Ex-ante evaluation of a policy's effect on productivity: the substitution and scale effects of carbon taxation on power plant productivity

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Abstract

I develop a general framework for *ex-ante* analysis of a policy's effect on productivity. I use this framework to study the effect of carbon taxation on power plant productivity in the United States. Carbon taxes increase the price of burning fossil fuels to produce electricity, potentially encouraging power plants to be more fuel efficient. Whether carbon taxes do so is ambiguous because carbon taxes also increase the overall cost of electricity production, encouraging power plants to reduce output which reduces the incentive to be more productive in a broad class of economic models. I find carbon taxation reduces fuel productivity and quantify by how much at various proposed carbon taxes.

Keywords: carbon taxation, taxation and productivity, ex-ante policy evaluation, endogenous productivity, reallocation, prospective policy evaluation, electricity generation industry, the effect of carbon taxation on power plant productivity

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1 Introduction

I develop a general framework for evaluating how *prospective* policies affect productivity. The vast empirical literature on how policy affects productivity focuses on retrospective policy analysis[1]. While the production function estimation literature develops methods to identify productivity[2], the literature's focus on retrospective analysis influences the nature of the methods developed. Typically, productivity is recovered in a first stage by estimating the production function and then the standard policy evaluation toolkit (regression methods, like difference in differences or instrumental variable strategies) is used to estimate the policy effect of interest[3]. But this framework cannot be used to evaluate potential policies before they have been tried. In this paper, I want to understand the effect of various levels of carbon taxation on power plant productivity in the United States and there has been no such tax, motivating the development of a framework for ex-ante policy evaluation.

When power plants burn fuel to produce electricity, they emit carbon dioxide so a carbon tax increases their cost of production. But because it is burning fossil fuels that emits carbon dioxide not just producing electricity in general, carbon taxes also affect the *relative* prices of the inputs used in production. Fuel *use* becomes more costly relative to factors of production that make the power plant more fuel *efficient*. But because carbon taxes increase the plant's cost of producing output, plants choose to reduce output in response. In a broad class of economic models, smaller power plants choose to be less efficient because they have less revenue over which to spread the fixed and sunk costs required to become more productive, see Flynn (2019). So theory does not sign the effect of carbon taxation on productivity. I estimate empirically the effect of carbon taxation on power plant productivity and decompose it into the effect due to the change in relative prices and the effect due to the change in plant size.

Carbon taxation's effect on productivity matters not only because it directly affects the costs of electricity production but also because it determines the level of carbon taxation required to achieve a given reduction in emissions. The greater the productivity of the power plant,

[1] See Olley and Pakes (1996) for one among many examples and see the literature review of Syverson (2011).

[2] See Olley and Pakes 1996, Levinsohn and Petrin 2003, Ackerberg, Caves, and Frazer 2015, Gandhi, Navarro, and Rivers 2019, De Loecker 2013, Doraszelski and Jaumandreu 2013, and Flynn 2019.

[3] See De Loecker 2013, Doraszelski and Jaumandreu 2013, and Flynn 2019 for methodological discussion of evaluating the policy on productivity. For particular empirical applications, see Olley and Pakes (1996) for how restructuring affected aggregate productivity in the telecommunications equipment industry, De Loecker (2011) for how trade liberalization affected productivity in the textile industry, and Flynn (2019) for a study of how restructuring affected power plant productivity, among many other papers, including those cited in Syverson (2011)'s review.

the less fuel it needs to burn to produce a given level of output. So if carbon taxation increases productivity, a lower the carbon tax is required.

The methodological contribution of this paper is a model that can evaluate how various levels of carbon taxation affect productivity and a proof that it is nonparametrically identified with production data on inputs, outputs, and input prices. For a model to allow carbon taxation (or any policy change) to affect a power plant's productivity, it must allow the plant to adjust its productivity in response to the change in incentives. To evaluate what productivity would be at a variety of prospective carbon tax rates, a model needs a productivity demand equation relating productivity choice to the "price" of productivity. Taken together, the two requirements imply we have to model productivity as a unobserved choice variable, as a *factor* of production not a *parameter* of the production function.

I model productivity as an index of unobserved factors of production. From this perspective, a change in the price of fuel will naturally cause the plant to choose a different level of productivity like the change in the price of any input will affect the firm's demand for other inputs. The paper's approach can be viewed as an extension of the cost minimization approach to the production problem (Nerlove, 1963) to allow for unobserved factors of production. I show that productivity's cost function and the production function itself are separately, nonparametrically identified in a standard model of cost minimization given data on output, inputs, and input prices with some instrumental variable assumptions.

The empirical contribution of the paper is an estimate of the scale, substitution, and total effect of carbon taxation on power plant fuel productivity, both at the plant and aggregate level, at a variety of carbon prices. The scale effect of carbon taxation is the effect of greater overall costs reducing plant size. The substitution effect is the effect of a change in the relative prices of fuel use and fuel efficiency.

I find evidence *against* the intuitive and a priori reasonable argument that increasing carbon prices will cause power plants to offset the increased cost by being more fuel efficient. I find carbon taxation *reduces* plant productivity because the scale effect of the policy dominates the substitution effect, but it has a positive effect on aggregate productivity, average productivity weighted by output share as in Olley and Pakes (1996), because carbon taxation reallocates output towards more productive plants even though average productivity (unweighted) falls. At a carbon price of $50 per metric ton, I predict between a 3% and 6% decrease in average fuel productivity depending on which types of fuels the plant uses. Productivity falls by less for natural gas plants than for coal plants (natural gas emits less carbon dioxide than coal).

The most closely-related empirical literature studies "directed technical change", technical change that results from regulation and tax policy. This literature asks whether carbon taxes and other policies cause firms to invest in technologies that pollute less or achieve other objectives. In this context, the technological change would be a switch from fossil fuel power generation to "greener" production technologies, see, for example, Aghion, Dechezlepretre, Hemous, Martin, and Van Reenan (2016), Acemoglu, Aghion, Bursztyn, and Hemous (2012), Fried (2018), and Peretto (2009). I study how carbon taxes affect decision-making at the power plant level: how power plants make changes in the employment of non-fuel factors of production[4] and the size of the power plant to adjust their fuel efficiency in response to carbon taxation without changing the type of fuel the plant uses. The difference between this paper and the directed technical change literature is that I study the effects of carbon taxation on "small", short-to-medium-run changes in productivity choice, a complement to the literature studying "large", long-run technology choice. My results can also be viewed as the effect of a small carbon tax that is not large enough to induce plants to spend the additional costs required to switch fuel types. Taxes at this level may be the most politically feasible.

For other studies on the effects of carbon taxation, see Lin and Li (2011) who study the effect of carbon taxes implemented in Europe on per-capita carbon emissions using a difference-in-difference strategy, finding that the level of carbon tax implemented in those countries had mostly small, statistically insignificant negative effects on per-capita carbon emissions. Martin, de Preux, and Wagner (2014) study the effect of carbon taxation on various measures of performance for manufacturing plants in the UK, finding that the tax reduced electricity use by 22.6%. See also a survey on the experience of countries that have implemented a carbon tax in Baranzini, Goldemberg, and Speck (2000).

This paper is distinct from many of the above papers on the effect of carbon taxation in that it uses a structural model to estimate the policy counterfactual. We might ask, "Why not evaluate how carbon taxes affect observable measures of productivity in those countries that have implemented the policy?", as a way of understanding how carbon taxation affects productivity. I pursue the structural approach because it has a few advantages over the retrospective approach in terms of evaluating how the policy would affect power plant productivity in the United States:

1. We want to know what will happen at a variety of carbon tax rates so policymakers can choose the "best" tax rate, and in any particular country, only one rate is in effect.

[4] Broadly-interpreted, not necessarily physical factors of production but potentially *methods* of production.

2. The mix of fuel sources and regulation in the electricity generation sector differs across countries and is difficult to control for without a precise model of how these differences influence plant decisions and outcomes.

3. Observed measures of plant efficiency, like heat efficiency (the ratio of power produced to fuel used in units of heat energy), are not independent of the scale effects of carbon taxation if returns to scale are not constant. Because the policy increases the cost of production at power plants, they will tend to reduce output which may increase or decrease measured heat efficiency without any change in the underlying capability of the power plant. My structural measure of productivity is scale independent.

4. Retrospective analysis is difficult even when the policy has been implemented because there is not always a natural control group: carbon taxes tend to apply to all power plants. Establishing how taxes causally affect productivity then requires stating how input prices relate to plant productivity choices which requires a structural model.

In Section 2, I describe the economic model I take to the data.

In Section 3, I show formally the model is nonparametrically identified.

In Section 4, I discuss my estimation strategy.

In Section 5, I describe the data I use and give estimates of the parameters of the model.

In Section 6, I present the empirical results: the substitution, scale, and total effects of carbon taxes on plant productivity, aggregate productivity, and carbon emissions at a variety of carbon prices.

In Section 7, I conclude.

2 Model

The power plant i chooses its output (Q), its use of coal (C) and natural gas (G), and its fuel productivity (A) to solve the problem,

$$\max_{Q,C,G,A} B(Q)\, D_i - W_C C - W_G G - M(A)\, U_i \quad \text{ST:} \quad Q \leq \left(V_i C^\theta + G^\theta\right)^\rho A. \tag{1}$$

The CES functional form of the production function is not necessary for identification, but the resulting estimator is convenient and counterfactuals are easy to compute so I introduce it now because I use it in the empirical part of the paper. I prove nonparametric identification in Section 3. V_i is power plant specific heterogeneity in the efficiency of using coal relative to natural gas.

B is the "benefit" function of output. It is not clear exactly how the benefit function of output should relate to electricity demand because power plants are regulated (even in restructured states where markets determine price, see Borenstein and Bushnell 2015) so I treat the benefit function in a "reduced-form" way and do not assume it is tied to demand. I will infer the marginal benefit function by assuming that plants set the marginal benefit of output equal to the marginal cost of output. D_i is the power plant specific shock to the benefit function.

$M(\cdot)$ is the cost function for fuel productivity and U_i is the plant-specific shock to the cost function. We can view M as being the result of a cost-minimization problem among non-fuel inputs. Suppose there is a latent vector of unobserved factors of production, Z, and the plant has a latent innate, policy-invariant efficiency, E, then we can write the minimum cost of producing productivity A as,

$$\min_{Z} W_{Z,i}^{\top} Z \quad \text{ST:} \quad H(Z) E_i \geq A_i. \tag{2}$$

If $H(\cdot)$ is Cobb-Douglas, then $M(A)$ will have a constant elasticity functional form and U will be a function of W_Z and innate efficiency, E. I use this specification in my application.

A power plant i is differentiated from other power plants by $(D_i, V_i, U_i, W_C, W_G)$ where (W_C, W_G) are observable plant-level heterogeneity and (D_i, V_i, U_i) are unobservable plant-level heterogeneity.

For power plants that use only coal or only natural gas, I assume they do so because they have not paid a necessary cost to use the other fuel type, and add the constraint $C = 0$ or $G = 0$ to the above problem. Because technology likely varies by fuel type, I allow all the parameters of the model to vary by the types of fuel the power plant uses (whether coal only, gas only, or both). I estimate the model separately for each set of fuel types used.

The first order conditions of the model form the equations I use to estimate the model's parameters. Let λ_i be the Lagrange multiplier on the output constraint.

$$
\begin{aligned}
(G): \quad & W_G = \lambda_i \theta G^{\theta-1} \rho \left(V_i C^\theta + G^\theta\right)^{\rho-1} A \\
(C): \quad & W_C = \lambda_i V_i \theta C^{\theta-1} \rho \left(V_i C^\theta + G^\theta\right)^{\rho-1} A \\
(A): \quad & M'(A) U_i = \lambda_i \left(V_i C^\theta + G^\theta\right)^{\rho} \\
(Q): \quad & B'(Q) D_i = \lambda_i
\end{aligned}
$$

The first estimating equation takes the ratio of the (C) and (G) first order conditions,

$$
\begin{aligned}
\left(\frac{C}{G}\right): \quad & \frac{W_C}{W_G} = \left(\frac{C}{G}\right)^{\theta-1} \times V_i && (3) \\
\implies \quad & \log\left(\frac{W_C C}{W_G G}\right) = \theta \times \log\left\{\frac{C}{G}\right\} + \log V_i. && (4)
\end{aligned}
$$

V_i is correlated with the choice of coal and natural gas use so I need instruments to identify the equation, which I discuss in Section 3.

The second estimating equation takes the ratio of the sum of the (C) and (G) first order conditions, weighted by coal and natural gas use, and the (A) first order condition. Let $\mathrm{RTS}(C, G, V_i)$ be the returns to scale (the sum of the output elasticities of the production function).

$$
\begin{aligned}
\left(\frac{(C) \times C + (G) \times G}{(A)}\right): \quad & \frac{W_G G + W_C C}{M'(A) U_i} = \mathrm{RTS}(C, G, V_i) \times A && (5) \\
\implies \quad & W_G G + W_C C = \mathrm{RTS}(C, G, V_i) \times M'(A) A \times U_i && (6) \\
\implies \quad & \log(W_G G + W_C C) = \log \mathrm{RTS}(C, G, V_i) && (7) \\
& + \log\left[M'(A(Q, C, G, V_i)) A(Q, C, G, V_i)\right] + \log U_i && (8)
\end{aligned}
$$

The first term is the log of the returns to scale of the production function, the log of the sum of the C and G output elasticities. While returns to scale will be fixed with the CES functional form, I include the RTS term explicitly to preview the nonparametric identification results. The second factor we can write as $K(A) = M'(A) A$ where $A = Q\left[VC^\theta + G^\theta\right]^{-\rho}$ so, in its reduced form, $K(A) = \widetilde{K}\left(Q, VC^\theta + G^\theta\right)$ where both terms are observed after estimating the first stage equation. The third factor U_i plays the role of the residual. The left hand side is known to us because we have estimated the first equation and recovered V_i for plants that use both fuel types. For plants that only use natural gas, we do not need to recover V_i. For plants that use only coal, we can subtract $\log V_i$ from the right hand to form the residual as $\log U_i - \log V_i$. It is sufficient to recover counterfactual productivity and fuel choices for coal only power plants that we know the ratio of U_i and V_i.

In Section 3, I show that from this second equation we can identify the production function and M' given some instrumental variable assumptions. We need instruments because U_i will be correlated with input and output choices.

The third equation sets the output first order condition (Q) equal to the expression of λ implied by solving for λ in the (A) first order condition,

$$\log \left\{ M'(A) \times \left[V_i C^\theta + G^\theta \right]^{-\rho} \times U_i \right\} = \log B'(Q) + \log D_i. \tag{9}$$

From the results in the first and second equations, we know the left hand side. Output choice (Q) is correlated with the shock to the benefit of output function (D), but with a cost-side instrument correlated with output use but not with benefit-side shocks, we can recover B'. The three equations identify the parameters of the model necessary to compute counterfactual productivity from a change in input prices.

3 Nonparametric Identification

I establish identification of the production function using instrumental variable methods that do not depend on the CES functional form of the production function I use in my application. Nonparametric identification is important because it establishes that the curvature of the cost of productivity function (M) and the production function itself are separately identified without whatever functional form assumption we impose in estimation.

The nonparametric identification result is more convenient to show if we initially consider a production function $F(C, G)$ (without V_i) and encode the unobserved plant-specific heterogeneity in the efficiency of using coal versus natural gas (V_i) as unobserved heterogeneity in relative fuel prices. I then show that identification of this model implies identification of the model I use in my application, the model in Section 2.

3.1 Nonparametric identification with plant-specific heterogeneity in input prices

Suppose fuel prices vary unobservably by power plant, but that we observe state-level fuel prices (W_C and W_G). Power plants then solve the following problem,

$$\max_{Q,C,G,A} B(Q) D_i - W_C \widetilde{V}_i C - W_G G - M(A) U_i \quad \text{ST:} \quad Q \le F(C,G) A, \tag{10}$$

The scale of the objective function can not be identified if fuel prices vary unobservably by power plant so this formulation is arrived at after re-scaling. $\widetilde{V}_i$ is heterogeneity in the *ratio* of fuel prices.

To identify the model, I rely on exclusion restrictions to deal with the endogeneity problem in the three estimating equations. I need a demand shifter, X, in addition to the previously mentioned variables. I use state population as X_s where s indexes U.S. state. The two classes of exclusion restrictions I use are that log state-level fuel prices and demand side shocks are uncorrelated with both shocks to the cost of productivity and to plant-level fuel price heterogeneity.

Assumption 1. $\log \widetilde{V}_i$ is mean independent of $W_{C,s}$, $W_{G,s}$, and X_s, conditional on plant type τ (the set of fuels it uses),

$$\mathbb{E}\left[\log \widetilde{V}_i | W_{C,s}, W_{G,s}, X_s, \tau_i\right] = 0 \quad \text{where } j \in \{C, G\}.$$

Assumption 2. $\log U_i$ is mean independent of $W_{C,s}$, $W_{G,s}$, and X_s, conditional on plant type τ (the set of fuels it uses),

$$\mathbb{E}\left[\log U_i | W_{C,s}, W_{G,s}, X_s, \tau_i\right] = 0$$

Assumption 3. $\log D_i$ is mean independent of $\log U_i$, $\log W_{C,s}$, and $\log W_{G,s}$ the plant specific shocks to the cost of fuel and nonfuel inputs, conditional on plant type τ (the set of fuels it uses),

$$\mathbb{E}\left[\log D_i | \log U_i, \log W_{C,s}, \log W_{G,s}, \tau_i\right] = 0$$

Assumption 4. The "reduced-forms" are identified by the instrumental variable assumptions, Assumption 1, 2, and 3. That is, there is a unique function $\mathcal{F}_0$ such that,

$$\mathbb{E}\left[\log\left(\frac{W_{G,s}G}{W_{C,s}C}\right)|W_{C,s},W_{G,s},X_s\right]=\mathbb{E}\left[\mathcal{F}_0\left(C,G\right)|W_{C,i},W_{G,i},X_s\right],$$

there is a unique function $\mathcal{F}_1$ such that,

$$\mathbb{E}\left[\log\left(W_{G,s}G+W_{C,s}\widetilde{V}_iC\right)|W_{C,s},W_{G,s},X_s\right]=\mathbb{E}\left[\mathcal{F}_1\left(C,G,Q\right)|W_{C,s},W_{G,s},X_s\right],$$

and there is a unique function $\mathcal{F}_2$ such that,

$$\mathbb{E}\left[\log\left\{\frac{M'\left(\frac{Q}{F(C,G)}\right)}{F\left(C,G\right)}\times U_i\right\}|U_i,W_{C,s},W_{G,s}\right]=\mathbb{E}\left[\mathcal{F}_2\left(Q\right)|U_i,W_{C,s},W_{G,s}\right].$$

The three assumptions making up Assumption 4 can be established either nonparametrically via completeness assumptions as in Newey and Powell (2003) or parametrically, by restricting $\mathcal{F}_{0,1,2}$ to have parametric forms, and imposing standard instrumental variable rank conditions.

Given the reduced form functions are identified as in Assumption 4, I show the structural parameters of the model are identified given one of two additional assumptions.

Theorem 1. Given Assumptions 1, 2, 3, and 4: $B'(\cdot)$, $M'(\cdot)$, and $F(\cdot,\cdot)$ are identified if *either* of the following two conditions are true:

(1) For each (C,G), there exists an A such that the density of (A,C,G) is positive (the reduced-form function, $\mathcal{F}_1\left(F\left(C,G\right)A,C,G\right)$, can be identified) and $\frac{\partial^2\log M}{\partial\log A^2}\left(A\right)\neq0$.

(2) Or: F is homogeneous.

Proof. Because the function $\mathcal{F}_1$ is identified and,

$$\begin{aligned}\mathcal{F}_1\left(C,G,Q\right)&=\log\left(\frac{F_G\left(C,G\right)G+F_C\left(C,G\right)C}{F\left(C,G\right)}\right)\\&\quad+\log\left[K\left(\frac{Q}{F\left(C,G\right)}\right)\right]\\&=\log\text{RTS}\left(C,G\right)+\log\left[K\left(\frac{Q}{F\left(C,G\right)}\right)\right],\end{aligned}$$

Taking the derivative of $\mathcal{F}_1$ with respect to Q gives,

$$\begin{aligned} \frac{\partial \mathcal{F}_1}{\partial Q} &= \frac{K'\left(\frac{Q}{F(C,G)}\right)}{K\left(\frac{Q}{F(C,G)}\right)} \times \frac{1}{F\left(C,G\right)} \\ \implies \frac{\partial \mathcal{F}_1}{\partial \log Q} &= \frac{\partial \log K}{\partial \log A}\left(\frac{Q}{F\left(C,G\right)}\right). \end{aligned}$$

Taking the derivative with respect to C gives,

$$\begin{aligned} \frac{\partial \mathcal{F}_1}{\partial C} &= \frac{\frac{\partial \mathrm{RTS}}{\partial C}}{\mathrm{RTS}} - \frac{K'\left(\frac{Q}{F(C,G)}\right)}{K\left(\frac{Q}{F(C,G)}\right)} \times \frac{Q}{F\left(C,G\right)^2} \times \frac{\partial F}{\partial C} \\ \implies \frac{\partial \mathcal{F}_1}{\partial \log C} &= \frac{\partial \log \mathrm{RTS}}{\partial \log C} - \frac{\partial \log K}{\partial \log A}\left(\frac{Q}{F\left(C,G\right)}\right) \times \frac{\partial \log F}{\partial \log C} \end{aligned}$$

Substituting the result from taking the derivative with respect to Q,

$$\implies \frac{\partial \mathcal{F}_1}{\partial \log C} = \frac{\partial \log \mathrm{RTS}}{\partial \log C} - \frac{\partial \mathcal{F}_1}{\partial \log Q} \times \frac{\partial \log F}{\partial \log C}$$

Recall that returns to scale (RTS) is the sum of the coal and natural gas output elasticities. Because $\mathcal{F}_0$ is identified and,

$$\mathcal{F}_0\left(C,G\right) = \log\left\{\frac{F_G\left(C,G\right)}{F_C\left(C,G\right)} \times \frac{G}{C}\right\},$$

we know the ratio of the two output elasticities.

Log returns to scale can then be written as,

$$\log \mathrm{RTS} = \log\left[\frac{\partial \log F}{\partial \log C}\right] + \log\left[1 + \frac{\frac{\partial \log F}{\partial \log G}}{\frac{\partial \log F}{\partial \log C}}\right],$$

where the second term is identified because it depends only on the ratio of the output elasticities.

Substituting this expression for $\log \text{RTS}$,

$$\frac{\partial \log F}{\partial \log C} \times \left[\frac{\partial \mathcal{F}_1}{\partial \log C} - \frac{\partial}{\partial \log C} \log \left[1 + \frac{\frac{\partial \log F}{\partial \log G}}{\frac{\partial \log F}{\partial \log C}} \right] \right] = \frac{\partial^2 \log F}{\partial \log C^2} - \frac{\partial \mathcal{F}_1}{\partial \log Q} \times \left(\frac{\partial \log F}{\partial \log C} \right)^2$$

Two cases:

(1) Suppose that, at the relevant C and G, there exists a positive mass of plants with an A such that $(\partial^2 \log M / \partial \log A^2) \neq 0$ so that there exists a (Q, C, G) such that $(\partial^2 \mathcal{F}_1 / \partial \log Q^2) \neq 0$. Then, taking the derivative of this expression with respect to $\log Q$ gives,

$$\begin{aligned} \frac{\partial \log F}{\partial \log C} \times \frac{\partial^2 \mathcal{F}_1}{\partial \log C \partial \log Q} &= -\frac{\partial^2 \mathcal{F}_1}{\partial \log Q^2} \times \left(\frac{\partial \log F}{\partial \log C} \right)^2 \\ \implies -\frac{\frac{\partial^2 \mathcal{F}_1}{\partial \log Q \partial \log C}}{\frac{\partial^2 \mathcal{F}_1}{\partial \log Q^2}} &= \frac{\partial \log F}{\partial \log C}, \end{aligned}$$

so the coal output elasticity is identified because $\mathcal{F}_1$ is identified. Symmetrically, the natural gas elasticity is identified and so, the production function is.

(2) If F is homogeneous, then returns to scale are constant. So,

$$\begin{aligned} \frac{\partial \mathcal{F}_1}{\partial \log C} &= -\frac{\partial \log K}{\partial \log A} \times \frac{\partial \log F}{\partial \log C} \\ &= -\frac{\partial \mathcal{F}_1}{\partial \log Q} \times \frac{\partial \log F}{\partial \log C} \\ \implies -\frac{\frac{\partial \mathcal{F}_1}{\partial \log C}}{\frac{\partial \mathcal{F}_1}{\partial \log Q}} &= \frac{\partial \log F}{\partial \log C}, \end{aligned}$$

so the coal output elasticity is identified. Symmetrically, the natural gas output elasticity is identified.

In either case, the production function F is identified (up to a multiplicative constant). Normalize $F\left(\overline{C}, \overline{G}\right) = 1$ for some vector $\left(\overline{C}, \overline{G}\right)$, then,

$$\frac{\partial \log \mathcal{F}_1}{\partial \log Q} \left(Q, \overline{C}, \overline{G}\right) = \frac{\partial \log K}{\partial \log A} (Q).$$

Varying Q then identifies $K'(A)$. Because $K(A) = M'(A)A$, we know $K(0) = 0$. So we can recover $K(A)$ from knowledge of $K'(A)$. So $M'(A)$ is identified.

Lastly, B' is identified given that the reduced form function $\mathcal{F}_2$ is identified because,

$$\mathcal{F}_2(Q) = \log B'(Q).$$

$\square$

3.2 Nonparametric identification with heterogeneity in the production function

When heterogeneity in the efficiency of coal versus natural gas enters in the production function instead of shifting input prices (as in the model I use empirically, introduced in Section 2), we have to decide how efficiency enters the production function, but we do not need to parametrically specify the industry-level parts of the production function. A flexible class of production functions that works (among many other specifications) is,

$$F(V_i, C, G) = F_0[V_i F_1(C) + F_2(G)], \tag{11}$$

where F_0, F_1, F_2 are unknown functions.

The ratio of marginal products is,

$$F_C(V_i, C, G) = F_0' \times V_i F_1'(C) \tag{12}$$

$$F_G(V_i, C, G) = F_0' \times F_2'(G) \tag{13}$$

$$\implies \frac{F_C}{F_G} = \frac{F_1'(C)}{F_2'(G)} V_i. \tag{14}$$

Then, the first order condition which equates marginal products to fuel prices gives,

$$\log \frac{W_C}{W_G} = \log \frac{F_1'(C)}{F_2'(G)} + \log V_i, \tag{15}$$

and the instrumental variable strategy presented in Theorem 1 can be applied to this equation (which has an identical form) to recover the ratio of F_1' and F_2' as well as V_i. Because the residual to the above estimating equation can be interpreted either as unobserved heterogeneity in fuel prices (as in Theorem 1) or as heterogeneity in efficiency of coal use in production (as in the above), the data does not reveal which is the case[5].

In addition, $F_1(C)$ and $F_2(G)$ are identified from the above equation up to an additive constant. So we have,

$$F = F_0\left[V_i \times \left[\widetilde{F}_1(C) + \mathcal{C}_1\right] + \widetilde{F}_2(G) + \mathcal{C}_2\right], \tag{16}$$

where $\widetilde{F}_1$ and $\widetilde{F}_2$ are identified functions such that $F_{1,2} = \widetilde{F}_{1,2} + \mathcal{C}_{1,2}$ and V_i is also identified. Of course, we are not going to be able to identify the level of the argument of $F_0(\cdot)$ because we could always come up with an alternative $\widetilde{F}_0(x) = F_0(x - \mathcal{C}_2)$ and it would be observationally equivalent. So setting $\mathcal{C}_2 = 0$ is without any loss of generality.

To remove the $\mathcal{C}_1$ constant, I assume that $F_1(0) = 0$ in Assumption 5. The idea behind this assumption is that $F(0,0) = 0$ because fuel is necessary to produce output, and we can set $F_0(0) = 0$ to implement this assumption.

Assumption 5. Suppose that,

$$F_1(0) = 0 \tag{17}$$

Given Assumption 5,

$$F_1(C) = \widetilde{F}_1(C) + \mathcal{C}_1 \implies F_1(0) = \widetilde{F}_1(0) + \mathcal{C}_1 \implies \mathcal{C}_1 = -\widetilde{F}_1(0). \tag{18}$$

So $\mathcal{C}_1$ is identified and we know the entire argument of F_0.

The returns to scale of the production function are,

$$F_0' \times V_i \times F_1'(C) \times \frac{C}{F} + F_0' \times F_2'(G) \times \frac{G}{F} = \text{RTS} \tag{19}$$

$$\log \text{RTS} = \underbrace{\log\left(\frac{F_0'(\cdot)}{F_0(\cdot)}\right)}_{\text{unknown function of known argument}} + \underbrace{\log\left[V_i \times F_1'(C)\,C + F_2'(G)\,G\right]}_{\text{known}} \tag{20}$$

We can then write the main estimating equation for power plants that use both fuel types

[5]Heterogeneity in efficiency allows us to compute the carbon tax counterfactual. Unobserved heterogeneity in fuel prices would not because we would only identify the ratio of the unobserved fuel price shocks so we would not identify a plant's specific fuel price. Because carbon taxation is an additive shift in fuel prices, we would not be able to compute what this shift should be.

as,

$$\log\left(W_C C + W_G G\right) - \log\left[V_i \times F_1'\left(C\right) C + F_2'\left(G\right) G\right] = \log\left(\frac{F_0'\left(\cdot\right)}{F_0\left(\cdot\right)}\right) + \log K\left(\frac{Q}{F_0\left(\cdot\right)}\right) + \log U_i, \tag{21}$$

which has the same form as the main estimating equation in Theorem 1 and the same identification argument applies, establishing identification of the function F_0 which gives identification of the full production function.

4 Estimation

The model is nonparametrically identified. I could choose flexible functional forms and estimate the model using a sieve-GMM estimator like the estimator proposed in Ai and Chen (2003), but solving the nonconvex optimization problem that results is computationally difficult and computing the counterfactual itself would be more difficult with a very flexible model. The size of my particular dataset once I have split it up by fuel types used also limits how flexible I can really make the model. So I use a simple specification for the production function and the cost of productivity function that can be estimated by two-stage least squares but that allows for a wide variety of substitution patterns between coal and natural gas.

The model is defined by three functions, (F, M, B), which I parameterize as,

$$F\left(C, G\right) = \left[V C^{\theta} + G^{\theta}\right]^{\rho} \tag{22}$$

$$M\left(A\right) = A^{\gamma} \tag{23}$$

$$B\left(Q\right) = Q^{\eta}. \tag{24}$$

I allow (θ, γ, ρ) to vary by power plant type (coal only, natural gas only, and plants that use both fuel types), and I allow η to vary by whether the power plant is in a restructured state or not because restructuring affects the benefit of producing output. For power plants that use only a single fuel type, supposing that $\theta > 0, \rho > 0$, which is true when coal and natural gas are substitutes, the production function has a constant elasticity form (the elasticity is $\rho\theta$). The CES production function allows for a wide range of elasticities of substitution between coal and natural gas.

The model is estimated in three stages with three linear instrumental variable regressions.

Each subsequent stage depends on the results from the previous stage. I do the first two stages (which estimate the production part of the model) separately for the power plants that use different fuel types to allow for differences in technology between plants that use different fuel types.

Because,

$$\begin{aligned} F_C(C,G) &= \rho\left[VC^\theta + G^\theta\right]^{\rho-1} \times V\theta C^{\theta-1} \\ F_G(C,G) &= \rho\left[C^\theta + G^\theta\right]^{\rho-1} \times \theta G^{\theta-1} \\ \implies \frac{F_C(C,G)}{F_G(C,G)} &= V \times \frac{C^{\theta-1}}{G^{\theta-1}}, \end{aligned}$$

the first estimating equation, which equalizes the ratio of the output elasticities and the ratio of spending on fuels, can be written as,

$$\log\left(\frac{W_{C,i}C}{W_{G,i}G}\right) = \theta\left[\log C - \log G\right] + \log V_i. \tag{25}$$

I use two-stage least squares with the instruments $(\log W_{C,i}, \log W_{G,i}, \log X_s)$ to identify θ and V_i from data on power plants that use both fuel types. An important empirical point: the identification argument and model does not use the panel, but my data has a panel structure. For statistical power, I pool the data over the time dimension (year, in my data) and include time dummies in the above regression to allow the mean of $\log V_i$ to vary by time. **All regressions include time dummies, but they are omitted from the notation for compactness.**

The second estimation equation is,

$$\log\left(W_{C,i}C + W_{G,i}G\right) = \underbrace{\log\rho\theta}_{\text{log RTS}} + \underbrace{\gamma\log Q - \gamma\rho\log\left[VC^\theta + G^\theta\right]}_{\text{log [M'(A)A]}} + \log U_i. \tag{26}$$

The second and third terms have unknown coefficients multiplying variables that are known (given identification of θ and V in the previous step). For power plants that use both fuel types, the coefficients are γ on $\log Q$ and $\gamma\rho$ on $\log\left[C^\theta + G^\theta\right]$. For power plants that use a single fuel type, the coefficients are γ on $\log Q$ and $\gamma\rho\theta_C$, say, on $\log C$ for coal plants.

I estimate the model using two-stage least squares with instruments $(\log W_{C,i}, \log W_{G,i}, \log X_s)$, identifying γ and ρ.

$A = Q\left[C^{\theta} + G^{\theta}\right]^{-\rho}$ is now identified. The third estimating equation can be written as,

$$\log Q = \frac{1}{\eta - 1} \times \log\left\{\gamma A^{\gamma-1} \times U_i \times \left[C^{\theta} + G^{\theta}\right]^{-\rho}\right\} + \log D_i. \tag{27}$$

The parameter η is estimated via two-stage least squares. This model is estimated across all fuel types because, while different fuel type use likely implies differences in production technology, the incentive to produce output is unaffected by the particular means of production given the cost function.

I use the instrument, $\log U_i$, the shock to the power plant's cost of fuel productivity, as an instrument to identify η. The identifying assumption is that the demand side shocks are uncorrelated with cost shocks. **This requires controlling for fuel type with dummies because U_i has a different mean for different fuel types so the regression includes these dummies as well.**

5 Data and parameter estimates

I use publicly-available, power plant-level, annual data from the Energy Information Administration for the years 2001 to 2015 (form EIA-923). The data is fuel used and power produced by US power plants as well as fuel costs by fuel type which I deflate into constant 2015 dollars using the Consumer Price Index. There are $18,036$ plant-years in the dataset (the data is annual) after I subset it to include only power plants that use a positive amount of either natural gas or coal. I measure natural gas and coal use in units of heat energy (millions of British thermal units) and output as power produced net of any electricity consumed by the power plant itself (in megawatt-hours). For descriptive statistics, see Table 1.

For most states, I observe average coal and natural gas prices, but for some states the data is withheld because there are only a few purchasers of the fuel. For the states with missing data, I impute the average coal and gas prices by using the coal and gas price from the state nearest to them measured in distance between the latitude and longitude of the centers of the states.

Table 2 gives estimates and confidence intervals of the parameters of the model by fuel type. The main findings from the parameter estimates are: returns to scale in fuel use are slightly decreasing, the elasticity of substitution between coal and natural gas is positive for plants that use both fuel types, and the elasticity of the benefit of output is greater in regulated states than in restructured states.

Table 1: Descriptive Statistics

Variable	Statistic	Value
Coal Price (2001 dollars per million Btu)	Mean (across states, in 2015)	3.09
	Median (across states, in 2015)	3.01
	IQR (across states, in 2015)	2.25
Gas Price (2001 dollars per million Btu)	Mean (across states, in 2015)	6.03
	Median (across states, in 2015)	5.54
	IQR (across states, in 2015)	1.60
Heat Rate (million Btu per megawatt-hours)	Mean (across plants, in 2015)	12.13
	Median (across plants, in 2015)	10.98
	IQR (across plants, in 2015)	3.24
Power produced (megawatt-hours)	Mean (across plants, in 2015)	$1,727,291$
	Median (across plants, in 2015)	$223,574$
	IQR (across plants, in 2015)	$1,919,906$
Percentage of coal out of total heat energy	Mean (plants that use both, 2015)	89.72%
	Median (plants that use both, 2015)	98.83%
	IQR (plants that use both, 2015)	10.89%
Number of Power Plants	Count (in 2015)	1029
Years	Range	2001 to 2015
Plant-Years	Count	$18,036$

Table 2: Parameter estimates

Parameter	Plant Type	Estimate	90% CI (LB)	90% CI (UB)
ρ	Coal	0.93	0.87	0.97
	Natural Gas	0.96	0.93	0.99
	Both	0.65	0.43	0.83
θ	Both	0.21	0.07	0.38
γ	Coal	30.75	22.34	58.62
	Natural Gas	13.34	9.66	21.03
	Both	4.27	2.89	7.01
η	Plants in Restructured States	0.47	0.29	0.65
	Plants in Regulated States	0.66	0.55	0.78

ρ for coal-only and natural gas-only plants combine ρ and θ (which are not separately identified for single-fuel plants).

6 The substitution and scale effects of carbon taxation on power plant productivity

Does carbon taxation induce fossil fuel power plants to become more productive? The answer hinges on the relative size of the substitution effect (that power plants now find fuel efficiency relatively cheaper than fuel use) and the scale effect (that power plants have higher general costs, encouraging them to reduce their scale and lower their productivity). I use the model I estimated in the previous sections to recover the total effect of carbon taxation on productivity and the magnitude of both the scale and substitution effect separately. I do this decomposition for both plant-level productivity and aggregate productivity measures.

Carbon taxes change the effective price of burning fossil fuels so computing counterfactual fuel use and productivity given a carbon tax is the same as computing what the plant would do if the price of fuel increased by the relevant amount. Let r_C be the emissions rate from burning coal and r_G be the emissions rate from burning natural gas (in metric tons carbon dioxide per million British thermal unit of fuel). I use the emission rates provided by the Energy Information Administration: $r_C = 0.09535$ and $r_G = 0.05307$ metric tons per million BTU. A carbon tax changes the power plant's decision problem by shifting the price of fuel,

$$\max_{Q,C,G,A} D_i Q^\eta - [W_C + \tau r_C] C - [W_G + \tau r_G] G - U_i A^\gamma \quad \text{ST:} \quad \left(V_i C^\theta + G^\theta\right)^\rho A \geq Q. \tag{28}$$

To compute the counterfactual, I re-solve the optimization problem at the new fuel prices (the first order conditions can be solved analytically for the functional form I use).

I consider a range of carbon taxes from $\tau = 0$ dollars per metric ton to $\tau = 50$ dollars per metric ton which coincides with recently-proposed policies. For example, Bernie Sanders, a United States senator, proposed a \$15 per metric ton carbon tax in 2015 that would increase by about \$3 per year, and Representative John Dulaney suggested a tax of \$30 per metric ton (Center, 2017). A 2017 plan proposed by the Climate Leadership Council suggests a \$40 per (Imperial) ton tax which is near the upper end of the range considered, but the proposed plan would also eliminate other regulations so the total effect of the plan may not increase the cost of fuel or reduce carbon emissions by as much as suggested by looking at the corresponding tax rate in my results, see Council (2017) for full details. Various estimates of the social cost of carbon dioxide emissions are available from the EPA (2017) and are all in this range.

In Table 3, I give the effective fuel price increase for the various carbon tax levels. At carbon tax levels commonly proposed, the effective price of both coal and natural gas would increase significantly as a fraction of current price levels. Coal would more than double. If a general carbon tax were to be implemented, it is possible power plants would face lower carbon taxes than would be applied generally because of how drastically their costs would increase and because many regions of the country are still heavily dependent on coal for electricity. For an example of this political economy playing out, see the recent experience in Washington state where a $20 per metric ton carbon tax was proposed and the political process ended up granting the state's lone coal power plant an exemption (the tax did not pass anyway), see Bernton and O'Sullivan 2018 (the Seattle Times).

I compute the substitution effect of carbon taxation by solving the cost minimization problem for the same output the power plant produced in the data. The resulting productivity choice is the choice of productivity the plant would make in response to the new price if it received an output subsidy to offset the cost of the carbon tax and cause the plant to choose the same level of output as it would have without the tax,

$$(A_{\text{sub}}, C_{\text{sub}}, G_{\text{sub}}) = \arg\min_{A,C,G} \left[W_C + \tau r_C\right] C + \left[W_G + \tau r_G\right] G + U_i A^\gamma \tag{29}$$

$$\text{ST:} \quad \left(V_i C^\theta + G^\theta\right)^\rho A \geq Q_i, \tag{30}$$

where Q_i is observed output.

I compute the scale effect of the policy by finding the output that would be chosen by the power plant after the carbon tax and then determining what productivity would be if that output were chosen but no carbon tax were implemented (the relative price of fuel and productivity remained unchanged). It is the effect of taxing a power plant's output instead of its fuel at a rate such that both taxes cause plants to make the same output choice.

$$(Q_\tau, A_\tau, C_\tau, G_\tau) = \arg\max_{Q,A,C,G} D_i Q^\eta - \left[W_C + \tau r_C\right] C - \left[W_G + \tau r_G\right] G - U_i A^\gamma \tag{31}$$

$$\text{ST:} \quad \left(V_i C^\theta + G^\theta\right)^\rho A \geq Q \tag{32}$$

$$(A_{\text{scale}}, C_{\text{scale}}, G_{\text{scale}}) = \arg\min_{A,C,G} W_C C + W_G G + U_i A^\gamma \tag{33}$$

$$\text{ST:} \quad \left(V_i C^\theta + G^\theta\right)^\rho A \geq Q_\tau, \tag{34}$$

the scale effect tells how much of the productivity change is due to the reduction in power plant size. The total effect of the policy is given by $(Q_\tau, A_\tau, C_\tau, G_\tau)$.

I find carbon taxation *decreases* plant productivity; the positive substitution effect is not strong enough to overcome the scale effect. Figure 1 shows increasing carbon taxes drive down productivity, by more for coal power plants and by less for natural gas power plants because the effective price of coal increases more than the effective price of natural gas.

The substitution effect, on the other hand, is positive and the effect size is not small, between 1% to 3%. There is substantial substitution between fuel use and fuel efficiency. The result suggests that if some of the revenue from the carbon tax were returned to plants as some function of their size, we would see a productivity effect between the effect of the carbon tax and the substitution effect.

Figure 2 shows the effect of carbon taxation on carbon emissions decomposed into both a substitution and scale effect. The figure shows that the substitution effect — the decrease in the relative price of fuel efficiency compared to fuel use — plays an important role in reducing carbon dioxide emissions from the carbon tax. If we ignored the substitution effect, we would require a much larger carbon tax to achieve the same reduction in carbon dioxide emissions as we can see by comparing the plot for the scale effect (which has no substitution effect) and the total effect (which does include it). The productivity effect of carbon taxation is important both for understanding the full effect of the policy on the costs of electricity production and to understand how large a carbon tax we need to achieve a desired reduction in emissions.

In addition to the plant-level effects, I also compute how aggregate (output-share weighted) productivity changes in the counterfactual where aggregate productivity is measured similarly to Olley and Pakes (1996) but for log productivity. The purpose in also looking at share-weighted productivity measures is that carbon taxation also changes the distribution of output across plants so the aggregate effect may be very different than the plant-level effect.

I compute aggregate productivity as,

$$S_i = \frac{Q_i}{\sum_{j=1}^{n} Q_j} \tag{35}$$

$$\log \widetilde{A}_i = \log A_i - \frac{1}{N_{\text{type}}} \sum_{j \in \text{ type}} \log A_j \tag{36}$$

$$\text{GAP} = \prod_{i=1}^{N} \widetilde{A}_i^{S_i}, \tag{37}$$

where GAP stands for geometric aggregate productivity (because the mean is a weighted geometric mean) and "type" indicates the kinds of fuel used. Productivity is re-centered

Table 3: Effective fuel price increase

Carbon tax ($ 2015/metric ton)	Average coal price (2015)	Average natural gas price (2015)
0	2.31	3.29
5	+0.48	+0.27
10	+0.95	+0.53
15	+1.43	+0.80
20	+1.91	+1.06
25	+2.38	+1.33
30	+2.86	+1.59
35	+3.34	+1.86
40	+3.81	+2.12
45	+4.29	+2.39
50	+4.77	+2.65

to have zero log mean for each type *in the status quo* because the mean normalization is different for each kind of fuel type use. I use GAP instead of an arithmetic weighted average because it is useful numerically to stay in log scale.

Aggregate productivity after a carbon tax changes not only because of the carbon tax's direct effect on productivity, but also because the tax affects the distribution of output. Olley and Pakes (1996) decompose aggregate productivity into two terms, average productivity,

$$\overline{\log \widetilde{A}} = \frac{1}{n}\sum_{i=1}^{n} \log \widetilde{A}_i,$$

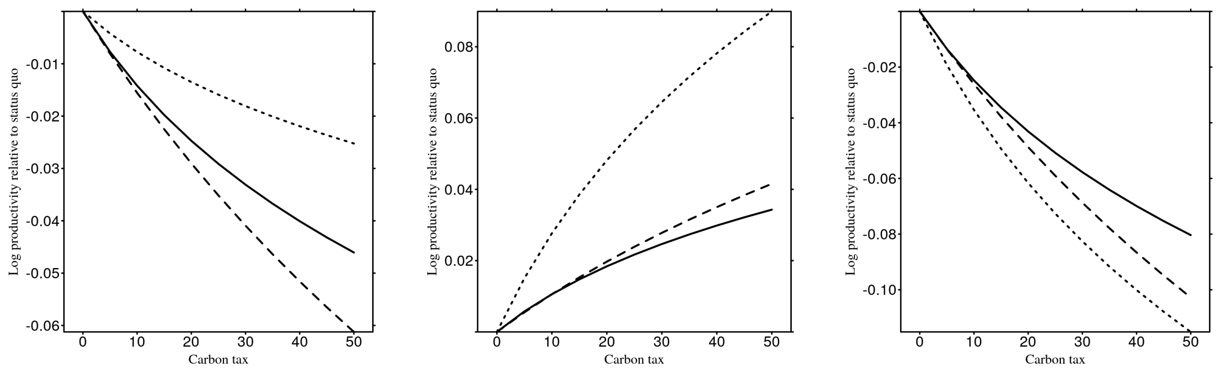
and a reallocation term,

$$\sum_{i=1}^{n}\left(S_i - \overline{S}\right) \times \left(\log \widetilde{A} - \overline{\log \widetilde{A}}\right).$$

The effect of carbon taxation on average productivity is the same as in Figure 1 (so it will be negative). But the reallocation effect, the change in the correlation of productivity and output share, may be very different than the average plant-level effect.

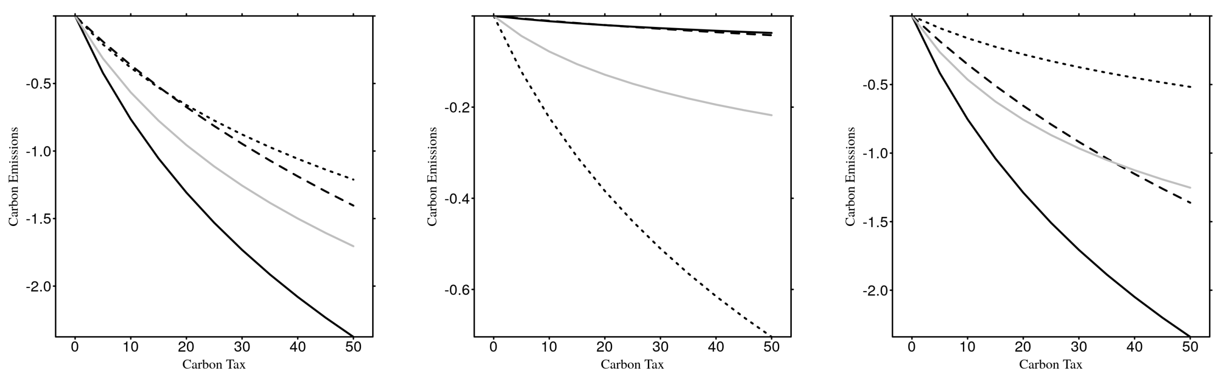
I plot aggregate productivity, the average productivity term, and the reallocation term against different levels of the carbon tax in Figure 3. I find aggregate productivity *rises* with carbon taxation: while the average productivity term falls, the reallocation term increases by enough that aggregate productivity increases. The result is mainly driven by reallocation from coal power plants to natural gas power plants (as seen in Figure 4) while natural gas plants become relatively more productive (as seen in Figure 1). For all results included in the figures, I include tables with confidence intervals in Appendix A.

Figure 1: The effect of carbon taxation on power plant productivity in 2015 (coal power plants are solid line, natural gas power plants are dashed line, and plants that use both are the dotted line; all plots are the difference in average log productivity relative to no carbon tax). For confidence intervals, see Appendix A.



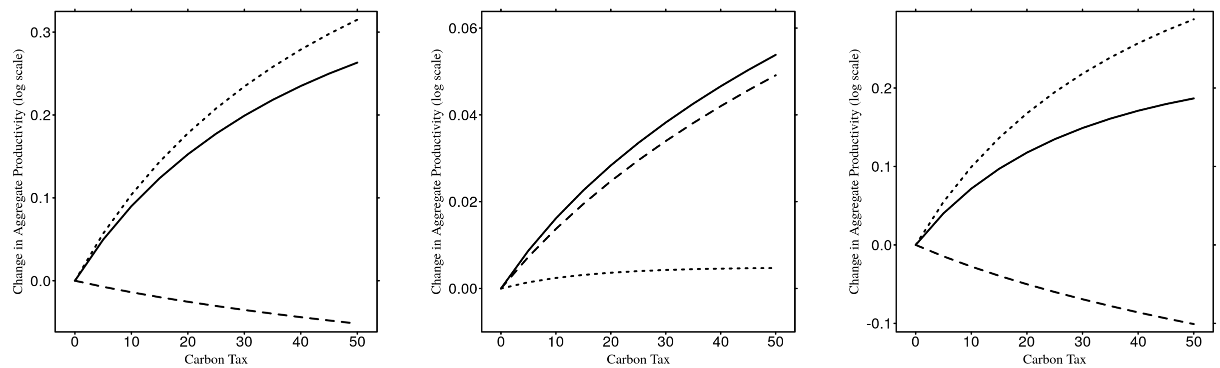
(a) Total effect (b) Substitution effect (c) Scale effect

Figure 2: The effect of carbon taxation on power plant carbon emissions in 2015 (coal power plants are solid line, natural gas power plants are dashed line, plants that use both are the dotted line, and the gray, solid line is all plants; all plots are the log difference in total carbon emissions relative to no carbon tax). For confidence intervals see Appendix A



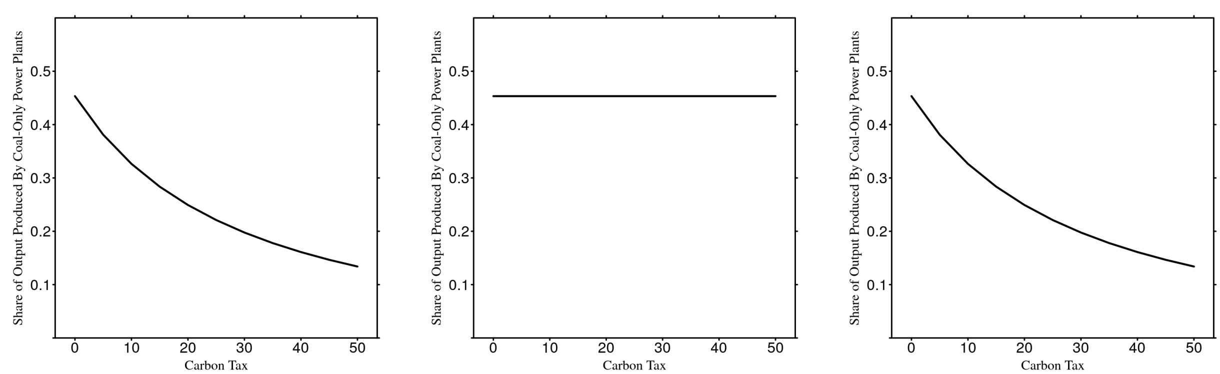
(a) Total effect (b) Substitution effect (c) Scale effect

Figure 3: Aggregate productivity as a function of the carbon tax in 2015 (solid line is total aggregate productivity, dashed line is average productivity, and dotted line is reallocation term); all plots are log difference in aggregate productivity relative to no carbon tax. For confidence intervals, see Appendix A.



(a) Total effect (b) Substitution effect (c) Scale effect

Figure 4: Coal's share of output as a function of the carbon tax in 2015 (power produced by power plants that use any coal).



(a) Total effect (b) Substitution effect (c) Scale effect

7 Conclusion

I propose a structural model that can be used to evaluate how a prospective policy would affect productivity (equivalently, how it would affect unobserved factor choice). The model can be used to understand how policies affect productivity for a large class of economic problems. It is nonparametrically identified. The curvature of the production function and the cost of productivity function can be separately identified. I also present a highly-tractable version of the model with a CES production function that lends itself to standard linear instrumental variable estimation techniques.

I use the model to study how carbon taxation would affect power plant productivity in the United States, identifying two effects of the policy on productivity: a scale effect, increased costs of production reduce the scale at which power plants operate and smaller plants produce less electricity, and a substitution effect, increased costs of fuel use relative to other factors of production encourages substitution to those factors, increasing fuel productivity. I find that, at the plant level, the scale effect is greater than the substitution effect: carbon taxation decreases fuel productivity. But, at the aggregate level, carbon taxation reallocates output from power plants that emit more carbon dioxide (coal power plants) to power plants that emit less carbon dioxide (natural gas power plants) and the productivity of natural gas power plants is less affected by carbon taxation than the productivity of coal power plants. Reallocation causes output-share weighted productivity to rise while average productivity falls.

I find evidence against the reasonable intuition that a carbon tax increases the incentive for plants to be fuel efficient. Carbon taxes will reduce power plant productivity because the scale effect of carbon taxation is larger than the substitution effect. *But* carbon taxes do reallocate output to more productive power plants, increasing output share-weighted productivity.

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A Confidence intervals

In this section, I give 90% confidence intervals (computed via 2000 bootstrap simulations) for each number that appears in the graphs of the figures in Section 6.

A.1 Total effect of carbon taxation

Table 4: Effect of carbon taxation in 2015 on productivity at coal-only power plants (in log points relative to no carbon tax)

Carbon Tax ($/metric ton CO2)	LB 95% CI	UB 95% CI
0.00	0.00	0.00
5.00	-0.01	-0.00
10.00	-0.02	-0.01
15.00	-0.03	-0.01
20.00	-0.04	-0.01
25.00	-0.05	-0.02
30.00	-0.05	-0.02
35.00	-0.06	-0.02
40.00	-0.06	-0.02
45.00	-0.07	-0.02
50.00	-0.07	-0.02

Table 5: Effect of carbon taxation in 2015 on productivity at natural gas-only power plants (in log points relative to no carbon tax)

Carbon Tax ($/metric ton CO2)	LB 95% CI	UB 95% CI
0.00	0.00	0.00
5.00	-0.02	-0.00
10.00	-0.04	-0.01
15.00	-0.06	-0.01
20.00	-0.08	-0.01
25.00	-0.10	-0.01
30.00	-0.11	-0.01
35.00	-0.13	-0.02
40.00	-0.14	-0.02
45.00	-0.15	-0.02
50.00	-0.17	-0.02

Table 6: Effect of carbon taxation in 2015 on productivity at power plants that use coal and natural gas (in log points relative to no carbon tax)

Carbon Tax ($/metric ton CO2)	LB 95% CI	UB 95% CI
0.00	0.00	0.00
5.00	-0.01	-0.00
10.00	-0.02	-0.00
15.00	-0.03	-0.00
20.00	-0.04	-0.01
25.00	-0.04	-0.01
30.00	-0.05	-0.01
35.00	-0.05	-0.01
40.00	-0.06	-0.01
45.00	-0.06	-0.01
50.00	-0.06	-0.01

Table 7: Effect of carbon taxation in 2015 on carbon dioxide emissions from all power plants (in log points relative to no carbon tax)

Carbon Tax ($/metric ton CO2)	LB 95% CI	UB 95% CI
0.00	0.00	0.00
5.00	-0.41	-0.25
10.00	-0.73	-0.46
15.00	-0.99	-0.63
20.00	-1.20	-0.78
25.00	-1.39	-0.92
30.00	-1.56	-1.04
35.00	-1.71	-1.15
40.00	-1.84	-1.25
45.00	-1.97	-1.34
50.00	-2.07	-1.42

Table 8: Effect of carbon taxation in 2015 on aggregate productivity (in log points relative to no carbon tax)

Carbon Tax ($/metric ton CO2)	LB 95% CI	UB 95% CI
0.00	0.00	0.00
5.00	0.05	0.11
10.00	0.09	0.20
15.00	0.13	0.27
20.00	0.16	0.34
25.00	0.19	0.39
30.00	0.21	0.44
35.00	0.24	0.48
40.00	0.26	0.52
45.00	0.27	0.55
50.00	0.29	0.58

Table 9: Effect of carbon taxation in 2015 on aggregate average productivity (in log points relative to no carbon tax)

Carbon Tax ($/metric ton CO2)	LB 95% CI	UB 95% CI
0.00	0.00	0.00
5.00	-0.02	-0.00
10.00	-0.03	-0.01
15.00	-0.05	-0.01
20.00	-0.06	-0.01
25.00	-0.07	-0.01
30.00	-0.08	-0.02
35.00	-0.09	-0.02
40.00	-0.10	-0.02
45.00	-0.11	-0.02
50.00	-0.12	-0.02

Table 10: Effect of carbon taxation in 2015 on the reallocation term in aggregate productivity (in log points relative to no carbon tax)

Carbon Tax ($/metric ton CO2)	LB 95% CI	UB 95% CI
0.00	0.00	0.00
5.00	0.06	0.12
10.00	0.10	0.22
15.00	0.15	0.31
20.00	0.18	0.38
25.00	0.21	0.45
30.00	0.24	0.51
35.00	0.27	0.56
40.00	0.29	0.60
45.00	0.31	0.64
50.00	0.33	0.67

Table 11: Effect of carbon taxation in 2015 on the share of output produced by coal-only power plants

Carbon Tax ($/metric ton CO2)	LB 95% CI	UB 95% CI
0.00	0.38	0.47
5.00	0.31	0.41
10.00	0.26	0.36
15.00	0.21	0.32
20.00	0.18	0.29
25.00	0.15	0.27
30.00	0.13	0.25
35.00	0.11	0.23
40.00	0.10	0.21
45.00	0.09	0.20
50.00	0.07	0.19

A.2 Substitution effect of carbon taxation

Table 12: Effect of carbon taxation in 2015 (substitution effect only) on productivity at coal-only power plants (in log points relative to no carbon tax)

Carbon Tax (\$/metric ton CO2)	LB 95% CI	UB 95% CI
0.00	0.00	0.00
5.00	0.00	0.01
10.00	0.00	0.02
15.00	0.01	0.02
20.00	0.01	0.03
25.00	0.01	0.03
30.00	0.01	0.04
35.00	0.01	0.04
40.00	0.01	0.04
45.00	0.01	0.05
50.00	0.01	0.05

Table 13: Effect of carbon taxation in 2015 (substitution effect only) on productivity at natural gas-only power plants (in log points relative to no carbon tax)

Carbon Tax (\$/metric ton CO2)	LB 95% CI	UB 95% CI
0.00	0.00	0.00
5.00	0.00	0.01
10.00	0.01	0.01
15.00	0.01	0.02
20.00	0.01	0.03
25.00	0.01	0.03
30.00	0.02	0.04
35.00	0.02	0.04
40.00	0.02	0.05
45.00	0.02	0.05
50.00	0.02	0.06

Table 14: Effect of carbon taxation in 2015 (substitution effect only) on productivity at power plants that use coal and natural gas (in log points relative to no carbon tax)

Carbon Tax ($/metric ton CO2)	LB 95% CI	UB 95% CI
0.00	0.00	0.00
5.00	0.00	0.02
10.00	0.01	0.03
15.00	0.01	0.04
20.00	0.01	0.05
25.00	0.01	0.06
30.00	0.01	0.07
35.00	0.02	0.08
40.00	0.02	0.09
45.00	0.02	0.09
50.00	0.02	0.10

Table 15: Effect of carbon taxation in 2015 (substitution effect only) on carbon dioxide emissions from all power plants (in log points relative to no carbon tax)

Carbon Tax ($/metric ton CO2)	LB 95% CI	UB 95% CI
0.00	0.00	0.00
5.00	-0.06	-0.03
10.00	-0.11	-0.05
15.00	-0.15	-0.07
20.00	-0.18	-0.08
25.00	-0.21	-0.10
30.00	-0.23	-0.11
35.00	-0.25	-0.12
40.00	-0.27	-0.13
45.00	-0.28	-0.14
50.00	-0.30	-0.14

Table 16: Effect of carbon taxation in 2015 (substitution effect only) on aggregate productivity (in log points relative to no carbon tax)

Carbon Tax ($/metric ton CO2)	LB 95% CI	UB 95% CI
0.00	0.00	0.00
5.00	0.00	0.01
10.00	0.01	0.02
15.00	0.01	0.02
20.00	0.02	0.03
25.00	0.02	0.04
30.00	0.02	0.04
35.00	0.02	0.05
40.00	0.03	0.05
45.00	0.03	0.06
50.00	0.03	0.06

Table 17: Effect of carbon taxation in 2015 (substitution effect only) on aggregate average productivity (in log points relative to no carbon tax)

Carbon Tax ($/metric ton CO2)	LB 95% CI	UB 95% CI
0.00	0.00	0.00
5.00	0.00	0.01
10.00	0.01	0.02
15.00	0.01	0.02
20.00	0.02	0.03
25.00	0.02	0.03
30.00	0.02	0.04
35.00	0.02	0.04
40.00	0.03	0.05
45.00	0.03	0.05
50.00	0.03	0.06

Table 18: Effect of carbon taxation in 2015 (substitution effect only) on the reallocation term in aggregate productivity (in log points relative to no carbon tax)

Carbon Tax ($/metric ton CO2)	LB 95% CI	UB 95% CI
0.00	0.00	0.00
5.00	-0.00	0.00
10.00	-0.00	0.00
15.00	-0.00	0.01
20.00	-0.00	0.01
25.00	-0.00	0.01
30.00	-0.00	0.01
35.00	-0.01	0.01
40.00	-0.01	0.01
45.00	-0.01	0.01
50.00	-0.01	0.01

Table 19: Effect of carbon taxation in 2015 (substitution effect only) on the share of output produced by coal-only power plants

Carbon Tax ($/metric ton CO2)	LB 95% CI	UB 95% CI
0.00	0.38	0.48
5.00	0.38	0.48
10.00	0.38	0.48
15.00	0.38	0.48
20.00	0.38	0.48
25.00	0.38	0.48
30.00	0.38	0.48
35.00	0.38	0.48
40.00	0.38	0.48
45.00	0.38	0.48
50.00	0.38	0.48

A.3 Scale effect of carbon taxation

Table 20: Effect of carbon taxation in 2015 (scale effect only) on productivity at coal-only power plants (in log points relative to no carbon tax)

Carbon Tax ($/metric ton CO2)	LB 95% CI	UB 95% CI
0.00	0.00	0.00
5.00	-0.02	-0.01
10.00	-0.04	-0.01
15.00	-0.05	-0.02
20.00	-0.06	-0.02
25.00	-0.07	-0.03
30.00	-0.08	-0.03
35.00	-0.09	-0.03
40.00	-0.10	-0.04
45.00	-0.11	-0.04
50.00	-0.12	-0.04

Table 21: Effect of carbon taxation in 2015 (scale effect only) on productivity at natural gas-only power plants (in log points relative to no carbon tax)

Carbon Tax ($/metric ton CO2)	LB 95% CI	UB 95% CI
0.00	0.00	0.00
5.00	-0.03	-0.01
10.00	-0.06	-0.01
15.00	-0.09	-0.02
20.00	-0.11	-0.02
25.00	-0.13	-0.03
30.00	-0.15	-0.03
35.00	-0.18	-0.04
40.00	-0.19	-0.04
45.00	-0.21	-0.04
50.00	-0.23	-0.05

Table 22: Effect of carbon taxation in 2015 (scale effect only) on productivity at power plants that use coal and natural gas (in log points relative to no carbon tax)

Carbon Tax ($/metric ton CO2)	LB 95% CI	UB 95% CI
0.00	0.00	0.00
5.00	-0.03	-0.01
10.00	-0.05	-0.01
15.00	-0.07	-0.01
20.00	-0.09	-0.02
25.00	-0.10	-0.02
30.00	-0.11	-0.02
35.00	-0.13	-0.02
40.00	-0.14	-0.03
45.00	-0.15	-0.03
50.00	-0.16	-0.03

Table 23: Effect of carbon taxation in 2015 (scale effect only) on carbon dioxide emissions from all power plants (in log points relative to no carbon tax)

Carbon Tax ($/metric ton CO2)	LB 95% CI	UB 95% CI
0.00	0.00	0.00
5.00	-0.37	-0.19
10.00	-0.65	-0.33
15.00	-0.87	-0.44
20.00	-1.05	-0.54
25.00	-1.20	-0.62
30.00	-1.33	-0.68
35.00	-1.44	-0.74
40.00	-1.55	-0.79
45.00	-1.64	-0.83
50.00	-1.71	-0.87

Table 24: Effect of carbon taxation in 2015 (scale effect only) on aggregate productivity (in log points relative to no carbon tax)

Carbon Tax ($/metric ton CO2)	LB 95% CI	UB 95% CI
0.00	0.00	0.00
5.00	0.04	0.10
10.00	0.08	0.19
15.00	0.11	0.26
20.00	0.13	0.32
25.00	0.15	0.37
30.00	0.17	0.42
35.00	0.19	0.45
40.00	0.20	0.49
45.00	0.21	0.51
50.00	0.22	0.54

Table 25: Effect of carbon taxation in 2015 (scale effect only) on aggregate average productivity (in log points relative to no carbon tax)

Carbon Tax ($/metric ton CO2)	LB 95% CI	UB 95% CI
0.00	0.00	0.00
5.00	-0.02	-0.01
10.00	-0.05	-0.02
15.00	-0.07	-0.02
20.00	-0.09	-0.03
25.00	-0.11	-0.04
30.00	-0.12	-0.04
35.00	-0.14	-0.05
40.00	-0.15	-0.05
45.00	-0.17	-0.05
50.00	-0.18	-0.06

Table 26: Effect of carbon taxation in 2015 (scale effect only) on the reallocation term in aggregate productivity (in log points relative to no carbon tax)

Carbon Tax ($/metric ton CO2)	LB 95% CI	UB 95% CI
0.00	0.00	0.00
5.00	0.06	0.12
10.00	0.10	0.22
15.00	0.14	0.31
20.00	0.17	0.39
25.00	0.20	0.45
30.00	0.23	0.51
35.00	0.25	0.55
40.00	0.28	0.59
45.00	0.29	0.63
50.00	0.31	0.66

Table 27: Effect of carbon taxation in 2015 (scale effect only) on the share of output produced by coal-only power plants

Carbon Tax ($/metric ton CO2)	LB 95% CI	UB 95% CI
0.00	0.38	0.48
5.00	0.31	0.41
10.00	0.26	0.36
15.00	0.21	0.32
20.00	0.18	0.29
25.00	0.15	0.26
30.00	0.13	0.24
35.00	0.11	0.22
40.00	0.10	0.21
45.00	0.08	0.20
50.00	0.07	0.18