Technology Lock-In and Optimal Carbon Pricing*

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November 28, 2021

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Abstract

This paper studies the implications of low energy prices today for energy efficiency and climate policy in the future. If adjustment costs mediate manufacturing plants' responses to increases in energy prices, incumbents may be limited in their ability to re-optimize energy-inefficient production technologies chosen based on past market incentives. Using U.S. Census data and quasi-experimental variation in state energy prices, we first show that the initial electricity prices that manufacturing plants pay in their first year of operations are important determinants of long-run energy intensity. Plants that open when the prices of electricity and fossil fuel inputs into electricity are low consume more energy throughout their lifetime, regardless of current electricity prices. We then measure the relative contributions of initial productivity and capital adjustment frictions to creating this "technology lock-in" by estimating a model of plant input choices. We find that lock-in can be largely explained by persistent differences in the relative productivity of energy inputs chosen at entry. We discuss how these long-run effects of low entry-year energy prices increase the emissions costs of delayed action on carbon policy.

*We thank Jason Abaluck, Joe Altonji, Steve Berry, Matt Kotchen, Rohini Pande, Nick Ryan, Joe Shapiro, Stephanie Weber, and seminar participants at Arizona State University, Harvard, the Stanford Junior Faculty Lunch, the Stanford Institute for Economic Policy Research (SIEPR), and the UC Berkeley Energy Camp for helpful discussions, Andrew Tang and Benji Reade Malagueno for excellent research assistance, and the Cowles Foundation, the Yale Economic Growth Center, and SIEPR for funding. Any views expressed are those of the authors and not those of the U.S. Census Bureau. The Census Bureau's Disclosure Review Board and Disclosure Avoidance Officers have reviewed this information product for unauthorized disclosure of confidential information and have approved the disclosure avoidance practices applied to this release. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 2309. (Release numbers CBDRB-FY21-P2309-R8908 and CBDRB-FY21-P2309-R9137) Contact: Hawkins-Pierot: jonathan.hawkins@yale.edu; Wagner: katherine.wagner@berkeley.edu.

1 Introduction

Does the lack of carbon pricing today mediate the effectiveness of carbon pricing in the future? Abundant fossil fuel resources priced below their social cost have set industrial economies on a path of energy-inefficient development and rising anthropogenic carbon emissions. Current global energy infrastructure comprises tens of trillions of dollars of assets and reflects two centuries of technological innovation—and approximately 80% of energy produced comes from burning fossil fuels that contribute to climate change (Seto et al., 2016). Climate change impacts such as extreme temperatures, hurricanes, and wildfires are now causing billions of dollars of economic damage annually, but carbon pricing policies intended to curb greenhouse gas emissions continue to face global opposition. In the United States, over fifty carbon pricing bills have been introduced by Congress in the last three decades; none has passed. Jurisdictions that have successfully implemented carbon pricing schemes, such as the European Union and Canada, struggle to set prices that fully internalize the social costs of energy consumption. Some policymakers have despaired at the political feasibility of such reforms, instead proposing alternative policies such as clean energy subsidies and technology standards (Shearer and Nace, 2010).

In the absence of such policies, global energy usage is projected to increase by more than 50% by mid-century. The largest consumer of this energy is the industrial sector, and the durable nature of capital means that many energy-inefficient manufacturing plants that open when energy is dirty and cheap will contribute to global emissions for many years (EIA, 2019). The increasing trend in energy usage is even steeper in developing countries such as India and China, which are opening the equivalent of one new coal power plant every week (Myllyvirta and Shearer, 2021). Carbon emissions from existing coal power plants are already 150% higher than permissible in optimistic climate scenarios that limit global temperature increases to 2 degrees Celsius above pre-industrial levels—even before accounting for planned construction (Shearer and Nace, 2010).

This paper quantifies the extent to which the energy prices that manufacturing plants pay in their first year of operations determine their future energy usage and the outcomes of subsequent climate policy. When a plant enters the market, it chooses a combination of factor inputs to use in production based on entry-year prices and beliefs about future prices. We explore the extent to which these initial prices have persistent effects on long-run energy usage, which we refer to as "technology lock-in", and mechanisms for these effects. If adjustment costs mediate responsiveness to changes in input prices, incumbent plants may be limited in their ability to reoptimize their energy usage when energy prices increase. Such a constrained response could cause low energy prices today to undermine the effectiveness of future carbon pricing policies, and also increase the importance of technology subsidies to encourage turnover of energy-inefficient capital.

The first part of this paper provides empirical evidence of technology lock-in. We assess how both initial and contemporaneous electricity prices affect manufacturing plants' energy intensity, defined as energy use per dollar of revenue. We measure plants' energy intensities and input prices using restricted-access microdata from the U.S. Census of Manufactures (CMF) and the Annual Survey of Manufacturing (ASM) for the years 1976 to 2011. Since electricity prices may be correlated with other shocks to manufacturing plants' input demands, we use shift-share instruments to isolate plausibly exogenous price variation (Bartik, 1991; Goldsmith-Pinkham et al., 2020). The instruments exploit national changes in coal, natural gas, and petroleum prices, weighted by each state's use of these fuels to generate electricity in a base year (Ganapati et al., 2020). As an alternative measure of lock-in, we also directly examine how the prevailing prices of these fuels in plants' entry year affect subsequent energy intensity. We show that the results are robust to estimation using alternative energy intensity definitions, different data subsamples, and different energy data sources.

Motivated by this empirical evidence, the second part of the paper explores the extent to which this lock-in arises due to differences in production technologies chosen at entry. To do so, we estimate the parameters of plants' production technologies and the relative productivities of different manufacturing inputs at entry and in subsequent years. The model allows us to quantify the efficiency of plants' energy inputs relative to labor in each year of operations. Using these estimates, we assess whether entry-year energy prices lead to different initial production choices and whether any differences persist over time.

These analyses yield two primary results. First, technology lock-in is important in manufacturing production. We show that plants' entry-year electricity prices are significant determinants of current energy intensity, even conditional on current prices. While energy intensity declines when contemporaneous electricity prices increase, we estimate an initial electricity price elasticity of approximately -0.20—25% of the elasticity with respect to current electricity prices. In addition, we show that the entry-year prices of fuel inputs into electricity generation themselves have persistent effects on manufacturing energy intensity. Separate analysis of the contributions of the prices of different raw fuels reveals that entry-year coal and petroleum prices continue to be important determinants of energy use. Specifically, manufacturing plants established when coal and petroleum were cheap are still consistently more energy-intensive. The persistent effect of these fuel prices on manufacturing energy intensity is surprising because electricity generation in the U.S. is much less reliant on these fuels today. These findings underscore the long-run effects of development based on cheap fossil fuel energy and the emissions implications of expansion of fossil fuel power plants: dirty capital investments undertaken in response to current cheap coal prices around the world seem likely to lock in higher emissions levels in the future.

This lock-in has the potential to increase emissions if carbon pricing is delayed: entrants who choose production technologies based on current prices choose dirtier technologies than they otherwise would, and cannot subsequently fully adjust them. We find limited heterogeneous effects of initial electricity prices by plant age, which suggests that these entry-year prices remain important throughout a plant's lifetime. Of course, energy-inefficient plants may close if prices increase substantially, which motivates using the model of plants' input choices to directly assess the extent to which plants can adjust their production processes over time.

The second main results show that persistent differences in the relative productivity of energy inputs appear to explain much of the effect of initial electricity prices on subsequent manufacturing energy use. We estimate that a 10% increase in entry-year electricity prices increases relative energy productivity by approximately 3% in subsequent years. Conversely, we find no evidence that entry-year electricity prices have long-term effects on total factor productivity. These results suggest that when electricity prices are low, new manufacturing plants chose production technologies that use energy inputs relatively less efficiently compared with their labor inputs, and these productivity differences persist even if electricity prices change in the future.

This paper seeks to make three primary contributions to existing literature. First, we believe that this paper provides the first estimate of the importance of entry-year energy prices for industrial energy intensity in subsequent years. In addition to identifying this technology lock-in, we explain how it arises. Previous "efforts to characterize the types and causes of carbon lock-in, or to quantitatively assess and evaluate its policy implications, have been limited and scattered across a number of different disciplines" (Seto et al. (2016), p. 425).[1] Our findings contribute to a growing literature on how different initial conditions mediate transitions from dirty to clean energy (i.e., path dependence). Several papers in this literature use macroeconomic dynamic models and

[1] In the climate context, the literature refers to technology lock-in as "the inertia of carbon emissions ... associated with the technologies and infrastructure that indirectly or directly emit CO2", which is distinct from carbon lock-in arising from behavioral or institutional constraints more commonly studied by sociologists (Seto et al. (2016), p.427).

more aggregate data to study incentives to develop clean energy technologies, typically simulating how changes in energy prices affect carbon emissions through innovation (Acemoglu et al., 2012; Acemoglu et al., 2019; Atkeson and Kehoe, 1999; Fried, 2018; Hassler et al., 2012). Other work uses microdata, particularly from the electricity sector, to show that initial regulatory structure and fuel mix choices (e.g., coal versus natural gas) are important determinants of subsequent fuel use (Cullen and Mansur, 2017; Knittel et al., 2015; Meng, 2021). One paper shows that entrant and incumbent manufacturing plants respond differently to current energy prices (Linn, 2008). We depart from these studies by quantifying the extent to which initial energy prices matter after a plant's entry year and by analyzing the contribution of initial energy efficiency and technology choices to creating this lock-in.

These dynamics are relevant for policy. Current U.S. government proposals earmark $400 billion for industrial energy efficiency improvements (DNC, 2021). Understanding whether lock-in exists and how it arises is necessary to predict the outcomes of this suite of policies and to efficiently design them. Ignoring the dynamic effect of current energy prices on energy use tomorrow underestimates the benefits of pricing carbon today.

Second, this paper contributes to literature that models the responses of industrial energy use and productivity to environmental regulation. Research using microdata to study energy implications of environmental policy typically analyze the dynamics of one industry (e.g., cement or electricity) over the long-run (Fowlie et al., 2016; Meng, 2021; Ryan, 2012; Clay et al., 2021) or use static models to study important contemporaneous effects across many industries (Ganapati et al., 2020; Greenstone et al., 2012; Shapiro and Walker, 2018). Our contribution is to bring these two literatures together to provide a new generalizable explanation for why some of the dynamic responses arise. Classic "putty-clay" models of capital investment emphasize that capital adjustment frictions may constrain changes in input mix, but we identify that productivity differences appear to be at least as important as this more common explanation for lock-in (Atkeson and Kehoe, 1999). Showing that entry-year electricity prices have persistent effects on the efficiency of manufacturing inputs requires estimating the relative productivity of these inputs over time. Since commonly used models of manufacturing production functions, such as Cobb-Douglas, assume away the possibility of complementarity between inputs that creates lock-in, studying the causes of persistent effects of entry-year energy prices requires extending more general models of production to include energy (Ackerberg et al., 2015; Demirer, 2020; Doraszelski and Jaumandreu, 2018; Olley and Pakes, 1996).

Finally, we provide a new microfoundation for the rate of decarbonization frequently used in standard models of climate-economy interactions. These Integrated Assessment Models (IAMs) are the basis for calculating the full social costs of carbon emissions and for evaluating national and international climate policy recommendations. Despite their widespread use in regulatory analyses, economists have criticized these models for allowing "a great deal of freedom in choosing functional forms, parameter values, and other inputs" and for "lacking transparency in key underlying assumptions, such as energy resource costs, constraints on technology take-up, and demand responses to carbon pricing" (Pindyck, 2020, p.863; Gambhir et al., 2019, p.5). Standard models extrapolate future rates of decarbonization based on past decarbonization trends, which may overestimate attainable emissions reductions if lock-in is important. We provide a novel estimate of the response of industrial carbon emissions to emissions constraints assumed in climate-economy model, which is "the most important calibration for policy purposes" (Nordhaus and Boyer, 2000, p.44).

The rest of this paper proceeds as follows. Section 2 provides background on energy use in U.S. manufacturing to contextualize the analysis. Section 3 presents a conceptual framework outlining how technology lock-in might arise. Section 4 describes the data and section 5 presents descriptive statistics and trends in energy use. Section 6 discusses our econometric model for identifying technology lock-in and Section 7 presents our empirical evidence of it. Section 8 discusses the implications for climate change policy. Section 9 concludes.

2 Institutional Background

Manufacturing accounts for about one-quarter of total U.S. energy consumption and one-quarter of total U.S. greenhouse gas emissions. Energy consumption in the industrial sector, which comprises manufacturing, mining, construction, and agriculture, is increasing both in absolute terms and as a share of total consumption, and this sector accounts for almost all of the predicted increase in U.S. energy use in the next decade (EIA, 2015; EPA, 2021). Most manufacturing energy is consumed as electricity; a subset of manufacturing plants use raw fuels, such as coal, natural gas, and petroleum, as direct inputs. On average during this study's time period, electricity expenditures account for approximately 75% of total energy expenditures and 95% of thermal energy consumed (measured in British thermal units, or BTUs). Only 0.1% of this electricity is produced on-site. By contrast, manufacturing plants in developing countries such as India are typically more reliant on raw fuel inputs and on-site generation of electricity (Allcott et al., 2016).

Although total U.S. manufacturing energy consumption has increased, energy intensity of production has declined during the past thirty years. The adoption of more energy efficient technology by new manufacturing plants explains some of this decline, while energy prices and energy efficiency regulation are weakly correlated with energy efficiency improvements in aggregate (Levinson, 2021; Linn, 2008). Despite recent entrants' higher energy efficiency, manufacturing energy policy typically does not differentially regulate plants depending on their entry date.[2] Manufacturing energy efficiency is administered by a mix of federal, state, and local governments that usually target specific industries or technologies. Oregon, for example, offers subsidies for the installation of energy efficient manufacturing capital.[3] Landmark federal industrial environmental regulations, such as the Clean Air Act, more commonly target pollution that is the by-product of energy use rather than targeting energy efficiency directly (NREL, 2009).

The amount and type of energy used depend on plants' production processes. Primary uses include powering production machinery and fueling boilers, while secondary uses include heating and cooling, lighting, on-site transportation, and direct inputs into the finished product (Ganapati et al., 2020). Improving the energy of efficiency of many of these processes requires replacing equipment or machinery. For example, upgrading an energy inefficient turbine involves pausing or re-arranging operations to install an expensive replacement, and such capital adjustment costs create the possibility for technology lock-in. If energy inefficient machinery is installed when energy prices are low, incurring these adjustment costs to replace it may only be worthwhile if energy prices increase substantially.

Though raw fuels account for a small portion of direct energy inputs, the production of the electricity consumed by manufacturing involves important indirect use of raw fuels. At the start of our sample in 1976, electric utilities in the U.S. generate electricity using coal (40%), natural gas (12%), petroleum oil (21%), hydro (15%), and other renewable sources. Natural gas and renewables (e.g., solar) have become more important in the last two decades, with a reduction in the use of petroleum and, to a lesser extent, coal. Appendix Figure A.1 shows that the contribution of these different fuel sources to electricity generation varies widely across the U.S. Electric utilities have distinct regional markets that typically comprise a few states, and in 2011 industrial users paid between 0.04 and 0.28 dollars per kWh for electricity on average (EIA, 2020). Local electricity rates depend on the national prices for prevailing fuel inputs and distances to procurement sources.

[2] Vintage-differentiated energy efficiency regulations are more common in other sectors, such transportation and construction (Jacobsen and Kotchen, 2013; Levinson, 2021; Stavins, 2006; West et al., 2017).

[3] See NREL (2009) for a detailed review of federal, state, and local energy efficiency policies.

In what follows, we exploit variation in the national prices of these raw fuels to construct instruments for electricity prices.

3 Conceptual Framework

In this section, we show how technology lock-in operates in a stylized "putty-clay" model of the manufacturing sector (Atkeson and Kehoe, 1999), to which we introduce the importance of entry-year input productivities for energy use. We define the *energy intensity* of a plant as the ratio of energy inputs to output, $\frac{E}{Y}$. Technology lock-in is the elasticity of current energy intensity with respect to entry-year energy prices, conditional on current energy prices. For new entrants, current energy intensity depends on current prices only.

In our model, only new entrants can flexibly choose all inputs without adjustment costs. Incumbent plants can adjust their energy intensity in response to price changes through three margins. First, they can change their static inputs, such as energy and labor, which are chosen in each period. Unlike energy and labor, plants' capital inputs are subject to adjustment costs. The adjustment of potentially sticky capital stocks is the second margin through which plants adjust their energy intensity. Finally, plants enter or exit on the basis of differences in production technology, including the relative productivity of energy inputs. Changes in energy prices will change the composition of plant productivity within entry cohorts, and therefore average energy intensity.[4]

The first margin of adjustment—static reoptimization—operates in the short-run even for small, temporary fluctuations in relative prices. The other two, capital adjustment and energy productivity, prevent full reoptimization and are sources of technology lock-in. If capital and energy are complementary in the plant's production function, incomplete adjustment of capital stocks attenuates the response of energy intensity to changes in energy prices, leading to lock-in. Empirically, capital investment is characterized by infrequent spikes interspersed with periods of no or minimal investment. Investment is also slow to respond to large changes in economic fundamentals. These stylized facts suggest that both fixed and convex capital adjustment costs are important (Cooper and Haltiwanger, 2006; Khan and Thomas, 2008).

[4] The energy productivity shocks in our model play a similar role to vintage capital effects in the classic putty-clay model of Atkeson and Kehoe (1999). Our model weakens the assumption of perfect complementarity between capital and energy. More importantly, it emphasizes plant-level cross-sectional differences in productivity which arise through entry and exit decisions, as opposed to differences in the energy efficiency of capital within an individual plants' capital stock.

Some plants may also use production technologies which are more energy-efficient than others, leading to lock-in based on productivity differences. Given their expectations of future energy prices, plants choose to enter at a given level of energy productivity. This induces selection. In periods where energy is cheap, it will be profitable for plants with low energy productivity to enter. Since entry costs are sunk, these energy-inefficient plants may continue to operate even when energy prices rise. This generates lock-in by vintage: if energy prices increase, the *average* entrant will have a lower energy intensity than the average incumbent not only because they can flexibly choose their level of capital, but because they have higher energy productivity.

To illustrate how such lock-in might arise, we characterize these three margins of adjustment in a simple two-period model of myopic manufacturing plants. We then describe how these intuitions carry over into the richer model that we estimate.

3.1 A Model of Lock-In

To fix ideas, suppose the plant has a constant elasticity of substitution (CES) production technology:

$$Y(K,L,E;\beta) = \alpha\left(K^\rho + L^\rho + (\beta E)^\rho\right)^{\frac{\nu}{\rho}} \tag{1}$$

where K, L, and E are the quantities of capital, labor and energy inputs, respectively, $\sigma = \frac{1}{1-\rho}$ is the elasticity of substitution between energy and capital, $\nu \in (0,1]$ is a returns to scale parameter, α is total factor productivity, and β captures the productivity of energy relative to labor.[5] Labor and energy are assumed to be fully flexible static inputs, chosen optimally in each production period. As detailed below, an incumbent plant's level of capital is only partially flexible due to non-linear adjustment costs. The relative productivity of energy, β, is fixed at entry and is fully locked in.[6]

A potential entrant i draws productivity levels α_i and β_i and solves the static optimization problem:

$$\max_{K,L,E} \pi(K,L,E;\alpha_i,\beta_i) = pY(K,L,E;\alpha_i,\beta_i) - rK - wL - p_e E$$

[5] We estimate a CES production technology rather than the more common Cobb-Douglas function to allow for factor-specific productivities and complementarity between inputs. The Cobb-Douglas specification is equivalent CES where $\rho = 0$. In this case, input expenditure shares are fixed and capital stocks do not affect the optimal energy input.

[6] In the empirical specification, we allow total factor and energy-specific productivities, as well as prices, to evolve over time following AR(1) processes. We discuss estimation details in Section 6.2.

The potential entrant chooses to enter if profits exceed the fixed costs of entry, that is if:

$$\pi^*(p, w, r, p_E; \alpha_i, \beta_i) = pY(K^*, L^*, E^*) - wL - rK - p_E E \geq FC$$

In this equation, L^* and E^* solve the static profit maximization problem and FC is the fixed entry cost. We assume that the capital stock is fully flexible on entry, subject to a linear cost of capital investment. To clarify the role of the relative price of energy p_e in this example, we set the price of output p, the wage w, and the rental rate of capital r to be equal to one.

The first channel through which lock-in arises is the selection effect on the productivity of plants that choose to enter in the first period. Because profits are monotonically increasing in energy productivity, the potential entrant's problem yields a cutoff rule, where all else equal plant i enters if its energy productivity is sufficiently high. That is, if:

$$\beta_i \geq \beta^{entry}(p_E)$$

The cutoff, $\beta^{entry}(p_E)$, determines the distribution of energy productivity β_i for plants that entered in a period with energy price p_E. Because the cutoff is increasing in p_E, the cohort-average energy productivity will also be increasing in the initial energy price.[7]

Capital adjustment costs provide the second channel through which lock-in arises. Plants that enter earn their period one profits and continue to the second stage with their current capital stock, K. At the end of period one, plants observe prices in the next period and choose their capital in the next period, K', to solve

$$\max_{K'} \begin{cases} \pi^*(K'; p'_E, \beta_i) - \gamma_0 - r(K' - K) - \gamma_1(K' - K)^2 & \text{if } K' \neq K \\ \pi^*(K; p'_E, \beta_i) & \text{otherwise} \end{cases}$$

Here, $\pi^*(K; p_E, \beta)$ is the maximum profit holding capital fixed at K given prices and productivity. In addition to the cost of capital r, γ_0 and γ_1 are fixed and convex adjustment costs, respectively. The fixed cost to capital adjustment, γ_0, implies that plants will not reoptimize capital at all for marginal changes in the energy price. The convex adjustment cost, γ_1, implies that while plants

[7] We can see that $\beta^{entry}(p_E)$ is increasing in p_E because, algebraically, we can write Y in terms of "effective energy", $\hat{E} = \beta E$, and the price of an effective unit of energy will be $\frac{p_e}{\beta}$. This implies that if $p'_E > p_E$, then the distribution of β_i conditional on entry at price p'_E first-order stochastic dominates the distribution of β_i conditional on entry at price p_E. This, in turn, implies that $\mathbb{E}[\beta_i|$ entered at $p'_E] > \mathbb{E}[\beta_i|$ entered at $p_E]$

may invest in response to larger prices changes, they will only partially close the gap relative to frictionless entrants, because large capital investments are increasingly more costly than small ones. One implication of this is that, without policies such as technology subsidies, plants with both fixed and convex adjustment costs may never reach the optimal level of energy intensity.

Incumbent plants will shut down if their scrap value exceeds their profit: $\pi^* < S$. As with entry, there is a cutoff value $\beta^{exit}(p_E)$ such that for a given energy price p_E plants with energy productivity below $\beta^{exit}(p_E)$ will exit.[8] As the least efficient plants exit, cohort-average energy productivity will rise as p_E increases. However, if scrap values are lower than entry costs, $\beta^{exit}(p_E) < \beta^{entry}(p_E)$, and incumbents will, on average, have higher energy intensity than new entrants.

Figure 1 plots simulated current energy intensity as a function of energy prices at entry, relative to the energy intensity of a fully flexible entrant. The blue, long-dashed line plots the magnitude of lock-in for plants which cannot adjust their capital stock. The only margins of adjustments are exiting or changing energy and labor inputs. This represents an extreme case of lock-in. The orange, short-dashed line plots lock-in for plants which can partially adjust capital, subject to both fixed and convex capital adjustment costs. The green, solid line isolates the energy productivity effect by setting $\gamma_0 = \gamma_1 = 0$, shutting down capital adjustment frictions. Even without fixed or convex capital adjustment costs, the average plant from a low energy price vintage will be more energy intensive than the average new entrant. The gap is due to the difference between the entry cost and the scrap value. At higher energy prices, it is no longer profitable to open a new energy-intensive plant, but existing plants may continue to operate and pollute.[9]

We conclude this section with a brief discussion of how insights from this highly stylized example carry over into more general models. For energy productivity to play a role, we require selection at entry and persistence over time. Partial irreversibility of entry costs or capital investments is one natural way to generate more intense selection for entrants than incumbents. Large exit subsidies or buyouts for low-energy productivity incumbents might result in a higher productivity threshold for exit than for entry, which would result in the opposite sign for our estimated entry-year energy price elasticities.

[8]In the dynamic model used in the empirical application, we need only substitute the present discounted expected value of future profits, V, for profits, π^*. Since V inherits the same qualitative properties of π^*, all of these results will go through.

[9]Figure 1 illustrates the lock-in that arises when plants are myopic. The other extreme, where plants have perfect foresight regarding future prices, looks qualitatively similar but with a smaller difference between the energy intensity of incumbents who entered at high and low energy price (i.e., a less steep slope of energy intensity). Discounting future energy price changes creates lock-in even in the presence of perfect foresight.

For capital adjustment frictions to generate lock-in, it is sufficient that capital and energy are complements in production. The intuition is that an increase in energy prices lowers the marginal product per dollar of energy and causes the optimal energy input to decrease. If capital and energy are complements, this will decrease the marginal product per dollar of capital and, by extension, the optimal capital stock. If capital can optimally adjust, this drives further decreases in energy inputs. Incomplete capital adjustment will attenuate this change and result in higher energy intensity than for a fully flexible plant. If capital and energy are substitutes in production instead, this logic would be reversed and capital adjustment costs would increase plants' sensitivity to current price changes. Empirically, capital and energy are typically estimated to be complements (Hassler et al., 2012; Ryan, 2018).

3.2 From Theory to Data

In the remainder of the paper, we exploit exogenous variation in current and initial electricity prices to measure the persistent effect of electricity prices at entry. Technology lock-in is important if plants facing the same current electricity prices have systematically higher energy intensity if they entered in years when electricity was less expensive. This overall estimate of lock-in is analogous to the orange, short-dashed line in Figure 1, which captures lock-in due to both capital adjustment frictions and persistent energy-specific productivity.

The regressions of energy intensity on electricity prices cannot, by themselves, distinguish between these two sources of lock-in. To do so, we estimate a structural production function for each industry and recover the energy-specific productivity shocks for each plant. This allows us to measure the contribution of energy-specific productivity differences to lock-in, which corresponds to green, solid line in Figure 1. By comparing the total effect with the productivity estimates, we quantify the relative importance of these two mechanisms. The contribution of capital adjustment costs is then analogous to the residual distance between the green, solid line and the orange, short-dashed line.

4 Data

We draw on restricted microdata from the U.S. Census Bureau on manufacturing inputs and outputs and on energy data from publicly available government sources. Additional data details are in

Appendix A.

4.1 Manufacturing Inputs and Outputs

Our primary sources of data are administrative records on annual plant-level inputs and outputs from the Annual Survey of Manufacturing (ASM) and the Census of Manufactures (CMF) from the U.S. Census Bureau for the years 1976 to 2011. The CMF is conducted in years ending with 2 or 7 and surveys all manufacturing plants in the United States. The ASM annually surveys plants in the years between censuses and comprises a nationally representative sample of approximately 50,000 establishments per year. These surveys report quantity of electricity purchased and expenditures on electricity and raw fuels (e.g., coal, natural gas, petroleum oil) separately. We calculate each plant's annual average electricity price as reported total electricity expenditure divided by electricity purchased.[10] We measure plants' annual capital investment using total capital outlays, materials, electricity, and raw fuels inputs using reported expenditures, and labor inputs using worker hours, available in both the ASM and CMF.[11] The CMF also contains information on plants' capital stocks, measured as reported book values of equipment and machinery.[12]

We supplement these data with the Manufacturing Energy Consumption Survey (MECS) and the ASM Fuel Trailers. Together with the ASM and CMF, these surveys allow us to calculate three measures of energy intensity of production: electricity consumed per dollar of revenue, carbon dioxide (CO2) emissions produced per dollar of revenue, and British thermal units (BTU) of energy consumed per dollar of revenue. The MECS and ASM Fuel Trailers include a probabilistic sample of about 15,000 manufacturing plants, for the years 1976-1981 for the ASM Fuel Trailers and for every three years between 1985 and 1994 and every four years thereafter for the MECS. These more detailed energy surveys provide breakdowns of expenditure on and quantity consumed of raw fuels that are not available from the ASM and CMF, which report detailed quantity and expenditure information on electricity but not other energy sources. We calculate plant-level CO2 emissions and BTU consumption from electricity directly from the ASM and CMF using conversion factors from the U.S. Energy Information Administration (EIA) and from eGRID, which incorporates

[10] We verify the reliability of our calculated average electricity prices by comparing against utilities' posted industrial rate schedules, available from the OpenEI rate database, and against state-level electricity prices reported by the Energy Information Administration.

[11] We calculate worker hours as plants' reported production-worker hours times the ratio of total payroll to payroll for production workers (Ganapati et al., 2020; Baily et al., 1992)

[12] Appendix B describes how we calculate annual capital stocks implied by ASM investment and depreciation.

the carbon intensity of each state's electricity grid. To obtain total CO_2 emissions and BTU consumption including raw fuels, we use plant-level annual raw fuel expenditures times industry-average estimates of energy consumption per dollar of raw fuels expenditures from the MECS and the ASM Fuel Trailers (Lyubich et al., 2018). We calculate CO_2 emissions and BTU consumption per dollar of raw fuels expenditure by converting quantities of raw fuels into common units using fuel-specific conversion factors from the EIA and the Environmental Protection Agency (EPA). In years in which neither the ASM Fuel Trailer or the MECS surveys are conducted, we linearly interpolate these coefficients by six-digit North American Industry Classification System (NAICS) industry. Estimating total BTU consumption and CO_2 emissions allows us to measure energy intensity using BTU per dollar of revenue and CO_2 per dollar of revenue—measures which incorporate the use of raw fuels in a way that electricity intensity does not.[13]

Our final source of manufacturing data is the Longitudinal Business Database (LBD). This census provides information on all plants' entry year, which we link to the other data sets using unique plant identifiers. We match plants to their own initial electricity prices using these plant identifiers if the plant was surveyed in its initial year of operations. If a plant is not observed in its entry year, we impute its initial electricity price using the average of other contemporaneous entrants in its state and industry where possible, or simply the same year and state if there are no other contemporaneous entrants in its industry. A short-coming of the LBD is that any plant that began operations before the start of the survey (i.e., 1975) is recorded as opening in 1975; we therefore restrict the sample to plants that enter after 1975, for which we observe their entry year. Appendix A describes additional restrictions imposed during the cleaning of the data, such as excluding observations with missing or negative input values. The primary analysis sample includes approximately 1,294,000 plant-year observations. Throughout, we deflate all monetary values to 2011 dollars using the input- and industry-specific price indices available from the National Bureau of Economic Research-Census of Economic Studies (NBER-CES) Productivity Database.

4.2 State Energy Use and Fuel Prices

The data on state energy input prices and fuel shares in the electricity sector are from the EIA State Energy Data System (SEDS) (EIA, 2020). We use these data to calculate average national

[13]While measuring energy intensity using CO_2 and BTU per dollar of revenue has the benefit of incorporating use of raw fuels, the more intermittent measurement of raw fuels use means that the time series of these energy intensity measures discussed in Section 5 are noisier.

prices for coal, natural gas, and petroleum as well as the share of each of these fuels used to generate electricity in each state. We deflate fuel prices using the average of the energy deflators from the NBER-CES Database.

5 Trends in Energy Use and Prices

This section reports descriptive statistics and discusses trends in energy intensity and the productivity of energy relative to labor. We highlight trends in energy intensity using microdata for a longer time period than previous studies (Linn, 2008; Levinson, 2021; Huntington, 2010; Metcalf, 2008) and estimates of the trend in relative energy productivities based on less aggregated data (Hassler et al., 2012).

Appendix Table A.1 presents summary averages on manufacturing inputs and outputs separately for all industries and excluding industries which use energy sources other than electricity in important ways (i.e., including only industries for which electricity accounts for at least 70% of total energy expenditures). Overall, plants consume approximately 0.2 kWh of electricity, 0.1 kg of CO2, and 0.001 million BTU per dollar of revenue, with about 10% higher energy usage in the electricity-intensive subsample. On aggregate, current electricity prices are slightly lower than prices paid in plants' entry year.

These summary averages mask important heterogeneity in energy prices over the 1976-2011 time period. Figure 2 shows that electricity prices paid by the industrial sector vary widely, generally trending downward until the late 1990s before increasing back to their 1976 level. These changes in electricity prices track the trends in the prices of raw fuels used to generate electricity, shown in Appendix Figure A.2. Since 1976, petroleum prices have tripled, while coal and natural gas prices have risen less steeply over this same time period. These fuel price increases appear to have contributed to important changes in the mix of fossil fuel mix used to generate electricity. Appendix Figure A.3 shows that the contributions of coal, natural gas, and petroleum to generating electricity vary substantially across the U.S. at the start of our sample in 1976, while Appendix Figure A.1 shows that this distribution has changed over the past four decades.[14] As a plausible consequence of the rising price of oil, the use of petroleum in electricity generation has declined almost everywhere and is barely used at all today. Coal use has also declined, though less steeply than oil, while

[14]Appendix Figure A.4 summarizes the fuel mix changes at the state-level.

natural gas generation has increased substantially after the fracking boom in the 2000s.[15]

Manufacturing energy intensity has also changed in the last four decades. Figure 3.a shows that aggregate electricity intensity has declined by approximately 30% since 1976, with comparable changes in CO2 and BTU intensities.[16] Some of this reduction is attributable to energy efficiency improvements, while manufacturing has also shifted toward producing less energy-intensive products locally and more energy-intensive goods abroad (NAM, 2014). Entrants have also adopted more energy efficient technologies over time (Linn, 2008). Of course, if lock-in is important, then we expect that some of this decline could also be driven by the exit of more energy-intensive plants that entered the market at low energy prices.

Conversely, the relative productivity of energy inputs shows no significant trend over most of this time period. The time series of estimated energy productivity relative to labor productivity, shown in Figure 3.b, is relatively constant, with a decline beginning in the mid-2000s. This trend implies similar growth in the productivities of labor and energy inputs over much of this time period.[17] Meanwhile, the total factor productivity trend in this figure shows that the productivity of all inputs has more than doubled over this time period. This result is consistent with prior work using conducted over shorter time periods using similar data (Greenstone et al., 2012).

Overall, this discussion highlights that manufacturing plants beginning production in different years face very different initial electricity prices. We now test whether these price differences have led to persistent differences in energy intensity and productivity.

[15]We focus on electricity prices as opposed to composite indices of electricity and any raw fuels used for two reasons. First, plant-level prices of these inputs are available only approximately every four years, for a small subset of our full sample. As a result, we almost never observe entry-year raw fuel prices, which require that a plant is surveyed in the ASM Fuel Trailer or MECS in its entry year. Second, electricity accounts for over 95% of BTUs of energy consumed on average and therefore captures most energy used.

[16]Consistent with out results, Linn (2008) and Levinson (2021) document declining energy intensity of manufacturing production over approximately half of our time period. Huntington (2010) and Metcalf (2008) additionally analyze sector- and state-level data, respectively. The CO2 and BTU intensity measures in Figure 3.a are more highly variable since these are surveyed less frequently and on fewer plants than the electricity measures, and also reflect the changing composition of inputs into electricity.

[17]Doraszelski and Jaumandreu (2018) find that labor productivity increased by roughly 40% relative to materials inputs in aggregate using data from Spanish manufacturing plants from 1991 to 2006; though this other study is conducted in a different context, an implication is that energy productivity may have grown more than other materials inputs.

6 Econometric Model

6.1 Instrumental Variables Analysis

In this section, we discuss how we assess whether the electricity prices that manufacturing plants pay in their entry year are important determinants of subsequent energy usage and relative energy productivity. We estimate the following equation:

$$y_{it} = \beta_0 p_{it_0} + \beta_1 p_{it} + \alpha_{js} + \tau_{jtt_0} + \epsilon_{it} \tag{2}$$

In this equation, y_{it} is an energy outcome for plant i in year t (i.e., the log of energy use per dollar of revenue $\frac{E}{R_{it}}$ or the log of relative energy productivity ω_{it}^{E}), p_{it_0} is the log of the average price of electricity in the year t_0 that plant i enters the market, and p_{it} is the log of the average price of electricity paid by plant i in year t. Industry $\times$ state fixed effects α_{js} control for time-invariant characteristics common to industry j in a given state s, such as geography, industry $\times$ year $\times$ entry year fixed effects τ_{jtt_0} control for time-variant changes that affect all plants in a given industry that entered the market in the same year, such as new regulation, and ϵ_{it} is the error term. We cluster standard errors at the state-level throughout and we weight regressions using the Census sampling weights.

The main parameter of interest in equation (2) is β_0, which measures the effect of initial electricity prices on current energy intensity or current (relative) energy productivity. The second parameter of interest, β_1, measures the effect of contemporaneous electricity prices on these outcomes. If technology lock-in is important, we expect initial electricity prices to affect current energy usage $\frac{E}{R_{it}}$ even conditional on current electricity prices (i.e., $\beta_0 < 0$ in models where energy intensity is the outcome variable). In addition, if lock-in arises through persistent differences in the relative productivity of inputs, then we also expect higher initial electricity prices to lead to higher productivity of current energy inputs relative to labor inputs ω_{it}^{E} (i.e., $\beta_0 > 0$ in models where relative energy productivity is the outcome variable).

Even conditional on the fixed effects, it is possible that omitted variables or measurement error could introduce bias into the OLS estimation of the price elasticities β_0 and β_1. For example, classic reverse causality would arise if unobserved shocks to plants' aggregate energy demand (e.g., new demand for certain products) also affect electricity prices, leading to estimates of the price elasticities that are biased upward (i.e., less negative). In addition, plants' entry-year electricity prices are, in some cases, measured with error: if a plant is not surveyed in its entry year, we approximate its initial electricity price using the average of other entrants in the same state, industry, and year. As a result, the effect of entry-year prices may be biased toward zero.

To address these concerns, we construct instrumental variables Z_{st} to isolate changes in plants' electricity prices that are uncorrelated with other shocks to energy intensity. These Bartik-style shift-share instruments isolate exogenous variation in electricity prices using the interaction of historical state electricity generation shares and current national fuel prices (Ganapati et al., 2020). Specifically, the instruments are:

$$Z_{st} = [\rho_{-s,f,t} \times \sigma_{s,f,1976}] \tag{3}$$

where $\sigma_{s,f,1976}$ is the share of total fuel expenditure of each fuel in electricity generation in state s in 1976, for each fuel $f \in \{\text{coal, natural gas, petroleum oil}\}$, and $\rho_{-s,t,f}$ is the mean of all other states' log fuel price in year t. The intuition is that a plant's electricity price will be more strongly affected by changes in national fuel prices if the electricity sector in its state is more dependent on this fuel source. Appendix Figure A.2 shows that there is significant variation in the prices of these fuels between 1976 and 2011. We find that these instruments are strong predictors of electricity prices (Table 1).[18]

The identifying assumption is that plants' differential exposure to changes in national fuel prices are uncorrelated with other production shocks, conditional on the variables in the model:

$$\mathbb{E}[Z_{st} \times \epsilon_{it} | \alpha_{js}, \tau_{jtt_0}] = 0 \tag{4}$$

For example, the inclusion of industry × year × entry year fixed effects controls for annual macroeconomic conditions that could affect both plant's production choices and national fuel prices.[19] The identifying assumption would be violated if states' fuel generation shares in 1976, which determine exposure to national fuel prices changes, are correlated with other factors that affects plants' production decisions. The availability of skilled labor, for instance, is one such factor that could be

[18] We focus on electricity generation shares from fossil fuels that are traded in commodity markets, as opposed to fuels without clearly defined market prices (e.g., hydro and nuclear generation).

[19] Specifically, industry × year × entry year fixed effects control for e.g., annual shocks that are common to all cement plants that opened in 1990. The geographic clustering of entrants in specific industries reduces concern about exposure to state × year variation since our instrument precludes the inclusion of state × year fixed effects. Appendix Tables A.7 and A.8 shows that the results are robust to the inclusion of state × year trends.

correlated with shocks to plants' labor demand. We assess the validity of the identifying assumption by examining whether state fuel electricity generation shares are correlated with state characteristics that could suggest other channels through which the instruments could affect the outcomes of interest (Goldsmith-Pinkham et al., 2020).[20] Reassuringly, Appendix Table A.3 shows no evidence of significant systematic relationships between state fuel shares and these characteristics, which supports the identifying assumption.[21] Appendix C discusses this test of instrumental exogeneity in greater detail.

In equation (2), both current electricity prices p_{it} and initial electricity prices p_{it_0} are potentially endogenous. We therefore include instruments Z_{st} based on the contemporaneous fuel prices measured at t as instruments for log current prices p_{it} and Z_{st_0} based on the fuel prices in the year t_0 when the plant opened as instruments for log initial prices p_{it_0}. Specifically, the first stage regression equation for current prices p_{it} is:

$$p_{it} = \gamma_1 Z^{coal}_{-s,t} + \gamma_2 Z^{gas}_{-s,t} + \gamma_3 Z^{oil}_{-s,t} + \gamma_4 Z^{coal}_{-s,t_0} + \gamma_5 Z^{gas}_{-s,t_0} + \gamma_6 Z^{oil}_{-s,t_0} + \alpha_{js} + \tau_{jtt_0} + \psi_{it} \tag{5}$$

and the first stage regression equation for initial prices replaces p_{it_0} as the outcome variable.

In some specifications, we also examine whether the importance of initial prices depends on the plant's age. To do so, we extend equation (2) by interacting the log of initial electricity prices with the age of the plant in years:

$$y_{it} = \beta_0 p_{it_0} + \beta_1 p_{it} + \beta_3 p_{it_0} \times age_{it} + \alpha_{js} + \tau_{jtt_0} + \epsilon_{it} \tag{6}$$

In these heterogeneous effects models, we also include the interaction of the shift-share instruments Z_{st_0} with the variable age in the first stage.

6.2 Production Function Estimation

In this section, we estimate a model of plants' production decisions to separately recover plants' total factor and energy-augmenting productivity shocks. We apply approaches measuring relative

[20] Jaeger et al. (2019) highlight the importance of controlling for dynamic adjustments to past shocks when using Bartik-style instruments for causal inference. Our inclusion of both initial and current electricity prices in the regression equation (2) addresses this issue.

[21] Data on state characteristics are from the Federal Reserve Bank of St Louis database (FRED) and the 5 percent sample of the Integrated Public Use Microdata Series (IPUMS) of US Census Data. We examine the correlation of fuel shares with state characteristics in 1980, rather than in 1976 when our Bartik weights are measured, because 1980 is the closest year for which American Community Survey data from IPUMS are available.

labor productivity to energy (Demirer, 2020; Doraszelski and Jaumandreu, 2018).

As discussed in Section 3, we use a constant elasticity of substitution (CES) production function, which is sufficiently rich to allow for complementarity between inputs and factor-specific productivity while remaining empirically tractable. That is, a plant's output is:

$$Y_{jt} = \exp(\omega_{jt}^H)\left(\beta_K K_{jt}^{\frac{\sigma-1}{\sigma}} + L_{jt}^{\frac{\sigma-1}{\sigma}} + (\exp(\omega_{jt}^E)E_{jt})^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\nu\sigma}{\sigma-1}} \times \exp(\epsilon_{jt})$$

where σ and ν are respectively the elasticity of substitution and returns to scale, $\exp(\omega_{jt}^H)$ is the Hicks-neutral total factor productivity, and β_K and $\exp(\omega_{jt}^E)$ are the productivity of capital and energy inputs relative to labor inputs, respectively.[22] The two productivity shocks, ω_{jt}^H and ω_{jt}^L, are known by the plant when it choses inputs, whereas ϵ_{jt} represents unanticipated randomness in the output of the production process.[23]

In each period, plants choose their static inputs, labor L_{jt} and energy E_{jt}, given their capital stock, K_{jt}, productivity draws, and prices to maximize their profits:

$$\max_{L,E} p_Y Y(L, E; K_{jt}, \omega_{jt}^H, \omega_{jt}^E) - w_{jt}L - p_{jt}^E E$$

where w_{jt} and p_{jt}^E are the prices of labor and electricity, respectively. By taking the log of the ratio of the first-order conditions for profit maximization we obtain the expression:

$$l_{jt} - e_{jt} = -\sigma(w_{jt} - p_{jt}^E) + (1-\sigma)\omega_{jt}^E \tag{7}$$

Given the elasticity of substitution, σ, equation (7) allows us to obtain the energy-augmenting productivity shocks ω_{jt}^E from the (log) ratios of static inputs and their prices. Intuitively, if labor and energy are complementary inputs (i.e. $\sigma < 1$), then conditional on prices a higher ratio of labor to energy inputs implies a higher relative productivity of energy.

Conditional on knowing ω_{jt}^E, we can then recover the total factor productivity, ω_{jt}^H, from the first-order condition for energy, given the values for the rest of the production functions' parameters. As in Ackerberg et al. (2015), estimation proceeds based on moment conditions formed by the evolution

[22] Note that the level of factor-specific productivities are not separately identifiable from total factor productivity, so without loss of generality we normalize labor productivity to one and express factor productivity relative to labor productivity.

[23] For example, unscheduled maintenance or deviations from anticipated product defect rates could introduce unanticipated production fluctuations.

of these two productivity shocks. We assume that both productivity shocks follow AR(1) processes:

$$\omega_{jt}^{H} = \alpha_H + \beta_H \omega_{jt-1}^{H} + \xi_{jt}^{H}$$

$$\omega_{jt}^{E} = \alpha_E + \beta_E \omega_{jt-1}^{E} + \xi_{jt}^{E}$$

where ξ_{jt}^{H} and ξ_{jt}^{E} are unknown by plants at time $t-1$, and therefore uncorrelated with lagged inputs.

We estimate the model separately for each industry as follows. First, we take candidate parameters of the production technology, $\tilde{\theta} = (\sigma, \nu, \beta_K)$, and use these to recover the productivities $\omega_{jt}^{H}, \omega_{jt}^{E}$ from each plants' input choices in each year. Second, we estimate the parameters of the AR(1) processes by ordinary least-squares to obtain the productivity innovations ξ_{jt}^{H} and ξ_{jt}^{E}. We form moments based on these innovations:

$$\mathbb{E}[\xi_{jt}^{H} Z_{jt}] = 0$$

$$\mathbb{E}[\xi_{jt}^{L} Z_{jt}] = 0$$

where Z_{jt} are a set of instruments. The timing of decisions and the Markov structure for productivity shocks implies that all past input choices are uncorrelated with the productivity innovations, ξ_{jt}^{H} and ξ_{jt}^{L}. We use lagged (log) inputs, l_{jt-1}, e_{jt-1}, and k_{jt-1}, and lagged wage and energy prices, w_{jt-1} and p_{jt-1}^{E}. This forms a total of 10 moments, collected in the vector $g(X_i, \theta)$, where i flattens the time and plant indices. These lagged-input instruments, and the identifying assumption that past inputs and prices are determined before and do not affect the unanticipated innovations to productivity, are standard in the production function literature (Ackerberg et al., 2015; Doraszelski and Jaumandreu, 2018; Olley and Pakes, 1996).

For each industry, we obtain estimates $\hat{\theta}$ and standard errors using the two-step generalized method of moments (GMM) estimator (Hansen, 1982). We minimize the objective function:

$$C(\theta, \cdot) = \left(\frac{1}{N} \sum_{i=1}^{N} g(X_i, \theta) \right)' \hat{W} \left(\frac{1}{N} \sum_{i=1}^{N} g(X_i, \theta) \right)$$

where $g(X_i, \theta)$ are 10x1 vectors defined above and the weight matrix $\hat{W}$ is the inverse covariance matrix obtained using the initial parameters $\hat{\theta}_0$ from the minimization of the objective function using the identity matrix as the weight matrix.

Overall, we find that our estimates of the production function parameters have reasonable signs and magnitudes. Appendix Table A.4 shows that we find that capital, labor, and energy are strongly complementary; our average estimate of σ is around 0.25.[24] Our estimate of the returns to scale parameter ν, which is around 0.65, is also consistent with estimates from the literature.[25] In what follows, we focus on the relative energy productivity and total factor productivity estimates shown in Figure 3, and their relationship with initial and current energy prices.

7 Results

7.1 Energy Intensity

First, Table 1 shows that weighted national fuel prices are strongly predictive of both entry-year and current electricity prices, respectively in Columns 1 and 2. These results form a strong first stage for the instrumental variables analyses. Coal prices are the largest determinant of entry-year electricity prices, and are approximately four to five times as important as natural gas and petroleum prices (Column 1). If a state generated its electricity entirely from coal in 1976, then a 10% increase in coal prices in a plant's entry year would increase its entry-year electricity price by approximately 2.2%. In practice, the state average 1976 coal share is approximately 0.40, and so a 10% increase in coal prices increases electricity prices by 0.9%.[26] Reassuringly, fuel prices in the future are not predictive of entry-year electricity prices in the past. Initial fuel prices have small effects on current electricity prices, possibly reflecting some stickiness in electricity prices paid by plants, but current fuel prices become significantly more important (Column 2). Contemporaneous natural gas prices have the largest effect on current electricity prices, reflecting the shift toward natural gas electricity generation in recent years shown in Appendix Figure A.4. Ganapati et al. (2020), who examine the effects of contemporaneous fuel prices on manufacturing marginal costs, similarly highlight the importance of natural gas as a recent determinant of manufacturing costs.

[24]There are relatively few estimates of CES production function parameters involving energy inputs. Our results are comparable to Hassler et al. (2012) and Ryan (2012), who also estimate a strongly complementary relationship between energy and other inputs.

[25]Our ν estimates are smaller than Doraszelski and Jaumandreu (2018)'s estimates of around 0.9, which can be explained by the fact that our returns to scale parameter combines the effects of returns to scale and downward-sloping demand that are separately estimated in this other paper.

[26]Appendix Table A.3 shows the 1976 state fuel generation shares that can be used to adjust the parameters in Table 1 to interpret them as elasticities.

Table 2 presents our first evidence of technology lock-in. This table shows that both initial and current fuel prices have significant effects on current energy intensity. We consider effects on four different measures of energy intensity. Column 1 measures energy intensity using electricity consumed (in kWh) per dollar of revenue, which accounts for most energy use by manufacturing plants. Column 2 focuses on this same measure of energy intensity in "electricity-intensive industries", excluding industries that spend more than 30% of total energy expenditures on raw fuels. Columns 3 and 4 use kg CO2 and million BTU per dollar revenue as measures of energy intensity, respectively. These last two measures include energy from raw fuels and therefore account for changes in energy intensity due to any substitution between fuel sources.

We find consistent results across each of these measures of energy intensity. In all models in Table 2, the current natural gas price has a larger impact on current energy intensity than contemporaneous coal or petroleum prices, which is indicative of the recent shift toward natural gas electricity generation after the fracking boom in the 2000s. The precisely estimated zero effect of current petroleum oil prices is consistent with the limited use of petroleum in generating electricity today, shown in Appendix Figure A.1.[27] By contrast, despite the declining roles of petroleum and coal in electricity generation, entry-year coal and petroleum prices have persistent effects on energy intensity. This is lock-in: the prices of these fossil fuels continue to affect plants' energy intensity even after the economy has transitioned to other fuel sources. The elasticity of energy intensity with respect to entry-year coal prices is more than twice the current natural gas price elasticity even before accounting for the higher 1976 coal generation share. These results underscore that the continued expansion of coal power capacity, particularly in developing countries, could lead to higher manufacturing energy intensity even if these economies eventually transition to cleaner fuel sources.

This evidence of lock-in is also apparent in both the OLS and instrumental variables analyses of the effects of initial and current electricity prices on energy intensity (Table 3, Panels A and B respectively). In both analyses and across our four energy intensity measures, entry-year electricity prices have significant effects on energy intensity in subsequent years. In our preferred IV specifications, the initial price elasticity is between -0.14 and -0.35, which is approximately 25% of the elasticity with respect to current electricity prices. As a result, failing to price carbon in plants' entry year leaves an average of 25% of the energy-reduction benefits on the table. Though not sta-

[27] Comparing Appendix Figures A.1 and A.4 shows that most states generating electricity using petroleum oil in 1976 substantially reduce their use of it by 2011.

tistically different from the elasticity of electricity intensity with respect to initial electricity prices, the slightly larger elasticity of CO2 intensity suggests that plants may slightly increase their use of more CO2-intensive fuels in response to increases in electricity prices. Overall, it is unsurprising that the price effects on energy intensity measures that include and exclude raw fuels are similar because electricity comprises well over 70% of energy expenditures on average; manufacturing plants therefore have more limited ability to substitute toward other raw fuel types than in other sectors, such as electricity generation (Meng, 2021). We highlight that the inclusion of industry × year × entry year fixed effects controls for plant vintage within each industry, so that the estimates comprise the effect of changes in the price of electricity for plants with the same technologies available to them.

The initial electricity price elasticity is larger in the IV models than in the OLS models, consistent with measurement error in the entry-year electricity prices that are annual averages across entrants in each industry and state if a plant is not surveyed in its entry year. Such measurement error biases the estimates against finding evidence that initial electricity prices are persistent. The elasticity of energy intensity with respect to current electricity prices is about -0.80 (i.e., relatively elastic) and is similar in sign, magnitude, and precision in both the OLS and IV models. Current electricity prices are always measured at the plant level and are therefore less likely to be subject to measurement error in the OLS estimates.[28] Appendix Table A.7 shows that both our initial and current price elasticities are robust to estimation using different covariates, data subsamples, and electricity price data sources. We discuss these additional estimates in Appendix D.

We find limited evidence that the importance of entry-year electricity prices declines as plants age, suggesting that lock-in is persistent (Table 6, Column 1-3). Each additional year of operations reduces the entry-year price elasticity by 4%, though for most energy intensity measures this small effect of age is not statistically distinguishable from zero. At this rate, it would take 25 years for the effect of entry-year prices to fade, which Appendix Table A.2 shows is 10 years longer than the average plant lifetime of 15 years. Any decline in the average importance of entry-year prices could be due to plants' gradual investments in energy efficiency improvements or due to changes in entry and exit; the IV estimates combine both of these effects for surviving plants, providing an upper bound on plants' ability to respond to energy price changes and mitigate lock-in without

[28] Our estimated elasticity of energy intensity with respect to current electricity prices is somewhat larger than estimates in Linn (2008) using fixed weight price indices as instruments for energy prices. We are unaware of any estimates of entry-year price elasticities against which to compare ours.

ceasing operations. We turn now to assess the effects of initial energy prices on the productivity of plants' inputs to understand whether capital adjustment costs can fully explain the persistent differences in energy use or whether plants that enter at different energy prices inherently choose different production technologies.

7.2 Productivity

Table 4 begins to show that initial energy prices lead to persistent differences in plants' production technologies. Columns 1 and 2 show that both initial and current energy prices have long-run effects on the energy bias of technological change, for all industries and electricity-intensive industries respectively. Plants that enter when petroleum or coal prices are high consistently use their energy inputs more efficiently relative to their labor inputs; a 10% increase in the entry-year price of one of these raw fuels increases energy productivity by 0.7% and 0.1%, respectively.[29] Similarly to our energy intensity results, we find that contemporaneous natural gas prices are important determinants of relative energy efficiency. Conversely, the effects of initial and contemporaneous fuel prices on total factor productivity are an order of magnitude smaller and are generally statistically indistinguishable from zero: higher entry-year raw fuel prices bias technological change toward energy relative to labor, but do not affect total factor productivity in meaningful ways.

Turning to the OLS and instrumental variables estimates of the effects of electricity prices on productivity, we again find evidence of lock-in of plants' productivity bias (Table 5). Plants that pay higher electricity prices in their entry year exhibit persistently higher energy productivity relative to labor productivity, both in the OLS estimates (Panel A) and in the instrumental variables estimates (Panel B). We again find instrumental variables estimates of the relative energy productivity effects in that are larger in magnitude than the OLS estimates, consistent with measurement error in initial electricity prices. Focusing specifically on our preferred instrumental variables estimates, we find that a 10% increase in entry-year electricity prices increases relative energy productivity by 3%, with no effect on total factor productivity. Taken together, this pattern of results indicates that plants that begin operations at higher electricity prices are not only using fewer energy inputs per dollar of revenue, as we showed above; they are also using these inputs more efficiently.[30] The effect of entry-year electricity prices is almost as important as contemporaneous electricity prices: the elasticities

[29] Similarly to Table 2, we adjust the energy elasticity estimates in Table 4 by the average 1976 fuel generation shares in Appendix Table A.3 to arrive at the average weighted elasticity.

[30] Recall that the energy productivity estimate gives the relative productivity of energy inputs to labor inputs, and hence alone does not indicate an overall increase in energy productivity.

are statistically indistinguishable in Table 5. The overall effect of entry-year electricity prices on relative energy productivity is more than five times as large as the same increase in coal transport costs on relative coal capital investment (Meng, 2021) and the effects of air pollution regulation on manufacturing total factor productivity (Greenstone et al., 2012). These economically meaningful estimates highlight the important role of higher energy prices and, by extension, carbon pricing policies in directly incentivizing reductions in energy use.

Our results suggest that persistent differences in the relative productivity of energy inputs chosen at entry can fully explain why technology lock-in arises. The magnitudes of the relative energy productivity effects of initial electricity prices are slightly larger and statistically indistinguishable from the effects on energy intensity in Table 3. An implication therefore is that the contribution of capital adjustment costs to creating lock-in appears to be comparatively small on average.[31] Relative to the model in Section 3, our estimate of the effect of entry-year electricity prices on energy intensity is analogous to slope of the curve showing lock-in for plants facing capital adjustment costs, averaged across plants. Under the assumption that energy productivity enters multiplicatively with energy inputs, for fully flexible plants, the elasticity of energy productivity will be equal to the elasticity of energy intensity, which corresponds to the slope of the orange, short-dashed line for fully flexible incumbents in Figure 1.

In Appendix Table A.9, we also show estimates of the effects of entry-year electricity prices on quantities of energy inputs consumed, as opposed to energy intensity; we find that the effects in levels can also be explained by persistent differences in relative productivity, though the level effects are somewhat less precisely estimated than the intensity elasticities. We discuss these estimates in more detail in Appendix D, and Appendix Table A.8 discusses the robustness of the elasticity estimates to the use of different covariates, data subsamples, and data sources. The results using these alternative models are similar in sign, magnitude, and precision to our main estimates.

Similarly to the energy intensity results, we find that the effects of entry-year electricity prices on relative energy productivity persist throughout a plant's lifetime. Table 6 shows that there is limited evidence of a decline in the effects of initial electricity prices as plants age; an additional year of operations reduces the effect of entry-year electricity prices on relative energy productivity by 2%.

[31] The non-linearity of capital adjustment frictions implies that there may be heterogeneous effects depending on the size of the price change. The difference between lock-in for a plant facing adjustment costs and for a hypothetical plant with fully flexible capital is non-monotonic in the price change, and largest for plants which are close to the threshold at which paying fixed adjustment costs is optimal. This implies that targeted capital adjustment subsidies are likely to be more effective than ones applied to all firms.

These results indicate significant path dependence in the productivity bias of energy inputs and the importance of correctly aligning plants' incentives when they choose their production technologies.

8 Discussion and Implications for Climate Policy

Overall, we find robust evidence of technology lock-in. However, this lock-in isn't complete: on average, plants' energy intensity and energy productivity also respond to changes in contemporaneous electricity prices, though less than one-for-one (Tables 3 and 5). These average effects combine adjustment through investment and through entry and exit.

There are at least three reasons why these estimates of lock-in may be a lower bound on the effects of entry-year electricity prices on subsequent energy efficiency. That is, the estimates may underestimate the effect of a carbon tax on the ability of plants to adjust to higher energy prices without ceasing operations. First, these effects are measured on surviving plants, and reduced entry or increased exit may be important channels through which plants respond to higher prices. The effects that we estimate combine adjustment through investment and through entry and exit; if the entirety of the improvements in average energy efficiency are due to changes in entry and exit, then this means that the ability of plants to adjust their energy use through investment while operating is more limited than our estimates suggest.[32]

Second, our use of revenue-based total factor productivity measures also understates the effects of energy prices compared with measures based on quantity produced. Revenue-based productivity measures are standard in the literature due to limitations of most plant-level data sets, which typically do not collect detailed output price and quantity data (Allcott et al., 2016; Ganapati et al., 2020; Greenstone et al., 2012). When marginal costs rise as energy becomes more expensive, standard theory predicts that plants with market power will increase prices for their products and reduce quantities supplied. The revenue-based productivity measures will capture any negative effects of increasing energy costs as well as any positive price change, which could cause us to understate the effect of electricity prices on total factor productivity.

Third, we investigate the persistent effects of short-run electricity price variation resulting from year-on-year variation in raw fuels prices. Conversely, a goal of carbon pricing is to implement long-run increases in energy prices through policy. The responses to the short-run price changes that we study are consistent with firms' basing their best guess of energy prices tomorrow on observed

[32] Separately analyzing the importance of investment relative to entry and exit is the focus of on-going work.

energy prices today (i.e., with prices following a random walk). Our lock-in estimates again may understate the energy efficiency effects of sustained commitment to higher energy prices because plants may initially install more energy efficient capital investment with the knowledge that prices will be higher throughout their lifetime.

This discussion highlights the importance of plants' beliefs about future energy prices when they undertake investments in durable capital. Prior research suggests that plants may adopt new technologies in anticipation of environmental regulation in the future (Clay et al., 2021). Commitment to federal carbon pricing in the U.S. could reduce lock-in when prices increase by correctly aligning plants' beliefs about the future path of energy prices, though some lock-in may still arise given that plants may discount higher energy costs in the distant future in favor of lower costs of investment today.

It is worth noting that our lock-in elasticity estimates are agnostic about plants' beliefs about future prices. Our estimates are conditional on whatever firms' actual beliefs are about the evolution of electricity prices. The interpretation of the empirical results does not require us to take a stand on what these beliefs are.

Overall, these results suggest that delayed action on carbon pricing comes at the expense of significant energy efficiency gains. Timely implementation of carbon pricing is one policy that could incentivize early reductions in energy use. However, our results also suggest that there appears to be a role for vintage energy efficiency regulations. Targeting efficiency mandates or technology adoption subsidies to plants that enter during low energy price regimes could help adjust for relative misalignment of incentives when these plants were established, and therefore help address the inefficiencies resulting from failing to incentivize internalization of greenhouse gas externalities initially.

9 Conclusion

This paper provides new evidence of technology lock-in in the manufacturing sector and analyzes its causes and consequences. Using 35 years' worth of U.S. Census microdata, we show two main ways in which technology lock-in arises. First, we estimate that the prices of fossil fuel inputs into electricity generation have persistent effects on manufacturing plants' energy usage—even after the use of these fuels has declined. Second, we show that the prevailing electricity price in a plant's entry year affects their energy usage throughout their lifetime: plants that are established when electricity prices are low, below the full social cost of energy consumption, consume more energy in subsequent years. On average, we estimate that at least 25% of the energy reductions benefits from carbon pricing are lost by failing to implement these policies in a plants' entry year.

By estimating plant-level total factor productivity and the relative productivity of energy to labor, we demonstrate that an initial and persistent effect of electricity prices on energy productivity is a key explanation for this lock-in. Plants may choose not to undertake later energy efficiency improvements due to capital adjustment costs, but we provide new evidence that their production functions are also different to start out. Our results indicate that a 10% increase in entry-year electricity prices improves the productivity of energy relative to labor by approximately 3% in subsequent years. Since the analysis focuses on plants that continue to operate and choose to enter at higher electricity prices, these estimates exclude effects on energy-inefficient plants that cease operations in response to higher prices. As a result, our estimates plausibly provide a lower bound on the energy reductions resulting from increasing electricity prices.

The implications of these results for climate policy are consequential. Ignoring lock-in underestimates the benefits of pricing carbon today. In the absence of current commitments to do so, future policy will have to be more stringent to counteract the current path of energy-inefficient manufacturing production: small carbon taxes or clean technology subsidies may be insufficient to incentivize existing plants to reverse sunk and partially irreversible capital investments or otherwise to exit. Meanwhile, continued expansion of cheap fossil fuel power around the world seems likely to entrench energy-inefficient technologies and lock in higher emissions levels for many years. A major push to increase energy efficiency worldwide is a key part of proposals to constrain carbon emissions to "safe" levels, which will require annual improvements exceeding three times the annual rate achieved in the last two decades (IEA, 2021). The global trend in increasingly severe natural disasters suggests that it would be inadvisable to delay further action on climate change policy.

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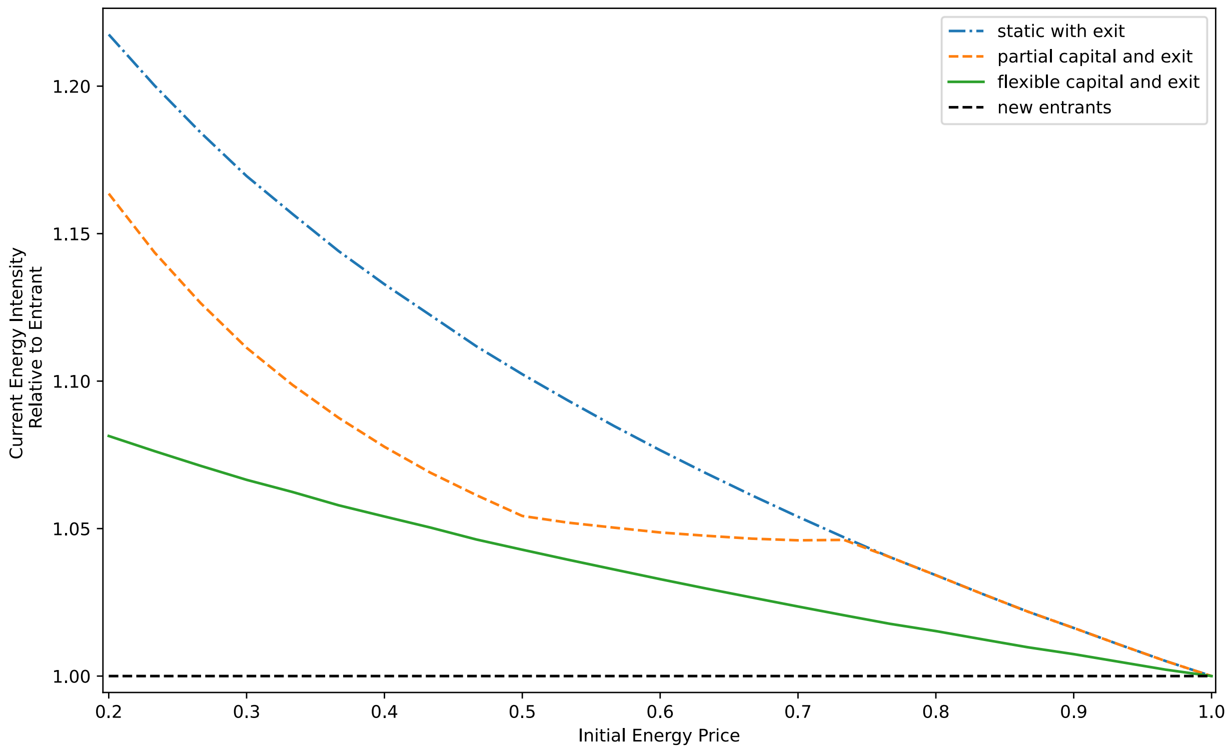
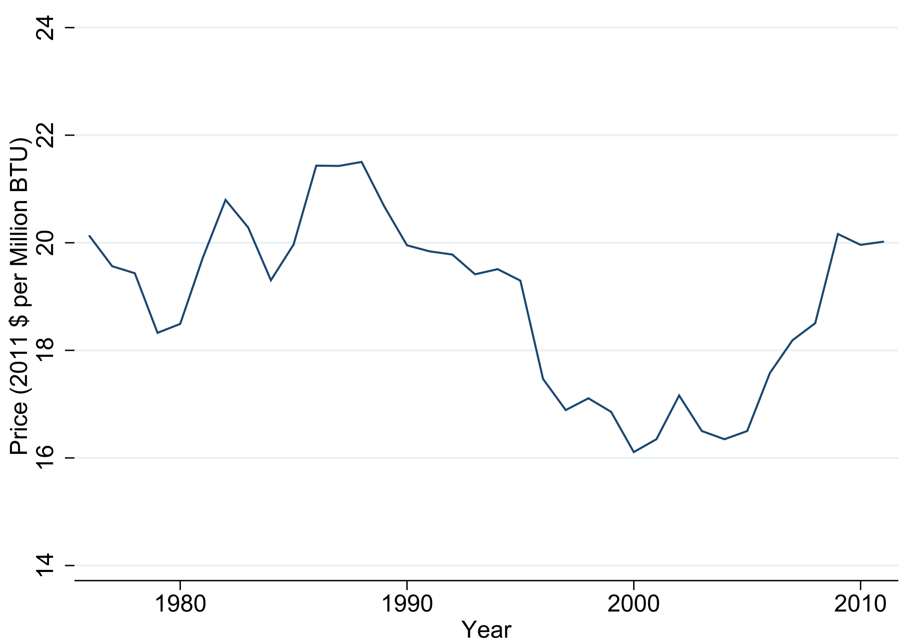
10 Figures and Tables

Figure 1: Simulated Lock-in



Notes: This figure shows simulation results for the energy intensity of incumbent manufacturing plants relative to entrants as a function of last year's energy price. The x-axis shows initial energy price as a fraction of the current price. "Static with exit" shows relative energy intensity in scenarios where plants cannot adjust their capital stocks after they enter. "Partial capital and exit" shows relative energy intensity in scenarios where incumbents can reoptimize their capital stock subject to fixed and convex adjustment costs. "Flexible capital and exit" shows relative energy intensity in scenarios where all inputs can be reoptimized without adjustment costs. Energy intensity of entrants is normalized to 1.

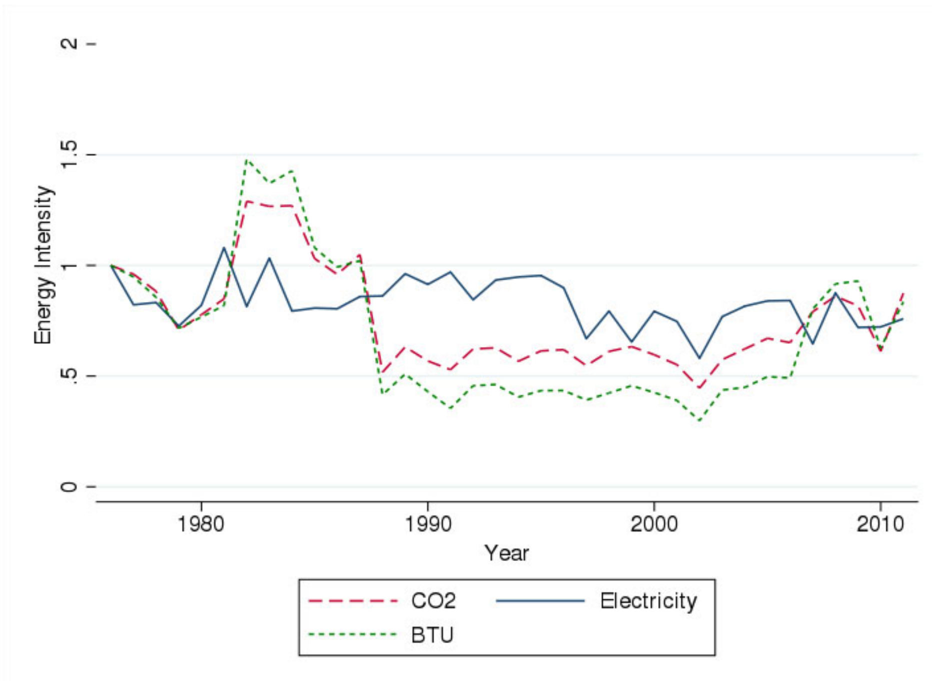
Figure 2: Time Series of Electricity Prices



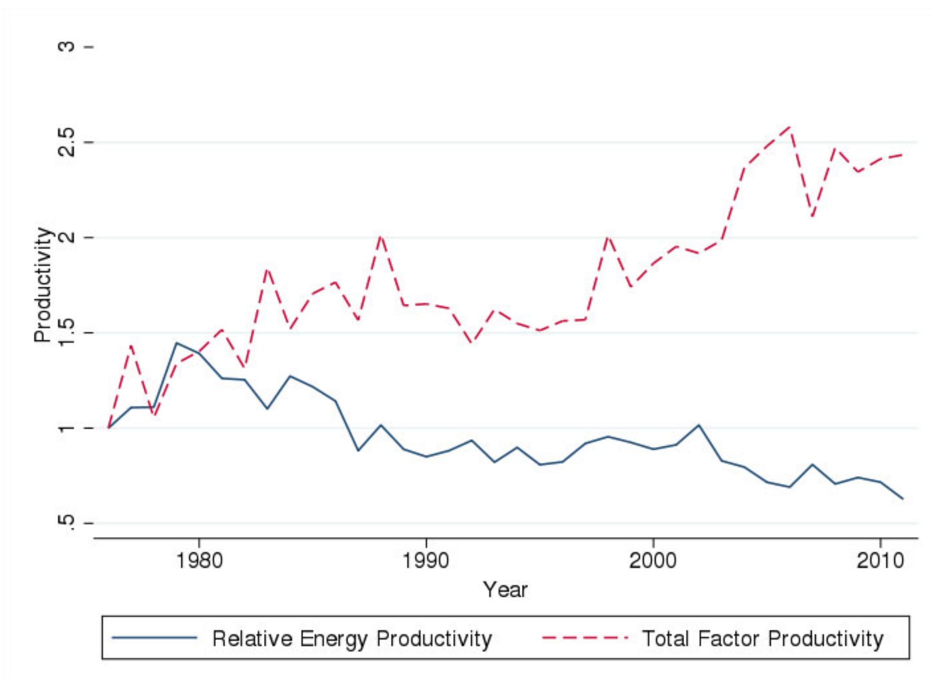
Notes: This figure shows the time series of average electricity prices paid by the industrial sector in the United States. Prices are in 2011 dollars per million British thermal units (BTU).

Figure 3: Time Series of Energy Intensity and Productivity

Panel A: Energy Intensity Trends



Panel B: Productivity Trends



Notes: This figure shows the time series of average energy intensity (Panel A) and relative energy productivity and total factor productivity (Panel B) of the manufacturing sector in the United States. Energy intensity is calculated as electricity consumption (kWh) per dollar of revenue, kg CO2 produced per dollar revenue, and million BTU per dollar revenue. The productivity of energy inputs is measured relative to labor.

Table 1: First Stage Effects of Weighted Fuel Prices on Electricity Prices

	$\log(Initial\_Electricity\_Price_{i,t_0})$ (1)	$\log(Current\_Electricity\_Price_{i,t})$ (2)
$Coal\_Share_{s,1976} \times Current\_Coal\_Price_{-s,t}$	0.013	0.065*
	(0.009)	(0.035)
$Natural\_Gas\_Share_{s,1976} \times Current\_Natural\_Gas\_Price_{-s,t}$	-0.006*	0.058***
	(0.003)	(0.012)
$Petroleum\_Share_{s,1976} \times Current\_Petroleum\_Price_{-s,t}$	0.003	0.012
	(0.003)	(0.010)
$Coal\_Share_{s,1976} \times Initial\_Coal\_Price_{-s,t_0}$	0.220***	0.055**
	(0.049)	(0.023)
$Natural\_Gas\_Share_{s,1976} \times Initial\_Natural\_Gas\_Price_{-s,t_0}$	0.056***	0.011*
	(0.012)	(0.006)
$Petroleum\_Share_{s,1976} \times Initial\_Petroleum\_Price_{-s,t_0}$	0.036***	0.019***
	(0.012)	(0.005)
N	1294000	1294000
Industry × Year × Entry Year Fixed Effects	Yes	Yes
Industry × State Fixed Effects	Yes	Yes

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table shows the effects of initial and contemporaneous coal, natural gas, and petroleum prices on the log of initial and contemporaneous electricity prices. Fuel prices are calculated as the leave-out-mean log price across states and weighted by the share of each fuel in electricity generation in each state. Electricity prices are measured in USD per kWh (2011). Regressions are weighted using Census sampling weights. Standard errors clustered by state are in parentheses.

Table 2: Reduced Form Effects of Weighted Fuel Prices on Energy Intensity

	$\log(Electricity\_Intensity_{i,t})$	$\log(Electricity\_Intensity_{i,t})$ Electricity-Intensive Industries	$\log(CO_2\_Intensity_{i,t})$	$\log(BTU\_Intensity_{i,t})$
	(1)	(2)	(3)	(4)
$Coal\_Share_{s,1976} \times Current\_Coal\_Price_{-s,t}$	0.043	0.055	-0.019	0.073*
	(0.031)	(0.036)	(0.041)	(0.039)
$Natural\_Gas\_Share_{s,1976} \times Current\_Natural\_Gas\_Price_{-s,t}$	-0.053***	-0.052***	-0.053***	-0.056***
	(0.011)	(0.012)	(0.011)	(0.012)
$Petroleum\_Share_{s,1976} \times Current\_Petroleum\_Price_{-s,t}$	-0.000	-0.004	0.001	0.001
	(0.009)	(0.009)	(0.010)	(0.010)
$Coal\_Share_{s,1976} \times Initial\_Coal\_Price_{-s,t_0}$	-0.121***	-0.123***	-0.163***	-0.129***
	(0.028)	(0.031)	(0.029)	(0.029)
$Natural\_Gas\_Share_{s,1976} \times Initial\_Natural\_Gas\_Price_{-s,t_0}$	-0.003	-0.013	0.001	0.002
	(0.009)	(0.012)	(0.008)	(0.008)
$Petroleum\_Share_{s,1976} \times Initial\_Petroleum\_Price_{-s,t_0}$	-0.028***	-0.031***	-0.028***	-0.024***
	(0.005)	(0.006)	(0.005)	(0.005)
N	1294000	955000	1294000	1294000
Industry × Year × Entry Year Fixed Effects	Yes	Yes	Yes	Yes
Industry × State Fixed Effects	Yes	Yes	Yes	Yes

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table shows the effects of initial and contemporaneous coal, natural gas, and petroleum prices on the log of plants' energy intensity. Electricity intensity is measured in kWh per dollar of revenue, CO2 intensity is kg CO2 per dollar of revenue, and BTU intensity is BTU per dollar of revenue. Electricity-intensive industries are industries for which electricity accounts for at least 70% of total energy expenditures. Fuel prices are calculated as the leave-out-mean log price across states and weighted by the share of each fuel in electricity generation in each state. Regressions are weighted using Census sampling weights. All dollar values are in 2011 USD. Standard errors clustered by state are in parentheses.

Table 3: Effects of Initial and Current Electricity Prices on Energy Intensity

	$\log(Electricity\_Intensity_{i,t})$	$\log(Electricity\_Intensity_{i,t})$ Electricity-Intensive Industries	$\log(CO_2\_Intensity_{i,t})$	$\log(BTU\_Intensity_{i,t})$
	(1)	(2)	(3)	(4)
Panel A: OLS				
$\log(Current\_Electricity\_Price_{i,t})$	-0.851***	-0.831***	-0.824***	-0.807***
	(0.012)	(0.011)	(0.010)	(0.009)
$\log(Initial\_Electricity\_Price_{i,t_0})$	-0.040***	-0.037***	-0.028***	-0.026**
	(0.009)	(0.010)	(0.010)	(0.010)
Panel B: IV				
$\log(Current\_Electricity\_Price_{i,t})$	-0.764***	-0.734***	-0.829***	-0.761***
	(0.090)	(0.104)	(0.072)	(0.087)
$\log(Initial\_Electricity\_Price_{i,t_0})$	-0.165***	-0.232***	-0.289***	-0.144**
	(0.051)	(0.059)	(0.079)	(0.059)
K-P F stat	12.1	11.9	12.1	12.1
N	1294000	955000	1294000	1294000
Industry × Year × Entry Year FE	Yes	Yes	Yes	Yes
Industry × State FE	Yes	Yes	Yes	Yes

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table shows the effects of initial and contemporaneous log electricity prices on the log of plants' energy intensity. Models in Panel A are estimated using OLS and models in Panel B are estimated using IV. In IV models, electricity prices are instrumented using initial and contemporaneous prices for coal, natural gas, and petroleum, weighted by the share of each fuel in state electricity generation. Electricity prices are measured in dollars per kWh, electricity intensity is kWh per dollar of revenue, CO2 intensity is kg CO2 per dollar of revenue, and BTU intensity is BTU per dollar of revenue. Electricity-intensive industries are industries for which electricity accounts for at least 70% of total energy expenditures. Regressions are weighted using Census sampling weights. All dollar values are in 2011 USD. Standard errors clustered by state are in parentheses.

Table 4: Reduced Form Effects of Weighted Fuel Prices on Productivity

	$\log(Energy\_Productivity_{i,t})$	$\log(Energy\_Productivity_{i,t})$ Electricity-Intensive Industries	$\log(TFP_{i,t})$	$\log(TFP_{i,t})$ Electricity-Intensive Industries
	(1)	(2)	(3)	(4)
$Coal\_Share_{s,1976} \times Current\_Coal\_Price_{-s,t}$	-0.088*	-0.082	-0.035**	-0.034*
	(0.048)	(0.051)	(0.017)	(0.018)
$Natural\_Gas\_Share_{s,1976} \times Current\_Natural\_Gas\_Price_{-s,t}$	0.037***	0.046***	0.012***	0.005
	(0.013)	(0.012)	(0.004)	(0.004)
$Petroleum\_Share_{s,1976} \times Current\_Petroleum\_Price_{-s,t}$	0.008	0.013	-0.010***	-0.009***
	(0.013)	(0.012)	(0.002)	(0.003)
$Coal\_Share_{s,1976} \times Initial\_Coal\_Price_{-s,t_0}$	0.178***	0.171***	0.037*	0.041*
	(0.041)	(0.044)	(0.022)	(0.025)
$Natural\_Gas\_Share_{s,1976} \times Initial\_Natural\_Gas\_Price_{-s,t_0}$	-0.018	-0.011	0.006*	0.011***
	(0.017)	(0.017)	(0.004)	(0.004)
$Petroleum\_Share_{s,1976} \times Initial\_Petroleum\_Price_{-s,t_0}$	0.035***	0.035***	-0.005	-0.002
	(0.008)	(0.011)	(0.005)	(0.006)
N	1294000	955000	1294000	955000
Industry × Year × Entry Year Fixed Effects	Yes	Yes	Yes	Yes
Industry × State Fixed Effects	Yes	Yes	Yes	Yes

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table shows the effects of initial and contemporaneous coal, natural gas, and petroleum prices on the log of plants' productivities. Electricity prices are measured in dollars per kWh, energy productivity is the productivity of electricity relative to labor, and total factor productivity is the productivity common to all manufacturing inputs. Electricity-intensive industries are industries for which electricity accounts for at least 70% of total energy expenditures. Fuel prices are calculated as the leave-out-mean log price across states and weighted by the share of each fuel in electricity generation in each state. Regressions are weighted using Census sampling weights. All dollar values are in 2011 USD. Standard errors clustered by state are in parentheses.

Table 5: Effects of Initial and Current Electricity Prices on Productivity

	$\log(Energy\_Productivity_{i,t})$	$\log(Energy\_Productivity_{i,t})$ Electricity-Intensive Industries	$\log(TFP_{i,t})$	$\log(TFP_{i,t})$ Electricity-Intensive Industries
	(1)	(2)	(3)	(4)
Panel A: OLS				
$\log(Current\_Electricity\_Price_{i,t})$	0.881***	0.860***	0.060***	0.060***
	(0.023)	(0.020)	(0.007)	(0.009)
$\log(Initial\_Electricity\_Price_{i,t_0})$	0.080***	0.093***	-0.037***	-0.047***
	(0.019)	(0.023)	(0.008)	(0.012)
Panel B: IV				
$\log(Current\_Electricity\_Price_{i,t})$	0.525***	0.673***	0.088	-0.017
	(0.138)	(0.139)	(0.127)	(0.119)
$\log(Initial\_Electricity\_Price_{i,t_0})$	0.349***	0.319***	0.049	0.124
	(0.122)	(0.126)	(0.077)	(0.083)
K-P F stat	12.1	11.9	12.1	11.9
N	1294000	955000	1294000	955000
Industry × Year × Entry Year FE	Yes	Yes	Yes	Yes
Industry × State FE	Yes	Yes	Yes	Yes

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table shows the effects of initial and contemporaneous log electricity prices on the log of plants' energy productivity relative to labor productivity and on the log of plants' total factor productivity. Models in Panel A are estimated using OLS and models in Panel B are estimated using IV. In IV models, electricity prices are instrumented using initial and contemporaneous prices for coal, natural gas, and petroleum, weighted by the share of each fuel in state electricity generation. Electricity prices are measured in dollars per kWh, energy productivity is the productivity of electricity relative to labor, and total factor productivity is the productivity common to all manufacturing inputs. Electricity-intensive industries are industries for which electricity accounts for at least 70% of total energy expenditures. Regressions are weighted using Census sampling weights. All dollar values are in 2011 USD. Standard errors clustered by state are in parentheses.

Table 6: Heterogeneous Effects of Initial Electricity Prices on Energy Intensity and Productivity, by Plant Age

	$\log(Electricity\_Intensity_{i,t})$	$\log(CO_2\_Intensity_{i,t})$	$\log(BTU\_Intensity_{i,t})$	$\log(Energy\_Productivity_{i,t})$	$\log(TFP_{i,t})$
	(1)	(2)	(3)	(4)	(5)
$\log(Current\_Electricity\_Price_{i,t})$	-0.871***	-1.136***	-0.903***	0.739***	0.109
	(0.061)	(0.097)	(0.069)	(0.131)	(0.096)
$\log(Initial\_Electricity\_Price_{i,t_0})$	-0.134**	-0.140**	-0.076	0.250*	0.097
	(0.052)	(0.061)	(0.054)	(0.130)	(0.095)
$\log(Initial\_Electricity\_Price_{i,t_0}) \times Age_{i,t}$	0.006**	0.006	0.004	-0.006	-0.010***
	(0.003)	(0.004)	(0.004)	(0.007)	(0.003)
K-P F stat	13.3	13.3	13.3	13.3	13.3
N	1294000	1294000	1294000	1294000	1294000
Industry × Year × Entry Year FE	Yes	Yes	Yes	Yes	Yes
Industry × State FE	Yes	Yes	Yes	Yes	Yes

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: All models are estimated using IV. Electricity prices are instrumented using initial and contemporaneous prices for coal, natural gas, and petroleum, weighted by the share of each fuel in state electricity generation, and initial electricity prices × plant age is instrumented using the interaction of the initial weighted fuel prices times age. Electricity prices are measured in dollars per kWh, electricity intensity is kWh per dollar of revenue, CO2 intensity is kg CO2 per dollar of revenue, BTU intensity is BTU per dollar of revenue, energy productivity is the productivity of electricity relative to labor, total factor productivity is the productivity common to all manufacturing inputs, and plant age is measured in years since entry. Regressions are weighted using Census sampling weights. All dollar values are in 2011 USD. Standard errors clustered by state are in parentheses.

Appendix

A Data

This section provides details on data sources and construction of the primary variables.

We impose several sample restrictions on the measures of firms' inputs and outputs in the ASM and CMF to reduce measurement error. These restrictions closely follow those imposed in other papers using the ASM and CMF (e.g., Ganapati et al., 2020). First, we drop observations for which electricity prices, electricity intensity, capital investment, revenue, labor costs, materials costs, electricity expenditures, or raw fuels expenditures are missing or negative. Second, we exclude observations for which electricity prices, revenue, labor costs, materials costs, or electricity expenditures are equal to 0. Third, we exclude imputed administrative records. Fourth, since some observations still appear to be errors, we drop outliers that have capital stocks, revenue, labor costs, materials costs, electricity expenditures, or raw fuels expenditures that exceed 100 times the 99th percentile of the distribution of these variables. Finally, we exclude observations with electricity prices that are more than ten times or less than one-tenth of the annual median price.

We calculate annual plant-level electricity prices using plants' reported electricity expenditures and purchased quantities from the ASM and CMF, but we do not always observe plants' initial energy prices since only a subset of plants are surveyed in their year of entry. We match plants to their own initial electricity prices using unique plant identifiers where possible. If a plant is not observed in its first year of operations, then we impute its initial electricity price using the average of entrants in the same year, state, and six-digit NAICS industry. For a small number of plants, we use the average of entrants in the same year and state since there are no other entrants in the same industry in the plants' state and year.

We use the MECS and ASM Fuels Trailers to calculate measures of energy intensity of production that include raw fuels inputs (e.g., coal, natural gas, oil) in addition to electricity. The ASM and CMF include information on total expenditures on raw fuels, but don't include information on how these costs are split between fuels or what quantities are consumed of each. This breakdown is available in the MECS every three years 1985-1994 and every four years 1994-2014 and in the ASM Fuels Trailers for the years 1976-1981. In these surveys, we convert quantities of raw fuels consumed to British thermal units (BTU) using conversion factors from the EIA and to CO2 using data from the EIA where possible and from the EPA for crude oil, biomass, blast furnace gas, coke oven gas, waste gas, and acetylene. We calculate the industry × year BTU and CO2 consumed per dollar of raw fuels expenditure, weighting by the survey weights provided. Expenditures on raw fuels are deflated to 2011 dollars using the industry's annual average energy deflator from the NBER-CES Productivity Database. We exclude fuels used as feedstocks and process emissions in these calculations (Lyubich et al., 2018).

We use these industry average measures of energy consumed per dollar of raw fuels to calculate the total BTU and CO2 implied by each plant's raw fuels expenditures in the ASM and the CMF. To do so, we merge the raw fuels coefficients with the ASM and CMF, and linearly interpolate the coefficients in the missing years separately for each industry. We replace resulting negative coefficients by 0 for 1% of observations; in these cases, all energy consumed comes from electricity. We then calculate the BTU and CO2 embodied in raw fuels as the annual industry average energy coefficient times expenditure on raw fuels in the ASM and CMF, and we calculate the BTU and CO2 embodied in electricity consumption at the plant level using quantities reported in the ASM and MECS. The conversion factors for mWh of electricity to BTU comes from the EIA and the conversion factors for mWh to kg of CO2 come from the EPA's eGRID, which includes separate emissions factors by state that consider the energy mix of each state's electricity grid.

These estimates of BTU and CO2 embodied in energy inputs allow us to calculate measures of BTU and CO2 per dollar of revenue; these alternative measures of energy intensity complement our use of electricity consumed per dollar of revenue in the regression analysis. Since some observations are obvious outliers, we trim the BTU and CO2 intensities that exceed the 99th percentile of the distribution of values. Our energy intensities are comparable to estimates in the literature. For example, the average CO2 intensity of manufacturing that we calculate is within 15% of estimates from Lyubich et al. (2018) using the same MECS year.

A final note about this imputation process is that the ASM Fuels Trailers include substantially less detail than the MECS. Raw fuels are presented at much higher levels of aggregation (e.g., aggregate coal consumption, rather than consumption of different types of coal) and several fuels are grouped into an "others" category, which we exclude. We therefore present results using only the MECS to impute energy consumption from raw fuels and results using both the MECS and ASM Fuels Trailers. We find very similar results using both approaches.

B Imputation of Missing Capital Stocks

Capital stocks are a necessary input into the production function estimation, but unlike other inputs are not measured every year. Capital stocks are measured in the CMF in years ending in 2 or 7, and capital investment is measured in both the CMF and, in the intervening years, in the ASM. To obtain estimates of capital stocks in all years, we first calibrate the depreciation rate δ using plants which we observe every year between Censuses. Approximately 12,000 plants are surveyed in the ASM every year between the two most recent Censuses in our sample period (i.e., 2002 and 2007). We iteratively apply the law of motion of capital $K_{i,t+1} = (1-\delta)K_{i,t} + I_{i,t}$ to back out the depreciation rate implied by beginning capital stock $K_{i,t}$ and ending capital stocks $K_{i,t+1}$ and intervening path of investment $I_{i,t}$. Specifically, for each plant i we solve:

$$K_{2007} = (1-\delta)^5 K_{2002} + (1-\delta)^4 I_{2002} + (1-\delta)^3 I_{2003} + (1-\delta)^2 I_{2004} + (1-\delta) I_{2005} + I_{2006} \tag{8}$$

We calculate the average depreciation rate over all plants.

We then use this depreciation rate to recursively calculate capital stocks in the years between Censuses using the law of motion of capital combined with observed investment in the ASM. Specifically, for plants surveyed in the years before and after a Census, we obtain their capital stock using investment from the ASM in those years combined with depreciation. We recursively apply the same approach to plants observed two years before and after a Census. A small number of capital stocks are still missing after applying this procedure. We predict these values using the interaction of (log) total value of shipments with six digit NAICS industry codes. Our results are robust to excluding these observations as well.

C Bartik Instruments and Identification

This section comprises a more detailed discussion of testing the validity of the identifying assumption underlying our Bartik-style shift-share instruments.

As Section 6 describes, our instrumental variables analysis uses an exposure design that isolates plausibly exogenous variation in electricity prices using states' differential exposure to national changes in the prices of raw fuels (e.g., coal, natural gas, petroleum), where the weights are the shares of electricity generated using each of these fuels. Goldsmith-Pinkham et al. (2020) show that such a research design requires exogeneity of the shares for the identifying assumption to hold because the Bartik instrument is numerically equivalent to a Generalize Method of Moments (GMM) estimator using shares as instruments. As a consequence, our identifying assumption in equation (4) is valid if the state fuel generation shares are uncorrelated with shocks leading to changes in the energy intensity outcomes.

The potential concern in our setting is centered on whether state fuel generation shares might be correlated to other shocks to plants' input mix that affect energy intensity directly, rather than through electricity prices. For example, if fuel generation shares are correlated with the availability of skilled labor, then we might be concerned that the instruments are correlated with unobserved shocks to labor inputs, and thus that the identifying assumption (4) would be violated.

We assess the validity of our research design by analyzing whether state characteristics that could be correlated with other input shocks also predict state fuel generation shares (Goldsmith-Pinkham et al., 2020). Appendix Table A.3 reports the results from regressing the shares of electricity generated using coal, natural gas, and petroleum on state characteristics plausibly related to input availability (e.g., unemployment rate, share college educated) and output demand (e.g., mean household income). Reassuringly, this now standard test yields no systematic correlation between the shares and these characteristics, which supports the validity of the research design.[33]

D Robustness of Instrumental Variables Analysis

D.1 Energy Intensity

Appendix Table A.7 shows that the sign, magnitude, and precision of the main estimates are robust to the use of different covariates, weightings, and data subsamples. For comparison, Panel A reproduces the main estimates of lock-in based on equation (2) and shown in Table 3.

Panels B and C show that both initial and current electricity prices elasticities are robust to the use of different covariates. Panel B presents results that are almost identical using higher-level fixed effects, which suggests that variation at the year × first year × industry level does not confound the estimates. Panel C includes state × year time trends, which allow for differential energy efficiency trends by state over time. The results again are comparable, with a small increase in the magnitude of the point estimates.

[33] We report what we consider more conservative estimates of the significance of these correlations that do not adjust for the multiple hypotheses that we are testing.

Panel D presents estimates that are not weighted by the Census sampling weights to create a representative sample. Since the ASM oversamples large plants, these plants are assigned higher weight in these regressions relative to the main estimates. The initial price elasticity falls by approximately one-third, suggesting that lock-in is not just driven by large plants, while the sign and significance are generally unchanged.

Panels E, F, and G show estimates using different subsamples of the data. Panel E linearly interpolates CO2 and BTU values from the MECS only, rather than the MECS and the ASM Fuels Trailers. The MECS contains approximately five times as many fuel categories as the ASM Fuel Trailers (e.g., detailed coal subtypes v. all coal), but the imputing the ASM years using the MECS barely changes the estimated effect of electricity prices on CO2 and BTU intensities at all (Columns 3 and 4). Panel F excludes years in which the ASM Fuels Trailers and the MECS are not collected. This skews the analysis sample toward the early years of the data since the ASM Fuels Trailers were collected every year between 1976 and 1981, while the MECS is subsequently collected every three or four years. The lock-in estimates are larger as a result: the effects of entry-year electricity prices on electricity, CO2, and BTU intensity all increase by approximately one-third. The change in the magnitude of the parameter estimates is the result of the changing time period, rather than the imputation, since the electricity intensities are never imputed. The parameter estimates in Panel G, which exclude the ASM Fuel Trailer years, are closer to the main estimates, though still oversamples the early years of the data.

D.2 Productivity

Appendix Table A.8 shows alternative estimates of the effects of initial and current electricity prices on productivity. We analyze the same models as in Appendix Table A.7 using relative energy productivity and total factor productivity as the outcome variables, and we find again find results that are consistent with the main estimates in Table 5. We reproduce these results in Panel A of Appendix Table A.8 for comparison.

Panels B and C use different covariates than the models in the main text. We find estimates that are similar in sign, magnitude, and precision to the main estimates using higher level fixed effects (Panel B) and using state $\times$ year time trends (Panel C). The magnitude of contemporaneous electricity prices for relative energy intensity increases slightly with the inclusion of state $\times$ year trends, suggesting that there may be some differential trends in energy productivity between states, though the estimates are not statistically different from each other. Meanwhile, the entry-year lock-in estimates of the effects of initial electricity prices on electricity intensity are almost entirely unchanged, as are the effects of both initial and contemporaneous prices on total factor productivity.

The estimates in Panel D are unweighted by Census sampling weights. As discussed above, the ASM oversamples large plants; the regression estimates again are similar or, in the case of relative energy productivity, slightly larger, suggesting again that the lock-in estimates are not driven by large plants, or by reweighting.

Panels E, F, and G show estimates using different subsamples of the data. Panel E uses linearly interpolates CO2 and BTU values from the MECS only, rather than the MECS and the ASM Fuels Trailers. The MECS contains approximately five times as many fuel categories as the ASM Fuel Trailers (e.g., detailed coal subtypes v. all coal), but imputing the ASM years using the MECS barely changes the estimated effect of electricity prices on CO2 and BTU intensities at all (Columns 3 and 4). Since the relative energy intensity estimates don't use imputed CO2 or BTU values, this sample is equivalent to the main sample for these productivity models, though is different in the case of Appendix Table A.7.

Panel F excludes years in which the ASM Fuels Trailers and the MECS are not collected. This skews the analysis sample toward the early years of the data since the ASM Fuels Trailers were collected every year between 1976 and 1981, while the MECS is subsequently collected every three or four years. The lock-in estimates again are similar in sign, magnitude, and precision, while the importance of contemporaneous electricity prices falls slightly, perhaps as a result of fewer intervening years between the measurement of initial and current prices. This same pattern is evident in Panel G, which excludes ASM Fuel Trailer years from the Panel F sample, though overall the results are quantitatively and qualitatively similar in all models.

E Electricity Price Effects on Other Manufacturing Outcomes

This section discuss the effects of initial electricity prices on manufacturing outcomes other than energy intensity and energy productivity.

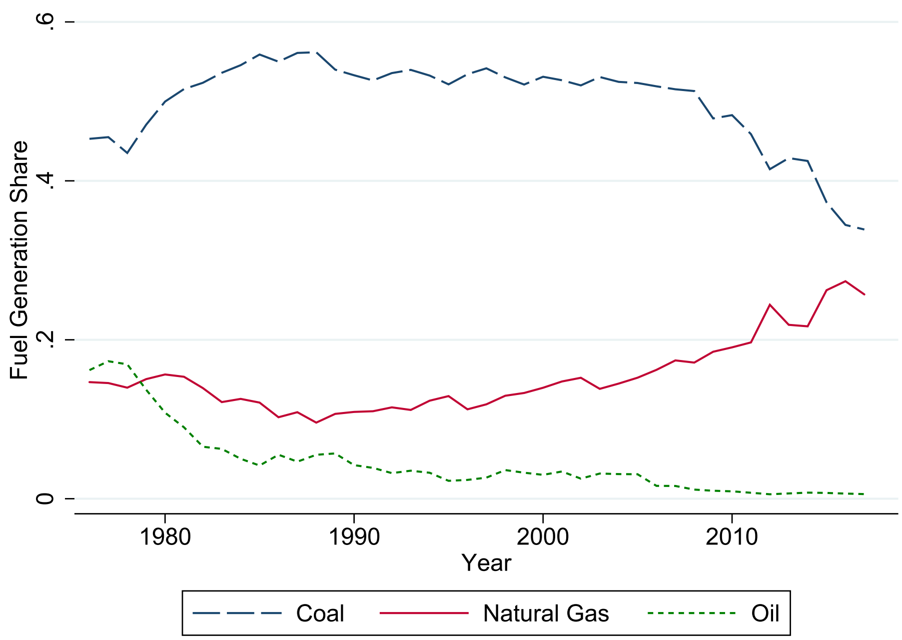
Panel A reports the effects of initial electricity prices on the amounts of electricity used, CO2 produced, and BTU consumed, rather than the intensity amounts measured per dollar of revenue.

These results are similar in sign and magnitude to the main energy intensity estimates, though in some instances are somewhat less precisely estimated. These estimates are again consistent with lock-in: plants use a greater quantity of all of these energy measures when they begin operations in a low energy price year. The magnitudes of the effects on energy quantities can again be explained by the persistent effect on relative productivity, shown in Table 5.

Panel B reports effects on other manufacturing inputs. The effects of initial electricity prices on labor hours, capital outlays, and materials costs (excluding energy) are generally statistically insignificant, with the exception of a weakly positive effect on capital. These findings suggest that while initial electricity prices have important effects on future energy inputs, they have a limited effect on other non-energy inputs. In particular, higher entry-year energy costs appear unlikely to lead to widespread unemployment, as has been raised as a potentially concerning effect of pricing carbon.

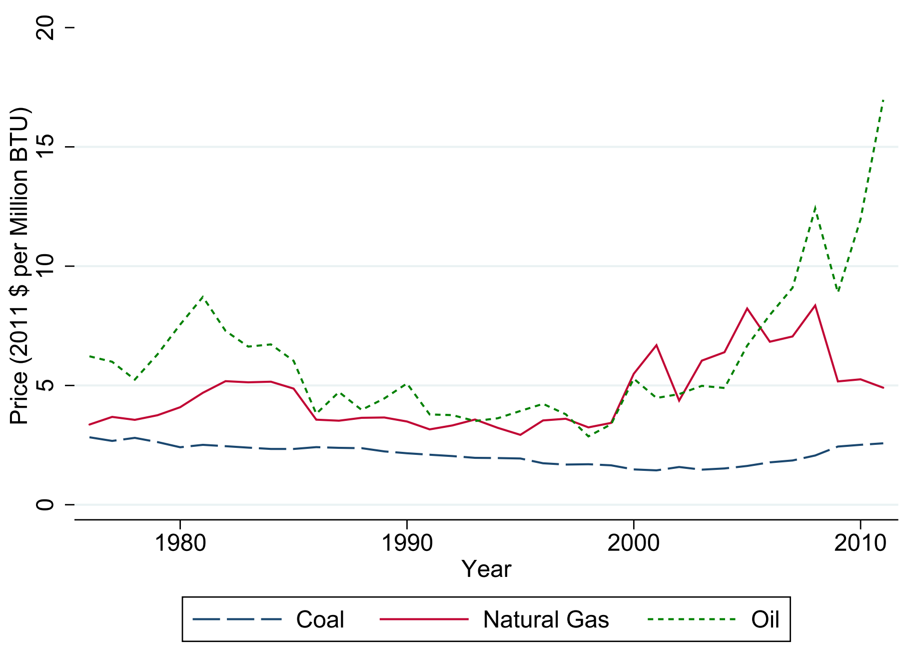
F Figures and Tables

Figure A.1: Time Series of Shares of Fossil Fuels used in Electricity Generation



Notes: This figure shows the time series of the fraction of British thermal units (BTU) of electricity generated by coal, natural gas, and petroleum oil in the United States.

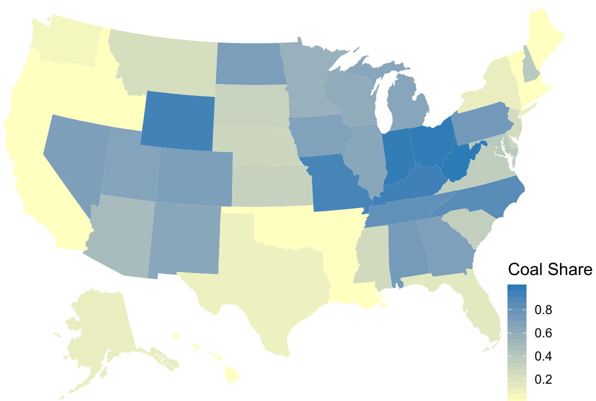
Figure A.2: Time Series of Fuel Prices



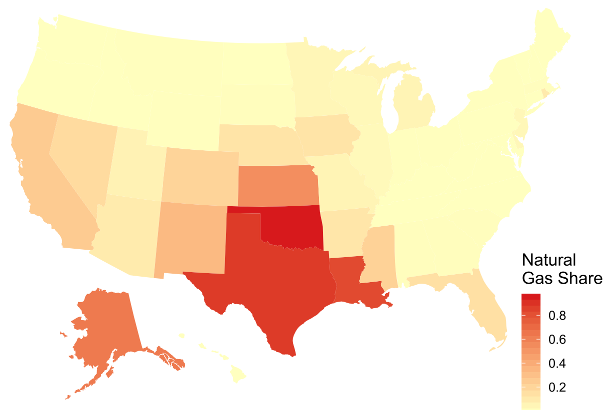
Notes: This figure shows the time series of average coal, natural gas, and petroleum oil prices paid by electric utilities. Prices are in 2011 dollars per million British thermal units (BTU) of fuel.

Figure A.3: Share of Electricity Generated by Coal, Natural Gas, and Petroleum Oil in 1976

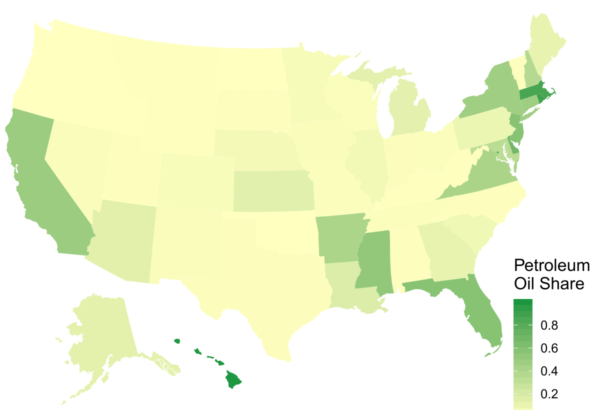
Panel A: Coal Share



Panel B: Natural Gas Share

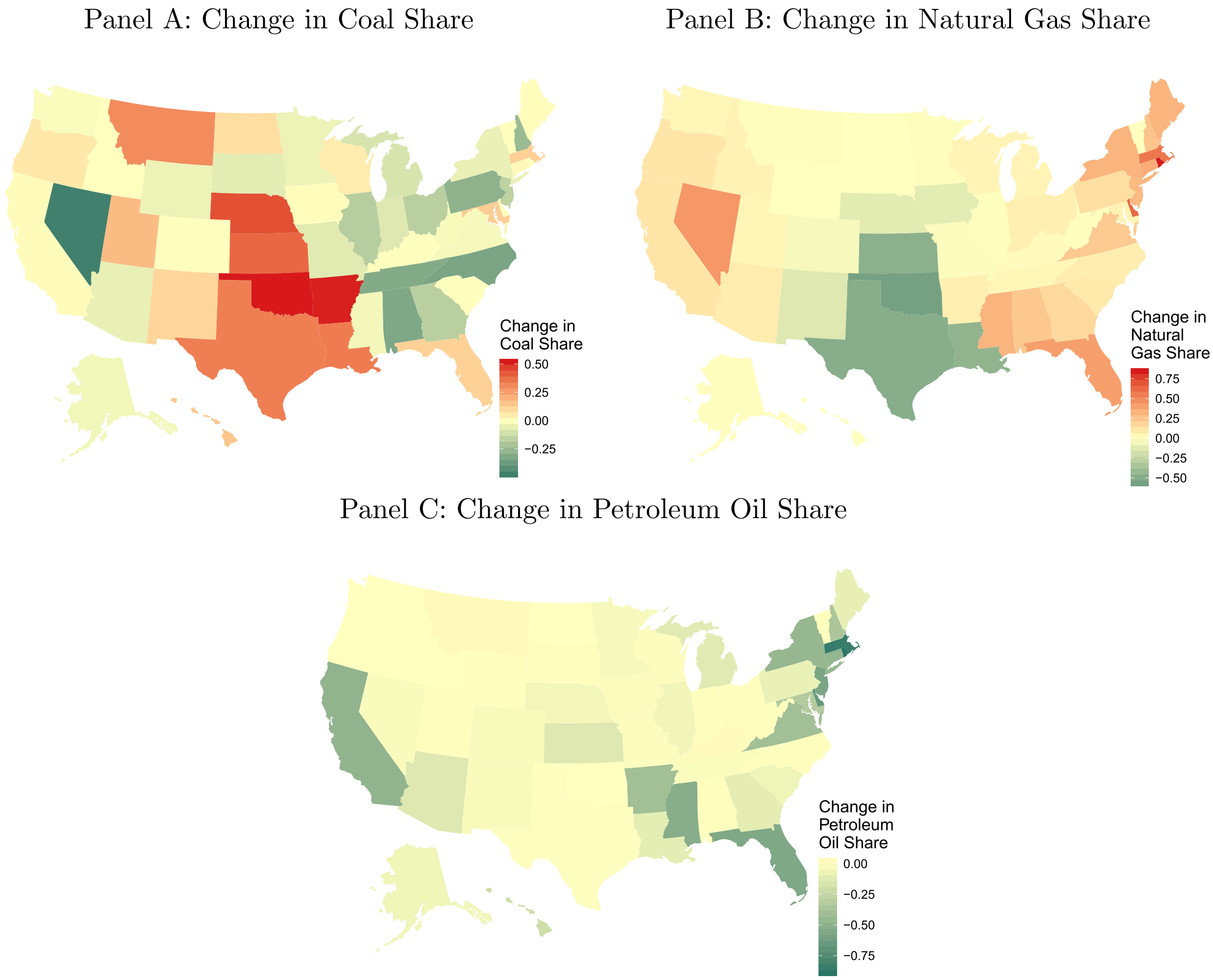


Panel C: Petroleum Oil Share



Notes: This figure shows the fraction of total British thermal units (BTUs) of electricity generated from coal, natural gas, and petroleum oil in each state in 1976. Shares need not add up to 1 due to the presence of other fuel sources (e.g., nuclear, hydro).

Figure A.4: Change in Share of Electricity Generated by Coal, Natural Gas, and Petroleum Oil, 1976-2011



Notes: This figure shows the change in the fraction of total British thermal units (BTUs) of electricity generated from coal, natural gas, and petroleum oil in each state between 1976 and 2011.

Table A.1: Summary Statistics

	All Industries (1)	Electricity-Intensive Industries (2)
Year	1997	1997
	(8.595)	(8.540)
Entry Year	1988	1988
	(8.894)	(8.760)
Plant Age (years)	9.243	9.297
	(8.000)	(7.997)
Current Electricity Price ($ per kWh)	0.087	0.085
	(0.036)	(0.034)
Initial Electricity Price ($ per kWh)	0.088	0.088
	(0.032)	(0.030)
Cost of Purchased Electricity (1000$)	275.4	203.4
	(2065)	(958)
Quantity of Purchased Electricity (1000 kWh)	4411	3175
	(51160)	(22430)
Electricity Intensity (kWh per $ revenue)	0.196	0.208
	(0.500)	(0.500)
CO2 Intensity (kg per $ revenue)	0.122	0.132
	(0.469)	(0.519)
BTU Intensity (million BTU per $ revenue)	0.001	0.002
	(0.006)	(0.007)
N	1294000	955000

Notes: This table shows variable means for U.S. manufacturing plants. Electricity-intensive industries are industries for which electricity accounts for at least 70% of total energy expenditures. All dollar values are in USD (2011). Standard errors are in parentheses.

Table A.2: Entry and Exit Summary Statistics

	All Industries	Elec. Intensive Industries
	(1)	(2)
Entrant Fraction	0.078	0.077
	(0.269)	(0.266)
Exit Fraction	0.004	0.004
	(0.060)	(0.060)
Observations per Plant	4.594	4.466
	(4.765)	(4.466)
Plant Age	9.243	9.297
	(8.00)	(7.997)
Age at Exit	14.960	15.010
	(9.150)	(9.142)

Notes: This table shows summary means for plant entry and exit behavior. Entry and exit fractions are the shares of total plant-year observations in our sample that are entrants or exiters, respectively. Plant age and age at exit are measured in years. Column 1 shows means across all industries and column 2 shows means for electricity-intensive industries. Standard errors are in parentheses.

Table A.3: Relationship between Fuel Generation Shares and State Characteristics

	Coal Share (1)	Natural Gas Share (2)	Petroleum Share (3)
Unemployment Rate	-0.022	-0.039*	-0.001
	(0.033)	(0.022)	(0.023)
State Per Capita Income (1000s)	0.005	0.048	0.034
	(0.043)	(0.029)	(0.029)
Mean Household Income (1000s)	-0.001	-0.000	0.001
	(0.001)	(0.001)	(0.001)
Share Any College Education	-0.030*	-0.015	0.007
	(0.016)	(0.011)	(0.011)
Share White	0.008	0.001	-0.009*
	(0.007)	(0.005)	(0.005)
Share Black	0.004	0.003	-0.003
	(0.007)	(0.005)	(0.005)
Population (1000s)	-0.004	0.005	0.001
	(0.010)	(0.007)	(0.007)
Household Size	0.506	0.517	-0.215
	(0.673)	(0.454)	(0.458)
Dep. Var. Mean (1980)	0.45	0.12	0.16
Dep. Var. Mean (1976)	0.40	0.12	0.21
R-square	0.266	0.154	0.443
N	51	51	51

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table shows the correlation between state fuel shares in electricity generation and state characteristics in 1980. Standard errors are in parentheses.

Table A.4: Estimated Production Function Parameters

	All Industries	Elec. Intensive Industries
	(1)	(2)
Returns to scale ν	0.620	0.679
	(0.292)	(0.256)
Elasticity of substitution σ	0.260	0.237
	(0.195)	(0.186)
Capital productivity β_K	3.411	3.498
	(2.200)	(2.220)
N	1294000	955000

Notes: This table shows the estimated production function parameters. Column 1 shows mean parameter estimates across all industries and column 2 shows means for electricity-intensive industries (i.e., industries for which electricity accounts for at least 70% of total energy expenditures). Standard errors are in parentheses.

Table A.5: Effects of Current Electricity Prices on Energy Intensity

	$\log(Electricity\_Intensity_{i,t})$	$\log(Electricity\_Intensity_{i,t})$ Electricity-Intensive Industries	$\log(CO_2\_Intensity_{i,t})$	$\log(BTU\_Intensity_{i,t})$
	(1)	(2)	(3)	(4)
Panel A: OLS				
$\log(Current\_Electricity\_Price_{i,t})$	-0.855***	-0.835***	-0.828***	-0.810***
	(0.012)	(0.011)	(0.010)	(0.009)
Panel B: IV				
$\log(Current\_Electricity\_Price_{i,t})$	-0.777***	-0.768***	-0.899***	-0.769***
	(0.086)	(0.102)	(0.070)	(0.084)
K-P F stat	11.7	10.9	11.7	11.7
N	1294000	955000	1294000	1294000
Industry × Year × Entry Year FE	Yes	Yes	Yes	Yes
Industry × State FE	Yes	Yes	Yes	Yes

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Models in Panel A are estimated using OLS and models in Panel B are estimated using IV. In IV models, electricity prices are instrumented using contemporaneous prices for coal, natural gas, and petroleum, weighted by the share of each fuel in state electricity generation. Electricity prices are measured in dollars per kWh, electricity intensity is kWh per dollar of revenue, CO2 intensity is kg CO2 per dollar of revenue, and BTU intensity is BTU per dollar of revenue. Electricity-intensive industries are industries for which electricity accounts for at least 70% of total energy expenditures. Regressions are weighted using Census sampling weights. All dollar values are in 2011 USD. Standard errors clustered by state are in parentheses.

Table A.6: Effects of Initial Electricity Prices on Energy Intensity

	$\log(Electricity\_Intensity_{i,t})$	$\log(Electricity\_Intensity_{i,t})$ Electricity-Intensive Industries	$\log(CO_2\_Intensity_{i,t})$	$\log(BTU\_Intensity_{i,t})$
	(1)	(2)	(3)	(4)
Panel A: OLS				
$\log(Initial\_Electricity\_Price_{i,t_0})$	-0.194***	-0.183***	-0.178***	-0.172***
	(0.013)	(0.014)	(0.011)	(0.012)
Panel B: IV				
$\log(Initial\_Electricity\_Price_{i,t_0})$	-0.554***	-0.589***	-0.707***	-0.538***
	(0.113)	(0.125)	(0.113)	(0.112)
K-P F stat	12.0	12.4	12.0	12.0
N	1294000	955000	1294000	1294000
Industry × Year × Entry Year FE	Yes	Yes	Yes	Yes
Industry × State FE	Yes	Yes	Yes	Yes

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Models in Panel A are estimated using OLS and models in Panel B are estimated using IV. In IV models, entry-year electricity prices are instrumented using entry-year prices for coal, natural gas, and petroleum, weighted by the share of each fuel in state electricity generation. Electricity prices are measured in dollars per kWh, electricity intensity is kWh per dollar of revenue, CO2 intensity is kg CO2 per dollar of revenue, and BTU intensity is BTU per dollar of revenue. Electricity-intensive industries are industries for which electricity accounts for at least 70% of total energy expenditures. Regressions are weighted using Census sampling weights. All dollar values are in 2011 USD. Standard errors clustered by state are in parentheses.

Table A.7: Effects of Initial and Current Electricity Prices on Energy Intensity

	log($Electricity\_Intensity_{i,t}$)	log($Electricity\_Intensity_{i,t}$) Electricity-Intensive Industries	log($CO_2\_Intensity_{i,t}$)	log($BTU\_Intensity_{i,t}$)
	(1)	(2)	(3)	(4)
Panel A: Main Results				
log($Current\_Electricity\_Price_{i,t}$)	-0.764***	-0.734***	-0.829***	-0.761***
	(0.090)	(0.104)	(0.072)	(0.087)
log($Initial\_Electricity\_Price_{i,t_0}$)	-0.165***	-0.232***	-0.289***	-0.144**
	(0.051)	(0.059)	(0.079)	(0.059)
K-P F stat	12.1	11.9	12.1	12.1
N	1294000	955000	1294000	1294000
Panel B: Year × Industry, First Year × Industry, State × Industry FE				
log($Current\_Electricity\_Price_{i,t}$)	-0.770***	-0.726***	-0.831***	-0.763***
	(0.097)	(0.106)	(0.080)	(0.095)
log($Initial\_Electricity\_Price_{i,t_0}$)	-0.178***	-0.226***	-0.319***	-0.186***
	(0.051)	(0.070)	(0.074)	(0.057)
K-P F stat	9.7	10.2	9.7	9.7
N	1294000	955000	1294000	1294000
Panel C: State × Year Trends				
log($Current\_Electricity\_Price_{i,t}$)	-0.958***	-1.033***	-1.003***	-1.053***
	(0.127)	(0.144)	(0.081)	(0.129)
log($Initial\_Electricity\_Price_{i,t_0}$)	-0.219***	-0.311***	-0.218***	-0.206***
	(0.062)	(0.075)	(0.062)	(0.059)
K-P F stat	11.9	11.3	11.9	11.9
N	1294000	955000	1294000	1294000
Panel D: Unweighted				
log($Current\_Electricity\_Price_{i,t}$)	-0.821***	-0.809***	-0.883***	-0.827***
	(0.044)	(0.044)	(0.045)	(0.041)
log($Initial\_Electricity\_Price_{i,t_0}$)	-0.109**	-0.153**	-0.172***	-0.074
	(0.052)	(0.067)	(0.059)	(0.045)
K-P F stat	11.6	10.8	11.6	11.6
N	1294000	955000	1294000	1294000
Panel E: Impute CO2, BTU from MECS only				
log($Current\_Electricity\_Price_{i,t}$)	-0.764***	-0.734***	-0.811***	-0.786***
	(0.090)	(0.104)	(0.085)	(0.085)
log($Initial\_Electricity\_Price_{i,t_0}$)	-0.165***	-0.232***	-0.193***	-0.152**
	(0.051)	(0.059)	(0.068)	(0.063)
K-P F stat	12.1	11.9	12.1	12.1
N	1294000	955000	1294000	1294000
Panel F: Exclude Years with Imputed CO2 and BTU Values				
log($Current\_Electricity\_Price_{i,t}$)	-0.625***	-0.585***	-0.800***	-0.564***
	(0.137)	(0.161)	(0.098)	(0.128)
log($Initial\_Electricity\_Price_{i,t_0}$)	-0.368***	-0.451***	-0.715***	-0.256**
	(0.091)	(0.099)	(0.134)	(0.106)
K-P F stat	11.1	11.9	11.1	11.1
N	312000	225000	312000	312000
Panel G: MECS Years Only				
log($Current\_Electricity\_Price_{i,t}$)	-0.685***	-0.696***	-0.722***	-0.725***
	(0.116)	(0.138)	(0.107)	(0.104)
log($Initial\_Electricity\_Price_{i,t_0}$)	-0.343***	-0.424***	-0.370***	-0.367***
	(0.089)	(0.125)	(0.085)	(0.086)
K-P F stat	9.4	10.0	9.4	9.4
N	266000	192000	266000	266000

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: All models are estimated using IV. Initial and contemporaneous electricity prices are instrumented using initial and contemporaneous prices for coal, natural gas, and petroleum, weighted by the share of each fuel in state electricity generation. Electricity prices are measured in dollars per kWh, electricity intensity is kWh per dollar of revenue, CO2 intensity is kg CO2 per dollar of revenue, and BTU intensity is BTU per dollar of revenue. Electricity-intensive industries are industries for which electricity accounts for at least 70% of total energy expenditures. Except for Panel B, all models include industry × year × entry year fixed effects and industry × state fixed effects. Regressions are weighted using Census sampling weights unless otherwise noted. All dollar values are in 2011 USD. Standard errors clustered by state are in parentheses.

Table A.8: Effects of Initial and Current Electricity Prices on Productivity

	$\log(Energy\_Productivity_{i,t})$	$\log(Energy\_Productivity_{i,t})$ Electricity-Intensive Industries	$\log(TFP_{i,t})$	$\log(TFP_{i,t})$ Electricity-Intensive Industries
	(1)	(2)	(3)	(4)
Panel A: Main Results				
$\log(Current\_Electricity\_Price_{i,t})$	0.525***	0.673***	0.088	-0.017
	(0.138)	(0.139)	(0.127)	(0.119)
$\log(Initial\_Electricity\_Price_{i,t_0})$	0.349***	0.319***	0.049	0.124
	(0.122)	(0.126)	(0.077)	(0.083)
K-P F stat	12.1	11.9	12.1	11.9
N	1294000	955000	1294000	955000
Panel B: Year × Industry, First Year × Industry, State × Industry FE				
$\log(Current\_Electricity\_Price_{i,t})$	0.512***	0.671***	0.136	0.047
	(0.169)	(0.150)	(0.118)	(0.113)
$\log(Initial\_Electricity\_Price_{i,t_0})$	0.330***	0.270***	0.021	0.087
	(0.100)	(0.115)	(0.074)	(0.098)
K-P F stat	9.7	10.2	9.7	10.2
N	1294000	955000	1294000	955000
Panel C: State × Year Trends				
$\log(Current\_Electricity\_Price_{i,t})$	0.928***	1.109***	0.040	-0.049
	(0.295)	(0.289)	(0.146)	(0.126)
$\log(Initial\_Electricity\_Price_{i,t_0})$	0.322***	0.352***	0.089	0.141
	(0.140)	(0.156)	(0.082)	(0.093)
K-P F stat	11.9	11.3	11.9	11.3
N	1294000	955000	1294000	955000
Panel D: Unweighted				
$\log(Current\_Electricity\_Price_{i,t})$	0.465***	0.589***	0.174	0.059
	(0.124)	(0.123)	(0.105)	(0.078)
$\log(Initial\_Electricity\_Price_{i,t_0})$	0.425***	0.412***	-0.078	0.017
	(0.087)	(0.092)	(0.049)	(0.055)
K-P F stat	11.6	10.8	11.6	10.8
N	1294000	955000	1294000	955000
Panel E: Impute CO2, BTU from MECS only				
$\log(Current\_Electricity\_Price_{i,t})$	0.525***	0.673***	0.088	-0.017
	(0.138)	(0.139)	(0.127)	(0.119)
$\log(Initial\_Electricity\_Price_{i,t_0})$	0.349***	0.319***	0.049	0.124
	(0.122)	(0.126)	(0.077)	(0.083)
K-P F stat	12.1	11.9	12.1	11.9
N	1294000	955000	1294000	955000
Panel F: Exclude Years with Imputed CO2 and BTU Values				
$\log(Current\_Electricity\_Price_{i,t})$	0.413***	0.421***	0.103	0.049
	(0.150)	(0.188)	(0.099)	(0.095)
$\log(Initial\_Electricity\_Price_{i,t_0})$	0.376***	0.557***	0.091	0.132
	(0.193)	(0.186)	(0.102)	(0.105)
K-P F stat	11.1	11.9	11.1	11.9
N	312000	225000	312000	225000
Panel G: MECS Years Only				
$\log(Current\_Electricity\_Price_{i,t})$	0.411***	0.415***	0.126	0.122
	(0.144)	(0.162)	(0.090)	(0.092)
$\log(Initial\_Electricity\_Price_{i,t_0})$	0.503***	0.573***	0.047	0.097
	(0.177)	(0.193)	(0.101)	(0.111)
K-P F stat	9.4	10.0	9.4	10.0
N	266000	192000	266000	192000

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: All models are estimated using IV. Initial and contemporaneous electricity prices are instrumented using initial and contemporaneous prices for coal, natural gas, and petroleum, weighted by the share of each fuel in state electricity generation. Electricity prices are measured in dollars per kWh, energy productivity is the productivity of electricity relative to labor, and total factor productivity is the productivity common to all manufacturing inputs. Electricity-intensive industries are industries for which electricity accounts for at least 70% of total energy expenditures. Except for Panel B, all models include industry × year × entry year fixed effects and industry × state fixed effects. Regressions are weighted using Census sampling weights unless otherwise noted. All dollar values are in 2011 USD. Standard errors clustered by state are in parentheses.

Table A.9: Effects of Initial and Current Electricity Prices on Manufacturing Outcomes

	(1)	(2)	(3)
Panel A: Energy Inputs (Levels)			
	log($Quantity\_Electricity_{i,t}$)	log($Total\_CO2_{i,t}$)	log($Total\_BTU_{i,t}$)
log($Current\_Electricity\_Price_{i,t}$)	-0.308*	-0.373**	-0.305*
	(0.170)	(0.183)	(0.178)
log($Initial\_Electricity\_Price_{i,t_0}$)	-0.240*	-0.364***	-0.218*
	(0.133)	(0.112)	(0.124)
Panel B: Other Manufacturing Inputs			
	log($Labor\_Hours_{i,t}$)	log($Materials\_Costs_{i,t}$)	log($Capital\_Investment_{i,t}$)
log($Current\_Electricity\_Price_{i,t}$)	0.470***	0.421*	0.391
	(0.153)	(0.239)	(0.287)
log($Initial\_Electricity\_Price_{i,t_0}$)	-0.109	-0.136	0.434*
	(0.124)	(0.146)	(0.247)
K-P F stat	12.1	12.1	12.1
N	1294000	1294000	1294000
Industry × Year × Entry Year FE	Yes	Yes	Yes
Industry × State FE	Yes	Yes	Yes

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: All models are estimated using IV. Initial and contemporaneous electricity prices are instrumented using initial and contemporaneous prices for coal, natural gas, and petroleum, weighted by the share of each fuel in state electricity generation. Electricity prices are measured in dollars per kWh, labor inputs in hours, materials costs and capital investment in 1000s, quantity of electricity purchased in 1000 kWh, quantity CO2 produced in kg, and quantity BTU consumed in million BTU. Regressions are weighted using Census sampling weights. All dollar values are in 2011 USD. Standard errors clustered by state are in parentheses.