}$	6 354.212	893.452
	(899.311)	(73.900)
$\hat{\zeta}_{2,\text{gas}}$	775.830	206.966
	(63.720)	(30.963)
Deterministic components of ζ_1		
$\hat{\beta}_{0,\text{coal}}$	−69.746	21.831
	(11.945)	(1.523)
$\hat{\beta}_{0,\text{gas}}$	17.339	32.648
	(2.367)	(1.025)
Cost shock components of ζ_1		
$\hat{\sigma}_{\text{coal}}$	71.767	18.334
	(8.995)	(0.460)
$\hat{\sigma}_{\text{gas}}$	44.966	18.652
	(1.428)	(0.491)
$\hat{\rho}_{\text{coal,coal}}$		0.764
		(0.032)
$\hat{\rho}_{\text{gas,gas}}$		0.806
		(0.041)
$\hat{\rho}_{\text{coal,gas}}$		0.774
		(0.034)
year	2015	2015
num. obs.	2 500	2 500

(b) Demand & Outage Distribution Estimates

	(1)	(2)
Demand distribution		
$\widehat{\text{const}}_{\log(\bar{Q})}$	6.941	6.941
	(0.003)	(0.003)
$\hat{\sigma}_{\log(\bar{Q})}$	0.172	0.172
	(0.002)	(0.002)
Wind outage distribution		
$\widehat{\text{const}}_{f^{-1}(\delta_{\text{wind}})}$	−1.215	−1.274
	(0.021)	(0.021)
$\hat{\sigma}_{f^{-1}(\delta_{\text{wind}})}$	1.772	1.779
	(0.012)	(0.013)
$\hat{\rho}_{f^{-1}(\delta_{\text{wind}}),f^{-1}(\delta_{\text{wind}})}$		0.528
		(0.008)
$\hat{\rho}_{f^{-1}(\delta_{\text{wind}}),\log(\bar{Q})}$		−0.038
		(0.022)
Thermal outage probabilities		
$\hat{p}_{\delta_{\text{coal}}}$	0.987	0.987
	(0.001)	(0.001)
$\hat{p}_{\delta_{\text{gas}}}$	0.987	0.987
	(0.001)	(0.001)
year	2015	2015
num. obs.	2 500	2 500

Note: Estimates are based on a random sample of 2 500 half-hour intervals in the year 2015. Specification 1 in table 4a corresponds to no correlation across generators in the cost shocks, while specification 2 allows for such correlation. Specification 1 in table 4b corresponds to no correlation between demand and wind generators' capacity factors. Specification 2 allows for correlation across these capacity factors as well as with demand.

5 Results

5.1 Wholesale Market Results

Table 4 provides estimates for the wholesale market costs, demand shocks, and capacity factors, as described in section 4.1. For the sake of computational feasibility, I use 2 500 randomly selected half-hour intervals in the year 2015. Column 1 includes estimates of a model in which there is no correlation in the cost shocks and there is no correlation among wind capacity factors or demand shocks. Column 2 relaxes those constraints: it presents estimates of a model that allows for correlation in all of the shocks. Allowing for correlation appears to matter. Correlation both within and across sources is quite high, and the inclusion of correlation results in substantially lower variance in the cost shocks as well as more sensible estimates of average costs.

Estimates of average costs per MWh are approximately in line with industry estimates. Using estimates from the second column (with correlation in shocks), I estimate that the per-MWh cost of electricity produced by coal is 21.83 AUD / MWh and that for gas is 32.65 AUD / MWh. Even accounting for correlation in cost shocks, the variance of these costs is quite high across time. The standard deviation for each source respectively is 18.33 and 18.65.

I estimate that it is costly to use a high fraction of capacity but that the costs are not very large. The estimate of this cost, given by ζ_2 in the model, is 893.45 AUD for coal and 206.97 AUD for gas. Note that this is not a per-unit cost but rather the *total* cost paid for using all of a generator's capacity. The marginal cost is twice that cost divided by the generator's capacity. While capacities vary across generators, they are usually between 50 and 150 MW, so the marginal cost of using capacity is on the scale of a few dollars.[28]

Wind capacity factors are estimated to be positively but weakly correlated with each other, with a correlation coefficient of 0.28. Wind capacity factors are virtually uncorrelated with demand.

5.2 Investment Decision Results

The wholesale market results provided in table 4 are used in the second stage dynamic parameter estimates to construct an estimate of yearly expected profits, $\hat{\mathbf{\Pi}}(\mathcal{G})$. I use the estimates in the second column that allow for a rich correlation structure to construct these estimated profit functions. The investment decision parameter estimates are provided in table 5. The

[28]The range of capacities given is the capacity at the *half-hourly level* rather than hourly (since wholesale intervals take place in half-hourly intervals).

first column corresponds to the model specification in which firms can no longer adjust their generator sets 5 years after the last year in the data, second column 10 years, and the third 15 years.

Table 5: Dynamic Estimates

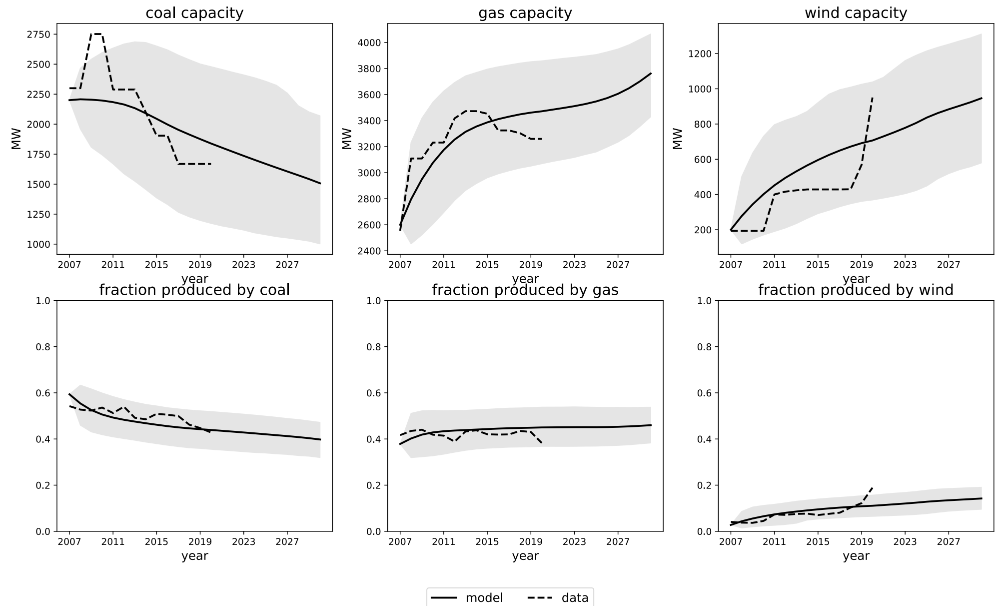
	(1) $T_{add} = 5$	(2) $T_{add} = 10$	(3) $T_{add} = 15$
Maintenance costs			
$\hat{M}_{\text{coal}}$	0.055	0.057	0.058
	(0.008)	(0.007)	(0.007)
$\hat{M}_{\text{gas}}$	0.021	0.017	0.016
	(0.029)	(0.030)	(0.030)
$\hat{M}_{\text{wind}}$	0.071	0.081	0.086
	(0.025)	(0.048)	(0.055)
Idiosyncratic costs			
$\hat{\sigma}$	185.700	184.085	183.181
	(54.845)	(44.229)	(41.091)

Note: Estimates are in 1 000 000 AUD. T_{add} represents the number of additional periods after the final period in the data before firms can no longer add or retire new generators. The discount factor, β, is set to 0.95.

The estimates are extremely similar across values of T_{add}, suggesting the choice of when the investment game ends does not matter much for the parameter estimates. The maintenance cost for coal is precisely estimated, but those for gas and wind are less precisely estimated, reflecting the absence of gas or wind retirements to aid in the identification of this parameter for gas and wind. Despite the imprecision of these estimates, the maintenance costs I estimate are close to engineering estimates. The Western Australian data source used for imputing new generator costs (Australian Bureau of Resources and Energy Economics, 2012) also provides maintenance cost estimates. The costs per MW for coal, gas, and wind are, respectively, 0.055, 0.010, and 0.040 (in millions AUD). The variance of the idiosyncratic cost shocks is estimated to be equal to about half of a year's profit for the largest firm (Synergy) in 2007, suggesting that idiosyncratic costs are non-trivial but that profits and costs have a high degree of explanatory power.

Figure 4 depicts the aggregate source-level capacities and fractions of total electricity production observed in the data and compares them to those predicted by the model. The only information the model is fed is the state in 2007. I match the general patterns in the data reasonably well, even in later years in the data far from the initial state fed to the model.

Figure 4: Model Prediction vs. Data



Note: The model path in each plot is the expectation over realizations of the idiosyncratic shocks given the initial state. The shaded region corresponds to the area in between the 10th and 90th percentiles. Since the state is discrete, percentiles are calculated by fitting a weighted Gaussian kernel to the implied distribution, with the weights corresponding to the probabilities. The 10th and 90th percentiles plotted are the 10th and 90th percentiles of the fitted kernel distribution.

6 Counterfactuals

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

In order to evaluate optimal policy, I construct a welfare function that depends on equilibrium investment and production costs, the price of electricity, the level of greenhouse gas emissions, and the frequency of blackouts. This welfare function includes a carbon externality, which is the sum of carbon emitted to produce electricity times the social cost of carbon. It also includes a blackout cost, which is the expected Megawatt-hours of electricity experiencing a blackout due to demand exceeding available supply times consumers' willingness to pay to avoid a Megawatt-hour of blackouts, which is referred to in the electricity literature as the *value of lost load.*[29,30]

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

$$\begin{aligned}\Delta^{P\to P'}W_t = \quad & \Delta^{P\to P'}CS_t \\ & +\Delta^{P\to P'}\textstyle\sum_f PS_{f,t} \\ & +\Delta^{P\to P'}G_t \\ & -SCC\times\Delta^{P\to P'}\text{ carbon emissions}_t \\ & -VOLL\times\Delta^{P\to P'}\text{ MWh experiencing blackout}_t,\end{aligned} \tag{21}$$

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

$$\Delta^{P\to P'}\mathcal{W}=\mathbb{E}\left[\sum_{t=0}^{\infty}\beta^t\Delta^{P\to P'}W_t\right]. \tag{22}$$

6.1 Electricity Market Policies

In this section I consider policies that are intended to address a specific market failure, both in isolation and as a policy bundle. In particular, I consider two policy tools, carbon taxes and capacity payments. Carbon taxes address the environmental externality by making electricity production using carbon-intensive technologies more costly, and in the absence of other market failures (such as market power or blackouts that exist in this market) they can achieve the social optimum. Capacity payments address blackouts by subsidizing capacity, increasing the returns to investment. Each of the policies are static, in the sense that they do not vary over time, and this is known by the firms at all points in time. In Section 6.3 I consider time-varying policies.

[29] I assume that blackouts are rolling and the grid operator can perfectly ration a fraction of consumers to equate demand with the maximum available supply. For example, if consumers demand 1 000 MWh in a given interval, but the available supply $\sum_g \bar{K}_{g,h}$ is only 900 MWh, then 100 MWh are randomly rationed. The consumers who are rationed receive zero electricity. These 100 MWh are multiplied by the value of lost load in order to determine the cost of the blackout in that interval.

[30] 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 specification outlined in Appendix B.3, the marginal utility at zero electricity for a consumer is infinite. Instead, I opt to separate the consumer surplus that reflects prices and quantity demanded and the cost of blackouts separately. CS_t in equation 21 is measured as if consumers never experienced a blackout, and is therefore only a function of the quantity-weighted average price $\bar{P}_t$. I use an outside value for the cost of a blackout, using as a baseline a value based on surveys conducted by the Western Australian grid operator. I also include results for a range of plausible values of lost load in Appendix D.

I simulate the market forward from the same state in year 2007 as that observed in the data and obtain the distribution of firms' investment decisions. I use the model presented in section 3 in which strategic firms receive shocks allowing them to adjust their generators and column 2 of the parameters in table 5 in which the firms cease to be able to adjust their sets of generators after 2030.

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. 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 6.1.2 I consider complimentarities between the policies.

Carbon Tax I consider a carbon tax levied on firms based on the emissions rate of each generator, given by table 11 in Appendix A.4. The value of the carbon tax, τ, enters the cost of each firm as described in equation 1. Figure 5 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 5 captures substitution along the extensive 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. Even a small carbon tax results in a substantially faster decline in coal capacity, and a tax higher than 50 AUD / tonne results in virtually complete retirement of coal generators. Gas generators, which are roughly half as carbon-intensive as coal, do not exhibit the same pattern. Rather, a small carbon tax *increases* the average number of gas generators, and the average number of generators is virtually invariant for higher values. This relationship reflects gas being an energy source that is less carbon intensive than coal and not intermittent. It also has a relatively small estimated maintenance cost, so the cost of maintaining gas capacity is smaller than that for coal. Wind, which has an emissions rate of zero, experiences a substantial increase in capacity as the carbon tax rises; firms adopt more wind generators, and they adopt them earlier. Since wind is intermittent and this intermittency is highly correlated across wind generators (see table 4b), these generators compete mostly in the same intervals. There remains significant gas capacity because it is used in intervals in which there is little available wind capacity.

The bottom row of the figure captures substitution along the intensive 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 wind capacity, 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 wind 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. Reflecting the same pattern as existed for investment, the value of the carbon tax has little impact on the share produced by gas in the final year (which is then repeated for all future years), but has a substantial influence on the share of coal and wind.

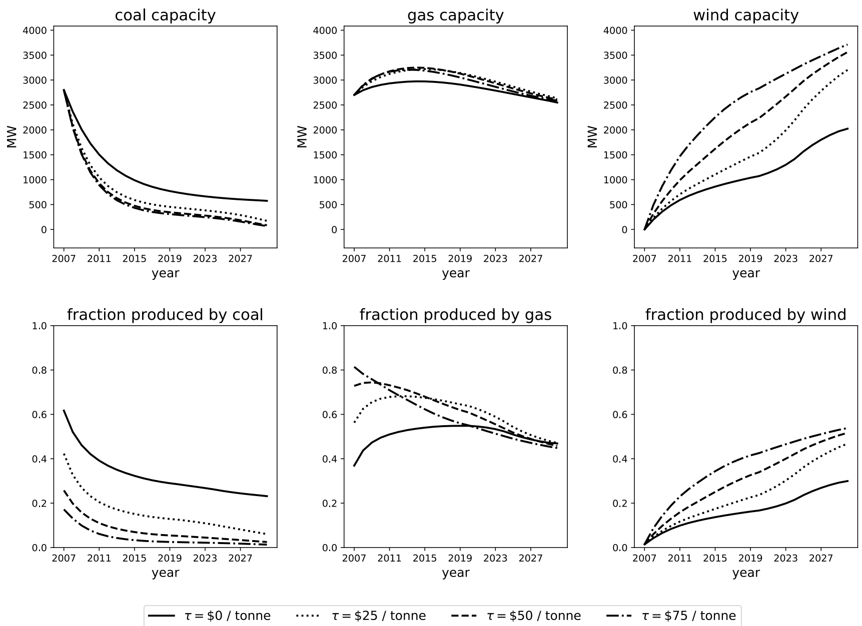
Capacity Payments I next consider the impact of capacity payments by varying the value of the payment, κ, as enters the net payment function $\Upsilon_{f,t}(\cdot)$, defined in equation 9. Unlike in the sample, in which the value varied over time, I simulate investment and production with a value of κ that is constant for all years. The simulated expected evolution of investment and production is given in figure 6 for four different values of the payments.

The results suggest that the high levels of payments observed in the data (payments vary between 100 000 AUD / MW and 200 000 AUD / MW during the sample period, which correspond to the third and fourth lines in figure 6) are what have kept coal capacity at only a slow decline in Western Australia. Gas capacity is also very responsive to the size of the capacity payments. Without capacity payments, average gas capacity experiences a small decline; however, with the payments, gas experiences a significant increase.

An active policy question regarding capacity payments is their impact on renewables. The results suggest that capacity payments do have a small but clear negative impact on wind capacity, mostly in the final years simulated (though note that the final year is repeated for all future periods). As the payment size increases, the average wind capacity decreases. This reflects the smaller fraction of payments for which wind qualifies, as well as the fact that additional coal and gas capacity reduce marginal costs of production from those sources, driving the market price down.

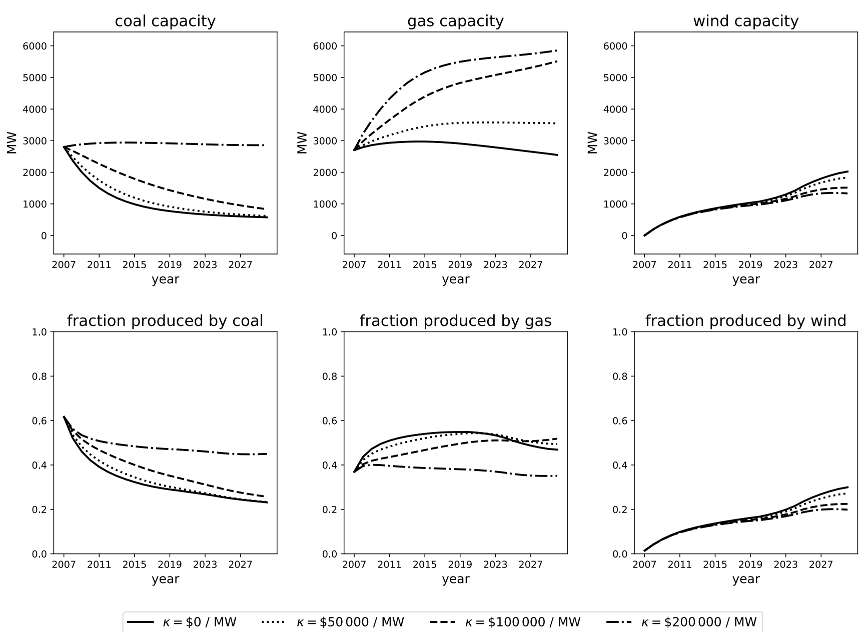
Lacking a carbon tax or any policy affecting the production margin, production follows a similar pattern to that of capacity. As the payment size increases, the share of electricity produced by coal rises with the associated capacity. Gas experiences a more nuanced pattern. While there is substantial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

Figure 5: 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.

Figure 6: Impact of Capacity Payments on Investment and Production

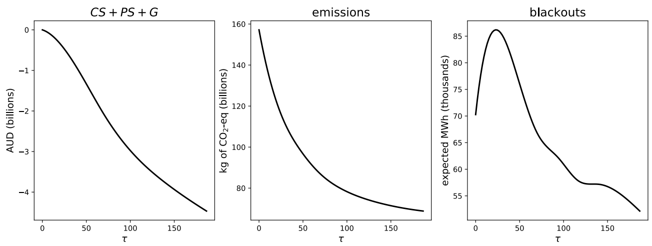


Note: Depicted in each panel is the *expectation* for a particular energy source summed across all strategic firms and the competitive fringe for a particular value of a capacity payment.

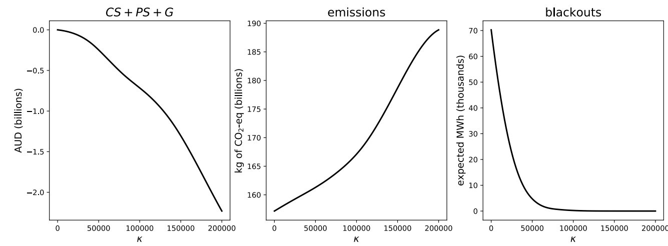
6.1.2 Welfare and Optimal Policy

Figure 7: Impact of Policies on Welfare-Relevant Variables

(a) Carbon Tax



(b) Capacity Payments



Note: Values are in expected present discounted terms with the same discount factor as that used by the firms, $\beta = 0.95$. For 7a, capacity payments are set to zero (i.e., $\kappa = 0$), and for 7b, the carbon tax is set to zero (i.e., $\tau = 0$). Values are smoothed using cubic spline interpolation. Consumer surplus, producer surplus, and government revenues are measured relative to a *laissez-faire* policy ($\tau = 0, \kappa = 0$).

In this section, I consider the impact of the policies introduced in the previous section on welfare, as defined by equation 22. Figures 7a and 7b plot product market welfare and government revenues, the level of emissions, and the level of blackouts, for carbon taxes and capacity payments, respectively.

A carbon tax decreases emissions as intended. As the carbon tax increases, however, the marginal reduction in emissions declines. Blackouts have a non-monotonic relationship with carbon taxes. For small and moderate carbon taxes, the frequency of blackouts rises as coal capacity falls and gas does not rise to a sufficiently high level to make up the difference. For higher values of the tax, however, the frequency of blackouts actually *declines*. This decline is a result of two endogenous responses to the carbon tax. The first is that effective capacity actually increases, since gas capacity remains roughly constant, but wind capacity increases. While wind capacity is less reliable, additional wind generators do decrease the probability of a blackout, holding all other generators fixed. The second is the response of consumers to the tax. As the tax increases, the wholesale spot market price of electricity increases, and therefore so too does the end-price that the consumers pay. While consumers are inelastic to this price, they are not perfectly inelastic, and therefore they respond by reducing their consumption, reducing the probability of a blackout, holding available capacity fixed.[31]

Capacity payments function as intended at reducing blackouts. Blackouts exhibit a substantial decline as the size of the capacity payment increases because the payments increase the available capacity in the market. Emissions, however, are increasing in the size of the payment since the share of electricity produced by fossil fuels is increasing and the share of renewables

[31]Note that the decline in surplus that results from this reduced consumption is captured by ΔCS.

Table 6: Wefare

τ	κ	ΔCS (billions AUD)	ΔPS (billions AUD)	ΔG (billons AUD)	Δ emissions (billions kg CO_2-eq)	Δ blackouts (thousands MWh)
0	0	0.0	0.0	0.0	0.0	0.0
	25 000	0.22	0.32	-0.63	2.1	-50.44
	50 000	0.39	0.61	-1.25	3.75	-64.75
	100 000	1.06	1.71	-3.57	10.91	-69.29
50	0	-7.9	2.06	4.63	-58.96	7.23
	25 000	-7.61	2.36	4.05	-58.77	-42.66
	50 000	-7.4	2.62	3.48	-58.64	-60.11
	100 000	-6.94	3.64	1.4	-57.85	-67.61
100	0	-15.12	4.83	7.46	-78.13	-7.64
	25 000	-14.77	5.1	6.89	-78.1	-43.15
	50 000	-14.49	5.33	6.34	-78.11	-60.03
	100 000	-14.05	6.26	4.24	-77.71	-68.01
150	0	-21.33	7.36	10.15	-85.57	-12.53
	25 000	-20.92	7.6	9.58	-85.6	-43.59
	50 000	-20.61	7.8	9.01	-85.7	-60.35
	100 000	-20.13	8.68	6.9	-85.6	-68.32

Note: Changes are with respect to the *laissez-faire* policy ($\tau = 0$, $\kappa = 0$). All values are in expected present discounted terms, using the same discount factor as that used by the firms, $\beta = 0.95$.

is declining.

I also consider complementarities between carbon taxes and capacity payments. Table 6 provides consumer surplus, producer surplus, government revenues, emissions, and blackouts for a range of values of both the carbon tax τ and the capacity payment size κ.

The pattern of emissions increasing with the size of the capacity payment weakens significantly when a carbon tax is introduced in addition to a capacity payment. Additionally, the pattern between blackouts and the size of the carbon tax weakens when a capacity payment is 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.

Using both policy tools, both blackouts and emissions can be substantially reduced due to the fact that these variables are a function of different margins. Emissions are a function of the production margin (which sources are used to produce electricity), and blackouts are a function of the investment margin (how much effective capacity is there in the market). While these two margins are linked (investment is a function of production, and vice versa), subsidizing reliable capacity reduces blackouts, and a carbon tax incentivizes firms to reduce the fraction of capacity they use from emissions-intensive sources. By using both a carbon tax and capacity payments, therefore, we can incentivize firms to invest in reliable capacity

Table 7: Optimal Policy

	carbon tax alone		capacity payments alone		joint policies		
SCC	τ^*	$\Delta\mathcal{W}$	κ^*	$\Delta\mathcal{W}$	τ^*	κ^*	$\Delta\mathcal{W}$
0	0.0	0.0	57 300	3.01	0.0	57 300	3.01
25	0.0	0.0	54 500	2.9	25.0	59 900	3.49
50	70.0	1.61	52 300	2.8	42.0	59 100	4.71
75	80.3	3.43	50 100	2.7	65.2	59 900	6.27
100	117.1	5.47	48 400	2.61	86.2	61 500	8.09
125	123.2	7.55	46 800	2.52	116.7	62 700	10.07
150	183.3	9.74	45 600	2.44	139.8	63 300	12.19
175	185.4	11.97	44 400	2.35	154.7	63 700	14.35
200	187.3	14.2	43 400	2.27	172.6	63 300	16.54

Note: Changes are with respect to the *laissez-faire* policy ($\tau = 0$, $\kappa = 0$). SCC is in AUD / tonne of CO_2-eq. Changes in welfare are in expected present discounted terms in billions of AUD, using the same discount factor as that used by the firms, $\beta = 0.95$. $VOLL$ is set to 50 000 AUD / MW. See Appendix D for the results for alternative values of $VOLL$.

but also incentivize them not to use that emissions-intensive capacity unless necessary.

Table 6 also provides the impact a policy has on product market welfare and government revenues. A carbon tax has a significant negative impact on consumer surplus, even if the tax revenue raised (given in the column ΔG) is rebated back to consumers, which may explain the political opposition to a carbon tax. The impact of the carbon tax to consumers and producers reflects the pass-through of the tax, which is discussed in detail in Appendix D.1.

Table 7 uses the results provided in table 6 to determine the policy that maximizes welfare as defined in equation 22. For a range of values of the SCC, the table provides the optimal policy with a carbon tax alone, capacity payments alone, and these policies jointly, as well as the change in welfare that these optimal policies yield. The range of values of the SCC reflects the wide range of estimates that exist for this value due to model uncertainty, differences in the discount factor chosen, treatment of "fat-tail" risks, and weighting of low-income countries (Stern, 2006; Nordhaus, 2017; Metcalf & Stock, 2017; Cai & Lontzek, 2019; Rennert *et al.* , 2021). For reference, the value determined by the U.S. Interagency Working Group on the Social Cost of Carbon was 51 USD in 2020, which is approximately 65 AUD (in 2015 AUD) (Interagency Working Group on Social Cost of Greenhouse Gases, 2021).

With a carbon tax alone, the tax is increasing with the SCC, although for low values, because the tax reduces product market welfare and increases blackouts, the optimal tax is 0. With capacity payments alone, the optimal capacity payment declines as the SCC increases, reflecting the fact that emissions are increasing in the size of the capacity payments.

Using the two policy tools jointly yields a large welfare gain over using only one alone because they can target different margins. The carbon tax targets the intensive production margin, and the capacity payments target the extensive investment margin. For values of the SCC

greater than 50 AUD / tonne of CO_2-eq, the welfare gain is over 2 billion AUD. Compared to the policies alone, the optimal carbon tax in this case is higher for small values of the SCC (since blackouts are increasing in the carbon tax for low values) and lower for higher values (since for high values of the carbon tax, blackouts are increasing). Unlike with a capacity payment alone, the optimal capacity payment is much less responsive to the SCC (and is increasing to a small degree).

6.2 Carbon Taxes vs. Renewable Investment Subsidies

Many electricity markets that have adopted environmental policies to reduce emissions have used policies other than a carbon tax. In this section, I consider the impact on investment, production, and welfare-relevant variables of renewable subsidies, which are alternative environmental policies that have been widely used in practice. The first type of renewable subsidy I consider is a renewable *production* subsidy, which pays renewable generators a fixed amount for each MWh they produce. I will denote the value of this subsidy by ς. This subsidy changes the generator cost function as provided in equation 1 to

$$c_{g,h}\left(q_{g,h}\right) = \left(\zeta_{1,g,h} - \varsigma \mathbb{1}\left\{s\left(g\right) \in \mathcal{S}_{\text{renewable}}\right\}\right) q_{g,h} + \zeta_{2,s(g)} \left(\frac{q_{g,h}}{K_g}\right)^2.$$

The second type is a renewable *investment* subsidy, which reduces the cost of investment of renewable generators. I will denote the value of this subsidy by s. Under this subsidy, generators pay $\tilde{C}_{s,t}\left(s\right)$ per MW for new generators, where $\tilde{C}_{s,t}\left(\cdot\right)$ is defined as

$$\tilde{C}_{s,t}\left(s\right) = C_{s,t} - s\mathbb{1}\left\{s\left(g\right) \in \mathcal{S}_{\text{renewable}}\right\} C_{s,t}.$$

A renewable generator therefore only pays $(1 - s) \times 100\%$ of the cost of a new generator (plus the idiosyncratic cost). Figures 13 and 14 in Appendix D display analogous results to those in figures 5 and 6.

Table 8 compares the welfare impact of these three policy tools in isolation without any capacity payments.[32] For each level of emissions reduction, this table provides the policy value that attains that reduction and the changes in blackouts, consumer surplus, producer surplus, and government revenues that result. Renewable investment subsidies, widely used in practice, are not very effective at reducing emissions, as demonstrated by the fact that no subsidy $s \leq 100\%$ can yield an emissions reduction greater than 30 billion kg of CO_2-eq. A carbon tax and a renewable production subsidy, in contrast, attain this emissions reduction at values of 15.80 AUD / tonne and 23.80 AUD / MWh, respectively. A renewable investment

[32] Table 18 in Appendix D.3 provides these results in the presence of capacity payments.

Table 8: Comparing Environmental Policies

Δemissions (billions CO_2-eq)	policy	policy value	Δblackouts (thousands MWh)	ΔCS (billions AUD)	ΔPS (billions AUD)	ΔG (billions AUD)	Δ (CS + PS + G) (billions AUD)
0	carbon tax	0.0	0.0	0.0	0.0	0.0	0.0
	renew. prod. subs.	0.0	0.0	0.0	0.0	0.0	0.0
	renew. inv. subs.	0.0	0.0	0.0	0.0	0.0	0.0
10	carbon tax	4.5	5.6	-0.8	0.1	0.6	-0.0
	renew. prod. subs.	5.5	10.2	0.1	0.2	-0.2	0.1
	renew. inv. subs.	49.7	3.5	0.2	0.7	-2.4	-1.5
20	carbon tax	9.4	10.2	-1.7	0.3	1.3	-0.1
	renew. prod. subs.	13.7	24.8	0.4	0.7	-0.7	0.3
	renew. inv. subs.	82.7	6.2	0.4	1.4	-6.0	-4.2
30	carbon tax	15.6	13.6	-2.7	0.5	2.0	-0.2
	renew. prod. subs.	23.3	37.7	0.7	1.4	-1.6	0.5
	renew. inv. subs.	-	-	-	-	-	-
40	carbon tax	23.6	15.0	-4.1	0.9	2.8	-0.4
	renew. prod. subs.	34.4	47.2	1.0	2.4	-2.9	0.5
	renew. inv. subs.	-	-	-	-	-	-
50	carbon tax	34.3	12.9	-5.9	1.4	3.7	-0.8
	renew. prod. subs.	53.5	57.0	1.6	4.7	-5.5	0.8
	renew. inv. subs.	-	-	-	-	-	-

Note: Changes in emissions, blackouts, and welfare variables are all in presented expected discounted values, which are the relevant values for evaluating the welfare function given in equation 22. Since simulated values are along a discrete grid, to back out the policy value that yields a given change in emissions, I interpolate values using cubic splines. I then use the interpolation to determine the policy value yielding the given change in emissions. For blackouts and welfare variables, I also use cubic spline interpolation, taking the implied policy value and determining the corresponding interpolated blackout or welfare variable value. For some of the higher levels of emissions reductions, there does not exist a renewable investment subsidy that would yield that level of an emissions reduction. In this case, the values in the corresponding columns are replaced with "-".

subsidy yields a low reduction in emissions because it does not incentivize emissions reduction during production, and it also results in less investment in wind capacity, as demonstrated in figure 14 in Appendix D. Moreover, a renewable investment tax subsidy is very expensive from the government's perspective, requiring 6 billion AUD to obtain an emissions reduction of 20 billion kg of CO_2-eq.

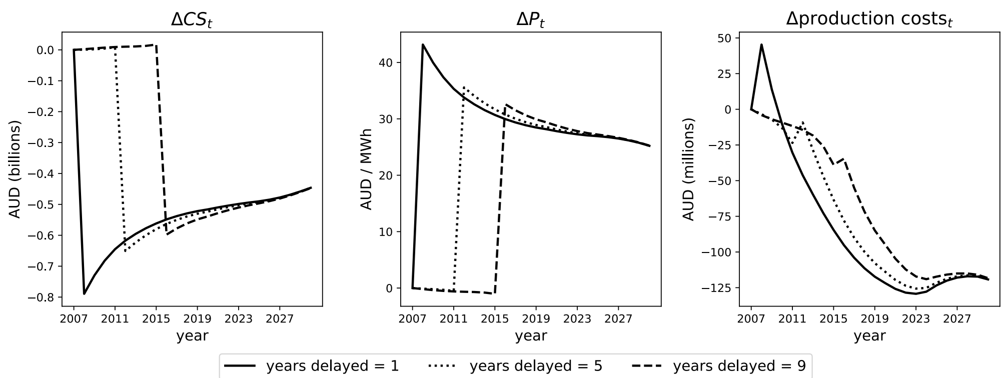
A renewable production subsidy is more effective than an investment subsidy at reducing emissions, and it also can in fact increase product market welfare (including government revenues). This subsidy better incentivizes emissions-reducing production decisions in the wholesale market; however, it is unable to distinguish between the emissions intensities of coal and natural gas (and therefore the maximum emissions reduction it can attain is lower than that of a carbon tax). The reason product market welfare net of government revenues is increasing in a renewable investment subsidy rather than decreasing (as is the case with a carbon tax) is because it reduces the market price of electricity. Market power increases the price of electricity above the competitive price, leading to under-production of electricity in the long run as the distribution of consumer demand adjusts. The renewable production subsidy increases total production, increasing product market welfare. This reduction in the market price decreases the returns to investment of fossil fuel generators, however, leading to increased retirements. The size and frequency of blackouts rises as a result, leading to a substantially higher increase in blackouts for a given level of emissions reduction than under a carbon tax yielding the same level of emissions reduction.

6.3 Policy Timing

Policies that induce large investments are often delayed to allow firms time to adjust to the policy. In this section, I explore the returns to delaying the implementation of a carbon tax in order to allow firms to first adjust their generator portfolios. Delaying a policy results in cost savings to firms since they can invest in low emissions generators, but the delay also reduces the mechanism that reduces emissions. I predict investment and production with the carbon tax *announced* in 2007 but not actually implemented until T_{delay} years later. This delay in the policy's implementation is known to the firms when the policy is announced in 2007.

Figure 8 displays the change in consumer surplus, wholesale prices, and production costs in each year relative to those variables in 2007 for three different values of T_{delay}. The first panel plots consumer surplus. In the year that the carbon tax becomes implemented, consumer surplus drops since the tax raises the price of electricity. 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 no emissions-free wind capacity

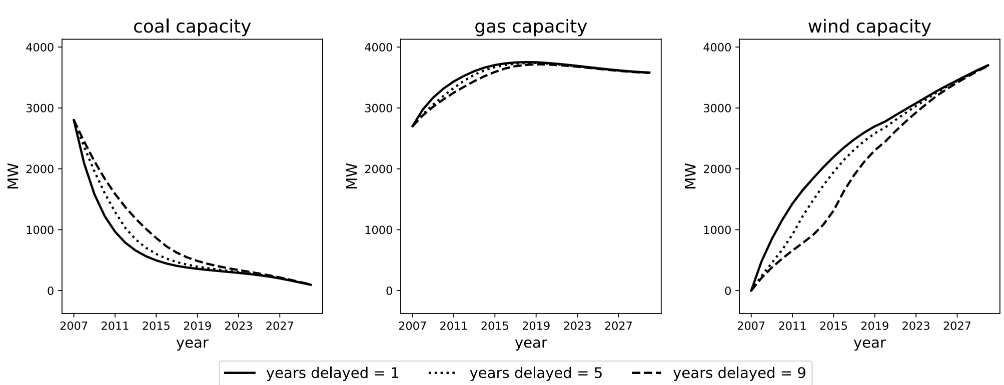
Figure 8: Impact of Delaying Policy



Note: Displayed is the expectation of each of the variables for a tax of 70 AUD / MW and a capacity payment of 50 000 AUD / MW. The capacity payment is implemented immediately, but the carbon tax's implementation is delayed based on the line. Average prices in the second panel are quantity-weighted.

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). The use of expensive generation technologies can be seen in the third panel, which is the change in production costs (not including the carbon tax), which spikes above zero in year one when $T_{delay} = 1$. When the tax is delayed, firms can respond in the years leading up to the implementation by investing investing in wind and, to a lesser extent, gas. Ultimately, this results in less of a spike in production costs (third panel), yielding a smaller spike in prices (second panel), and therefore a smaller reduction in consumer surplus.

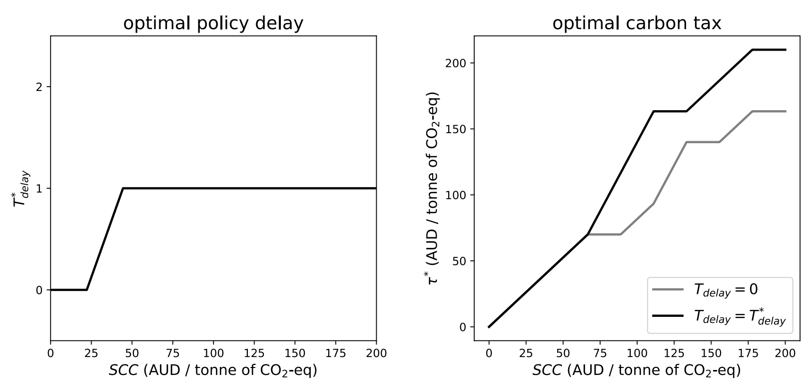
Figure 9: Impact of Delaying Policy on Investment



Note: Displayed is the expected investment for each source, summed across firms and the competitive fringe, for a tax of 70 AUD / MW and a capacity payment of 50 000 AUD / MW. The capacity payment is implemented immediately, but the carbon tax's implementation is delayed based on the line.

While the delay in the implementation of the carbon tax can increase product market welfare, it also results in time during which firms do not have as strong of an incentive to reduce emissions. This lack of emissions-reducing incentives is especially true at the production margin (e.g., there is no incentive to favor gas over coal), but also at the investment margin. While it could be possible that since the firms anticipate the tax investment in wind is similar regardless of the delay, figure 9 shows that without a near immediate tax, firms choose to delay investment in wind. Firms have a strong incentive to delay investment, even though that means they may not receive the ability to adjust before the tax's implementation, because the cost of wind is declining so much over time.

Figure 10: Optimal Delay and Carbon Tax



Note: The $VOLL$ is set to 50 000 AUD / MW, which is also the value of the capacity payment used in this simulation. The optimal policy is that which maximizes $\mathcal{W}$, as defined in equation 22.

Given that delaying the policy increases 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. For a given SCC and $VOLL$, we can determine the optimal delay to the carbon tax. Figure 10 plots the jointly optimal delay in the policy's implementation and the carbon tax. The optimal carbon tax is not necessarily the same (as a function of the SCC) as that found in section 6.1.2 because the increase in product market welfare with a delayed policy can allow for a higher carbon tax. Indeed, for all but the lowest values of the SCC, the optimal policy is a (small) delay in implementation but with a larger carbon tax.

The optimal policy delay is very small (either zero or one years) for all values of the SCC. The reason the delay is quite small is that the size of the tax scales with the SCC. When the SCC is low, so too is the carbon tax. A small tax is not very costly to consumers. A large tax is, and it is therefore for a large tax that the policy delay is most to consumers. It is precisely when the SCC is highest, however, that a high carbon tax is used. While delaying a policy is valuable at a high SCC, the environmental cost of delaying the policy outweighs the savings to product market welfare, resulting in a very small optimal delay in the policy.

7 Conclusion

Declining costs of renewables and the urgent need to reduce emissions have created a need to understand the impact electricity market regulations have on production and investment. This paper provides a framework that links the two in the setting of restructured electricity markets. This framework allows for the relevant margins of adjustment—production and investment—in all relevant energy sources, which is a necessary component for understanding the impact on emissions and reliability that play a key role in this paper. Using this framework, I show that without both environmental and reliability policy tools, there are tradeoffs between emissions and blackouts. Using both tools, we can simultaneously reduce emissions and blackouts, highlighting the need for joint regulation as the world adopts strict environmental policies to address the threat of climate change.

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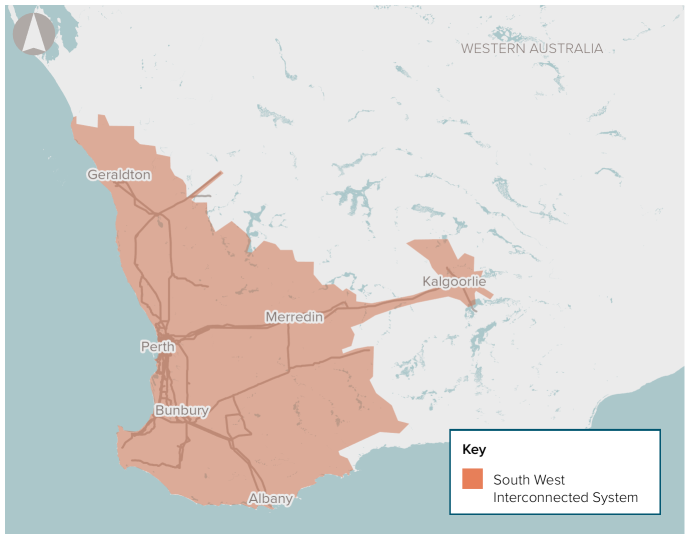
A Additional Industry Details

A.1 South West Interconnected System

Figure 11: Map of South West Interconnected System



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

A.2 Capacity Obligation Penality Rules

The capacity obligation penalty rules are based on the *Wholesale Electricity Market Rules* (esp. pages 279–292 of the June 24, 2020 version of the document). The energy source-specific component of the refund factor is

$$\lambda_s = \begin{cases} \frac{\rho}{17\,280} & \text{if } s \in \{\text{coal}, \text{gas}\} \\ \frac{\rho}{1\,440} & \text{if } s \in \{\text{wind}\}, \end{cases} \tag{23}$$

where $\rho = 6$.

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). Each report provides capital costs in USD / kW for different generator technologies. The reports are more detailed than the general categories I use in this paper (coal, gas, and wind). In general, I try to select capital costs from specific categories that represent the types of new generators commonly built today. For coal, I use the capital costs for ultra-supercritical coal plants.[33] For gas, I use the capital costs for a combined cycle gas turbine plant.[34] Finally, for wind, I use the capital costs of on-shore wind generators. All of these costs are summarized in table 9.

Table 9: EIA Generator Cost Estimates

Year	Coal (in USD / MW)	Gas (in USD / MW)	Wind (in USD / MW)
2010	3 167 000	978 000	2 438 000
2013	3 246 000	917 000	2 213 000
2016	3 636 000	978 000	1 877 000
2019	3 676 000	1 084 000	1 677 000

Note: U.S. Energy Information Administration (2010, 2013, 2016, 2020) report these values in USD / kW, but I convert the values here to USD / MW because the units used in this paper are MW and MWh.

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 therefore use the EIA reports to construct a time series for each source and AETA to convert the time series based on U.S. estimates to those for the electricity market in Western Australia. As with the EIA reports, AETA provides much more detailed generator categories than I use in this paper. I use the same representative categories as those described above: ultra-supercritical plants for coal, combined cycle plants for gas, and on-shore for wind. Table 10 provides the cost estimates that I use.

Table 10: Australian Energy Technology Assessment Generator Cost Estimates

Year	Coal (in AUD / MW)	Gas (in AUD / MW)	Wind (in AUD / MW)
2012	3 124 000	1 111 000	2 530 000

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,[35] providing me with $\hat{C}_{s,t}^{EIA}$ for each $t \in [2010, 2019]$. Next, I convert the interpolated EIA estimates to those for Western Australia.

[33] Ultra-supercritical power plants operate at high temperatures and pressures, requiring less coal per MWh of electricity. They are the current commonly-used technology for coal plants.

[34] Combined cycle power plants use exhaust heat from gas turbines to power steam turbines in order to generate more electricity for a given amount of natural gas. They are the currently commonly-used technology for natural gas plants.

[35] The sample covers a few years before 2010. For these years, I linearly extrapolate, but not for the years past 2019. For those past 2019, I use a separate method, explained later in this description.

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

$$C_{s,t}^{WA} = \alpha_s C_{s,t}^{EIA}.$$

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

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

These estimates allow me to construct the Western Australian time series through 2019. The model includes years past 2019. For these years, I apply a line of best fit for each source based on $\left\{\hat{C}_{s,t}^{WA}\right\}_{t=2007}^{2019}$, and use this line to extend cost estimates through 2025. Some versions of the model use years past 2025. For these versions, I assume that $\hat{C}_{s,t}^{WA} = \hat{C}_{s,2025}^{WA}$ for all $t > 2025$.

A.4 Emissions Rates

The Australian Energy Technology Assessment (Australian Bureau of Resources and Energy Economics, 2012) described in the previous section (section A.3) reports emissions rates for different generator technologies. This emissions rate corresponds to the value r_s in the model presented in section 3). As with capacity costs described above, this report provides more detailed generator technologies than the broad categories used in the model. I use the same representative technologies for emissions rates as in section A.3 for capacity costs. Table 11 provides a list of emissions rates.

Table 11: Australian Energy Technology Assessment Emissions Rates

Coal (in kgCO_2-eq / MWh)	**Gas (in kgCO_2-eq / MWh)**	**Wind (in kgCO_2-eq / MWh)**
783	358	0

Note: kgCO_2-eq means kg of CO_2-equivalent greenhouse gases. Greenhouse gases other than CO_2 are converted to CO_2-equivalent terms on the basis of global-warming potential. For example, 1 kg of methane is equal to 25 kgCO_2-eq.

B Model Details

B.1 Discussion of Wholesale Market Modeling Choices

Two modeling choices differentiate this model of the wholesale market from some of the recent work estimating costs in wholesale markets (e.g., Reguant (2014)). These modeling decisions make computation of the oligopolistic wholesale market across an extremely large number of possible sets of generators feasible, which is necessary for nesting a model of wholesale profits in a long-run model of generator investment. Moreover, I argue here that the more restrictive assumptions that I make for tractability do not significantly affect the results.

First, I model firms as competing in quantities (as in Bushnell *et al.* (2008)) rather than bidding in an auction (as in Wolak (2007) and Reguant (2014)). A supply function equilibrium is generally nonunique and computationally difficult. As noted by Klemperer & Meyer (1989), a supply function equilibrium is bounded between the competitive and Cournot equilibria, and the steeper the supply functions, the closer the equilibrium is to Cournot.

Second, I model the wholesale market as a static decision, in which the production decision in a given period does not affect costs in a future period. The alternative approach used in the wholesale market estimation literature adds start-up costs and sometimes ramp-up costs, which mean it is cheaper for a firm to produce in given period if it produced in the previous period.[36] Adding these dynamic costs would make the wholesale market a dynamic game since firms have market power. Given the heavy computational burden of computing such a game (along with the issue of choosing among potentially many equilibria), adding these costs would be infeasible. While Mansur (2008) notes that ignoring these costs can bias estimates and welfare, I believe that this bias is likely to be small in my setup. Reguant (2014) finds that these costs are relatively small for natural gas plants and much larger for coal plants. In a preview of the results, I find that policies that incentivize wind tend to reduce investment in coal capacity. Large start-up costs would likely make coal even more costly under such policies (due to the intermittent nature of wind), so not including start-up costs may bias coal investment levels upward. Since these levels are already very low in most of the counterfactuals I study, I do not believe that the lack of start-up costs impacts the results in a significant way.

[36] See, for example, Reguant (2014) and Butters *et al.* (2021).

B.2 Wholesale Market Equilibrium

In each interval h, there is a demand shock $\bar{Q}_h$, and firms draw cost shocks$\boldsymbol{\zeta}_{1,h}$ and capacity shocks $\boldsymbol{\delta}_h$. Competitive generators takes prices as given, yielding a competitive supply curve. The competitive supply curve is a piecewise function with $2G_c+1$ segments due to generators' lower and upper production constraints ($\underline{K}_g$ and $\bar{K}_{g,h}$).

Based on the production cost function (equation 1), the lower bound $\underline{P}_{g,h}$ and upper bound $\bar{P}_{g,h}$ at which a generator's constraints bind are:

$$\begin{aligned} \underline{P}_{g,h} &= \zeta_{1,g,h} + \tfrac{2\zeta_{2,g}\underline{K}_g}{K_g^2} \\ \bar{P}_{g,h} &= \zeta_{1,g,h} + \tfrac{2\zeta_{2,g}\bar{K}_{g,h}}{K_g^2}, \end{aligned}$$

and the competitive supply curve is given by

$$Q_{c,h}\left(P_h\right) = \sum_{g \in \mathcal{G}_c} q^*_{g,h}\left(P_h\right), \tag{24}$$

where

$$q^*_{g,h} = \begin{cases} 0 & \text{if } P_h < \underline{P}_{g,h} \\ \frac{\left(P_h - \zeta_{1,g,h}\right)K_g^2}{2\zeta_{2,s(g)}} & \text{if } P_h \in \left[\underline{P}_{g,h}, \bar{P}_{g,h}\right] \\ \bar{K}_{g,h} & \text{if } P_h > \bar{P}_{g,h}. \end{cases}$$

The competitive supply curve is an increasing, piecewise linear function, meaning that, based on equation 3, the residual demand curve the strategic firms face is a decreasing, piecewise linear function,

The strategic firms face the following inverse residual demand curve

$$P_h\left(Q_{s,h}\right) = \begin{cases} a_{h,1} - b_{h,1}Q_{s,h} & \text{if } Q_{s,h} \in \left[\underline{Q}_{h,1}, \bar{Q}_{h,1}\right] \\ \vdots & \\ a_{h,k} - b_{h,k}Q_{s,h} & \text{if } Q_{s,h} \in \left(\underline{Q}_{h,k}, \bar{Q}_{h,k}\right] \\ \vdots & \\ a_{h,2G_c-1} - b_{h,2G_c-1}Q_{s,h} & \text{if } Q_{s,h} \in \left(\underline{Q}_{h,2G_c-1}, \bar{Q}_{h,2G_c-1}\right], \end{cases} \tag{25}$$

where $Q_{s,h}$ is the total strategic quantity, and $\underline{Q}_k$ and $\bar{Q}_k$ denote the strategic quantities that would yield a particular linear function.

The first order condition for each generator is given by

$$\alpha_h - b_h \sum_{g' \in \mathcal{G}_{-f(g)}} q_{g',h} - 2b_h \sum_{g' \in \mathcal{G}_{f(g)}} q_{g',h} = \zeta_{1,g,h} + \zeta_{2,s(g)} q_{g,h},$$

where $f(s)$ denotes the identity of the firm to which generator g belongs, $\mathcal{G}_f$ denotes the set of generators belonging to the firm f, and $\mathcal{G}_{-f} = \mathcal{G}_s \setminus \mathcal{G}_f$.

This first order condition only holds for generators that are not constrained. Generators can be constrained either from above or from below. As in section 4, let $\mathcal{G}^+$ denote the generators constrained from above, $\mathcal{G}^-$ those from below, and $\mathcal{G}^u$ those that are unconstrained. Then for all $g \in \mathcal{G}^u_{s,h}$, if $Q_{s,h} \in \left[\underline{Q}_{h,k}, \bar{Q}_{h,k}\right]$ (a condition we will verify later),

$$\begin{aligned} q^*_{g,h} &= \frac{a_{h,k} - b_{h,k} \sum_{g' \in \mathcal{G}_{-f(g)}} q_{g',h} - 2b_{h,k} \sum_{g' \in \mathcal{G}_{f(g)} \setminus \{g\}} q_{g',h} - \zeta_{1,g,h}}{2b_h + \zeta_{2,s(g)}} \\ &= \frac{\alpha_{h,k} - b_{h,k} \left(\sum\limits_{g' \in \mathcal{G}^u_{-f(g),h}} q_{g',h} + \sum\limits_{g' \in \mathcal{G}^+_{-f(g),h}} \bar{K}_{g',h} + 2 \sum\limits_{g' \in \mathcal{G}^u_{f(g),h} \setminus \{g\}} q_{g',h} + 2 \sum\limits_{g' \in \mathcal{G}^+_{f(g),h}} \bar{K}_{g',h} \right) - \zeta_{1,g,h}}{2b_h + \zeta_{2,g,h}}. \end{aligned} \tag{26}$$

Let $\mathbf{q}^{u*}_h = \left[q^*_{g,h} \forall g \in \mathcal{G}^u_{s,h} \right]'$, and let $\mathbf{K}^u_h$, $\bar{\mathbf{K}}^u_h$, $\boldsymbol{\zeta}^u_{1,h}$, and $\boldsymbol{\zeta}^u_{2,h}$ be defined analogously. Then equation 26 can be rewritten as

$$\mathbf{q}^{u*}_h = \frac{1}{2b_{h,k} + \boldsymbol{\zeta}^u_{2,h}} \odot \left(\alpha_{h,k} - b_{h,k} \left(\Xi_{\mathcal{G}^u_{s,h}, \mathcal{G}^+_{s,h}} \bar{\mathbf{K}}^+_h + \Xi_{\mathcal{G}^u_{s,h}, \mathcal{G}^u_{s,h}} \mathbf{q}^{u*}_h \right) - \boldsymbol{\zeta}^u_{1,h} \right),$$

where $\odot$ is the Hadamard product, division is element-wise, and

$$\Xi_{A,B} = \begin{bmatrix} \ddots & & \\ & \xi_{g \in A, g' \in B} & \\ & & \ddots \end{bmatrix}_{|A| \times |B|},$$

where

$$\xi_{g,g'} = \begin{cases} 0 & \text{if } g = g' \\ 1 & \text{if } f(g) \neq f(g') \\ 2 & \text{if } g \neq g' \text{ and } f(g) = f(g'). \end{cases}$$

The above equation for $\mathbf{q}^{u*}_h$ can then be written explicitly as

$$\mathbf{q}^{u*}_h = \left(I_{\left|\mathcal{G}^u_{s,h}\right|} + \frac{b_{h,k}}{2b_{h,k} + \boldsymbol{\zeta}^u_{2,h}} \mathbf{1}'_{G^u_{s,h}} \odot \Xi_{\mathcal{G}^u_{s,h}, \mathcal{G}^u_{s,h}} \right)^{-1} \left[\frac{1}{2b_{h,k} + \boldsymbol{\zeta}^u_{2,h}} \odot \left(a_{h,k} - b_{h.k} \Xi_{\mathcal{G}^u_{s,h}, \mathcal{G}^+_{s,h}} \bar{\mathbf{K}}^+_h - \boldsymbol{\zeta}^u_{1,h} \right) \right], \tag{27}$$

where I_n is the identity matrix of size n and $\mathbf{1}_n$ is a column vector of ones of size n.

The conditions which would yield k as the segment of the residual demand curve, $\mathcal{G}^{+}_{s,h}$ as the firm-sources that are constrained from above, $\mathcal{G}^{-}_{s,h}$ those from below, and $\mathcal{G}^{u}_{s,h}$ unconstrained are:

$$\sum_{g\in\mathcal{G}^{u}_{s,h}} q^{*}_{g,h} + \sum_{g\in\mathcal{G}^{+}_{s,h}} \bar{K}_{g,h} \in \left(\underline{Q}_{h,k}, \bar{Q}_{h,k}\right], \tag{28}$$

and

$$\frac{1}{2b_{h,k}+\boldsymbol{\zeta}^{-}_{2,h}} \odot \left(a_{h,k} - b_{h,k}\left(\Xi_{\mathcal{G}^{-}_{s,h},\mathcal{G}^{u}_{s,h}}\mathbf{q}^{u*}_{h} + \Xi_{\mathcal{G}^{-}_{s,h},\mathcal{G}^{+}_{s,h}}\bar{\mathbf{K}}^{+}_{h}\right) - \boldsymbol{\zeta}^{-}_{1,h}\right) \ll \underline{\mathbf{K}}^{-}_{h}, \tag{29}$$

and

$$\frac{1}{2b_{h,k}+\boldsymbol{\zeta}^{+}_{2,h}} \odot \left(a_{h,k} - b_{h,k}\left(\Xi_{\mathcal{G}^{+}_{s,h},\mathcal{G}^{u}_{s,h}}\mathbf{q}^{u*}_{h} + \Xi_{\mathcal{G}^{+}_{s,h},\mathcal{G}^{+}_{s,h}}\bar{\mathbf{K}}^{+}_{h}\right) - \boldsymbol{\zeta}^{+}_{1,h}\right) \gg \bar{\mathbf{K}}^{+}_{h}, \tag{30}$$

and

$$\left(I_{G^{u}_{s,h}} + \frac{b_{h,k}}{2b_{h,k}+\boldsymbol{\zeta}^{u}_{2,h}}\mathbf{1}'_{G^{u}_{s,h}} \odot \Xi_{\mathcal{G}^{u}_{s,h},\mathcal{G}^{u}_{s,h}}\right)^{-1}\left[\frac{1}{2b_{h,k}+\boldsymbol{\zeta}^{u}_{2,h}} \odot \left(a_{h,k} - b_{h,k}\Xi_{\mathcal{G}^{u}_{s,h},\mathcal{G}^{+}_{s,h}}\bar{\mathbf{K}}^{+}_{h} - \boldsymbol{\zeta}^{u}_{1,h}\right)\right] \leq \bar{\mathbf{K}}^{u}_{h}. \tag{31}$$

Note that the above conditions are necessary but not sufficient to be an equilibrium. Let's call $\mathbf{q}^{*}_{h}$ (a vector of size G_s) a *potential equilibrium* if it satisfies the conditions above (equations 28–31). The conditions give *local* maxima for the profit function, but each firm seeks to *globally* maximize its profit function. If a firm has the ability to choose a quantity that would move aggregate demand to a different segment $k' \neq k$ of the residual curve, then its local maximum may not be its global maximum. For a potential equilibrium $\mathbf{q}^{*}_{h}$ to be an equilibrium, it must be the case that there does not exist $\tilde{\mathbf{q}}^{*}_{h} \neq \mathbf{q}^{*}_{h}$ such that equations 28–31 hold and $\pi_f\left(\tilde{\mathbf{q}}^{*}_{h}\right) > \pi_f\left(\mathbf{q}^{*}_{h}\right)$ for all f.

B.3 End-Consumer Demand

B.3.1 Consumer's Problem

A measure 1 of consumers has utility in a given interval h of

$$u_h\left(q,P\right) = \frac{\xi_h}{1-1/\epsilon}q^{1-1/\epsilon} - Pq, \tag{32}$$

where P is the *end-consumer price* (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 consumers' first order conditions imply that the optimal electricity consumption is

$$q^{*}_{h}\left(P\right) = \left(\frac{\xi_h}{P}\right)^{\epsilon}.$$

I assume that $\log(\xi_h) \sim \mathcal{N}(\mu, \sigma^2)$. Therefore, since $\bar{Q}_h = \int_0^1 q_h^* \,\mathrm{d}i$,

$$\log\left(\bar{Q}_h\right) \sim \mathcal{N}\left(\epsilon\mu - \epsilon\log(P), \epsilon^2\sigma^2\right).$$

Note that $E\bar{Q}(P) := \mathbb{E}\left[\bar{Q}_h \middle| P\right] = \exp\left(\epsilon\mu - \epsilon\log(P) + \frac{\epsilon^2\sigma^2}{2}\right)$, and the price elasticity is therefore given by

$$\frac{\mathrm{d}\log E\bar{Q}(P)}{\mathrm{d}\log P} = -\epsilon. \tag{33}$$

Consumers thus have a constant price elasticity.

Using this utility function, I can determine expected consumer surplus as a function of the end-consumer price.

$$\begin{aligned} u_h(q^*(P), P) &= \frac{\xi_h}{1-1/\epsilon}\left(\frac{\xi_h}{P}\right)^{\epsilon-1} - P\left(\frac{\xi_h}{P}\right)^{\epsilon} \\ &= \frac{1}{\epsilon-1}P^{1-\epsilon}\xi_h^{\epsilon}. \end{aligned}$$

The expected change in consumer surplus going from P_1 to P_2, $E\Delta CS(P_1, P_2)$, is therefore given by

$$\begin{aligned} E\Delta CS(P) &= \mathbb{E}\left[u_h(q^*(P_2), P_2) - u_h(q^*(P_1), P_1)\right] \\ &= \frac{1}{\epsilon-1}\exp\left(\epsilon\mu + \frac{\epsilon^2\sigma^2}{2}\right)\left(P_2^{1-\epsilon} - P_1^{1-\epsilon}\right). \end{aligned} \tag{34}$$

B.3.2 End-Consumer Price

Note that the price in equation 32 is the end-consumer price, which is not necessarily the same as the wholesale price or even the average wholesale price. Consumers buy electricity from intermediaries. I assume that intermediaries set prices equal to the marginal cost of providing electricity (over the long-run, averaging over the prices in the wholesale markets). I make this assumption because Western Australia regulates retail electricity prices. I assume that

$$P_t^{consumer}\left(\bar{P}_t\right) = c_{retail} + c_{network} + \bar{P}_t, \tag{35}$$

where $\bar{P}_t$ is the quantity-weighted average wholesale price defined in equation 8 and the elasticity comes from Deryugina *et al.* (2020),[37] c_{retail} is the marginal retail cost of delivering electricity, and $c_{network}$ is the marginal cost of using the network to deliver electricity. Both of these marginal costs come from AEMC (2014) and are given in table 12.

[37] I use the six-month elasticity estimate of -0.09.

Table 12: Marginal Costs of Retail Electricity

Price Component	Cost (in AUD / MWh)	Source
c_{retail}	29.50	AEMC (2014)
$c_{network}$	131.40	AEMC (2014)
$\bar{P}_t$	$\bar{P}_t\left(\mathcal{G}\right)$ (equation 8)	model, Deryugina *et al.* (2020)

C Computational Details

C.1 Wholesale Market Equilibrium

C.1.1 Identifying Capacity Constrained Firms

While it would be possible in theory to compute for a given segment of the residual demand curve k each possible $\left(\mathcal{G}^{+}_{s,h}, \mathcal{G}^{-}_{s,h}, \mathcal{G}^{u}_{s,h}\right)$ and determine which satisfy inequalities 29–31, this becomes computationally infeasible with a large number of generators, as the problem scales exponentially with G_s. In this section I present an equivalent algorithm capable of solving for the set of constrained firm-energy sources that scales quadratically, rather than exponentially, with G. I denote this set of constrained generators $\left(\mathcal{G}^{+}_{s,h,k}, \mathcal{G}^{-}_{s,h,k}\right)$ consistent with these inequalities as[38]

$$\mathcal{G}^{+*}_{s,h,k}, \mathcal{G}^{-*}_{s,h,k} := \left\{\mathcal{G}^{+}_{s,h} \in \wp\left(\mathcal{G}_s\right), \mathcal{G}^{-}_{s,h} \in \wp\left(\mathcal{G}_s\right) : \text{inequalities 29–31 hold}\right\}.$$

Note that I can rewrite the set of inequalities given by equation 31 in terms of the demand intercept a_h. Since the demand intercept is common to all generators, I can use the inequalities written in terms of the demand intercept to order the sequence in which generators would begin to produce and ultimately hit capacity constraints as I raise a_h from $-\infty$. The inequality given by equation 31 becomes

$$a_{h,k}\Psi^{-1}\boldsymbol{\gamma} \leq \bar{\mathbf{K}}^{u}_{h} + \Psi^{-1}\left(\boldsymbol{\gamma} \odot \left(b_{h,k}\Xi_{\mathcal{G}^{u}_{s,h,k},\mathcal{G}^{+}_{s,h,k}}\bar{\mathbf{K}}^{+}_{h} + \boldsymbol{\zeta}^{u}_{1,h}\right)\right), \tag{36}$$

where, for notational compactness, I have defined $\Psi = I_{G^{u}_{s,h,k}} + \frac{b_{h,k}}{2b_{h,k}+\zeta^{u}_{2,h}}\mathbf{1}'_{G^{u}_{s,h,k}} \odot \Xi_{\mathcal{G}^{u}_{s,h,k},\mathcal{G}^{u}_{s,h,k}}$ and $\boldsymbol{\gamma} = \frac{1}{2b_{h,k}+\zeta^{u}_{2,h}}$.

Note that $\Psi^{-1}\boldsymbol{\gamma}$ can be positive or negative. If we Hadamard multiply this quantity by both sides of Equation 36, the inequality will flip whenever this quantity is negative. We can rewrite

[38] Note that I am not imposing that the quantities $\mathbf{q}^{*}_{s,h}\left(\mathcal{G}^{+}_{s,h,k}, \mathcal{G}^{-}_{s,h,k}\right)$ would be consistent with the limits of the residual demand segment k. I will impose this after I have determined $\left(\mathcal{G}^{+*}_{s,h,k}, \mathcal{G}^{-*}_{s,h,k}\right)$ for each k.

Equation 36 as

$$a_{h,k} \lesseqgtr_{\text{sgn}(\Psi^{-1}\gamma)} \underbrace{\Psi^{-1}\boldsymbol{\gamma} \odot \bar{\mathbf{K}}_h^u + \left(\Psi^{-1}\boldsymbol{\gamma}\right) \odot \left[\Psi^{-1}\left(\boldsymbol{\gamma} \odot \left(b_{h,k}\Xi_{\mathcal{G}^u_{s,h,k},\mathcal{G}^+_{s,h,k}}\bar{\mathbf{K}}_h^+ + \boldsymbol{\zeta}_{1,h}^u\right)\right)\right]}_{=:\mathbf{q}^{*-1}_{\mathcal{G}^u_{s,h,k},\mathcal{G}^+_{s,h,k},h,k}\left(\bar{\mathbf{K}}_h\right)}. \quad (37)$$

The function $\mathbf{q}^{*-1}_{A,B,h,k}(\mathbf{q}_h)$ returns the demand intercepts $\mathbf{a}_{h,k}$ that would induce generators in A to produce $\mathbf{q}_h$, with generators in B producing their capacity constraints $\bar{\mathbf{K}}_h^B$.[39] The direction of the inequality depends on the sign of $\Psi^{-1}\boldsymbol{\gamma}$. If $\Psi^{-1}\boldsymbol{\gamma}$ is positive, the inequality will be $\leq$, and if $\Psi^{-1}\boldsymbol{\gamma}$ is negative, the inequality will be $\geq$.

Now I need to define a function that maps the residual inverse demand intercept a to a set of constrained generators $\mathcal{G}^+, \mathcal{G}^-$, where I have dropped s, h, k subscripts for notational ease. We will define this function recursively. Consider a sufficiently small that the condition holds for $\mathcal{G}_0^+ = \emptyset, \mathcal{G}_0^- = \mathcal{G}_s$.[40] The subscript denotes the iteration number.

Let's now determine the generator that has the lowest demand intercept a that would cause it to go either from $\mathcal{G}^-$ to $\mathcal{G}_u$ or from $\mathcal{G}^u$ to $\mathcal{G}^+$. Since the set of generators was initialized such that they all belong to $\mathcal{G}^-$ in iteration $\ell = 0$, the generator we identify must be from the first group, but in future iterations either are possible, so we will consider the general case in which we must determine to which group the generator belongs.

Let

$$g_1^- = \arg\min_{g \in \mathcal{G}_0^- : \left[\Psi_0^{-1}\gamma_0\right]_g > 0} \left\{\mathbf{q}^{*-1}_{\mathcal{G}_0^u,\mathcal{G}_0^+}\left(\bar{\mathbf{K}}\right)\right\}$$

and

$$g_1^u = \arg\min_{g \in \mathcal{G}_0^u : \left[\Psi_0^{-1}\gamma_0\right]_g > 0} \left\{\mathbf{q}^{*-1}_{\mathcal{G}_0^u,\mathcal{G}_0^+}\left(\bar{\mathbf{K}}\right)\right\},$$

where $[\mathbf{x}]_i$ denotes the ith element of the vector $\mathbf{x}$. Of the two possible generators, let g_1 be the one that yields the smaller demand intercept:

$$g_1 = \begin{cases} g_1^- & \text{if } q^{*-1}_{\mathcal{G}_0^u,\mathcal{G}_0^+,g_1^-}\left(\bar{\mathbf{K}}\right) \leq q^{*-1}_{\mathcal{G}_0^u,\mathcal{G}_0^+,g_1^u}\left(\bar{\mathbf{K}}\right) \\ g_1^u & \text{otherwise.} \end{cases}$$

Note that generator g_1 is the tightest constraint and therefore the first to bind.[41]

[39] Note that this function returns a vector of demand intercepts $\mathbf{a}_{h,k}$, one for each generator in A. This is the demand intercept $a_{g,h,k}$ that would compel generator g to produce $q_{g,h}$ *keeping other generators producing* $\mathbf{q}_{-g,h}$.

[40] Note that there always exists a sufficiently small a that this condition holds.

[41] I can ignore generators for which $\Psi_0^{-1}\gamma_0$ is less than 0. In this case, the quantity they produce is decreasing in a_h, and therefore their capacity constraints will not bind.

I can define the function $\mathcal{G}^{+*}_{s,h,k}, \mathcal{G}^{-*}_{s,h,k} : \mathbb{R} \to \wp(\mathcal{G}_s) \times \wp(\mathcal{G}_s)$, mapping residual demand to constrained firms, recursively:

$$
\begin{aligned}
g_\ell^- &= \arg\min_{g \in \mathcal{G}^-_{\ell-1} : \left[\Psi^{-1}_{\ell-1}\gamma_{\ell-1}\right]_g > 0} \left\{ \mathbf{q}^{*-1}_{\mathcal{G}^u_{\ell-1}, \mathcal{G}^+_{\ell-1}}\left(\bar{\mathbf{K}}\right) \right\}, \\
g_\ell^u &= \arg\min_{g \in \mathcal{G}^u_{\ell-1} : \left[\Psi^{-1}_{\ell-1}\gamma_{\ell-1}\right]_g > 0} \left\{ \mathbf{q}^{*-1}_{\mathcal{G}^u_{\ell-1}, \mathcal{G}^+_{\ell-1}}\left(\bar{\mathbf{K}}\right) \right\}, \\
g_\ell &= \begin{cases} g_\ell^- & \text{if } q^{*-1}_{\mathcal{G}^u_{\ell-1}, \mathcal{G}^+_{\ell-1}, g_\ell^-}\left(\bar{\mathbf{K}}\right) \leq q^{*-1}_{\mathcal{G}^u_{ell-1}, \mathcal{G}^+_{\ell-1}, g_\ell^u}\left(\bar{\mathbf{K}}\right) \\ g_\ell^u & \text{otherwise,} \end{cases} \\
a_\ell &= q^{*-1}_{\mathcal{G}^u_{\ell-1}, \mathcal{G}^+_{\ell-1}, g_\ell}\left(\bar{\mathbf{K}}\right), \\
\mathcal{G}^-_\ell &= \begin{cases} \mathcal{G}^-_{\ell-1} \backslash \{g_\ell\} & \text{if } g_\ell = g_\ell^- \\ \mathcal{G}^-_{\ell-1} & \text{otherwise,} \end{cases} \\
\mathcal{G}^+_\ell &= \begin{cases} \mathcal{G}^+_{\ell-1} \cup \{g_\ell\} & \text{if } g_\ell = g_\ell^u \\ \mathcal{G}^+_{\ell-1} & \text{otherwise,} \end{cases}
\end{aligned}
$$

yielding

$$
\mathcal{G}^{+*}(a), \mathcal{G}^{-*}(a) = \begin{cases} \mathcal{G}^+_0, \mathcal{G}^-_0 & \text{if } a \in (-\infty, a_1] \\ \mathcal{G}^+_1, \mathcal{G}^-_1 & \text{if } a \in (a_1, a_2] \\ \quad\vdots & \\ \mathcal{G}^+_\ell, \mathcal{G}^-_\ell & \text{if } a \in (a_{\ell-1}, a_\ell] \\ \quad\vdots & \\ \mathcal{G}^+_L, \mathcal{G}^-_L & \text{if } a \in (a_L, \infty), \end{cases} \tag{38}
$$

Note that I have not explicitly imposed the set of inequalities given by equations 29 and 30. This is because for a generator g_ℓ, the left hand sides of the inequalities imply that the optimal unconstrained quantity is increasing in a for any $a > a_\ell$. Intuitively, as a rises, generators' capacity constraints begin to bind. As a continues to rise, there are no constrained generators' for which capacity constraints will cease to bind.

This fact is what allows me to determine $\mathcal{G}^{+*}_{s,h,k}, \mathcal{G}^{-*}_{s,h,k}$ by solving for optimal production decisions only (at most) $\frac{(G_s+1)(G_s+2)}{2}$ times rather than 3^G times, which becomes computationally infeasible beyond a small number of generators.

Up until now I have treated the problem as if it was known ex ante which segment k of the residual demand function is consistent with the strategic firms' production decisions. In practice, I determine $\left(\mathcal{G}^{+*}_{s,h,k}, \mathcal{G}^{-*}_{s,h,k}\right)$ with the above formula for each k and then determine which are equilibria, as defined in section B.2.

C.1.2 Computing Full Equilibrium with Consumer Response

For a given distribution of demand $\mathcal{Q}_t$, I can compute the distribution of prices, quantities and profits. To compute the yearly expected wholesale profit function, I perform the above described computation for a large number of draws of the random variables of the model. I then average over these draws to determine the expected wholesale profits.

The above allows me to compute the distribution of wholesale market variables conditional on a distribution of demand $\mathcal{Q}_t$, but this distribution is an endogenous object that depends on wholesale prices. To compute the distribution of demand, I take an initial guess of average quantity-weighted wholesale prices $\bar{P}_t^0$ and compute the implied demand distribution and wholesale prices. I then update the quantity-weighted wholesale prices as follows. For a given quantity-weighted wholesale price $\bar{P}_t^k$,

$$\bar{P}_t^{k+1} = \frac{1}{H} \sum_{h=1}^{H} \frac{\bar{Q}_h\left(\bar{P}_t^k\right) P_h\left(\bar{Q}_h\left(\bar{P}_t^k\right)\right)}{\sum_{h=1}^{H} \bar{Q}_h\left(\bar{P}_t^k\right)},$$

where H is the number of draws of the wholesale market that I take. I then iterate on $\bar{P}_t^k$ until convergence, i.e.

$$\left|\bar{P}_t^k - \bar{P}_t^{k-1}\right| < \varepsilon_{tol},$$

where ε is some threshold convergence tolerance (rather than cost shocks, as this letter represents in the main text).[42] This iteration until convergence (approximately) solves for the equilibrium condition given by equation 8. In practice, I find that convergence is quick, converging after just a few iterations.

C.1.3 Algorithm Summary

Algorithm 1 summarizes the algorithm for computing the full equilibrium expected yearly profits.

C.2 Inverting Cost Shocks

I use the same notation as that introduced in sections 4.1 and B to partition variables into those belonging to unconstrained generators and those belonging to constrained ones. The local competitive supply curve is given by equation 24. I can rewrite this equation locally as

[42] I use a tolerance of $\varepsilon_{tol} = 0.001$.

Algorithm 1: Compute $\mathbf{\Pi}_t(\mathcal{G})$

Result: $\mathbf{\Pi}_t(\mathcal{G})$

seed random number generator;
Qbar_search $\leftarrow$ true;
initialize $\bar{P}$;
while *Qbar_search* **do**
  $\mathbf{P} \leftarrow \emptyset$;
  for $h \leftarrow 1$ ***to*** H **do**
    sample $\bar{Q}_h\left(\bar{P}\right)$, $\boldsymbol{\delta}_h$, $\boldsymbol{\zeta}_{1,h}$, $\boldsymbol{\zeta}_{2,h}$, convert $\left(\bar{Q}_h, \boldsymbol{\delta}_h, \boldsymbol{\zeta}_{1,h}, \boldsymbol{\zeta}_{2,h}\right)$ to $\left(\mathbf{a}_h, \mathbf{b}_h, \underline{\mathbf{Q}}_{h,c}, \bar{\mathbf{Q}}_{h,c}, \bar{\mathbf{K}}_h\right)$;
    $\mathbf{q}_h^* \leftarrow \emptyset$;
    $\mathbf{q}^* \leftarrow \emptyset$;
    $\boldsymbol{\pi} \leftarrow \emptyset$;
    for $k \leftarrow 1$ ***to*** G_c **do**
      G_search $\leftarrow$ true;
      $\mathcal{G}_{h,k}^+ \leftarrow \emptyset, \quad \mathcal{G}_{h,k}^- \leftarrow \mathcal{G}_s$;
      while *G_search* **do**
        $g^- \leftarrow g_{h,k}^-\left(\mathcal{G}_{h,k}^u, \mathcal{G}_{h,k}^+\right), \quad g^u \leftarrow g_{h,k}^u\left(\mathcal{G}_{h,k}^u, \mathcal{G}_{h,k}^+\right), \quad a \leftarrow a_{h,k}\left(\mathcal{G}_{h,k}^u, \mathcal{G}_{h,k}^+\right)$;
        if $a \geq a_{h,k}$ **then**
          G_search $\leftarrow$ false;
        else
          if $g^- \leq g^u$ **then**
            $\mathcal{G}_{h,k}^- \leftarrow \mathcal{G}_{h,k}^- \setminus \{g^-\}$;
          else
            $\mathcal{G}_{h,k}^+ \leftarrow \mathcal{G}_{h,k}^+ \cup \{g^u\}$;
          end
        end
      end
      $\mathbf{q}_{h,k}^* \leftarrow \mathbf{q}_h^*\left(\mathcal{G}_{h,k}^-, \mathcal{G}_{h,k}^+\right)$;
      if $Q_{s,h}^* \in \left(\underline{Q}_{h,c,k}, \bar{Q}_{h,c,k}\right]$ **then**
        $\mathbf{q}^* \leftarrow \mathbf{q}^* \cup \mathbf{q}_{h,k}^*$;
        $\mathbf{P} \leftarrow \mathbf{P} \cup P_{h,k}\left(\mathbf{q}_{h,k}^*\right)$;
        $\boldsymbol{\pi} \leftarrow \boldsymbol{\pi} \cup \boldsymbol{\pi}_{h,k}\left(\mathbf{q}_{h,k}^*\right)$;
      end
    end
    $\mathbf{\Pi} \leftarrow \frac{1}{H}\sum_{h=1}^{H} \boldsymbol{\pi}_h$;
    $\bar{P}_{new} \leftarrow \bar{P}\left(\mathbf{P}, \mathbf{q}^*\right)$;
    if $\left|\bar{P}_{new} - \bar{P}\right| < \varepsilon_{tol}$ **then**
      Qbar_search $\leftarrow$ false;
    else
      $\bar{P} \leftarrow \bar{P}_{new}$;
    end
  end
end

a function linear in cost shocks as well as the market price:[43]

$$Q_{c,h}\left(P_h\right)=\sum_{g\in\mathcal{G}_{c,h}^{+}}\bar{K}_{g,h}+\underbrace{\phi_h\left(\boldsymbol{\beta},\boldsymbol{\zeta}_2\right)+\mathbf{c}_h\left(\boldsymbol{\zeta}_2\right)'\boldsymbol{\varepsilon}_h^u}_{=\alpha_h}+\beta_h\left(\boldsymbol{\zeta}_2\right)P_h, \tag{39}$$

where

$$\mathbf{c}_h\left(\boldsymbol{\zeta}_2\right)=\begin{bmatrix}-\gamma_{1,h}\left(\zeta_{2,s(1)}\right) & -\gamma_{2,h}\left(\zeta_{2,s(2)}\right) & \ldots & -\gamma_{g,h}\left(\zeta_{2,s(g)}\right) & \ldots & -\gamma_{G_{u,h},h}\left(\zeta_{2,s\left(G_{c,h}^u\right)}\right)\end{bmatrix}',$$

where

$$\gamma_{g,h}\left(\zeta_{2,g}\right)=\begin{cases}\frac{1}{2\zeta_{2,s(g)}K_g^{-2}} & \text{if } g\in\mathcal{G}_{c,h}^u\\ 0 & \text{otherwise,}\end{cases}$$

$$\phi_h\left(\boldsymbol{\beta},\boldsymbol{\zeta}_2\right)=\sum_{g\in\mathcal{G}_h^u}-\gamma_{g,h}\left(\zeta_{2,s(g)}\right)\boldsymbol{\beta}_{s(g)}'\mathbf{x}_{g,h},$$

and

$$\beta_h\left(\boldsymbol{\zeta}_2\right)=\sum_{g\in\mathcal{G}_h^u}\gamma_{g,h}\left(\zeta_{2,1}\right).$$

Plugging equation 39 into equation 25, the strategic residual demand curve is also linear:

$$P_h\left(Q_{s,h}\right)=\underbrace{\psi_h\left(\boldsymbol{\beta},\boldsymbol{\zeta}_2\right)+\mathbf{d}_h\left(\boldsymbol{\beta},\boldsymbol{\zeta}_2\right)'\boldsymbol{\varepsilon}_h^u}_{=a_h}-b_h\left(\boldsymbol{\zeta}_2\right)Q_{s,h}, \tag{40}$$

where

$$\psi_h\left(\boldsymbol{\beta},\boldsymbol{\zeta}_2\right)=\frac{\bar{Q}_h-Q_h^{\text{wind}}-\sum_{g\in\mathcal{G}_{c,h}^{+}}\bar{K}_{g,h}-\phi_h\left(\boldsymbol{\beta},\boldsymbol{\zeta}_2\right)}{\beta_h\left(\boldsymbol{\zeta}_2\right)},$$

$$\mathbf{d}_h\left(\boldsymbol{\beta},\boldsymbol{\zeta}_2\right)=-\frac{1}{\beta_h\left(\boldsymbol{\zeta}_2\right)}\mathbf{c}_h\left(\boldsymbol{\zeta}_2\right),$$

and

$$b_h\left(\boldsymbol{\zeta}_2\right)=\frac{1}{\beta_h\left(\boldsymbol{\zeta}_2\right)}.$$

Given the demand curve, equation 27 provides a formula for the equilibrium strategic firms' production decisions:

$$\mathbf{q}_{s,h}^u=\mathbf{E}_h\left(\boldsymbol{\beta},\boldsymbol{\zeta}_2\right)\boldsymbol{\varepsilon}_h^u+\mathbf{f}_h\left(\boldsymbol{\beta},\boldsymbol{\zeta}_2\right), \tag{41}$$

where

$$\mathbf{E}_h\left(\boldsymbol{\beta},\boldsymbol{\zeta}_2\right)=\boldsymbol{\Psi}_h\left(\boldsymbol{\zeta}_2\right)^{-1}\left[\frac{1}{2b_h\left(\boldsymbol{\zeta}_2\right)\mathbf{1}_{G_{s,h}^u}+2\boldsymbol{\zeta}_{2,s}^u\odot\mathbf{K}^{u\circ-2}}\mathbf{1}_{G_h^u}'\odot\left(\mathbf{1}_{G_{s,h}^u}\mathbf{d}_h\left(\boldsymbol{\beta},\boldsymbol{\zeta}_2\right)'-\left[I_{G_h^u}\right]_{\mathcal{G}_{s,h}^u,\cdot}\right)\right],$$

[43] *Locally* means a neighborhood in which the constrained generators remain constrained and unconstrained generators remain unconstrained.

and

$$\mathbf{f}_h\left(\boldsymbol{\beta},\boldsymbol{\zeta}_2\right)=\boldsymbol{\Psi}_h\left(\boldsymbol{\zeta}_2\right)^{-1}\left[\frac{1}{2b_h\left(\boldsymbol{\zeta}_2\right)\mathbf{1}_{G^u_{s,h}}+2\boldsymbol{\zeta}^u_{2,s}\odot\mathbf{K}^{u\circ-2}}\odot\left(\psi_h\left(\boldsymbol{\beta},\boldsymbol{\zeta}_2\right)\mathbf{1}_{G^u_{s,h}}-b_h\left(\boldsymbol{\zeta}_2\right)\Xi_{\mathcal{G}^u_{s,h},\mathcal{G}^+_{s,h}}\bar{\mathbf{K}}^+_{s,h}-\mathbf{X}^u_{s,h}\boldsymbol{\beta}\right)\right],$$

where division is element-wise, $\mathbf{a}^{\circ2}$ is the vector $\mathbf{a}$ squared element-wise, and

$$\boldsymbol{\Psi}_h\left(\boldsymbol{\zeta}_2\right)=I_{G^u_{s,h}}+\frac{b_h\left(\boldsymbol{\zeta}_2\right)\mathbf{1}_{G^u_{s,h}}}{2b_h\left(\boldsymbol{\zeta}_2\right)\mathbf{1}_{G^u_{s,h}}+2\boldsymbol{\zeta}^u_{2,s}\odot\mathbf{K}^{u\circ-2}}\mathbf{1}'_{G^u_{s,h}}\odot\Xi_{\mathcal{G}^u_{s,h},\mathcal{G}^u_{s,h}}.$$

Plugging equation 41 into equation 40, we get a formula for prices as a function of cost shocks:

$$P_h=\mathbf{g}_h\left(\boldsymbol{\beta},\boldsymbol{\zeta}_2\right)'\boldsymbol{\varepsilon}^u_h+j_h\left(\boldsymbol{\beta},\boldsymbol{\zeta}_2\right),\tag{42}$$

where

$$\mathbf{g}_h\left(\boldsymbol{\beta},\boldsymbol{\zeta}_2\right)=\mathbf{d}_h\left(\boldsymbol{\beta},\boldsymbol{\zeta}_2\right)-b_h\left(\boldsymbol{\zeta}_2\right)\mathbf{E}_h\left(\boldsymbol{\beta},\boldsymbol{\zeta}_2\right)'\mathbf{1}_{G^u_{s,h}}$$

and

$$j_h\left(\boldsymbol{\beta},\boldsymbol{\zeta}_2\right)=\psi_h\left(\boldsymbol{\beta},\boldsymbol{\zeta}_2\right)-b_h\left(\left(\boldsymbol{\zeta}_2\right)\mathbf{1}'_{G^u_{s,h}}\mathbf{f}_h\left(\boldsymbol{\beta},\boldsymbol{\zeta}_2\right)+\sum_{g\in\mathcal{G}^+_{s,h}}\bar{K}_{g,h}\right).$$

Using the fact that for competitive generator g, $q_{g,h}=\frac{P_h-\boldsymbol{\beta}'_{s(g)}\mathbf{x}_{g,h}-\varepsilon_{g,h}}{2\zeta_{2,s(g)}K_g^{-2}}$, we have

$$\mathbf{q}^u_{c,h}=\mathbf{K}_h\left(\boldsymbol{\beta},\boldsymbol{\zeta}_2\right)\boldsymbol{\varepsilon}^u_h+\boldsymbol{\ell}_h\left(\boldsymbol{\beta},\boldsymbol{\zeta}_2\right),$$

where

$$\mathbf{K}_h\left(\boldsymbol{\beta},\boldsymbol{\zeta}_2\right)=\frac{1}{2\boldsymbol{\zeta}^u_{2,c,h}\odot\mathbf{K}^{u\circ-2}_c}\mathbf{1}'_{G^u_h}\odot\left(\mathbf{1}_{G^u_{c,h}}\mathbf{g}_h\left(\boldsymbol{\beta},\boldsymbol{\zeta}_2\right)'-\left[I_{G^u_h}\right]_{\mathcal{G}^u_{c,h},\cdot}\right)$$

and

$$\boldsymbol{\ell}_h\left(\boldsymbol{\beta},\boldsymbol{\zeta}_2\right)=\frac{1}{2\boldsymbol{\zeta}^u_{2,c,h}\odot\mathbf{K}^{u\circ-2}_c}\odot\left(j_h\left(\boldsymbol{\beta},\boldsymbol{\zeta}_2\right)\mathbf{1}_{G^u_{c,h}}-\mathbf{X}^u_{c,h}\boldsymbol{\beta}\right).$$

Therefore, I can combine the expressions for $\mathbf{q}^u_{c,h}$ and $\mathbf{q}^u_{s,h}$, which yields

$$\mathbf{q}^u_h=\mathbf{M}_h\left(\boldsymbol{\beta},\boldsymbol{\zeta}_2\right)\boldsymbol{\varepsilon}^u_h+\mathbf{n}_h\left(\boldsymbol{\beta},\boldsymbol{\zeta}_2\right),\tag{43}$$

where

$$\mathbf{M}_h(\boldsymbol{\beta},\boldsymbol{\zeta}_2)=\begin{bmatrix}\mathbf{m}_{1,h}(\boldsymbol{\beta},\boldsymbol{\zeta}_2)\\ \mathbf{m}_{2,h}(\boldsymbol{\beta},\boldsymbol{\zeta}_2)\\ \vdots\\ \mathbf{m}_{g,h}(\boldsymbol{\beta},\boldsymbol{\zeta}_2)\\ \vdots\\ \mathbf{m}_{G_h^u,h}(\boldsymbol{\beta},\boldsymbol{\zeta}_2)\end{bmatrix}\quad\text{and}\quad \mathbf{n}_h(\boldsymbol{\beta},\boldsymbol{\zeta}_2)=\begin{bmatrix}n_{1,h}(\boldsymbol{\beta},\boldsymbol{\zeta}_2)\\ n_{2,h}(\boldsymbol{\beta},\boldsymbol{\zeta}_2)\\ \vdots\\ n_{g,h}(\boldsymbol{\beta},\boldsymbol{\zeta}_2)\\ \vdots\\ n_{G_h^u,h}(\boldsymbol{\beta},\boldsymbol{\zeta}_2)\end{bmatrix},$$

where

$$\mathbf{m}_{g,h}(\boldsymbol{\beta},\boldsymbol{\zeta}_2)=\begin{cases}[\mathbf{K}_h(\boldsymbol{\beta},\boldsymbol{\zeta}_2)]_{g,\cdot} & \text{if } g\in\mathcal{G}_{c,h}^u\\ [\mathbf{E}_h(\boldsymbol{\beta},\boldsymbol{\zeta}_2)]_{g,\cdot} & \text{if } g\in\mathcal{G}_{s,h}^u\end{cases}$$

and

$$n_{g,h}(\boldsymbol{\beta},\boldsymbol{\zeta}_2)=\begin{cases}[\boldsymbol{\ell}_h(\boldsymbol{\beta},\boldsymbol{\zeta}_2)]_{g} & \text{if } g\in\mathcal{G}_{c,h}^u\\ [\mathbf{f}_h(\boldsymbol{\beta},\boldsymbol{\zeta}_2)]_{g} & \text{if } g\in\mathcal{G}_{s,h}^u.\end{cases}$$

Now I show that we can invert the quantities $\mathbf{q}_h^u$ and the price P_h to obtain the vector of cost shocks for unconstrained generators $\boldsymbol{\varepsilon}_h^u$. While the dimension $\mathbf{q}_h^u$ is the same as that of $\boldsymbol{\varepsilon}_h^u$, we cannot simply invert equation 43 in order to recover $\boldsymbol{\varepsilon}_h^u$. The rank of $\mathbf{M}_h(\boldsymbol{\beta},\boldsymbol{\zeta}_2)$ is one less than its dimension (i.e., $\operatorname{rank}(\mathbf{M}_h(\boldsymbol{\beta},\boldsymbol{\zeta}_2))=|\mathbf{q}_h^u|-1$). The equilibrium is constructed such that the sum of generators' quantities is equal to $\bar{Q}_h$. Intuitively, the "final" quantity is not independent; it is a linear function of the others' quantities.

By using information on the realized price, P_h, however, I can still recover the vector $\boldsymbol{\varepsilon}_h^u$. Specifically, I remove a row i in $\mathbf{q}_h^u$, $\mathbf{M}_h(\boldsymbol{\beta},\boldsymbol{\zeta}_2)$, and $\mathbf{n}_h(\boldsymbol{\beta},\boldsymbol{\zeta}_2)$ that is linearly dependent in $\mathbf{M}_h(\boldsymbol{\beta},\boldsymbol{\zeta}_2)$. I then replace row i with P_h, $\mathbf{g}_h(\boldsymbol{\beta},\boldsymbol{\zeta}_2)'$, and $j_h(\boldsymbol{\zeta}_2)$, respectively. Let's call the new vectors/matrices $\tilde{\mathbf{q}}_h^u$, $\tilde{\mathbf{M}}_h(\boldsymbol{\beta},\boldsymbol{\zeta}_2)$, and $\tilde{\mathbf{n}}_h(\boldsymbol{\beta},\boldsymbol{\zeta}_2)$, respectively. The matrix $\tilde{\mathbf{M}}_h(\boldsymbol{\beta},\boldsymbol{\zeta}_2)$ is full rank and therefore invertible. I can therefore solve for $\boldsymbol{\varepsilon}_h^u$ as follows:

$$\boldsymbol{\varepsilon}_h^u(\mathbf{q}_h^u,P_h;\boldsymbol{\beta},\boldsymbol{\zeta}_2)=\tilde{\mathbf{M}}_h(\boldsymbol{\beta},\boldsymbol{\zeta}_2)^{-1}\left(\tilde{\mathbf{q}}_h^u-\tilde{\mathbf{n}}_h(\boldsymbol{\beta},\boldsymbol{\zeta}_2)\right). \tag{44}$$

C.3 Wholesale Market Log-likelihood

In order to compute the likelihood given in equation 16, I need to determine a tractable way to compute $\Pr\left(\boldsymbol{\varepsilon}_h^+\geq\boldsymbol{\nu}_h^+ \text{ and } \boldsymbol{\varepsilon}_h^-\leq\boldsymbol{\nu}_h^-\,\middle|\,\boldsymbol{\varepsilon}_h^u=\mathbf{e}_h^u;\boldsymbol{\Sigma}_{\varepsilon}\right)$. Note that the conditional distribution of a subset of the components of a multivariate normal, conditioning on the other elements, is also normal:

$$\left.\boldsymbol{\varepsilon}_h^{-u}\right|\boldsymbol{\varepsilon}_h^u=\mathbf{e}_h^u\sim\mathcal{N}\left(\tilde{\boldsymbol{\mu}}_{\varepsilon}(\mathbf{e}_h^u),\tilde{\boldsymbol{\Sigma}}_{\varepsilon}(\mathbf{e}_h^u)\right),$$

where

$$\tilde{\boldsymbol{\mu}}_{\varepsilon}\left(\mathbf{e}_h^u\right) = \boldsymbol{\Sigma}_{\varepsilon}^{-u,u}\left(\boldsymbol{\Sigma}_{\varepsilon}^{u,u}\right)^{-1}\mathbf{e}_h^u$$

and

$$\tilde{\boldsymbol{\Sigma}}_{\varepsilon}\left(\mathbf{e}_h^u\right) = \boldsymbol{\Sigma}_{\varepsilon}^{-u,-u} - \boldsymbol{\Sigma}_{\varepsilon}^{-u,u}\left(\boldsymbol{\Sigma}_{\varepsilon}^{u,u}\right)^{-1}\boldsymbol{\Sigma}_{\varepsilon}^{u,-u}.$$

Therefore,

$$\Pr\left(\boldsymbol{\varepsilon}_h^+ \leq \boldsymbol{\nu}_h^+ \text{ and } \boldsymbol{\varepsilon}_h^- \geq \boldsymbol{\nu}_h^- \middle| \boldsymbol{\varepsilon}_h^u = \mathbf{e}_h^u; \boldsymbol{\Sigma}_{\varepsilon}\right) = \Pr\left(\boldsymbol{\varepsilon}_h^+ \leq \boldsymbol{\nu}_h^+ \text{ and } \boldsymbol{\varepsilon}_h^- \geq \boldsymbol{\nu}_h^-; \tilde{\boldsymbol{\mu}}_{\varepsilon}\left(\mathbf{e}_h^u\right), \tilde{\boldsymbol{\Sigma}}_{\varepsilon}\left(\mathbf{e}_h^u\right)\right).$$

Therefore, equation 16 can be rewritten as

$$\begin{aligned}\ell\left(\boldsymbol{\beta}, \boldsymbol{\zeta}_2, \boldsymbol{\Sigma}_{\varepsilon}\right) \quad &= \textstyle\sum_h \log\left(\phi_{G_h^u}\left(\boldsymbol{\varepsilon}_h^u\left(\boldsymbol{\beta}, \boldsymbol{\zeta}_{\mathbf{2}}\right); \boldsymbol{\Sigma}_{\varepsilon}\right)\right) \\ &\quad + \log\left(\Phi_{G_h^{-u}}\left(\underline{\boldsymbol{\nu}}_h^{-u}\left(\boldsymbol{\beta}, \boldsymbol{\zeta}_{\mathbf{2}}\right), \bar{\boldsymbol{\nu}}_h^{-u}\left(\boldsymbol{\beta}, \boldsymbol{\zeta}_{\mathbf{2}}\right); \tilde{\boldsymbol{\mu}}_{\varepsilon}\left(\boldsymbol{\varepsilon}_h^u\left(\boldsymbol{\beta}, \boldsymbol{\zeta}_{\mathbf{2}}\right)\right), \tilde{\boldsymbol{\Sigma}}_{\varepsilon}\left(\boldsymbol{\varepsilon}_h^u\left(\boldsymbol{\beta}, \boldsymbol{\zeta}_{\mathbf{2}}\right)\right)\right)\right),\end{aligned} \tag{45}$$

where

$$\Phi_k\left(\mathbf{a}, \mathbf{b}; \boldsymbol{\mu}, \boldsymbol{\Sigma}\right) = \int_{a_1}^{b_1} \ldots \int_{a_k}^{b_k} \phi_k\left(\mathbf{x}; \boldsymbol{\mu}, \boldsymbol{\Sigma}\right) \mathrm{d}\mathbf{x}$$

and

$$\underline{\boldsymbol{\nu}}_h^{-u}\left(\boldsymbol{\beta}, \boldsymbol{\zeta}_{\mathbf{2}}\right) = \begin{bmatrix} \underline{\nu}_{1,h}\left(\boldsymbol{\beta}, \boldsymbol{\zeta}_{\mathbf{2}}\right) \\ \vdots \\ \underline{\nu}_{g,h}\left(\boldsymbol{\beta}, \boldsymbol{\zeta}_{\mathbf{2}}\right) \\ \vdots \\ \underline{\nu}_{G_h^{-u},h}\left(\boldsymbol{\beta}, \boldsymbol{\zeta}_{\mathbf{2}}\right) \end{bmatrix} \quad \text{and} \quad \bar{\boldsymbol{\nu}}_h^{-u}\left(\boldsymbol{\beta}, \boldsymbol{\zeta}_{\mathbf{2}}\right) = \begin{bmatrix} \bar{\nu}_{1,h}\left(\boldsymbol{\beta}, \boldsymbol{\zeta}_{\mathbf{2}}\right) \\ \vdots \\ \bar{\nu}_{g,h}\left(\boldsymbol{\beta}, \boldsymbol{\zeta}_{\mathbf{2}}\right) \\ \vdots \\ \bar{\nu}_{G_h^{-u},h}\left(\boldsymbol{\beta}, \boldsymbol{\zeta}_{\mathbf{2}}\right) \end{bmatrix},$$

where

$$\underline{\nu}_{g,h}\left(\boldsymbol{\beta}, \boldsymbol{\zeta}_{\mathbf{2}}\right) = \begin{cases} \nu_{g,h}\left(\boldsymbol{\beta}, \boldsymbol{\zeta}_2\right) & \text{if } g \in \mathcal{G}_h^- \\ -\infty & \text{if } g \in \mathcal{G}_h^+. \end{cases} \quad \text{and} \quad \bar{\nu}_{g,h}\left(\boldsymbol{\beta}, \boldsymbol{\zeta}_{\mathbf{2}}\right) = \begin{cases} \infty & \text{if } g \in \mathcal{G}_h^- \\ \nu_{g,h}\left(\boldsymbol{\beta}, \boldsymbol{\zeta}_2\right) & \text{if } g \in \mathcal{G}_h^+ \end{cases}$$

Note that equation 45 requires computing

$$\Phi_{G_h^{-u}}\left(\underline{\boldsymbol{\nu}}_h^{-u}, \bar{\boldsymbol{\nu}}_h^{-u}; \tilde{\boldsymbol{\mu}}_{\varepsilon}, \tilde{\boldsymbol{\Sigma}}_{\varepsilon}\right). \tag{46}$$

This integral has no closed form solution and is numerically difficult to compute. In order to approximate the integral given in equation 46, I first decompose the the covariance matrix in order to obtain the correlation matrix, as follows:

$$\tilde{\boldsymbol{\Sigma}}_{\varepsilon} = \mathbf{D}\mathbf{R}\mathbf{D}',$$

where $\mathbf{D}$ is the diagonal matrix

$$\mathbf{D} = \begin{bmatrix} \sigma_1 & & & & \\ & \ddots & & \mathbf{0} & \\ & & \sigma_g & & \\ & \mathbf{0} & & \ddots & \\ & & & & \sigma_{G_h^{-u}} \end{bmatrix} \quad \text{and} \quad \mathbf{R} = \begin{bmatrix} 1 & \rho_{1,2} & \cdots & \rho_{1,g} & \cdots & \rho_{1,G} \\ \rho_{2,1} & 1 & & & \ddots & \\ \vdots & & \ddots & & & \\ \rho_{g,1} & & & 1 & & \\ \vdots & \ddots & & & \ddots & \\ \rho_{G,1} & & & & & 1 \end{bmatrix}.$$

Then

$$\Phi_{G_h^{-u}}\left(\underline{\boldsymbol{\nu}}_h^{-u}, \bar{\boldsymbol{\nu}}_h^{-u}; \tilde{\boldsymbol{\mu}}_{\boldsymbol{\varepsilon}}, \tilde{\boldsymbol{\Sigma}}_{\boldsymbol{\varepsilon}}\right) = \Phi_{G_h^{-u}}\left(\mathbf{a}, \mathbf{b}; \mathbf{R}\right),$$

where $\Phi_k\left(\cdot, \cdot; \cdot\right)$ is the standardized analogue of $\Phi_k\left(\cdot, \cdot; \cdot, \cdot\right)$ and

$$\mathbf{a} = \mathbf{D}^{-1}\left(\underline{\boldsymbol{\nu}}_h^{-u} - \tilde{\boldsymbol{\mu}}_{\boldsymbol{\varepsilon}}\right) \quad \text{and} \quad \mathbf{b} = \mathbf{D}^{-1}\left(\bar{\boldsymbol{\nu}}_h^{-u} - \tilde{\boldsymbol{\mu}}_{\boldsymbol{\varepsilon}}\right).$$

I next note that the structure placed on $\rho_{g,g'}$ allows me to use a useful transformation to transform equation 46 from a G_h^{-u}-dimensional integral to a lower-dimensional one. Genz & Bretz (2009) show that if a correlation matrix has a reduced rank of ℓ,[44] as the correlation matrix does,[45] then the multivariate integral has the following simplified form:

$$\Phi_k\left(\mathbf{a}, \mathbf{b}; \mathbf{R}\right) = \int_{\mathbb{R}^\ell} \phi_\ell\left(\mathbf{y}; \mathbf{I}_\ell\right) \prod_{i=1}^{k} \left(\Phi\left(\frac{b_i - \sum_{j=1}^{\ell} v_{ij} y_j}{\sqrt{d_i}}\right) - \Phi\left(\frac{a_i - \sum_{j=1}^{\ell} v_{ij} y_j}{\sqrt{d_i}}\right)\right) \mathrm{d}\mathbf{y}, \tag{47}$$

where $\Phi\left(\cdot\right)$ is the one-dimensional c.d.f. of the standard normal.

I can then approximate the integral given in equation 47 using Gauss-Hermite quadrature:

$$\Phi_k\left(\mathbf{a}, \mathbf{b}; \mathbf{R}\right) \approx \pi^{-\ell/2} \sum_{k_1=1}^{n_1} \overset{\ell}{\cdots} \sum_{k_\ell=1}^{n_\ell} \left(\prod_{\ell} w_{\ell,k_\ell}\right) \prod_{i=1}^{k} \left(\Phi\left(\frac{b_i - \sqrt{2}\sum_{j=1}^{\ell} v_{i,j} x_{j,k_j}}{\sqrt{d_i}}\right) - \Phi\left(\frac{a_i - \sqrt{2}\sum_{j=1}^{\ell} v_{i,j} x_{j,k_j}}{\sqrt{d_i}}\right)\right),$$

where x_{ℓ,k_ℓ} is a sample point with associated weight w_{ℓ,k_ℓ} for dimension ℓ.

In the case of the multivariate integral I must compute (equation 46), $\ell = 2$, yielding a feasible method of computing the multivariate integral.

[44] A correlation matrix $\mathbf{R}$ exhibits a *reduced rank* of ℓ if $\mathbf{R} = \mathbf{D} + \mathbf{V}\mathbf{V}'$ where $\mathbf{D}$ is a diagonal matrix with nonzero entries d_i along the diagonal, and $\mathbf{V}$ is a $k \times \ell$ matrix, where $\ell < k$.

[45] The matrix $\boldsymbol{\Sigma}_{\boldsymbol{\varepsilon}}$ has a reduced rank because the correlation in generators comes solely through the generator energy source. Since $\boldsymbol{\Sigma}_{\boldsymbol{\varepsilon}}$ has this reduced rank, $\tilde{\boldsymbol{\Sigma}}_{\boldsymbol{\varepsilon}}$ also has the same reduced rank, according to Corollary 1.1 in Appendix F.

C.4 Construction of Γ

Due to computational constraints, I must restrict the set of possible generator combinations, Γ, in two ways: the size of the generators and the number of generators. While estimation of the wholesale market allows for heterogeneous generators within a source (e.g., a coal generator of size 100 MW and one of size 200 MW), I will restrict all generators in Γ to be of some representative size for each energy source, provided in table 13. The reason I limit generators to be of a particular size is to avoid determining which generators to retire or add. If I allowed all of the different sizes of generators that I observe in the data (or that a firm might theoretically build), then each firm would decide not only how many generators to have at a given time, but which of the many sizes to have. Allowing for heterogeneous generators (apart from the energy source) creates an extremely large number of possible combinations. For example, there are 8 different sizes of coal generators if I round to the nearest 10 MW. Assuming I don't allow for any heterogeneity in sizes apart from those observed in the data, a firm with the ability to build up to N coal generators would have as its set of possible options not $N+1$ options but $\frac{(8+N-1)!}{N!(8-1)!}$ options. This is a large number, but it is also only one firm and one energy source. When I consider that I must consider all firms and all energy sources, the number is clearly computationally intractable. I therefore assume all generators of a particular source are identical.

Table 13: Representative Generator Sizes

source	generator size (in MW)
coal	200
gas	100
wind	50

The second restriction I must make is with respect to the number of generators. Ideally, I would allow for the set of possible generators a firm could build of a particular source to be $\{0, 1, \ldots, N\}$, where N is a very high number. While I do not have the combinatorial problem outlined above when I assume generators of a particular source are homogenous in size, this fine grid of generator combinations becomes intractably large when I consider all combinations across firm and energy sources. The state space is created as follows

$$\Gamma = \bigtimes_{f \in \{1,\ldots,N,c\}} \bigtimes_{s \in \mathcal{S}} \Gamma_{f,s},$$

where $\Gamma_{f,s}$ is the uni-dimensional grid of possible generators. If N were 30, with three strategic firms, I would have a state space of size $(N+1)^{4\times|\mathcal{S}|} \approx 7.9 \times 10^{17}$, an intractably large number for computing the equilibrium. I therefore use a much sparser set of generator combinations in each $\Gamma_{f,s}$, where the grid is chosen to include generator combinations observed in the data, as well as some above and below. Sources that a firm never chooses to use are assumed to not be available to that firm (e.g., firm 1 (WPGENER) has virtually no wind generators, so I set $\Gamma_{f,s} = [0]$. Table 14 lists the set of possible generators $\Gamma_{f,s}$ for each firm and energy source. With this set of generators, the size of the state space $|\Gamma| = 155\,520$.

Table 14: Γ used in Estimation

f	s	$\Gamma_{f,s}$
1	coal	[2, 4, 6, 8, 10, 12]
1	gas	[15, 16, 17, 18, 19, 20]
1	wind	[0]
2	coal	[0]
2	gas	[5, 7, 9, 11]
2	wind	[0, 4, 8, 12]
3	coal	[0, 2, 4]
3	gas	[0]
3	wind	[0]
c	coal	[0, 1, 2]
c	gas	[2, 4, 6, 8, 10]
c	wind	[0, 2, 6, 10, 14, 18]

Of course, in the data there are heterogeneous generators. I therefore must match heterogeneous generator sets in the data to sets with homogeneous generators. Rather than simply counting the number of generators, I determine which state the data corresponds to in each period in the following way. I first add up the capacities of all of the generators for each firm and energy source, $K_{f,s,t}$. I then determine the number of energy homogeneous generators, $G_{f,s,t}$, that would yield $K_{f,s,t}$, i.e.

$$G_{f,s,t} = \frac{K_{f,s,t}}{K_s},$$

where K_s is the generator size from table 13.

In my counterfactuals, I explore policies that may cause investment patterns to look very different. I therefore use a more expansive grid of possible generator combinations. For estimation, the goal in choosing $\Gamma_{f,s}$ was to have a sufficiently fine Γ that I could track changes to generator levels observed in the data. In counterfactuals, the imposition of a carbon tax might, for example, substantially increase the level of wind investment. I therefore use the grid given in table 15 as that state space for the counterfactuals, which is more expansive, but also sparser. Similarly to estimation, I restrict the sources in which strategic firms can invest. I use the same restriction as in the estimation (e.g., firm 1 can only invest in wind), but I allow firm 3 to also invest in wind. This creates three firms, each of which can invest in only two sources, and no two firms can invest in the same two sources. I use the same $\Gamma_{f,s}$ for each s, i.e., $\Gamma_{f,s} = \Gamma_s$. The size of the state space for the counterfactuals, $|\Gamma|$, is therefore

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Table 15: Γ used in Counterfactuals

f	s	$\Gamma_{f,s}$
1	coal	[0, 3, 6, 10]
1	gas	[5, 11, 18, 25]
1	wind	[0]
2	coal	[0]
2	gas	[5, 11, 18, 25]
2	wind	[0, 10, 20, 30]
3	coal	[0, 3, 6, 10]
3	gas	[0]
3	wind	[0, 10, 20, 30]
c	coal	[0, 3, 6, 10]
c	gas	[5, 11, 18, 25]
c	wind	[0, 10, 20, 30]

In determining the initial state in which the counterfactuals begin, I use the state observed in the first year of the data. To determine which state in table 15 corresponds to that observed in the data, I use the same method of determining the state as that described above for estimation.

C.5 Model of $\mathcal{G}_t^*(\cdot)$ and Computation

I assume that the competitive fringe can only adjust one energy source in a year, and this energy source is randomly chosen. This assumption is made for the following reasons. First, since only one strategic firm can move in a period, this restricts the competitive fringe from having an advantage over strategic firms simply due to the timing assumptions. Second, in the data, it is never the case that more than one energy source in the competitive fringe adjusts in a given year.

The equilibrium set of generators after competitive entry, conditional on the source s being chosen to adjust, is given by

$$\mathcal{G}_t^*(\mathcal{G}, \boldsymbol{\eta}_c, s) = \underbrace{\mathcal{G}_{s,t}}_{\substack{\text{existing}\\ \text{strategic}\\ \text{generators}}} \cup \underbrace{\mathcal{G}_{c,-s,t}}_{\substack{\text{existing competitive}\\ \text{generators of source}\\ s' \neq s}} \cup \underbrace{\mathcal{G}_{c,s,t}^*(\mathcal{G}, \boldsymbol{\eta}_{c,s})}_{\substack{\text{set of competitive generators}\\ \text{of source } s \text{ after}\\ \text{adjustment decisions}}},$$

where $\mathcal{G}_{c,s,t}^*(\mathcal{G}, \boldsymbol{\eta}_{c,s})$ is the set of competitive generators that belong to energy source s after generator entry and retirements in year t. Explicitly,

$$\mathcal{G}^*_{c,s,t}\left(\mathcal{G}, \boldsymbol{\eta}_{c,s}\right) = \mathcal{G}^R_{c,s,t}\left(\mathcal{G}, \boldsymbol{\eta}_{c,s}\right) \cup \mathcal{G}^E_{c,s,t}\left(\mathcal{G}, \boldsymbol{\eta}_{c,s}\right),$$

where $\mathcal{G}^R_{c,s,t}\left(\mathcal{G}, \boldsymbol{\eta}_{c,s}\right)$ is the set of competitive generators of source s that were already in the market in period $t-1$ and choose to remain in the market in period t, and $\mathcal{G}^E_{c,s,t}\left(\mathcal{G}, \boldsymbol{\eta}_{c,s}\right)$ is the set of potential entrant competitive generators of source s that choose to enter into the market in period t.

These two sets are determined in two stages. In a first stage, the existing generators in $\mathcal{G}_{c,s}$ make retirement decisions, and in a second stage potential entrant competitive generators belonging to source s make entry decisions. Existing generators make retirement decisions by comparing the value of remaining in the market and leaving the market, taking an expectation over the potential entrants' entry decisions. The potential entrants observe the existing generators' retirement decisions and then proceed to make entry decisions.

In each stage, a generator will enter if the value of being in the market in period t exceeds the value of being out of the market in that period, where the value is defined by equation 12. Since there is no heterogeneity in generators belonging to the same source and firm, we can reduce the sets $\mathcal{G}^R_{c,s,t}$ and $\mathcal{G}^E_{c,s,t}$ to integers $G^R_{c,s,t}$ and $G^E_{c,s,t}$, respectively, corresponding to the number of generators in the set.[46] Let $\mathcal{G}^R\left(G^R_{c,s,t}\right)$ and $\mathcal{G}^E\left(G^E_{c,s,t}\right)$ convert the integer values back into generator sets.

For each of these stages, I can then define $\bar{\eta}_{s,t}\left(G\right)$ as value for which if $\eta_{g,\text{in},t} - \eta_{g,\text{out},t} \geq \bar{\eta}_{s,t}\left(G\right)$, then a generator would choose to be in the market in period t in which there are G competitive generators of source s (either entering or remaining depending on the stage), and the set of generators $\mathcal{G}$ are already in the market prior to the firm's entry or remaining decisions. Explicitly,

$$\begin{aligned}
\bar{\eta}^R_{s,t}\left(G^R\right) &= \mathbb{E}\left[v^{\text{out}}_{s,t}\left(\text{in}, \mathcal{G}_{s,t} \cup \mathcal{G}_{c,-s,t} \cup \mathcal{G}^R\left(G^R\right) \cup \mathcal{G}^E\left(G^E_{c,s,t}\left(G^R, \boldsymbol{\eta}_{c,s,t}\right)\right)\right)\right] \\
&\qquad -\mathbb{E}\left[v^{\text{in}}_{s,t}\left(\text{in}, \mathcal{G}_{s,t} \cup \mathcal{G}_{c,-s,t} \cup \mathcal{G}^R\left(G^R\right) \cup \mathcal{G}^E\left(G^E_{c,s,t}\left(G^R, \boldsymbol{\eta}_{c,s,t}\right)\right)\right)\right] \\
\bar{\eta}^E_{s,t}\left(G^E\right) &= v^{\text{out}}_{s,t}\left(\text{out}, \mathcal{G}_{s,t} \cup \mathcal{G}_{c,-s,t} \cup \mathcal{G}^R_{c,s,t} \cup \mathcal{G}^E\left(G^E\right)\right) \\
&\qquad -v^{\text{in}}_{s,t}\left(\text{out}, \mathcal{G}_{s,t} \cup \mathcal{G}_{c,-s,t} \cup \mathcal{G}^R_{c,s,t} \cup \mathcal{G}^E\left(G^E\right)\right).
\end{aligned}$$

The first definition represents the cutoff value for generators currently in the market (hence, the first argument of each value function denotes a generator currently in the market). Note that the values of remaining in the market or exiting are expected values, where the expecta-

[46] As detailed in section C.4, for computational reasons in practice I cannot use a grid of integers $0, 1, \ldots, \bar{G}$, and instead use a coarser grid, e.g., $0, G, 2G, \ldots, \bar{G}$. In practice, I assume that each group of generators (e.g., $1, 2, \ldots, G$) draw the same $(\eta_{g,\text{in},t}, \eta_{g,\text{out},t})$.

tion is taken over what potential entrants will do. The second definition represents the cutoff value for potential entrant generators (captured again by the first argument in the value functions). Unlike the generators currently in the market, they do not take an expectation since profits are realized immediately following their entry decisions.

I assume that in both stages, the generator with the highest $\eta_{g,\text{in},t} - \eta_{g,\text{out},t}$ makes its decision first, then the generator with the next highest, and so on until all existing or potential entrant generators have decided whether to be in the market or out of it in period t. Let $\eta_{g,t}^{\text{diff}} = \eta_{g,\text{in},t} - \eta_{g,\text{out},t}$. This timing implies that a generator need only consider its realized cost shocks when it makes its decision of whether to be in the market, not any of the other generators making decisions at the same stage. The values $\bar{\eta}_{s,t}^{R}\left(G^{R}\right)$ and $\bar{\eta}_{s,t}^{E}\left(G^{E}\right)$ are increasing in G^R and G^E, respectively.[47] When a generator makes its decision to be in the market, it observes the number of generators in the market G based on the decisions within the stage made before its turn. A generator need only consider the value of being in the market with G generators, since all generators following it have lower values of $\eta_{g,t}^{\text{diff}}$. If a generator following it also decides to be in the market, then it would be profitable for the generator in question to remain in the market.

For simplicity, index generators from lowest to highest $\eta_{g,t}^{\text{diff}}$. The condition yielding G^R or G^E in equilibrium is therefore given by the following, where I drop s and t subscripts for notational simplicity:

$$\eta_{g}^{\text{diff}} \geq \bar{\eta}^{e}\left(G^{e}\right) \forall g > \bar{G}^{e} - G^{e} \qquad \text{and} \qquad \eta_{g}^{\text{diff}} < \bar{\eta}^{e}\left(G^{e}+1\right) \forall g \leq \bar{G}^{e} - G^{e} \qquad \text{for } e \in \{R, E\},$$

where $\bar{G}^e$ corresponds to the number of existing generators (in the case of R) or the number of potential entrants (in the case of E). Note that this is equivalent to

$$\eta_{\left(\bar{G}^{e}-G^{e}+1\right)}^{\text{diff}} \geq \bar{\eta}^{e}\left(G^{e}\right) \qquad \text{and} \qquad \eta_{\left(\bar{G}^{e}-G^{e}\right)}^{\text{diff}} < \bar{\eta}^{e}\left(G^{e}+1\right) \qquad \text{for } e \in \{R, E\},$$

where $\eta_{(i)}^{\text{diff}}$ corresponds to the ith order statistic out of $\bar{G}^e$.

The probabilities of a particular set of existing or potential entrant competitive generators belonging to source s being in the market in period t is therefore given by

$$\begin{aligned}
&\Pr\left(\left|\mathcal{G}_{c,s,t}^{e}\left(\mathcal{G}, \boldsymbol{\eta}_{c,s}\right)\right| = G\right) \\
&\quad = \Pr\left(\eta_{\left(\bar{G}^{e}-G+1\right)}^{\text{diff}} \geq \bar{\eta}^{e}\left(G\right) \text{ and } \eta_{\left(\bar{G}^{e}-G\right)}^{\text{diff}} \geq \bar{\eta}^{e}\left(G+1\right)\right) \\
&\quad = \int_{\bar{\eta}^{e}(G)}^{\infty} \int_{-\infty}^{\bar{\eta}^{e}(G+1)} \frac{\bar{G}^{e}!}{\left(\bar{G}^{e}-G-1\right)!(G-1)!} F\left(\eta_{\bar{G}^{e}-G}^{\text{diff}}\right)^{\bar{G}^{e}-G-1} \left(1 - F\left(\eta_{\bar{G}^{e}-G+1}^{\text{diff}}\right)\right)^{G-1} \\
&\qquad\qquad \cdot f\left(\eta_{\bar{G}^{e}-G}^{\text{diff}}\right) f\left(\eta_{\bar{G}^{e}-G+1}^{\text{diff}}\right) \mathbb{1}\left\{\eta_{\bar{G}^{e}-G+1}^{\text{diff}} > \eta_{\bar{G}^{e}-G}^{\text{diff}}\right\} \mathrm{d}\eta_{\bar{G}^{e}-G}^{\text{diff}} \, \mathrm{d}\eta_{\bar{G}^{e}-G+1}^{\text{diff}},
\end{aligned}$$

[47] See Appendix F for a proof of this claim.

where $F(\cdot)$ is the c.d.f. of the distribution of η. Evaluating this integral yields the following closed form solution

$$\begin{aligned}\Pr\left(\left|\mathcal{G}^{e}_{c,s,t}\left(\mathcal{G},\boldsymbol{\eta}_{c,s}\right)\right|=G\right) &= \tfrac{\phi\left(G,\bar{G}^{e}\right)}{\bar{G}^{e}-G}\left(\mathrm{B}_{F\left(\bar{\eta}^{e}(G+1)\right)}\left(\bar{G}^{e}-G+1,G\right)-\mathrm{B}_{F\left(\bar{\eta}^{e}(G)\right)}\left(\bar{G}^{e}-G+1,G\right)\right)\\ &\quad+\tfrac{\phi\left(G,\bar{G}^{e}\right)}{G\left(\bar{G}^{e}-G\right)}F\left(\bar{\eta}^{e}\left(G+1\right)\right)^{\bar{G}^{e}-G}\left(1-F\left(\bar{\eta}^{e}\left(G+1\right)\right)\right)^{G},\end{aligned}$$

where $\phi\left(G,\bar{G}^{e}\right)=\frac{\bar{G}^{e}!}{\left(\bar{G}^{e}-G-1\right)!(G-1)!}$ and $\mathrm{B}_{\cdot}\left(\cdot,\cdot\right)$ is the incomplete Beta function.[48] Note that I assume $\eta\sim\mathrm{T1EV}\left(\sigma\right)$, where σ is the scaling parameter, so

$$F\left(\bar{\eta}\right)=\frac{\exp\left(\bar{\eta}/\sigma\right)}{1+\exp\left(\bar{\eta}/\sigma\right)}.$$

D Additional Results

D.1 Carbon Tax Pass-through

As shown in figure 12, using estimated production costs, capacity factors, and demand distribution, the pass-through rate of a carbon tax conditional on the set of generators is commonly greater than 100%. The greater than 100% pass-through of the carbon tax is what drives producer surplus to *increase* with the carbon tax in table 6.

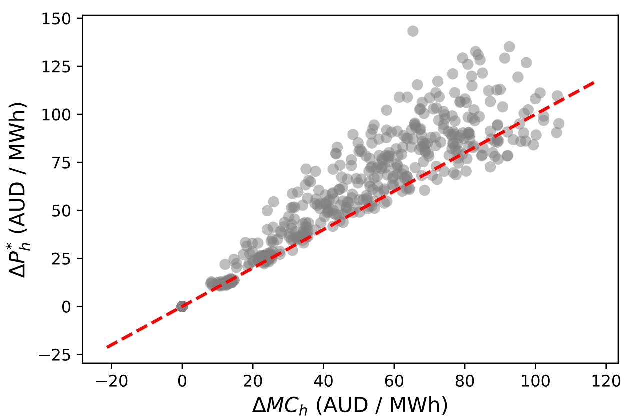
While pass-through greater than 100% is perhaps a surprising result, it is consistent with both empirical evidence and theoretical intuition. Nazifi *et al.* (2021) estimate the pass-through rate of a carbon tax in the Australian National Electricity Market (the electricity market on the eastern side of the country, not the one studied in this paper) during a brief period in time in which a carbon tax was implemented, and find evidence that the pass-through rate was greater than 100%.[49] Fabra & Reguant (2014) also study the pass-through rate of emissions costs and find near 100% pass-through in Spain.

Conditional on a given level of investment, a carbon tax increases the marginal cost of production for some generators. This change in marginal cost impacts both the strategic firms' costs as well as the residual demand curve the strategic firms face through the change in marginal costs of the competitive fringe. This change in the residual demand curve is what generates the possibility of greater than 100% pass-through. Strategic firms can induce the competitive fringe to produce using a high marginal cost generators (which have increased in cost due to

[48] The incomplete Beta function is defined as $\mathrm{B}_{x}\left(a,b\right)=\int_{0}^{x}u^{a-1}\left(1-u\right)^{b-1}\mathrm{d}u$.

[49] The carbon tax in Australia was in effect between July 2012 and July 2014, when it was repealed after a change in government. Importantly for this study, due to the political opposition to this tax, it was widely expected to be temporary. I therefore assume that firms predict the end of the temporary nature of the tax.

Figure 12: Relationship between Marginal Cost Changes and Price Changes



Note: Each dot corresponds to a particular carbon tax and generator combination. Changes are relative to the marginal costs and prices for the generator combination without a carbon tax. Marginal costs are the quantity-weighted average marginal costs for the strategic firms at the quantities they endogenously choose, and prices are the quantity-weighted average wholesale market prices. Depicted are 500 randomly selected carbon taxes and generator combinations from the combinations described in table 15. The dashed red line is a 45-degree line. Values above the 45-degree line correspond to a pass-through rate of greater than 100%.

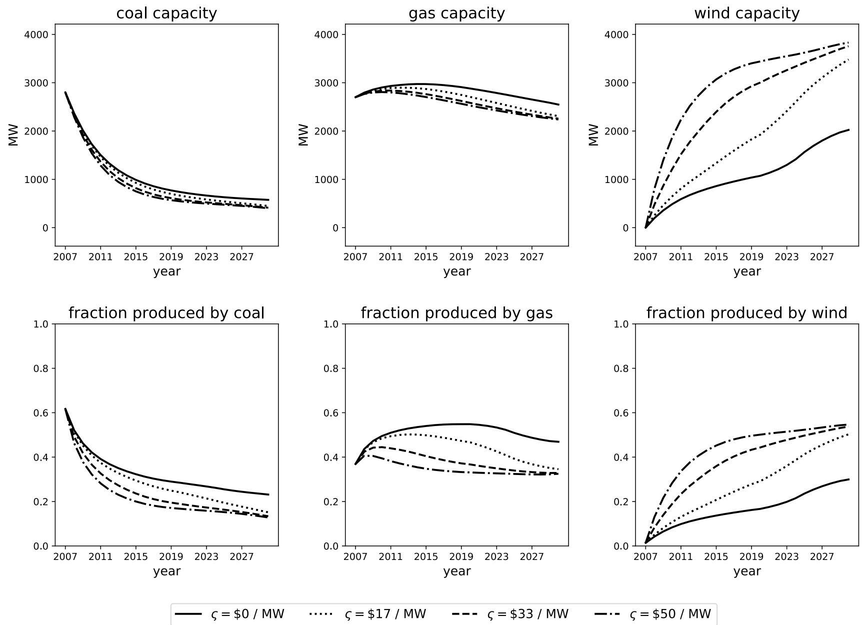
the tax) but continue to use generators that have low marginal costs after the tax.

D.2 Welfare

Figures 13 and 14 display the impact of renewable subsidies on capacity and production. Tables 16 and 17 display the optimal policies for different values of $VOLL$.

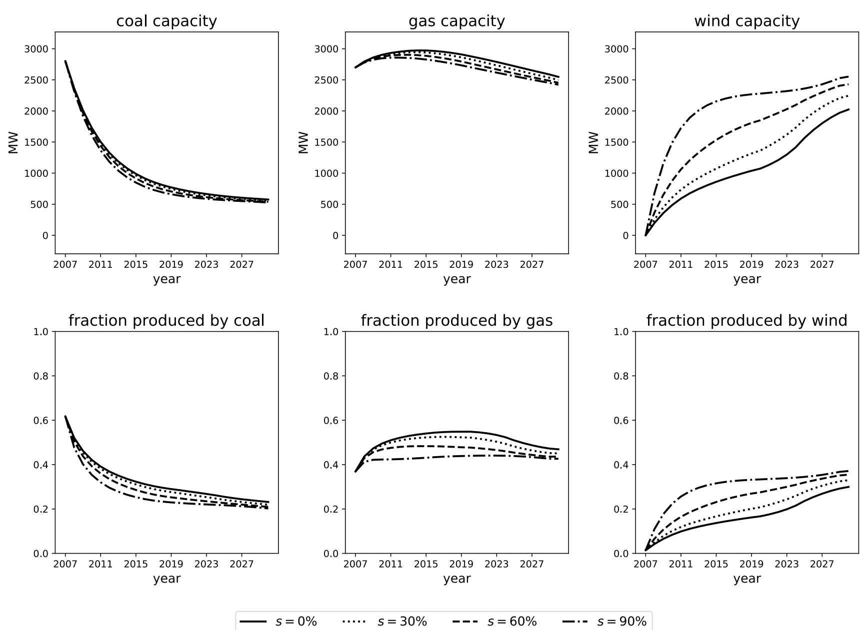
D.3 Alternative Environmental Policies with Capacity Payments

Figure 13: Impact of Renewable Production Subsidy on Investment and Production



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

Figure 14: Impact of Renewable Investment Subsidy on Investment and Production



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

Table 16: Optimal Policy for $VOLL = 10\,000$

	carbon tax alone		capacity payments alone		joint policies		
SCC	τ^*	$\Delta\mathcal{W}$	κ^*	$\Delta\mathcal{W}$	τ^*	κ^*	$\Delta\mathcal{W}$
0	0.0	0.0	36 400	0.45	0.0	36 400	0.45
25	24.0	0.41	33 400	0.38	26.1	42 000	1.03
50	43.9	1.66	30 600	0.32	41.8	43 400	2.27
75	66.2	3.26	28 000	0.26	62.2	44 200	3.8
100	83.2	5.07	25 200	0.21	83.5	46 200	5.6
125	115.0	7.06	22 600	0.17	108.7	47 200	7.56
150	133.9	9.15	19 800	0.13	137.9	47 800	9.66
175	162.9	11.31	17 000	0.09	154.7	48 600	11.81
200	176.4	13.51	14 200	0.06	168.4	48 600	14.01

Note: Changes are with respect to the *laissez-faire* policy ($\tau = 0$, $\kappa = 0$). SCC is in AUD / tonne of CO_2-eq. Changes in welfare are in expected present discounted terms, using the same discount factor as that used by the firms, $\beta = 0.95$.

Table 17: Optimal Policy for $VOLL = 30\,000$

	carbon tax alone		capacity payments alone		joint policies		
SCC	τ^*	$\Delta\mathcal{W}$	κ^*	$\Delta\mathcal{W}$	τ^*	κ^*	$\Delta\mathcal{W}$
0	0.0	0.0	49 600	1.69	0.0	49 600	1.69
25	25.9	0.11	47 000	1.6	25.6	53 300	2.23
50	61.0	1.58	45 000	1.51	42.0	53 500	3.46
75	74.6	3.33	43 200	1.43	63.7	54 300	5.01
100	111.4	5.24	41 600	1.35	84.9	55 900	6.82
125	121.1	7.3	40 200	1.28	112.0	57 100	8.79
150	176.2	9.41	38 800	1.2	138.9	57 900	10.89
175	181.4	11.63	37 400	1.13	154.5	58 300	13.05
200	184.8	13.85	36 000	1.06	170.7	58 100	15.25

Note: Changes are with respect to the *laissez-faire* policy ($\tau = 0$, $\kappa = 0$). SCC is in AUD / tonne of CO_2-eq. Changes in welfare are in expected present discounted terms, using the same discount factor as that used by the firms, $\beta = 0.95$.

Table 18: Comparing Environmental Policies with Capacity Payment

Δemissions (billions CO_2-eq)	policy	policy value	Δblackouts (thousands MWh)	ΔCS (billions AUD)	ΔPS (billions AUD)	ΔG (billions AUD)	Δ (CS + PS + G) (billions AUD)
0	carbon tax	1.8	-64.3	0.1	0.7	-1.0	-0.3
	renew. prod. subs.	1.7	-64.4	0.4	0.7	-1.3	-0.2
	renew. inv. subs.	22.5	-64.4	0.5	0.9	-2.1	-0.7
10	carbon tax	6.3	-63.4	-0.7	0.8	-0.3	-0.3
	renew. prod. subs.	8.1	-62.3	0.7	0.9	-1.6	0.0
	renew. inv. subs.	63.0	-63.6	0.7	1.5	-4.7	-2.4
20	carbon tax	11.1	-62.5	-1.5	0.9	0.3	-0.3
	renew. prod. subs.	16.5	-58.0	1.0	1.4	-2.1	0.3
	renew. inv. subs.	95.2	-62.9	1.0	2.3	-9.2	-5.9
30	carbon tax	17.0	-61.7	-2.5	1.2	1.0	-0.4
	renew. prod. subs.	25.8	-52.7	1.4	2.2	-3.0	0.5
	renew. inv. subs.	-	-	-	-	-	-
40	carbon tax	24.8	-60.9	-3.8	1.5	1.7	-0.6
	renew. prod. subs.	37.0	-47.5	1.8	3.2	-4.4	0.7
	renew. inv. subs.	-	-	-	-	-	-
50	carbon tax	35.1	-60.3	-5.5	2.0	2.6	-0.9
	renew. prod. subs.	58.0	-41.6	2.5	5.8	-7.1	1.2
	renew. inv. subs.	-	-	-	-	-	-

Note: All of the notes in table 8 apply. Policies in this table are additionally simulated with a capacity payment equal to 50 000 AUD / MW / year. Changes are with respect to the *laissez-faire* market without capacity payments *or* environmental policies. Note that the addition of a capacity payment impacts emissions even without any environmental policy; therefore, the policy values at Δemissions = 0 are not zero.

Table 18 shows similar results to table 8 but in the presence of a capacity payment of 50 000 AUD / MW. Similarly to the results provided in table 6, the capacity payment significantly reduces the size and frequency of blackouts. The relationship between the environmental policy and blackouts weakens less for renewable production subsidies than for carbon taxes, however. For a 50 billion kg of CO_2-eq reduction in emissions, a carbon tax increases blackouts by 13 400 MWh without a 50 000 AUD / MW capacity payment, and 4 100 MWh with. A renewable production subsidy, in contrast, increases blackouts by 57 200 MWh without and 23 300 with. For the carbon tax, the capacity payment reduces blackouts by 69%, but for the renewable production subsidy, it reduces blackouts by only 59%.

E Robustness Checks

E.1 Capacity Imputations

Since I only observe the nameplate capacities for generators that still exist in the market at the end of the sample (2021), I must impute the capacities for those that exited prior to the sample end date. To determine the quality of this imputation (using the maximum electricity ever generated), I compare the nameplate capacities provided with the values I would have imputed. There are 37 generators for which I observe official nameplate capacities (7 coal, 14 natural gas, and 16 wind). Defining imputation quality of generator g as

$$\text{imputation quality}_g = \frac{\text{imputed capacity}_g}{\text{official capacity}_g},$$

the average imputation quality, weighted by official capacity, is 95.32%. By energy source, this is 93.95% for coal, 93.24% for natural gas, and 100.89% for wind. These high values suggest that the imputed capacity is probably very similar to the official capacities for the generators without official capacities provided.

F Proofs

Proposition 1. *If the covariance matrix $\mathbf{\Sigma}$ has a reduced rank of ℓ, then its Schur complement also has a reduced rank of (at most) ℓ.*

Proof. Partition $\mathbf{\Sigma}$ into $\mathbf{\Sigma} = \begin{bmatrix} \mathbf{\Sigma}_{11} & \mathbf{\Sigma}_{12} \\ \mathbf{\Sigma}_{21} & \mathbf{\Sigma}_{22} \end{bmatrix}$, where $\mathbf{\Sigma}_{11}$ and $\mathbf{\Sigma}_{22}$ are square matrices. By assumption, $\mathbf{\Sigma}$ has a reduced rank of ℓ, which by definition means

$$\mathbf{\Sigma} = \mathbf{F}\left[\mathbf{D} + \mathbf{V}\mathbf{V}'\right]\mathbf{F},$$

where $\mathbf{F}$ is a diagonal matrix with standard deviations along the diagonal, $\mathbf{D}$ is a diagonal matrix with values $d_i = 1 - \mathbf{v}_{i,\cdot}\mathbf{v}'_{i,\cdot}$ along the diagonal, and $\mathbf{V}$ is a $k \times \ell$ matrix. These variables are functions of $\mathbf{\Sigma}$, but, for the sake of space, I omit the dependence in the notation. I can partition $\mathbf{F}$, $\mathbf{D}$, and the rows of $\mathbf{V}$ analogously to $\mathbf{\Sigma}$.[50] Then,

$$\begin{aligned} \mathbf{\Sigma}_{ij} = \quad & \left(\mathbf{F}_{i1}\left[\mathbf{D}_{11} + \mathbf{V}_1\mathbf{V}'_1\right] + \mathbf{F}_{i2}\left[\mathbf{D}_{21} + \mathbf{V}_2\mathbf{V}'_1\right]\right)\mathbf{F}_{1j} \\ & + \left(\mathbf{F}_{i1}\left[\mathbf{D}_{12} + \mathbf{V}_1\mathbf{V}'_2\right] + \mathbf{F}_{i2}\left[\mathbf{D}_{22} + \mathbf{V}_2\mathbf{V}'_2\right]\right)\mathbf{F}_{2j}. \end{aligned} \tag{48}$$

The Schur complement of $\mathbf{\Sigma}$ is given by

$$\tilde{\mathbf{\Sigma}} = \mathbf{\Sigma}_{11} - \mathbf{\Sigma}_{12}\mathbf{\Sigma}_{22}^{-1}\mathbf{\Sigma}_{21}.$$

Using the above formula as well as the fact that that $\mathbf{F}_{12}$, $\mathbf{F}_{21}$, $\mathbf{D}_{12}$, and $\mathbf{D}_{21}$ are all zero matrices (since $\mathbf{F}$ and $\mathbf{D}$ are diagonal matrices and the submatrices along the diagonal are square), I can substitute equation 48 into the above formula to get

$$\begin{aligned} \tilde{\mathbf{\Sigma}} &= \mathbf{F}_{11}\left[\mathbf{D}_{11} + \mathbf{V}_1\mathbf{V}'_1\right]\mathbf{F}_{11} - \left(\mathbf{F}_{11}\left[\mathbf{V}_1\mathbf{V}'_2\right]\mathbf{F}_{22}\right)\left(\mathbf{F}_{22}\left[\mathbf{D}_{22} + \mathbf{V}_2\mathbf{V}'_2\right]\mathbf{F}_{22}\right)^{-1}\left(\mathbf{F}_{22}\left[\mathbf{V}_2\mathbf{V}'_1\right]\mathbf{F}_{11}\right) \\ &= \mathbf{F}_{11}\left(\mathbf{D}_{11} + \mathbf{V}_1\mathbf{V}'_1 - \mathbf{V}_1\mathbf{V}'_2\mathbf{F}_{22}\mathbf{F}_{22}^{-1}\left[\mathbf{D}_{22} + \mathbf{V}_2\mathbf{V}'_2\right]^{-1}\mathbf{F}_{22}^{-1}\mathbf{F}_{22}\mathbf{V}_2\mathbf{V}'_1\right)\mathbf{F}_{11} \\ &= \mathbf{F}_{11}\left(\mathbf{D}_{11} + \mathbf{V}_1\left(\mathbf{I}_\ell - \mathbf{V}'_2\left[\mathbf{D}_{22} + \mathbf{V}_2\mathbf{V}'_2\right]^{-1}\mathbf{V}_2\right)\mathbf{V}'_1\right)\mathbf{F}_{11} \\ &= \tilde{\mathbf{F}}\left(\tilde{\mathbf{D}} + \tilde{\mathbf{V}}\tilde{\mathbf{V}}'\right)\tilde{\mathbf{F}}, \end{aligned}$$

where $\tilde{\mathbf{F}} = \left(\operatorname{diag}\left(\mathbf{D}_{11} + \mathbf{V}_1\mathbf{G}\mathbf{V}'_1\right)\right)^{1/2}\mathbf{F}_{11}$, $\tilde{\mathbf{V}} = \tilde{\mathbf{F}}^{-1}\mathbf{F}_{11}\mathbf{V}_1\mathbf{G}^{1/2}$, and $\tilde{\mathbf{D}}$ has $\tilde{d}_i = 1 - \tilde{\mathbf{v}}_{i,\cdot}\tilde{\mathbf{v}}'_{i,\cdot}$ along the diagonal, where

$$\mathbf{G} = \mathbf{I}_\ell - \mathbf{V}'_2\left[\mathbf{D}_{22} + \mathbf{V}_2\mathbf{V}'_2\right]^{-1}\mathbf{V}_2.$$

Since $\tilde{\mathbf{F}}$ is a diagonal matrix, $\tilde{\mathbf{D}}$ has values $\tilde{d}_i = 1 - \tilde{\mathbf{v}}_{i,\cdot}\tilde{\mathbf{v}}'_{i,\cdot}$ along the diagonal, and $\tilde{\mathbf{V}}$ is $k \times \ell$, $\tilde{\mathbf{\Sigma}}$ has a reduced rank of ℓ. □

Corollary 1.1. *If a multivariate normal random variable* $\mathbf{X}$ *is distributed* $\mathcal{N}\left(\boldsymbol{\mu}, \mathbf{\Sigma}\right)$, *where* $\mathbf{\Sigma}$ *has a reduced rank of* ℓ, *then the covariance matrix of the conditional distribution also has a reduced rank of (at most)* ℓ.

Proof. Consider $\mathbf{X} \sim \mathcal{N}\left(\boldsymbol{\mu}, \mathbf{\Sigma}\right)$, where by assumption $\mathbf{\Sigma}$ has a reduced rank of ℓ. The distri-

[50] $\mathbf{V}$ will be partitioned into $\mathbf{V}_1$ and $\mathbf{V}_2$, which both contain all ℓ columns of $\mathbf{V}$.

bution of $\mathbf{X}_1|\,\mathbf{X}_2 = \mathbf{x}_2$ is a multivariate normal with mean $\tilde{\boldsymbol{\mu}} = \boldsymbol{\mu}_1 + \boldsymbol{\Sigma}_{12}\boldsymbol{\Sigma}_{22}^{-1}(\mathbf{x}_2 - \boldsymbol{\mu}_2)$ and covariance $\tilde{\boldsymbol{\Sigma}} = \boldsymbol{\Sigma}_{11} - \boldsymbol{\Sigma}_{12}\boldsymbol{\Sigma}_{22}^{-1}\boldsymbol{\Sigma}_{21}$. By proposition 1, $\tilde{\boldsymbol{\Sigma}}$ has a reduced rank of ℓ. □

Proposition 2. *If for all s, t, $\Pi_{c,s,t}(e, \mathcal{G} \cup \mathcal{G}^e(G^e)) \geq \Pi_{c,s,t}(e, \mathcal{G} \cup \mathcal{G}^e(G'))$ for all $G' > G^e$, then $\bar{\eta}^e_{s,t}(G^e) \leq \bar{\eta}^e_{s,t}(G')$ for all $G' > G^e$ for $e \in \{R, E\}$.*

Proof. I begin by showing by that $V^{\text{out}}_{s,t}(e, \mathcal{G} \cup \mathcal{G}^e(G^e)) - V^{\text{in}}_{s,t}(e, \mathcal{G} \cup \mathcal{G}^e(G^e))$ is increasing in G^e for all e and $\mathcal{G}$. Denote this value as $V^{\text{diff}}_{s,t}(e, \mathcal{G} \cup \mathcal{G}^e(G^e))$. Note that

$$V^{\text{diff}}_{s,T}(e, \mathcal{G} \cup \mathcal{G}^e(G^e)) = -\frac{1}{1-\beta}\left(\Pi_{c,s,t}(e, \mathcal{G} \cup \mathcal{G}^e(G^e)) + \Upsilon_{c,s,t}(\{g_s\}, \kappa_T)\right),$$

where g_s is a generator of source s. Since $\Pi_{c,s,t}(e, \mathcal{G} \cup \mathcal{G}^e(G')) \leq \Pi_{c,s,t}(e, \mathcal{G} \cup \mathcal{G}^e(G))$ for all $G' > G$, it is therefore the case that in the final period of generator adjustments, T,

$$V^{\text{diff}}_{s,T}(e, \mathcal{G} \cup \mathcal{G}^e(G')) \geq V^{\text{diff}}_{s,T}(e, \mathcal{G} \cup \mathcal{G}^e(G))$$

for all $G' > G$.

I next show that $V^{\text{diff}}_{s,t+1}(e, \mathcal{G} \cup \mathcal{G}^e(G')) \geq V^{\text{diff}}_{s,t+1}(e, \mathcal{G} \cup \mathcal{G}^e(G))$ for all $G' > G$ implies $V^{\text{diff}}_{s,t}(e, \mathcal{G} \cup \mathcal{G}^e(G')) \geq V^{\text{diff}}_{s,t}(e, \mathcal{G} \cup \mathcal{G}^e(G))$. Note that

$$V^{\text{diff}}_{s,t}(e, \mathcal{G} \cup \mathcal{G}^e(G)) = \eta_{g,\text{out},t} - \eta_{g,\text{in},t} - \Pi_{c,s,t}(e, \mathcal{G} \cup \mathcal{G}^e(G)) - \Upsilon_{c,s,t}(\{g_s\}, \kappa_t) + \beta\mathbb{E}\left[V^{\text{diff}}_{s,t+1}(e, \mathcal{G}' \cup \mathcal{G}^e(G))\right].$$

By our assumption and the fact that $\Pi_{c,s,t}$ is decreasing in G, the statement is true. By induction, it is therefore the case that

$$V^{\text{diff}}_{s,t}(e, \mathcal{G} \cup \mathcal{G}^e(G')) \geq V^{\text{diff}}_{s,t}(e, \mathcal{G} \cup \mathcal{G}^e(G)) \quad \text{for all } G' > G. \tag{49}$$

The proposition follows from the above inequality. Note that by definition

$$\bar{\eta}^e_{s,t}(G) = -\Pi_{c,s,t}(e, \mathcal{G} \cup \mathcal{G}^e(G)) - \Upsilon_{c,s,t}(\{g_s\}, \kappa_t) + \beta\mathbb{E}\left[V^{\text{diff}}_{s,t+1}(e, \mathcal{G}' \cup \mathcal{G}^e(G))\right].$$

Using the result given in equation 49 and the fact that $\Pi_{c,s,t}$ is decreasing in G, $\bar{\eta}^e_{s,t}(G^e) \leq \bar{\eta}^e_{s,t}(G')$ for all $G' > G^e$. □

Table 19: Notation

Symbol	Description
t	indexes years (going from October 1 – September 30)
h	indexes wholesale intervals, which belong to a particular year t
f	indexes all firms (including competitive fringe)
N	number of strategic firms
c	indexes competitive fringe
$\mathcal{G}_t$	set of generators in year t
g	indexes generators
K_g	nameplate capacity of generator g (in MW)
$s(\cdot)$	returns the energy source of a generator
$\mathcal{S}$	the set of energy sources
$\mathcal{Q}_t$	distribution of demand in year t
$\bar{Q}_h$	perfectly inelastic demand shock in interval h
$\delta_{g,h}$	generator-specific capacity factor in interval h
$\bar{K}_{g,h}$	generator-, interval-specific effective capacity (in MW)
$\underline{K}_g$	minimum production level of generator g (in MW)
$q_{g,h}$	quantity generated by generator g in interval h (in kWh)
$c_{g,h}(\cdot)$	cost function for generator g in interval h
$\zeta_{1,g,h}$	linear cost parameter for generator g in interval h
$\zeta_{2,s}$	quadratic cost parameter for source s
τ_t	carbon tax in year t (in AUD / kg of CO_2-eq)
r_s	emissions rate (in kg of CO_2-eq / MWh)
$\mathbf{x}_{g,h}$	linear cost covariates for generator g in interval h
$\boldsymbol{\beta}_s$	linear cost covariate parameters for source s
$\varepsilon_{g,h}$	idiosyncratic linear parameter cost shock for generator g in interval h
P_h	wholesale market price in interval h
$P_h(\cdot)$	inverse residual demand for strategic firms in interval h
$\pi_{f,h}(\cdot)$	wholesale profit function for firm f in interval h
M_s	yearly capacity maintenance cost for energy source s (in AUD / MW)
$\Pi_{f,t}(\cdot)$	yearly expected profit function for firm f in year t
$\bar{P}_t$	$\bar{Q}_h$-weighted average wholesale price in year t
$\mathcal{Q}_t(\cdot)$	returns the demand distribution in t as a function of $\bar{P}_t$
γ_g	fraction of capacity of generator g that is committed
κ_t	capacity price in year t (in AUD / MW)
$\psi_{f,h}(\cdot)$	penalty for firm f in interval h for failing to make available committed capacity (in AUD)
λ_s	source-specific refund penalty factor
$\Upsilon_{f,t}(\cdot)$	optimal net capacity payment for firm f in year t
Γ	set of possible combinations of generators
$C_{s,t}$	cost of new generator capacity of energy source s in year t (in AUD / MW)
$\eta_{f,\mathcal{G}}$	idiosyncratic generator adjustment cost for firm f and adjustment decision $\mathcal{G}$
β	discount rate (at yearly level)
$\sigma_{f,t}(\cdot)$	policy function for firm f in year t
T	final year in which possible to adjust set of generators