Supplemental Appendix

Energy Transitions in Regulated Markets

Gautam Gowrisankaran, Ashley Langer, and Mar Reguant

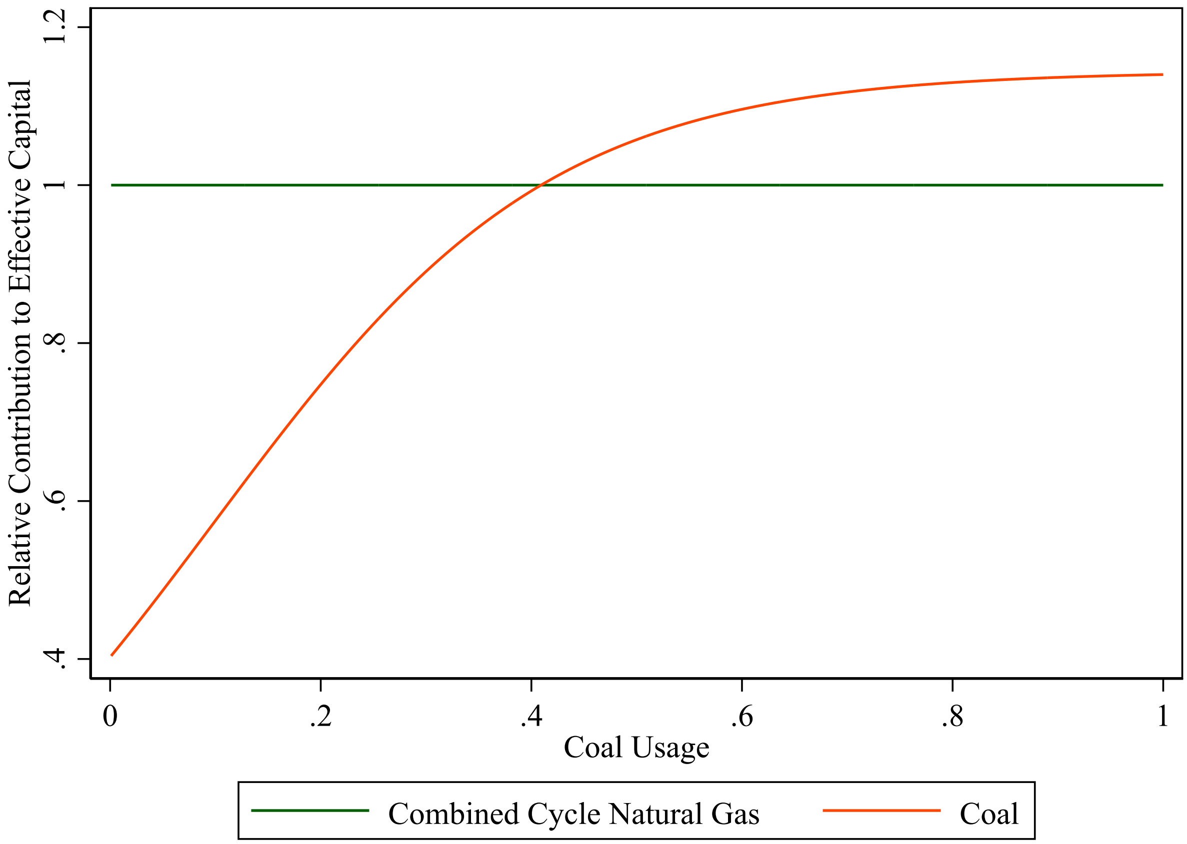
A1 Additional Tables and Figures Referenced in Main Paper

Table A1: Operations Model Fit

	Data	Model
Annual Electricity Production (TWh):		
Coal	16.11	21.03
CCNG	4.93	1.10
Imports	11.97	10.69
Mean Usage Share (%):		
Coal	55.35	71.73
CCNG	34.60	8.85
Annual Costs (Millions of Dollars):		
Coal Fuel	355.67	467.40
CCNG Fuel	159.22	29.38
NGT Fuel	27.46	49.13
Coal O&M	207.71	271.16
CCNG O&M	43.49	9.73
NGT O&M	21.80	30.23
Coal Ramping	12.69	11.80
CCNG Ramping	5.20	2.62
Imports	460.28	165.45
Total Variable Production Costs	1,294	1,037
Electricity Revenues (Dollars/MWh):	61.58	77.58

Note: Table presents key outcomes from the data and the model simulated at the estimated parameter values for the analysis sample. In the "data" column, we use observed operations decisions but calculate O&M and ramping costs using estimated parameters and import costs using estimated import supply curves.

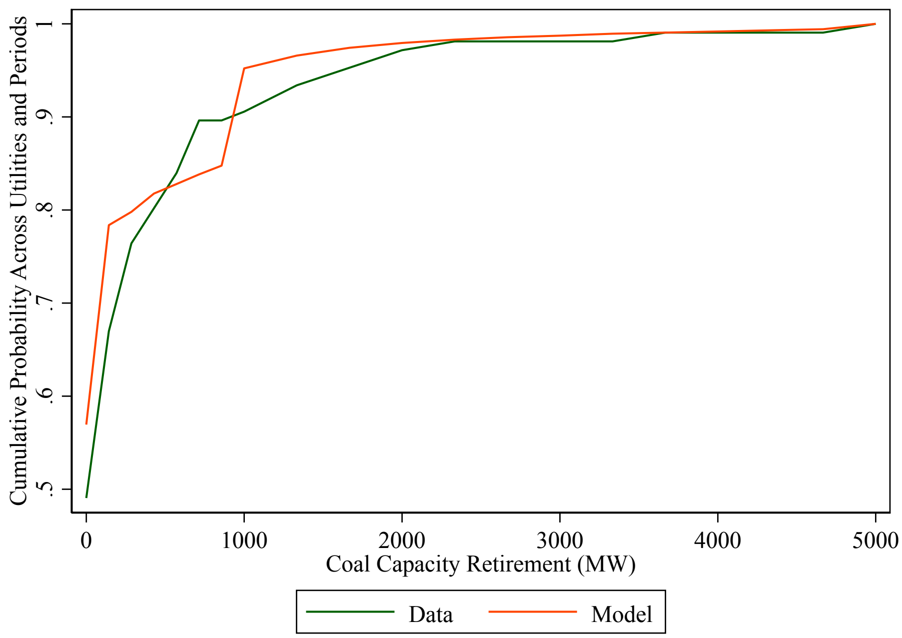
Figure A1: Coal Contribution to Rate Base Relative to CCNG



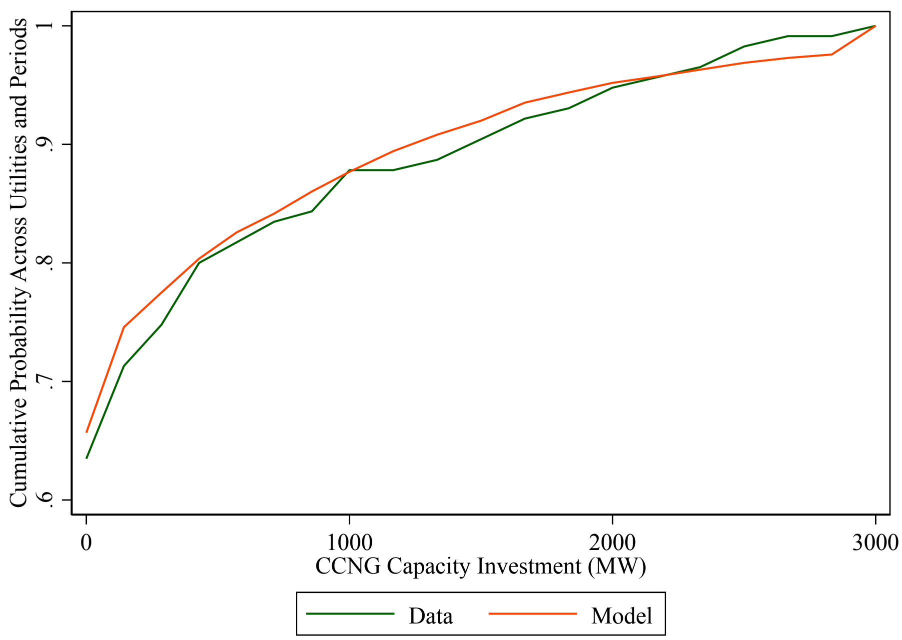
Note: Figure calculated from estimated model coefficients.

Figure A2: Model Fit for Investment and Retirement

(a) Coal Retirement Model Fit



(b) CCNG Investment Model Fit



Note: Figure displays coal retirement and CCNG investment CDFs in data and predicted by model at estimated parameters.

Table A2: Indirect Inference Coefficient Matching

Dependent Variable	Regressor	Analysis Data	Simulated Data
Coal Usage:			
	Constant	0.553 (3.0e-4)	0.650 (4.0e-4)
CCNG Usage:			
	Constant	0.346 (4.0e-4)	0.056 (3.0e-4)
NGT Usage:			
	Constant	0.064 (3.0e-4)	0.117 (4.0e-4)
Variable Profits:			
	Constant	847.769 (65.055)	1538.328 (65.638)
Rate of Return Proxy:			
	Total Variable Cost	-4.3e-5 (6.0e-6)	-4.0e-6 (1.0e-6)
Variable Profits:			
	Coal Capacity (MW)	−0.314 (0.045)	−0.120 (0.030)
	Coal Capacity x Usage	0.540 (0.082)	0.455 (0.043)
	CCNG Capacity (MW)	0.255 (0.017)	0.264 (0.007)
	NGT Capacity (MW)	0.136 (0.056)	0.361 (0.023)
Log Coal Share:			
	$\mathbb{1}\{\text{Coal First Quintile}\} \times (MC^{COAL} - MC^{CCNG})$	0.790 (0.086)	1.011 (0.043)
	$\mathbb{1}\{\text{Coal Second Quintile}\} \times (MC^{COAL} - MC^{CCNG})$	1.050 (0.086)	1.730 (0.038)
	$\mathbb{1}\{\text{Coal Third Quintile}\} \times (MC^{COAL} - MC^{CCNG})$	0.922 (0.087)	1.047 (0.036)
	$\mathbb{1}\{\text{Coal Fourth Quintile}\} \times (MC^{COAL} - MC^{CCNG})$	1.493 (0.089)	0.663 (0.035)
Log CCNG Share:			
	$\mathbb{1}\{\text{CCNG First Quintile}\} \times (MC^{COAL} - MC^{CCNG})$	−2.697 (0.004)	0.0 (0.002)
	$\mathbb{1}\{\text{CCNG Second Quintile}\} \times (MC^{COAL} - MC^{CCNG})$	−1.233 (0.005)	0.0 (0.002)
	$\mathbb{1}\{\text{CCNG Third Quintile}\} \times (MC^{COAL} - MC^{CCNG})$	−0.578 (0.004)	−1.086 (0.001)
	$\mathbb{1}\{\text{CCNG Fourth Quintile}\} \times (MC^{COAL} - MC^{CCNG})$	−0.263 (0.023)	−0.891 (.)
Coal Usage:			
	Lagged Coal Usage	0.975 (3.0e-4)	0.974 (3.0e-4)
CCNG Usage:			
	Lagged CCNG Usage	0.969 (4.0e-4)	0.959 (3.0e-4)

Note: Table presents matched regression coefficients estimated on the analysis data and data simulated from the model. The quintiles are of utilization across all utility-years. MC^{COAL} and MC^{CCNG} are the marginal fuel costs ($p^f \times heat^f$) for coal and CCNG, respectively.

Table A3: Operations Model Estimates With Heterogeneity Based on Market Dispatch

Parameter	Notation	Estimate	Std. Error
Penalty for High Electricity Rates	γ	0.622	(0.66)
Extra Rate Penalty with Market Dispatch	Extra γ	-0.008	(0.02)
CCNG Capacity Weight in Rate Base (Mil. \$/MW)	α^{CCNG}	0.229	(0.05)
Coal Relative Weight in Rate Base	$\frac{\alpha^{COAL}}{\alpha^{CCNG}}$	1.136	(0.74)
Coal Usage Logit Base	μ_1	-0.612	(0.63)
Coal Usage Logit Slope	μ_2	6.217	(0.24)
NGT Relative Weight in Rate Base	$\frac{\alpha^{NGT}}{\alpha^{CCNG}}$	1.815	(1.48)
Ramping Cost for Coal (100 \$/MW)	ρ^{COAL}	0.476	(0.50)
Ramping Cost for CCNG (100 \$/MW)	ρ^{CCNG}	0.437	(1.01)
O&M Cost for Coal (\$/MW)	om^{COAL}	13.031	(3.09)
O&M Cost for CCNG (\$/MW)	om^{CCNG}	8.688	(14.17)
O&M Cost for NGT (\$/MW)	om^{NGT}	43.282	(101.85)

Note: Structural parameter estimates from indirect inference nested fixed point estimation. All values are in 2006 dollars.

A2 Data

A2.1 Construction of Analysis Data

Our analysis data include information principally from the EIA, the EPA, FERC, and two ISOs (as obtained from Cicala, 2022a). To construct our analysis data, we need to merge together information from these four sources at the utility-year and utility-hour levels and in some cases also separately by fuel-technologies. The EIA data contain a plant ID and the EPA CEMS data contain a facility ID. We merge these two datasets together using these fields. The EIA Form 861 data contain a utility ID, which we use to collapse the data across generators with the same fuel-technology within the same utility. The FERC Form 714 data and the data we obtained from Cicala (2022a) include fields that are equivalent to EIA's utility ID field, which further allows us to merge these data to the combined EIA/EPA data.

The CEMS data also include information for the U.S. state within which each plant is located (Gowrisankaran et al., 2024). We used this information to convert each hour in these data to Eastern Standard Time. In some cases, this required us to approximate the time zone by U.S. state; e.g., we assumed that Kentucky is in the Eastern Time Zone and Tennessee is in the Central Time Zone. The FERC data include the time zone at which each utility reports hourly load. We used this reported information to convert each hour in these data to Eastern Standard Time. In some cases, this required us to interpret utilities' responses to the time zone question, e.g., that "CEN" refers to the central time zone. We also converted hours in the FERC data from daylight savings time to standard time.

We deflate all revenues and prices to January, 2006 dollars. We used the Consumer Price Index for all urban consumers as our measure of inflation (Bureau of Labor Statistics (BLS), 2025).

We retain in our sample only those utilities with at least five years of revenue and load data. We also drop three utilities which reported excessive exports or very low capacity.

We collected nodal prices from ISOs and then constructed an average hourly wholesale electricity price for each U.S. state and hour, downloaded from each ISO's website.[44] Given

[44]For IL, in which several ISOs are present, we take the LMPs from MISO, which is the most relevant network for the regulated utilities south of IL (IA, KS, LA, MO, MT, and OK), many which are now part of the MISO footprint.

that, by construction, most utilities do not have an ISO in their U.S. state, we assign utilities without an ISO in their U.S. state to their closest neighbor U.S. state. As we describe in Section A4.3, to estimate import supply curves, we pair these wholesale electricity price data with functions of average daily temperature at the U.S. state level, which we obtain from PRISM.[45]

Finally, for our coal and gas fuel price measures, we aggregate the EIA Form 423 information on annual contracted fuel prices by plant to the U.S. state-year level by taking the mean, weighting by annual generation at each plant. Using these data at the U.S. state-year level—rather than at the plant-year level—captures utilities' opportunity cost of fuel.

A2.2 Summary Statistics on Data

Table A4 presents summary statistics of our analysis data at the utility-year level. The first column presents overall averages and standard deviations while the second and third columns present the values for the first year of our data (2006) and the last year (2017), respectively. Mean coal capacity declines substantially over our analysis sample—from 3.57 GW to 2.70 GW per utility—while CCNG capacity increases from 0.79 GW to 1.99 GW per utility. Average coal fuel prices are \$2.18/MMBtu over our sample, and marginal costs of coal generation are over \$22/MWh over our sample. In contrast, natural gas fuel prices fall from a high of \$7.72/MMBtu in 2006 to only \$2.93/MMBtu in 2017. This drop in fuel prices caused CCNG marginal fuel costs to fall by 66% over our time period. Finally, our data record information on 39 unique utilities. The average annual revenues of these utilities is approximately \$1.8 billion per year (in January, 2006 dollars), a figure that is fairly consistent across years.

Table A5 presents similar summary statistics for our hourly-level analysis data. Utilities in our data serve an average of 3.82 gigawatt hours of load per hour. In 2006, the majority (65%) of this load was met by coal and only a small amount (12%) was met by CCNG. By 2017, this situation had changed substantially, with 38% of load met by coal on average and 33% met by CCNG. The remainder of load is generally met with imports,[46] with NGT

[45] We downloaded these data from Prof. Wolfram Schlenker's website, `http://www.columbia.edu/~ws2162/links.html`. Data are also available at Gowrisankaran et al. (2025b).

[46] We allow exports to be represented as negative imports, so some utilities will have more generation from

Table A4: Summary Statistics from Data at Utility/Year Level

	Overall	2006	2017
Capacity (GW):			
Coal	3.34	3.57	2.70
	(3.76)	(4.19)	(2.53)
CCNG	1.43	0.79	1.99
	(3.16)	(2.43)	(3.93)
NGT	0.78	0.67	1.03
	(1.02)	(0.93)	(1.21)
Fuel Price ($/MMBtu):			
Coal	2.18	1.78	2.00
	(0.76)	(0.66)	(0.59)
Natural Gas	5.05	7.72	2.93
	(2.22)	(0.96)	(0.41)
Fuel Cost ($/MWh):			
Coal	22.29	18.22	20.20
	(7.63)	(6.30)	(6.35)
CCNG	37.60	63.48	21.80
	(18.76)	(11.74)	(3.75)
NGT	68.50	101.95	60.64
	(47.47)	(21.92)	(123.16)
Utility Revenues (Billions of Dollars):			
	1.81	1.76	1.75
	(2.08)	(2.25)	(1.99)
Number of Unique Utilities:			
	39	38	38

Notes: The first column reports summary statistics over the entire 2006–17 period. We report fuel costs conditional on a utility having positive capacity for that fuel-technology. Standard deviations are in parentheses.

Table A5: Summary Statistics from Data at Utility/Hour Level

	Overall	2006	2017
Load Served (GWh):			
	3.82	3.89	3.80
	(4.34)	(4.44)	(4.23)
Production (GWh):			
Coal	2.03	2.53	1.44
	(2.16)	(2.80)	(1.28)
CCNG	0.88	0.47	1.27
	(1.57)	(1.14)	(2.01)
NGT	0.07	0.05	0.12
	(0.20)	(0.17)	(0.28)
Import Quantity (GWh):			
	1.37	1.30	1.51
	(2.35)	(2.35)	(2.29)
Import Price ($/MWh):			
	31.84	41.53	22.31
	(19.47)	(23.11)	(8.03)
Number of Observations:			
	4,013,487	322,795	332,876

Notes: The first column reports summary statistics over the entire 2006–17 period. Standard deviations are in parentheses.

consistently producing only a small percentage of load. This is consistent with many NGT plants being used as "peakers" that only generate in times with high load. Finally, import prices reflect the overall decrease in natural gas prices, displaying a 46% drop between 2006 and 2017.

A3 Reduced Form Evidence Using Rate Hearing Data

To better understand the impact of costs on the reported authorized rate base and RoR, we obtained and integrated data from Regulatory Research Associates (RRA) with our base analysis data. RRA provides cleaned rate hearing data, using information that it obtains from public records. For our purposes, each RRA record focuses on one rate hearing case and includes the utility name, hearing data, case type (vertically integrated or limited-issue rider), and authorized rate base and return on rate base.[47] We merged the RRA data with our base data at the utility-year level, performing a hand match using the string variable that records the utility names.

There are three central issues with using RRA data for our analysis. First, the coverage of utilities in the RRA data is very incomplete. Many of the utilities in our base analysis data are not investor-owned, which may explain why they are not in the RRA data.

Second, there are utilities in our base data that match to the RRA data but that do not have hearing information in the RRA data for extended periods of time, some for over 20 years. This is important because, using these data, a rate hearing determines utility profits until the next hearing. To minimize measurement error, we assumed that the hearing decision applies to the utility until the next rate hearing, as long as the next hearing is within seven years. Thus, we could not use utilities in years before the first RRA observation or with extended gaps between rate hearings.

Third, the RRA data contained a number of other anomalies. It reported zero rates of

Coal, CCNG, and NGT than total load in particular hours.

[47]RRA lists these fields as "Increase Authorized Rate Base" and "Increase Authorized Return on Rate Base," and does not provide documentation on their exact meaning. After studying the data and discussing this with other authors who have used RRA data, we interpreted these fields as levels and not increases. Furthermore, though its units are not specified, the return on rate base also appears to be reported as a percent.

return for a number of utilities, which we dropped. For one utility, it only reported limited-issue riders. We were able to construct a rate base for this utility in each year by summing the reported rate base from each rider that preceded the year.

Our merged sample contained 186 utility-year observations (out of 459 in our base analysis sample) over 23 utilities (out of 39 in our base analysis sample). Despite these limitations, we used the merged sample to investigate whether higher costs affect utilities' authorized rate bases, authorized rates of return on their rate base, or authorized profits (the product of the above two variables).

Table A6 presents results using the merged sample that are analogous to Table 1. Starting with panel (a), we investigate the association between variable profits, as calculated from RRA data, and the three proxies for costs that we used in Table 1. We find that, after controlling for utility fixed-effects and clustering at the rate hearing level, higher costs are associated with lower profits, and this result is statistically significant across the three specifications.

Panel (b) reports the association between the authorized RoR, as reported by RRA, and the same proxies for costs. All three specifications show that higher costs are associated with *higher* rates of return, that is statistically significant in two of the three specifications. These results are in the opposite direction from the panel (a) results and the Table 1 results.

Finally, panel (c) reports the association between the rate base and the same proxies for costs. It shows results that are consistent with panel (a). Specifically, after controlling for utility fixed effects, higher costs are associated with a significantly lower rate base in all three specifications.

Overall, we believe that these results broadly support our base results in Table 1: they show that profits are decreasing in variable costs. However, they also highlight that this is not necessarily occurring through official reductions in the authorized rates of return. Instead, the reductions in profits may be occurring through changes in the authorized rate base. We believe that this latter channel may occur through certain capital costs being disallowed as part of the rase base when variable costs are high. For instance, in an Indiana decision, the regulator disallowed a utility's previously incurred capital costs for coal ash disposal, deeming them to be inappropriately incurred and therefore requiring the utility to

Table A6: Regressions of RRA Data on Total Variable Cost Measures

Panel (a): Dependent Variable: Variable Profits (Billion $)			
Principal Regressor:			
Variable Costs (Bil. $)	−0.119		
	(0.048)		
Variable Costs per Capacity (Mil. $/MW)		−0.621	
		(0.314)	
Variable Costs per High Load (Mil. $/MWh)			−1.005
			(0.413)
Panel (b): Dependent Variable: Rate of Return			
Principal Regressor:			
Variable Costs (Bil. $)	0.464		
	(0.247)		
Variable Costs per Capacity (Mil. $/MW)		7.063	
		(2.203)	
Variable Costs per High Load (Mil. $/MWh)			8.543
			(4.317)
Panel (c): Dependent Variable: Rate Base			
Principal Regressor:			
Variable Costs (Bil. $)	−1.840		
	(0.800)		
Variable Costs per Capacity (Mil. $/MW)		−10.059	
		(4.749)	
Variable Costs per High Load (Mil. $/MWh)			−16.045
			(6.228)
Utility FE	Y	Y	Y

Note: Each column in each panel presents regression results from a separate regression on our analysis data merged with Regulatory Research Associates data on reported RoR and rate base, with standard errors in parentheses. We calculate variable profits as reported RoR times reported rate base. Variable costs include fuel and import costs. High load is the 95th percentile of hourly load by utility-year. Standard errors cluster at the rate hearing level.

lower consumer rates (Indiana Utility Regulatory Commission, 2023).

A4 Details of Estimation

This appendix section details the assumptions underpinning the estimation of our model. We begin with details of the investment/retirement model estimation. We then discuss the estimation of the operations model, which we use to estimate regulatory and operations cost parameters. Finally, we explain how we recover import supply curves, which are an input into operations decisions.

A4.1 Investment and Retirement Decisions

We estimate investment and retirement decisions with a nested fixed point GMM estimator that requires solving for the dynamically optimal investment/retirement decisions across states. We compute the optimal investment/retirement decisions with a Bellman equation. After the final decision period, when $t > 10$, the state no longer evolves and the utility no longer makes investment/retirement decisions. Hence, we solve for the value at this state as the discounted flow of π^*, evaluated at the terminal state. We then solve the remaining 10 period problem with backward recursion, starting with the CCNG investment decision for all states at $t = 10$, then the coal retirement decision for all states at $t = 10$, the CCNG investment decision for all states at $t = 9$, etc.

We can write utility i's CCNG investment decision Bellman equation for $t \leq 10$ as:

$$\begin{aligned} V_i^{CCNG}(K^{COAL'}, K^{CCNG}, p^{NG}, t, \varepsilon^{CCNG}) = \max_{x^{CCNG} \geq 0} \Big\{ &- InvCosts^{CCNG}(x^{CCNG}|\varepsilon^{CCNG}) \\ &+\beta \int EV_i^{COAL}(K^{COAL'}, K^{CCNG} + x^{CCNG}, p', t+1) dg(p'|p^{NG}) \Big\}, \end{aligned} \tag{A1}$$

where we include an index i to account for the effect of the utility's fixed states on profits, $K^{COAL'}$ is the coal capacity after the coal retirement decision, $g(p'|p^{NG})$ is the conditional density of the next period's fuel prices, and EV_i^{COAL} is the expectation of the value function at the start of the next period, integrating over the ε^{COAL} investment cost shock.

For its coal retirement decision, the Bellman equation is:

$$V_i^{COAL}(K^{COAL}, K^{CCNG}, p^{NG}, t, \varepsilon^{COAL}) \quad = \quad \pi_i^*(K^{COAL}, K^{CCNG}, p^{NG}) + \tag{A2}$$

$$\max_{x^{COAL} \leq 0} \left\{ -InvCosts^{COAL}(x^{COAL}|\varepsilon^{COAL}) + EV_i^{CCNG}(K^{COAL} + x^{COAL}, K^{CCNG}, p^{NG}, t) \right\},$$

where EV_i^{CCNG} is the expectation of the value function at the start of the CCNG investment decision, before the ε^{CCNG} investment cost shock is realized.

Equation (A2) includes utility i's variable profits, $\pi_i^*(K^{COAL}, K^{CCNG}, p^{NG})$, since they are a function of its state at this stage. These variable profits reflect optimizing decisions within a period, as calculated from the operations model. Although the value function varies across period t, variable profits do not, and vary only across utility and the three indicated (time-varying) states. For our estimation of the investment/retirement model, we calculate variable profits by solving the operations model across a counterfactual grid of coal capacity, CCNG capacity, and natural gas fuel prices that enter our Bellman equation, using the estimated operations model parameters and the utility i's mean NGT capacity and coal fuel price over the sample period.

For load and the import supply curve parameters—which are fixed across periods but vary across hours within a period—we use hours from the first year that utility i is observed in our data, generally 2006. We use data from one year here rather than using the mean across years to preserve the level of fluctuations that occurs between hours and accurately capture ramping and other costs.

Equations (A1) and (A2) show that the utility can adjust its next period's capital deterministically but is faced with a stochastic evolution of fuel prices and cost shocks. For $t > 10$, both Bellman equations look similar to these equations except that the utility does not make investment or retirement decisions and natural gas fuel prices do not evolve. The assumption that the state does not evolve when $t > 10$ allows us to solve the dynamic programming problem by backward induction, with the state-contingent value function at $t = 10$ being the discounted sum of future profits.

We discretize the state space and compute continuation values by interpolating across discretized states. Here, we use 10 evenly divided bins for each of the time-varying states of coal capacity, CCNG capacity, and natural gas fuel price. Since we consider only retirements for coal, we let the coal capacity bins range from 0 to the observed coal capacity at the beginning of the sample. Since we consider only investment for CCNG, we let CCNG capacity bins range from the observed CCNG capacity at the beginning of our sample to 110% of peak load, defined as the 95th percentile of hourly load. Finally, we let the natural gas fuel price bins range from 75% of the lowest three-year mean fuel price (as described below) to the maximum three-year mean price. Given that there are 10 evaluation time periods and two decisions (investment and retirement) in each period, we solve for continuation values at $10^4 \times 2 = 20{,}000$ states per utility.

For each of the 20,000 states, we solve for the continuation value using the GSD algorithm (Gowrisankaran and Schmidt-Dengler, 2025). This algorithm discretizes the continuous (in our case, investment/retirement) decision and requires that we specify the number and values of the discrete levels and suggests using a relatively large number of choice bins. Based on our examination of changes in the data, we specify 20 bins each for CCNG and coal capacity change, ranging from 0 to 3,000 MW of CCNG investment and between 0 and 5,000 MW of coal retirement. We allow for smaller bins for capacity changes between 0 and 1,000 MW to capture investment/retirement of single plant, which typically lie within this range. We also exclude coal retirement bins that would imply negative coal capacity.

We chose 10 discrete bins for the state space discretization instead of, for instance, 20 (as for the capacity change choices), because of computational cost. Doubling the number of state space bins for coal capacity, CCNG capacity, and natural gas fuel price would increase the number of states by a factor of eight, necessitating eight times as many solutions of the operations model. In contrast, increasing the number of capacity change bins is computationally much easier with the GSD algorithm, because it does not require solving the operations model for more states. Given this, we suggest potentially trying a greater number of choice bins when using the GSD algorithm, as a robustness check.

We estimate our GMM objective function with 18 moments. Each of the moments indicates the difference between the estimated model value of a statistic and the value in the data. For a given parameter vector, we calculate the model probability for each of the 20,000 states in our grid along with the Bellman equations and then find the model probability for any element of the data by interpolating the computed policy function across the three continuous and time-varying states. We use 9 moments each for coal and CCNG decisions. For coal, we include (1) an indicator for positive retirement, (2) the quantity of capacity retired, (3) quantity squared, and (4) an indicator for retirement of more than 500 MW. We interact these four moments with coal capacity (5–8) and include (9) the retirement quantity variance. For CCNG, we include the analogous moments, but for investment (10-18).

We estimate an asymptotically optimal GMM weighting matrix by bootstrapping the model moment values across observations and using the inverse estimated variance-covariance matrix as the weighting matrix. We calculate standard errors using the standard GMM formulas. Because of computational complexity, our standard errors for the investment/retirement model do not account for the fact that π^* is estimated.

Finally, we estimate the natural gas fuel transitions using a panel of Henry Hub natural gas spot prices as reported by `https://www.eia.gov/dnav/ng/hist/rngwhhdM.htm`. We use data from 2003–20, and let each observation denote the three-year mean price. We then estimate gas price transitions with a simple autoregressive specification of price on lagged price. We take the slope and residual from the regression and discretize quantiles of the prediction to obtain transition probabilities of the natural gas fuel price state from period to period.

A4.2 Operations Decisions

We estimate regulatory and operating cost parameters from utilities' operating decisions by solving for the utility's optimal actions given an investment/retirement state and candidate parameter vector and then running indirect inference regressions on those actions. We then find the parameter vector that best matches these indirect inference coefficients to those obtained when the same regressions are run on the data. We present the details of how we solve for utilities' optimal actions before turning to the details of the indirect inference regressions.

To solve for utilities' optimal operations decisions, we construct a sample of 8 weeks across the year. This sample includes four two-week spans starting at midnight on February 8th, May 8th, August 8th, and November 8th of each year. We assume that utilities pay ramping costs between hours within these two-week spans but not between the spans.

As discussed in the main text, the utility's Bellman equation in a given hour depends upon four states: (1) cumulative TVC up to that hour, (2) cumulative coal usage up to that hour, (3) lagged coal generation, and (4) lagged CCNG generation. As in the investment/retirement estimation discussed in Section A4.1, we discretize each of these states into ten bins. In this case, we have $10^4 = 10,000$ states for each utility-hour and interpolate across discretized states. For the cumulative TVC state, we keep track of the average variable cost—so that the state has a similar scale for earlier and later hours of the year—and divide the bins evenly between a minimum marginal cost (defined as 50% of the utility's lowest marginal fuel cost for available fuel-technologies in the year) and a maximum marginal cost (defined as the maximum of \$200/MWh or 150% of the utility's highest marginal fuel cost for available fuel-technologies in the year). For cumulative coal usage, we choose evenly divided bins between 0 and 1. For the lagged generation states, we choose evenly divided bins between zero and the capacity of the respective fuel-technology.

In each hour, the utility chooses its coal and CCNG generation levels, both of which affect the future state. We allow the utility to choose between 10 potential values of each of coal and CCNG generation, for 100 possible generation choices. We define the minimum of these equally-spaced bins as either 500 MWh below the lagged generation for that fuel-technology or zero, whichever is bigger. We define the maximum of the bins as either 500 MWh above the lagged generation for the fuel-technology or the fuel-technology's installed capacity for the utility, whichever is smaller. Thus, we do not allow utilities to ramp or deramp more than 500 MW per hour, for both fuel-technologies.

For each hourly choice of coal and CCNG generation, the utility meets the remaining load with some combination of NGT or imports. Since these fuel choices do not enter into the utility's end-of-year payoff except through TVC, the utility is incentivized to make the cost-minimizing choice across these options. For each potential choice of coal and CCNG, we find the quantity of imports that sets the price of imports equal to the marginal cost of NGT. We then check whether this choice is feasible, or implies an NGT choice less than 0 or more than NGT capacity. In the first case, we use the computed quantity of imports. In the latter cases, we choose the boundary condition of NGT of 0 or capacity, as this will minimize costs. We then compute variable costs for the hour with this combination of generation and import choices and find the expected continuation value given this choice.

As discussed in the main text, we assume that the utility receives its regulatory profit in the terminal hour. We implement this by scaling annual outcomes (e.g. revenues and fuel and import costs) from the 8 week sample to the annual level by multiplying by the hours in a year divided by the hours in the sample, 8760/1344 for non-leap years and 8784/1344 for leap years. The RoR that the regulator offers the utility increases as its costs decrease with the implicit function given by $r \times \ell = TVC + (r/r_0)^{\gamma} \times B$. We calculate the RoR at each terminal hour state by iterating on this implicit function until convergence. In calculating its RoR, we limit TVC to be at least 10% of TVC in the utility's first year in the data in order to avoid some utilities choosing to export so much that they reach a negative, and hence unrealistic, TVC.

For a given parameter vector, we first solve for the utility's optimal operations decisions. We then use these simulated data in our indirect inference regressions. For the regressions using hourly data, we run these regressions on the same 8 weeks of data on which we solve for the utilities' optimal operations decisions. For the regressions run on annual data, we run the regressions on the true annual data and the model-simulated data scaled to the annual level.

We run a total of 10 regressions on both the observed data and the model-simulated data and match 29 coefficients from these regressions. These regressions include:

1. **Scale of Generation:** We run regressions of the hourly utilization (generation divided by capacity) for each fuel-technology on a constant. This yields three regressions, one for each of coal, CCNG, and NGT. We cluster the standard errors of these regressions at the utility level and match the three coefficients on the constants.

2. **Scale of Variable Profit:** We run one regression at the utility-year level of revenues net of fuel and import costs on a constant. We cluster the standard errors of this regression at the utility level and match the coefficient on the constant.

3. **Determinants of Rate of Return:** We run one regression of a proxy for the utility's RoR on a proxy for total variable costs. Specifically, our dependent variable is the utility's revenues net of fuel and import costs divided by the utility's total coal, CCNG, and NGT capacity in the year. Our independent variable is fuel and import costs. We include utility fixed effects in this regression, but we only match the coefficient on our

TVC proxy, not the fixed effect estimates, and we do not cluster these standard errors.

4. **Determinants of Variable Profit:** We run one regression at the utility-year level of a proxy for variable profits (revenues net of fuel and import costs) on the utility's coal capacity, coal capacity multiplied by coal usage rate, CCNG capacity, and NGT capacity. We cluster the standard errors at the utility level and match the three coefficients on capacity and the interaction term.

5. **Usage of Coal and CCNG:** We run two regressions at the hourly level where the dependent variables are the log of coal (or CCNG) generation divided by the sum of coal and CCNG generation in the hour. For the coal regression, the primary dependent variables are quintiles of annual coal utilization across all utility-years where a utility has positive coal capacity and these quintiles interacted with the difference in marginal cost between coal and CCNG. We include analogous regressors in the CCNG generation share regression. We also include utility fixed effects in both regressions. We run these regressions only on hours of the year where the load is between 75% and 125% of the utility's CCNG capacity (for the coal regression) or coal capacity (for the CCNG capacity) in that year. We cluster the standard errors at the utility level. We match the nine coefficients in each regression on the usage shares and their interactions with fuel prices.

6. **Extent of Ramping:** We run two regressions at the hourly level of current coal or CCNG generation on lagged generation with the same fuel-technology. In these regressions, we control for the fuel price of coal, the fuel price of CCNG, the current electricity price, current load, and six leads for each of load, the import supply curve intercept, and the electricity price. We include utility, month-of-year, and hour-of-year fixed effects and cluster standard errors at the utility and hour-of-year level. We only match the one coefficient from each regression (two coefficients total) on lagged generation.

This indirect inference approach also requires us to choose a weighting matrix to determine how differences across moments will be summed. We use a weighting matrix based on the inverse of the variance-covariance matrix of the regressions on the actual data above. We assume that there is no covariance across regressions.

A4.3 Import Supply Curves

We estimate import supply curves for each utility in each hour in an initial step before these curves enter into the estimation of the operations model. Each hour, a utility u chooses the share of load to meet with its own generation and the share to import from facilities it does not own. To understand these decisions, we follow Bushnell et al. (2008), Gowrisankaran et al. (2016), and Reguant (2019) and estimate a linear import supply curve that models the quantity of electricity imported to the utility as a function of import price and controls.

Building on this literature—and important in our context, because the supply curves in exporting regions will change as fuel prices change—we allow the intercept and slope of the import supply curve to vary with the natural gas fuel price:

$$q^m_{uth} = (\psi_{u0} + \psi_{u1} p^{NG}_{ut}) p^m_{uth} + \psi_{u2} p^{NG}_{ut} + \psi_{u3} X_{uth} + \varepsilon^m_{uth}. \tag{A3}$$

We allow all parameters to vary across utilities and, as discussed in Section 2.2, we approximate the import price with the wholesale market price in the closest state in an ISO and define import quantity as the difference between load and generation with coal, CCNG, and NGT. The controls, X_{uth}, capture demand shocks in the exporting region, and include cooling degree days, heating degree days, and their squares for every U.S. state in the nearest ISO, interacted with hour of the day. We also include fixed effects for the day of week, month of year, and hour of day.

Recovering the import supply curves requires understanding the causal impact of import price on import quantity, but an OLS regression of (A3) would not consistently estimate the supply curve because the data reflect variation in both demand and supply. Therefore, we identify the import supply curve using instruments that plausibly shift the demand for imports without affecting the import supply curve. Specifically, as in the literature discussed above, we instrument for the import price with the utility's local load, after controlling for

X_{uth}.[48] In many contexts, demand shifters are used as instruments for price in supply estimation. In electricity markets, since local load is nearly perfectly inelastic, load itself instruments for price in supply curve estimation. This instrument is valid if, in addition to local load being perfectly inelastic, it is unaffected by local supply shocks and uncorrelated with shocks to demand (conditional on X_{uth}) in exporting regions.

We use the estimates from (A3) to recover a supply curve for each utility-year-hour. We follow the above papers and specify intercepts of these curves as including the residual from (A3), i.e. $\hat{\psi}_{u2} p_{ut}^{NG} + \hat{\psi}_{u3} X_{uth} + \hat{\varepsilon}_{uth}^{m}$ where the hats indicate estimated values.

In a few utility-years, we estimated import supply curves where the slope—of import quantity with respect to import price—was negative and very flat. With those slopes, utilities' profits became implausibly large with exports, which could result in utilities who export unreasonable amounts. To avoid this issue, we limited the slope to be less than or equal to -100 when we estimated a negative slope.

A5 Implementation of Counterfactuals

This appendix provides details on our implementation of the counterfactuals for both the operations decisions and the long-run decisions that simulate an energy transition. These counterfactuals compare the current regulatory structure to (1) the cost minimization solution and (2) the social planner solution. They also analyze changes to the current regulatory framework, specifically (3) imposing carbon taxes within the context of RoR regulation, (4) adjusting the usage incentives, and (5) altering the penalties for high electricity rates.

To simulate operations decisions, we start with each utility-year in our analysis sample and simulate how operations would change under these counterfactual environments. To simulate the long-run decisions under counterfactual environments, we calculate a grid of state-contingent profits π_i^* for each utility i observed in our sample under these environments. Our simulation process then follows the computation described in the estimation of the investment and retirement parameters, in On-Line Appendix A4.1, but with different profit

[48] Given that we interact import price with natural gas fuel price, we also use the interaction of local load with the natural gas price as an additional instrument.

grids from those used in the baseline estimation.

We report outcomes for each counterfactual that include information on the generation decisions, carbon externalities, and—in the case of the long-run counterfactuals—coal and CCNG capacity. To calculate the carbon externalities, we multiply the EPA's 2023 carbon cost (Environmental Protection Agency, 2023b) by the carbon intensity of each fuel source in CO_2 tons per MWh. We calculate the carbon intensity of each utility and fuel-technology by multiplying its heat rate, measured in MMBtu per MWh, by its emissions tons per heat input, measured in CO_2 tons per MMBtu. We recover the heat rate by utility and fuel-technology from our analysis data and the emissions per heat input for coal and natural gas from Energy Information Administration (2023). Our reported counterfactual carbon cost measures further account for the carbon intensity of imports. We assume that the carbon intensity for imports is the 2019 national mean carbon intensity of generation, which we calculate from Environmental Protection Agency (2023a). Because we fix the carbon intensity of imports across counterfactual policies, the carbon impacts of these policies most accurately indicate the impact of a policy change affecting a *single* utility.

Finally, we discuss our implementation of each of the five types of counterfactuals.

1. **Cost minimization.** For the operations model, cost minimization is equivalent to the current regulatory problem with μ_2 set to 0. This is because, without usage incentives, the regulated utility is incentivized to minimize operations costs. In the long run, however, investment/retirement decisions will differ between the cost minimization solution and the current regulatory framework with $\mu_2 = 0$, since utilities earn regulated profits. To solve the cost minimization solution for the energy transition, we maximize a value function where the period objective is the negative of total cost, rather than profits.

2. **Social planner.** The social planner in our model seeks to minimize the expected discounted costs of electricity production plus the CO_2 externality from this production. Thus, we compute the social planner solution in the same way as the cost minimization solution, except that we subtract from the criterion function the social cost of carbon from generation with each of the fuels and from imports.

3. **Carbon tax within existing regulatory structure.** We assume here that utilities are charged a carbon tax of \$190/ton on both their generation and imports. Because this carbon tax then enters TVC, utilities can partly increase consumer rates in response. The penalty for high electricity rates limits their ability to fully pass through this tax, and creates long-run incentives to invest in and generate with low-carbon fuel sources. Our carbon tax counterfactual results account for these mechanisms.

4. **Altering usage incentives.** We consider counterfactuals that eliminate or double the logit slope μ_2 on coal capacity's extra contribution to the rate base with additional usage. As noted above, $\mu_2 = 0$ is equivalent to cost minimization in operations decisions. However, it is different in its long-run implications, and hence we report the impact of an energy transition separately for cost minimization and for the regulatory framework with $\mu_2 = 0$.

5. **Altering the penalties for high electricity rates.** We consider counterfactuals that increase or decrease γ by 50%, which indicates the penalty that a high electricity rate gives the utility in terms of a lower RoR, s. An increase in γ implies both a steeper drop in profits from higher electricity rates and a drop in profits overall. For these counterfactuals, we would like to study the impact of changing the slope of profits with respect to electricity rates rather than the level. Thus, for these counterfactuals, we also proportionally adjust the α parameters—which indicate the rate base per MW of capacity—to hold mean variable profits across utility-year observations at the baseline operating decisions constant.

A6 Additional Long-Run Counterfactual Results

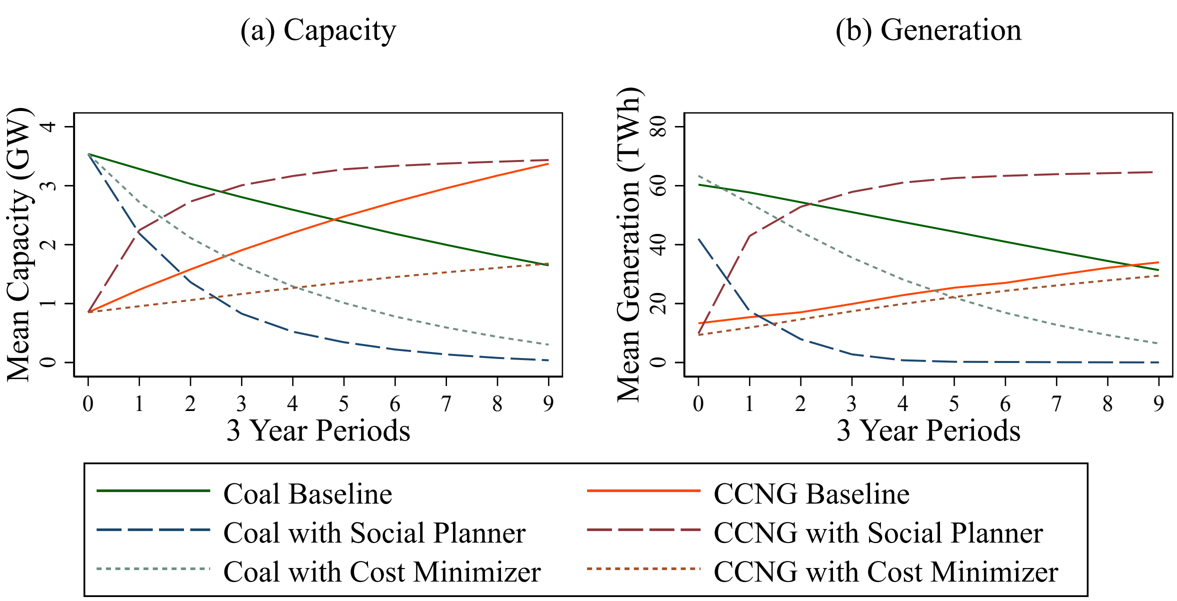
This appendix considers three additional sets of long-run counterfactuals. First, the long-run counterfactuals in the main text keep import curves fixed, consistent with a single utility facing alternate incentives. This allows the utility to increase imports when coal generation is costly, for instance when it faces the social planner's incentives. This assumption is consistent with counterfactual outcomes for a single utility rather than a setting where many regulated utilities across the Eastern Interconnection simultaneously move to, for instance, cost minimization. An alternative assumption is that the utility holds constant its import *quantities* at the 2006 baseline level. Import prices will vary because they will reflect the different natural gas prices.

Figure A3 shows the decisions of the social planner and cost-minimizing utility in this environment. Comparing panel (a) of this figure to that of Figure 4, coal retirement decisions look quite similar. However, the social planner invests in CCNG more quickly since it cannot rely on imports to reduce carbon emissions in the short run. Turning to generation, panel (b) of Figure A3 shows that the social planner continues to generate with coal in the short-run since it cannot rely on imports to lower costs and carbon emissions. In the long run, however, investments in CCNG capacity allow the social planner to move completely away from coal generation, as when we allow import quantities to vary.

Second, we investigate the impact of changing the penalty for high electricity rates, γ. The results, in Figure A4, show that changing this penalty leads to changes in both coal and CCNG capacity, with lower electricity rate penalties leading to higher capital investment. Increasing the electricity rate penalty by 50% decreases coal capacity by 18% relative to the baseline over the 30 year horizon, and leads to 18% less CCNG investment, but still does not bring the utility close to the cost minimizing solution. Differences in electricity rate penalties cause somewhat different coal generation levels but do not substantially affect CCNG generation levels.

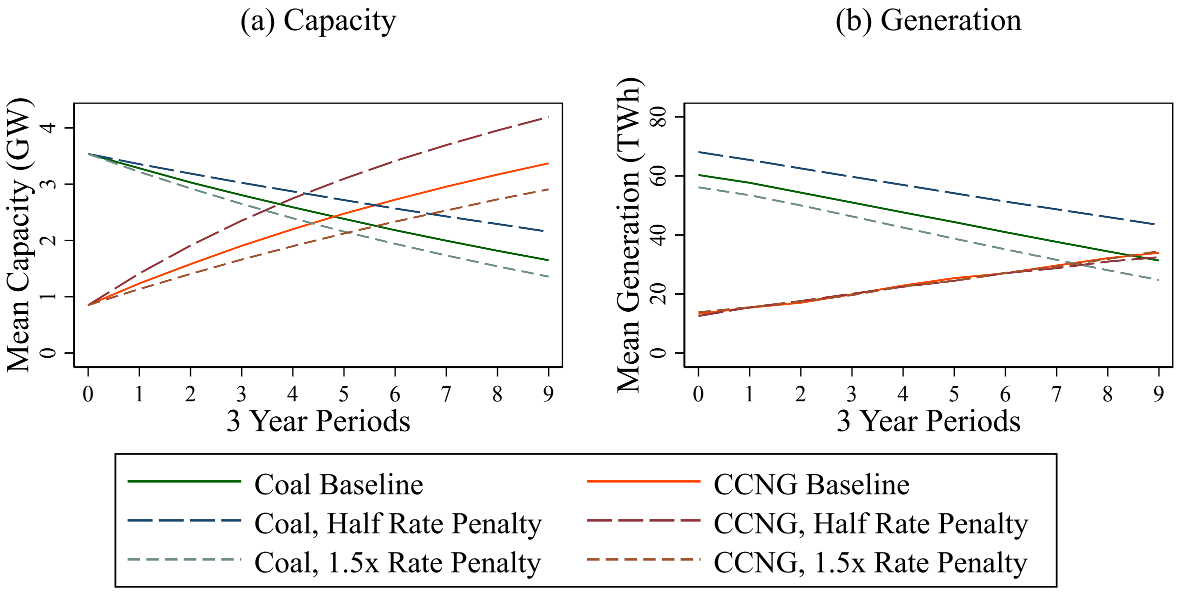
Finally, Figure A5 reports total carbon emissions over time for four counterfactuals: the baseline, the cost minimizer, the planner, and the regulated utility facing carbon taxes. We find distinct differences in immediate carbon emissions following a sudden drop in natural gas fuel prices. However, by the end of our 30-year horizon, the carbon emissions for the social planner, cost minimizer, and regulated utility facing a carbon tax are all roughly 25% below the baseline level, consistent with substitution from coal to CCNG generation.

Figure A3: Capacity and Generation for Baseline, Social Planner, and Cost Minimizer with Fixed Imports



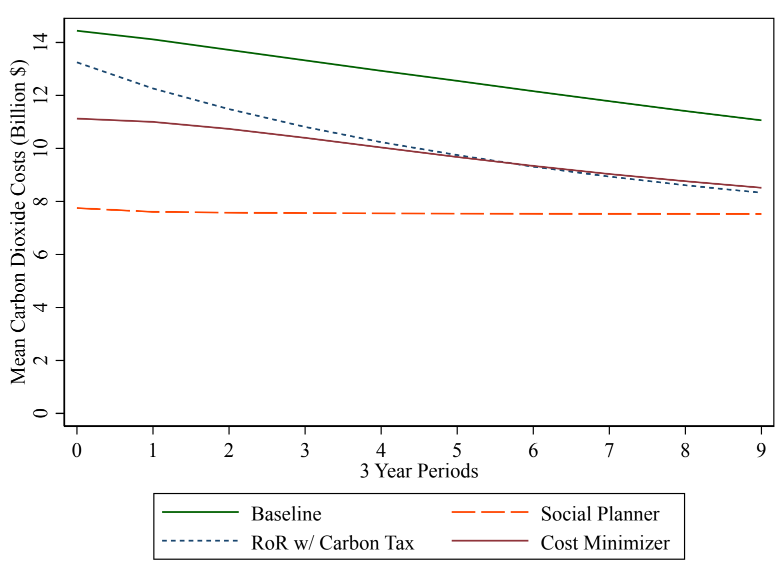
Note: Figures present counterfactual simulations over 10 3-year periods starting with 2006 capacities but imposing 2018–20 natural gas fuel prices. The social planner minimizes costs including a $190/ton carbon cost. The cost minimizer has the same incentives but does not value carbon externalities. In both of these cases, we hold hourly imports for each utility fixed at their simulated quantities for the first year the utility appears in the analysis sample.

Figure A4: Capacity and Generation for Different Electricity Rate Penalties



Note: Figures present counterfactual simulations over 10 3-year periods starting with 2006 capacities but imposing 2018–20 natural gas fuel prices. The counterfactuals change the electricity rate penalty, γ, as indicated.

Figure A5: CO_2 Carbon Costs for Baseline, Planner, Cost Minimizer, and Carbon Tax



Note: The Figure presents counterfactual simulations over 10 3-year periods starting with 2006 capacities but imposing 2018–20 natural gas fuel prices. The social planner minimizes costs including a \$190/ton carbon cost. The cost minimizer has the same incentives but does not value carbon externalities. The carbon tax counterfactual leaves the regulatory structure unchanged but adds the carbon cost to TVC.

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