

# The Effects of Fuel Costs on New Electricity Generators in the United States

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## Abstract

We estimate the effect of the natural gas fuel cost on the choices for a new power generator, the energy source gas, wind, or solar and its capacity. Higher fuel costs increase odds of more renewable capacity, as opposed to gas, with large, significant effects for both wind and solar. As the U.S. has yet to implement nationwide carbon policies, we use fuel cost to proxy for a carbon tax. Our scenarios of \$10-to-\$50 per ton of carbon dioxide (CO<sub>2</sub>) reduce emissions from new generators by 22 to 47 percent, equivalent to 2 to 4 percent of total electricity emissions.

## 1 Introduction

Burning of fossil fuels releases carbon dioxide, causing climate change. Yet the fuels also propel 99 percent of vehicle use, provide more than 30 percent of buildings' heat, and power nearly 65 percent of the industrial sector (EIA 2022). Many are pushing toward electrification and updates in technologies are replacing the raw energy sources with electricity one promising pathway to decarbonize these sectors and mitigate climate change. However, existing electricity generation also emits carbon dioxide (CO<sub>2</sub>), producing 32 percent of 2021 emissions in the U.S. (EIA 2022). And electrification can increase demand for electricity, which requires construction of new generators that may produce emissions depending on the energy source. We focus on the latter, estimating firms' choices of energy source and capacity for new power plants, as a function of fossil fuel costs. We then use the variation in fuel costs as a proxy for carbon pricing, similar to previous literature. We evaluate policy scenarios using several hypothetical carbon prices. We assess the effect on new capacity of gas, wind, and solar energy, which in turn provides our estimates of reductions in emissions, additional tax revenue, and fewer social costs of carbon.

Previous work estimates how lower fuel costs for natural gas reduces carbon emissions from electricity. The market responds by demanding more natural gas, and less of its close substitute, coal. Both gas and coal create emissions; however, gas is less dirty than coal. Thus, net emission reductions occur in several cases: when a firm switches from coal to gas for a generator's fuel source, when gas generators move before coal in the dispatch order, or when a coal plant retires. The seminal paper, Cullen and Mansur (2017), estimates how variation in the coal-to-gas fuel-cost ratio influences U.S. firms' electricity production from active generators. Then, the authors convert the ratio into a hypothetical carbon price, inferring that a tax of \$10 per ton CO<sub>2</sub> reduces emissions by four percent. Fell and Kaffine (2018) assess the Eastern U.S.,

using fuel costs combined with intermittency of renewable generation to estimate changes in coal generation. They find lower natural gas fuel costs and cheaper wind turbines caused a large reduction of coal-generated electricity and emissions. Brehm (2019) considers how natural gas prices, from 2008 to 2013, affect the emissions from (1) switching from coal to gas plants and (2) newly constructed gas generators. Their estimates indicate halving the gas price reduced emissions by six percent due to the first mechanism and one percent due to new gas capacity. Linn and McCormack (2019) model of revenue and operating costs of coal plant retirements during 2005-2017 in the Eastern U.S., assessing the impacts of four shocks: regulations, renewable technology, natural gas price, and demand. The latter two explain the majority of retirements jointly reducing coal-plant generation by 41 percent. Coglianesse, Gerarden, and Stock (2020) reach a similar empirical conclusion regarding the fraction of each state's electricity generated by burning coal: From 2009 to 2016, coal-plant generation decreased by 37 percent, due largely to retirements. Linn and Muehlenbachs (2018) use nationwide plant-level data on fuel consumption and generation, finding that the decrease in natural gas prices during 2008 to 2012 induced coal retirements, but only in the Southeast and Northeast. Davis, Holladay, and Sims (2021) model a firm's decision to retire coal generation. Using variation in coal costs and electricity prices, the authors create policy scenarios: a tax of \$51 per ton CO<sub>2</sub> shortens the lifespan of the average plant by six years, whereas a subsidy of \$20 per MWh of coal generation extends it by five years. This previous literature establishes the decline of coal generation, which is now uneconomical; we look to reduction of natural gas as the next frontier of emission abatement.

Our paper assesses firm choices for construction of new electricity plants. We first set up a theoretical framework of a firm's optimization problem, a parsimonious equation of present-

discounted value of electricity generation as a function of determinants of energy source and size. We solve analytically for the firm's optimal responses to changes in fuel cost, which provides testable hypotheses. We distinguish between deregulated markets, comprised of independent power producers, and regulated markets with publicly owned utilities. The distinction is crucial, as firms in each regulatory status may respond differently; for example, Knittel, Metaxoglou, and Trindade (2015) compare these two types of firms and show that natural gas cost causes more fuel switching in regulated markets. For the empirical approach, we use firm-level data of construction of new generators, from 2001 to 2020 for the contiguous 48 states. We focus on gas, wind, and solar, the energy sources for 93 percent of generators built. We implement the discrete-continuous specification introduced by Dubin and McFadden (1984), which provides estimates of the discrete choice of energy source, jointly with the continuous choice, the capacity size. Of primary interest is the impacts of natural gas fuel costs, which we use to infer carbon policy outcomes. We convert these effects into changes in emissions and project policy outcomes from several carbon-price scenarios. With this step, we add insights to three questions: If adopted, how much does a carbon price reduce the construction of natural gas capacity, while promoting new solar and wind power? How does a range of policy prices, from \$10 to \$50 per ton of carbon, affect emissions in total and per megawatt-hour (MWh)? And finally, what are the net externality costs remaining, relative to those based on prominent estimates of the social cost of carbon?

We identify and fill a gap in the literature; to our knowledge, no empirical studies exist that estimate additional construction of capacity and the type of fuel used for the new capacity. This is a novel extension of previous research that looks at how increases in the relative cost for coal increases the use of existing generators with a relatively less dirty fuel, natural gas.

Understanding the factors affecting future choices of energy source for new power plants is critical in order to reduce emissions. Carbon abatement from the current fuel mix is finite due to (1) limited technical improvements and substitution, (2) the continued burning of fossil fuels, albeit one with less emissions, and (3) fixed short-run capacity of alternative power plants and energy sources. Construction of renewables can and will reduce the majority of emissions going forward. We also contribute a transparent theoretical model for our empirical approach. Furthermore, our regressions provide direct estimation based on observed decisions, in contrast to an engineering model. The leading example is the National Energy Modeling System (NEMS), which simulates the technologies and financials of the electricity industry. We compare their predictions to our estimates.

Our findings confirm the model hypotheses. During our study period, gas fueled two-thirds of new capacity built. However, we find that higher costs of natural gas increase the odds of new wind and solar generators, by 31 percent and 29 percent respectively. In addition, higher costs increase the size of new utility wind plants without discernible impact on the size of other new capacity.

Higher fuel costs of natural gas mimic a carbon price, and, as we find, creates an incentive for cleaner new capacity. Such a policy is yet to be implemented nationwide. Thus, we construct hypothetical carbon-price scenarios in which we use our results to assess the changes in energy source composition of the U.S. generating capacity built in 2021. We calculate the reduction of emissions, relative to business-as-usual. Under business-as-usual, the average carbon intensity of a MWh generated in the U.S. is 0.16 tons CO<sub>2</sub> per MWh, as of 2021. In one scenario, we find that a tax of \$50 per ton of CO<sub>2</sub> reduces emissions from new capacity by 47 percent, with an average carbon intensity of new capacity decreasing from 0.16 to 0.09 tons per

MWh. We find that the \$50 tax reduces total emissions by seven million tons in the first year. As cleaner new capacity stock accumulates, the effect quickly increases. As a comparison, Larsen et al. (2018) use NEMS to predict emissions reductions for the same tax and time period. Their simulations isolate the effect of new capacity, which is ten percent of their projected declines the first year eliminates 30 million tons and by the tenth, 100 million. In conclusion, we find credible and useful estimates of the effects of fuel costs on construction of electricity plants.

The next section models the effects of fuel costs on the energy source and size of new generators. Section 3 presents the econometric model and data. Section 4 gives our findings. The penultimate section considers carbon policies. We close with discussion, contextualizing our findings.

## 2 Theory of generator choice: Energy source and size

We model the choices of electricity-generating firms. Each firm makes a two-part, discrete-continuous decision regarding the energy source for and the size of new generators by optimizing their discounted present value, conditional on these two decisions. Previous literature refers to this set up as a real options model (Davis, Holladay, and Sims 2021). We start by describing the objective functions, which depend on the regulatory status of the firm as either an independent power producer (IPP) or a utility. IPPs sell electricity to distributors at competitive rates. Therefore, the IPPs choose energy sources and the size of new capacity that maximize profits. Utilities negotiate with regulators, the public service commissions, to determine electricity price schedules. Thus, utilities choose new capacity that minimizes cost. Then, we obtain the optimality conditions separately for the two firm types. These derivations provide the factors that affect the capacity type and size, informing our data collection and empirical approach.

To develop the decision theory for an IPP, we first focus on the basic objective function and ignore the shares of each energy source: A firm maximizes profit the revenue from selling some quantity  $Q$  of electricity in MWh, less the costs of producing it. A firm owns generators with  $x$  MW of production capacity. However, actual electricity output in a year is less than capacity because of factors such as technological constraints and dispatch needs. This proportion is the capacity factor,  $CF$ , a unit-less ratio. Thus, the quantity of electricity the firm produces is  $Q = x \cdot CF$ ; multiplying by hours in the time period converts MW to MWh. Generators produce electricity for several decades or more, thus, the firm considers the present-discounted stream of profits. In any given year  $t$ , the firm chooses to build new capacity, if it is profitable:

$$\max_x \pi = \sum_{t=0}^{\infty} \delta^t \{x_t \cdot CF \cdot [P_t - C_t] - OM(x)_t\} - CC_{dx}. \quad (1)$$

The discount factor is  $\delta$ . The firm sells their electricity at exogenous price  $P_t$  in \$/MWh.  $C_t$  is the variable cost of generation in \$/MWh. Two fixed costs reduce profit, each in dollars: operations and maintenance  $OM_t$  is an annual cost, whereas construction costs  $CC_{dx}$  occur only if the firm builds new capacity.

Our primary goal is understanding how changes in fuel costs  $C$  affects the firm's choice of  $dx$ , the size of new capacity. In order to derive this first-order condition, we impose a few simplifying assumptions. The first is that firms use the current prices and fuel costs for their decision making:  $P_t = P$  and  $C_t = C$ . In other words, this year's values are the best indicators of future values. Energy price forecasts support the price conjecture; these show no significant trend and little variation over a 20-year horizon, for each sector. Our conjecture about costs also stems from solid rationale: firms use levelized costs, which is the average net present cost of generation over a plant's lifetime. Levelized costs provide consistent comparison of different energy sources for investment planning (Nissen and Harfst 2019). Also, the U.S. Energy Information

Administration (EIA) projections of natural gas costs are consistently inaccurate in their Annual Energy Outlooks (AEOs). Absent better information, and until the realization of the future values, expected fuel costs are stationary. Wind and solar are free energy sources constant and certain. With these modifications, the profit-maximizing objective reduces to a static condition.

Our secondary modeling aim is inferring the effects of a carbon price. Thus, we incorporate a carbon tax,  $tax$  in \$ per ton of  $CO_2$ . If implemented, the tax mirrors fuel costs, deducting from profit for each unit of generation. However, we must convert the tax to \$/MWh; we multiply by the carbon intensity of the firm's generators,  $CO_2$ , which is the emission of carbon dioxide in tons per MWh.

We apply these modifications to Equation (1). Then, using the geometric series principle, the objective function becomes

$$\max_x \pi = (x \cdot CF \cdot [P - C - tax \cdot CO_2] - OM - (1 - \delta) \cdot CC_{dx}).$$

We then incorporate the energy sources for electricity,  $F = g, w, s, \dots$  gas, wind, and solar, among others such as nuclear, coal, and hydro. The capacity is the sum of all the firm's generators of any energy source,  $\sum_{F=g,w,s,\dots} x_{F,t}$ . In any given year, the firm can choose to build a new generator with a source of  $f = g, w, s$ ; these three sources comprise 93 percent of capacity built in the last two decades; we discuss limitations of this restriction in the conclusions.

The size of new capacity for the chosen energy source is  $dx_f$ , and the objective expands to a sum:

$$\max_{x_f} \pi = \sum_{F=g,w,s,\dots} (CF_F [P - C_F - tax \cdot CO_{2,F}] - OM_F) - (1 - \delta) CC_{dx_f}.$$

The firm typically owns multiple types of generators, which differ by energy source. Therefore, capacity factor is a weighted average,  $CF = \sum_{F=g,w,s,\dots} (CF_F \cdot x_{F,t}) / x_t$ . Capacity factor is

constant because it is a technological constraint based on how and when a firm can dispatch the energy source. Cost is a capacity-factor weighted average, explicitly:  $\sum_{F=g,w,s\dots} (C_{F,t} \cdot CF_F \cdot x_{F,t}) / CF \cdot x_t$ . Similarly,  $CO_{2,F}$  is the weighted average carbon intensity of the firm's generators in tons per MWh. Operations and maintenance is  $OM_t = \sum_{F=g,w,s\dots} OM(x_F)_{F,t}$ . And construction costs are a total cost  $CC_{dx_f}$ , based on the energy source and respective size constructed.

The firm uses backward deduction, first assessing the profit maximizing quantity for each option of gas, wind, and solar, giving the vector  $dx_f^*$ . The firm's size choice for each energy source is independent from the others because profit is additively separable in choice of  $f$ . Each component of the summation is a constant with respect to all energy sources  $\neq f$ . Thus, the first-order condition of Equation (2) with respect to  $dx_f$  specifies the optimal size of new generation for each fuel source in terms of electricity price, fuel costs, carbon tax, as well as O&M and construction costs:

$$dx_f^* = \frac{dOM_f + (1-\delta) \cdot dCC_{dx_f}}{CF_f \cdot [P - C_f - tax \cdot CO_{2,f}]} \quad (2)$$

Then, the firm chooses to build any energy source with a positive profit,  $\pi(dx_f^*) > 0$ . Our theory predicts how each factor affects new capacity:  $dx$  increases with greater capacity factors and electricity prices, whereas it decreases with higher fuel costs and the cost per MWh of a carbon tax. New capacity also increases with growth of the firm's operations and maintenance costs and of construction costs. We observe if a firm opts to build in each year and its decision of the total generation constructed for each energy source. This equation indicates the relevant covariates and provides the hypotheses to assess with estimations, informing our empirical approach. Each of these effects are intuitive and testable.

In contrast to independent power producers, a public utility receives a fixed price set by the region's public service commission. The utility chooses the energy source and capacity that minimize the present value of their costs. As a constraint, the utility must produce enough electricity to meet consumer demand for power at the set price,  $P'_t$ .

$$\min_x TC = \sum_{t=0}^{\infty} \delta^t \{x_t \cdot CF_t \cdot C_t + OM_t\} + CC_{dx} \text{ s.t. } Q_{D,t}^* = x_t(P'_t) \cdot CF. \quad (3)$$

We employ the same assumptions and modifications as above to obtain a static expression for the total cost:

$$\min_x TC = x \cdot CF \cdot [C + tax \cdot CO_2] + OM + (1 - \delta) \cdot CC_{dx} \text{ s.t. } Q_D^* = x(P') \cdot CF.$$

However, we are assuming knowledge of total costs as a function of capacity, rather than inputs such as capital and labor. Thus, we can incorporate the constraint, converting cost minimization to profit maximization, with total revenue of  $x \cdot CF \cdot P'$ . The first order condition gives optimal new capacity size as identical to Equation 2 with  $P = P'$ . Thus, we use the same explanatory variables in our empirical analysis for both IPPs and public utilities.

### 3 Empirical strategy and data

We implement a two-step discrete-continuous model, following Dubin and McFadden (1984), for choice of electric appliances and consumption of electricity. More recently, Mansur, Mendelsohn, and Morrison (2008) adapted the model to describe household choices of fuels for heating and cooling, and how much they spend on it. We apply the model to new electricity generation. The discrete choice is the firm selecting the energy source of the new generator, either gas, wind, or solar. We omit the choices of coal, hydro, nuclear and other because they constitute less than seven percent of new capacity during our study period. Our model is simple yet parsimonious in describing the marginal effect of fuel costs on choices for the new generation.

Each firm assesses the net present value of each energy source:

$$V_f^* = \mathbf{z}'_f \boldsymbol{\gamma}_f + \eta_f, \quad f = g, s, w.$$

For IPP, this value function is profit; for utilities, the value is the negative of total cost. Then the firm chooses the energy source that produces the highest value,  $V_f^* > V_{j \neq f}$ . Vector  $\mathbf{z}_f$  contains the factors of the energy source decision: costs of gas, coal, firm's capacity stock, average capacity factor, electricity price, average fuel cost, operations and maintenance cost, construction cost, and carbon intensity. The coefficient vector,  $\boldsymbol{\gamma}_f$ , is marginal effect of each factor. Error term is  $\eta_f$ , of extreme-value type-I distribution.

We observe if a firm builds, the chosen energy source  $f$  and respective size of the new generator,  $dx_f$ , but do not observe choices not to build. Therefore,  $V_f^*$  is a latent function for the firm's value of construction. To determine the probabilities of an energy source, we specify the firm's choice of energy source with a multinomial logit estimator and derive coefficients using maximum likelihood:

$$\theta_f = Pr(\mathbf{z}'_f \boldsymbol{\gamma}_f > \eta_f) = \frac{\exp(\mathbf{z}'_f \boldsymbol{\gamma}_f)}{\sum_{f=g,s,w} \exp(\mathbf{z}'_f \boldsymbol{\gamma}_f)}. \quad (4)$$

Terms  $\mathbf{z}'_f \boldsymbol{\gamma}_f$  are equal to the log odds of the renewable energy source, wind or solar, relative to the base outcome, gas. We take the exponent and convert the odds to probabilities of an energy source,  $\theta_f$ , for every observation.

The continuous step of the model estimates the size of the generator:

$$dx_f = \mathbf{X}'_f \boldsymbol{\beta}_f + \sigma_f \sum_{j \neq f} r_j \frac{\theta_j \ln \theta_j + (1 - \theta_j) \ln \theta_f}{1 - \theta_j} + \epsilon_f. \quad (5)$$

The regressor vector,  $\mathbf{X}_f$ , includes costs of gas and coal, electricity price, the average fuel cost of the firm's energy mix, as well as the firm's average capacity factor and carbon intensity. Based on our theory, we add a flow variable, change in the firm's operations and maintenance costs.

Change in the firm's construction cost is equal to the firm's construction cost because it changes from zero to the observed value. All variables are in logs, with the exception of variables that take on non-positive values: firm's averages of fuel cost, capacity factor, and carbon intensity, operations and maintenance cost, and changes in the operations and maintenance costs. The stochastic term,  $u_f$ , is distributed normally with the zero mean and variance  $\sigma_f^2$ , conditional on the regressors in both steps of the model.

As in Dubin and McFadden (1984), we assume the correlation between the stochastic terms in the discrete,  $\eta_f$ , and continuous,  $u_f$ , stages is  $E(u_f|\eta_g, \eta_s, \eta_w) = \sigma_f \sum_{j \neq f} r_j (\eta_j - E(\eta_j))$ . The weights,  $r_j$ , sum to zero by construction,  $\sum_{f=g,s,w} r_j = 0$ . For a given fuel type,  $j \neq f$ , weight  $r_j$  pre-multiplies the inverse Mills ratio for  $j$ . Such weighted sum of the Mills ratios is a correction term that introduces the effect of the choice of the energy source into the generator size decision (Mansur, Mendelsohn, and Morrison 2008). With this correction term, the OLS estimates of (5) are consistent.

We collect data for new generators from 2001 to 2020. Figures 1-4 detail the geographic distribution of average state-level gas cost in relation to new construction of gas, wind, and solar generators. Each figure shades the states by quartiles, with 12 states per bin; the darkest shade indicates highest values as \$/MWh or percentage of new capacity. White denotes no new capacity. Fig. 1 shows that natural gas is generally more expensive in the Northwestern and Eastern States. At a glance, this corresponds to less gas construction in the same areas; Fig. 2. However, the characteristics and the substitutability of renewable energy sources complicate the story: Regional climate patterns are strong determinants. Wind turbines occur where wind quality is better, in the West and Central U.S.; these locations also use wind to offset lower capacity from natural gas; Fig. 3. Solar capacity has more optimal conditions in the Southwest

and Southeast; Fig. 4. Solar plants built in five states account for 69 percent of solar electricity capacity, which in order of size are California, North Carolina, Texas, Nevada, and Arizona. Moving beyond this visualization, we use empirical analysis to quantify the link between fuel costs and new construction.

We define a new generator as one with “proposed” status EIA-923 codes V, U, T, L, P, or TS, and which changes its status to “operational” during our study period, i.e., all these plants are built. Through the 20 years of our data, 313 gigawatts (GW) of new generators advanced from proposed to operational, 184 by IPP and 129 by utilities. Utilities built a slight majority the gas capacity, 103 of 189 GW. IPP dominated the renewables, building 67 of 86 total GW of wind and 32 of 39 GW of solar. For each generator, we also obtain the firm’s characteristics, published by the EIA: regulatory status as an IPP or a utility, total capacity of all owned generators, average fuel costs weighted by energy source, and average carbon intensity. Our level of analysis requires firm-year observations by energy source; gas, wind, or solar.

We treat unique EIA utility IDs as separate firms, even if these firms are held by the same parent company, following EIA convention. If a firm proposes a single generator of one of the energy sources in a given year, it is an observation. When a firm proposes more than one generator with the same energy source in the same year, we treat it as one decision, summing the capacities. When several firms own a generator, we split it by proportion of the ownership shares. Where firm-level data are unavailable, we obtain average state-level values. These include the retail electricity price, coal and gas fuel costs, and the capacity factor for each energy source. For operations and maintenance costs and construction costs, there is national-level per-unit data, \$ per MWh; we use each firm’s capacities as factors to obtain firm-level values for these. The summary statistics are in Table 1.

Our outcome variable is the firm-year change in generating capacity in MW by energy source,  $dx_f$ . We have 1,729 observations for IPPs wherein 71 percent are firms without prior record, which we designate as new firms. For utilities, we have 721 observations; most built by established firms, with only 77 new firms. Combined-cycle gas turbines (CCGT), which provide our baseload power, are larger for IPPs, at 666 MW on average versus 476 for utilities. Gas peaker proposals are 190 MW for IPPs and 122 for utilities. Peakers fire up quickly in response to spikes in energy demand and use 50 percent more natural gas to operate than cleaner combined-cycle plants. The average sizes of renewable builds are similar across the type of ownership: wind projects average 149 and 170 MW; solar projects are 27 and 37 MW. Overall, the size of a new build is smaller for IPP because numerous, small solar projects bring down the IPP average.

The second block of Table 1 provides summary statistics for the determinants of energy source. For the fuel costs of coal and gas, we use state averages. The average values for gas are lower for states with more IPP firms than those with more public utilities, at \$40 and \$46 per MWh. Coal prices are higher in those states with more observations of IPPs, at \$24 versus \$20 per MWh. Total nameplate capacity is a summation of the firm's generators by size, all energy sources including those outside of the scope of this paper, such as coal, nuclear, and hydro. IPPs operate 481 MW on average, an order of magnitude smaller capacity than utilities, which generate 4,762 MW on average. Capacity factor is the proportion of the year a generator operates. On average, the capacity factor for gas is 0.53. Coal capacity factor average is 0.59. The average capacity factors for wind and solar are 0.31 and 0.19; the low values reflect intermittent weather and time of day. We use these energy source capacity factors (CF) to construct each firm's CF as a weighted average based on their shares of each energy source. IPPs

generate at 27 percent of their total capacity, where utilities produce at 49 percent of their capacity. The lower average capacity factor for IPPs is due to a higher share of renewables. Retail electricity price for the IPP observations is \$110 per MWh, on average, and for utilities is \$94.

Firm-level data on fuel costs are unavailable. We approximate these using the quantity of electricity the firm generates by fuel source. We adjust the firm's capacity of each energy source by state-averaged capacity factors, then convert the generation to firms' shares from each energy source. We use the shares as weights on the state-average costs of fuels and sum these components, giving a measure of costs by firm-year. The fuel costs include gas, coal, and nuclear, wind, and solar, where the latter two are \$0 per MWh. The mean fuel costs are \$5 per MWh for IPPs and \$26 for public utilities. IPPs' costs are lower due to a larger share of renewables.

We compute the firms' operations and maintenance (OM) values from national-level year averages for energy sources, in \$ per MWh. We use the firm's MWh of electricity generation from respective energy sources, then sum across energy sources,  $OM_t = \sum_{F=g,w,s,\dots} o m_{F,t} \cdot x_{F,t} \cdot CF_F$ . EIA provides OM values for gas, coal, and nuclear annually for 2011-2021. There are no data prior to 2011. Given low variability and no discernible trends, we use the 2011 values for all the preceding years. We use Wisser, Bolinger, and Lantz (2019) for wind costs and Bolinger, Seel, and Robson (2019) for solar. The costs are much lower for IPP at \$4 million per firm relative to \$189 million for utilities because IPPs operate smaller numbers and sizes of generators.

Data on construction costs are also limited. We obtain national-level costs per MW for several sizes of generators of each energy source; these are available from EIA for 2013-2020.

To interpolate costs for any size generator, we estimate a linear fit of these per-MW costs as function of size as well as year and census region dummies. We use the estimates to create per unit costs for every generator we have in our sample, in \$ per MW. For 2001-2012, we use the 2013 values.

Our data for estimation are the total construction cost, in \$, of each new generator:  $CC_{f,t} = dx_{f,t} \cdot cc_{f,t} \cdot \omega_{f,st,t}$ ; the product of the generator size, the per-MW cost for a generator of that energy source that size that year, and census region cost variation.

Carbon intensity measures the tons of CO<sub>2</sub> emitted by generating a MWh of electricity. We use state-level averages of CO<sub>2</sub> emissions by energy source and weight them by the firm's share that type of generation. The CO<sub>2</sub> averages differ greatly between IPPs and utilities, 0.1 and 0.56 tons per MWh, respectively.

We construct two additional measures, which our theory in Equation (2) indicates are determinants of generator size. The change in O&M costs,  $dOM$ , reflect year-to-year differences of these costs and the new capacity built by the firm:  $dOM_t = \sum_{F=g,w,s,\dots} om_{F,t=1} \cdot x_{F,t=1} \cdot CF_F - om_{F,t=0} \cdot x_{F,t=0} \cdot CF_F$ . In addition, we convert construction costs to per-MW,  $cc = CC/dx$ .

## 4 Estimation results

We identify how fuel costs affect the energy source and size of new generators using a discrete-continuous choice specification. The measure of the discrete choice is the change in odds of building wind or solar, each relative to building a gas plant; for example, if odds are 10:1, then a five percent increase is 10.5:1. Simultaneously, we estimate the continuous choice, the size of new capacity, conditional on each energy source. The change in size is given as an elasticity, a percent response to a one percent change in each covariate, all else held constant; the exceptions

are O&M and construction costs, which change by units of \$-million. We provide separate results for independent power producers and public utilities. All results are in Table 2. We check robustness using a linear probability model of energy source, finding the same sign with similar magnitudes and significance; results available on request.

#### 4.1 Effects on the choice of energy source

First we assess how fuel costs affect the chosen energy source for a generator. Higher costs should improve the odds of renewable capacity relative to gas turbines. Indeed, we estimate a higher relative likelihood of renewables. The odds of a gas peaker versus a combined-cycle gas turbine are unaffected. As a reference point, the observed odds of an IPP constructing a wind generator rather than CCGT are 4.4 to 1 the ratio of the two types of generators from Table 1, 437 wind to 102 CCGT. The observed odds of solar as opposed to CCGT are 11:1. When IPPs face one-percent more expensive natural gas, the odds that these firms build wind increase by 10 percent and a solar increase by 7 percent, each relative to CCGT. The odds rise to 4.7:1 for wind relative to CCGT and to 12.8:1 for solar. The observed odds for utilities are 0.8:1 wind to CCGT and 1.3:1 for solar over CCGT. A one-percent cost increase, 0.46 cents per MWh, increases solar over gas by six percent, raising the odds to 1:3.4. The effects of gas cost on all the odds of renewables are statistically significant. The other results, row-by-row from the upper panel of Table 2, are as follow. We estimate an insignificant effect of the cost of coal on IPP energy source choices. Whereas for utilities, a one-percent increase in coal price reduces odds of wind relative to gas by three percent; the effect on solar is insignificant. This implies that they build more gas generation to fulfill consumer demand. In the next row, a percent increase in an IPP's current nameplate capacity has small and insignificant effects on the odds of renewables. There is a marginally significant effect on the odds of a peaker gas generator instead of CCGT: A one-

percent larger IPP is three percent more likely to build a peaker generator instead of combined cycle. For utilities, more existing capacity decreases the odds of wind by three percent. Changes in capacity factor the weighted utilization of current capacity indicate that for an IPP, a one percentage point larger value indicates a 18 percent decrease in odds for wind generation and a 26 percent decrease for solar. A larger capacity factor also decreases the odds of peaker gas generators versus CCGT. The effects are similar but smaller for utilities. An additional percentage point of capacity factor corresponds to a four percent reduction in the odds of peaker gas, four percent decrease of wind odds, and an 11 percent decrease of solar. Firms with high capacity factors demonstrate path dependence by continuing to build CCGT as their baseload. The next factor, retail price of electricity, only impacts IPP peak gas capacity; a one percent increase implies a five percent decrease in odds of peakers opposite CCGT. For utilities, a one percent higher electricity price makes wind three percent more likely. Firm average fuel costs for existing capacity uniformly increases the odds of CCGT versus all other generating technologies. For IPP, the effect on the odds of gas peakers is small and insignificant. But the effect on renewables is large and significant: a one percent higher IPP fuel cost decreases the odds of wind by 0.4 percent and of solar by 0.3 percent. For public utilities, the odds of a gas peaker decrease by 0.03, the odds of wind by 0.14, and the solar odds by 0.16 percent. We may overestimate the changes in odds for capacity factor and average fuel cost because of new firms, which comprise half of all observations. For these firms, we use the values of its first generator for fuel cost and capacity factor. Both of these are low for renewables and relatively large for gas. Thus, we reinforce a correlation: If the firm has low average fuel cost and capacity factor, the odds of a renewable are higher. We lessen this effect by controlling for size of firm capacity.

Operations and maintenance and construction costs also affect the construction of renewables. However, we caveat these results because of poor data quality, which are constructed from national-level averages, interpolated over capacity sizes and between years, and weighted by firms' shares of each energy source; in the case of construction, we add a census region adjustment and year. The IPP results correlate larger operations and maintenance costs with an increase in odds of solar, by 1.7 percent per \$ million of costs. The wind and peaker gas are unaffected. For utilities, having one \$ million larger O&M correlates with lowered odds of wind by half a percent and higher odds of solar by 0.4 percent. All are statistically significant but of little practical significance. Higher construction costs are associated with significantly higher odds of CCGT versus peak gas and renewables. For IPP, a one percent construction cost increase results in a one percent decrease in the odds of peak gas, one percent drop for wind, and two percent drop for solar. With public utilities, peak gas is half a percent less likely, wind odds decrease half a percent, and solar odds two percent. This is simply evidence that CCGT capacity is cheaper than renewables: If the firm's construction costs are low, chances are the firm is building a CCGT.

Higher current carbon emissions significantly increase the odds of renewables for IPP. An additional million tons of CO<sub>2</sub> relates to a 42 percent increase of the odds of wind and 28 percent for solar. There are no significant effects on utilities.

Finally, we control for time with a year variable and for state effects with shares of generating technology in the state's electricity production. Wind and solar become more likely in more recent years, although the effect is only significant for public utilities. The states with large shares of nuclear and coal have reduced odds of building wind and solar, both by IPP and utilities.

## 4.2 Effects on generator size

Capacity results are also reported in Table 2. The effect of natural gas cost on the size of new capacity is small and not significantly different from zero for any fuel source of IPP firms. For utilities, a one percent increase in cost increases the size by 0.3 percent the expected size of a CCGT generator and by 0.6 percent the size of a wind generator. A one percent increase in the cost of coal decreases the size of an utility gas peaker by 0.5 percent. The effects on other energy sources and regulatory types are insignificant. A higher price of electricity makes smaller gas generators viable for both the IPP and utilities. Larger increases in operations and maintenance cost is associated with larger gas plants. The relationship is only significant for IPP CCGT and is insignificant for IPP gas peakers and utility gas. Conversely, larger hikes in O&M costs correlate to smaller expected sizes of new renewable capacity (insignificantly for IPP wind and utility solar).

Construction cost of a MW of new capacity is inversely related to the size of new capacity, demonstrating economies of scale. The estimates range from 1 to 10 percent smaller capacity size for one percent increase of the construction cost of a MW.

## 4.3 The impact of shares of technologies in existing generation

The impact of natural gas cost may be different for firms and states with large amounts of one type of generation. We estimate these effects on the odds by replacing the technology shares and the time effect with their interactions with gas cost and report the effects in Appendix Table A1.

The gas cost retains its direction, significance, and magnitude from the main specification results. For IPP, additional ten percentage points of the share of nuclear in the state decrease the gas cost effect on odds of wind by 0.6 percentage points from +12.7 to +12.1 percent. An extra ten percentage points of the coal share reduce the gas cost effect on odds of wind by 0.4 percentage points from +12.7 to +12.3 percent. The shares of nuclear and coal modulate

similarly the effect of gas cost on solar odds. For public utilities, an additional ten percentage points of the share of nuclear reduce the effect of gas cost by 0.1 percent wind odds per one percent of gas price. The effect of coal share is twice as strong. The coal share has small but significant negative effect on how gas cost affects the odds of a utility building wind instead of CCGT. It does not influence the effect of gas cost on odds of solar.

‡We omit shares of nuclear and coal generation in IPP analysis because no IPP operate nuclear and only three operate coal capacity. Similarly, we omit solar for utilities because the six technologies add up to an average 97% of utility capacity. We suppress the rest of the estimates. With the exception of the generating portfolio technology shares, the explanatory variables are as in the main specification.

Complements and substitutes present in the state legacy capacity affect the odds of renewables against gas. We check if the firm capacity stock affects the odds as well. We interact the shares of generating technologies in the firm's portfolio with the gas cost. For IPP, we omit the shares of nuclear and coal because no IPP in the US have ever operated nuclear and there are only three IPP with coal in our sample. As such, the interpretation of the baseline effect of gas cost on odds is for an IPP where 'other' technologies dominate. Appendix Table A2 shows that for IPP, at zero shares of gas, wind, and solar, the effect of gas cost on wind reverses sign and the effect on solar loses significance. However, the mean share of gas is ten percent, of wind 25 percent, and of solar 62 percent of an IPP capacity in our sample. The shares of all four fuel types are estimated to increase the effect of gas cost on wind odds. A better interpretation is that for IPP with high shares of technologies other than gas, wind, and solar gas cost is not a factor in deciding between gas and renewables.

For utilities, we omit the share of solar for collinearity reasons as the six technologies on average add up to 97 percent of a utility's capacity. Accordingly, the baseline effect of gas cost on utilities' odds is for a solar-dominant utility. The effect of the cost on peak gas and wind odds is insignificant; a higher gas cost makes solar more probable. For utilities with a larger share of CCGT, gas peakers, nuclear, and/or coal, the gas cost effect on odds of wind becomes smaller; the effect on odds of solar decreases by statistically insignificant amounts. By contrast, a higher share of wind increases the tendency of gas cost to promote gas peakers, wind, and solar versus CCGT.

#### 4.4 Early versus late sample results

Our sample spans 20 years of generator construction. We control for the linear effect of time on the fuel cost effect on the choice of technology. The main specification estimates show that time does not affect the choices of independent power producers. Whereas utilities are more likely to choose wind and solar in the later years. We do not capture individual year effects as the model becomes overly complex for the multinomial logit specification to deliver reliable estimates. Rather, we verify the validity and significance of estimates across time by looking at early and late subsamples. The key events of 2001-2013 are the proliferation of CCGT and the introduction of production tax credit (PTC) that precipitated a wind turbine rush before the expiry in 2013. The 2014-2020 period is dominated by the renewed PTC incentives for wind, this time set to expire in 2021, as well as photovoltaic solar becoming a relevant generating technology. Both subsamples suffer from small numbers of observations for individual generating technologies. In the early years IPP build few gas generators and utilities seldom build solar. In the late period there's dearth of gas generators. To reliably maximize likelihood, we omit the controls for time and generating portfolio shares for IPP.

The estimates carry over largely unchanged from the main estimation to the 2001-2013 early sample (Appendix Table A3). Because of too few solar builds by utilities, the effect of gas cost on solar odds loses significance but retains its value. Similarly, the average construction cost loses significance for IPP peaker gas and wind against CCGT. Nonetheless the effects retain their values. Firms' carbon emissions do not promote wind and solar with IPP in the early sample. This is likely because regulation such as renewable portfolio standards (RPS) was less stringent in the early years. The effects of costs of gas and coal on generator size are not robust to the sample change. Gas cost tends to increase the expected size of most types of generators, but the effect is sparsely significant. The cost of coal effect is not significantly different from zero. In the full sample, electricity price decreases the size of all generators, whereas in the early sample the effect loses its strength and significance with most generating technologies.

In the 2014-2020 late sample (Appendix Table A4), the gas cost effect on the odds of gas peakers against CCGT reverses direction: now a higher gas cost reduces the probability of a gas peaker. Consequently, the effect of gas cost on odds of wind and solar is not significant against CCGT but becomes significant against peaker gas (with the exception of IPP solar). Overall, the gas cost increases the odds of renewables against peak gas generators but not CCGT in the recent years sample. The significant positive effect of the share of coal on odds of renewables suggests that the drive to replace coal with renewables is currently overshadowing the competition between CCGT and renewables. Proliferation of battery storage will allow the renewables to compete with gas peakers in the coming years.

The cost of coal does not have any statistically significant effect on the odds of generating technologies. As with the full and the early samples, a higher average construction cost increases the odds of CCGT against the other three generating technologies. The effect is

only significant for solar. Firm's carbon emissions increase the odds of renewables for IPP in the full sample and lose significance in the early sample. The effect regains its significance in the late sample. Which suggests that IPP have become more attuned to the composition of their generating portfolios, perhaps due to regulation such as RPS.

#### **4.5 Robustness to policies and state and year effects**

Multiple policies influence the choice of new electricity generators. One example is renewable portfolio standards (RPS) that require a share of the firm's electricity to come from renewable technologies. The federal government issues investment and production tax credits (ITC and PTC) to builders of renewable generators. States implement the Public Utility Regulatory Policies Act of 1978 (PURPA) by requiring utilities to buy electricity from IPP. In many regions electric utilities and public utility commissions negotiate the market price of electricity. They plan capacity expansion based on load expectations, rather than price signals.

We control for the RPS requirements and demand expectations by directly including their values into the estimation. The other policies do not have uniform reconcilable metrics, therefore we rely on state and year dummies to capture their effects. Inclusion of these controls into our main specification is problematic. The 47 state and 19 year dummies introduce too many variables to reliably find the likelihood maximum in the multinomial logit framework. The growth forecasts in are reported by utilities in only 39 states, significantly reducing our sample and likewise leading to problems in convergence to maximum likelihood. Our solution is to discard the controls predicted by the theory in Section 2, maintain the key explanatory variables of the gas cost and coal cost, and introduce the state and year dummies, as well as RPS and growth controls.

In Section 4.1, high gas prices increase the odds of renewables relative to gas both in the case of IPP and utilities. With state and year effects, the gas cost remains robust in sign, significance, and the order of magnitude for IPP (Appendix Table A5). The fuel cost effect loses significance for utilities. We next add RPS nominal state weighted average requirements, as percent of capacity, to the state and year effects (Appendix Table A6). As before, the cost of gas still significantly promotes renewables with IPP but the effect is not robust for utilities. RPS themselves do not have a significant effect on the odds of renewables against gas. This is because RPS goals are shares of generating capacity (Barbose 2023). If the firms are compliant, the RPS does not push for renewables further.

The third control not predicted by our firm theory nor captured by state and year effects is the electricity demand forecast submitted by public utilities to balancing authorities . Every year from 2006 to 2020 firms project annual demand for ten years ahead. We calculate the average growth rate. Only 185 public utilities submit demand forecasts. Using firm-level data would cut our sample to 370 observations, all of them public utilities – too few for our method. Thus, we convert firm growth projections to the state level as weighted averages. The 183 utilities are in 39 states which covers 76 percent of the IPP and 59 percent of the utility new generators in our sample. To achieve convergence to maximum likelihood with this reduced sample, we replace state effects with shares of generating technologies in state electricity output – as in the main specification (Appendix Table A7). We keep the year dummies. The forecasts have no significant effects on odds of any given generating technology. The effect of gas cost on the odds of renewables for IPP remains robust. The cost of coal increases the odds of CCGT versus wind for all firms and versus peaker gas for utilities. The RPS requirement now decreases the odds of utilities building CCGT as opposed to the other three technologies. We know from Appendix

Table A6, however, that this relationship is not robust to the state effect. Finally, the year effects demonstrate a steady growth in odds for solar and to a lesser extent for wind with both types of firms. A major factor in the decision on wind turbines is investment and production tax credit. Installations of wind turbines built up to and spiked in 2012 and 2020 because the credits were set to expire in 2013 and 2021 respectively. The lack of year effects on the odds of wind in those years is because we track proposals rather than completions. Our results suggest that expiration of tax credits causes a rush to complete rather than a tapering of proposals of new wind turbines.

## 5 Effects of a carbon price policy on new electricity capacity

Most economists suggest putting a price on carbon to mitigate climate change. These policies discourage dirty generation by raising the cost of burning fossil fuels. And they shift the market toward alternative, cleaner sources. In practice, no U.S. state has adopted carbon tax. Many instead pursue renewable portfolio standards (RPS) which require an electricity firm to generate a share of its output from renewable sources. Mullen and Dong (2022) examine the impact of RPS on renewable generating capacity. In absence of a nationwide carbon price, we create several hypothetical scenarios, leveraging the fact that fuel cost and a per-ton carbon tax play the same role. We follow Brehm (2019) in focusing on natural gas costs. We use our estimates of how the cost, in \$ per MWh, affects odds and sizes of new generators and convert these into the corresponding effects of a carbon policy. We formalize the policy as a tax in \$ per ton CO<sub>2</sub> levied on the firm's carbon intensity in tons CO<sub>2</sub> per MWh. We consider carbon taxes of \$10, \$35, and \$50 per ton CO<sub>2</sub>. These values would reflect an increase in the 2021 cost of gas of 10, 35, and 50 percent.

Table 3 provides the policy outcomes. We create scenarios in reference to the 2021 construction: IPP built 3 combined cycle gas turbines with 1.7:1 new gas peakers relative to

CCGT, 15.3:1 new wind generators, and 86:1 solar to CCGT. Utilities also built 3 CCGT and constructed gas peakers at a rate of 3.7:1, wind at 3.3:1, and solar at 10.3:1 to CCGT. The aggregate new generation from each technology, by share, is 19 percent CCGT, 13 percent gas peakers, 41 percent wind, and the remaining 27 percent solar. For our range of carbon taxes, we calculate the change in shares using our estimates of the discrete and continuous natural gas impacts the change in energy source and size and adjusting by the tax and capacity factors. A \$10 per ton tax would decrease CCGT-generated electricity to 14 percent and increase wind to 48 of generation with a small increase in solar. The change in solar share is small because while gas cost increases the odds of the new generator being solar, it reduces its expected size. The total output of MWh generated would grow by two percent. At the high end of the tax spectrum, a \$50 per ton tax would reduce the gas share in new generation by half, from 32 to 17 percent. The wind grows to 55 percent and the solar share increases to 28 percent. Overall, new generation would grow by eight percent.

We calculate carbon emissions from the electricity generation of newly constructed CCGT and other gas plants, which have a carbon intensity of 0.5 tons per MWh. Whereas, the renewables have zero emissions. The actual 2021 emissions from new capacity were 15 million tons of CO<sub>2</sub>. As the carbon price increases, the generation from natural gas decreases, as do the emissions, to 12 million tons with a \$10 tax declining to 8 million with a \$50 tax. These values reflect a relative change in emissions ranging from -32 percent to -47 percent. Thus, a tax also reduces the weighted-average carbon intensity of a megawatt-hour. For generators built in 2021 this is 0.16 tons/MWh. We find that a \$10 carbon tax reduces average carbon intensity to 0.13 tons/MWh and a \$50 tax cuts it to 0.09.

Any tax generates revenue. A \$10 per ton tax on the respective emission from new generation yields \$118 million nationally in annual tax revenue, which increases to \$310 million with a \$35 tax and \$402 million for a \$50 tax. But ideally, the marginal tax should be equal to the marginal externality from emissions, called the social cost of carbon (SCC). Numerous entities model the impacts of climate change and estimate the SCC; we use the Interagency Working Group on Social Cost of Carbon (2010) value of \$35 per ton as a lower bound and the value from Moore and Diaz (2015) of \$220 per ton, as the upper frontier. Comparing the emissions under the tax relative to the emissions with true SCC, we can calculate how the net total externality cost deviates. Suppose the true SCC is \$35 per ton of CO<sub>2</sub> and the tax is also set at that value, then emissions are 9 million tons, but these are perfectly internalized by the tax revenue. However, if there is no tax, the excess emissions cost \$220 million in damages. On the other hand, if the tax is set too high, to \$50 per ton, then the emissions are too low by 0.82 million tons, which burdens society with  $0.82 * \$35 = \$29$  million. For a \$220 social cost of carbon, the optimal emission level from new generation is one million tons of CO<sub>2</sub> per year. All our policies fall short of eliminating the externality. The total external cost ranges from \$3.1 billion down to \$1.5 billion annually.

We extrapolate the results above and provide a rough estimate of the effects over a ten-year horizon. If the electricity industry continues with the 2021 capacities and carbon intensity each year for a decade, the stock of emissions accumulates to 832 million tons. Whereas, the carbon taxes reduce these emissions by the percentages in Table 3, abating 183, 345, and 390 million tons over the decade, respectively. Our results are on the order of magnitude of NEMS-based forecasts by Larsen et al. (2018) in which a \$50 per ton tax abates 30 million tons in the first year increasing to over 100 million tons in the tenth year. With a \$35 social cost of carbon

and no carbon price implemented, the business-as-usual emissions inflict \$18 billion of damages over the decade. These large values come into starker relief when we note that new capacity is only two percent of total electricity generation improving these construction choices is an opportunity to abate emissions over the lifetime of the newly built plants.

## 6 Conclusion

Modern society emits vast amounts of greenhouse gases that are causing rapid climate change with destructive consequences. The choices of electricity generators have profound effects on carbon emissions. Over the last 20 years, the share of coal receded, natural gas use tripled, while both wind and solar power became substantial sources of energy. The legacy of stock built today will affect emissions for the next 50 years or more.

A carbon price, though yet to be implemented in the U.S., will affect construction of new generators and make newly built capacity cleaner, or less carbon-intensive, on average. We infer its effect from the relationship between the fuel cost and new generating capacity. Fuel cost is a major component of the marginal cost of a megawatt-hour. For a new generator entering the market with a given price of electricity, a high marginal cost reduces the project's viability. A carbon price effectively increases the marginal cost of dirty electricity equivalently to fuel cost.

We estimate how the gas cost affects the odds of new generating capacity being renewable as opposed to natural gas. The natural gas cost increases the odds that the new construction of electricity generation is wind- and solar-powered, relative to natural gas. The effect is strong and statistically significant. We find that effect of the cost on the conditional expectation of the size of the newly built wind and solar capacity is positive but small and statistically insignificant. We conclude that implementing even a modest carbon price of \$10 per ton of CO<sub>2</sub> makes new generating capacity 22 percent cleaner.

Existing literature offers a range for the effects of fuel prices on emission reductions for comparison. With that caveat that each study varies in approach and time period, we convert others results to an equivalent carbon tax, then normalize all to a \$35 per ton carbon tax. Cullen and Mansur (2017) estimate that a \$40 per ton carbon price leads to a ten percent carbon emission abatement. We convert results from Fell and Kaffine (2018); a \$20 per ton carbon price associates with 12.5 percent emission abatement in four Eastern interconnections. Brehm (2019) connects a \$20 per ton tax to a seven percent drop in annual emissions nationally in 2008-2013. Similarly, findings from Knittel, Metaxoglou, and Trindade (2015) suggest that a 60 percent drop in gas price in 2008, equivalent to a \$ 36 per ton carbon price, led to a 33 percent reductions for regulated power plants and 19 percent for deregulated plants, nationally. Then from 2009 to 2012 an additional 25 percent decrease in gas price occurs without further abatement. The results from Linn and Muehlenbachs (2018) suggest that a ten percent increase in gas cost, about \$5 per ton of carbon, results in a 0.93 percent reduction in CO<sub>2</sub> emissions rate nationally in 2008. Davis, Holladay, and Sims (2021), in results-based policy simulations, find that a \$51 per ton carbon tax leads to a four percent reduction in carbon emissions over ten years nationally. Linn and McCormack (2019) attribute a 12 percent decrease in emissions to the decrease of the coal to gas price ratio, equivalent to a \$20 per ton carbon tax. Finally, Coglianesse, Gerarden, and Stock (2020) find that an equivalent to a \$20 per ton tax, corresponds to a 63 percent emission abatement. Emission reductions from switching away from coal and toward gas or other generation range from 3 to 35 percent. Our calculations of abatement of emissions from new generation are comparable with these results.

Throughout this paper, we establish internal validity and a causal interpretation of the cost of natural gas changes construction choices. Our approach overcomes the major threats to

identification: The theory provides for the appropriate variables, while the empirical method of including state and year fixed effects controls for other unobservable patterns. Simultaneity is not of concern: new construction does not affect natural gas costs, which are determined in a large-scale market. With regard to possible sample selection bias, we omit 7 percent of the capacity all generators that use sources other than gas, solar, or wind.

One threat that we have deferred is an aspect of functional form, in that we ignore intermittency of wind and solar generation. These renewable energy sources are contingent on the weather and thus cannot readily replace fossil-fuel generation. We can overlook this because, at present, the imperfect substitution between natural gas and renewables is not a binding constraint. Existing gas capacity generates five times more electricity than wind and solar combined, and often operates when renewables are also available. The U.S. has an abundance of gas capacity throughout the continent and most generators have decades of lifetime remaining.

External validity is impossible to confirm, especially given the potential changes and innovations in the electricity market into the future. Some external threats to our policy scenarios include improved or cheaper versions of current technology and new technology such as alternative energy sources or carbon capture and storage. While these advances will occur, they have low probability of large-scale adoption within the ten-year projections we create. Our projections give realistic estimates of how fuel costs affect the construction choices for electricity generation. And our approach provides a replicable framework as more years of data ensue.

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**Table 1: Summary statistics: 2001–2022 for the contiguous U.S.**

Variable & description (unit)	IPP Mean (SD)	Utilities Mean (SD)	Source, relevant details, & granularity
<b>Outcomes: energy source &amp; size</b>			
$dx$ , size of added capacity (MW)	101.40 (194.86)	176.82 (275.08)	EIA-860, Schedule 3. Multiple generators by a firm in same state-year are summed and treated as one.
Observations:	1,729	721	
New firms:	1,227	77	
• $dx_{gas}$ , gas capacity (MW)	665.44 (338.26)	476.21 (117.62)	<i>Ibid.</i>
Observations:	102	143	
• $dx_{gas}$ , gas capacity (MW)	190.30 (241.72)	122.06 (153.79)	<i>Ibid.</i>
Observations:	62	276	
• $dx_{wind}$ , wind capacity (MW)	149.46 (123.47)	169.82 (172.80)	<i>Ibid.</i>
Observations:	437	110	
• $dx_{sun}$ , solar capacity (MW)	26.88 (56.58)	36.55 (103.00)	<i>Ibid.</i>
Observations:	1,128	192	
<b>Determinants of energy source</b>			
$C_{gas}$ , cost of gas (\$/MWh)	37.70 (13.91)	45.61 (17.38)	EIA State Electricity Profiles (SEP) 2021, Table 6. State average.
$C_{coal}$ , cost of coal (\$/MWh)	24.17 (7.83)	20.76 (7.92)	<i>Ibid.</i>
$x$ , firm's total nameplate capacity of all energy sources (MW)	481.22 (1,522.61)	4,761.88 (7,123.04)	EIA-860 Schedule 3. Multi-owner capacity split in proportion to ownership share, EIA-860 Schedule 4. Firm level; inclusive of $dx$ .
$CF$ , capacity factor of generators, weighted by energy sources (%)	0.25 (0.11)	0.38 (0.21)	EIA SEP 2021, Table 15. State average by energy source, weighted by the respective capacity sizes in the individual firm's portfolio, inclusive of $dx$ .
$P$ , retail electricity price (\$/MWh)	109.73 (29.91)	94.06 (27.40)	EIA SEP 2021, Table 8. State average.
$C$ , fuel cost per MWh generated by firm, weighted average, (\$/MWh)	4.64 (14.10)	26.08 (18.31)	EIA SEP 2021, Table 6. State average by fuel source, weighted by the respective capacity sizes in the individual firm's portfolio.
$OM$ , operations and maintenance costs (\$ millions)	3.54 (18.35)	189.25 (332.45)	Gas: EIA AEO 2021 and EIA Electric Power Annual 2021, Table 8.4; wind: Wiser et al. (2019); solar: Bolinger et al. (2019). National average by energy source, multiplied by the firm's respective generation.
$CC$ , construction cost of the new generator, (\$ millions)	194.90 (303.84)	267.66 (340.56)	EIA-860, construction cost for electric generators installed. National level, linear approximation based on energy source, size, and state cost variation.
$CO_2$ , carbon emissions (mln. tons per year)	0.33 (1.76)	10.97 (16.26)	EIA SEP 2021 Table 7. State average, weighted by the respective capacity sizes in the individual firm's portfolio.
<b>Determinants of generator size<sup>†</sup></b>			
$dOM$ , change in operations and maintenance costs, (\$ millions)	0.33 (1.14)	2.48 (6.85)	Calculated from $OM$ as a first difference: $\sum_{F=g,w,s\dots} om_{F,1} \cdot x_{F,1} \cdot CF_F - om_{F,0} \cdot x_{F,0} \cdot CF_F$
$CC/dx$ , construction cost per MW of new capacity, (\$ million/MW)	2.73 (0.97)	2.23 (0.89)	Calculated as $CC/dx$

<sup>†</sup>Variables  $C_{gas}$ ,  $C_{coal}$ ,  $P$ ,  $CC$  are also determinants of generator size, and defined as above.

Variables  $x$ ,  $CF$ ,  $C$ ,  $O\&M$ , and  $CO_2$  are not determinants of generator size.

**Table 2: Estimation results.**

	Independent power producers				Public electric utilities			
	CCGT	Peak Gas	Wind	Solar	CCGT	Peak Gas	Wind	Solar
<b>Determinants of generating technology<sup>‡</sup></b>								
Cost of gas (\$/MWh)	3.962 (2.829)	<b>10.102***</b> (2.846)	<b>6.662**</b> (2.973)			<b>1.094**</b> (0.442)	<b>2.518***</b> (0.576)	<b>2.765***</b> (0.910)
Cost of coal (\$/MWh)	<b>3.173*</b> (1.758)	-2.343 (2.591)	1.414 (2.621)			0.028 (0.581)	<b>-2.592***</b> (0.897)	1.406 (1.096)
Firm's total nameplate capacity (MW)	<b>-0.958*</b> (0.512)	0.013 (0.569)	0.421 (0.578)			-0.164 (0.131)	0.240 (0.170)	<b>0.995***</b> (0.194)
Firm's average capacity factor (%)	<b>-19.083***</b> (3.566)	<b>-17.695***</b> (5.454)	<b>-25.842***</b> (5.197)			<b>-4.182***</b> (1.039)	<b>-3.925**</b> (1.526)	<b>-11.112***</b> (2.205)
Electricity price (\$/MWh)	<b>-5.470*</b> (2.929)	4.153 (3.953)	-2.515 (3.967)			-1.214 (0.835)	<b>2.738**</b> (1.370)	0.994 (1.427)
Firm's average fuel cost (\$/MWh)	-0.070 (0.049)	<b>-0.369***</b> (0.063)	<b>-0.319***</b> (0.064)			<b>-0.032***</b> (0.012)	<b>-0.144***</b> (0.021)	<b>-0.162***</b> (0.024)
Operations and maintenance costs (\$m)	0.227 (0.544)	-0.358 (0.575)	<b>1.705***</b> (0.590)			0.073 (0.095)	<b>-0.478***</b> (0.128)	<b>0.435***</b> (0.127)
Construction cost of new generator (\$m)	<b>-0.867*</b> (0.485)	<b>-1.171**</b> (0.592)	<b>-2.196***</b> (0.606)			<b>-0.541**</b> (0.149)	<b>-0.529**</b> (0.206)	<b>-2.031***</b> (0.226)
Firm's carbon emissions (mln. tons per year)	0.185 (0.162)	<b>0.334**</b> (0.157)	<b>0.372**</b> (0.162)			-0.004 (0.012)	0.019 (0.013)	<b>0.304***</b> (0.085)
Year proposed	0.101 (0.141)	0.143 (0.184)	0.272 (0.194)			0.009 (0.043)	<b>0.268***</b> (0.062)	-0.006 (0.021)
Share of CCGT in the state electricity generation	-2.354 (4.592)	-9.569 (6.235)	-1.177 (6.379)			<b>3.597**</b> (1.467)	<b>-3.552*</b> (2.117)	<b>5.566**</b> (2.583)
Share of peaker gas in the state electricity generation	<b>-20.796*</b> (11.760)	-27.173 (16.831)	-24.286 (17.203)			-0.371 (3.197)	-4.831 (5.565)	-2.199 (6.384)
Share of wind in the state electricity generation	3.687 (13.864)	12.178 (16.188)	-0.183 (16.251)			<b>10.543**</b> (4.159)	5.294 (4.399)	1.326 (5.265)
Share of solar in the state electricity generation	-31.638 (20.906)	-70.309 (28.430)	-36.578 (28.625)			9.937 (21.585)	-20.681 (25.346)	-0.686 (22.963)
Share of nuclear in the state electricity generation	<b>-14.149**</b> (4.718)	<b>-22.914***</b> (6.502)	<b>-21.148***</b> (6.539)			1.007 (1.416)	<b>-3.838**</b> (1.876)	<b>-7.046***</b> (2.694)
Share of coal in the state electricity generation	<b>-12.099***</b> (3.991)	<b>-14.692***</b> (5.338)	<b>-12.189**</b> (5.487)			0.874 (1.008)	<b>-2.378**</b> (1.171)	-0.337 (2.031)
<i>Pseudo-R<sup>2</sup></i>		0.907					0.516	
<b>Determinants of generator size</b>								
Cost of gas (\$/MWh)	0.222 (0.199)	0.480 (0.708)	0.206 (0.167)	-0.149 (0.237)	<b>0.280**</b> (0.136)	0.091 (0.139)	<b>0.629**</b> (0.262)	-0.308 (0.485)
Cost of coal (\$/MWh)	-0.203 (0.336)	0.972 (0.900)	<b>-0.343*</b> (0.195)	-0.066 (0.272)	0.041 (0.216)	<b>-0.497**</b> (0.231)	0.221 (0.522)	0.501 (0.581)
Electricity price (\$/MWh)	0.038 (0.437)	<b>-2.417*</b> (1.323)	<b>-1.129***</b> (0.277)	<b>-1.650***</b> (0.296)	<b>-0.671**</b> (0.330)	<b>-0.952***</b> (0.297)	<b>-1.584**</b> (0.767)	0.162 (0.744)
Construction cost of new generator (\$ mln. per MWh)	<b>-2.962***</b> (0.406)	<b>-6.650***</b> (1.572)	<b>-6.893***</b> (0.320)	<b>-1.317***</b> (0.140)	<b>-3.126***</b> (0.370)	<b>-8.921***</b> (0.520)	<b>-6.270***</b> (0.687)	<b>-2.242***</b> (0.373)
Change in operations and maintenance costs (\$ m)	<b>0.082***</b> (0.029)	0.042 (0.071)	<b>-0.041**</b> (0.016)	-0.005 (0.009)	0.041 (0.036)	0.023 (0.025)	-0.060 (0.074)	<b>-0.046**</b> (0.019)
Observations	102	62	437	1,128	143	276	110	192
<i>R<sup>2</sup> (adjusted)</i>	0.514	0.563	0.603	0.320	0.813	0.823	0.830	0.530

<sup>‡</sup> Determinants log-transformed: Cost of gas, Cost of coal, Electricity price, Firm's capacity, and both Construction cost variables. Estimates for energy source are the percent change in odds for a one percent change in the covariate, if log-transformed, or one unit, if not. Estimates for size are elasticities except O&M. Not displayed: year effect and the technology share effects in the generator size estimation. Significance denoted by \*\*\*, \*\*, and \* at 1%, 5%, and 10% levels, respectively.

**Table 3: The same-year effect of a national-level carbon tax in the U.S., if adopted in 2021.**

Outcome	2021	Carbon price (\$/ton CO <sub>2</sub> )		
	no tax	10	35	50
Generation of new capacity, by energy source, %				
• combined cycle gas	19	14	8	7
• gas	13	12	11	10
• wind	41	48	53	55
• solar	27	27	28	28
Change in generation from new capacity, %	n/a	2%	6%	8%
Emissions from new capacity, million tons CO <sub>2</sub>	15	12	9	8
Effect on emissions, million tons CO <sub>2</sub>	n/a	-3	-6	-7
Relative effect on new emissions, %	n/a	-22%	-41%	-47%
Carbon intensity of new generation, tons CO <sub>2</sub> /MWh	0.16	0.13	0.09	0.09

Fig. 1: Natural gas cost, \$/MWh, average of 2001 to 2020. Standard errors in parentheses.

Fig 2: New gas capacity in MW and as a percentage of the state's total new capacity built in 2001-2020.

Fig 3: New wind capacity in MW and as a percentage of the state's total new capacity built in 2001-2020.

Fig 4: New solar capacity in MW and as a percentage of the state's total new capacity built in 2001-2020.







