Supplemental Appendix

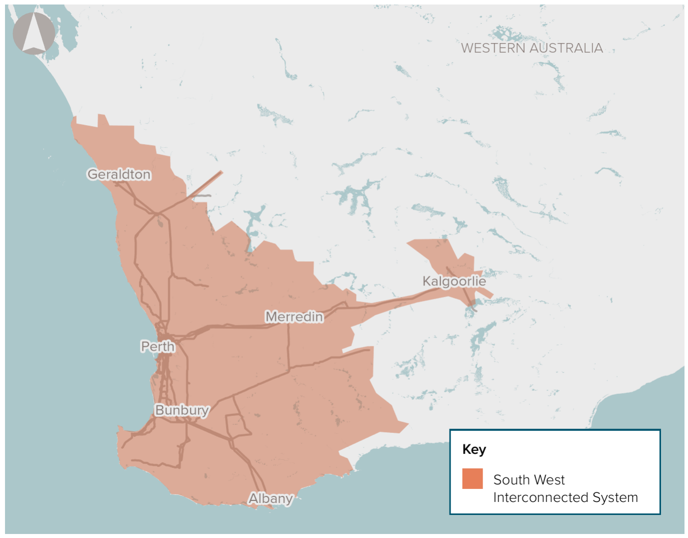
Investment, Emissions, and Reliability in Electricity Markets

Jonathan T. Elliott

A Additional Industry Details

A.1 South West Interconnected System

Figure A-1: Map of South West Interconnected System



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

A.2 Generators in Western Australian Electricity Market

Table A-2 lists all generators observed in the market during the data sample that use a technology considered in this paper (namely, coal, combined cycle natural gas (CCGT), open cycle natural gas (OCGT), wind, or solar) and have a non-trivial capacity. Capacity cutoffs are based on a *plant*'s capacity (rather than a generator's) since some plants (e.g., PINJAR) have several small generators. These cutoffs are 20 MW for solar and wind and 100 MW for coal and gas plants. Generators below this threshold are excluded from estimating production costs and investment decisions.[1] This capacity threshold for inclusion in investment decisions serves two purposes. First, not allowing small changes in capacity to alter the state reduces the size of the state space. Including all changes in the set of generators that result from small generators entering or exiting would make the state space intractably large. Second, as described in section B.1, the generators that enter or exit when a firm adjusts its set of generators are identified using a heuristic of profitability. This heuristic does not take into account capacity. By only focusing on large generators, there is less dispersion in capacities, meaning the heuristic is a better approximation of the true profitability ranking of different plants.

[1]Small generators are excluded from this analysis (accounting for just 3.49% of energy produced and 4.36% of fossil fuel capacity), so I adjust the total demand for electricity in an interval downward by the amount produced by these when estimating the distribution of wholesale market variables.

Table A-1: Summary Statistics

	Mean	Std. Dev.	5th Pctile.	95th Pctile.	Num. Obs.
Half-hourly variables					
price (A$/MWh)	49.51	32.11	21.54	106.99	179 712
total production (MWh)	970.69	199.70	679.75	1 331.95	280 512
load curtailed (MWh)	0.03	2.20	0.00*	340.00*	280 512
demand response dispatched (MWh)	0.01	1.61	0.00*	276.59*	179 712
demand response quantity available (MWh)	296.00	220.22	57.43	560.19	179 712
fraction generated by					
coal (%)	50.99	8.88	35.16	64.62	280 512
natural gas (%)	39.48	8.07	26.36	53.02	280 512
solar (%)	0.37	1.41	0.00	1.94	280 512
wind (%)	9.17	8.28	0.68	26.67	280 512
fraction capacity available					
coal (%)	83.28	34.67	6.62	100.00	3 217 200
natural gas (%)	92.34	24.03	14.40	100.00	5 927 856
solar (%)	13.06	24.40	0.00	81.67	221 040
wind (%)	36.45	29.98	0.00	89.85	1 351 488
Yearly variables					
capacity price (thousand A$/MW)	125.68	32.68	71.85	183.17	18
price cap (A$/MWh)	277.85	49.20	214.60	350.41	16
retail price variable component (A$/MWh)	81.26	12.22	59.82	97.07	15
Generator variables					
capacity					
coal (MW)	161.83	79.17	58.37	251.14	17
natural gas (MW)	148.40	97.64	42.28	345.22	23
solar (MW)	69.98	30.18	42.82	97.14	2
wind (MW)	122.40	67.25	33.58	211.92	8
heat rate					
coal (GJ/MWh)	10.75	0.81	9.70	11.70	17
natural gas (GJ/MWh)	11.70	1.65	9.00	13.50	23
CO_2 emissions rate					
coal (kgCO_2-eq/MWh)	916.47	61.90	850.00	1 028.00	17
natural gas (kgCO_2-eq/MWh)	633.46	82.55	471.60	754.42	23

Note: Values followed by "*" are minimum and maximum values rather than 5th and 95th percentiles. All prices in this table and presented in this paper are in 2015 A$. Prices are converted to 2015 A$ using the consumer price index from the Australian Bureau of Statistics. The number of observations for prices and demand response is smaller than that for other half-hourly variables because the prices used come from the balancing market, which only began on July 1, 2012, and the demand response program began on the same day.

Table A-2: List of Generators in Data

Generator	Firm	Technology	Capacity (MW)	Heat Rate (GJ/MWh)	Emissions Rate (kgCO_2-eq/MWh)	Entered Year	Exit Year
ALBANY_WF1	ALBGRAS	wind farm	22	–	0.0	–	–
ALINTA_PNJ_U1	ALINTA	OCGT	157	12.0	627.0	–	–
ALINTA_PNJ_U2	ALINTA	OCGT	151	12.0	627.0	–	–
ALINTA_WGP_GT	ALINTA	OCGT	371	11.5	601.0	2007‡	–
ALINTA_WGP_U2	ALINTA	OCGT	210	11.5	601.0	2007‡	–
ALINTA_WWF	ALINTA	wind farm	88	–	0.0	–	–
BADGINGARRA_WF1	ALINTA	wind farm	131	–	0.0	2018	–
BW1_BLUEWATERS_G2	GRIFFINP	coal	223	9.8	908.0	2008	–
BW2_BLUEWATERS_G1	GRIFFINP	coal	229	9.8	908.0	2008	–
COCKBURN_CCG1	WPGENER	CCGT	265	9.0	470.0	–	–
COLLIE_G1	WPGENER	coal	342	9.5	884.0	–	–
EDWFMAN_WF1	EDWFMAN	wind farm	83	–	0.0	–	–
GREENOUGH_RIVER_PV1	GRENOUGH	solar pv	40	–	0.0	2018§	–
INVESTEC_COLLGAR_WF1	COLLGAR	wind farm	214	–	0.0	2010	–
KEMERTON_GT11	WPGENER	OCGT	173¶	12.2	638.0	–	–
KEMERTON_GT12	WPGENER	OCGT	173¶	12.2	638.0	–	–
KWINANA_G1	WPGENER	coal*	116	11.7†	850.0†	–	2010
KWINANA_G2	WPGENER	coal*	117	11.7†	850.0†	–	2010
KWINANA_G3	WPGENER	coal*	113	11.7†	850.0†	–	2010
KWINANA_G4	WPGENER	coal*	117	11.7†	850.0†	–	2010
KWINANA_G5	WPGENER	coal*	189	11.7	850.0	–	2014‡
KWINANA_G6	WPGENER	coal*	195	11.7	850.0	–	2014‡
KWINANA_GT2	WPGENER	OCGT	109	9.3	486.0	2011	–
KWINANA_GT3	WPGENER	OCGT	110	9.3	486.0	2011	–
MERSOLAR_PV1	SUNAUST22	solar pv	100	–	0.0	2019	–
MUJA_G1	VINALCO	coal	58	10.4†	972.5†	–	2016
MUJA_G2	VINALCO	coal	58	10.4†	972.5†	–	2016
MUJA_G3	VINALCO	coal	59	10.4†	972.5†	–	2016
MUJA_G4	VINALCO	coal	60	10.4†	972.5†	–	2016
MUJA_G5	WPGENER	coal	214	11.0	1 028.0	–	2022‡
MUJA_G6	WPGENER	coal	207	11.0	1 028.0	–	2022‡
MUJA_G7	WPGENER	coal	228	9.8	917.0	–	–
MUJA_G8	WPGENER	coal	226	9.8	917.0	–	–
MWF_MUMBIDA_WF1	MUMBIDA	wind farm	55	–	0.0	2012	–
NEWGEN_KWINANA_CCG1	NEWGEN	CCGT	345	7.9	759.8	2007	–
NEWGEN_NEERABUP_GT1	NGENEERP	OCGT	345	11.1	659.7	2008	–
PERTHENERGY_KWINANA_GT1	WENERGY	OCGT	122	14.1	763.0	2009	–
PINJAR_GT1	WPGENER	OCGT	43	13.5	706.0	–	–
PINJAR_GT10	WPGENER	OCGT	122	12.1	653.0	–	–
PINJAR_GT11	WPGENER	OCGT	138	12.0	638.0	–	–
PINJAR_GT2	WPGENER	OCGT	42	13.5	706.0	–	–
PINJAR_GT3	WPGENER	OCGT	43	13.2	690.0	–	–
PINJAR_GT4	WPGENER	OCGT	43	13.2	690.0	–	–
PINJAR_GT5	WPGENER	OCGT	45	13.2	690.0	–	–
PINJAR_GT7	WPGENER	OCGT	41	13.2	690.0	–	–
PINJAR_GT9	WPGENER	OCGT	128	12.1	653.0	–	–
PPP_KCP_EG1	WPGENER	OCGT	108	9.0	470.0	–	2021
SWCJV_WORSLEY_COGEN_COG1	WPGENER	OCGT	128	12.0	627.0	–	2015
WARRADARGE_WF1	WARADGE	wind farm	178	–	0.0	2019	–
YANDIN_WF1	ALINTA	wind farm	208	–	0.0	2019	–

Entry and exit years are based on the calendar used by the WEM, which runs from October 1 through September 30 of the next year. If a generator first began producing in January of 2015, therefore, its entry year is 2014 (corresponding to the year beginning in October 2014. An entry year of "–" means the generator entered before the sample period. Firm names are provided using the names reported by AEMO; for the three largest firms, WPGENER is commonly known as "Synergy," ALINTA as "Alinta," and GRIFFINP as "Bluewaters Power." *These generators are capable of using coal, natural gas, or distillate and have historically used all three. During the sample period they mostly used coal (Global Energy Monitor, 2023). They are therefore classified as coal plants. †The data sources used for heat rates and emissions rates did not include data for these generators. The values used are therefore an average of either the other generators within a power plant for which data is available or, lacking that, an average of others with the same technology. ‡These entry/exit years have been adjusted by at most a year so that generators part of the same plant that enter/exit around the same time have the same entry/exit year (since they presumably were part of a single decision by the firm). §GREENOUGH_RIVER_PV1 was first constructed as a 10 MW facility in 2011; however, in capacity year 2018, it was expanded by 30 MW, so this facility is classified as entering in 2018 since that is when most of its capacity was installed. ¶Kemerton Power Plant underwent a capacity upgrade of 15% in capacity year 2007, so I use its post-upgrade capacity since that constitutes nearly all of the sample period.

A.3 Capacity Costs

Generator cost data comes from two different sources. The first source is a series of reports produced by the U.S. Energy Information Administration (EIA) on capital costs of electricity generators (U.S. Energy Information Administration, 2010, 2013, 2016, 2020, 2022). The reports are for the years 2010, 2013, 2016, 2019, and 2022. Each report provides capital costs in US$/kW for different generator technologies, including all of those considered in this paper.[2] The second source is the 2012 Australian Energy Technology Assessment (Australian Bureau of Resources and Energy Economics, 2012), which I shall refer to as AETA. While this report only provides a snapshot in time, unlike the series of EIA reports that construct a panel, AETA does helpfully provide cost estimates specific to the South West Interconnected System in Western Australia that I study in this paper.

I use the EIA reports to construct a time series for each technology and AETA to convert the time series based on U.S. estimates to those for the electricity market in Western Australia. In order to construct a complete time series of generator costs over time for Western Australia, I first interpolate the time series provided by the EIA report. For each energy source, I linearly interpolate values in years not covered by an EIA report,[3] providing me with $\hat{C}_{st}^{EIA}$. Next, I convert the interpolated EIA estimates to those for Western Australia. To do so, I assume that Western Australia costs are a source-specific proportion α_s of the EIA costs, common over time. Explicitly, I assume

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

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

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

For years past 2022, I use National Renewable Energy Laboratory (NREL) predictions to discipline the evolution of costs. Specifically, I use the costs predicted by NREL based on their "moderate" scenario for the technology, and scale 2022 Western Australia estimates $\hat{C}_{s,2022}^{WA}$ by the ratio of the NREL prediction for that year to their 2022 cost (National Renewable Energy Laboratory, 2023). Explicitly,

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

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

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

Calibrated investment costs $\left\{\hat{C}_{st}^{WA}\right\}_{s,t}$ are summarized in table 5.

A.4 WEM Details

Capacity Payments The WEM has used capacity payments since its commencement. The market uses a system of allocating capacity credits called the "Reserve Capacity Mechanism." A capacity credit corresponds to a megawatt (MW) of certified electricity generation capacity that a firm commits to make available in the wholesale market. The WEM chooses the price of a capacity credit for a year, and firms choose a level of capacity for which to receive capacity credits. This process occurs three years prior to when firms will receive payments (e.g., the capacity price for 2020 is announced in 2017), allowing time for firms to build or retire capacity. The price is based on a formula that depends in large part on the cost in that year of building an open cycle gas turbine generator. Firms are then contractually obliged in the year of the capacity payments to make available at least as much electricity as they have capacity credits or otherwise pay a penalty. Electricity consumers pay for the cost of these payments as part of the fixed component of their electricity bills,[4] suggesting the size of these payments does not influence how much electricity consumers choose to consume.

Making electricity "available" is not the same as actually producing that level of electricity. In practice, firms bid quantities and prices in an auction with a price cap. Firms are required to bid at least as much electricity as they have capacity credits, with no limit on the prices other than a universal price cap. Renewables are allowed to receive capacity payments; however, they typically commit only a small fraction of their nameplate capacities. In the model, therefore, I treat only non-intermittent technologies as eligible and do not model penalties and the commitment choice since in practice it results in minimal payments to intermittent technologies and almost full payments to non-intermittent technologies.

Demand Response Participation The WEM allows for the participation of "demand response programmes" that provide some flexibility to the otherwise perfectly inelastic load. These participants receive capacity payments in exchange for agreeing to reduce their contribution to the demand for electricity in a given interval if called upon by the system operator. Unlike in many electricity markets with demand response participants, they do not receive a payment when they are called upon; instead, they are compensated via a fixed capacity payment (like generators are). The system operator instructs them to curtail demand if the system is at risk of demand exceeding available supply. In practice, this has been extremely rare (see table A-1).

[4] According to Western Power (2021), "reference tariffs are similarly split so that fixed costs are recovered by fixed charges and variable costs by variable charges." Capacity payments from the perspective of the retailer (which pays the capacity payments and then passes them along to consumers) are fixed costs.

The WEM is unusual in compensating participants via a fixed payment rather than payments when load is curtailed based on the market clearing price. In the model (section 3) I allow for demand response that depends on the wholesale market spot price (equation 4), capturing the typical structure of demand that is part of a demand response program. In the empirical application for Western Australia, I treat all demand response load as having a cost equal to the price cap.[5] Specifically, I model the demand reduction from demand response participants as

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

where $\bar{Q}_h^{DR}$ is the maximum reduction from demand response participants and $\bar{P}_t$ is the price cap. This ensures that demand response participants are only called upon when necessary to avoid blackouts. The quantity available for demand curtailment from demand response participants (captured by $Q_h^{DR}(\cdot)$) is treated as exogenous, and therefore does not change in the counterfactuals.

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

B Technical Details

B.1 State Space

The state space is defined by which generators are in the market and the year (which captures the investment costs, the distribution of wholesale market variables, and how many years remain until generator portfolios are locked in). Section 3.3.2 describes how firms' choice sets are constructed, and I provide more detail in this section. Firms' choice sets are potentially multidimensional, with each dimension corresponding to a different technology (e.g., coal, natural gas, etc.). The generator portfolio component of the state space is the cross product of all firms' possible portfolios. Table A-3 provides a complete description of the generator portfolio state space.

Dimensions Each firm's component of the state space may include multiple technologies. For each firm f, the set of available technologies, $\mathcal{S}_f$, corresponds to the technologies I observe it using in the data (see section 3.3.2). For WPGENER, which owns many legacy assets, I distinguish between two types of natural gas technologies: modern and old. In the data, WPGENER both retires older generators and builds new ones. I therefore represent its choice set with two separate technology dimensions: "gas (modern)" for newer, more efficient generators and "gas (old)" for less efficient generators it may retire even while continuing to invest in gas. Other firms have newer natural gas plants, so I don't distinguish between the two types. Small firms (with at most one generator) are collapsed into a single dimension per technology. At most one small firm in each technology can adjust per year, similar to large firms' restriction that at most one generator grouping can adjust per year.

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

Specifically, if I observe in the data a firm retire plant 1 and several years later plant 2, I assume plant 1 is less profitable and will always be retired before plant 2. Since not all plants are adjusted, if I do not observe an adjustment, I order the plants by heat rates. For example, suppose the firm in the example also has plants 3 and 4 of the same technology. If plant 3

Table A-3: Description of Generator Portfolio State Space

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

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

has a higher heat rate than plant 4 (meaning a higher marginal cost of production), I assume the firm would retire plant 3 before it would retire plant 4.[6]

New Generators The definition of the state space extends beyond just those generators that have been observed in the data. It also includes the possibility of building additional natural gas, solar, and wind generators. I assume that new natural gas plants use combined cycle technology, have a heat rate of 8.0 GJ/MWh, an emissions rate of 450 kgCO_2-eq/MWh, and a capacity of 400 MW. New solar and wind generators are assumed to have a capacity of 200 MW and the same capacity factors as existing solar and wind generators.

B.2 Equilibrium Computation Details

The wholesale equilibrium characterized by equation 12 involves a fixed point in the retail price and an expectation over wholesale market stochastic variables. I solve for expectations of wholesale operations by first clustering, for each group of four years (e.g., 2006–2009, 2010–2013, etc.), blocks of 60 wholesale market intervals into 10 groups using a modified version of K-means++ that ensures the highest demand interval is included as a centroid that represents the group.[7] This clustering implies weights for each of these groups, and I use these weights in calculating average outcomes for the four-year interval. For each centroid, I solve the wholesale operator's problem (equation 5).[8] Using this procedure I can calculate the implied quantity-weighted average wholesale prices for a given retail price, and I iterate on the fixed point in the retail price to calculate the equilibrium for a given four year period for a given portfolio. This procedure is given explicitly by Algorithm 1.

[6] A potential concern is that a carbon tax could change profitability rankings. Emissions rates, conditional on a technology, depend primarily on a generator's heat rate, however, so profitability orderings are therefore unlikely to change in response to a carbon tax.

[7] Because blackouts are rare and occur during extreme demand, I force the highest-demand block to be an initial centroid. I then run standard K-means++ to select the remaining centroids based on Euclidean distance. Although this extreme-demand centroid receives little weight, it prevents low-probability blackouts from being approximated as zero.

[8] The Bellman equation corresponding to the wholesale operator's problem is given by

$$V_h\left(\tilde{\mathbf{q}}\right) = \min_{\mathbf{q}, q_{DR}, b \in \mathcal{A}_h} \left\{ \sum_{g \in \mathcal{G}} c^b_{gh}\left(q_{gh}, \tilde{q}_{gh}\right) + c^{DR}_h\left(q_{DR}\right) + c^{ration}\left(b\right) + V_{h+1}\left(\mathbf{q}\right) \right\},$$

with a terminal condition

$$V_{H+1}\left(\tilde{\mathbf{q}}\right) = 0$$

and feasible action set $\mathcal{A}_h$ defined as the same set of constraints for interval h as in equation 5. I solve this problem using Gurobi through the `gurobipy` package, which is available for free with an academic license.

Algorithm 1: Wholesale Equilibria Calculation for Year t

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

Cluster Sequences of Intervals using Modified K-means++

standardize data;

$k_1 \leftarrow \arg\max_b \{\max_{h \in b} \{\Xi_h\}\}$;

for $i = 2, \dots K$ **do**

  select k_i randomly with prob. $\propto$ to Euclidean distance to nearest $k_{i-1}, \dots, k_1$;

for $b = 1, \dots, B$ **do**

  $k(b) \leftarrow \arg\min_k \{\|\textbf{standardized variables}_b - \textbf{standardized variables}_k\|\}$;

assign weights w_k based on share of b assigned to k;

Solve Wholesale Equilibria

for $\mathcal{G} \in \Gamma$ **do**

  initialize P^{avg}, P^{diff};

  while $P^{diff} >$ *convergence threshold* **do**

    for $i = 1, \dots, K$ **do**

      solve operator's problem (equation 5) for sequence k_i with $\mathcal{G}$ using Gurobi;

    $P^{new} \leftarrow \frac{\sum_{i=1}^{K} w_{k_i} \sum_{h \in k_i} Q_h P_h}{\sum_{i=1}^{K} w_{k_i} \sum_{h \in k_i} Q_h}$;

    $P^{diff} \leftarrow |P^{new} - P^{avg}|$;

    $P^{avg} \leftarrow P^{new}$;

C Additional Counterfactuals

C.1 Alternative Welfare Goals

Table A-4 presents optimal policies using the carbon tax and capacity payment scheme from section 5.1 for different welfare goals. I consider to what extent these tools can minimize emissions without making consumers worse off. I consider a narrow definition of consumer welfare without taking into account transfers (column 1) as well as a definition that includes blackouts and in which carbon tax revenue is rebated to consumers but they also finance capacity payments (column 2).[9] It is feasible to substantially reduce emissions without reducing consumer surplus, captured in the first column. Doing so requires a moderately sized carbon tax coupled with a large capacity payment financed by the government. If carbon tax revenue is rebated back to consumers (but consumers also must finance capacity payments), the maximum feasible emissions reduction is similar.

C.2 Alternative Capacity Payment Structures

Table A-5 considers different ways of structuring capacity payments. I simulate a structure in which the capacity price can be different for coal and gas generators. This structure is motivated by the fact that the two technologies have very different emissions intensities. I also consider a structure that ties the capacity price to the quantity-weighted average wholesale spot price, making it inversely proportional to the price so that the higher the price, the lower the capacity payment. This structure reflects that firms may need less of an incentive to invest or delay retirement when wholesale prices are high. For both of these structures, I solve for optimal policies, including both a total welfare-maximizing policy (analogous to the exercise in the main text), reported in the final column, as well as the optimal policy for the alternative goals considered in section C.1.

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

[9] The final column simply presents the total welfare-maximizing exercise from the main text.

Table A-4: Optimal Policies to Achieve Alternative Welfare Goals

	min ΔE s.t. ΔCS ≥ 0	min ΔE s.t. ΔCS + ΔT + ΔC $-VOLL \times \Delta$B ≥ 0	max $\Delta\mathcal{W}$
policy	$\tau^* = 87.1$, $\kappa^* = 200\,000$	$\tau^* = 128.5$, $\kappa^* = 138\,700$	$\tau^* = 214.7$, $\kappa^* = 155\,600$
ΔCS	0.0	-9.5	-21.1
ΔPS	7.5	4.1	9.3
ΔT	10.7	14.9	22.1
ΔC	-23.3	-13.0	-17.0
ΔE	-52.9 (-29%)	-55.2 (-30%)	-70.7 (-38%)
ΔB	-9.5 (-99%)	-8.4 (-88%)	-9.5 (-100%)
$\Delta\mathcal{W}$	14.5	15.7	16.9

Note: Welfare values are in thousand A$ per customer. Columns correspond to goal-constraint pairs. Values are determined via interpolation using cubic splines, see note in table 7. Values in dollar terms (ΔCS, ΔPS, ΔT, ΔC, $\Delta\mathcal{W}$) are in thousand A$ per customer, while ΔE is in billion kg CO_2-eq and ΔB is in million MWh.

Table A-5: Optimal Alternative Capacity Payment Structures

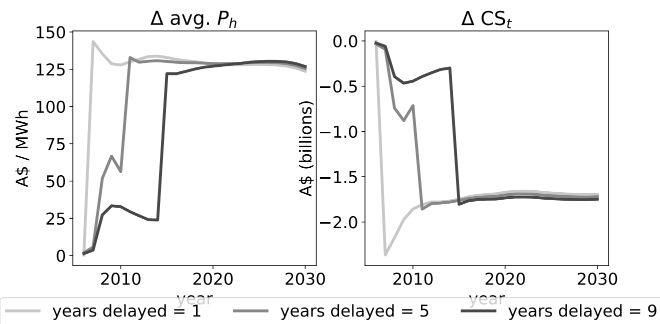
	min ΔE s.t. ΔCS ≥ 0	min ΔE s.t. ΔCS + ΔT + ΔC $-VOLL \times \Delta$B ≥ 0	max $\Delta\mathcal{W}$
		separate κ_{coal}, κ_{gas}	
policy	$\tau^* = 88.9$, $\kappa^*_{\text{coal}} = 200\,000$ $\kappa^*_{\text{gas}} = 250\,000$	$\tau^* = 121.0$, $\kappa^*_{\text{coal}} = 50\,500$ $\kappa^*_{\text{gas}} = 206\,500$	$\tau^* = 235.7$, $\kappa^*_{\text{coal}} = 24\,400$ $\kappa^*_{\text{gas}} = 192\,400$
ΔCS	0.0	-7.2	-23.6
ΔPS	11.2	5.5	8.7
ΔT	10.8	13.9	23.7
ΔC	-27.4	-13.8	-13.5
ΔE	-53.8 (-29%)	-57.4 (-31%)	-73.0 (-40%)
ΔB	-9.5 (-100%)	-7.9 (-83%)	-9.5 (-100%)
$\Delta\mathcal{W}$	14.4	17.4	19.2
		$\kappa = \alpha / P_t^{avg}$	
policy	$\tau^* = 94.9$, $\alpha^* = 40\,000\,000$ ($\bar{\kappa} = 407\,500$)	$\tau^* = 106.6$, $\alpha^* = 16\,700\,000$ ($\bar{\kappa} = 151\,800$)	$\tau^* = 223.7$, $\alpha^* = 24\,300\,000$ ($\bar{\kappa} = 140\,700$)
ΔCS	0.0	-4.1	-23.6
ΔPS	34.0	3.8	9.3
ΔT	11.0	12.6	23.2
ΔC	-53.2	-16.8	-15.3
ΔE	-57.1 (-31%)	-54.5 (-30%)	-70.3 (-38%)
ΔB	-9.5 (-100%)	-9.1 (-96%)	-9.3 (-98%)
$\Delta\mathcal{W}$	12.4	15.2	16.8

Note: Same notes as in table A-4 apply. The block of rows corresponds to the case where capacity prices vary by energy source. The second block sets a capacity price inversely proportional to the quantity-weighted average wholesale spot price. The reported policy for this block includes in parentheses $\bar{\kappa}$, which is the average capacity price as a result of the optimal policy (τ^*, α^*).

C.3 Policy Timing

Policies that induce large investments are often delayed to allow firms time to adjust to the policy. I explore the returns to delaying the implementation of a carbon tax in order to allow firms to first adjust their generator portfolios. This highlights one of the advantages of my framework using a non-stationary, randomly-ordered sequential moves dynamic game with lock in: it allows for non-stationary policy environments in addition to non-stationary costs and demand. Delaying a policy results in cost savings since firms have time to react and invest in low emissions generators, but the delay also reduces the effectiveness of the mechanism that reduces emissions. I predict investment and production with the carbon tax *announced* in 2006 but not actually implemented until T_{delay} years later.[10] This delay in the policy's implementation is known to the firms when the policy is announced in 2006.[11]

Figure A-2: Impact of Delaying Policy



Note: Displayed is the expectation of the difference in each of the variables for a tax of A\$200/ton CO_2-eq and a capacity payment of A\$100 000/MW relative to no tax (but maintaining the capacity payment). The capacity payment is implemented immediately, but the carbon tax's implementation is delayed based on the line.

Figure A-2 displays the change in consumer surplus and quantity-weighted average wholesale prices in each year relative to those without a carbon tax for three different values of T_{delay}.[12] 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 almost no emissions-free renewable capacity and instead use a high fraction of gas capacity (since it is less emissions-intense) and some coal (which is expensive

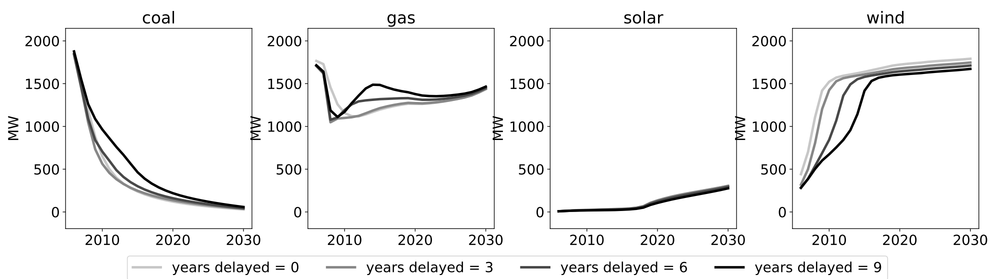
[10] This exercise shares some similarities with the demand-side exercise in Langer & Lemoine (2022), exploring optimal consumer subsidy dynamics to spur residential solar adoption.

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

[12] Instead of using the year-specific estimated profit function $\hat{\mathbf{\Pi}}t(\cdot)$, I hold profits fixed at their 2015 estimate, $\hat{\mathbf{\Pi}}2015(\cdot)$, in all years. This isolates the effects of delaying the carbon tax from year-to-year changes in demand shocks and input prices.

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

Figure A-3: Impact of Delaying Policy on Investment



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

While the delay in the implementation of the carbon tax can increase product market welfare, it also results in time during which firms do not have as strong of an incentive to reduce emissions. This lack of emissions-reducing incentives is especially true at the production margin (e.g., there is no incentive to favor gas over coal), but also at the investment margin. While it could be possible that, since the firms anticipate the tax, investment in renewables is similar regardless of the delay, figure A-3 shows that without a near immediate tax, firms choose to delay investment in renewables (particularly wind since there is virtually no solar investment early on). Firms have a strong incentive to delay investment, even though that means they may not receive good adjustment cost shocks before the tax's implementation, because the cost of building new renewable generators is declining so much over time.

Given that delaying the policy can increase product market welfare but does not result in the same level of an emissions decline during the delayed years, the impact on total welfare of delaying the policy is ambiguous. Table A-6 provides the impact of delaying the policy for different values of the tax on the welfare-relevant variables. Since firms significantly delay changing their generator portfolios when a carbon tax is delayed, the impact of delaying a tax on emissions is substantial. The impact on consumer surplus and government revenues is also large, while producer surplus is relatively unaffected by delaying. One might think that delaying the tax's implementation could alleviate blackouts that occur in the transition to a long-run set of generator portfolios; however, blackouts are nearly unaffected by the delay, driven primarily by the fact that delaying implementation results in more coal and less natural gas capacity, even in the long run (which contributes to higher emissions levels).

Ultimately, despite the cost savings delaying a carbon tax can generate, there is little evidence

Table A-6: Welfare Impact of Delaying Policy

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

Note: Changes are with respect to a policy environment with no carbon tax (i.e., $\tau = 0$) in all years. Capacity payments are set equal to A$100 000/MW and the price cap to A$300/MWh. All values are in expected present discounted terms. Note that values are not necessarily exactly the same as those that would be implied by table 6 because rather than using the estimated profit functions for each year ($\hat{\boldsymbol{\Pi}}_t(\cdot)$), I use the same profit function in each year ($\hat{\boldsymbol{\Pi}}(\cdot)$) in this exercise, for the reason described in footnote 12. Values "from baseline" compare the welfare measure to no carbon tax, values "from no delay" compare the welfare measure to that tax implemented immediately.

it is worthwhile to delay implementation except for a low social cost of carbon. With a higher social cost of carbon, emissions are more costly. With a higher tax, the cost savings of delaying implementation are higher; however, so too is the cost of increased emissions. If a policy maker can simultaneously choose a carbon tax and a number of years to delay, I find that for any social cost of carbon greater than about A$116/ton CO_2-eq, the optimal delay is zero years.

Because the environment is non-stationary, the impact of delaying a carbon tax may depend on the year from which the delay is evaluated. To assess this, table A-7 reports welfare outcomes when the analysis begins in 2012, so a one-year delay corresponds to a carbon tax's implementation in 2013. The welfare function, analogous to equation 24, is defined as

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

The results in table A-7 are broadly consistent with those in table A-6 across all carbon tax and delay combinations, suggesting that the conclusions are not sensitive to the initial year from which delay is considered.

C.4 The Role of Market Power

Market power influences both the investment level and type (the technology). I consider the role market power plays in these decisions as well as in the optimal policy by simulating a market in which every power plant is owned by a separate firm. In other words, there are no

Table A-7: Welfare Impact of Delaying Policy after 2012

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

Note: Same notes as in table A-6 apply. Values are with respect to a starting point of 2012 rather than 2006.

large firms (as defined by the model), all firms are small.[13] I refer to this as the competitive framework. A firm therefore does not internalize the impact of its constructing or retiring a generator on other generators' profits.

Market power leads to reduced investment, as shown in Figure A-4, with an average of 591 MW less capacity under the market power framework (without a carbon tax). Fossil fuel capacity is higher under competition because fossil fuel generators are disproportionately owned by the largest firms in the data. These firms have an incentive to underinvest in capacity to increase wholesale prices, so when these generators are reallocated to small firms that only own single generators, they invest more. Since under market power wholesale prices are higher due to underinvestment by the largest firms, renewable capacity, which is disproportionately owned by small firms in the data, is actually higher under market power and under competition.

Table A-8: Comparison between Market Power and Competitive Frameworks

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

Note: Changes in welfare are with respect to the *laissez-faire* policy ($\tau = 0$) under market power in expected present discounted terms in thousand A$ per customer. The value $\tau^*_{\text{mkt pwr}}$ is the carbon tax that maximizes total welfare in a framework in which some firms are large, and the value τ^*_{comp} is the tax that maximizes total welfare in a framework in which all firms are small. The capacity price is set to 0 for this comparison, and the price cap is set to A$300/MWh.

Table A-8 compares optimal policies and their distributional impacts under the framework

[13] While firms are all small in this specification, I keep the main model's adjustment timing for comparability. Plants adjust in random order, with those originally owned by large firms moving first and those originally owned by small firms second. This ensures differences in results are not driven by timing differences correlated with technology.

with market power and under the competitive one. All plants being owned by separate firms increases investment, reducing quantity-weighted average prices by A$33/MWh (a decrease of 31%).[14] This leads to higher consumer surplus, fewer blackouts, and higher total surplus despite increased emissions. The size of these differences is quantitatively significant, suggesting that even if there is no market power exercised in wholesale markets, the impact on investment decisions can be meaningful.

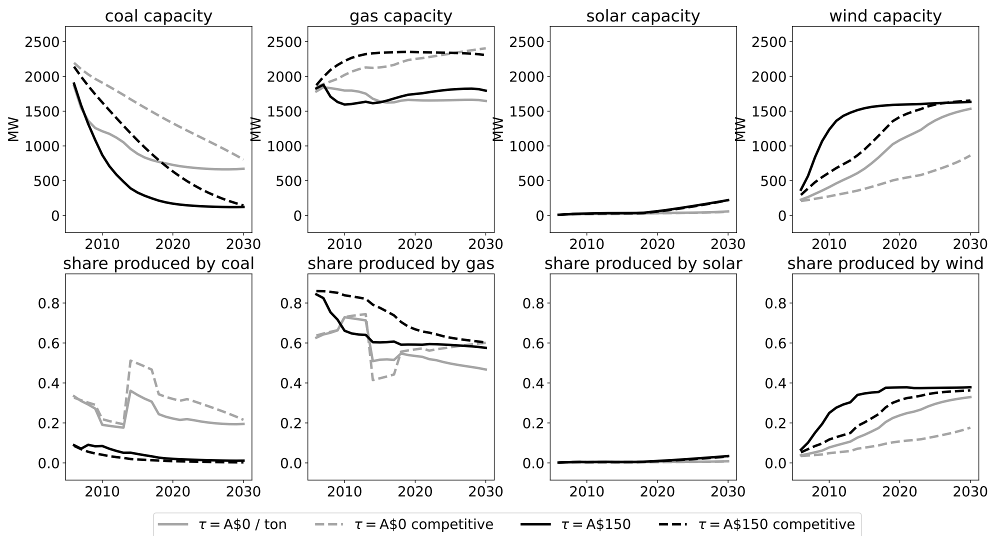
A carbon tax changes investment and production patterns, decreasing emissions; however, comparing the third set of results (optimally chosen carbon tax under market power) to the fourth (the same carbon tax but under competitive framework), the reduction in emissions is lower under competition, though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

C.5 Supplementary Tables and Graphs for Main Text Counterfactuals

This section provides additional results corresponding to the counterfactuals in the main text. Table A-9 presents optimal policies, analogous to table 7 in the main text, for a higher value of lost load of A$10 000/MWh. Table A-10 presents different measures of welfare that combine columns in table 6 in the main text, including broader measures of consumer surplus that include the cost of blackouts and different tax transfers. Table A-11 presents the optimal policy, analogous to table 7 in the main text, when a battery as described in section 5.3 is present and compares the results to when it is not.

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

Figure A-4: Impact of Market Power vs. Competition on Investment and Production



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

Table A-9: Total Welfare-Maximizing Policies ($VOLL$ = A$10 000/MWh)

	carbon tax alone		joint policies	
	low $\bar{P}$	high $\bar{P}$	low $\bar{P}$	high $\bar{P}$
	$\tau^* = 0.0$	$\tau^* = 219.8$	$(\tau^* = 219.8, \kappa^* = 155\,600)$	$(\tau^* = 285.0, \kappa^* = 176\,200)$
$\Delta\mathcal{W}$	0.0	72.6	94.6	95.3
ΔCS	0.0	-53.0	-21.1	-43.5
ΔPS	0.0	23.2	9.3	22.0
ΔT	0.0	24.2	22.1	30.4
ΔC	0.0	0.0	-17.0	-14.1
$-SCC \times \Delta$E	0.0	13.2	14.8	13.9
$-VOLL \times \Delta$B	0.0	65.0	86.4	86.4

Note: Same notes as in table 7 in the main text apply.

Table A-10: Alternative Welfare Measures

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

Note: Changes are with respect to the *laissez-faire* policy ($\tau = 0$, $\kappa = 0$) at the low price cap ($\bar{P}$ = A\$300). The high price cap is A\$1 000/MWh. Welfare measures use SCC =A\$230/ton CO_2-eq and $VOLL$ =A\$1 000/MWh.

Table A-11: Total Welfare-Maximizing Policies with Storage

	carbon tax alone		joint policies	
	no battery	battery	no battery	battery
	$\tau^* = 154.1$	$\tau^* = 139.6$	$(\tau^* = 214.7, \kappa^* = 155\,600)$	$(\tau^* = 249.5, \kappa^* = 126\,300)$
$\Delta\mathcal{W}$	9.8	15.6	16.9	19.7
ΔCS	-23.2	-21.0	-21.1	-29.5
ΔPS	5.3	6.8	9.3	12.0
ΔG	16.3	15.7	5.2	13.8
$-SCC \times \Delta$E	14.2	12.8	14.8	15.3
$-VOLL \times \Delta$B	-2.8	1.4	8.6	8.1

Note: Changes in welfare are with respect to the *laissez-faire* policy ($\tau = 0$, $\kappa = 0$) with no battery. For all columns, a price cap of $\bar{P} =$ A\$300/MWh is used. Same notes as in in table 7 apply.

D Robustness Checks

Table A-12 compares production cost function parameter estimates for the unrestricted sample and for a sample that drops the period in which Synergy was found to have overstated its costs, March 31, 2016–July 10, 2017. Results are fairly similar across the two samples.

Table A-12: Production Cost Estimate Comparison

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

Note: The sames notes as in table 3 in the main text apply.

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