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ENERGY TRANSITIONS IN REGULATED MARKETS

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ABSTRACT

Natural gas has replaced coal as the dominant fuel for U.S. electricity generation. However, utilities in regulated U.S. states have retired coal more slowly than others. We build a structural model of rate-of-return regulation during an energy transition where utilities face tradeoffs between lowering costs and maintaining and using legacy capacity. A regulated utility facing carbon taxes lowers short-run coal generation 48% as much as a cost minimizer would. Thirty years after a sudden energy transition, a cost minimizer has retired 71% more coal capacity than the regulated utility. Alternative regulations may jeopardize affordability and reliability goals during energy transitions.

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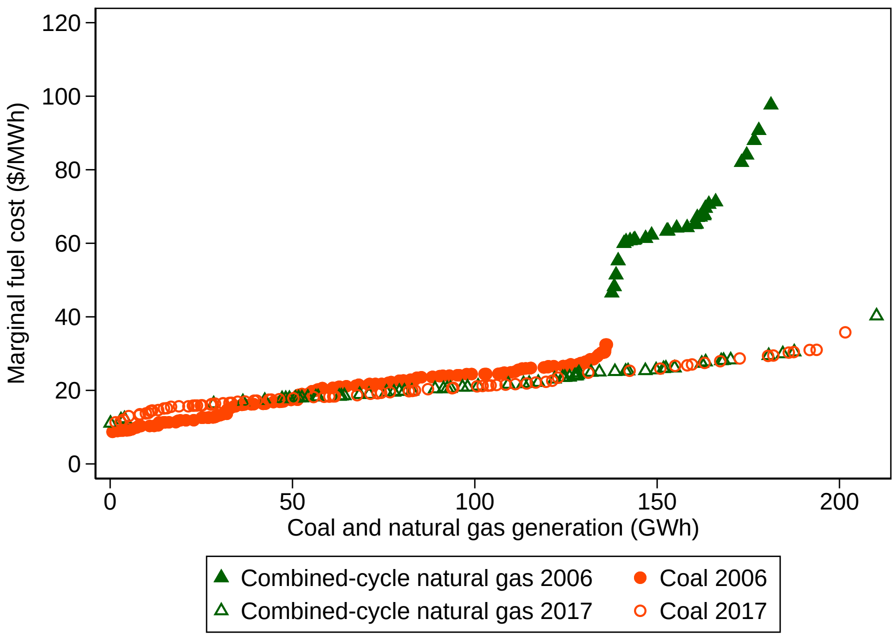
1 Introduction

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

Amid growing concerns about the damages from electricity emissions, two major energy transitions are underway. The first transition, occurring since the start of the 21st century, is marked by the significant reduction in the cost of generating electricity with natural gas, thanks to combined-cycle technology and hydraulic fracturing (fracking). Figure 1 illustrates the marginal electricity fuel costs in 2006 and 2017 for combined-cycle natural gas (CCNG) and coal plants in our sample. The figure sorts plants by dispatch order—i.e., in order of increasing fuel cost—with capacities displayed cumulatively. In 2006, CCNG plants (in solid green triangles) had uniformly higher fuel costs than coal (in solid orange circles). Yet, by 2017, there were substantially more CCNG plants, and their fuel costs were similar to or below coal. The resulting shift in generation toward natural gas has led to a 28% reduction in CO_2 emissions between 2005 and 2018 and lower local air pollution (Energy Information Administration, 2018). The second transition stems from a significant decrease in the costs of renewable energy, with both solar panel and battery costs having dropped over 80% since 2010 (International Renewable Energy Agency, 2020; Goldie-Scot, 2019). Given these cost declines and the substantially lower pollution externalities from renewables, a second transition—to renewable energy—has started.

Since electricity generation has high fixed costs and low marginal costs, electric utilities were historically considered natural monopolies and faced rate-of-return (RoR) regulation, where the regulator grants a utility a monopoly but, in exchange, limits its prices (or rates). The 1990s saw extensive restructuring in the U.S. and Europe, where electricity generation—and sometimes retailing—was opened to competition. In the U.S., this deregulatory push ended with the California electricity crisis of the early 2000s, leaving a patchwork system where states have substantially different levels of regulatory control. The impact of falling

Figure 1: Marginal Fuel Costs Over Time



Note: Plant-level data on marginal fuel costs and capacities from analysis sample.

natural gas generation costs varied across regulated and restructured markets. For instance, between 2006 and 2018, 26.0% of coal capacity exited in restructured states, whereas only 17.2% exited in regulated states.[1] This suggests that it is important to study whether electricity regulation increases social costs by slowing transitions to new energy sources.

This paper develops and estimates a model of electricity regulation. In the model, the utility optimizes against the regulatory structure by choosing investment and retirement capacity levels in the long run and generation quantities by fuel-technology and electricity imports in each hour. We estimate our model using publicly available data on utilities' electricity generation, load (demand), revenues, and capacity. We use our model to evaluate how both the current and alternative regulatory structures would affect energy transitions.

RoR electricity regulation aims to ensure reliability—to literally keep the lights on—while maintaining affordability (Energy, Climate, and Grid Security Subcommittee, 2023) in the presence of incomplete information about the current and future costs of alternative utility investment and operation decisions. To achieve these goals, the regulator creates a

[1] Authors' calculations based on analysis data, discussed in Section 2.2.

structure under which utilities are incentivized to have sufficient resources to meet demand while encouraging low costs and limiting underused capital (Joskow, 1974). This structure sets electricity rates to reimburse utilities for their variable costs and provide a “fair” RoR on their capital, referred to as their “rate base” (Viscusi et al., 2018). The literature has shown that RoR regulation has at least two limitations. First, RoR regulation may not provide adequate incentives for cost minimization, since the regulator reimburses variable costs (Joskow, 2007). Second, RoR regulation can lead to capital over-investment (called the AJ effect, after Averch and Johnson, 1962): since the utility earns profits proportional to capital, it endogenously responds by increasing capital.

In response to these limitations, regulators have implemented incentive regulation and prudence standards. Incentive regulation provides utilities a RoR that is decreasing in costs relative to a benchmark (Joskow, 2007), which encourages cost reductions. Prudence standards require that only “prudent” capital investments be included in the rate base, which helps limit capital over-investment. For older, existing technologies needing maintenance, repair, or upgrade, one common approach to determining prudence is a generation standard where only capital that is “used and useful” is fully included in the rate base (Gilbert and Newbery, 1994; Fisher et al., 2019). Energy transitions further complicate the regulator’s task of determining prudence as they may cause technologies, fuel prices, and environmental concerns to change over time. When combined with a used-and-useful standard, these transitions may create perverse incentives for utilities, such as causing them to overuse legacy capital to ensure that it fully contributes to the rate base.

Our model captures these key features of RoR regulation. The regulator in our model accomplishes its objectives via two instruments. First, it offers a maximum rate of return that is declining in consumer electricity rates to incentivize cost reductions. This instrument encourages the utility to invest in low-cost plants and use low variable cost sources. Second, the regulator considers capacity usage in assessing the extent to which capital is included in the rate base.

The utility optimizes against this regulatory structure in its investment and operations decisions. Each three-year period, the utility chooses coal capacity retirement and CCNG capacity investment, facing quadratic adjustment costs. Investments increase its rate base and therefore its variable profits, conditional on the rate of return and usage. When choosing which fuel-technologies to operate, the utility has two potentially conflicting incentives. On the one hand, to increase its allowable rate of return, the utility seeks to lower costs. On the other hand, particularly after the decline in natural gas generation costs, it may use expensive coal plants to ensure that they are deemed used and useful.

Our model relies on both regulatory and cost parameters. The regulatory parameters include the determinants of the allowable rate of return and each fuel-technology's contribution to the rate base, which for coal capacity depends on its usage. We observe fuel costs and estimate operations and maintenance, ramping, and investment/retirement cost parameters. We estimate the regulatory and operations parameters with a nested fixed-point indirect inference approach that seeks to match important data correlations. Specifically, we run regressions on our actual data that capture key features such as utilities' revenues, ramping behavior, and usage, and find the structural parameters that yield the most similar regression coefficients in simulated data generated by the model. We also estimate the investment and retirement costs with a GMM nested fixed-point approach, following the Gowrisankaran and Schmidt-Dengler (2025) algorithm that facilitates the computation of models with continuous choices, in our case investment and retirement decisions.

We use our structural parameter estimates to analyze the impact of counterfactual policies on short-run operations decisions for our historical analysis sample and long-run outcomes during an energy transition. We consider four sets of counterfactuals: (1) cost minimization, (2) a social planner which minimizes costs including a \$190/ton carbon cost (Environmental Protection Agency, 2023b), (3) imposing carbon taxes on regulated utilities, and (4) adjusting existing regulatory parameters.

We first consider counterfactual operations decisions across utilities and years in our sample. Here, we find that carbon taxes and eliminating coal usage incentives both lower carbon emissions. However, they also yield variable profits that are much lower than the baseline, implying that implementing them without transfers could reduce resource adequacy and thereby affect reliability. In the short run, carbon taxes imposed on regulated utilities only reduce coal generation 48% as much as when imposed on a cost minimizer.

We next evaluate outcomes for regulated utilities faced with an energy transition by simulating decisions with their observed 2006 capital stocks suddenly shocked with low 2018-20 natural gas fuel prices. In the 30 years following this shock, regulated utilities, on average, would retire 53% of coal capacity and gradually reduce coal usage while increasing CCNG capacity by 296%. A cost minimizer would transition away from coal much more quickly, immediately reducing coal generation by 50% and, over 30 years, eliminating most coal capacity while only increasing CCNG capacity by 58%. A cost minimizer that considers carbon costs—the social planner—would eliminate almost all coal capacity over the same time frame and also immediately reduce coal generation by 99%. In contrast to the limited long-run impact of carbon taxes for the cost minimizer, the regulated utility would retire 85% of its coal capacity over the 30-year horizon when faced with a carbon tax. Changing regulatory parameters by increasing the coal usage incentive or changing the penalty for high electricity rates does not come close to replicating the speed of the energy transition under a cost minimizer.

Literature: This paper relates to three broad literatures. First, we build on a long-standing literature on the theory of regulation. A number of papers have examined the optimal design of RoR regulation (e.g., Averch and Johnson, 1962; Baumol and Klevorick, 1970; Klevorick, 1971, 1973; Joskow, 1974; Gilbert and Newbery, 1994; Joskow, 2007). Other papers have focused on setting incentives with asymmetric information about costs and effort (Baron and Myerson, 1982; Laffont and Tirole, 1986). We extend the models in this literature by investigating the role of regulation in the face of an energy transition.

Second, we extend the empirical literature on the impact of electricity regulation, which includes Fowlie (2010); Davis and Wolfram (2012); Cicala (2015); Abito (2020); Lim and Yurukoglu (2018); MacKay and Mercadal (2019); Cicala (2022b); Dunkle Werner and Jarvis (2025); Aspuru (2023); and Jha (2023). The closest paper in this literature to ours is Abito (2020), which structurally estimates a Laffont and Tirole style model of regulation under asymmetric information where an electric utility makes operations decisions trading off effort against costs. We contribute by integrating the theoretical and empirical literatures on regulation with a structural model of both utilities' operations and investment and retirement decisions when facing RoR regulation. Understanding RoR regulation is important because, despite parts of the U.S. restructuring electricity generation, RoR (or similar) regulations are the dominant approach in countries including India, Italy, and the United Kingdom (Jha et al., 2022; Joskow, 2024; Anthony et al., 2020), and settings such as natural gas, water, and electricity transmission and distribution (Ernst and Hlinka, 2024b,c; Doerr, 2024; Joskow, 2024).

Finally, we contribute to the growing empirical literature on the dynamics of investment and exit in electricity markets, which includes Myatt (2017); Eisenberg (2020); Linn and McCormack (2019); Abito et al. (2022); Elliott (2022); Butters et al. (2025); and Gowrisankaran et al. (2025). Gowrisankaran et al. (2025)—written by an overlapping set of co-authors—considers coal retirement decisions for independent power producers (IPPs), focusing on the role of policy uncertainty. This paper extends this literature in modeling decisions of regulated utilities.

2 Industry Background and Data

2.1 Industry Background

Regulated electric utilities own most of the generation capacity within their territory (Shwisberg et al., 2020), but also trade electricity with outside firms, either bilaterally or through regional electricity markets. U.S. state regulatory agencies, generally called Public Utility Commissions (PUCs), regulate these utilities with the goals of reliability and affordability. PUCs collect information from utilities, advocacy groups, and other interested parties largely via Integrated Resource Plans (IRPs) and rate hearings. IRPs lay out utilities' long-run capital investment and retirement needs. Rate hearings are opportunities for the regulator to adjust consumer rates (Joskow, 2014; Abito, 2020). Before these hearings, utilities submit documentation of their recent performance—including usage of existing plants, costs, and revenues—as well as expected future performance.

PUCs make three different types of decisions.[2] First, they approve capital investments and retirements. These decisions then affect what is included in the rate base, i.e. the capital stock on which PUCs give utilities their RoR. Second, they determine which of utilities'

[2]Our discussion of the regulatory process draws heavily from a guide to electricity regulation written by an independent think tank (Lazar, 2016) and a classic textbook on regulation (Viscusi et al., 2018).

reported variable costs are reimbursable. Third, they choose the allowable RoR which, together with the first two decisions, determine the profits that utilities can earn. PUCs then set consumer rates so that utilities can expect to cover their reimbursable variable costs and earn a fair return, which is determined by the product of the RoR and the rate base.

RoRs are intended to provide utilities with fair profit margins by covering their opportunity cost of capital (Dunkle Werner and Jarvis, 2025). However, if regulators simply reimbursed utilities on a "cost-plus" basis, then utilities would not have an incentive to minimize costs. Therefore, regulators often use *incentive regulation*, where profits decline as costs rise (Lyon, 1994; Joskow, 2007), implementing it by adjusting either the RoR or the rate base in response to high costs.[3] In particular, regulators may adjust the rate base for construction in progress, investments in terminated projects, and fuel stocks (Indiana Utility Regulatory Commission, 2023). Indeed, the intricacies in the process imply that the concept of the rate base is hard to quantify.[4] Beyond incentive regulation, PUCs may explicitly look at metrics such as usage when deciding on the rate base. As Lazar (2016) explains on page 52: "Generally, to be allowed in rate base, an investment must be both used and useful in providing service and prudently incurred. The utility has the burden of proving that investments meet these well-established tests, but often enjoys presumption of use and usefulness, and prudence in the absence of evidence to refute it."

Despite this focus on incentives, advocacy groups and research organizations have argued that this regulatory structure leads to inefficient operating decisions. Multiple groups have found that utilities that trade in wholesale electricity markets may choose to "self-commit" (or mandate that their own plants must run) even when these plants' costs exceed the market price (Fisher et al., 2019; Daniel et al., 2020; Potomac Economics, 2020). Further, regulated utilities may have a preference to build their own capacity rather than signing power purchase agreements with third parties who can produce electricity at lower cost (Cross-Call et al., 2018; Wilson et al., 2020). This inclination has extended to recent decisions concerning renewable energy, where certain groups have expressed concern that regulated utilities have an undue focus on fossil fuel generation that leads them to under-invest in

[3]This declining RoR is observed in other regulated sectors such as natural gas (Hausman, 2019).

[4]Regulatory Research Associates explains that "efforts to estimate [the rate base's] value are at best an arduous task and at worst fraught with inaccuracies" (Ernst and Hlinka, 2024a).

renewables (Bottorff et al., 2022; Biewald et al., 2020; Daniel, 2021).

Ultimately, the regulatory process involves an extensive back-and-forth between the regulator, utility, and other stakeholders. Our structural model aims to capture the key forces of this process in a simplified setting.

2.2 Data

We use data on the electricity industry in the U.S. from a variety of publicly available sources. Our data include both annual measures—such as plant capacity, fuel prices, and utility revenues—and hourly measures—such as load, generation, and wholesale electricity prices. Our main estimation sample extends from 2006 to 2017.

Our primary annual data derive from the Energy Information Administration (EIA). We merge together information from three EIA forms. First, EIA Form 861 provides annual total revenue for electric utilities that are obligated to report this information. Form 860 records information about each power plant's capacity, fuel-technology type, and U.S. state. We retain information on plants with three fuel-technologies: coal (COAL), combined-cycle natural gas (CCNG), and other (non combined-cycle) natural gas turbines (NGT), many of which are used to meet peak load. Finally, Form 923 has annual plant-level data on fuel energy input in MMBtus and electricity generation in MWhs. We combine these data to recover heat rates, which indicate fuel energy input per unit of generation. We calculate heat rates that vary by utility and fuel-technology, using the capacity-weighted average heat rates across plants.

We merge these data with hourly plant-level data on the quantity of electricity generated from the Environmental Protection Agency's (EPA's) Continuous Emissions Monitoring System (CEMS). We then collapse the combined EIA/EPA data across plants of the same fuel-technology type within a utility-hour. Our main analysis data uses utilities in U.S. states defined as regulated in Cicala (2022b) in the Eastern Interconnection.[5]

We limit our data geographically because regulated utilities in the Eastern Interconnection all have relatively nearby Independent System Operators (ISOs), which allows us to

[5]Our reduced-form evidence in Section 4.2 also uses data form restructured U.S. states, comparing them to regulated U.S. states.

construct import price measures. For every U.S. state with an ISO, we construct a mean wholesale electricity price for every sample hour by using the locational marginal prices (LMPs) within the U.S. state.[6] For each utility in our main analysis sample, we then use the wholesale price from the nearest U.S. state as the import price.[7] We also merge coal and natural gas fuel prices at the U.S. state-year level derived from regulated utilities' reported prices in EIA Form 423.

Finally, we obtain hourly load by utility from multiple sources. Cicala (2021, 2022a) provide data and code to construct hourly load through 2012 by power control area (which often coincide with regulated utilities). We lightly edited his code to extend the hourly load to 2017 for utilities in MISO and SPP. The utilities in MISO and SPP are regulated, but also subject to market dispatch, in that they bid their generation capacity into wholesale markets. For additional utility-years, we obtain load from Federal Energy Regulatory Commission (FERC) Form 714. We then use the combined data to define hourly imports into the utility, or exports from the utility if negative, as load net of our three primary generation fuel-technology types. Thus, imports will include utility generation from both renewables (which are relatively moderate during this time-frame) and nuclear.

On-Line Appendix A2 discusses details of our data construction and includes summary statistics of our analysis data at the utility-year and utility-hour levels, respectively. Our final analysis data consist of over 4 million utility-hour observations across 459 utility-years for 39 unique utilities.

3 A Simplified Model of Electricity Regulation

This section presents a simple model of RoR regulation that highlights the key tradeoffs in the interactions between the regulator and utility. We first start with a model of RoR regulation over two stable periods. We then consider the impact of an energy transition in the second period. Section 5 extends this theoretical model to allow us to estimate key

[6]We retrieved these data from the ISO New England (ISONE), Midcontinent Independent System Operator (MISO), New York Independent System Operator (NYISO), and PJM Interconnection websites. We do not use Southwest Power Pool (SPP) prices since they are not reported before June 2013.

[7]In some cases, the prices are somewhat distant, e.g., we use data from VA for the price in FL.

parameters and conduct counterfactual simulations.

3.1 Regulatory Structure

Following Viscusi et al. (2018), we model the regulator as having two objectives: first, it wants enough generation and imports to meet load in every hour ("reliability"), and given that, it wants to keep consumer rates low ("affordability"). It might also potentially be concerned about mitigating environmental harm. The regulator observes the utility's costs and usage decisions, but does not observe the costs of alternative decisions (Joskow, 2007). This asymmetric information means that, instead of dictating choices, the regulator imposes an incentive structure that encourages the utility to take actions that meet these goals. To avoid ex-post renegotiation, the regulator commits to a fixed structure. The utility faced with this regulatory structure aims to maximize its expected profits over the two periods.

The regulator sets electricity rates, r, on electricity demand, or load, ℓ, which we approximate as being perfectly inelastic (Borenstein et al., 2023). The regulator requires the utility to meet load and chooses r such that revenues equal the sum of variable costs, TVC, and an allowable return, s, on the rate base, B. Utility revenues are then:

$$r \times \ell = TVC + s \times B. \tag{1}$$

This subsection considers an environment where the utility maximizes profits when facing a fixed load and one generation technology, coal, that lasts two periods. We represent the per-unit cost of investment with δ^{COAL}, the amount of capacity with K^{COAL}, and the marginal cost with MC^{COAL}. The regulator provides the utility profits, $\pi \equiv s \times \alpha^{COAL} \times K^{COAL} - \delta^{COAL} \times K^{COAL}$, where α^{COAL} converts generation capacity from MWs into the rate base in dollars. It sets α^{COAL} sufficient to cover the utility's capacity investment and its transmission, distribution, and administrative costs, and also earn a "fair" rate of return.[8] Since all capacity has identical marginal costs, load is fixed, and the utility is required to meet load, the utility does not choose generation. Thus, capacity investment is its only

[8] Though not the focus of our study, transmission and distribution infrastructure is critical for maintaining reliability (Lim and Yurukoglu, 2018).

meaningful choice.

Because demand is perfectly inelastic, if the regulator provided the utility a fixed RoR over costs as in a cost-plus setting, increases in capital would proportionally increase revenues. In this case, capacity investments would always increase utility profits, exacerbating the Averch and Johnson [AJ] effect. This over-investment in capacity would lead to overly high electricity rates, undermining the regulator's goal of affordability and potentially causing consumer backlash. Recognizing these issues, the regulator uses incentive regulation, where it offers the utility a lower RoR as consumer electricity rates rise, conditional on the utility keeping the lights on. This penalty captures a political economy constraint that the regulator limits the utility's profits when faced with consumer pressure from high rates (as seen in regulatory evidence, e.g. Indiana Utility Regulatory Commission, 2020).

We model incentive regulation by allowing the regulator to offer a RoR that is a declining function of reported costs, in the spirit of Baron and Myerson (1982). Specifically, the regulator offers a RoR each period that is decreasing in the electricity rate, $s \equiv (r/r_0)^{-\gamma}$, where $\gamma > 0$ is the regulatory parameter that determines the extent to which rates affect the RoR, and r_0 is a benchmark, "reasonable" rate against which rates are compared. Substituting this formulation and TVC into (1) defines r as an implicit function of costs, in this case K^{COAL}: $r \times \ell = \ell \times MC^{COAL} + (r/r_0)^{-\gamma} \alpha^{COAL} K^{COAL}$. This regulatory structure partially overcomes the lack of consumer demand elasticity, providing efficiency incentives but departing from the first-best.

To illustrate the implications of this regulatory structure on equilibrium outcomes, we simulate the model, calculating the utility's optimal coal investment levels for different values of γ and calibrating the other parameters. For every value of γ and a grid of K^{COAL}, we iterate on the implicit function that defines r until a fixed point. Given these solutions, we then find the K^{COAL} that maximizes two-period profits for each γ.

The solid blue line of Figure 2 panel (a) shows the utility's optimal K^{COAL}.[9] Coal investment decreases in γ until it hits the planner solution of $K^{COAL} = \ell = 1$, as shown by the thin grey line. While panel (a) only presents values of γ greater than 0.3, investment

[9] We calibrate $\alpha^{COAL} = 1.1$, $\delta^{COAL} = 1$, $MC^{COAL} = 1$, and $r_0 = 1$, and $\ell = 1$ in each period. While we present results varying γ, the regulatory structure involves choosing both γ and α^{COAL}.

increases roughly exponentially as γ decreases and is infinite at $\gamma = 0$. If there were no participation constraint for the utility, the regulator would just choose γ high enough to ensure that $K^{COAL} = \ell$, i.e., $\gamma > 0.905$ in our simulation. However, since optimized profits—indicated with the dashed red line—are also declining in γ, a γ that is sufficiently high to ensure that $K^{COAL} = \ell$ may leave the utility with insufficient revenues to achieve resource adequacy. The regulator would then be forced to choose a low γ where $K^{COAL} > \ell$ even though this will not perfectly address the AJ over-investment incentive.

In the real world, an additional complication is that load is not fixed and instead varies by hour, with some level of unpredictability, e.g., there are extremely hot days with high air conditioning needs. The utility likely has better information than the regulator regarding the underlying distribution of current and future ℓ. This may provide another reason why the regulator cannot incentivize $K^{COAL} = \ell$: the utility has an incentive to justify additional capacity investment as necessary for resource adequacy due to high load stochasticity (or future load growth). To manage informational asymmetries while avoiding ex-post renegotiation, the regulator allows capacity that is "used and useful" to contribute more to the rate base. This combines the principle that only "prudent" capital investments should be included in the rate base (Viscusi et al., 2018) with the fact that capacity's usage is one objective way to measure its prudence (Gilbert and Newbery, 1994).

We thus extend our simple model to add a used-and-useful standard. We model capital's contribution to the rate base with a simple logit functional form:

$$UU\left(\frac{Q^{COAL}}{K^{COAL}}\right) = \frac{\exp\left(\mu_1 + \mu_2 \frac{Q^{COAL}}{K^{COAL}}\right)}{1 + \exp\left(\mu_1 + \mu_2 \frac{Q^{COAL}}{K^{COAL}}\right)}, \tag{2}$$

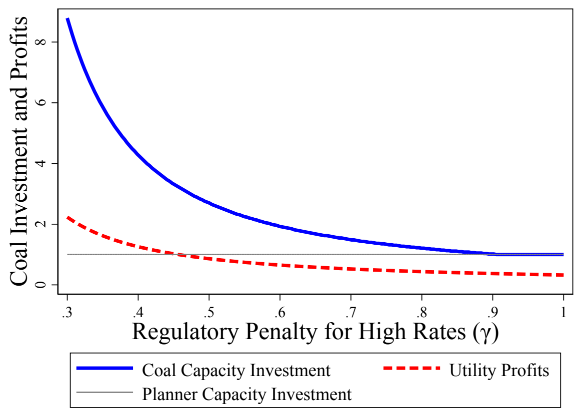
where Q^{COAL} is the quantity of coal generation, and μ_1 and μ_2 are model parameters. Combining terms, the rate base becomes $B = \alpha^{COAL} \times K^{COAL} \times UU(Q^{COAL}/K^{COAL})$.

Figure 2, panel (b) investigates the role of the used-and-useful standard in our simulation.[10] The solid green line compared to the solid blue line in panel (a) shows that the used-and-useful standard substantially reduces the utility's optimal capacity investment, be-

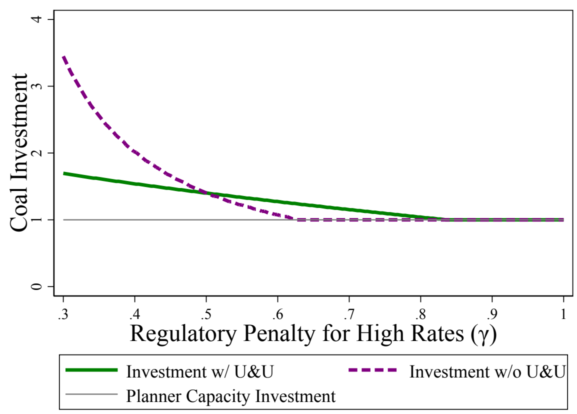
[10]We calibrate a used-and-useful standard that is similar to the parameters we ultimately estimate, setting $\mu_1 = -1$ and $\mu_2 = 6$.

Figure 2: Simulation of Regulated Outcomes Across Simplified Settings

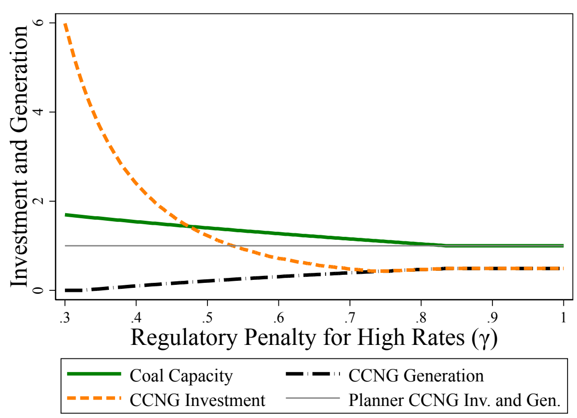
(a) Stable Environment Without Used-and-Useful Standard



(b) Stable Environment With a Used-and-Useful Standard



(c) Period 2 Energy Transition With a Used-and-Useful Standard



Note: Panel (a) presents simulated coal capacity investment and profits in a stable environment with RoR regulation and a penalty for high electricity rates. Panel (b) presents simulated coal capacity investment in a stable environment with and without a used-and-useful standard, where the latter adjusts α^{COAL} to match capacity investment at $\gamma = 0.5$. Panel (c) presents simulated CCNG and coal capacity and coal usage in period 2, following an energy transition.

cause an increase in investment lowers usage which lowers B. Yet, without adjusting capital's contribution to the rate base, the used-and-useful standard will also decrease utility profits. To understand how a used-and-useful standard affects *marginal* investment incentives, we compare capacity investments with used-and-useful incentives to those without the incentives where the utility invests the same amount of capacity when $\gamma = 0.5$.[11] We find that K^{COAL} again changes steeply with γ, although the rate of change is less steep than in panel (a), because the utility's return from additional capacity investment is reduced.

Overall, our simulations show that traditional RoR regulation can lead to substantial over-investment in capacity in the electricity setting. The regulator therefore uses two tools—a RoR that decreases in electricity rates and a used-and-useful standard—to limit this over-investment. The combination of these tools limits the utility's incentive to over-invest, yet the regulator still may not achieve the socially optimal level of investment.

3.2 Regulation During Energy Transitions

While the electricity industry has experienced long periods of relative stability, a substantial energy transition has occurred and another is ongoing. To understand how RoR regulation performs when the environment is not stable, we consider a period 2 energy transition. Specifically, in period 1, we let expectations be that the world will be similar enough in period 2 that the incentives in Section 3.1 hold. In period 2, a shock occurs, where a new technology, CCNG, is suddenly inexpensive to install and use for electricity generation.

We therefore assume that the investment and marginal costs of CCNG—δ^{CCNG} and MC^{CCNG} respectively—are sufficiently low that the social planner would want to build enough CCNG capacity to exclusively meet load with CCNG, i.e., $K^{CCNG} = Q^{CCNG} = \ell$. Because coal capacity is hard to repurpose, it is not possible to retire coal and recover the initial investment cost.[12] For simplicity, we assume a small but positive scrap value for coal so that the social planner would want to retire all coal capacity, but the utility does not retire any coal, since its contribution to the rate base exceeds its scrap value.[13]

[11] This exercise sets $\mu_2 = 0$ but increases α^{COAL} to equate optimizing capacity levels.

[12] In fact, Raimi (2017) and Gowrisankaran et al. (2025) both find that coal capacity is costly to retire on average, likely due to site remediation costs.

[13] The utility will also not want to invest in new coal capacity in period 2 given that its marginal incentives

The regulator maintains the incentive structure from Section 3.1 in period 2 because it committed to this fixed structure in period 1. This commitment is a bedrock of RoR regulation: if the regulator did not commit, the utility may not have had sufficient incentives to invest in period 1, because it would worry that the regulator would not reimburse this expense in period 2 (Lim and Yurukoglu, 2018).

Because CCNG's investment costs are different from coal, the regulator specifies its contribution to the rate base with a new parameter, α^{CCNG}.[14] The utility enters period 2 with an installed base of coal capacity, which yields different incentives from a de novo utility. Given its state, K^{COAL}, the period 2 utility chooses K^{CCNG} and Q^{COAL} to maximize:

$$\begin{aligned} \pi(K^{CCNG}, Q^{COAL}|K^{COAL}) = \quad & \underbrace{\left(\frac{r}{r_0}\right)^{-\gamma}}_{\text{Rate of Return, } s} \underbrace{\left(\alpha^{COAL}K^{COAL}UU\left(\frac{Q^{COAL}}{K^{COAL}}\right) + \alpha^{CCNG}K^{CCNG}\right)}_{\text{Rate Base, } B} \\ & - \underbrace{\delta^{CCNG}K^{CCNG}}_{\text{Investment Costs}} \\ \text{s.t.} \quad & Q^{COAL} + K^{CCNG} \geq \ell, \quad Q^{COAL} \leq K^{COAL}, \quad \text{and} \qquad (3) \\ r \times \ell = & \underbrace{Q^{COAL}MC^{COAL} + \left(\ell - Q^{COAL}\right)MC^{CCNG}}_{TVC} + \left(\frac{r}{r_0}\right)^{-\gamma} B. \end{aligned}$$

In (3), the first constraint requires the utility to have sufficient CCNG capacity to meet load. The second constraint limits coal generation to be less than coal capacity. The final constraint implicitly defines electricity rates.

The same AJ investment distortion from Section 3.1 remains in (3): the utility has an incentive to over-invest in CCNG capacity just as it over-invested in coal capacity in period 1. However, it also faces two new and opposing incentives. It wants to invest in and use low-cost CCNG to keep electricity rates low and thereby raise its RoR, but it also wants to use expensive legacy capacity out-of-dispatch order to prove that it is used-and-useful. Overall, this regulatory structure will result in the utility keeping more coal capacity and using weakly more coal to meet load than the social planner, which retires all coal. Moreover, although the utility will invest in less CCNG capacity than a period 2 de novo utility without

to do so are strictly worse than in period 1.

[14]For simplicity, we do not model a CCNG used-and-useful incentive. In such an environment, the regulator may choose a lower α^{CCNG} to create similar incentives.

any existing coal capacity, it may *either* over- or under-invest in CCNG capacity relative to the social planner.

To understand the interaction between these opposing incentives, we again simulate our model, incorporating this period 2 energy transition. In period 2, for each γ and the accompanying period 1 K^{COAL} choice, we simulate the utility's optimal K^{CCNG} and Q^{CCNG}.

Figure 2 panel (c) presents the results of this simulation.[15] Because the utility does not retire any coal capacity, the solid green line is the same as in panel (b). As represented by the black dashed-dotted line, the regulated utility's choice of Q^{CCNG} is weakly increasing in γ, but always below the planner's choice of 1 as shown by the thin grey line. For relatively low levels of γ, we see both CCNG generation below 1 and unused CCNG capacity, even though $MC^{CCNG} < MC^{COAL}$. Thus, while the used-and-useful standard reduced excessive coal investment for low levels of γ in the stable environment, it creates a generation inefficiency in the presence of an energy transition.

The orange dashed line shows that CCNG investment could either be too high or too low relative to the social planner's choice of $K^{CCNG} = 1$.[16] As with coal investment in the stable setting, CCNG investment approaches infinity as γ approaches 0. Notably, as γ increases, we find that K^{CCNG} does not decline monotonically, because of two conflicting incentives. On the one hand, the higher regulatory penalty for high rates leads the utility to invest in less CCNG. On the other hand, this penalty also leads the utility to substitute CCNG for coal generation. Thus, as γ rises, the utility both invests less in CCNG and uses it more. Eventually, the utility invests more in CCNG capacity and fully uses its CCNG in meeting load. At high levels of γ, as γ further increases, coal capacity is fixed at 1, and the utility still partially uses this capacity to maintain coal's used-and-usefulness. At this point, there is no additional benefit from higher CCNG capacity, so K^{CCNG} also stabilizes.

Our simulations show that an energy transition in regulated markets could lead to either over- or under-investment in the new technology, depending on the particulars of the regulatory parameters and the technology. However, RoR regulation will encourage the util-

[15] We calibrate the fixed and marginal costs of CCNG as $\delta^{CCNG} = 0.6$ and $MC^{CCNG} = 0.1$, respectively. We calibrate α^{CCNG} to twice the ratio of CCNG to coal fixed costs, $\alpha^{CCNG} = 2\delta^{CCNG}/\delta^{COAL}$, since the utility recovers coal costs over two periods.

[16] A used-and-useful standard for CCNG will change the level of K^{CCNG}, but not the result that investment could be either too high or too low relative to the social planner.

ity to keep and use the legacy technology. The implications of RoR regulation for energy transitions therefore require understanding utilities' real-world regulatory incentives.

4 Reduced Form Evidence

Section 3 extended the standard model of RoR regulation with two regulatory instruments that fit the electricity sector. First, we specified the utility's RoR to vary based on consumer rates. Second, we specified that the regulator uses generation to evaluate prudence, and thus utilities may generate with coal even when uneconomical to increase its contribution to the rate base. Before turning to the estimation of our structural model, we analyze the extent to which our data support these assumptions.

4.1 Relation Between Costs and Rate of Return

Our regulatory model specifies that the utility's RoR, $s = (r/r_0)^{-\gamma}$, is declining in electricity rates with $\gamma > 0$, consistent with incentive regulation. This results in electricity rates—and RoR—being implicit functions of costs and capital: $r \times \ell = TVC + (r/r_0)^{-\gamma}B$. Thus, in our model, an exogenous increase in costs will increase r but will also decrease the RoR.

To understand the determinants of the allowable RoR, this section investigates whether increases in costs are associated with lower RoR. Specifically, we create proxies for total costs using fuel and import costs, omitting ramping, O&M, and fixed costs, which are less directly observable. We proxy for RoR with a measure of variable profits—revenues net of fuel and import costs—divided by the sum of coal, CCNG, and NGT capacity in MW. Our hypothesis is that exogenous increases in costs will lower the RoR, as in our model.

Our specifications address two potential concerns. First, total costs include capacity investment, transmission, and distribution costs, which vary substantially across utilities, for example because of geography. This implies that what the regulator considers a high cost for one utility may be a low cost for another, which then affects the allowable RoR.[17] We therefore estimate specifications with utility fixed effects and scale variable costs by the

[17] Our structural model accounts for these differences by dividing electricity rates by the utility's benchmark electricity rate, r_0.

utility's size, measured in different ways.

Second, our principal regressor, fuel and import costs, is a potentially noisy measure of the utility's true costs, reflecting optimizing decisions given idiosyncratic unobservables. This is an issue because our dependent variable—utility profits—subtracts our measure of costs from revenues, which may mechanically create a negative relationship between profits and measured costs. We therefore also estimate instrumental variable specifications. During our time period, fracking reduced natural gas fuel prices, which affected utility costs independently from their contemporaneous decisions. We exploit this variation with a shift-share instrument: we instrument for fuel and import costs with the current state-level natural gas fuel price interacted with the share of the utility's generation from CCNG in the first year the utility appears in our data (generally 2006).

Table 1 presents the results of these regressions. Starting with panel (a), all the specifications report negative coefficients on cost, and these coefficients are always statistically significant with utility fixed effects. We believe that the regressions with fixed effects more plausibly recover causal relationships, since they do not compare costs across utilities, which we view as inappropriate. In terms of magnitudes, from the first fixed effects regression (with TVC as the principal regressor), a 10% increase in TVC is associated with a 2.5% decrease in variable profits per MW of capacity at the mean.

Turning to panel (b), the IV results all show that our instruments have sufficient power. The results without utility fixed effects have a counterintuitive sign, but, as above, we view the utility fixed effects results as more appropriate. The IV results with fixed effects report negative and statistically significant coefficients, with similar magnitudes to those in panel (a).

These results use revenue data to show that utilities earn higher rates of return when they decrease variable costs. This is consistent with our model assumption that the regulator uses incentive regulation to keep consumer rates low and with Table 3 of Dunkle Werner and Jarvis (2025).[18]

[18] On-Line Appendix A3 investigates this hypothesis using Regulatory Research Associates' rate hearing data. These data support our main finding that profits rise when variable costs decrease, though through the rate base and not the stated RoR.

Table 1: Regressions of Rate of Return on Total Variable Cost Measures

	Dependent Variable: Variable Profits per Unit Capacity (Mil. \$/MW)					
Panel (a): Ordinary Least Squares						
Principal Regressor:						
Variable Costs (Bil. \$)	−0.016	−0.044				
	(0.004)	(0.006)				
Variable Costs per Capacity (Mil. \$/MW)			−0.246	−0.421		
			(0.063)	(0.039)		
Variable Costs per High Load (Mil. \$/MWh)					−0.115	−0.581
					(0.090)	(0.046)
Panel (b): Instrumental Variables						
Principal Regressor:						
Variable Costs (Bil. \$)	0.057	−0.030				
	(0.019)	(0.011)				
Variable Costs per Capacity (Mil. \$/MW)			0.983	−0.233		
			(0.340)	(0.081)		
Variable Costs per High Load (Mil. \$/MWh)					0.686	−0.257
					(0.193)	(0.088)
First stage F statistic:	39.1	155.2	30.9	139.6	159.5	182.8
Utility FE	N	Y	N	Y	N	Y

Note: Each column in each panel presents regression results from a separate regression on our analysis data, with standard errors in parentheses. Variable costs include fuel and import costs. Variable profits are revenues net of these variable costs. High load is the 95th percentile of hourly load by utility-year. IV regressions instrument for the independent variable with time-varying natural gas fuel prices interacted with the share of the utility's generation from CCNG in the first year the utility appears in the data. Standard errors cluster at the utility level.

4.2 Evidence on Uneconomical Coal Usage

We next explore our assumption that regulated utilities face incentives to operate coal capacity out of dispatch order to increase its contribution to the rate base and thus their profits. We examine this hypothesis by exploring the extent to which utilities choose to generate with coal when its costs exceed the electricity import price.

However, it is difficult to understand the relative costs of using coal in any hour, in part because ramping and O&M costs are not observed. We address this issue with a specification that is similar to a triple-difference approach. First, we investigate coal usage levels when its fuel costs are above or below import prices. Second, we examine how this usage differs between regulated and restructured utilities.[19] Finally, we compare these differential responses for CCNG and coal.

Specifically, we examine hourly regressions of CCNG or coal generation on whether the fuel-technology is out-of-dispatch order interacted with regulatory status. Our hypothesis is that, because regulated utilities face an incentive to run legacy technology even when it is not cost-effective, they may use coal when it is otherwise uneconomical. This incentive will not hold for restructured utilities or CCNG plants. Although utilities owning coal in restructured U.S. states may face similar ramping and O&M costs, they are not subject to used-and-useful considerations. Similarly, we believe that CCNG usage—even for regulated utilities—is not constrained by a used-and-useful standard during this time period. These factors make restructured U.S. states and CCNG plants useful comparison groups.

Table 2: Out-of-Dispatch-Order Generation by Regulatory Status

	$\mathbb{1}$\{Fuel-Technology On\}		$\mathbb{1}$\{Plant On\}	
	CCNG	Coal	CCNG	Coal
$\mathbb{1}$\{Fuel Cost > Price\}	−0.211	−0.042	−0.116	−0.042
	(0.028)	(0.031)	(0.018)	(0.009)
$\mathbb{1}$\{Fuel Cost > Price\}× Not Regulated	0.014	−0.119	−0.010	−0.048
	(0.027)	(0.050)	(0.020)	(0.020)
Unit of Observation	Utility-Fuel-Hour		Plant-Hour	
R^2	0.131	0.090	0.423	0.290

Note: Regressions are linear probability models on Eastern Interconnection data and include both regulated and restructured electric utilities. The first two columns use data aggregated to the utility-fuel-technology-hour level where the fuel cost is for the lowest cost plant in that cell. These regressions include U.S. state and year fixed effects and are clustered at the U.S. state and year level. The final two columns use data at the plant-hour level, include plant and year fixed effects, and cluster at the plant and year level. "Not Regulated" utilities are those in restructured U.S. states while "Not Regulated" plants are IPPs.

Table 2 presents the results of these regressions. For both CCNG and coal, we estimate two specifications, one where the unit of observation is the utility-fuel-technology-hour and

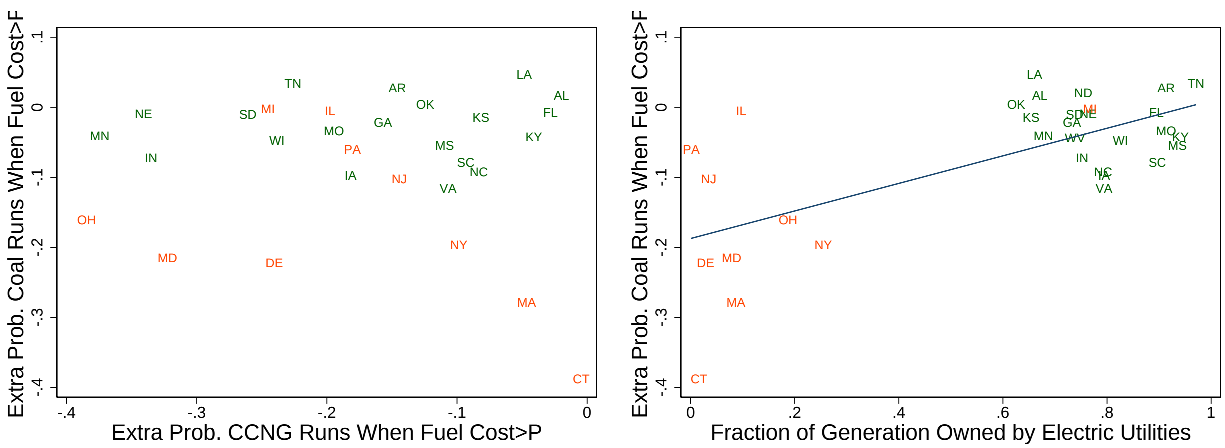
[19] We use our merged EIA/EPA dataset (before we merge in the FERC data) for these results. For both regulated and restructured markets, we define utilities using the EIA's definition.

the other where it is the plant-hour.[20] Focusing first on the utility-level regressions, which are in columns 1 and 2, utilities in both regulated and restructured U.S. states respond similarly and strongly to low import prices by decreasing their CCNG generation, with a 21.1 percentage point decrease in regulated U.S. states and a 19.7 percentage point decrease in restructured U.S. states. However, the results are different for coal generation. Utilities in restructured U.S. states reduce their coal generation by 16.1 percentage points, but regulated utilities only decrease generation by a statistically insignificant 4.2 percentage points. Columns 3 and 4—which are at the plant-hour level—reinforce these results. CCNG generation responds to low import prices in both regulated and restructured U.S. states. Coal generation responds significantly more for restructured plants than regulated ones, although, unlike in column 2, both coal coefficients are statistically significant. Table 2 supports the hypothesis that regulated utilities gain value from generating with coal even when it is out-of-dispatch order.

Figure 3: Generation When Fuel Cost > Price in Regulated Versus Restructured Markets

(a) Out-of-Dispatch-Order Generation for Coal and CCNG

(b) Coal Out-of-Dispatch-Order Generation vs. Utility Ownership Share



Note: Panel (a) presents coefficients on coal and CCNG out-of-dispatch-order generation by U.S. state. Panel (b) plots the fraction of generation owned by electric utilities against the same coal coefficients. In both panels, green U.S. states are regulated and red U.S. states are restructured.

Figure 3 presents estimates from similar regressions to columns 3 and 4 of Table 2 on

[20] For our utility-level regressions, we use the minimum fuel cost across all plants of that fuel-technology type as our measure of fuel cost. For the plant-level regressions, we exclude IPP plants in regulated U.S. states and non-IPP plants in restructured U.S. states from the data.

out-of-dispatch-order generation, but allowing the coefficients to vary by U.S. state. Panel (a) shows the out-of-dispatch-order coefficients for coal (vertical axis) and CCNG (horizontal axis). We plot regulated U.S. states in green and restructured U.S. states in red. Out-of-dispatch-order coal generation is clearly related to regulatory status while there is little pattern for CCNG. The six U.S. states with largest response of coal usage to low market prices—which are at the bottom of the graph—are all restructured U.S. states. This reinforces the idea that regulatory status significantly impacts coal usage decisions.

Panel (b) of Figure 3 plots the share of generation owned by electric utilities in the U.S. state (as reported by Shwisberg et al., 2020) against the same coal coefficients as in panel (a). Regulated U.S. states generally have utility ownership shares over 60%, whereas all restructured U.S. states but one have utility ownership shares under 30%. The best fit line shows that coal's responsiveness to low wholesale prices correlates strongly with utility ownership share.

5 Empirical Model and Estimation Approach

This section discusses how we extend Section 3 to take the model to data, our accompanying estimation approach, and identification of our model, with further details in On-Line Appendix A4. Our empirical approach separates the simple model into two parts. We estimate a model of capital investment and retirement to recover the costs of these actions. This model is dependent on the state-contingent variable profits for each utility. We therefore also estimate a model of utilities' operations decisions in which we recover regulatory incentives, operations costs, and ultimately variable profits across long-run investment/retirement states. We estimate both models with full-solution approaches and thus compute counterfactual outcomes with the same techniques.

Broadly, identification of our parameters follows from the intuition that the observed sharp decline in natural gas fuel prices had different implications across utilities, depending upon the utilities' capital mixes. For instance, consider a utility with substantial coal and CCNG capacity. Early in our sample, when natural gas prices were high, this utility would have generated with coal first, and only used natural gas in hours with high load. After natural gas prices fell, the utility faced conflicting incentives: it wanted to run natural gas capacity to keep fuel costs low and be allowed a higher RoR, but it also wanted to use—and not retire—coal plants to increase its rate base. This contrasts with a utility with predominantly coal capacity that needed to meet load with coal even after natural gas prices fell. By comparing the investment/retirement and operations decisions across utilities and over time, we are able to identify the structural parameters.

We now discuss the investment/retirement and operations models in turn.

5.1 Investment and Retirement Model

Extending our model in Section 3 to fit the empirical context, we allow for an infinite horizon and discounting, fixing an annual discount factor of $\beta = 0.95$. We let each period, $t \geq 1$, represent three years, consistent with the long time horizons necessary to build or decommission fossil fuel plants. We assume that the utility only makes decisions for 10 periods (30 years) and that the long-run state remains fixed after that point since we view predictions after this time horizon as overly uncertain.[21]

We extend our model to three fuel-technology types, adding NGT to coal and CCNG. We allow for each fuel-technology to contribute to the rate base at different levels, α^{COAL}, α^{CCNG}, and α^{NGT}, respectively. Unlike in our simple model, we assume that investments or retirements take one period to be realized.

We treat each of the three fuel-technologies differently, reflecting their characteristics during our sample period. As in Section 3.2, we assume that the utility chooses only investment for CCNG capacity and only retirement for coal capacity. Letting x denote the investment amount, we specify $x_t^{CCNG} \geq 0$ and $x_t^{COAL} \leq 0$. We make these choices since the vast majority of entry decisions are for CCNG capacity, and the vast majority of exit decisions are for coal capacity.[22] Finally, to limit the complexity of our model, we do not endogenize the choice of NGT capacity, which is fairly stable over our sample period.

Given the extensions to our model, the utility makes optimizing investment/retirement

[21] We found that our estimation results are essentially unchanged with a 15-period decision horizon.

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

decisions based on a high-dimensional state, Ω, and earns state-contingent variable profits, $\pi^*(\Omega)$. In principle, Ω can include any factor that affects expected current or future profits. For tractability, we restrict the time-varying component of Ω to t itself and three additional variables. These include coal and CCNG capacities, both of which vary deterministically with the utility's decisions, $K^f_{t+1} = K^f_t + x^f_t$, and natural gas fuel price, p^{NG}_t, which we assume follows an exogenous AR(1) process, estimated in an initial step with average period natural gas fuel prices from 2003-17. Beyond the time-varying state, Ω includes a number of fixed state variables (that vary across utilities): heat rates for all fuel-technologies, NGT capacity, coal fuel price,[23] the comparison electricity rate, r_0, and hourly import supply curves and load (discussed in the next subsection).

Building on Ryan (2012) and Fowlie et al. (2016), we extend the Section 3 model, which had linear costs, to allow each fuel-technology's investment costs to include time-invariant fixed and quadratic terms and a stochastic cost shock:

$$InvCosts^f(x^f_t|\varepsilon^f_t) = \delta^f_0 \mathbb{1}\{x^f_t \neq 0\} + x^f_t(\delta^f_1 + x^f_t\delta^f_2 + \sigma^f\varepsilon^f_t), \tag{4}$$

where $(\delta^f_0, \delta^f_1, \delta^f_2, \sigma^f)$ for $f \in \{COAL, CCNG\}$ are parameters to estimate. Unlike in Ryan (2012) and Fowlie et al. (2016), where the stochastic shock is on the fixed cost of investment, we use a more recent specification where each period's shocks, ε^f_t, increase *marginal* investment costs and are distributed *i.i.d.* with a standard normal density (Kalouptsidi, 2018; Caoui, 2023). This approach generates a distribution of capacity changes in any state, which allows us to match the data variation.

Focusing on the timing of the investment decisions, each period the utility first observes the natural gas fuel price shock. It then observes its shock to the coal marginal cost of retirement, ε^{COAL}_t, and makes its coal retirement decision. Next, it observes its shock to the CCNG marginal cost of investment, ε^{CCNG}_t, and makes its CCNG investment decision. It then earns variable profits over the three-year period (which are a function of its state at the time of the coal investment decision). At the end of the period, capacity adjusts to reflect investment and retirement decisions.

[23] The state fixes coal fuel prices since their mean within-U.S. state standard deviation is much smaller than for natural gas and modeling their variation would dramatically increase computational time.

We estimate the time-invariant terms, δ_0^f, δ_1^f, δ_2^f, and standard deviations of unobservable components of investment and retirement costs, σ^f, with a GMM nested fixed-point estimator. Our coal moments include the difference between the data and the model in the retirement amount and its square conditional on a non-zero amount and indicators for non-zero retirement and whether retirement exceeds certain thresholds. We also interact each of these terms with the utility's starting capital. Finally, we include the variance of the retirement amount. For CCNG, we include the analogous moments, but for investment.

We estimate the structural parameters with a search over candidate parameters to minimize the moment condition. For each candidate parameter vector, we solve the investment/retirement dynamic programming problem and find the moment values. Our moment function uses an asymptotically efficient weighting matrix, which we construct by bootstrapping the data to solve for the variance of the moments and then taking the inverse of the variance.

For each potential parameter vector, we solve the value function and calculate the distributions of investment and retirement decisions by discretizing the continuous investment/retirement choices into a finite grid of 20 levels.[24] We use the Gowrisankaran and Schmidt-Dengler (2025) (GSD) algorithm, which provides a computationally quick way of evaluating the probability that the utility would choose each grid point and accompanying value function, allowing for a large number of choices and for some of the choices never to be chosen, which occurs in our context. This approach allows us to estimate investment/retirement over time discretized investment levels as in an ordered choice model based on a single cost shock, using the probability of the chosen investment/retirement action at the observed state in the moment condition.[25] GSD reduces the implementation costs of a nested fixed-point estimation relative to simulation by making the moment condition continuous in the structural parameter vector. On-Line Appendix A4.1 provides more details, including Bellman equations.

[24] We experimented with increasing the number of investment/retirement levels in our GMM estimator but found that our results were not sensitive to this change.

[25] A common alternative approach specifies an *i.i.d.* shock to each candidate choice in a multinomial logit model (e.g., Chatterjee et al., 2023). With *i.i.d.* shocks, agents will substitute to the most commonly chosen alternative rather than similar choice levels (Gowrisankaran and Schmidt-Dengler, 2025). This is unrealistic in our setting.

Identification of the investment and retirement cost parameters comes from the extent to which utilities choose to retire coal or invest in CCNG given differences in expected profits across these states. For instance, utilities' delay in CCNG investment—even when profits are potentially higher with additional capacity—identifies the average investment costs for CCNG. The amount of heterogeneity in utilities' investment and retirement decisions given similar differences in expected profits conditional on an action identifies the standard deviation of the investment and retirement cost shocks. Declines in natural gas fuel prices, together with heterogeneity across utilities in their capital mixes, provide variation in profit differences across states that identify the investment/retirement parameters.

5.2 Operations Model

Investment and retirement decisions in each period depend critically on period variable profits π^* that the utility would earn at any long-run capacity and fuel price state. Although a period in our investment/retirement model represents three years, we estimate π^* separately by utility-year to use annual revenue, capacity, and fuel price data.[26] While our simplified model in Section 3 specified that load was fixed within a period, we now assume that each period is comprised of hours, $h \in \{1, \ldots, H\}$, and that load, ℓ_h, while remaining inelastic, varies across hours. The utility must meet this load at each hour with generation from each fuel-technology type, q_h^f, and—also in a generalization relative to Section 3—imports from outside of its service area, q_h^m, which we combine into $\vec{q}$. Note that $Q^f = \sum_{h=1}^{H} q^f$, for each fuel-technology type f.

As in our simple model, we do not model a used-and-useful standard for CCNG capacity because it would be difficult to credibly identify. Specifically, early in our sample, CCNG was only intended to generate in hours with high load and, therefore, would not have been held to a similar used-and-useful standard to coal. Later, once natural gas fuel prices had fallen, CCNG was typically the cheapest option, and hence there would be little potential for the out-of-dispatch-order generation discussed in Section 3.2. Thus, α^{CCNG} will incorporate the average effect of any used-and-useful standard for CCNG. We similarly do not model a

[26]For ease of notation, in this subsection we suppress the t subscript and refer to a year as a period, though our investment/retirement estimation aggregates three years into a period.

NGT used-and-useful standard, since NGT serves a different purpose.[27] Compared to our simple model, we therefore add an additional term to the rate base from (3), $\alpha^{NGT} \times K^{NGT}$.

The utility faces hourly inverse import supply curves, $S_h^m(q_h^m)$, when making operations decisions. We assume that the utility imports electricity from various sources with separate contracts, and hence it pays different sources different amounts. Following the literature (Bushnell et al., 2008; Gowrisankaran et al., 2016; Reguant, 2019), we let the utility's import costs be the integral under the inverse supply curve rather than the maximum import price times quantity imported. We estimate each utility's hourly import supply curve using generation, load, weather, and price data. On-Line Appendix A4.3 provides details of the import supply curve estimation.

The utility chooses $\vec{q}$ to maximize period variable profits, which, as in (1), are its RoR on its rate base, $s \times B$. However, TVC now includes fuel, operation and maintenance (O&M), and ramping costs for each fuel-technology and import costs:

$$TVC(\vec{q}) = \sum_h \left[\sum_f \left[q_h^f \times (heat^f \times p^f + om^f) + \rho^f \times Ramp(q_{h-1}^f, q_h^f) \right] + \int_0^{q_h^m} S_h^m(q) dq \right].$$

Each marginal fuel cost is the product of a constant heat rate, $heat^f$, and a fuel price per MMBtu, p^f, which can vary across years. We model O&M costs, om^f, as constant per MWh of generation, and ramping costs, ρ^f, as constant per MW of generation increase, i.e., $Ramp(q_{h-1}^f, q_h^f) = q_h^f - q_{h-1}^f$ in the case where $q_h^f > q_{h-1}^f$ and zero otherwise. We assume that NGT plants do not have ramping costs, so $\rho^{NGT} = 0$.

From the operations decisions, we estimate the cost parameters ρ^{COAL}, ρ^{CCNG}, om^{COAL}, om^{CCNG}, om^{NGT}, the regulatory penalty for high electricity rates, γ, each fuel-technologies' rate base contributions, α^{COAL}, α^{CCNG}, and α^{NGT},[28] and the used-and-useful terms, μ_1 and μ_2,

The utility's optimization problem is now similar to (3), but with the addition of multiple sources of costs, multiple hours in the year, imports, and NGT capacity. The existence of ramping costs creates a dynamic linkage between hours, which means that we need to

[27] NGT plants often serve as "peakers," which would not need to prove usefulness via high usage rates.

[28] We do not explicitly measure depreciation due to data limitations. Hence, the α parameters capture the average contribution of one MW of capital of each fuel-technology type to the rate base B in dollars.

consider profit maximization jointly across hours of the year. To simplify the operations decision problem, we assume that the utility observes all hourly loads and import supply curves at the beginning of the year.

We estimate the structural parameters via a nested fixed-point indirect inference approach (Gouriéroux et al., 1993; Smith, 1993). This involves a non-linear search to find the parameters that most closely match coefficients from regressions run on model-simulated data to those run on actual data. The solution of our model depends on r_0, which captures differences in fixed characteristics across utilities, such as size, that will influence the regulator's perception of reasonable electricity rates. We define r_0 as the electricity rates—measured as revenues divided by load—in the first year the utility appears in the data, which allows for a consistent scale of γ across utilities.[29]

To compute the model solution for a given structural parameter vector, we conceptualize this problem as a discretized finite-horizon Bellman equation. Without loss of generality, our model allows us to specify that the utility receives its only payoff, the regulatory profit, in the terminal hour. This payoff is an implicit function of costs and coal usage, Q^{COAL}. Ramping costs further imply that TVC depends on the hourly sequence of coal and CCNG generation. Thus, in any hour, h, the state for the Bellman equation includes the cumulative TVC and coal usage prior to this hour (which will eventually determine profits), last hour's coal and CCNG generation (which affect ramping costs), and the hour of year h. These five variables are sufficient for the utility to evaluate the impact of its actions on its state-contingent value starting at hour $h + 1$.

Having solved for the state-contingent value functions backwards to the first hour of the year, we then forward simulate—using the calculated state-contingent optimal policies—to recover the optimal action path. Specifically, we start in the first hour and record the optimal generation choices. We then use these choices to update the state for the next hour, which in turn allows us to record the state-contingent optimal actions for that hour. Iterating through hours of the year, we obtain the utility's optimal operations decisions.

Solving for optimal operations decisions results in simulated hourly and annual data on

[29] In most cases, this will be 2006, before natural gas prices declined, and hence during a period when utilities' optimal generation choice was simpler.

which we run our indirect inference regressions. Indirect inference is a form of generalized method of moments (GMM), which specifies equilibrium levels and correlations in the data we would most like the model to match. For this reason, indirect inference regressions do not require a causal interpretation. We choose indirect inference regressions that we believe best reflect the important equilibrium features of the data.[30]

We run indirect inference regressions at both the utility-hour and utility-year level. We summarize each of these sets of regressions here and include a more complete discussion in On-Line Appendix A4.2. While identification of the structural parameters derives from all of the indirect inference regressions together, we motivate particular regressions as aiding identification of particular parameters. Fundamentally, much of the variation that identifies these parameters will stem from the sharp decline in natural gas fuel prices, as discussed in the beginning of Section 5.

At the hourly level, we regress generation by fuel-technology on a constant to match the scale of generation of each fuel. Because utilities have an incentive to reduce costs, these scales are particularly useful for identifying O&M costs. We also regress current generation on lagged generation, controlling for current and future predictors of demand, separately for coal and CCNG. These regressions help identify ramping costs, because the higher the ramping costs the less the utility will change generation from hour to hour.

We also regress the log of the share of hourly generation from coal and CCNG that is met by coal on quintiles of annual coal usage,[31] the coal fuel price minus the natural gas fuel price, their interactions, and utility fixed effects. We run an analogous regression for CCNG. These regressions help us to understand the utility's incentive to run coal out of dispatch order, which identify coal usage's contribution to the rate base. We would expect that, to the extent that used-and-useful incentives bind, coefficients on coal quintiles—unlike for CCNG—should exhibit an inverse U-shape, with the marginal incentive to use coal in an hour being highest when the return to coal usage via the used-and-useful incentive is the highest. However, this relationship may be confounded by the fact that the use of a fuel in

[30]An alternative estimator could match outcomes such as the rate base or the RoR between the simulated model and the data. However, because these elements are conceptually hard to measure (Ernst and Hlinka, 2024a), we instead match observable outcomes that relate to them, notably revenues, generation, and fuel and import costs.

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

a given hour also reflects the fuel's overall value. To isolate hours where the incentive to increase coal's contribution to the rate base is most likely to affect generation, we limit our regressions to hours where total load is between 75% and 125% of total capacity of the other fuel-technology.

At the annual level, we regress an observable measure of variable profits—revenues net of fuel and a measure of import costs—on a constant. We further regress this same measure on capacity by fuel-technology and coal capacity interacted with coal usage. These regressions help recover the conversion between MW of each fuel's capacity and their relative contributions to the rate base, α^{COAL}, α^{CCNG}, and α^{NGT}. These regressions also combine with the hourly regressions to help identify the coal usage incentives, μ_1 and μ_2. Finally, we regress a measure of the RoR on fuel and import costs and utility fixed effects to help identify γ, which indicates how the RoR responds to changes in electricity rates.

There are two sets of parameters that are jointly identified. Both the α parameters and γ determine how generation capital translates into dollars of allowable return. Similarly, α^{COAL}, μ_1, and μ_2 combine to translate coal capital and usage into the rate base. For both of these sets, we identify them jointly with multiple indirect inference regressions.

6 Results and Counterfactuals

This section begins by presenting our estimation results. Section 6.2 presents short-run counterfactuals that evaluate the impact of alternate regulatory policies on operations decisions, holding capacity constant. Section 6.3 then explores long-run counterfactuals that simulate an energy transition over a 30-year horizon following a sudden fall in natural gas prices.

6.1 Estimation Results

Table 3 presents estimates and standard errors for the structural parameters estimated using operations decisions.[32] Focusing first on how much a change in a utility's capacity would

[32]Table A1 in On-Line Appendix A1 displays how simulations of our operations model compare to observed data and Table A2 in the same appendix displays how the indirect inference coefficients estimated on the data match those estimated on the simulated data. Overall, we find that the model replicates patterns in the data reasonably well, including usage across CCNG and coal usage quantiles. However, the model

Table 3: Coefficient Estimates for Operations Model

Parameter	Notation	Estimate	Std. Error
Penalty for High Electricity Rates	γ	0.620	(0.04)
CCNG Capacity Weight in Rate Base (Mill. $/MW)	α^{CCNG}	0.229	(0.07)
Coal Relative Weight in Rate Base	$\frac{\alpha^{COAL}}{\alpha^{CCNG}}$	1.144	(0.18)
Coal Usage Logit Base	μ_1	-0.612	(0.13)
Coal Usage Logit Slope	μ_2	6.229	(0.13)
NGT Relative Weight in Rate Base	$\frac{\alpha^{NGT}}{\alpha^{CCNG}}$	1.791	(1.24)
Ramping Cost for Coal (100$/MW)	ρ^{COAL}	0.477	(0.08)
Ramping Cost for CCNG (100$/MW)	ρ^{CCNG}	0.386	(0.19)
O&M Cost for Coal ($/MW)	om^{COAL}	12.894	(0.76)
O&M Cost for CCNG ($/MW)	om^{CCNG}	8.820	(5.46)
O&M Cost for NGT ($/MW)	om^{NGT}	44.627	(45.51)

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

affect variable profits—which is primarily determined by both the γ and α parameters[33]—we find that, across sample observations, a 10% increase in TVC would decrease variable profits by 1.96%, while a 10% decrease in TVC would increase variable profits by 2.05%, which is comparable to the 2.5% change predicted by the reduced-form fixed effects specification in Table 1. We find that a 500 MW change in the rate base, which is roughly the mean CCNG plant capacity, would change variable profits by 5.5% on average across our sample.[34]

We next turn to the α and μ parameters, which determine how each fuel-technology contributes to the rate base. The α^{CCNG} estimate shows that each MW of CCNG capacity increases the rate base by $229,000. When fully used, each MW of coal capacity contributes $\frac{\alpha^{COAL}}{\alpha^{CCNG}} = 1.144$ times as much as CCNG.[35] However, when coal is not fully used, the μ_1 and μ_2 parameters of the used-and-useful function determine the extent to which each coal MW contributes to the rate base. Both parameters are statistically significant, and unused

over-predicts overall revenues and coal usage.

[33]Recall that we do not have data on the rate base and hence the α parameters are not separately identified from γ.

[34]Table A3 in On-Line Appendix A1 presents estimates where γ can vary based on whether the utility is subject to market dispatch—i.e., if the utility is in MISO or SPP—because market dispatch may allow regulators to better observe the costs of alternative actions and thus potentially lead to more price discipline. We find coefficients that are very similar to Table 3, though many lose statistical significance.

[35]We estimate the contribution of coal and NGT capacity to the rate base *relative to CCNG*.

coal capacity contributes 40% as much to the rate base as CCNG.[36] Finally, NGT capacity contributes to the rate base 79% more than a unit of CCNG capacity, though the coefficient $\frac{\alpha^{NGT}}{\alpha^{CCNG}}$ is not significant.

Turning to other operations costs, a 100 MW coal ramp in one hour—which corresponds to increasing output by 15% for a coal plant with mean capacity—would cost the utility $4,770, while the figure is lower for a CCNG ramp at $3,860. The coal estimates are between the Reguant (2014) estimates for ramping a unit that is already generating and a startup. They are lower than Borrero et al. (2023), but pertain to ramping across plants in a utility rather than for a specific generator as in that paper. We estimate statistically significant O&M costs of $12.89/MWh for coal capacity. This figure is similar to Linn and McCormack (2019) and Borrero et al. (2023). Our O&M costs for CCNG and NGT are $8.82/MWh and $44.63/MWh respectively, though neither is statistically significant. For CCNG, this number is somewhat higher than the reported variable O&M costs for single-shaft and multi-shaft CCNG turbines of $2.67 and $1.96, respectively (Energy Information Administration, 2022).

Table 4: Coefficient Estimates for Investment and Retirement Decisions

	Quadratic Model	Linear Model
Fixed Cost of Coal Retirement (1e8 $)	−1.294 (0.898)	−1.071 (2.488)
Linear Coal Cost (1e6 $/MW)	1.465 (1.011)	1.643 (0.749)
Quadratic Coal Cost (1e3 $/MW^2)	0.073 (0.111)	—
Coal Shock Standard Deviation (1e6 $/MW)	0.860 (0.638)	0.564 (0.614)
Fixed Cost of CCNG Investment (1e8 $)	−0.124 (0.426)	−0.034 (5.941)
Linear CCNG Cost (1e6 $/MW)	2.797 (0.488)	2.820 (1.457)
Quadratic CCNG Cost (1e3 $/MW^2)	0.089 (0.073)	—
NGCC Shock Standard Deviation (1e6 $/MW)	0.442 (0.509)	0.020 (0.592)

Note: Structural parameter estimates from GMM nested fixed point estimation.

Column 1 of Table 4 presents our primary investment/retirement parameter estimates, which have quadratic costs.[37] The fixed costs of adjusting coal or gas capacity are small

[36] Figure A1 in On-Line Appendix A1 displays the impact of coal capacity on the rate base by usage level relative to the impact of CCNG capacity.

[37] Figure A2 in On-Line Appendix A1 compares the CDFs of coal capacity retirement and CCNG capacity investment for the simulated model and the data, showing that the model fits the data reasonably well. The correlation between the data and the model is 0.966 for coal retirement level probabilities and 0.997 for CCNG investment level probabilities.

and not statistically significant,[38] while the marginal adjustment costs are convex, with positive quadratic terms. A 250 MW CCNG investment costs \$692 million, while a 250 MW coal retirement yields \$491 million in scrap value, both with the mean cost shock. The investment/retirement cost shock standard deviations are \$442,000 per MW for CCNG and \$860,000 per MW for coal. Column 2 of Table 4 presents parameter estimates with linear investment/retirement costs. The results are largely similar to the quadratic model, although coal retirement yields significantly positive scrap values.

Our estimates of the mean capital cost of CCNG investment are slightly larger than the high end of the capital costs reported in Energy Information Administration (2022). We would expect our estimates to be higher since they are based on revealed preferences and thus include substantially more than just capital costs. For instance, they also include permitting costs, the costs of the PUC approval processes, and any additional regulatory costs (or avoided regulatory costs in the case of coal capacity retirement). Moreover, investments in our model generally occur when the utility receives a favorable draw of the CCNG cost shock, resulting in lower realized costs than the mean. Similarly, for coal retirement, we estimate large scrap values, but these estimates include avoided investments in coal plants that would have been necessary to keep these plants running (e.g., mercury abatement technologies as in Gowrisankaran et al., 2025).

6.2 Operations Counterfactuals

Table 5 presents counterfactuals that evaluate the impact of regulation on operations decisions, using historical capacity levels and natural gas fuel prices. For each utility-year in our analysis sample, we report how baseline model outcomes would vary from those of the social planner, cost minimizer, and regulated utilities faced with a carbon tax, different used-and-useful incentives, and alternative electricity rate penalties,

Both the social planner and cost minimizer minimize variable costs, but the social planner perceives these costs as including a \$190/ton carbon tax.[39] For these counterfactuals, we focus on generation and carbon costs rather than revenues or profits, which are not

[38]CCNG investment costs are positive when investment exceeds 4.4 MW, a negligible size.
[39]We assume that electricity imported from restructured markets has the U.S. average carbon intensity.

well-defined without additional assumptions, since the social planner and cost minimizer solutions do not result from a regulatory process. A utility faced with no used-and-useful standard will have the same short-run incentives as the cost minimizer, but earn regulated utility profits. Finally, our carbon tax counterfactual assumes that the government rebates exogenous, predetermined amounts as lump sums to the utility and/or individuals. We take this approach because, although the regulator could adjust the rate penalty function in response to carbon taxes or rebate collected tax revenue, either of these modifications could change utility incentives in more complex ways.[40]

Table 5: Operations Counterfactuals

	Coal Usage (%)	CCNG Usage (%)	Total Var. Production Costs (Mil. \$)	Carbon Costs (Mil. \$)	Electricity Rates (\$/MWh)	Variable Profits (Mil. \$)
Baseline	71.73	8.85	1,037	4,960	77.58	1,213
Social Planner	3.05	44.41	1,234	2,696	–	–
Cost Minimizer	37.62	26.83	910	4,008	–	–
Carbon Tax w/ RoR	55.03	26.76	1,251	4,421	224.18	663
No Usage Incentive, $\mu_2 = 0$	37.62	26.83	910	4,008	60.25	890
$2\times$ Usage Incentive, μ_2	55.71	15.00	984	4,481	76.17	1,233
Half Rate Penalty, γ	78.72	8.33	1,067	5,170	83.41	1,337
$1.5\times$ Rate Penalty, γ	67.63	9.68	1,022	4,837	73.26	1,117

Note: Table presents counterfactual simulations of operations decisions at estimated parameter values. 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 next four counterfactuals change regulatory incentives as indicated. The final counterfactual preserves the ROR regulatory structure, adding the \$190/ton cost to TVC. Counterfactuals use every utility-year in sample and hold capacities and natural gas fuel prices fixed at their observed, historical levels.

The first row of Table 5 presents outcomes from the baseline model as a point of comparison. The second row shows that the social planner reduces coal usage from 72% to 3% of capacity—a 96% reduction—by substituting to other sources. Specifically, CCNG capacity usage increases by a factor of five. This results in an increase in variable production costs of approximately \$200 million, but also \$2.3 billion lower carbon costs. The cost minimizer,

[40]On-Line Appendix A5 provides further counterfactual implementation details.

presented in the third row, also uses 48% less coal than in the baseline, resulting in \$1.0 billion lower carbon costs.

The fourth row shows that when carbon taxes are added to current regulated utilities, carbon costs only fall by about \$500 million relative to the baseline. This is 41% as much as the \$1.3 billion carbon cost savings from imposing carbon taxes on the cost minimizer (the difference in carbon costs between the third and second rows). The regulated utility also passes through most of the carbon costs to consumers,[41] resulting in electricity rates nearly tripling, from \$77.58/MWh in the baseline to \$224.18/MWh. Despite this, carbon taxes cause regulated utility variable profits to drop by over \$500 million, which may need to be offset by lump-sum transfers to cover other costs such as transmission and distribution.

The remaining rows of Table 5 present modifications of existing regulatory incentives. We find that eliminating the usage bonus for coal—setting $\mu_2 = 0$—would cause regulated utilities to engage in cost minimization over the short run but would reduce utility variable profits by over \$300 million, implying that RoR regulation may not be able to achieve cost minimization without jeopardizing reliability.

Doubling μ_2 allows the utility to demonstrate that coal is used and useful with less usage, which might either increase or decrease the marginal incentive to use coal. Empirically, doubling this incentive decreases coal usage by 22%, implying that, on average across our sample, it allows utilities to demonstrate adequate usefulness with less usage. We next simulate changing the penalty for high electricity rates. Halving the penalty results in 10% more coal usage, while increasing it by 50% decreases coal usage by 6% relative to the baseline. None of these three counterfactuals result in operations outcomes that are close to the social planner or cost minimizing levels, but all have similar utility profits to the baseline.

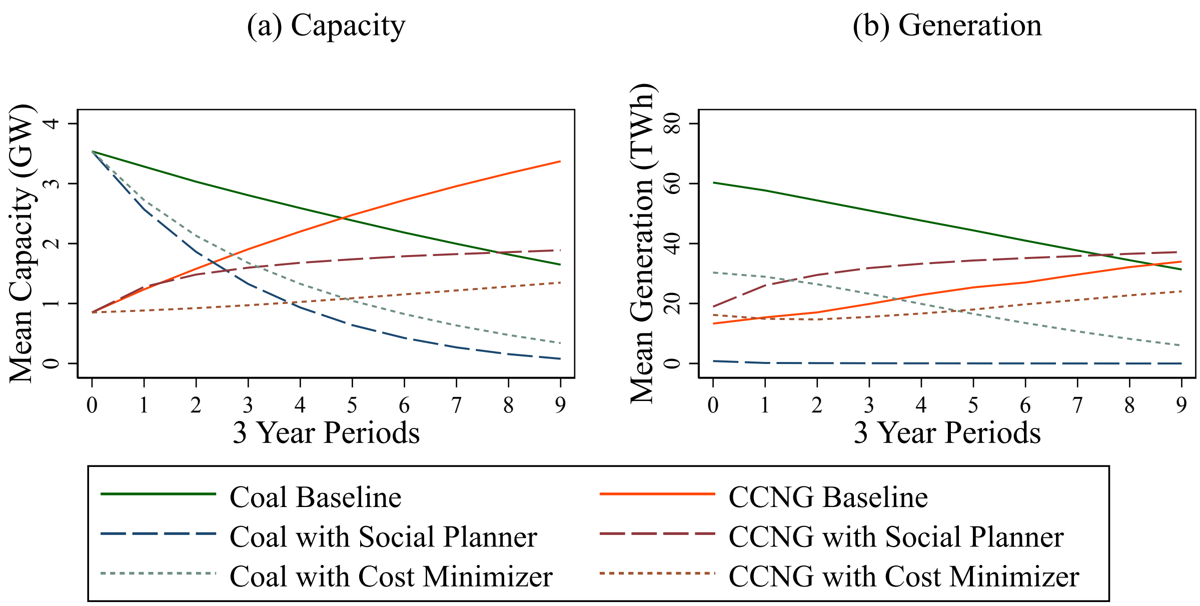
6.3 Long-Run Counterfactuals

Changing regulatory incentives would have long-run ramifications for utilities' investment and retirement decisions, especially during an energy transition. Rather than using the observed decline in natural gas prices from fracking, this section presents counterfactuals

[41] Carbon costs with the carbon tax are \$4.4 billion while average utility revenues (not shown in Table 5) increase from \$2.25 to \$6.33 billion with a carbon tax, representing a 92% pass through.

that examine the long-run impact of utilities with 2006 capacities suddenly facing the average 2018–20 natural gas fuel price. Specifically, this means imposing a price of \$2.01/MMBtu—instead of the 2006 price of \$7.24—and the same fuel price evolution process we used in estimation. This approach allows us to simulate an immediate energy transition, rather than the observed, more gradual decline in natural gas prices.[42]

Figure 4: Capacity and Generation for Social Planner and Cost Minimizer



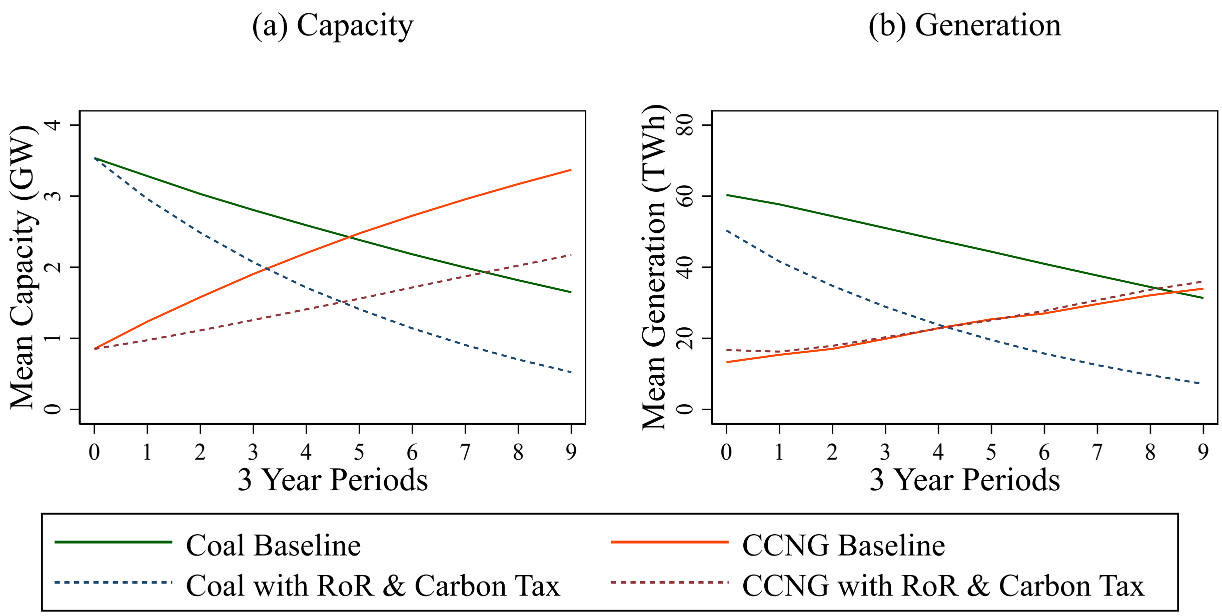
Note: Figures present counterfactual simulations over 10 3-year periods starting with 2006 capacities but imposing 2018–20 natural gas fuel prices. The social planner minimizes costs including a \$190/ton carbon cost. The cost minimizer has the same incentives but does not value carbon externalities.

Figure 4 presents the results of these counterfactuals for the social planner and cost minimizer. Panel (a) shows that while baseline utilities only retire 53% of their coal capacity over 30 years, the social planner and cost minimizer eliminate most coal capacity over this horizon. Panel (a) further shows that CCNG investment is substantially higher in the baseline than under either the social planner or the cost minimizer, demonstrating that the AJ over-investment effect dominates the other incentives. From panel (b), in the first period, the social planner effectively stops using coal while the cost minimizer only reduces coal generation by 50%, relative to the baseline. The cost minimizer approaches the planner coal

[42]On-Line Appendix A6 presents three further sets of results: (1) counterfactuals that fix import quantities, (2) counterfactuals that vary the rate penalty, and (3) the carbon costs of some counterfactuals in this section.

generation level by the end of the 30-year horizon. Thus, during the energy transition that we study, the primary benefit of carbon taxes relative to cost minimization would have been in reducing coal generation rather than encouraging coal retirement.

Figure 5: Capacity and Generation for Social Planner, and Carbon Tax with Regulation

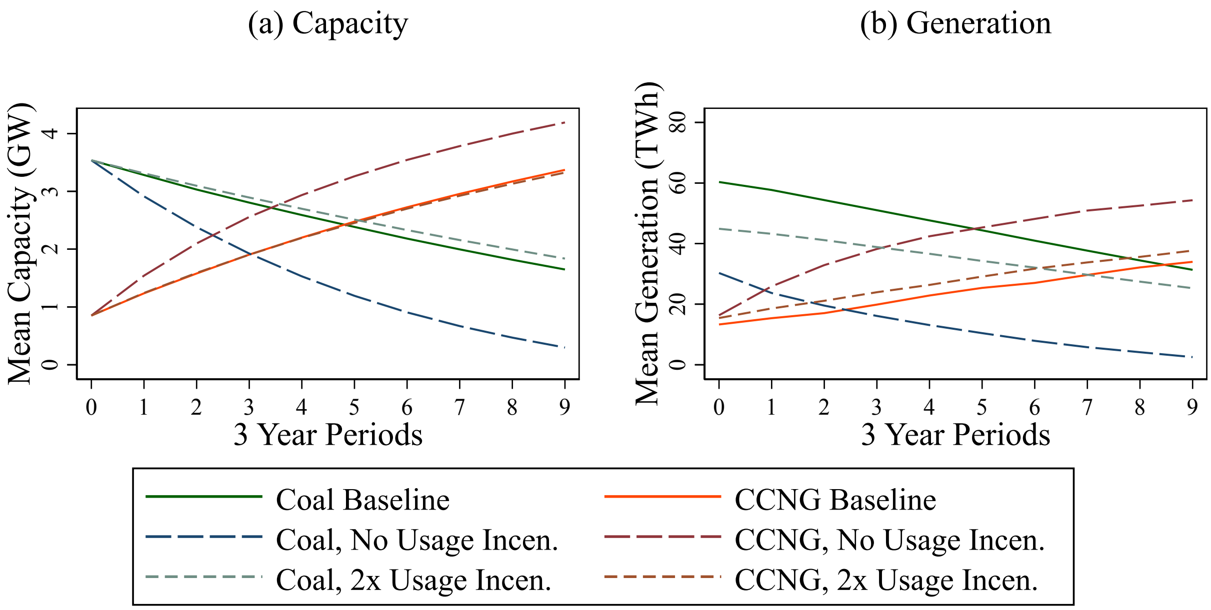


Note: Figures present counterfactual simulations over 10 3-year periods starting with 2006 capacities but imposing 2018–20 natural gas fuel prices. The social planner minimizes costs including a \$190/ton carbon cost. The carbon tax counterfactual leaves the regulatory structure unchanged but adds the carbon cost to TVC.

Figure 5 presents counterfactuals that impose carbon taxes on the regulated utility. Mirroring the results in Section 6.2, the immediate effects of a carbon tax for a regulated utility faced with an energy transition relative to the baseline are moderate. Comparing panel (b) of Figure 5 to Figure 4, imposing a carbon tax on the regulated utility leads to an immediate drop in coal generation only 34% as large as when one is imposed on the cost minimizer. However, by the end of our 30-year horizon, imposing a carbon tax on a regulated utility reduces coal capacity and generation by 68% and 77% respectively, relative to the baseline, with imports largely replacing coal generation. These effects are *larger* than the effects of a carbon tax on a cost minimizer from Figure 4. Thus, while carbon taxes achieve more in the short run when imposed on the cost minimizer, in the long run they are more impactful when imposed on the regulated utility.

Finally, Figure 6 considers alternative coal usage incentives. Setting $\mu_2 = 0$ causes coal

Figure 6: Capacity and Generation for Different Coal Usage Incentives



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 coal usage incentive, μ_2, as indicated.

capacity to decrease 82% and coal generation to decrease 92% by the end of the 30-year horizon relative to the baseline. The generation drop is slightly larger than for the cost minimizer, though at the cost of over twice as much CCNG capacity, due to the AJ effect. Doubling the coal usage incentive leads to slightly slower retirement of coal capacity, but also lower generation with that capacity.[43]

Overall, we view these counterfactuals as illustrating how RoR regulation impacts energy transitions and how regulation interacts with Pigouvian taxes. They show that legacy technology plays an important role in slowing energy transitions under RoR regulation. However, they do not account for the continuous and ongoing shocks to technologies and environmental preferences that have been occurring in reality. We find that the AJ effect leads to substantial over-investment in CCNG, which may slow the *next* transition to renewables. Understanding the impact of RoR regulation on this next transition would require adjusting parameters to reflect these evolving technologies.

[43]On-Line Appendix A6 shows that changing γ also does not come close to replicating the cost-minimizing outcome.

7 Conclusion

This paper develops and estimates a model of rate-of-return regulation and analyzes how regulation performs when confronted with an energy transition. The regulator creates an incentive structure that seeks to make electricity reliable and affordable. The utility optimizes against this structure, facing a tension between keeping costs low and proving that coal capacity is prudent by keeping its usage high.

We show with a simple theoretical model that regulation leads to the overuse of legacy technologies and slows their retirement, but whether regulation leads to over- or under-investment in the new technology is an empirical question. We find that regulation leads to over-investment in CCNG capacity but over-use of coal capacity, and thereby higher emissions than under cost minimization. Imposing carbon taxes on regulated utilities has a smaller short-run impact on carbon costs than adding them to a cost-minimizer, but this relative effect is reversed in the long-run as regulated utilities respond to carbon taxes by retiring much more coal capacity in the face of an energy transition. Adjustments to the regulatory structure mostly do not achieve the carbon cost reductions of the cost minimizer, and those that do would require transfers to maintain resource adequacy. This is consistent with the 2022 Inflation Reduction Act including substantial transfers for clean energy investment rather than carbon taxes.

Our study has many limitations, including the fact that while we estimate the energy transition from coal to CCNG, it is beyond our scope to estimate the transition to renewables and storage. This is because we do not have enough variation in the data to understand the extent to which regulators would react to CCNG becoming the legacy technology by imposing a used-and-useful standard or how renewables and storage would contribute to the rate base. Nonetheless, our results further suggest that to the extent there has been over-investment in CCNG capacity, this may reduce future electricity affordability by requiring ratepayers to fund stranded assets, and that usage incentives for combined-cycle capacity are likely to further hinder the transition to renewables.

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On-Line Appendix

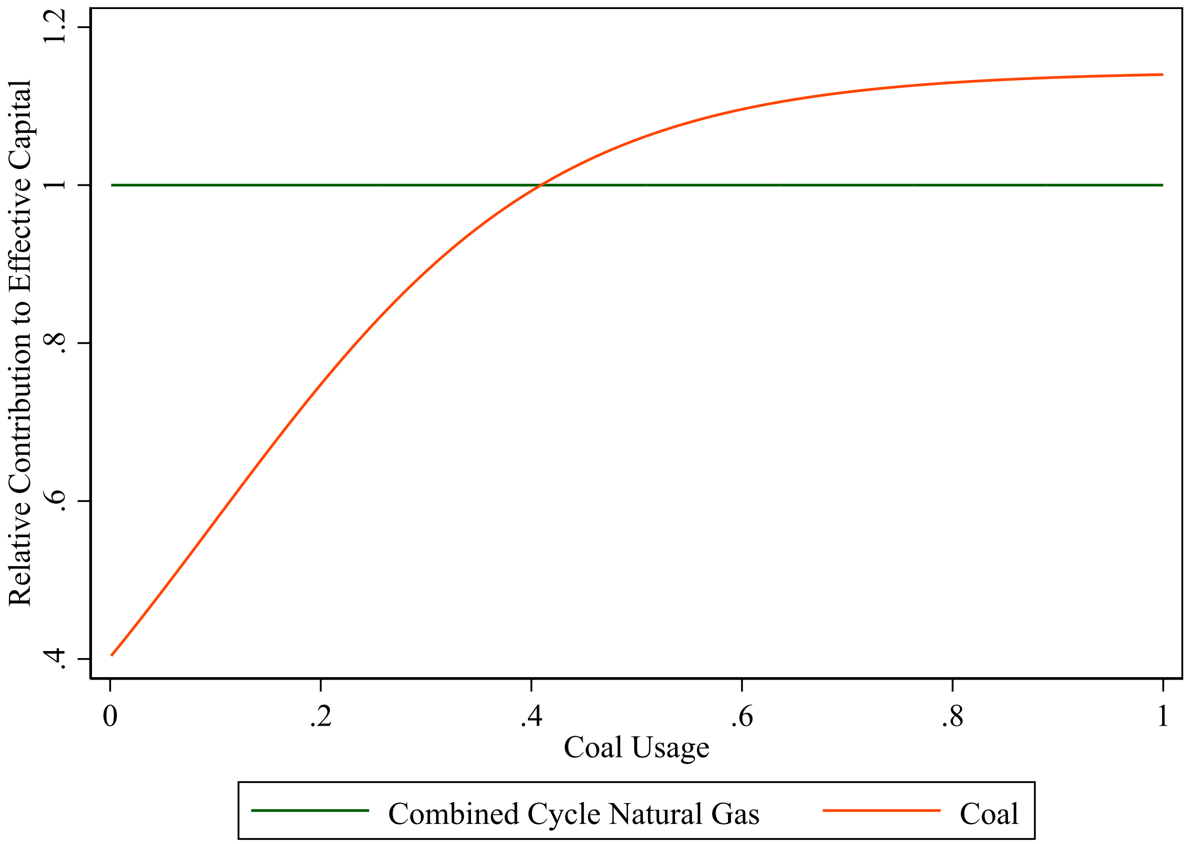
A1 Additional Tables and Figures Referenced in Main Paper

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.

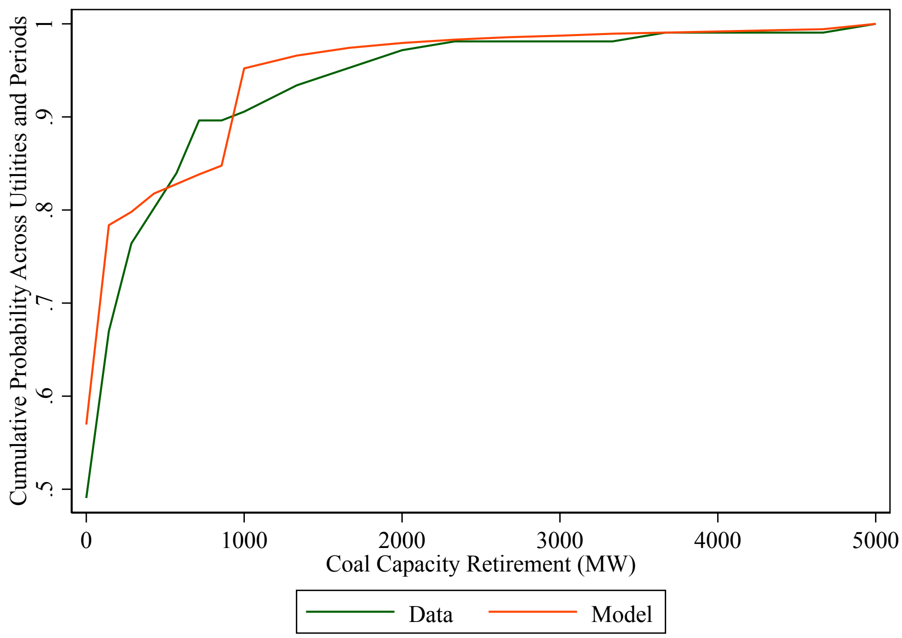
Figure A1: Coal Contribution to Rate Base Relative to CCNG



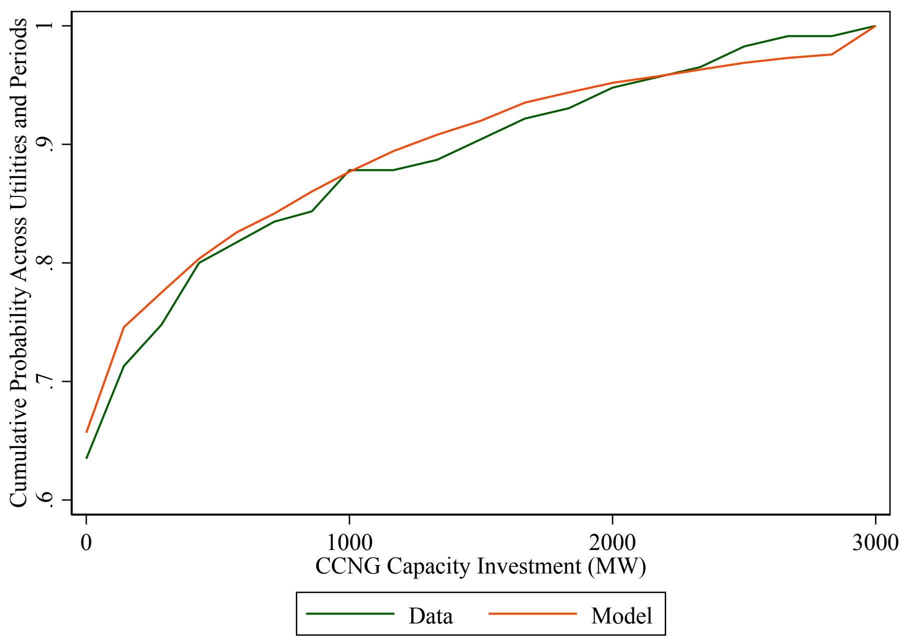
Note: Figure calculated from estimated model coefficients.

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. 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 CPI net of food and energy as our measure of inflation.

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 that, by construction, most utilities do not have an ISO in their U.S. state, we assign utilities

[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.

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`.

[46] We allow exports to be represented as negative imports, so some utilities will have more generation from Coal, CCNG, and NGT than total load in particular hours.

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 return for a number of utilities, which we dropped. For one utility, it only reported limited-

[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.

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

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.

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:

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

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:

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

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

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

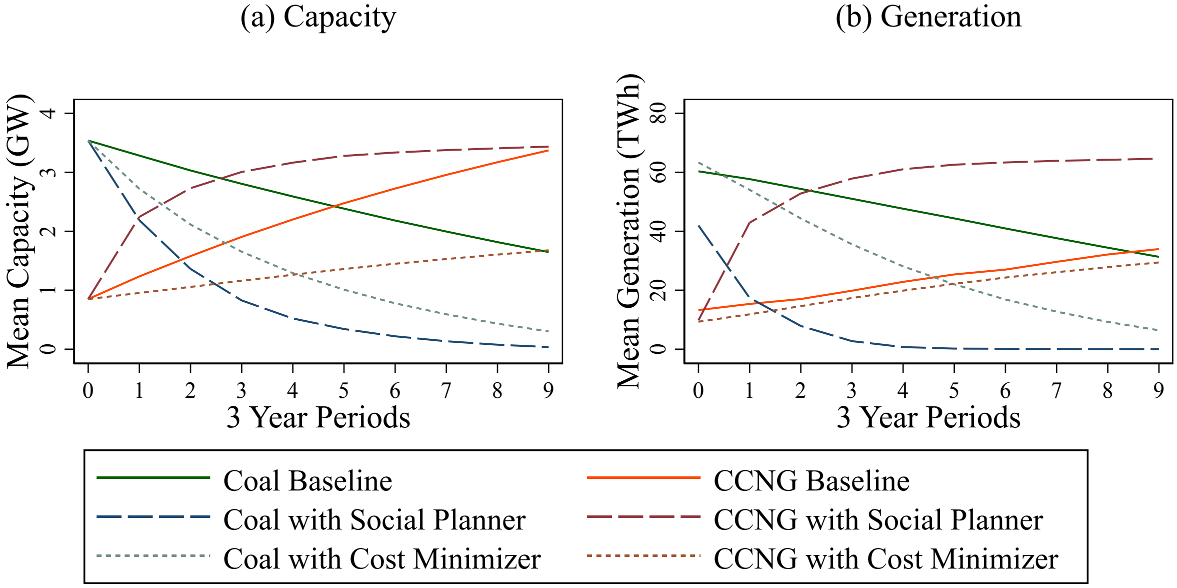
This appendix considers three additional sets of long-run counterfactuals. First, the long-run counterfactuals in the main text keep import curves fixed, consistent with a single utility facing alternate incentives. This allows the utility to increase imports when coal generation is costly, for instance 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.

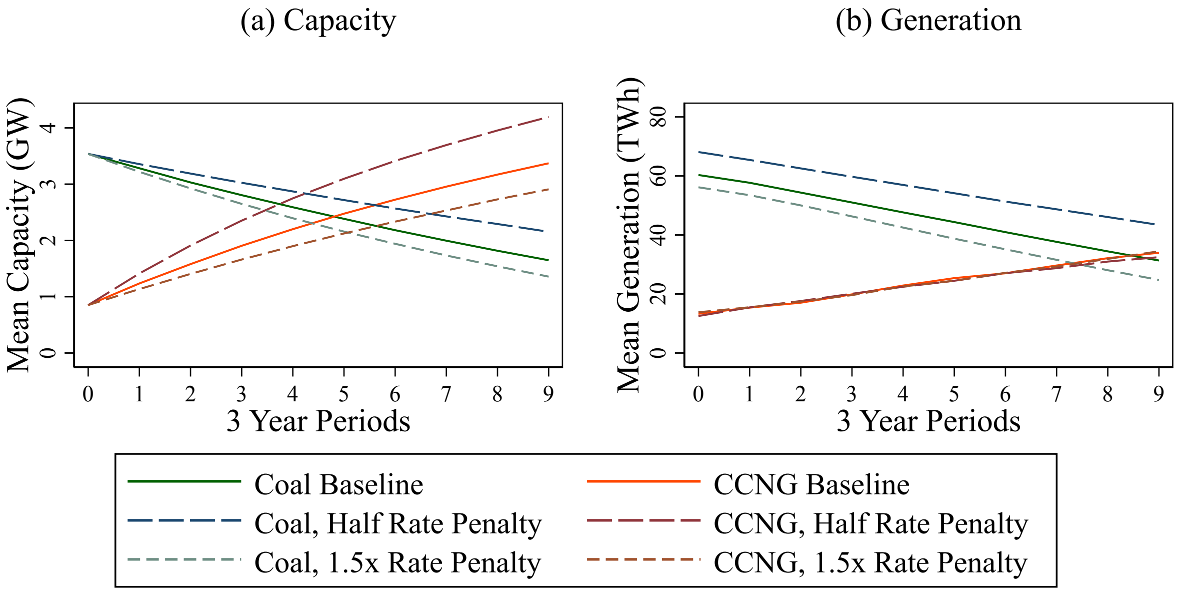
Finally, Figure A5 reports total carbon emissions over time for four counterfactuals: the baseline, the cost minimizer, the planner, and the regulated utility facing carbon taxes. We find distinct differences in immediate carbon emissions following a sudden drop in natural gas fuel prices. However, by 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



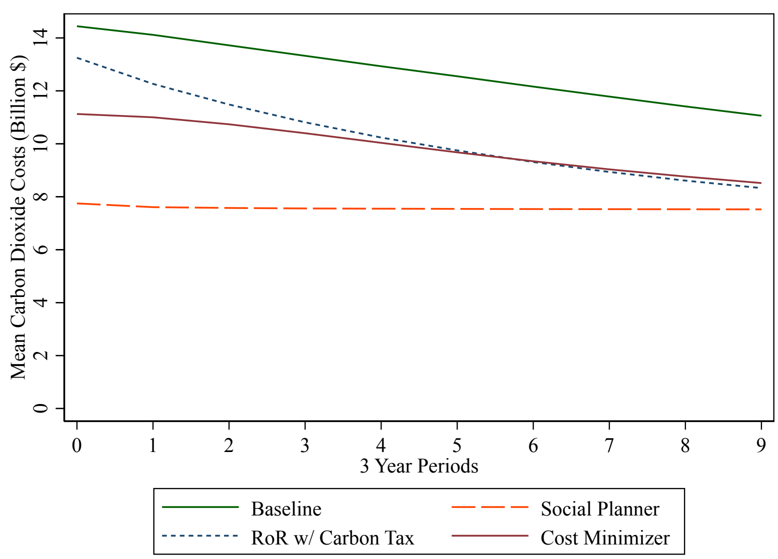
Note: Figures present counterfactual simulations over 10 3-year periods starting with 2006 capacities but imposing 2018–20 natural gas fuel prices. The social planner minimizes costs including a \$190/ton carbon cost. The cost minimizer has the same incentives but does not value carbon externalities. 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.