# Energy Transitions in Regulated Markets*

Gautam Gowrisankaran† Ashley Langer‡ Mar Reguant§

November 17, 2022

**Abstract**

Regulated U.S. electricity markets have transitioned from coal to natural gas more slowly than restructured markets. This contrasts with the predictions from canonical models of regulation that regulated utilities would over-invest in new capital because they are allowed a fair rate of return on capital. In addition, observers have alleged that regulated utilities are operating coal plants even when this is inefficient because they are subject to a "used and useful" standard that only allows them a return on power plants that they use sufficiently. We develop and estimate a dynamic model of energy transitions in regulated electricity markets that can explain these stylized facts. In our model, regulators reimburse utilities for using productive assets while aiming to keep electric rates low by limiting returns on capital when variable costs are high. In the short run, utilities make hourly operations decisions to maximize profits, given the incentives set up by the regulatory structure. This regulatory structure provides two opposite incentives: utilities will overuse expensive coal plants to meet the used and useful standard, but this overuse will be constrained to the extent that it results in high variable costs. In the long run, utilities decide which plants to retire and which new technologies to invest in. We show that regulation slowed the energy transition from coal to natural gas and that it may have important consequences for the transition to renewable electricity generation.

**JEL Codes:**
**Keywords:** electricity regulation, used and useful, stranded assets.

*We thank seminar participants for their helpful comments. We are grateful to Kelli Marquardt and Claire Petersen for excellent research assistance.

†University of Arizona, HEC Montreal, CEPR, and NBER
‡University of Arizona and NBER
§Northwestern University, BSE, CEPR, and NBER

# 1 Introduction

Electricity generation is a critically important component of the economy and modern life. However, it also generates substantial negative externalities. In particular, electricity generation in the U.S. contributed 31% of U.S. $CO_2$ emissions in 2019 (Energy Information Agency, 2020). Beyond its climate change impacts, electricity generation also emits substantial local pollutants that harm human health, with damages for the U.S. estimated at $57.3 billion in 2017 (Holland et al., 2020).

At the same time that research has highlighted the importance of the damages from emissions, we are in the middle of two major transitions in electricity generation. First, over the past two decades, the cost of generating electricity with natural gas has plummeted. This was caused by the pairing of combined cycle generation technology with hydraulic fracturing, which has resulted in gas plants becoming more efficient at the same time that natural gas fuel prices have fallen. Second, the costs of large-scale solar panels and batteries have both dropped over 80% since 2010 (International Renewable Energy Agency, 2020; Cole and Frazier, 2019; Goldie-Scot, 2019). Given these cost declines and the substantially lower pollution externalities from renewables, a transition to renewable energy appears imminent.

These transitions are occurring in a highly regulated environment. Electric utilities' investment and pricing decisions have historically been regulated as natural monopolies. The 1990s saw extensive electricity deregulation in the U.S. and Europe. In the U.S., this deregulatory push ended with the California electricity crisis of the early 2000s, leaving a patchwork system where different states have substantially different levels of regulatory control.

In its simplest form, regulation of utilities' pricing and investment sets electricity prices such that firms earn a "fair" rate-of-return on their capital. The canonical model of rate-of-return regulation, Averch and Johnson (1962) (AJ), shows that utilities will respond to this type of regulation by over-investing in capital, suggesting that regulated utilities may have an incentive to over-invest in capacity in these new technologies. However, AJ cannot directly be applied to electricity generation since many of their fundamental assumptions

(e.g. elastic demand) do not fit this sector. Moreover, anecdotal evidence suggests that regulated utilities transition more slowly than others: the restructured states of Texas and California lead the U.S. in renewable energy production by a substantial margin (U.S. Energy Information Agency, 2020), and nuclear power plants in states undergoing restructuring disproportionately closed (Davis and Wolfram, 2012).

In this paper we investigate whether the regulatory structure has impeded energy transitions to new technologies and whether it incentivizes utilities to use the existing capital stock inefficiently. To do this, we will develop and estimate a model of regulation with plant investment and exit over the long-run and electricity generation and import decisions in the short-run. Our model builds on the AJ framework in a way that allows us to model the electricity industry. The ultimate goal of this paper is to evaluate how potential regulatory structures could impact the transition to renewable energy.

In the twenty-first century, the fuel used to generate the majority of electricity in the U.S. has transitioned from coal to natural gas. This has led to a 28% reduction in $CO_2$ emissions between 2005 and 2018 and lower local air pollution (U.S. Energy Information Administration, 2018). Two major technological innovations facilitated the evolution toward natural gas. First, combined cycle natural gas generation technology dramatically increased the efficiency with which generators could turn natural gas into electricity. Second, hydraulic fracturing (fracking) has drastically increased the quantity of economically accessible natural gas reserves in the U.S., thereby lowering natural gas prices.

With the recent declines in solar and battery technology prices, we are on the cusp of another energy transition. These transitions are occurring in a partially regulated environment, with investment and pricing requiring state Public Utility Commission (PUC) approval in some states but not in others. Even in restructured markets—which have undergone some deregulation—while investment into and exit out of generation are deregulated, decisions on the transmission and distribution of electricity and final consumer prices often still require PUC approval. This makes understanding the policies that facilitated (or hindered) the transition from coal to natural gas paramount.

This paper seeks to understand how the regulatory structure affects energy transitions.

In particular, we ask two key questions. First, how does regulation affect the rate at which electricity generation transitions to new technologies? Second, given the existing generation capacity at any point in time, how does regulation affect the use of different generators? To answer these questions, we develop and estimate a model of utility investment and usage under regulation. Our model has both long-run investment and exit and short-run operations components. In the long-run, the regulated utility decides on the amount of coal generation to retire and of natural gas generation to adopt. Within each year, however, the utility makes generation decisions given its investment decisions and exogenous fuel prices. We seek to understand how different regulatory structures would affect energy transitions—both from coal to natural gas generation and, looking forward, to renewable electricity generation.

To understand the current regulatory structure, we adapt the canonical model of regulation (Averch and Johnson, 1962, AJ). In the AJ model, the regulated utility is constrained to a maximum return on capital but can price as a monopolist given this constraint. This model is limited in the context of electricity, because electricity demand is highly inelastic implying that the AJ prices are infinite under many functional forms. Thus, our goal is to develop and estimate an updated model of electricity regulation that incorporates key specifics of this sector and that generates predictions that are in line with the observed data. To do this, we start with a model where, each period, regulators deem a set of capital owned by the utility to be effective, representing the "used and useful" standards that state PUCs typically employ. The regulator then reimburses the utility for marginal costs and allows it to earn a rate-of-return on its effective capital. This rate-of-return decreases in consumer electricity rates in order to incentivize the utility to lower costs. The utility chooses its generation and investment decisions to maximize profits in this regulatory environment.

Our model of regulation innovates relative to AJ in three dimensions. First, unlike AJ, the rate-of-return that the utility can earn is declining in the final consumer price of electricity. This both recognizes political economy constraints (Wilson, 2019; Hausman, 2019) and prevents the utility from charging arbitrarily high prices, which it could feasibly do under AJ's rate-of-return formulation by investing in an immense capital stock. Second, in order to model the used and useful standard, we assume that if the utility does not operate the

plant sufficiently, it will not receive the rate-of-return on the entire plant capital. This allows for regulation to potentially distort short-run operation decisions in addition to investment decisions, in particular leading to the overuse of old, inefficient generators (Daniel et al., 2020). Third, we adapt AJ to a dynamic setting in order to understand the role of regulation in the adoption of new technologies and in the retirement of existing capital.

**Literature:** This paper relates to three broad literatures. First, it builds on the theory of regulation. Beyond AJ, papers in this literature include Demsetz (1968); Posner (1974); Laffont and Tirole (1986), and Joskow (2007). Second, it extends the empirical literature on the impact of electricity regulation, which includes Fowlie (2010); Davis and Wolfram (2012); Cicala (2015, 2017); Abito et al. (2018); Lim and Yurukoglu (2018), and MacKay and Mercadal (2019). Finally, we contribute to the growing empirical literature on the dynamics of investment and exit in electricity markets, which includes Myatt (2017); Eisenberg (2019); Linn and McCormack (2019); Abito (2020); Zhang (2020), and Butters et al. (2021).

# 2 Model of Electricity Regulation

We consider a regulated utility whose role is to meet electricity load at every point in time. The regulated utility begins each year, $t$, with capacity for a number of different fuel/technology types, $f = 1, \ldots, F$, which are represented by $K_{ft}$. It uses this capacity together with electricity imports to meet load in each hour. We assume that load, $\ell_{th}$, varies across each hour, $h$, of each year, $t$, but that load in any hour is fixed. In other words, electricity demand is perfectly inelastic but varies at the hourly level. In each hour, the utility can meet load by a combination of electricity generated with each fuel type, $q_{fth}$, or by importing $q^m_{th}$ units of electricity from an interchange outside its service area. At the end of the year, the utility chooses new capacity investment and exit, $I_{ft}$ and $X_{ft}$ respectively, which determine next year's capacity, $K_{ft+1} = K_{ft} + I_{ft} - X_{ft}$.[1]

The regulator is faced with a natural monopoly and uses rate-of-return regulation. It sets

[1]Regulated utilities also provide transmission and distribution services, but this is not the focus of our study. See for example Lim and Yurukoglu (2018).

electricity prices each year to guarantee that the utility is limited in its maximum rate of return, $\bar{s}$. Let effective capital $K_t^e$, be the utility's year $t$ capital that the regulator deems "used and useful" (a concept we discuss below) measured in dollars and $TVC_t$ be total variable (generation and import) costs. We define the rate of return to be $s_t \equiv (Revenues_t - TVC_t)/K_t^e$. The regulatory constraint is, therefore, $s_t \leq \bar{s}$. We will assume that regulation is binding in equilibrium, so that $s_t = \bar{s}$.

Underlying the rate-of-return regulation is the idea that the regulator can observe and contract on some aspects of the utility's behavior but not others. On the one hand, the regulator must observe some utility costs to choose an appropriate electricity price. On the other hand, if the regulator could perfectly observe and contract on the utility's cost function, then it could simply dictate the utility's actions. We assume that the regulator can observe usage by generator, variable costs, and load—which are all fundamentally recorded on utilities' balance sheets—but cannot perfectly observe fixed costs, sunk costs, or the opportunity cost of capital.

Rate-of-return regulation ensures that the utility does not go out of business (because returns are "too low") or earn "excessive" returns. However, it does not ensure utilities have incentives to operate or invest efficiently.

We develop a model of a regulator that seeks to encourage the appropriate use of and investment in capital given inelastic demand. Beyond adding the regulated utility's investment and exit dynamics, our approach modifies AJ in two ways. First, in our setting, the regulator offers a lower rate of return, the higher the utility's variable costs relative to the variable costs in a baseline year.[2] This encourages the utility to use its existing generators efficiently—operating them from lowest to highest marginal cost—and incentivizes the utility to invest in low-variable-cost generators. Thus we write the maximum rate of return as a decreasing function: $\bar{s}(TVC_t/TVC_0) \equiv (TVC_t/TVC_0)^{-\gamma}$, where $\gamma > 0$. Second, the regulator adjusts effective capital based on a "used and useful" criterion, where generators' contribution to effective capital depends on their utilization.

The regulator needs both of these additional policy levers. The declining rate-of-return

[2]This declining rate of return is observed in other regulated sectors such as natural gas (Hausman, 2019).

lever prevents the utility from investing in (and using) capital with inefficiently high marginal costs. However, this lever alone does not prevent the utility from vastly overinvesting in capital. The used and useful lever directly addresses this issue by penalizing the utility for any underused generators. Still, on its own, it does not provide an incentive for the utility to invest in low-cost generators.

Focusing on the determinants of costs, total variable costs are the sum of variable costs across fuel and generator technology types, $f$, and imports. We let $f \in \{COL, CCNG, NCCNG\}$ represent coal, combined cycle natural gas, and non-combined cycle natural gas, respectively. And we represent the generation across all fuels and hours of the year, $q_{fth}$, and import quantities, $q^m_{th}$, across all hours of the year as $\vec{q}_t$. Thus, we define:

$$TVC_t(\vec{q}_t) = \sum_f \sum_h \left[ q_{fth}(heat_f \times p_{ft} + om_f) + \rho_f (q_{fth} - q_{fth-1})^2 + q^m_{th} \times S^m_{th}(q^m_{th}) \right]. \quad (1)$$

In equation (1), each fuel-technology type has a "heat rate," $heat_f$, and the utility pays a market price for fuel per MMBtu in each year, $p_{ft}$. Further, the utility must pay operation and maintenance (O&M) costs, $om_f$, per MWh of generation, and ramping costs, $\rho_f$, for each squared change in hourly generation. In practice, we assume that non-combined cycle natural gas plants do not have ramping costs, so $\rho_{NCCNG} = 0$. Finally, the utility is a monopsony purchaser of electricity imports, facing a supply curve $S^m_{th}(q^m_{th})$.

Across years, the utility incurs capital investment and exit costs. It pays an exit cost of $C^X_f + \sigma^X \varepsilon^X_{ft}$ per unit of the exiting capacity, $X_{ft}$, and an investment cost of $C^I_f + \sigma^I \varepsilon^I_{ft}$ per unit of new capacity, $I_{ft}$. The $\vec{\varepsilon}$ cost shocks are *i.i.d.* across exit or entry, fuel, and periods and are multiplied by the standard deviation parameters, $\sigma^X_f$ and $\sigma^I_f$. In practice, we will only model utilities as choosing whether to add natural gas combined cycle capacity and retire coal capacity. We observe a few instances of entry of large coal generators in the data but the decisions to undertake these investments largely occurred before our sample period.

Turning now to the used and useful standard, we assume that effective capital, $K^e_t$, is an aggregation of capital valuations across fuel and generator technology types, $f = 1, \ldots, F$. We let $f \in \{COL, CCNG, NCCNG\}$, represent coal, combined cycle natural gas, and non-

combined cycle natural gas respectively.

We assume that the used and useful standard only binds for coal generators. To model this, let $\overline{Q}_t^{COL}$ be the average hourly generation of coal, let $K^f$ be the total megawatts of capital of fuel-technology type $f$. We define effective capital as:

$$K_t^e \equiv \alpha \left[ \alpha^{CCNG} K^{CCNG} + \alpha^{NCCNG} K^{NCCNG} + \left( \alpha^{COL} + b \frac{\overline{Q}^{COL}}{K^{COL}} \right) K^{COL} \right]. \tag{2}$$

In equation (2), $\alpha^{CCNG}$ and $\alpha^{NCCNG}$ are the relative contributions of these fuel-technology types to effective capital. The parameter $\alpha^{COL}$ indicates the contribution of coal capacity to effective capital if coal were completely unused, while $\alpha^{COL} + b$ is the contribution if it were fully used. Finally, the parameter $\alpha$ converts these relative capital levels into dollars of effective capital. We normalize $\alpha^{CCNG} = 1$ such that $\alpha$ can be interpreted as the effective capital (in dollars) of one MW of combined cycle natural gas capacity.

The utility's variable profit in each year is:

$$\pi^V(\vec{q}_t) = Revenues(\vec{q}_t) - TVC(\vec{q}_t). \tag{3}$$

In equilibrium, the utility obtains its maximum allowable rate of return and, thus, $Revenues(\vec{q}_t) = \overline{s} K_t^e + TVC(\vec{q}_t)$.

We can split the optimization decision for the utility into investment/exit decisions and operations decisions. Focusing first on operations decisions, we assume that the utility observes load and the import supply curve for every hour of the year before it makes its operations decisions, $\vec{q}_t$, to maximize variable profits over the year subject to meeting load and satisfying regulatory constraints. Because ramping costs and used and useful considerations connect generation decisions across hours, the utility solves for the full vector of generation and import decisions, $\vec{q}_t$ given its capacities, $K_1, \ldots, K_F$ and fuel prices, $p_1, \ldots, p_F$. We denote the utility's expected variable profits given these state variables as $\pi^{V*}(K_1, \ldots, K_F, p_1, \ldots, p_F)$.

The utility makes investment and exit decisions to maximize the constrained expected discounted long-run sum of these operating profits net of investment and exit costs. In

practice, we will only model utilities as choosing whether to add natural gas combined cycle capacity and retire coal capacity since these are the overwhelming majority of entry and exit observed during our sample period.[3]

The utility's Bellman equation for its investment and exit decisions is:

$$\begin{aligned} V(K_1,\ldots,K_F,p_1,\ldots,p_F,\vec{\varepsilon}) &= \pi^{V*}(K_1,\ldots,K_F,p_1,\ldots,p_F) \\ &+\max_{I_f,X_f}\{-\sum_{f=1}^{F}\left((C_f^I+\sigma^I\varepsilon_f^I)I_f+(C_f^X+\sigma^X\varepsilon_f^X)X_f\right) \\ +\beta\int EV[K_1+I_1-X_1,\ldots,K_F+I_F-X_F,p_1',\ldots,p_F']dg(p'|p)\}, \end{aligned} \tag{4}$$

where $EV$ is the expectation of the value function, integrating over the $\vec{\varepsilon}$ cost shocks, and $g(p'|p)$ is the conditional density of the next period's fuel prices. Equation (4) shows that the utility can adjust its next period's capital deterministically but is faced with a stochastic evolution of fuel prices and cost shocks.

Regulation in our model thus creates multiple inefficiencies. First, utilities may operate generators out of dispatch order to increase their effective capital. We expect this to be a particular concern for utilities that operate older coal generators rendered economically inefficient by the decrease in the marginal cost of generating electricity with natural gas. Second, our model incorporates the standard concerns that rate-based regulations will distort the utility's incentives to invest in capital. Estimating our model will allow us to quantify these distortions.

# 3 Data

The data we use includes state, utility, and generator information. Our main estimation sample extends from 2006 to 2018, though some datasets start earlier. At the state level, we use data on regulatory status, fuel prices, electricity import prices, and weather. We follow Cicala (2017) in our definitions of electricity regulatory status. We combine these data with

[3]While we observe a few instances of entry of coal generators in the data, the decision to undertake these investments largely occurred before our sample period.

coal and gas contract fuel prices from the Energy Information Administration (EIA). We average these contract prices to the state-month level to generate a measure of the likely marginal cost of fuel. We also generate an import price for each hour at the state level for each regulated state by finding the nearest restructured interchange and using the market price at that interchange. Finally, we use data on average daily temperatures at the state level based on the PRISM data as downloaded from Prof. Wolfram Schlenker's website, which we use to construct electricity import supply curves.

At the utility level, we use the Federal Energy Regulatory Commission (FERC) form 714 data. These data include the hourly load for each load-serving entity. We merge these data with EIA form 861 data on utilities' annual revenues and state service territories using the EIA utility identifier provided in the FERC data.

Finally, at the generator level, we use three datasets. First, we use annual data from EIA form 860 on the capacity, fuel type, and utility that owns the generator. Second, EIA form 923 provides the annual heat rate data. Finally, we merge these two datasets with data from the EPA's Continuous Emissions Monitoring System (CEMS) database on the hourly generation for each generator.

Most of these elements enter directly into our model. However, we do not directly observe the import quantities for each utility-hour. We construct this variable by subtracting the total quantity generated from the hourly load.

# 4 Reduced Form Evidence

We now present reduced-form evidence that illustrates the identification of the structural model and motivates its specification, using data from the Eastern Interconnection of the U.S. We first provide support for our assumption that the regulator permits lower rates of return when variable costs relative to the base year are higher and then for our assumption that the effective capital depends on whether the capital is used and useful. Finally, we provide evidence on entry and exit.

**Determinants of the allowable rate of return:** In order to understand whether the

regulator adjusts the maximum allowable rate of return, $\bar{s}$, as $TVC_t/TVC_0$ changes, we regress the observed rate of return on measures of $TVC_t/TVC_0$. We construct total variable generation and import costs using heat rate and fuel price data from EIA and calculating import costs following Bushnell et al. (2008). Ideally, we would directly measure the observed rate of return as equal to the allowable rate of return, so $\bar{s} = (Revenues(\vec{q}_t) - TVC(\vec{q}_t))/K_t^e$, at the utility's profit maximizing choice of $\vec{q}_t$.

The central issue with this approach is how to measure $K_t^e$ and $TVC_t$. There are at least two important measurement concerns. First, we do not observe effective capital, $K_t^e$, directly in the data. One substitute for the effective capital is to measure the utility's actual generation capital by summing the MWs of capacity across different fuel-technology types. However, the dollar cost of capital will vary across and within types—because of different capital costs and depreciation—implying that this does not appropriately capture the value of a utility's capital. In addition, this measure does not incorporate the fact that the regulator may decrease effective capital if it does not deem some generators to be used and useful.

Second, we also only observe the variable generation and import costs, and do not observe other variable costs such as those for transmission and distribution. This is problematic because utilities may have underlying differences in these variable costs. For instance, utilities that serve a large geographic area may have higher marginal transmission costs. These extra variable costs are an omitted variable that varies across utilities and may lead to biased estimates of the effect of $TVC_t/TVC_0$ on the maximum allowable rate of return.

Thus, to motivate our assumption that the regulator permits lower rates of return when $TVC_t/TVC_0$ is high, we construct measures of $s_t$ using revenues minus $TVC_t$ divided by two different proxies for effective capital $K^e$: (1) total period load and (2) total MWs of capacity. The structural model directly specifies the determinants of the rate base, so these measures serve to provide evidence on its underlying identification. Further, we take two approaches to controlling for the omitted variable bias. We run the regressions with utility fixed effects—which are difficult to incorporate into a structural model—and with both the dependent and independent variables differenced from their average in an initial set of years. The fracking boom provides substantial within-utility variation in costs that will help identify

these specifications. We also report results without fixed effects or differencing.

Table 1 presents the results of these 6 regressions. For ROR defined with load, the coefficient on $TVC_t/load$ in the regression without fixed effects or differencing is not statistically significant. Once we add utility fixed effects, $TVC_t/K_t^e$ has a negative association with ROR that is highly statistically significant, using both definitions. The results that difference total variable costs from the first year of the data show similar patterns to the results with fixed effects, and are more directly tied to the identification of our structural estimates.

**Determinants of the effective capital, $K_t^e$:** Beyond the determinants of $\bar{s}$, we also motivate our assumption that generators must be used and useful to be included in the measure of effective capital. In principle, we could observe these incentives by evaluating whether utilities operate generators in hours when operation would be uneconomical in the absence of regulatory constraints, and in particular for generators where operation would be pivotal in convincing the regulator that the generator is used and useful, such as coal generators in the post-fracking era. Because of complex issues in generator scheduling, such as ramping costs and operations and maintenance costs, we identify the used and useful effect by comparing the scheduling of generators in regulated markets to restructured markets. This allows us to tie this potential out-of-dispatch-order generation to the presence of regulation. Thus, we examine the likelihood of coal generators operating when wholesale electricity prices are low relative to the generator's marginal fuel costs, and compare this between regulated and restructured markets. We also examine whether this likelihood varies with generator usage in the previous year.

We therefore run regressions at the generator-hour level of whether a generator is operating on an indicator variable for the generator's marginal cost being above wholesale price and this indicator interacted with whether the generator is in a restructured state, controlling for state and year fixed effects.[4] Because there are no wholesale markets in regulated states, we recover the effective wholesale price using the closest market price from a restructured state, which proxies for the price the utility pays for imports. Since our structural model

[4]Regulatory status is completely determined by state during our sample years, so we do not include a separate control for regulatory status.

Table 1: Regressions of Rate of Return on Total Variable Cost per Effective Capital

| | ROR: Variable Profit Over Load | | | ROR: Variable Profit Over MW Capacity | | |
|---|---|---|---|---|---|---|
| | ROR | ROR | ΔROR | ROR | ROR | ΔROR |
| $TVC$/load | −0.014 | −0.693*** | | | | |
| | (0.102) | (0.044) | | | | |
| $\Delta TVC$/load | | | −0.528*** | | | |
| | | | (0.050) | | | |
| $TVC$/capacity | | | | −0.090* | −0.466*** | |
| | | | | (0.054) | (0.045) | |
| $\Delta TVC$/capacity | | | | | | −0.384*** |
| | | | | | | (0.047) |
| Utility FE | N | Y | N | N | Y | N |
| $R^2$ | 0.000 | 0.948 | 0.240 | 0.008 | 0.941 | 0.162 |
| N | 352 | 351 | 352 | 340 | 339 | 340 |

Note: the Δ symbol represents the difference between the variable in the current year and initial year, 2006. *** indicates significance at the 1% level and * indicates significance at the 10% level.

aggregates generators by fuel-technology types, we also run our regressions at this level.

Table 2 shows the results of these regressions for both coal and combined cycle natural gas generators. Focusing first on the generator-level regressions, column 1 shows that coal generators in regulated states are 7.8 percentage points less likely to operate when their marginal fuel costs exceed the wholesale price. This effect is 6.0 percentage points larger in restructured markets, although the difference is not statistically significant. Column 2 shows that the differential usage between regulated and restructured states is not present for combined cycle natural gas generators. The fact that the used and useful standards appear to bind for coal generators fits with coal generators becoming uneconomical in many instances due to the fracking boom. In contrast, combined cycle natural gas generators are unlikely to be on the margin for used and useful standards in the post-fracking era.

Figure 1 provides further graphical evidence on utilization by fuel-technology type in regulated versus restructured markets. Panel (a) shows that the difference in utilization between regulated and restructured markets in periods when $MC > P$ is highest when coal

Table 2: Generator Use and Used and Useful Standards

| | 𝟙{Generator Operating} | | 𝟙{Fuel-Technology Operating} | |
|---|---|---|---|---|
| | Coal | Combined Cycle Natural Gas | Coal | Combined Cycle Natural Gas |
| 𝟙{MC > price} | $-0.078^{***}$ | $-0.197^{***}$ | $-0.032$ | $-0.203^{***}$ |
| | (0.021) | (0.028) | (0.031) | (0.030) |
| 𝟙{MC > price}× | $-0.060$ | $-0.002$ | $-0.122^{**}$ | 0.004 |
| Restructured | (0.042) | (0.027) | (0.050) | (0.029) |
| $R^2$ | 0.059 | 0.124 | 0.089 | 0.132 |
| N | 34,780,519 | 24,280,694 | 19,782,462 | 20,723,458 |

Note: Regressions are linear probability models that include state and year fixed effects. Standard errors are clustered at the state and year level. *** indicates significance at the 1% level and ** indicates significance at the 5% level.

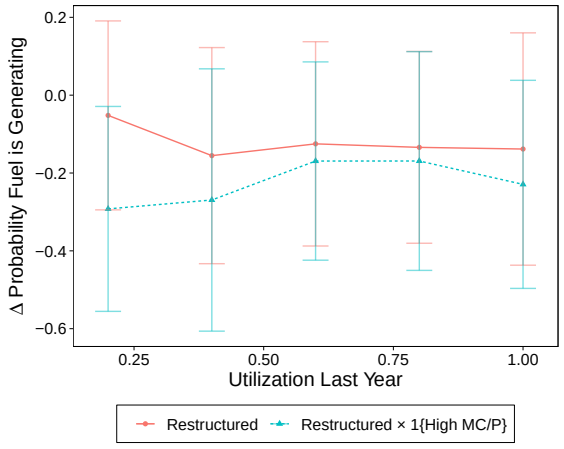
generators are used in fewer than 40% of the hours in the previous year. This suggests that utilities in regulated markets are concerned about having lower effective capital when their coal utilization falls below this threshold. This threshold in turn informs our structural modeling of the used and useful standard.

Panel (b) presents the differential usage when $MC > P$ by state for both coal and natural gas generators. The seven states with the lowest differential coal utilization—which are at the bottom of the graph—are all regulated states. In contrast, there is no clear differential usage pattern for gas generators. This reinforces the idea that regulatory status dramatically impacts utilization for expensive, older technologies. The heterogeneity across restructured states is also consistent with different extents of deregulation across these states, with CT, NH, DE, and NY displaying the least out-of-dispatch-order generation by coal plants, perhaps because they are the most deregulated.

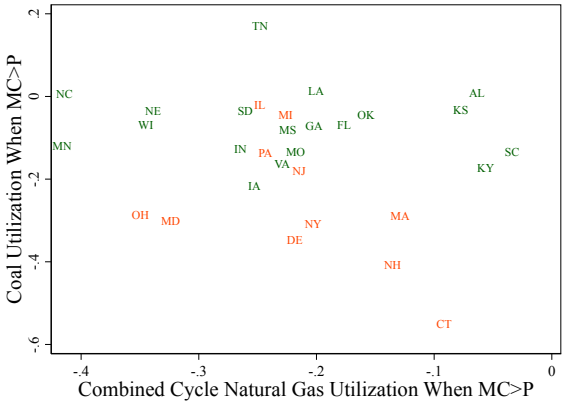
**Determinants of entry and exit rates:** We also investigate whether the same forces discussed above have led to differential exit rates for coal generators in regulated markets. In the entire U.S. between 2006 and 2018, 19.7% of coal capacity exited the market in regulated states, whereas 30.3% exited in restructured states. This suggests that regulated utilities are responding to regulatory incentives not just by overusing coal generators but

Figure 1: Utilization When $MC > P$ in Regulated Versus Restructured Markets

(a) Restructured Usage by Prior Utilization




(b) Utilization When $MC > P$ by State




Note: Panel (a) shows results from a regression of whether a fuel is generating on a spline of last year's utilization, and the spline interacted with indicators for restructured, $MC > P$, and both. The red solid line shows the probability of generation in restructured relative to regulated markets, and the blue dotted line shows the probability of generation in restructured markets when $MC > P$. The error bars show 90% confidence intervals calculated with the delta method. Panel (b) shows coal and gas extra utilization when $MC > P$ by state. Green states are regulated and red states are restructured.

also by keeping them in operation longer. In contrast, regulated utilities have a higher entry rate for combined cycle natural gas generators—47.7% additional capacity versus 37.5% in restructured markets—which is consistent with AJ's result that regulated utilities over-invest in capital to increase their effective capital.

# 5 Estimation Approach

Our model developed in Section 2 is dependent on structural parameters that specify the regulator's rate-of-return function and standards for generators being used and useful, and generators' ramping and O&M costs, import supply curves, and investment and exit cost distributions. We estimate investment and exit cost parameters with a nested fixed-point dynamic estimation, using the utility's state-contingent investment in gas generation and retirement of coal generation as the dependent variables. Within the operations model, we estimate import supply curve parameters with an instrumental variables approach that follows the literature. We calibrate O&M parameters from the literature. We estimate the remaining parameters of our model by solving for utilities' optimizing operations decisions and resulting revenues within a year, and matching these elements to data with an indirect inference approach. We now focus on our estimation for each of these parameters, and finish with a discussion on identification.

## 5.1 Investment and Exit Cost Parameters

As we explained in Section 2, the utility makes investment and exit decisions to maximize its constrained expected discounted sum of operating profits net of investment and exit costs, with the Bellman equation for these decisions in equation (4). We estimate the structural parameters of this model—mean investment and exit costs and the standard deviation of investment and exit cost shocks—with a full solution nested-fixed point method.

Specifically, we will assume that fossil fuel investments operate for 30 years. At each capacity and fuel price state we solve for generator optimizing decision of whether to invest in gas generation and/or retire coal generation and then find the vector of structural parameters

that maximizes the simulated likelihood of the observed actions of investment and exit. These methods are quite tractable in our setting since the utility optimizes as a single agent playing against a fixed regulatory structure.

Note: The estimation of dynamic parameters is in progress.

## 5.2 Import Supply Curve and O&M Parameters

Within each year, the utility needs to make operations decisions to maximize profits, conditional on its capacity and fuel price state. The utility takes this state, as well as hourly load and each hour's import supply curve, as given. While load is observed in the data, we estimate import supply curves following Bushnell et al. (2008), Gowrisankaran et al. (2016), and Reguant (2019). Specifically, we regress the quantity of electricity imported into the utility on the import price, controlling for weather in the exporting region with heating and cooling degree days and their squares in each state in the exporting region. We instrument for import price in these regressions with the local electricity demand for the regulated utility.

We also assume that O&M costs for each fuel-technology type are known and fixed. We take estimates of these costs from the literature (e.g. Linn and McCormack, 2019), and assume that O&M costs are 15, 5, and 10 for coal, combined-cycle natural gas, and non-combined-cycle natural gas, respectively in dollars per MWh of generation.

## 5.3 Operations Model Parameters

The remaining parameters that we need to estimate are $\gamma$, which is how the rate of return changes with variable costs; $\alpha^{COL}$, $\alpha^{NGGNC}$, which convert MWs of installed capacity into relative MWs of capacity (relative to CCNG capacity, for which we normalized $\alpha^{NGGNC} = 1$; $\alpha$, which converts MWs of CCNG capacity into dollars; $b$, which measures the slope of the used and useful criterion for coal generation; and $\rho^{COL}$, $\rho^{CCNG}$, which are ramping parameters by fuel. We estimate these parameters with an indirect inference approach (Gourieroux et al., 1993). The idea behind indirect inference is that we would like to recover coefficient estimates that allow our model to simulate data that matches correlations in the observed

data.

While indirect inference is a form of generalized method of moments, it allows us to specify which correlations in the data we would most like to match. We choose correlations similar to the reduced-form evidence presented in Section 4. Note that we do not need a causal interpretation of our indirect inference coefficients since we replicate relationships in the data rather than directly estimating the structural parameters. Hence, we employ different specifications from the reduced-form evidence.

The key concern with indirect inference is to choose correlations in the observed data that capture the variation induced by utility optimizing behavior vis-à-vis the regulatory structure. We run ten indirect inference regressions, which we summarize here and provide additional details in On-line Appendix A.

Four of these are regressions on a constant term, meant to capture the scale of parameters. Specifically, we run a regression for each fuel (coal, combined-cycle natural gas, and non-combined-cycle natural gas) of hourly utilization (generation divided by capacity) on a constant. We use utilization instead of generation in levels because of the vast differences in the scale of utilities for different fuels.

The fifth indirect inference regression captures how allowable rates of return vary with utilities' total variable costs. While we do not observe the maximum allowable rate of return, $\overline{s}$, a transformation of equation (3) gives us that $\overline{s}_t K^e = Revenues_t - TVC_t$, and we do observe revenues, total variable costs, and capacities. The concern is then that effective capital, as defined in equation (2), depends upon both used and useful considerations and the value of MW of capacity as expressed in dollars. We, therefore, run a regression of revenues net of total variable costs divided by total MW of capacity on total variable costs and utility fixed effects. This is effectively a regression of the rate of return, with MW of capacity proxying for effective capital.

While this regression controls for utility fixed effects to account for differences in base year total variable costs, $TVC_0$, we do not match these coefficients with indirect inference and instead focus only on matching the coefficient on total variable costs. We view these fixed effects as capturing features that are outside of our model, such as, for instance, high

transmission costs for utilities where customers are spread out.

Our sixth regression aims to understand how capacity is valued directly, via the $\alpha$ parameters. This regression complements our fifth regression, which uses a proxy for effective capital. In particular, our sixth regression is of total variable profits, $Revenue_t - TVC_t$ on coal capacity, coal capacity interacted with coal utilization, combined-cycle natural gas capacity, and non-combined cycle natural gas capacity.[5] One key point to note here is that $\alpha$, the conversion of MW of combined-cycle natural gas capacity into dollars of effective capital, does not affect the operation decisions conditional on fuel-technology capacities, which are fixed within a year. However, $\alpha$ does affect overall revenues (and therefore profits), so the identification of $\alpha$ largely comes from the scale regressions.

The seventh and eighth regression are intended to capture utilities' incentives to have the regulator regard coal capacity as used and useful. The basic objective of these regressions is to understand whether coal and combined-cycle natural gas have different incentives to increase generation when total utilization of that fuel-technology's capacity is low. The key endogeneity concern here is that whether a utility uses a particular fuel-technology type in a given hour will be connected to its overall utilization of that fuel-technology type via omitted variables. We therefore look at hours where a utility is likely to be considering a combination of both coal and combined-cycle natural gas generation.

Specifically, for the seventh regression, we calculate the log of the share of total generation from coal and combined-cycle natural gas that is met by coal (following Berry, 1994). We then look at hours where total load is between 75% and 125% of total combined cycle natural gas capacity, so that the utility is likely to generate with a combination of fuels. For these hours, we regress our logged coal share on quintiles of annual coal utilization, the coal price per MMBtu minus the natural gas price per MMBtu, their interactions, and utility fixed

[5]Relative to the fifth indirect inference regression, this specification does not control for variation in $TVC$. Therefore, the coefficients can be interpreted as incorporating both the $\alpha$ and the $TVC$ terms. We explicitly do not account for utility fixed effects in this regression because the variation in total capacity for each fuel-technology type is somewhat limited within utilities. While this means that variation in the coefficients in this regression comes largely from the cross-section, it also accounts for the fact that utilities with larger capacities need larger payments to finance that capacity.

effects.[6] Identification of the utilization quartile coefficients therefore comes from variation over time within a utility in the coal utilization.

Our eighth regression is similar, but examines the extra use of gas generation in a similar window to the above. Here, we run a similar regression for the log of the combined-cycle natural gas generation share, but for hours where load is between 75% and 125% of coal capacity. From these two regressions, we match the coefficients on the first through fourth quintile of utilization. This regression is meant as a falsification, since we do not expect gas capacity to be subject to the used and useful standard.

Finally, the ninth and tenth regressions relate to the ramping costs for both coal and combined-cycle natural gas capacity. The intuition behind these regressions follows from Gowrisankaran et al. (2022), where ramping costs are identified by comparing hours where continuation values given generation decisions are very similar, but past generation values may differ. Specifically, we run two regressions, one for coal and one for combined-cycle natural gas, where the dependent variable is hourly utilization (the share of capacity that is generating) and the independent variables are the hourly generation from the previous hour, coal and gas fuel prices, and six hourly future values of load, the import intercept, and the electricity price. Our indirect inference approach only matches the coefficient on lagged generation in each regression to the results generated from the model.

To implement our indirect inference estimation approach, we begin by estimating these ten regressions in our data and recovering the coefficient and their standard errors. We then choose a candidate parameter vector and solve the operations model to generate data for each utility and year. We use these simulated data to run the same regressions and recover the coefficients and standard errors of interest. Finally, we search over parameter values using a non-linear search for the vector of values that best matches the coefficients and standard errors across the two sets.

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 on the variance-covariance matrix of the regressions on the actual data above, where all regressions

[6] We define the quintiles of utilization across all utility-years where the utility has positive coal capacity.

are clustered at the utility level, and the hourly regressions are also clustered at the month-of-year and hour-of-day. We assume that there is no covariance across regressions.

## 5.4 Identification

Identification of the model follows from the intuition that changing fuel prices change utilities' incentives to retire and invest in new technologies and generate using different fuels, and that these incentives will vary across utilities. The fracking boom in the U.S. had led to substantial changes in the dispatch order by 2010, with combined cycle natural gas generators becoming less expensive than coal generators. This variation in fuel prices combines with differences in utilities' fuel-technology capacity investments before the fracking boom to allow us to understand how utilities trade off decreasing total variable costs—by running their least expensive fuel-technology capacities—versus using coal enough to guarantee that the regulator considers coal capacity used and useful.

Imagine a utility with a mix of coal and combined cycle natural gas capacity. Early in our sample, when natural gas prices were high, this utility would have generated with coal first, and only use natural gas when electricity demand is high. After natural gas prices fell, the utility faced conflicting incentives: it wanted to run natural gas generators in order to keep total fuel costs low and be allowed a higher $\overline{s}$, but it also wanted to continue sufficiently using—and not retire—coal generators to increase its effective capital. Thus changes in fuel prices differentially affect utilities with different types of initial capacity, marginal costs by fuel-technology, and import costs, which helps identify the parameters that determine operation and retirement decisions.

Finally, the extent to which utilities choose to continue operating coal capacity given differences in expected profits with lower levels of coal capacity identifies the average exit costs for coal. The extent to which utilities choose to delay entry for combined-cycle natural gas—even when profits are potentially higher with additional natural gas capacity, which can reduce total variable costs—identifies the average investment costs for combined-cycle natural gas. The extent to which there is heterogeneity in differences in profit with investment

or exit across utilities who choose to invest or exit identifies the standard deviation of the investment and exit cost shocks, respectively.

# 6 Results

## 6.1 Operations Model Results

Table 3 presents the indirect inference regression coefficient estimates from the data and from the model simulated using the estimated structural parameters. Table 4 presents preliminary structural parameter estimates for the operations model. For our preliminary results, we use a subsample of 26 weeks for each utility/year in the data.

The first three indirect inference regressions seek to match the levels of coal, CCNG, and NCCNG utilization, respectively. Our preliminary structural parameter estimates overstate coal utilization, reporting that coal is used 94.4% of the time, while the usage is 52.1% in the actual data, and understate CCNG utilization, with 11.6% utilization versus 35.7% in the actual data. Because of these results, we plan to improve the operations model to improve power plant decisions. We will also consider modifying our model to cap the return on coal utilization at some level of utilization. Our structural parameter estimates fit NCCNG utilization very closely.

Our fourth indirect inference regression matches the level of utility revenues. The model predicts that average utility-year revenues are 1.2 billion dollars, while the average is 875 million in the data. The fifth indirect inference regression matches the relationship between total variable costs and a proxy for the maximum allowable rate of return. The model and data match this relationship very closely, with coefficients of 0.028 in both cases. These two regressions help us identify the structural parameter estimate of $\gamma$, the rate-of-return penalty from having high total variable costs. From Table 4, we find that $\gamma = 0.724$.

The sixth indirect inference regression relates realized variable profits ($Revenue_t - TVC_t$) to fuel-technology capacities and coal capacity interacted with utilization. For most coefficients, the model and the data are quite close. In particular, the model and data both predict

Table 3: Indirect Inference Coefficient Matching

| Reg # | Dependent Variable | Regressor | Actual Data | Simulated Data |
|---|---|---|---|---|
| 1-3 | Utilization Levels: | | | |
| | Coal | Constant | 0.521 (0.032) | 0.944 (0.079) |
| | CCNG | Constant | 0.357 (0.040) | 0.116 (0.032) |
| | NCCNG | Constant | 0.082 (0.023) | 0.083 (0.015) |
| 4 | Utility Revenue Level: | | | |
| | | Constant | 874.789 (350.86) | 1223.9 (423.43) |
| 5 | $\overline{s}$ proxy: $(Revenue_t - TVC_t)/\sum_f K_f$ | | | |
| | | Total Variable Cost | -0.0282 (7.26e-3) | -0.0283 (1.68e-3) |
| 6 | Variable Profits: $Revenue_t - TVC_t$ | | | |
| | | Coal Capacity (MW) | -0.381 (0.268) | -0.398 (0.215) |
| | | Coal Capacity × Utilization | 0.651 (0.279) | 0.651 (0.231) |
| | | CCNG Capacity | 0.259 (0.024) | 0.257 (0.07) |
| | | NCCNG Capacity | 0.097 (0.210) | 1.219 (0.69) |
| 7 | Log Coal Share: | | | |
| | | First Quantile Coal | 0.083 (0.422) | 0.000 (0.00) |
| | | Second Quantile Coal | 1.587 (0.447) | 2.609 (0.331) |
| | | Third Quantile Coal | 1.610 (0.397) | -0.353 (0.147) |
| | | Fourth Quantile Coal | 1.223 (0.121) | -0.250 (0.078) |
| 8 | Log CCNG Share: | | | |
| | | First Quantile CCNG | -2.361 (0.355) | 0.000 (0.00) |
| | | Second Quantile CCNG | -1.069 (0.243) | -0.463 (0.147) |
| | | Third Quantile CCNG | -0.3875 (0.185) | -0.289 (0.098) |
| | | Fourth Quantile CCNG | 0.090 (0.217) | -0.231 (0.069) |
| 9-10 | Ramping: | | | |
| | Coal Utilization | Lagged Coal Utilization | 0.978 (0.003) | 0.966 (0.002) |
| | CCNG Utilization | Lagged CCNG Utilization | 0.971 (0.006) | 0.970 (0.003) |

Note:

Table 4: Structural Parameter Results

| Parameter | Notation | Value |
|---|---|---|
| Penalty for High $TVC_t$ | $\gamma$ | 0.7235 |
| Coal Capacity Contribution to Effective Capital | $\alpha^{Coal}$ | $-0.4598$ |
| NCCNG Capacity Contribution to Effective Capital | $\alpha^{NCCNG}$ | 0.0048 |
| Dollars of Effective Capital per MW of CCNG Capacity | $\alpha$ | 187.2091 |
| Benefit of Coal Utilization | $b$ | 2.2594 |
| Ramping Cost for Coal | $\rho^{Coal}$ | 16.1723 |
| Ramping Cost for CCNG | $\rho^{CCNG}$ | 0.0432 |

that coal capacity would have a negative impact on realized variable profits for the regulated utility if we extrapolate to zero coal utilization, with values of $-0.38$ and $-0.40$ in the data and model respectively. The slope of profits with respect to coal utilization are also similar for the model and the data, at 0.65 in both cases. These two values help to identify both the contribution of coal to effective capital at zero utilization, $\alpha^{COL}$ and the benefit of increasing coal utilization, $b$. We recover a structural parameter estimate of $-0.46$ for $\alpha^{COL}$ and of 2.26 for $b$. This suggests that utilities need keep coal utilization above 20% in order to have coal contribute positively to effective capital.

The model and data also generate very similar coefficients of 0.26 for the relationship between CCNG capacity and variable profits. This relationship help identify the $\alpha$ structural parameter, which converts MW of CCNG capacity into dollars of effective capital. Recall that we have normalized $\alpha^{CCNG}$ to one. We estimate a structural $\alpha$ parameter of 187.21, suggesting that each MW of CCNG capacity—or the comparable amount of coal or non-combined-cycle natural gas capacity—will generate \$187 million in additional effective capital for the utility. Finally, the sixth indirect inference equation also relates NCCNG capacity to variable profits. This relationship is not particularly well fit in the current specification, with a coefficient of 1.22 for the model relative to a coefficient of 0.10 in the data. We estimate a related $\alpha^{NCCNG}$ structural parameter of 0.005.

Comparing the three $\alpha^f$ coefficients is informative about the relative contributions of capacity using each fuel-technology type. Relative to $\alpha^{CCNG} = 1$, coal needs to be used 65% of the time to make the same contribution to variable profits per unit of capacity. This result likely stems from the fact that coal plants tend to be older than combined-cycle natural gas plants, which would mean that more of their initial capital has already depreciated and therefore requires lower capital reimbursement each year.

Indirect inference regressions seven and eight relate the share of coal and combined-cycle natural gas generation that comes from each fuel to quantiles of the utilization of that fuel over the year. These regressions further help to identify the extent to which used and useful changes the incentive to generate electricity with coal, the structural parameter $b$ discussed above. Currently, the model is not fitting these correlations particularly well. Since we only run the coal regression for hours of the year where load is close (75%-125%) to the NGCC's capacity (and vice versa), we do not have any hours in our 26-hour sample that fit this criterion for utilities with coal or natural gas utilization in the lowest quintile.

Finally, the ninth and tenth indirect inference regressions relate hourly coal and natural gas utilization to lagged utilization. The model matches the data correlations quite well, with coal coefficients of 0.98 and 0.97 for the data and model, respectively. For combined-cycle natural gas the coefficients are 0.97 for both the data and model. These regressions help to identify the ramping cost structural parameters, $\rho^{COL}$ and $\rho^{CCNG}$. We estimate that $\rho^{COL} = 16.17$ and $\rho^{CCNG} = 0.04$, which reflects the well-established fact that ramping costs are substantially higher for coal than for combined-cycle natural gas.

## 6.2 Counterfactuals

Table 5 presents a preliminary assessment of the importance of the used and useful parameter $b$ in our model. The first column presents some key average values of data simulated from our baseline model. We include production by major fuel sources and imports, utilization by these fuels, and the major sources of utilities' costs. The second column replaces the $b$ parameter in our model with one-half its estimated value. It also adjusts the $\alpha^{COL}$ parameter

so that at the mean coal utilization in the data, the contribution of coal capacity to effective capital is the same as in our baseline model. This gives utilities half as much marginal incentive to use coal capacity while maintaining average incentives.

With the used and useful incentive halved, we find that coal generation decreases by 5.1 percent, CCNG generation increases by 3.2 percent, and imports increase by 27.2 percent. This suggests that the used and useful standard is leading to an increase in coal use. Further, we find that when this marginal incentive is reduced, the utility mostly substitutes for decreased coal production with relatively inexpensive imports from other utilities. The average annual total variable cost declines 4.8 percent when the used and useful incentive is cut in half.

The final column of Table 5 doubles the incentive to increase coal utilization, again leaving coal's contribution to effective capital the same at the average utilization rate at the data. Unsurprisingly, we find that coal generation increases (2.7%), combined-cycle natural gas generation decreases (0.2%), imports decrease (14.9%), and total variable costs increase (4.0%) relative to the baseline. These changes are less substantial than the difference between the baseline and the case where the used and useful incentive is halved because coal is approaching full utilization, so there is relatively little additional margin for adjustment.

### 6.3 Investment and Exit Model Results

IN PROGRESS

## 7 Conclusion

In this paper we investigate how the electric utility regulation framework affected the energy transition from coal generation to natural gas generation. To do this, we extend the canonical model of Averch and Johnson (1962) to incorporate regulator disutility for high costs, incentives for utilities to assure that capital is "used and useful," and dynamic capital investment decisions.

Table 5: Counterfactual Simulations

| Fuel type | Baseline | Half U&U | Double U&U |
|---|---|---|---|
| Mean Annual Electricity Production (GWh): | | | |
| Coal | 16908.3 | 16043.3 | 17368.2 |
| CCNG | 882.4 | 910.7 | 880.4 |
| Imports | 2613.9 | 3325.1 | 2225.1 |
| Mean Utilization Share: | | | |
| Coal | 0.94 | 0.88 | 0.97 |
| CCNG | 0.11 | 0.11 | 0.10 |
| Mean Annual Variable Costs (Millions of Dollars): | | | |
| Total | 1513.7 | 1441.4 | 1574.7 |
| Coal Fuel Costs | 870.4 | 824.2 | 894.4 |
| Coal Ramp Costs | 1.26 | 2.23 | 0.65 |
| Coal O&M Costs | 516.9 | 490.5 | 531.0 |
| CCNG Fuel Costs | 54.16 | 55.35 | 54.0 |
| CCNG O&M Costs | 9.0 | 9.3 | 8.98 |
| Import Costs | 265.52 | 252.75 | 294.82 |
| Profits (Millions of Dollars): | | | |
| | 6.59 | 5.29 | 9.30 |

Note: Authors' simulations from estimated model. Baseline column presents model values at estimated parameters and other columns present model values at counterfactual parameters that change utilities' used and useful incentives for coal utilization.

We find evidence that regulators reduce utilities' allowable rate of return when costs increase. We also find that utilities make generation decisions that are consistent with higher coal utilization increasing their profits. The combination of these two factors creates a tension where utilities would like to generate with (higher marginal cost) coal generators in order to increase coal capacity's contribution to effective capital, but also would like to keep fuel and ramping costs low. If the regulatory framework were altered to reduce the marginal incentive to use coal capacity by 50%, total variable costs go down by 4.8% but profits also decrease by 19.7%.

In ongoing work, we will estimate the investment costs of combined-cycle natural gas capacity and the exit cost for coal capacity. This will allow us to more fully capture the effect of this regulatory structure on industry investments and emissions over the medium run. We also plan on simulating counterfactual scenarios for the on-going transition from combined-cycle natural gas to renewable electricity generation in order to understand how regulation affects the pace of this important energy transition.

# References


Abito, J. M. (2020). Measuring the welfare gains from optimal incentive regulation. *The Review of Economic Studies 87*(5), 2019–2048.

Abito, J.-M., C. R. Knittel, K. Metaxoglou, and A. Trindade (2018). Coordinating separate markets for externalities. Technical report, National Bureau of Economic Research.

Averch, H. and L. L. Johnson (1962). Behavior of the firm under regulatory constraint. *The American Economic Review 52*(5), 1052–1069.

Berry, S. (1994). Estimating discrete choice models of product differentiation. *RAND Journal of Economics 25*, 242–262.

Bushnell, J. B., E. T. Mansur, and C. Saravia (2008). Vertical arrangements, market structure, and competition: An analysis of restructured US electricity markets. *American Economic Review 98*(1), 237–66.

Butters, R. A., J. Dorsey, and G. Gowrisankaran (2021). Soaking up the sun: Battery investment, renewable energy, and market equilibrium.

Cicala, S. (2015). When does regulation distort costs? Lessons from fuel procurement in us electricity generation. *American Economic Review 105*(1), 411–44.

Cicala, S. (2017). Imperfect markets versus imperfect regulation in us electricity generation. Technical report, National Bureau of Economic Research.

Cole, W. J. and A. Frazier (2019). Cost projections for utility-scale battery storage. Technical report, National Renewable Energy Lab.(NREL), Golden, CO (United States).

Daniel, J., S. Sattler, A. Massie, and M. Jacobs (2020). Used, but how useful? how electric utilities exploit loopholes, forcing customers to bail out uneconomic coal-fired power plants. *Union of Concerned Scientists Report*. Available at `https://www.ucsusa.org/resources/used-how-useful`.

Davis, L. W. and C. Wolfram (2012). Deregulation, consolidation, and efficiency: Evidence from US nuclear power. *American Economic Journal: Applied Economics 4*(4), 194–225.

Demsetz, H. (1968). Why regulate utilities? *The Journal of Law and Economics 11*(1), 55–65.

Eisenberg, T. (2019). Regulatory distortions and capacity investment: The case of China's coal power industry.

Energy Information Agency (2020). Frequently asked questions. Available at `https://www.eia.gov/tools/faqs/faq.php?id=77&t=11`.

Fowlie, M. (2010). Emissions trading, electricity restructuring, and investment in pollution abatement. *American Economic Review 100*(3), 837–69.

Goldie-Scot, L. (2019, December). A behind the scenes take on lithium-ion battery prices. *BloombergNEF*. Available at `https://about.bnef.com/blog/behind-scenes-take-lithium-ion-battery-prices/`.

Gourieroux, C., A. Monfort, and E. Renault (1993). Indirect inference. *Journal of applied econometrics 8*(S1), S85–S118.

Gowrisankaran, G., A. Langer, and W. Zhang (2022). Policy Uncertainty and the in the Market for Coal Electricity: The Case of Air Toxics Standards. Available at `https://drive.google.com/file/d/1WEpoPI2R052mM76agtDdgrfMBfoOqH3i/view?usp=sharing`.

Gowrisankaran, G., S. S. Reynolds, and M. Samano (2016). Intermittency and the value of renewable energy. *Journal of Political Economy 124*(4), 1187–1234.

Hausman, C. (2019). Shock value: Bill smoothing and energy price pass-through. *The Journal of Industrial Economics 67*(2), 242–278.

Holland, S. P., E. T. Mansur, N. Z. Muller, and A. J. Yates (2020). Decompositions and policy consequences of an extraordinary decline in air pollution from electricity generation. *American Economic Journal: Economic Policy 12*(4), 244–74.

International Renewable Energy Agency (2020). Renewable power generation costs in 2019. Available at https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2020/Jun/IRENA_Costs_2019_EN.pdf?la=en&hash=BFAAB4DD2A14EDA7329946F9C3BDA9CD806C1A8A.

Joskow, P. L. (2007). Regulation of natural monopoly. *Handbook of law and economics 2*, 1227–1348.

Laffont, J.-J. and J. Tirole (1986). Using cost observation to regulate firms. *Journal of political Economy 94*(3, Part 1), 614–641.

Lim, C. S. and A. Yurukoglu (2018). Dynamic natural monopoly regulation: Time inconsistency, moral hazard, and political environments. *Journal of Political Economy 126*(1), 263–312.

Linn, J. and K. McCormack (2019). The roles of energy markets and environmental regulation in reducing coal-fired plant profits and electricity sector emissions. *The RAND Journal of Economics 50*(4), 733–767.

MacKay, A. and I. Mercadal (2019). Shades of integration: The restructuring of the US electricity markets. *Harvard Business School, Working Paper 18*.

Myatt, J. (2017). Market power and long-run technology choice in the US electricity industry.

Posner, R. A. (1974). Theories of economic regulation. Technical report, National Bureau of Economic Research.

Reguant, M. (2019). The efficiency and sectoral distributional impacts of large-scale renewable energy policies. *Journal of the Association of Environmental and Resource Economists 6*(S1), S129–S168.

U.S. Energy Information Administration (2018, October). Today in energy. Available at https://www.eia.gov/todayinenergy/detail.php?id=37392.

U.S. Energy Information Agency (2020, December). Utility scale facility net generation from renewable sources excluding hydroelectric. *Electric Power Monthly*. Available at https://www.eia.gov/electricity/monthly/epm_table_grapher.php?t=table_1_11_a.

Wilson, M. (2019, April). Denied: Indiana utility regulatory commission rejects Vectren's power plant proposal. *Courier & Press*. Available at https://www.courierpress.com/story/news/local/2019/04/24/utility-commission-rejects-vectren-natural-gas-power-plant-indiana-posey-county-a-b-b 3553798002/.

Zhang, W. (2020). Measuring policy uncertainty using coal power plants' entry and exit decisions.

# On-Line Appendix

IN PROGRESS