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Industrial Development:  
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Improve Energy Efficiency?**

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# Complementary Inputs and Industrial Development: Can Lower Electricity Prices Improve Energy Efficiency?

## Abstract

The transition from traditional labor intensive to modern capital intensive production is a key factor for industrial development. Using half a million observations from Indian manufacturing plants, I analyze the effects of a secular decrease in industrial electricity prices through the lens of a model with technology choices and complementarities between electricity and capital inputs. Using instrumental variables, I show how lower industrial electricity prices can increase both labor productivity and electricity productivity. Apart from positive effects on firm economic and environmental performance, cost-price pass through significantly benefitted consumers, and the productivity improvements limited increases in carbon emissions.

JEL-Codes: Q410, D240, D220, O140.

Keywords: industrial development, energy efficiency, electricity productivity, labor productivity, electricity prices, coal prices, incidence, climate policy.

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## I. Introduction

The transition from traditional labor intensive to modern capital intensive production is a central tenet of industrial development and essential for bridging international differences in industrial output per worker (Caselli, 2005). Lower prices of key inputs can substantially affect this process and improve manufacturing productivity, as observed, for example, following Indian reforms that reduced input tariffs (Goldberg et al., 2010). Complementarities in production inputs typically amplify such effects (Kremer, 1993). Most modern manufacturing requires electricity as a critical complementarity input to run machines. The price of electricity, conditional on physical access to power, can therefore play an important role in how countries and sectors upgrade to modern capital intensive and electricity-using production (Atkeson and Kehoe, 1999). In this paper, I show that lower electricity prices, as a result, not only improve labor productivity, but can surprisingly also improve electricity productivity (output per unit of electricity) through this mechanism. While energy prices are usually thought to involve trade-offs between developmental and environmental goals in highly industrialized countries (e.g. Marin and Vona, 2021), lower industrial electricity prices could deliver on both dimensions in a context of industrial development.

The findings in this paper can explain a puzzling pattern in Indian aggregate manufacturing data, where electricity prices fell substantially while electricity productivity increased at the same time. Intuition from standard models would predict the opposite: substitution towards the cheaper input, electricity, together with an unambiguous decrease in electricity productivity.<sup>1</sup> The key insight to resolve this apparent puzzle is that in the presence of discrete technological choices and complementarities, the substitution effect towards electricity can be overturned by a technology upgrading effect. A reduction in electricity prices can incentivize firms to move from a traditional labor-using technology to a more modern capital-using technology that requires complementary electricity use.<sup>2</sup> While this move increases both electricity consumption and employment, output can increase disproportionately due to more capital intensive production. As a result, lower electricity prices increase both labor and electricity productivity by speeding up the transition to more modern capital intensive production technology. An important insight is that this is achieved through lower costs of using a complementary input, rather than through a change in the relative investment cost of modern capital per se (Aghion et al., 2022) or through changing labor costs, e.g. from migration patterns (Imbert et al., 2022). This is also relevant for the broader ongoing electrification debate: in highly industrialized countries lower electricity prices for industry or transport may primarily facilitate a shift from fossil fuel to electric technologies, whereas in developing countries electrification from lower electricity prices may extend beyond switching fuel sources, encompassing a

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<sup>1</sup>The effect on labor productivity depends on substitutability and returns to scale (e.g. Acemoglu, 2002).

<sup>2</sup>Ryan (2018) shows with a field experiment in Gujarat (India) that electricity is a complementary input to modern machinery and production processes. Atkeson and Kehoe (1999) show that agents in a typical putty-clay models optimize by investing in complementary machines with changes in energy prices, which in turn magnifies positive effects on output and capital utilization compared to clay-clay models (Pindyck and Rotemberg, 1983). Ravago et al. (2019) find that higher electricity prices amplified premature deindustrialization and shifts towards more labor intensive manufacturing in the Philippines.

more fundamental transition from labor intensive to capital intensive technologies.

Apart from these broader implications for industrial development, the finding that lower electricity prices can induce energy conservation per unit of output is important in its own right. Energy efficiency receives much policy interest as one of the principal ways to reduce carbon intensity in manufacturing industries as countries struggle to achieve climate goals (IEA, 2018a; Fowlie and Meeks, 2021), especially in developing countries where production capacity and energy demand is expanding fast. While policy makers may fear that low industrial electricity prices could fail to provide sufficient incentives to improve energy efficiency, we have surprisingly little causal evidence of their effect on electricity productivity; indeed, this paper shows, to my knowledge, the first plausibly causal evidence of their potential to increase both labor and electricity productivity. I emphasize that this result is likely to be more relevant in contexts of industrial development and where industrial electricity prices are cut from comparatively high levels, which is both the case for India, the setting of this paper.<sup>3</sup>

While this paper focuses on the effects of electricity prices, a related literature focuses on the *reliability* of electricity and its implications. This is important in a developing country context where shortages are frequent. Allcott, Collard-Wexler and O’Connell (2016) show that power shortages in India reduce revenues by about 5% on average, and distort the plant size distribution due to returns to scale in self-generation.<sup>4</sup> Due to the institutional context in India, shortages are not systematically related to electricity prices, and I show that they are not significantly correlated.<sup>5</sup> Nevertheless, I provide robustness analyses for my estimates controlling for power shortages.

This paper proceeds in five steps. First, I set up a model to illustrate how such counter-intuitive effects of electricity prices are possible and generate testable predictions from these mechanisms. Second, I motivate the empirical analysis with puzzling trends in the data and the Indian institutional set-up. Third, I estimate the effects of electricity price reductions on industrial plants and test mechanisms. Fourth, I estimate pass-through to calculate incidence on consumers and welfare. Fifth, I estimate environmental implications, and contrast my results with coal price reductions.

I begin the paper by developing a nested constant elasticity of substitution (CES) production model with the innovation of non-convex discrete technology choices that have different degrees of complementarities across inputs. The purpose of the model is to illustrate how lower electricity prices can improve both electricity and labor productivity through more capital intensive technology adoption. The model generates a set of testable predictions I later take to the data, some of which are opposite predictions

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<sup>3</sup>India’s industrial electricity prices were around 80% higher than the G7 average in 1998, or seven times as high in PPP terms. For highly industrialized contexts, see Davis, Grim and Haltiwanger (2008) for the US, Marin and Vona (2021) for France, or von Graevenitz and Rottner (2022) for Germany.

<sup>4</sup>See also Alam (2013); Rud (2012); Jha, Preonas and Burlig (2022) for further evidence on India, Reinikka and Svensson (2002) and Foster and Steinbuks (2009) on African countries, Falentina and Resosudarmo (2019) on Indonesia, Fisher-Vanden, Mansur and Wang (2015) on China and Fried and Lagakos (2020) on general equilibrium effects. Ryan (2021) simulates the impact of transmission capacity improvements on the Indian electricity wholesale market.

<sup>5</sup>Note that electricity productivity accounts for self-generated electricity as it is the ratio of deflated output and electricity consumed, i.e. purchased and generated electricity minus electricity sold.

compared to standard CES models.

To motivate the empirical analysis and identification, I discuss price setting and other structural features of India's electricity sector and document key data patterns. Figure 1 presents puzzling trends at the aggregate level. First, Panel (a) shows a secular increase in India's manufacturing all-fuel energy productivity in the 2000s after remaining mostly flat for several decades since the 1960s. Panel (b) focuses on electricity and the period with more detailed data used for analysis. It shows aggregate electricity productivity improved by 34% from the 1998-2000 average to 2013.<sup>6</sup> Surprisingly, this improvement happened during a time when electricity became substantially cheaper. Real average industrial electricity prices fell by 48% during the same time (right axis), a robust pattern across various data sources including plant level data, official price indices and manually collected tariffs. It turns out that these at first counter-intuitive aggregate trends can be well explained with the empirical IV estimates from the micro data. To justify an analysis at the plant level, I document significant cross-sectional dispersion across plants in terms of electricity and labor productivity as well as electricity prices, even within states and industries.

To estimate the effect of electricity prices at the micro level, I use a large panel data set of Indian manufacturing plants from 1998 to 2013, which includes annual information on the quantity and average price of electricity consumed at the plant level. Industry by region by year fixed effects allow for flexible and unobserved aggregate trends in productivity, demand, and prices, differentiated by industry and region, but there remain several further identification challenges that I discuss for my empirical framework. For example, most Indian states have increasing block tariffs for industry such that plants with higher consumption pay higher prices, or plants may negotiate discounts or enjoy favorable relationships with state electricity providers, which could be correlated with their productivity.<sup>7</sup> To address these endogeneity concerns, I use two different instruments based on the institutional context of Indian electricity pricing. The first uses electricity prices paid by other plants in the same state but different industry, kernel weighted by the distance in the quantity of electricity purchased to smooth over block tariffs. The second is a [Bartik \(1991\)](#) shift-share instrument that affects upstream electricity generation costs, based on coal fired generating capacity shares and coal price shifts for power utilities, similar to [Abeberese \(2017\)](#).

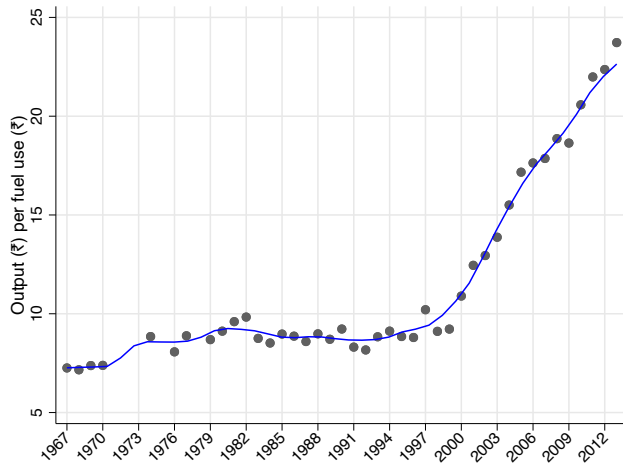
I find that a one-percent decrease in electricity prices increases labor productivity by 0.39-1.06 and electricity productivity by 0.24-0.78 percent for the two instruments respectively. The endogeneity bias in the OLS estimates, however, is large. While the OLS elasticity of labor productivity with respect to electricity prices is close to zero, the OLS elasticity of electricity productivity is of opposite sign as the IV elasticity and statistically significant. I provide a range of robustness checks including additional instruments based on policy shocks that affected electricity prices and an analysis of heterogeneous effects.

The proximate mechanism is that the effect of prices on output outweighs the effect on electricity

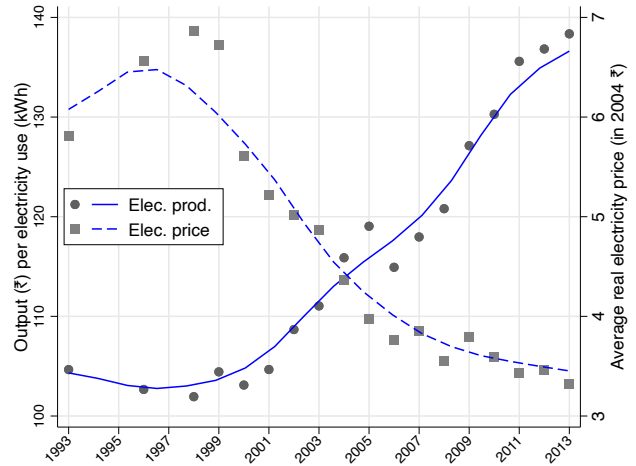
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<sup>6</sup>The patterns in Figure 1 hold within industries and are therefore not driven by mere reallocation between sectors.

<sup>7</sup>[Mahadevan \(2023\)](#) shows that household consumers in the constituencies of the winning party were allowed to manipulate electricity bills in India.



(a) Energy productivity (long run)



(b) Electricity productivity and prices

**Figure 1:** Long run energy productivity, electricity productivity and electricity prices

Notes: Panel (a) plots annual energy productivity ratios (aggregate value of output divided by the aggregate value of fuel and electricity used) in Indian manufacturing over the longer run. Output is deflated at the 2-digit industry level using 2-digit industry deflators before aggregating over industries. Fuel and electricity use is deflated using a general fuel and electricity wholesale price deflator. From 1967 to 1997 the raw ASI data in pre-aggregated form is used at the industry-state-year level. From 1998 the raw plant level ASI data is used and aggregated with sampling multipliers. Panel (b) plots annual aggregate electricity productivity ratios with the solid line (value of output divided by the quantity of electricity used in kWh) and real average electricity prices in the dashed line. Aggregate electricity productivity is calculated by first aggregating the value of output and the quantity of electricity consumed (bought and generated) by plants, and then taking the ratio of the aggregates. Real average electricity prices are calculated by first aggregating the value and quantity of electricity bought by plants, and then taking the ratio of the aggregates. Plant output is deflated using 3-digit industry deflators before aggregating over industries. Electricity values are deflated using a general fuel and electricity wholesale price deflator. All data points come from the raw plant level ASI data (from 711,166 observations including years before 1998) and aggregated with sampling multipliers. The base year for deflation is 2004 throughout this paper. Wholesale price deflators are from the Office of the Economic Adviser from the Government of India.

consumption or employment. I find that, as total variable costs increase, plants scale up with lower electricity prices. To shed more light on deeper mechanisms, I test predictions of the nested CES production model, use exogenous shocks to machinery capital for a subset of plants from the timing of India's FDI liberalization in 2006, and examine further plant decisions and outcomes. I present evidence that lower electricity prices significantly increase profits, plant total factor productivity (TFP), wages, investment in machinery, labor, machine to labor ratios, machine to electricity ratios, and markups. These results corroborate all model predictions including those that allow me to distinguish the model from standard CES models, and are consistent with a setting where electricity prices influence investment and technological decisions. Lower prices can incentivize firms to invest in modern electricity-using machinery, processes and products, especially for plants with initially low machinery penetration. This, in turn, improves productivity and output more than labor and electricity use.

I then estimate effects on welfare. While there are clear positive effects on firms, consumers can be affected by pass-through of electricity costs to output prices, while power utilities can be affected through decreased revenues.<sup>8</sup> I exploit detailed information on output quantities and prices in the data to estimate

<sup>8</sup>The degree to which consumers and producers share surplus is determined by how well producers can substitute to electricity, by their market power and demand elasticities, and how marginal costs are passed-through to prices.

pass-through elasticities by industry using the above instruments for marginal costs. I then combine these with my estimates of plant level market power and estimates of demand elasticities to recover plant level pass-through rates and consumer and producer incidence shares under imperfect competition in a generalized oligopoly. On average, two thirds of the incidence of lower electricity prices fell on consumers. Total welfare gains from the 48% reduction in electricity prices are US\$99 billion, which comprises US\$38 billion gains for firms, US\$64 billion gains for consumers, and US\$3 billion losses for utilities.

I end the paper by considering the environmental implications via CO<sub>2</sub> emissions and contrast the findings of electricity price effects with effects of coal prices on industries, which also provides an additional test of mechanisms. First, using emission factors for specific fuels and the Indian grid, I estimate a 41.7Mt increase in CO<sub>2</sub> emissions from the 48% price reduction, equivalent to an additional welfare loss of US\$4.2 billion at a social cost of carbon of US\$100 per tCO<sub>2</sub>. This increase in emissions is driven solely by scale as efficiency increased, and I show that without the estimated improvement in electricity productivity, the emission increases would have been over double.<sup>9</sup> Second, the effect of coal prices are opposite to the effects of electricity prices. I estimate that lower coal prices *decrease* coal productivity and have no significant effect on labor productivity and other measures of firm performance. Comparing the effects of electricity and coal prices provides further evidence on the mechanism that electricity, unlike coal, has a special role in industrial modernization as complementary input. This finding is also relevant for climate policy, particularly regarding relative taxation of fossil fuels and electricity in developing countries.

The remainder of the introduction gives a brief overview of the literature. Section II sets up the conceptual framework and generates testable predictions. Section III provides insights into the context of Indian electricity supply relevant for identification, describes the data, and presents patterns of labor and electricity productivity and prices in the data. Section IV develops the empirical strategy. Section V presents and discusses results along with robustness checks, evidence on mechanisms, and policy implications, before I conclude in Section VI.

### A. Related Literature

This paper contributes to the broader literature on industrial development and the importance of capital intensive production technologies (Caselli, 2005), and how cheaper prices of some inputs can help in this process (Acemoglu et al., 2012; Goldberg et al., 2010; Verhoogen, 2023; Aghion et al., 2022), especially with complementarity between energy and capital (Berndt and Wood, 1979; Pindyck and Rotemberg, 1983; Atkeson and Kehoe, 1999).<sup>10</sup> I show that cheaper access to a critical input for modern production,

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<sup>9</sup>Similarly, estimated firm fuel substitution from coal to electricity attenuated the increase in emissions.

<sup>10</sup>See Acemoglu et al. (2012) on how this matters for the direction of technical change, Goldberg et al. (2010) or Martin (2012) as an empirical example of traded inputs, Krusell et al. (2000) who show how cheaper ICT prices drove the skilled wage premium due to complementarities, or Ding et al. (2022) who show that a decline in input prices increases non-manufacturing “knowledge” employment in the presence of complementarities between physical and knowledge capital. Verhoogen (2023) provides a recent literature review on firm upgrading.



electricity, can increase capital investments and help transition to modern industrial technologies, while cheaper coal does not have the same benefits.<sup>11</sup> While electrical machines have a labor replacing effect, I find that this is overcompensated by labor demand increases through the associated boost in productivity and scale, similar to the two opposing effects of automation through direct labor replacement and indirect employment increases through productivity (Acemoglu and Restrepo, 2018; Aghion et al., 2022).

This paper also contributes to the literature on impacts of energy, and electricity prices in particular, on firm outcomes. Abeberese (2017) studies the effect of electricity prices on firm performance and industry switching in India, but there are important differences to this paper.<sup>12</sup> Her main finding is that higher electricity prices induce firms to switch to less electricity intensive industries and products, suggesting lower prices *decreased* electricity productivity in India, using pre-defined industry intensities which, however, ignore any improvements within industries by design. By instead measuring firm electricity productivity directly and using multiple instruments, I show that lower prices, on the contrary, made firms more electricity productive (i.e less electricity intensive) despite using more electricity, and show how this apparent puzzle can be rationalized with a model and testable predictions.<sup>13</sup> Davis, Grim and Haltiwanger (2008) is one of the first studies on plant level electricity productivity and prices. They find a positive elasticity for most industries in the US, which, however, is in a context of already highly mechanized production compared to the Indian context.<sup>14</sup> This comparison emphasizes that there are potentially differential impact of electricity prices depending on the stage in industrial development.<sup>15</sup>

In the developing context, there are several studies that find a positive elasticity of electricity productivity to electricity prices, but using OLS rather than instrumenting for prices, consistent with the OLS findings in this paper which are of opposite sign as the IV estimates (Fisher-Vanden et al., 2004; Hang and Tu, 2007; Fisher-Vanden et al., 2016; Rentschler and Kornejew, 2017). A range of studies analyze the impact of energy prices on outcomes other than electricity productivity, mainly on employment or output (Deschenes, 2011; Kahn and Mansur, 2013; Cox et al., 2014; Aldy and Pizer, 2015; Sadath and Acharya, 2015; Popp, 2002; Marin and Vona, 2021). Most of these estimates, however, either rely on state level prices that ignore the substantial heterogeneity in electricity prices across plants that this paper or Davis et al. (2013) reports, or use an index of all energy sources, not just electricity, mixing the potentially opposite effects of electricity and fossil fuel prices. The findings in this paper also tie into the literature of

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<sup>11</sup>Cali et al. (2022) show that lower coal prices could even lead to productivity losses. Macher, Miller and Osborne (2021) show that cement plants adopt efficiency enhancing technology when fossil fuel prices are high. Hawkins and Wagner (2022) show that energy price impacts on efficiency also depend on adjustment frictions to capital that may prevent firms from updating technology.

<sup>12</sup>Similarly, Elliott, Sun and Zhu (2019) study the effect of electricity prices on industry switching in China.

<sup>13</sup>I also use a longer panel with three times the observations to corroborate some of the findings on other firm outcomes.

<sup>14</sup>Using sectoral price data, Linn (2008) also finds a positive elasticity of electricity productivity to energy prices in the US. His findings suggest that entrants' energy efficiency respond more to energy prices than that of incumbents. See also Hawkins and Wagner (2022) for an analysis of persistent effects of electricity prices on entrants in the US, and Pizer et al. (2002) who study technology adoption, energy prices and aggregate energy efficiency.

<sup>15</sup>Their period of study was characterized by rising prices in the US, rather than declining prices from comparatively high levels as was the case in India, so another explanation could be that effects on production technologies are asymmetric.

the effects of environmental policy, especially carbon pricing, on firm performance (Martin, De Preux and Wagner, 2014; Martin, Muûls and Wagner, 2015; Calel and Dechezleprêtre, 2016; Dechezleprêtre and Sato, 2017). Carbon pricing tends to lower electricity prices relative to fossil fuel prices, and thus the relative price of clean and dirty energy that matters for directing investment and clean growth as in Acemoglu et al. (2012).<sup>16</sup> Finally, this paper also contributes to the literature on energy cost pass-through and incidence shares between firms and consumers (Weyl and Fabinger, 2013; Fabra and Reguant, 2014; Ganapati, Shapiro and Walker, 2020; De Loecker et al., 2016; Miller, Osborne and Sheu, 2017; Hausman, 2018).

## II. A Simple Model of Technology Choices with Electricity Price Changes

It is helpful to begin by showing how the presence of different production technologies can fundamentally alter the impact of electricity price decreases on firm outcomes. Suppose a firm has a standard nested CES production function to produce sales  $PQ$ , where the upper nest is given by:

$$PQ = A(\alpha_l L^{\rho_l} + (1 - \alpha_l) X^{\rho_l})^{\frac{\phi}{\rho_l}}, \quad (1)$$

where  $A$  is TFP,  $L$  is labor and  $X$  capital services. The returns to scale are  $\phi < 1$  which represents a bundle of (possibly increasing) returns to scale in production and decreasing returns in demand.<sup>17</sup> The elasticity of substitution between labor and capital services is governed by  $\rho_l \leq 1$  and the labor share parameter is  $\alpha_l$ . Capital services are produced in the inner nest combining machinery capital and electricity:

$$X = (\alpha_e E^{\rho_e} + (1 - \alpha_e) K^{\rho_e})^{\frac{1}{\rho_e}} \quad (2)$$

Capital  $K$  and electricity  $E$  are complementary inputs, i.e.  $\rho_e < 0$ , and  $\alpha_e$  is the shape parameter. The innovation in the model is that there are two discrete (i.e. non-convex) types of technology  $c$  available, both of which require all three inputs. The first type ( $c = 1$ ) is a traditional technology which is more labor intensive, and where capital relies to a smaller degree on electricity (e.g. traditional textiles manufacturing). The second type ( $c = c' > 1$ ) is a modern technology, which is capital service intensive, and uses modern machinery that relies to a larger degree on electricity as complementary input. The difference in technology is represented by altered parameters in the production function to capture three key features of modern production: changes in the capital service intensity ( $1 - \alpha_l$ ), the complementarity between capital and electricity  $\rho_e$ , and in fixed costs. The parameters are affected by technology choice

<sup>16</sup>The Porter and Van der Linde (1995) hypothesis, which postulates firm performance benefits from environmental regulation, may apply to fossil fuels, but not necessarily to electricity. See Lu and Pless (2021) for an empirical example focusing on fossil fuel regulation in China.

<sup>17</sup>The bundle consists of  $\phi = \hat{\phi}(\eta + 1)$ , where  $\hat{\phi}$  are the returns to scale and  $\eta$  the inverse demand elasticity.

$c \in \{1, c'\}$ , where  $c' > 1$ :

$$\begin{aligned}\alpha_l &= \hat{\alpha}_l/c \\ \rho_e &= \hat{\rho}_e \cdot c\end{aligned}\tag{3}$$

Compared to the traditional technology ( $c = 1$ ), the modern technology ( $c = c' > 1$ ) increases the share of capital services to  $(1 - \hat{\alpha}_l/c')$  and decreases the labor share to  $\hat{\alpha}_l/c'$ , capturing more capital intensive production. It also increases the complementarity between capital and electricity to  $\hat{\rho}_e c'$  (as  $\hat{\rho}_e < 0$  the absolute value of  $\hat{\rho}_e$  is increased), as modern machines are more reliant on electricity to produce.

There are fixed costs  $m \cdot c$  associated with choosing a particular technology  $c \in \{1, c'\}$ , where  $m \geq 0$  such that fixed costs are allowed to be higher for the modern electricity-using production process. A firm maximizes profits  $\Pi$  given input prices  $p_K, p_L$  and  $p_E$ :

$$\max_{K,L,E,c} \Pi = PQ - p_K \cdot K - p_L \cdot L - p_E \cdot E - m \cdot c\tag{4}$$

It is useful to recall the effect of prices in a standard set-up without technology choices, where the effect of an electricity price decrease on electricity productivity is unambiguously negative:

**Lemma 1.** *Without discrete technology choices ( $c = c' = 1$ ), an electricity price decrease from  $p_E$  to  $p_E - \Delta_{p_E}$  always decreases electricity productivity  $\frac{PQ^*}{E^*}$ .*

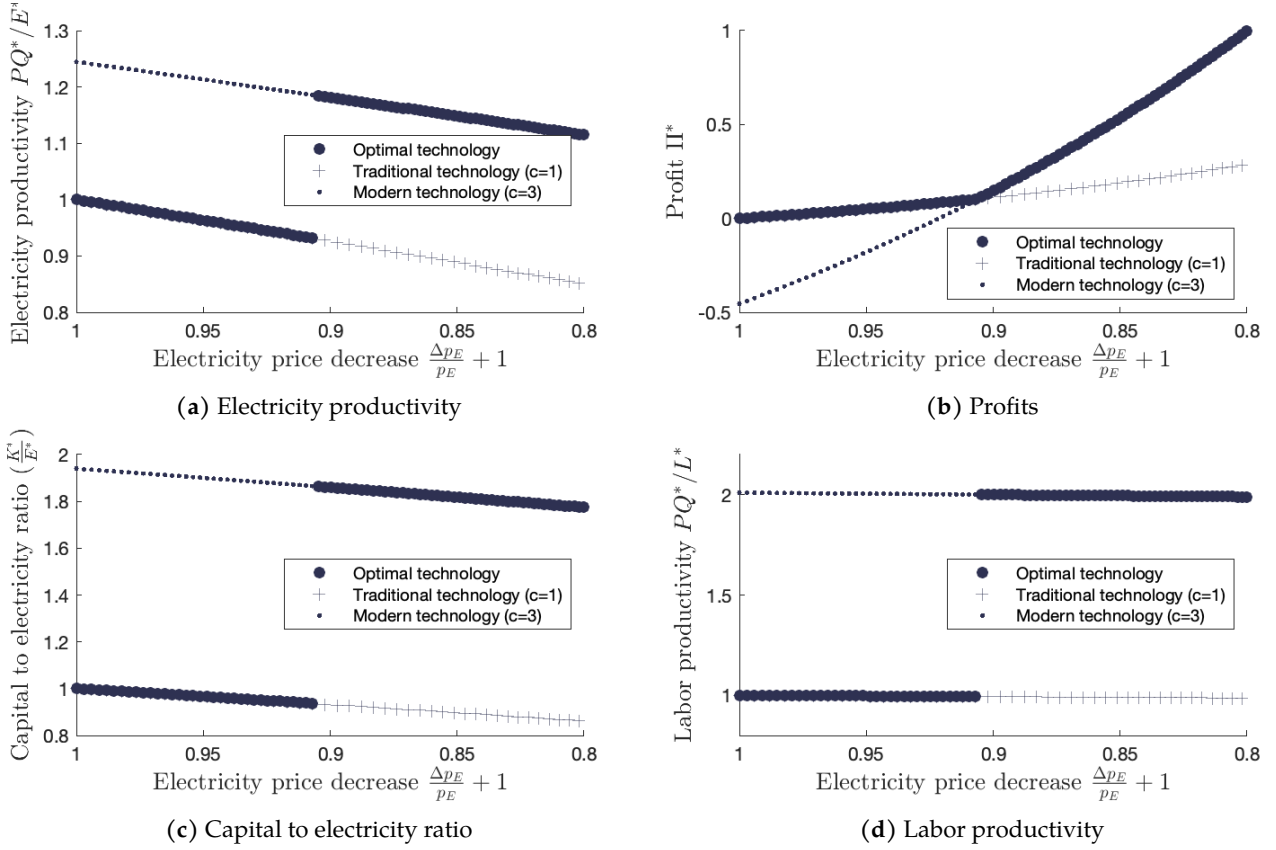
*Proof.* Since  $c = 1$  in all cases, factor demands and output is continuous in factor prices and we can derive the marginal effect  $\frac{\partial \frac{PQ^*}{E^*}}{\partial p_E} > 0$ . Appendix A.1 shows the full proof. ■

However, once we allow for non-convex production technologies, the firm can decide to switch technologies when prices decrease, which will affect electricity productivity. This across-technology effect from lower prices can be larger than the pure within-technology effect of Lemma 1:

**Proposition 1.** *With the availability of discrete technologies  $c \in \{1, c'\}$ , an electricity price decrease from  $p_E$  to  $p_E - \Delta_{p_E}$  can increase electricity productivity  $\frac{PQ^*}{E^*}$ .*

*Proof.* Appendix A.1 provides a proof. ■

Figure 2 provides visualizations of Proposition 1 by solving the model for a given parameter set. These patterns are not unique to this specific set of parameters; indeed they can arise for a broad range of substitution elasticities between labor, capital and electricity as shown in Appendix A.1 (Figure A.1). Panel (a) shows electricity productivity at the optimum  $\frac{PQ^*}{E^*}$  against electricity price decreases. The upper line shows the plot conditional on the modern technology  $c = 3$ , and the lower line for the traditional technology  $c = 1$ . Both are normalized by dividing by the electricity productivity of the traditional



**Figure 2:** The impact of technology choice with electricity price decreases

Notes: The figures plot firm outcomes on the vertical axes (all normalized) against relative electricity price *decreases* on the horizontal axis. Panel (a) shows electricity productivity, Panel (b) firm profits, Panel (c) the capital to labor ratio and Panel (d) labor productivity. The figures show optimal choices both conditional on a specific technology as indicated, and the overall optimum (thick line). All outcomes are normalized by dividing by (for profits: subtracting) its value at the traditional technology ( $c = 1$ ) and original electricity price ( $\Delta_{PE} = 0$ ). The parameter values for this simulation are set to  $\{p_K = 6, p_L = 5, p_E = 0.5, c = 3, \hat{\alpha}_l = 1/3, \alpha_e = 0.5, \rho_l = -0.5, \hat{\rho}_e = -0.5, \phi = 0.95, A = 9.15, m = 1\}$  and  $\Delta_{PE}$  varies from 0 (corresponds to  $p_E = 0.5$ , and 1 on the horizontal axis) to  $1/12$  (corresponds to  $p_E = 0.4$ , and 0.8 on the horizontal axis). As Appendix A.1 shows, these patterns are not unique to these parameter values, but instead exist for a broad range of values.

technology at the original prices. Conditional on technology, both lines are strictly decreasing in electricity price reductions, which reflects Lemma 1. However, as the evolution of profits in Panel (b) shows, the modern technology is preferred once electricity prices are low enough such that it yields higher overall profits. The technology adoption leads to a step change in electricity productivity as shown in Panel (a).

This increase in electricity productivity from lower electricity prices is driven by higher capital utilization required by the complementarity in the new technology. Panel (c) shows that the capital utilization effect can be so large that the capital to electricity ratio increases with the technology switch even though it is electricity that becomes cheaper, not capital. I will test this prediction of the model in the empirical part, which allows distinguishing the model from standard models without discrete technologies, since:

**Lemma 2.** *Without discrete technology choices ( $c = c' = 1$ ), an electricity price decrease from  $p_E$  to  $p_E - \Delta_{p_E}$  always decreases the capital to electricity ratio  $\frac{K^*}{E^*}$ .*

*Proof.* Appendix A.1 shows a proof. ■

Turning to labor productivity, without technology choices, an electricity price decrease can increase or decrease labor productivity, depending on whether labor and capital services are complements or substitutes (similar as in [Acemoglu \(2002\)](#)), illustrated in Figure A.2 in Appendix A.1. Irrespective of the effect under constant technology, the switch to modern technology provides an additional boost to labor productivity, as Panel (d) of Figure 2 shows, driven by a higher utilization of capital services.

Appendix A.2 shows similar graphs for further firm outcomes and input ratios. This provides model predictions that are tested and corroborated in the empirical part of this paper. Appendix A.2 also shows how the introduction of capital constraints, if binding enough, can delay the switch to the modern technology. Finally, Figure 2 only shows the effects on one firm, but for heterogeneous firms the thresholds for switching technologies are at different values of electricity prices, such that aggregate electricity productivity can increase more smoothly with electricity price decreases as shown in Appendix A.2.

### III. India's Electricity Sector, Data and Descriptive Statistics

To set up and guide empirical identification and interpretation, this section first describes the relevant institutional context, followed by an analysis of key trends and variation in the manufacturing data.

#### A. India's Electricity Sector

Where does electricity come from and how do prices come about? I next highlight five key contextual features: (i) electricity is predominately produced by coal fired plants, (ii) generation is mainly state owned with increasing private ownership after deregulation in 2003, (iii) industrial electricity prices came down from a high level, (iv) industrial electricity prices are to be set according to cost pressures and can follow block tariffs, and (v) power shortages and electricity prices are uncorrelated.

*Fuel mix of power generation.*— Electricity is mainly purchased from the grid and most of India's electricity is generated by coal fired power plants (roughly 60%), followed by hydro. The variation in the share of coal plants in generating capacity across states contributes to one of the shift-share instruments in the analysis. This variation in coal capacity shares is mainly determined by the presence of coalfields, as coal accounts for up to two-thirds of production costs in these plants ([IEA, 2015](#)). Appendix A.3 visualizes the geography of coal power plants and coalfields on maps and shows evidence from regressions.

*Ownership and deregulation.*— India's electricity generation is dominated by state and central governments. In 1998, they owned 65% and 30% of installed capacity respectively, with the remaining 5% owned privately ([Ministry of Power, 1998a](#); [Planning Commission, 2001](#)). The Electricity Act of 2003 aimed to open the heavily regulated sector to more competition, which led to an increase in the share of privately owned capacity to 31% by 2013. The opening up of the power market following the 2003 Electricity Act

appears to have contributed to lower electricity prices.<sup>18</sup> Appendix A.4 provides more details relevant for how I use the timing of the Electricity Act together with the location of coalfields to instrument for electricity prices in robustness checks.

*India's high industrial electricity prices.*— The context of India's high industrial electricity prices is important for interpretation of the results. Average electricity tariffs in 1998, the beginning of the analysis period, were the equivalent of 15.7 US cents per kWh (2004 US\$) for industrial users, around 80% higher than the G7 average in nominal terms, or seven times as high in PPP terms, and continued to be higher in nominal terms until 2004 (see Appendix A.5 for more details). This is in stark contrast to residential or agricultural prices (6.8 and 2.6 US cents per kWh in 1998). As a result, state electricity utilities have been loss-making almost across the board, despite industrial electricity prices being above cost recovery (Ministry of Power, 1998b). The main reason for the heavy cross-subsidization across sectors is political as farmers form important voting blocs that governments aim to cater to (Abeberese, 2017).

*Electricity pricing.*— Electricity prices vary locally across manufacturing plants, but have generally been heavily regulated, with price levels tied to cost pressures for generators. Generation, transmission and distribution was largely vertically integrated before 2003 with individual State Electricity Boards setting tariffs for different end-users and locations within their jurisdiction.<sup>19</sup> Unlike in many European countries, industrial electricity tariffs mostly follow flat or slightly increasing block tariffs, as I show in Appendix A.5 using manually collected data from government reports and by plotting plant average prices against quantities to visualize marginal electricity prices. Prices remained heavily regulated after the Electricity Act of 2003 despite some unbundling (Planning Commission, 2001; IEA, 2015). Coal prices are the main cost pressure for coal-fired generators and thus electricity prices. The largest coal producer, government owned Coal India Limited, acts as quasi-monopoly (81% market share in 1998) and supplies most power plants (Preonas, 2018). Coal prices for power generators and industry are set independently and often move in opposite directions (see Figure A.28), important context for identification with one of the instruments. Changes in coal prices for power generators are mainly due to changes in international coal prices and the cost of production (Minsitry of Coal, 2006, 2015).<sup>20</sup> Finally, the the observed fall in industrial electricity prices over the sample period is due to a combination of lower generation costs, deregulation and entry, and reductions in cross-subsidization.<sup>21</sup>

*Electricity prices, power shortages and self-generation.*— India's generated electricity usually falls short

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<sup>18</sup>See Cicala (2017) for how the introduction of market mechanisms reduced US electricity prices.

<sup>19</sup>Regional trading of electricity is highly limited. The networks across regions are in the process of getting better integrated (IEA, 2015). For additional information on unbundling and spot vs. longer term electricity markets see Planning Commission (2001); Cropper et al. (2011); IEA (2015); Ryan (2021); Preonas (2018); Mahadevan (2019).

<sup>20</sup>Since 2010, the coal price contains an additional tax of ₹ 50 per tonne (4% of the price), which also feeds into the coal cost shifting instrument.

<sup>21</sup>Three corresponding examples are in Figure A.28 that shows lower input costs for power plants, Table A.1 that shows lower prices from deregulation and entry following the 2003 Electricity act, and Section A.5 that shows that industrial prices have fallen more than their cross-subsidized counterparts (residential and agricultural).

of required electricity.<sup>22</sup> Distribution companies, however, are generally not allowed to adjust electricity pricing for end-users to clear markets as a response to shortages (Allcott, Collard-Wexler and O’Connell, 2016; Jha, Preonas and Burlig, 2022). Importantly, this institutional context implies that changes in electricity prices are not correlated with changing patterns of power shortages in India. Indeed, the correlation between annual state level power shortages and industrial electricity prices is insignificant and small (see Appendix A.6).<sup>23</sup> For the analysis, if anything, lower electricity prices would be expected to lead to more outages introducing a countervailing downward bias. Nevertheless, I control for shortages in robustness checks in Appendix A.12. One reason for power outages are failures in technical equipment or networks (Allcott, Collard-Wexler and O’Connell, 2016). Another reason is the failure of electricity prices in the wholesale market to account for supply and demand imbalances across hours and days (Jha, Preonas and Burlig, 2022). Coal supply issues, on the other hand, are only responsible for 0.2% to 3.3% of failures in thermal plants,<sup>24</sup> so while coal supply affects electricity prices, it is unlikely to affect outages. Finally, power outages led to adoption of electricity generators by a few larger industrial plants. Importantly, the adoption of electricity generators is mainly driven by insuring against outages and not by electricity prices, since self-generation is typically more expensive than buying electricity from the grid.<sup>25</sup>

## B. Data

*Manufacturing plant level data.*— The main data source is the Annual Survey of Industries (ASI), India’s mandatory annual establishment level manufacturing survey since 1953. Its long history makes it a relatively reliable data source in the development country context. The formal firms contained in the ASI are representative of two-thirds of manufacturing output (Allcott, Collard-Wexler and O’Connell, 2016), with the remaining one-third made up of informal firms or firms with less than 10 employees.<sup>26</sup> By matching panel and cross-sectional editions of the ASI, I retrieve panel identifiers and district codes otherwise only available in the respective editions, and use an annual panel from 1998 to 2013 for the main analysis.<sup>27</sup>

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<sup>22</sup>Total electricity shortages were between 4%-11% between 1998 and 2013 (Ministry of Power, 2018) despite falling average plant load capacity factors. India has one of the highest rates of transmission losses in the world (IEA, 2015).

<sup>23</sup>This is in line with Allcott, Collard-Wexler and O’Connell (2016) who provide further evidence and show that a rainfall based instrument for hydro generation is also not correlated with electricity prices in India. Also note that industrial consumers make up less electricity demand than agricultural and residential users, further watering down any relationship between industrial prices and outages. Finally, there was no substantial change in shortages over the sample period that matches the decline in industrial electricity prices.

<sup>24</sup>Calculated as share of total planned and unplanned outages, annually from 1998 to 2009 using data from Allcott, Collard-Wexler and O’Connell (2016).

<sup>25</sup>Bhattacharya and Patel (2008) estimate self-generation to be at least 25% more expensive than buying electricity. In other developing countries, the price ratio between self-generated and grid electricity is even larger (Fried and Lagakos, 2020).

<sup>26</sup>The survey divides plants into a census sector, where all plants are sampled that have  $\geq 100$  employees (until 2004  $\geq 200$ ), and a sampling sector where 20% within each state by 4-digit-industry strata are sampled. The sampling frame consists of all plants with  $\geq 10$  employees with electricity and all plants with  $\geq 20$  employees without electricity.

<sup>27</sup>The accounting year in India is from April to March. Throughout the paper, I refer to the first year of the accounting year for ASI data and Government reports. So for example, year April 2006 to March 2007 is referred to as 2006. For robustness checks and trends in aggregate statistics, I add the 1993 and 1996 cross sectional editions of ASI micro data. I also use aggregate

I use the quantity and value of electricity purchased, generated, and sold. By dividing the value of electricity purchased by its quantity, I can calculate the average price paid for electricity at the plant level.<sup>28</sup> Electricity productivity is deflated output divided by the quantity of electricity consumed, which includes net purchases and self-generation. Labor productivity is deflated output divided by the number of employees. I use further plant level data on output (sales), employees, wages, intermediate inputs, and other fuel expenditures and quantities (coal, gas and oil). Importantly, I can distinguish between different types of capital and will be using machinery capital, both in terms of book value and investment, as it is the most relevant for this analysis. I construct total variable costs as the sum of wages, input costs, and other variable expenses, and total revenues as the sum of sales and other receipts. The difference is total profits. For the analysis of cost pass-through and incidence, I exploit the information of output sales and output quantity at the plant-product level to construct a measure of output prices and quantity.

I drop observations in non-manufacturing industries, winsorize the lowest and highest percentile of each variable within each year to reduce sensitivity to outliers, and deflate all monetary values to a common base year 2004 throughout the paper.<sup>29</sup> I weight all regressions by the included sampling multiplier. Table 1 shows that after the cleaning steps, there are 485,342 plant year observations from 160,836 plants, and Appendix A.7 provides a brief discussion of the summary statistics.

*Coal prices for thermal power plants and for industry.*— Coal prices for thermal power plants (as opposed to manufacturing plants) are from the [Minsitry of Coal \(2012, 2015\)](#). I use the published annual pit-head prices specifically for power utilities customers and inclusive of royalties and taxes, based on a representative Coal India Limited (CIL) mine and grade selected by the [Minsitry of Coal \(2012\)](#).<sup>30</sup> Shares of coal fired power plants in state installed capacity in 1998 are from the [Ministry of Power \(1998a, 2003\)](#).<sup>31</sup> For the instrument for manufacturing plant level coal prices in Section V.F, I use the pit-head prices specifically for industry with the appropriate coal grades ([Minsitry of Coal, 2012, 2015](#)).

*Additional electricity tariff data and deflators.*— State level average tariffs by consumer type and size are collected from annual reports of the Indian [Central Electricity Authority \(2006-2015\)](#), from [Indiastat \(2019\)](#) and through Lok Sabha and Rajya Sabha (Parliament of India) questions. Data on international industrial energy prices comes from [IEA \(2018b\)](#), and international GDP deflators, exchange rates and

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ASI data at the industry by state by year level from 1967 to 1997 for long run trends.

<sup>28</sup>Average prices are similar to marginal prices as the slope of marginal prices is relatively flat i.e. pricing is fairly linear (Appendix A.5). Note that firms may also react to average rather than marginal prices ([Ito, 2014](#)).

<sup>29</sup>I winsorize final variables only. That is electricity productivity (sales divided by electricity use) is winsorized before sales and electricity use are winsorized to avoid double winsorization. I deflate outputs and inputs using 3-digit industry deflators, investment and installed machinery capital using a machinery deflator, wages, total revenues, total costs and total profits using a state deflator, and fuels and manually collected tariffs and prices (electricity, coal, gas, oil) using a fuel and electricity deflator.

<sup>30</sup>These are the ones of Eastern Coalfields Limited of Coal India Limited, Rajmahal field, Grade E, in line with those used by [Abeberese \(2017\)](#). After 2011, India switched the coal grading from Useful Heat Value (UHV) to Gross Calorific Value (GCV). I use the prices of the new grades G9 based on the correspondence given in [Minsitry of Coal \(2013\)](#). Prices are deflated with the electricity and fuel deflator from [Office of the Economic Adviser \(2019\)](#). Appendix Figure A.28 plots these prices in real terms.

<sup>31</sup>Thermal shares as on 31st of March 1998, one day before the beginning of the sample. Chhattisgarh, Jharkhand and Uttarakhand were created in 2000, and shares correspond to Jan 2003 when data is first available.



**Table 1:** Summary statistics from plant level data

Main variables:		Additional variables:		
	Mean		Mean	Obs.
Electricity bought (GWh)	0.82	Total capital (in mil. ₹)	36	482169
Electricity generated (GWh)	0.21	Mach. capital (in mil. ₹)	21	474372
Electricity sold (GWh)	0.03	Capital investment (in mil. ₹)	8.1	482621
Electricity consumed (GWh)	0.99	Mach. investment (in mil. ₹)	4.1	475490
Electricity price (₹ per kWh)	4.57	Total revenue (in mil. ₹)	119	485263
Electricity share in total var cost	0.058	Total variable costs (in mil. ₹)	101	485263
Electricity productivity (₹ per kWh)	448.5	Total profit (in mil. ₹)	17	485263
Electricity productivity (₹ per ₹)	107	AC-Markup (Price/AC)	1.2	485263
Labor productivity (in mil. ₹)	1.3	MC-Markup (Price/MC)	1.3	477710
Output (in mil. ₹)	119	TFP (Wooldridge)	7.3	477710
Employees	72	TFP (Levinsohn-Petrin)	9.8	477710
<i>Weighted by electricity consumed:</i>		TFP (Olley-Pakes)	7	379038
Electricity productivity (₹ per kWh)	130	Coal consumed (tonne)	383	485342
Electricity productivity (₹ per ₹)	33	Coal price (₹ per tonne)	4153	49605
<i>Weighted by fuel consumed:</i>		Coal price (₹ per kWh equivalent)	0.64	49605
Electricity share in fuel expenditure	0.63	Coal productivity (₹ per th. tonne)	1077	49605
Observations	485342	Coal productivity (₹ per ₹)	296	49605
Firms	160836	<i>Weighted by coal consumed:</i>		
Districts in sample	541	Coal productivity (₹ per th. tonne)	56	49605
States in sample	32	Coal productivity (₹ per ₹)	23	49605
Regions in sample	6			
4-digit industries in sample	133			
2-digit industries in sample	22			

Notes: The tables shows the sample means based on the pooled plant level data from 1998-2013. The means are calculated using the sampling multiplier as weights. Where indicated, the means are additionally weighted by the consumed electricity, fuel or coal to make the means more representative of aggregate productivities. Marginal cost (MC) markups are calculated following [De Loecker and Warzynski \(2012\)](#), and plant TFP are calculated using [Wooldridge \(2009\)](#), [Levinsohn and Petrin \(2003\)](#), or [Olley and Pakes \(1996\)](#) as indicated. See [Singer \(2019\)](#) for a detailed example of TFP estimation using [Wooldridge \(2009\)](#) in the Indian context.

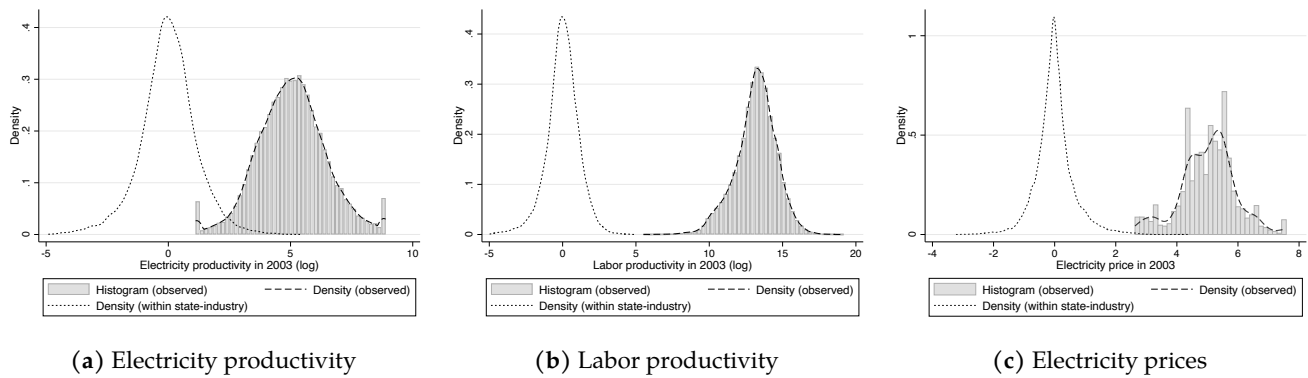
PPP conversion factors from [World Bank \(2017\)](#). Deflators for India (industry-wise, electricity and fuel, machinery) are from the [Office of the Economic Adviser \(2019\)](#) and the state-wise deflator is from the [Reserve Bank of India \(2019\)](#).

*Coalfields, power plants, and power shortages.*— Geo-located data on Indian coalfields is from [Trippi and Tewalt \(2011\)](#) which I combine with geo-located data of the 541 districts from the [Database of Global Administrative Areas \(GADM\)](#) to calculate distances. Geo-located data on the capacity, commissioning and ownership of coal fired power plants comes from the [Center for Media and Democracy \(2017\)](#), for gas plants from [KAPSARC \(2018\)](#), for nuclear plants from [NPCIL \(2015\)](#) and for hydro plants from [Gupta and Shankar \(2019\)](#). Data on state level power shortages comes from the [Central Electricity Authority \(2006-2015\)](#), and from [Allcott, Collard-Wexler and O’Connell \(2016\)](#) for before 2005.

### C. Trends and Heterogeneity in Electricity and Labor Productivity and Prices

To motivate the main analysis I next present key empirical patterns in the data.

*Industrial energy and labor productivity over 50 years.*— Panel (a) of [Figure 1](#) shows that there was a remarkable increase in energy productivity, more than doubling from 2000 until 2013, after staying roughly constant between 1967 and 1999. This was not driven by a particular state or industry alone (see



**Figure 3:** Heterogeneity in electricity and labor productivity and in electricity prices

Notes: Panel (a) plots the histogram of plant level logged electricity productivity in 2003. Electricity productivity ratios are the value of output divided by the quantity of electricity used in kWh. The kernel density plot to the left shows the distribution of the residuals of logged electricity productivity after partialling out state by 4-digit industry by year fixed effects. Panel (b) and Panel (c) show the same plots for labor productivity and electricity prices in 2003. The patterns are similar for all years as shown in Appendix Figures A.22, A.23 and A.24.

Appendix Figures A.12 and A.14), and is in contrast to the evolution in OECD countries (Figure A.18).<sup>32</sup> Figure A.11 shows that labor productivity increased more steadily during these five decades.

*Industrial electricity and labor productivity, and prices and wages 1993-2013.*— Panel (b) of Figure 1 shows that electricity productivity increased by 34% from 1998-2000 to 2013. This trend did not occur because of substitution away from electricity. If anything, there was substitution away from other fuels to electricity.<sup>33</sup> As noted in the beginning, this secular increase in electricity productivity occurred while electricity prices fell by 48% during the same period. As I will show below, the paper can explain these at first puzzling patterns. Indeed, simply taking the aggregate data points of Panel (a) in Figure 1 yields an elasticity of -0.4, remarkably close to the plant level IV estimates in the main analysis (but of opposite sign to the plant level OLS estimates). Appendix A.9 shows that this pattern is consistent across sectors and states, and not a story of mere across-sector or spatial reallocation.<sup>34</sup> The Appendix also confirms the trends using alternative production and price data sources (IEA, 2016; UNIDO, 2016; Office of the Economic Adviser, 2019), including manually collected tariffs from publications by the electricity regulator, and contrast the electricity price decline with the 40% price increase in OECD countries. Finally, during the electricity price decline from 1998-2000 to 2013, labor productivity and wages increased by around 90% and 60% respectively (see Figure A.11). The IV results below suggest that the electricity price decline explains a sizable portion of the increase in labor productivity and to a smaller extent in wages.<sup>35</sup>

*Heterogeneity in electricity and labor productivity and prices.*— Before setting up the econometric analysis at

<sup>32</sup>The increase in energy productivity is consistent with the drop in emission intensity from 1990-2010 for a subsample of large firms reported in Barrows and Ollivier (2018).

<sup>33</sup>The electricity share in the fuel mix grew from around 16 to 20% in energy units, as Appendix Figure A.19 shows. The share of electricity in fuel expenditure was roughly constant at 65% from 2000-2013 implying higher quantity used as price decreases substantially. This implies that fuel productivity of fuels other than electricity increased considerably since 2000, as Figure A.17.

<sup>34</sup>Ghani, Goswami and Kerr (2014) report an increase in electricity productivity in the 2000s mainly from within state-industry clusters.

<sup>35</sup>Note that a pure substitution towards electricity would decrease labor use and wages, absent increases in scale.

the plant level, it is crucial to ask how much variation in prices and productivities there is actually left when looking *within* industries and states. To this end, Figure 3 plots the histograms of electricity productivity, labor productivity and electricity prices in 2003.<sup>36</sup> It shows that there remains substantial variation even after partialing out state by industry (4-digit) effects. Plants at the 90th percentile pay still around 50% higher electricity prices than those at the 10th percentile within state by industry clusters within the same year. Plant labor and electricity productivity at the 90th percentile is 160% and 170% higher than at the 10th percentile, larger than many of the TFP dispersions found in the literature (Bartelsman and Doms, 2000; Syverson, 2004, 2011). Appendix A.10 presents a more formal variance decomposition following Davis et al. (2013), showing that state by industry effects can only account for about half the variation in input productivities or electricity prices.<sup>37</sup> Finally, I show in Appendix A.10 that plant electricity prices and productivity are persistent in the sense of first order stochastic dominance through time following Farinas and Ruano (2005). This persistence within plants, together with the substantial variation across plants in the data, suggests an empirical strategy that also includes between-plant variation.

#### IV. Empirical Strategy

Using plant level data, the first goal of the empirical analysis is to estimate the effect of electricity prices on outcome  $y_{jisrt}$ , for example on electricity productivity or labor productivity:

$$y_{jisrt} = \beta \log(P_{jisrt}^E) + \alpha_{irt} + \epsilon_{jisrt} \quad (5)$$

where  $y_{jisrt}$  is in logs and  $P_{jisrt}^E$  is the electricity price for plant  $j$  in industry  $i$  in state  $s$  in region  $r$  in year  $t$ .<sup>38</sup> The analysis is conditional on 4-digit industry by region by year fixed effects  $\alpha_{irt}$ . The fixed effects account for confounding aggregate trends that may be correlated with electricity prices and outcomes, such as technology and productivity, demographics, demand for manufacturing products, or industry structure and product prices. These unobserved trends are all allowed to be differentiated by both 4-digit industry as well as by region, in part because there is poor integration of electricity markets across Indian regions (IEA, 2015; Ryan, 2021; Ministry of Power, 2018).

The above specification deliberately avoids plant fixed effects for three reasons.<sup>39</sup> First, between-plant variation is likely to capture a substantial amount of the key mechanism that is technology differences and upgrading within industry-region-years, compared to mere within-plant variation.<sup>40</sup> As shown in Section

<sup>36</sup>Similar plots are shown in Appendix Figures A.22, A.23 and A.24 for all years.

<sup>37</sup>The Appendix also shows that there has been some convergence in prices over time.

<sup>38</sup>There are 133 4-digit industries, 32 states and 541 districts in the final sample. There are five power grid regions, where I split one of them to reflect standard groupings into six regions in national accounts.

<sup>39</sup>I rely on the plant identifiers for inference as discussed in Section IV.E. Including plant fixed effects in the main regression yields similar results, although with a loss of precision for one of the instruments.

<sup>40</sup>Including plant fixed effect can be thought of using short-run variation, while excluding plant fixed effects also exploits variation relevant for the medium or longer run, such as changes in production processes (Ganapati, Shapiro and Walker,

III.C, there is much interesting variation between plants that plant fixed effects would eliminate due to persistency within plants. A regression of logged electricity productivity on plant fixed effects can explain 80% of the variation ( $R^2$ ). Second, plant fixed effects require a strict exogeneity assumption, which is likely violated and can introduce further bias. Past shocks to output and electricity or labor productivity are likely correlated with current electricity prices, as block tariffs can change with consumption.<sup>41</sup> Third, plant fixed effects fail to address time-varying endogeneity issues at the plant level. To tackle these concerns effectively, I instead employ an instrumental variable strategy, as explained below.

#### A. Endogeneity Concerns

To structure the discussion about endogeneity concerns, it helps to think about the exogenous and endogenous components in  $\log(P^E)_{jisrt}$  within industry-region-year groups in Equation (5).

The exogenous components of prices can vary locally as discussed in Section III.A, determined by changes in costs of electricity generation or policies and tariff regulation that are orthogonal to plant level shocks. Suppose the endogenous elements contained in the price can be expressed as idiosyncratic component  $\xi_{jisrt}$  at the plant level and  $\lambda_{isrt}$  at the industry by state level. This allows me to rewrite the composite error  $\epsilon_{jisrt}$  as sum of endogenous elements and true random error  $\mu_{jisrt}$ :

$$\epsilon_{jisrt} = \xi_{jisrt} + \lambda_{isrt} + \mu_{jisrt}, \quad (6)$$

The nature of  $\xi_{jisrt}$  and  $\lambda_{isrt}$  comprises several factors, all conditional on controlling for 4-digit industry by region by year fixed effects  $\alpha_{irt}$ . First, shocks to output and electricity demand (in  $\xi_{jisrt}$ ) can also affect electricity prices due to different tariffs for different consumption bands (see Figures A.9 and A.10). Second, plants or groups of firms within an industry may negotiate or exert pressure for lower electricity prices ( $\xi_{jisrt}$  and  $\lambda_{isrt}$ ). Their bargaining power and possible price corruption is likely related to their economic performance, which leads to reverse causality problems.<sup>42</sup> Third, there may be factors within regions and industries not captured by the fixed effects that jointly affect economic performance, electricity productivity and electricity pricing (in  $\lambda_{isrt}$ ).<sup>43</sup> Fourth, even within states, plants and industries may locate where electricity prices are low and that may be correlated to their electricity productivity and consumption (in  $\xi_{jisrt}$  and  $\lambda_{isrt}$ ). Finally, average electricity prices at the plant level may suffer from

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2020). Atkeson and Kehoe (1999) show that responses to energy price changes may not show up in the very short run in typical putty-clay models (see also Hassler, Krusell and Olovsson (2021) or Hawkins and Wagner (2022)).

<sup>41</sup>Chamberlain (1982) describes the theoretical problem of plant fixed effects and strict exogeneity in such regressions (see also Griliches and Mairesse (1999)). Olley and Pakes (1996), for example, show that production function coefficients are even more biased with a plant fixed effects estimator than with pooled OLS.

<sup>42</sup>Furthermore, while manipulation of recorded electricity quantities is primarily an issue at the household level (Mahadevan, 2023) rather than at the firm level, prices here are derived from expenditures and recored quantities, so instrumenting for prices addresses remaining potential bias from this source.

<sup>43</sup>Prices may also respond to changes in aggregate electricity productivity and electricity demand from firms despite being strictly regulated. While the fixed effects account for these secular trends, I use lagged (instrumented) electricity prices in a robustness check to address remaining concerns of reverse causality and find similar results.

measurement error (in  $\xi_{jisrt}$ ). I next turn to my two instrumental variable strategies that aim to isolate exogenous components of the price variation.

### B. An Instrument Based on Other Plants ( $IV^A$ )

The idea of the first instrument ( $IV^A$ ) is that any exogenous components in the electricity price should also affect other plants nearby. Some weighted average of other plants, for example in the same state, could therefore extract the common exogenous signal while being agnostic about the specific source of the signal that could stem from changes in electricity generation costs or differences in regulation.<sup>44</sup>

By construction, some average of electricity prices of other plants removes the idiosyncratic endogenous component  $\xi_{jisrt}$ . To remove the industry level endogenous component, I rely exclusively on information of plants in the same state, but in different 2-digit industries  $i^{2d}$ . The underlying assumption is that the endogenous components  $\lambda_{isrt}$  are not correlated across 2-digit industries within a state, but are allowed to be correlated within 2-digit industries, e.g. through competition in the output market or supply chains.<sup>45</sup> Recall that industry by region by year effects are accounted for by  $\alpha_{irt}$ , so the elements in  $\lambda_{isrt}$  that are also common across regions are allowed to be correlated across 2-digit industries as well. It is worth noting that common endogenous components across plants could also derive from spatial proximity rather than sectoral proximity alone. This could be due to spatially organized bargaining and corruption and other place-based political economy considerations. Therefore, I relax Equation (6) in a robustness check by additionally excluding plants in the same district when constructing a version of this instrument ( $IV^C$ ) with very similar results.

Finally, I give more weight to other plants with similar purchase quantities for constructing  $IV^A$  to smooth over potential block tariffs that are based on purchase quantities. Specifically, I use a triangular kernel function with weights  $w_{q^*}(q_j)$  that is based on plants' distance in their purchase quantity:

$$w_{q^*}(q_j) = \begin{cases} \frac{b_{q^*} - |\log(q_j) - \log(q^*)|}{b_{q^*}^2} & \text{if: } \log(q_j) \in [\log(q^*) - b_{q^*}, \log(q^*) + b_{q^*}], \\ & \forall s_j = s_{j^*}, t_j = t_{j^*}, i_j^{2d} \neq i_{j^*}^{2d}. \end{cases} \quad (7)$$

0 otherwise

where  $q^*$  is the electricity quantity purchased in kWh by plant  $j^*$  that we want to create the instrument for, and  $q_j$  is the electricity quantity purchased by other plants  $j$ . The cutoff  $b_{q^*}$  is the 25th percentile of the distribution of the logged ratio of the purchase quantities in absolute terms  $|\log(q_j) - \log(q^*)|$ , and is thus allowed to vary by plant  $j^*$  that we want to instrument for.<sup>46</sup> That is, the support of the kernel weights is

<sup>44</sup>The instrument is somewhat reminiscent of Hausman instruments in demand estimation, which instruments goods prices with prices of the same good in other cities (Hausman et al., 1994; Hausman, 1996; Nevo, 2001). They are relevant because they share the common marginal costs of producing the good (electricity). In a robustness check I used a version of electricity prices with pre-partialed out fixed effects similar to the JIVE estimator in Akerberg and Devereux (2009), with highly similar results.

<sup>45</sup>There are 22 2-digit industries and 133 4-digit industries in the final sample.

<sup>46</sup>The advantage of a bandwidth that is flexible rather than fixed is to ensure that enough observations are used for the

over the 25% of plants that are closest in terms of electricity purchased, conditional on being in the same state  $s_j = s_{j^*}$  and year  $t_j = t_{j^*}$  and in different 2-digit industries  $i_j^{2d} \neq i_{j^*}^{2d}$ . The weight decreases linearly in the distance of logged purchase quantity. The first instrument  $IV^A$  for the electricity price of plant  $j^*$  is then the average of the electricity prices of other plants  $P_{jisrt}^E$ , weighted by the triangular kernel weights:

$$IV_{j^*isrt}^A = P_{jisrt}^E \frac{w_{q^*}(q_j)}{\sum_{q_j} w_{q^*}(q_j)} \quad (8)$$

Identification requires that there are no endogenous factors that are common across *different* (2-digit) industries that affect both electricity productivity and prices simultaneously, but only *conditional* on the industry by region by year fixed effects. Under the identification assumption, the instrument addresses the endogeneity concerns laid out above in Section IV.A. The advantage of  $IV^A$  is that it can be readily calculated in other settings. This can facilitate further analyses of the impact of electricity prices in different contexts, such as developing vs. developed, or high price vs. low price countries.

### C. A Shift-Share Instrument Based on Electricity Generation ( $IV^B$ )

The idea for the second instrument is to use a cost shifter for electricity generation, following [Abeberese \(2017\)](#).<sup>47</sup> Since coal is the largest cost factor in electricity generation (see Section III.A), the price of coal shifts electricity generation costs for power plants, and therefore downstream electricity prices. The instrument is based on a shift-share structure as in [Bartik \(1991\)](#). The shifters are nationally representative coal prices specifically for power utilities (see Section III.B). These shifters are weighted by the pre-sample (March 1998) shares of thermal coal fired capacity in total installed capacity at the state level:

$$IV_{srt}^B = \log(P_t^{CoalPower}) \frac{\text{coal-based installed capacity}_{sr1998}}{\text{total installed capacity}_{sr1998}} \quad (9)$$

Recent advances show that identification in shift-share designs requires only either exogenous shifters ([Borusyak, Hull and Jaravel, 2022](#)) or exogenous shares ([Goldsmith-Pinkham, Sorkin and Swift, 2020](#)). Regarding the shifters, one concern is that coal prices for power generation may also impact firms that use coal directly. As discussed in Section III.A and III.B, in India's case the coal price for power utilities is set independently from the coal price for industry, and is thus unlikely to directly affect manufacturing plants. Indeed, [Figure A.28](#) plots both coal prices in real terms, and shows that often one decreases while the other increases at the same time.<sup>48</sup> In a reassuring robustness check, I exclude all manufacturing plants

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construction of the instruments. I also tried the 10th and the 50th percentile, as well as a fixed cutoff based on the average 25th percentile with similar results.

<sup>47</sup>A similar shift-share instrument for energy prices relying on thermal shares in generation has also been used in [Ganapati, Shapiro and Walker \(2020\)](#) or [Elliott, Sun and Zhu \(2019\)](#). [Linn \(2008\)](#) and [Marin and Vona \(2021\)](#) use national energy prices directly interacted with fixed fuel shares at the plant level.

<sup>48</sup>See also [Abeberese \(2017\)](#) for a subsample.

that use coal directly, which are most likely to be affected by exclusion restriction violations if there are any, but the results are very similar (Table A.11). Regarding the shares, conditioning on industry by region by year fixed effects helps as exogeneity of shares is only required within regions, and allows for correlation of pre-sample shares with industrial structure. I provide a map of the pre-sample thermal shares in Figure A.29. I present additional evidence of exogeneity of shares in Appendix Table A.4, where I show state level regressions of shares on several pre-determined variables using data from Asher et al. (2020) to show that they are uncorrelated, such as with the share of rural population, access to electricity, labor productivity, capital labor ratio, share of wages spent on skilled workers, or fuel share in output. Finally, Adao, Kolesár and Morales (2019) show that standard errors may need adjustment for shift-share designs. Following their procedure, I recover standard errors that are similar or slightly smaller after adjustment, likely due to negative correlation of residuals within clusters that are based on thermal shares.<sup>49</sup>

Instrument  $IV^B$  isolates exogenous movements in electricity prices driven by cost pressures from input prices in upstream generation. An advantage of instrument  $IV^B$  is that it could be less susceptible to specific types of correlated shocks that may threaten the validity of instrument  $IV^A$ , if they exist. The two disadvantages of  $IV^B$  are that it tends to be much weaker than  $IV^A$  and that it is more difficult to replicate in other contexts as it relies on external data.

#### D. Recovering Pass-Through Rates and Consumer Incidence

To shed light on how changes in electricity prices impact consumers that buy from affected manufacturing plants, I need to identify several additional parameters. The incidence share of electricity price changes depend on how electricity prices affect marginal costs ( $MC$ ) through input substitution ( $\gamma \equiv dMC/dP^E$ ), and on the pass-through rate of marginal costs to output prices ( $P$ ) determined by market structure and market power ( $\rho_{MC} \equiv dP/dMC$ ). I employ a partial equilibrium analysis following Ganapati, Shapiro and Walker (2020) that allows for factor substitution, incomplete pass-through and imperfect competition. As they show, in a generalized oligopoly under the assumption that average variable costs are equal to marginal costs ( $AVC = MC$ ), incidence is defined as:

$$I \equiv \frac{dCS/dP^E}{dPS/dP^E} = \frac{\rho_{MC}}{1 - (1 - L\epsilon_D)\rho_{MC}} \quad (10)$$

where  $CS$  and  $PS$  are consumer and producer surplus,  $\rho_{MC} \equiv dP/dMC$  is the pass-through rate of marginal costs to prices,  $L \equiv (P - MC)/P$  is the Lerner (1934) index, and  $\epsilon_D \equiv -[dQ/dP][P/Q]$  the market elasticity of demand. I next describe how I recover the three required parameters  $L$ ,  $\epsilon_D$  and  $\rho_{MC}$ .

First, I draw on an established literature to recover markups  $\mu$  from the production side using firm revenue and input data (Hall, 1988, 1990; Hall and Jones, 1999; De Loecker and Warzynski, 2012). The

<sup>49</sup>For Table 2, the standard error for Column 3 falls from 0.105 to 0.028 and for Column 6 slightly increases from 0.103 to 0.112.

basic idea is that if plants are cost minimizing, we can use the first order condition of a variable input, which describes a relationship between markups, the output elasticity of that input and the revenue share of that input. I follow this literature to estimate plant level markups ( $\mu = P/MC$ ) using materials as variable input, which determine the plant level Lerner index  $L$  together with observed output prices. I estimate the output elasticity and plant TFP using [Levinsohn and Petrin \(2003\)](#) and [Wooldridge \(2009\)](#).

Second, I use the well-known mapping between markups and demand elasticities implied by first order conditions of profit maximization in oligopolistic environments. I define the market level demand elasticities  $\epsilon_D$  as the median of the plant level demand elasticities within a 4-digit industry by year by state cluster.<sup>50</sup> Market demand structure is thus allowed to vary across industries, time and space. This approach differs from [Ganapati, Shapiro and Walker \(2020\)](#), who instead estimate demand functions, which requires different assumptions. Both approaches require estimating production functions, oligopolistic competition, and cost minimization. The only additional assumption in the approach here is profit maximization, which appears innocuous given the existing assumptions.

Third, the main challenge is estimation of the pass-through parameter  $\rho_{MC}$ . The most direct way is to regress prices on marginal cost, which however requires output prices, not only revenues, as well as marginal cost at the plant level. I leverage the detailed data on plant by product level revenues and quantities that are separately reported for most plants, which allows me to calculate average sales prices at the plant-product level. I construct a plant level average price across products ( $P$ ), weighted by the quantity of each product. From the estimated plant level price marginal cost markups  $\mu$ , I can back out plant level marginal costs  $MC$  with these prices. I recover prices and marginal costs for 88% of the 485,342 observations, covering 121 of the 133 4-digit industries. Since I also construct total variable cost (Section III.B), I can recover  $AVC$  by dividing total variable costs by quantity sold. This allows me to examine the validity of the underlying assumption ( $AVC = MC$ ) for Equation (10). A regression of  $\log AVC$  on  $\log MC$  yields a coefficient of 1.03 and an  $R^2$  of 0.99, indicating that the assumption is reasonable.

With prices and marginal costs in hand, I estimate pass-through *elasticities* for each 4-digit industry separately, regressing prices ( $\log(P)$ ) on marginal costs ( $\log(MC)$ ). Crucially, I already have constructed instruments for electricity prices, so these instruments should also shift marginal costs. This allows me to instrument for endogenous marginal costs using  $IV^A$  and  $IV^B$ .<sup>51</sup> The pass-through elasticity is converted into the pass-through *rate*  $\rho_{MC}$  by multiplying it with the plant level markup  $\mu$ . Pass-through is therefore allowed to differ across industries and plants, where heterogeneity could arise, for example, through

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<sup>50</sup>Plant level markups (and demand elasticities) can diverge from the market demand elasticities, for example, due to distortions. [Singer \(2019\)](#) provides some examples of such distortions in the Indian context. Taking the median or mean of production or demand elasticities is common in the literature, see e.g. [Asker, Collard-Wexler and De Loecker \(2014\)](#).

<sup>51</sup>Endogeneity concerns arise, for example, because marginal costs are estimated leading to measurement error. I use the two instruments separately. Then, for each industry I take the weighted average of the two IV coefficients, where the weights are the t-statistics, to obtain a single pass-through elasticity.



market structure, concentration or market power. To summarize, the empirical components are:

$$\widehat{L}_{jisrt} = 1 - \frac{1}{\widehat{\mu}_{jisrt}}; \quad \widehat{\epsilon}_{D,isrt} = \text{median}_{isrt} \left( \frac{1}{1 - \frac{1}{\widehat{\mu}_{jisrt}}} \right); \quad \widehat{\rho}_{MC,jisrt} = \widehat{\mu}_{jisrt} \frac{d \log(\widehat{P}_{jisrt})}{d \log(\widehat{MC}_{jisrt})}$$

Finally, the incidence of consumer surplus as share of total incidence is:

$$I^{share} = I / (1 + I) \quad (11)$$

### E. Specification Choice, Estimation and Inference

I conclude this section by making a few remarks about model specification and estimation. First, I do not include state by year effects for the baseline specification. This is because  $IV^B$  only varies at the state by year level and much of the exogenous variation is also at the state by year level.<sup>52</sup> Second, I exploit the panel structure to calculate standard errors in all specifications. I two-way cluster errors at the plant level, and at the state by year level, since one of the instruments varies at that level. I provide robustness checks by two-way clustering at the district and the region by year level with similar results. Since I am running the same model with multiple outcomes, I apply the [Holm \(1979\)](#) Bonferroni correction for multiple hypothesis testing in Appendix Table A.23. Finally, I use the two instruments separately to enable comparisons, but also provide results based on an over-identified IV-regression with both instruments.

## V. Results

I first present the main results, along with robustness checks, before I explore mechanisms. Towards the end of this section I estimate the incidence on consumers, calculate the aggregate effects on welfare and emissions, and show the contrary effects of coal prices.

### A. Electricity Productivity, Labor Productivity, and Their Components

*First stages.*— The first stage coefficients, standard errors and Kleibergen-Paap F-statistic are reported in Table 2 and omitted in subsequent tables to avoid repetition. Table 2 shows that both instruments are strong and shift the endogenous electricity price in the expected direction.

*Lower electricity prices improve electricity productivity.*— The OLS correlation between electricity prices and electricity productivity is positive with an elasticity of 0.37 in line with common intuition (Column 1 in Table 2). However, the endogeneity bias in this estimate is large. The IV estimates in Column 2 and 3 are of opposite sign and statistically highly significant, with an elasticity of -0.24 and -0.78 for the two instruments  $IV^A$  and  $IV^B$  respectively. This positive OLS bias suggests that less efficient plants manage to obtain lower electricity prices through, e.g., exemptions, negotiations, corruption or location choices.

<sup>52</sup>Including state fixed effects and state trends generates similar but slightly less precise estimates.

**Table 2:** Electricity prices and electricity productivity

	Electricity productivity (log)			Labor productivity (log)		
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(P^E)$	0.365*** (0.044)	-0.239*** (0.070)	-0.777*** (0.105)	-0.0282 (0.043)	-0.389*** (0.085)	-1.063*** (0.103)
OLS/IV	OLS	$IV^A$	$IV^B$	OLS	$IV^A$	$IV^B$
Observations	485342	485342	485342	485342	485342	485342
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes
First stage coef.	-	0.97***	0.06***	-	0.97***	0.06***
First stage SE	-	0.005	0.003	-	0.005	0.003
F-stat (Kleib.-Paap)	-	43194.635	296.507	-	43194.635	296.507
SE clustered by	Plant	Plant	Plant	Plant	Plant	Plant
No. of first clusters	160836	160836	160836	160836	160836	160836
SE clustered by	State-year	State-year	State-year	State-year	State-year	State-year
No. of second clusters	501	501	501	501	501	501

Notes: The dependent variable is log electricity productivity (value of output divided by the quantity of electricity used in kWh) for the first three columns and log labor productivity for the second three (value of output divided by employees). Each column represents a separate regression at the plant level. The first column reports the results from an OLS regression on logged electricity prices. The second column uses the instrument  $IV^A$  based on the electricity prices of other plants. The third column uses the shift-share  $IV^B$ . The first stage statistics are reported. All regressions contain industry by year by region fixed effects. Regressions are weighted by the recorded sampling multiplier. Standard errors in parentheses are two-way clustered at the plant and the state by year level. Stars indicate p-values: \* < 0.1, \*\* < 0.05, \*\*\* < 0.01.

The effect is more strongly negative for  $IV^B$  than for  $IV^A$ . This could imply either that treatment effects are heterogeneous and the two instruments shift different subpopulations, or that one of the instruments is not completely exogenous assuming homogenous treatment effects.<sup>53</sup> To shed light on whether treatment effects are likely heterogeneous, I follow [Imbens and Angrist \(1994\)](#) and [Imbens and Rubin \(1997\)](#) and discretize electricity prices and both instruments by their median sample split after partialing out fixed effects. In particular, under their monotonicity assumption, I can distinguish between compliers, those observations for which the instrument affects treatment (electricity price), as well as never-takers and always-takers, those that have a low and high electricity price irrespective of the instrument. Comparing the outcome levels in electricity productivity between compliers, never-takers and always-takers for both instruments suggests that the two IV estimates are likely two different local heterogeneous treatment effects as they shift different subpopulations ([Imbens and Rubin, 1997](#)).<sup>54</sup> Importantly, the characteristics of the different subpopulations shifted by the two IVs is in line with the analysis of mechanisms below, where we would expect differential effects:  $IV^B$  shifts plants with relatively lower baseline machinery to labor ratios compared to  $IV^A$ , which results in a larger effect when using  $IV^B$ .<sup>55</sup>

The causal estimates derived from micro data offer a compelling explanation for the aggregate trends observed in electricity productivity and prices in [Figure 1](#). Specifically, with a 48% decline in electricity prices, taking the average local treatment effects between  $IV^A$  and  $IV^B$  of -0.508 predicts a 39% rise in

<sup>53</sup>Table [A.15](#) shows an over-identified model using both  $IV^A$  and  $IV^B$  simultaneously. The Sargan-Hansen J-test rejects that both instruments have the same effect under homogenous treatment assumption.

<sup>54</sup>For  $IV^A$ , electricity productivity is 21% higher for compliers with low electricity prices than for never-takers, while it is 62% for  $IV^B$ . The outcome is 13% lower for compliers with high electricity prices than always-takers for  $IV^A$ , and 32% for  $IV^B$ .

<sup>55</sup>Against an overall mean of the machinery to labor ratio of 0.22,  $IV^B$  compliers with low electricity prices have a previous period ratio that is 0.06 lower than for never-takers (0.01 higher for  $IV^A$ ), whereas the difference between compliers and always takers is near zero for both  $IV^B$  and  $IV^A$ .

**Table 3:** Electricity prices, output, electricity use and employment

	Output (log)			Electricity consumption (log)			Employees (log)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(P^E)$	-0.0268 (0.073)	-0.743*** (0.143)	-1.600*** (0.153)	-0.385*** (0.064)	-0.478*** (0.155)	-0.797*** (0.148)	0.0119 (0.041)	-0.339*** (0.076)	-0.518*** (0.079)
OLS/IV	OLS	$IV^A$	$IV^B$	OLS	$IV^A$	$IV^B$	OLS	$IV^A$	$IV^B$
Observations	485342	485342	485342	485342	485342	485342	485342	485342	485342
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First stage coef.	-	0.97***	0.06***	-	0.97***	0.06***	-	0.97***	0.06***
First stage SE	-	0.005	0.003	-	0.005	0.003	-	0.005	0.003
F-stat (Kleib.-Paap)	-	43194.6	296.5	-	43194.6	296.5	-	43194.6	296.5
Two-way clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is in logs and as indicated either value of output, kWh of electricity use, or employees. Each column represents a separate regression at the plant level. All regressions contain industry by year by region fixed effects. Regressions are weighted by the recorded sampling multiplier. Standard errors in parentheses are two-way clustered at the plant and the state by year level. Stars indicate p-values: \* < 0.1, \*\* < 0.05, \*\*\* < 0.01.

electricity productivity (calculated as  $(1 - 0.48)^{-0.508} - 1$ ). This aligns well with the observed 34% increase at the aggregate level. The IV estimates can therefore explain the secular aggregate trends remarkably well, especially considering that the simple OLS correlation at the micro level is of opposite sign.

*Lower electricity prices improve labor productivity.*— Lower industrial electricity prices have also contributed towards developmental goals. Columns 5 and 6 of Table 2 show that lower electricity prices substantially increase labor productivity, with an elasticity of -0.39 and -1.06 for  $IV^A$  and  $IV^B$  respectively. There is a significant bias in the OLS estimates in Column 4 that are close to zero, and the different local average treatment effect analysis for  $IV^A$  and  $IV^B$  from above applies here as well. Taking the average of the two IV estimates as -0.725, the 48% electricity price decline predicts a 61% increase in labor productivity, explaining two thirds of the 90% increase in labor productivity documented in Section III.C.

*Electricity prices and electricity consumption, employment, and output.*— Why have lower electricity prices improved electricity and labor productivity? I first present the more proximate reasons by unpacking the outcome ratios into its components. Electricity is not a Giffen good. I find that lower electricity prices increase electricity consumption and employment (i.e. labor), as expected, and consistent with the model predictions in Section II and Appendix A.2. Table 3 presents the regressions split up into the components of electricity productivity and labor productivity, with logged electricity consumption (in kWh), employees, or output as dependent variables. In both the OLS and IV regressions, lower electricity prices increase electricity consumption, with the causal effect being slightly larger. A one percent decrease in electricity prices increases physical electricity consumption by 0.48 to 0.80 percent. The OLS estimate for employees is insignificant, but the IV estimates are significant, with a one percent decrease in electricity prices increasing number of employees by 0.34 to 0.52 percent.

The OLS effect of electricity prices on output is close to zero. In contrast, the IV estimates of the output elasticity are large and negative (between -0.74 and -1.59). While the positive OLS bias operates through all three variables, it is most pronounced in output. This implies that the bias comes primarily from

output shocks correlated with electricity prices, for example through exemptions because of negative output shocks or because favorable prices may generate less competitive pressure to perform. The bias is also consistent with attenuation bias from measurement error or endogeneity bias from increasing tariff schedules where shocks to electricity consumption are positively correlated with electricity prices.

The effects on electricity consumption, employment and output are comparable to the ones in [Abeberese \(2017\)](#). Her main finding, however, is that firms with low electricity prices produce products that are on average more electricity intensive, i.e. are *less* electricity productive. That outcome is based on nation-wide average product level electricity intensities of 2000. By design, this ignores the salient differences across time and plants (see [Figure 3](#)) that are crucial in a world of technology differences within industries. Importantly, by instead analyzing firms' electricity productivity directly, I show that Indian firms became *more*, not less, electricity productive with lower prices. Using my larger sample, I also show that there is no evidence of firms producing more electricity intensive products when using nation-wide average product level electricity intensities of 2000 (see [Appendix A.13](#)).

### B. Robustness

Before moving to deeper mechanisms, I conduct a range of robustness checks, with most of the results in [Appendix A.12](#). Overall, these results reinforce the conclusion that the OLS estimates are significantly upward biased and lower electricity prices increased electricity productivity and labor productivity.

*Using lagged prices.*— First, I use lagged prices and instruments to allow for more adjustment time to prices.<sup>56</sup> Using lags cuts the sample roughly in half as spells of plant observations are required. [Tables A.5](#) and [A.6](#) show the contemporaneous effects for the reduced sample and then the lagged effects on electricity and labor productivity. Reassuringly, the IV estimates for electricity and labor productivity hardly change. The positive bias in the OLS estimates, however, is substantially reduced when using lags.

*Using alternative instruments yields similar estimate.*— Second, I use three alternative instruments. The first,  $IV^C$ , is similar to  $IV^A$  except that I exclude plants in the same districts for the construction of the instrument. This allows for endogeneity in electricity prices based on spatial proximity, for example, political economy considerations including corruption or lobbying within districts across industries. The second instrument,  $IV^{D1}$ , is similar to  $IV^B$  in that it is also a shift-share instrument. The shift is the timing of the 2003 Electricity Act and the shares are the distance of district centroids to coalfields, interacted with a dummy identifying states that have any coal power over the sample period.<sup>57</sup> The rationale for  $IV^{D1}$  builds on the findings in [Section III.A](#) and [Appendix A.4](#). The share of private power capacity can explain lower electricity prices, but only from 2003. Since local changes in private power share are likely to be

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<sup>56</sup>This may also address potential remaining reverse causality concerns. Instead of lagged prices, [Table A.14](#) interacts prices with a dummy for the first half of the sample period when prices were relatively higher. This shows that the effects on electricity productivity are larger during the high price period, consistent with the notion that positive implications of decreasing electricity price are particularly beneficial when baseline prices are high.

<sup>57</sup>The triple interaction helps avoid capturing irrelevant states that rely on hydro power as the North-West ([Appendix A.4](#)).

endogenous, I use the district distance to coalfields, as Table A.1 shows that this distance predicts shares in the private power capacity after 2003. Therefore,  $IV^{D1}$  leverages the distance to coalfields interacted with the timing of the 2003 Act as instrument, controlling for all lower order terms. The event study in Figure A.7 shows how higher distance to coalfields increases electricity prices relatively from 2003. The third instrument,  $IV^{D2}$  uses the staggered unbundling of generation, transmission and distribution by states identified by Cropper et al. (2011). Mahadevan (2019) uses the staggered implementation of unbundling in an event study and finds an effect on electricity prices. Appendix Table A.7 shows that the estimates using these alternative instruments are similar to the main IV estimates.<sup>58</sup>

*Controlling for power shortages and distance to coalfields.*— Third, I control for state-year level power shortages, for district distance to coalfields, or both simultaneously in Tables A.8 and A.9. Note that the included industry by region by year fixed effects may already account for a significant portion of power shortages, but directly controlling for these serves as an additional robustness check. The estimates remain negative and are similar in magnitude. This is somewhat expected as I already showed in Table A.3 that shortages are not associated with electricity prices. Both, the distance to coalfields and shortages, however, are significant in explaining electricity and to some extent labor productivity.

*Electricity intensive sectors, no direct coal users, and sector specific analysis.*— Fourth, I restrict the sample to electricity intensive sectors, loosely defined as the 2-digit sectors with an above average electricity intensity. Effects are similar as Table A.10 shows. Next, I restrict the sample to exclude all plants that use coal directly in their inputs in Table A.11 to show robustness to remaining concerns about the shifter based on coal prices for power utilities in  $IV^B$ . I also run the analysis separately for six broad industry groups in Tables A.12 and A.13. The effects are broadly similar across sectors, except perhaps for metals and minerals, where estimates are insignificant, but still correcting an upward bias in the OLS estimates.<sup>59</sup>

*Alternative clustering of standard errors and multiple hypothesis testing.*— Fifth, I two-way cluster at the district and the region year level to allow for more arbitrary correlation in errors, with slightly larger standard errors but still significant results (Table A.17). Finally, I adjust all p-values upwards to account for multiple hypothesis testing in Table A.23. Almost all estimates remain statistically significant.

### C. Mechanisms

I next explore deeper mechanisms by testing model predictions from Section II, exploiting additional exogenous variation, and showing the impacts of electricity prices on several outcomes.

*Testing model predictions: scaling up, investment and input ratios.*— In the model in Section II, electricity is a complementary input to modern production techniques. Lower electricity prices can incentivize to

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<sup>58</sup>With the exception of  $IV^{D2}$  and labor productivity as outcome, which, however, is a noisy estimate.

<sup>59</sup>Since the basic metals industry relies predominantly on coal across many production techniques, there could be a null effect, as that there is less scope to move to electricity-based production. Figures A.14 and A.15 support this hypothesis. While energy productivity rose in this sector, electricity productivity remained fairly stable.

**Table 4:** Electricity prices and firm performance: scale, substitution, productivity and markups

## (a) Profitability and scale

	Profits (mil. ₹)			Total revenues (mil. ₹)			Total variable costs (mil. ₹)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(P^E)$	-5.037*** (1.515)	-20.47*** (3.243)	-22.03*** (3.999)	-30.41*** (8.863)	-132.3*** (19.734)	-139.5*** (21.182)	-24.25*** (7.405)	-109.1*** (16.537)	-114.4*** (17.458)
OLS/IV	OLS	$IV^A$	$IV^B$	OLS	$IV^A$	$IV^B$	OLS	$IV^A$	$IV^B$
Observations	485263	485263	485263	485263	485263	485263	485263	485263	485263

## (b) Input ratios

	Machinery to labor (log)			Labor to electricity (log)			Machinery to electricity (log)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(P^E)$	-0.160** (0.065)	-0.627*** (0.114)	-1.517*** (0.151)	0.380*** (0.041)	0.122 (0.092)	0.283*** (0.103)	0.259*** (0.053)	-0.467*** (0.074)	-1.178*** (0.124)
OLS/IV	OLS	$IV^A$	$IV^B$	OLS	$IV^A$	$IV^B$	OLS	$IV^A$	$IV^B$
Observations	467686	467686	467686	485342	485342	485342	467686	467686	467686

## (c) Investment and fuel substitution

	Investment in machinery (IHS)			Ratio electricity to coal quantity			Other fuels' share in output		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(P^E)$	0.158 (0.204)	-0.852** (0.390)	-2.890*** (0.441)	-10.19*** (3.103)	-17.62*** (5.800)	-22.09* (12.383)	0.00440*** (0.001)	0.0135*** (0.002)	0.0234*** (0.003)
OLS/IV	OLS	$IV^A$	$IV^B$	OLS	$IV^A$	$IV^B$	OLS	$IV^A$	$IV^B$
Observations	475489	475489	475489	47968	47968	47968	485342	485342	485342

## (d) Average wages, TFP and markups

	Average wage per worker (log)			TFP (log) (Wooldridge, 2009)			Price-MC markups $\log(\mu)$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(P^E)$	0.0314** (0.014)	-0.142*** (0.028)	-0.177*** (0.033)	-0.00699*** (0.002)	-0.0156*** (0.003)	-0.0330*** (0.006)	-0.0183*** (0.006)	-0.0404*** (0.011)	-0.106*** (0.019)
OLS/IV	OLS	$IV^A$	$IV^B$	OLS	$IV^A$	$IV^B$	OLS	$IV^A$	$IV^B$
Observations	444064	444064	444064	477697	477697	477697	484943	484943	484943

Notes: Each column represents a separate regression at the plant level. The dependent variables are indicated and described in Section III.B. In Panel (a), the outcomes are in levels because profits cannot be negative. In Panel (b), the ratio of electricity to coal is in quantity terms in MWh per tonne. Other fuels refer to gas, coal and oil. In Panel (c), the inverse hyperbolic sine (IHS) of investment is taken to deal with zeros in investment. All regressions contain industry by year by region fixed effects. Regressions are weighted by the recorded sampling multiplier. Standard errors in parentheses are two-way clustered at the plant and the state by year level. Stars indicate p-values: \* < 0.1, \*\* < 0.05, \*\*\* < 0.01.

use these more modern capital intensive production techniques which generates the increase in electricity and labor productivity. I next test all predictions of the model visualized in Figure 2 and Figure A.3 using reduced form regressions without placing restrictions on complementarities or other model parameters. All predictions of the model can be confirmed with economic and statistically significant estimates.

First, total costs increase despite lower input prices because plants scale up overturning the cost saving effect of lower prices. Table 4a shows the effect on profits, total revenues and total variable costs (in levels). A one percent decrease in electricity prices increases total profits by ₹ 0.21-0.22 million (US\$4,800) per plant, increases revenues by ₹ 1.3-1.4 million (US\$30,000), but also *increases* total variable costs by ₹ 1.1 million (US\$24,000). The increase in variable costs from a decrease of electricity prices is consistent with the prediction of the model in Section II, and implies that plants scale up with declining electricity prices. The increase in employment echoes this scaling up effect (Columns 8-9 in Table 3).

Second, turning to input ratios, lower electricity prices increase machine to labor ratios (Columns 1-3 in Table 4b), driven by additional investment in machinery (Columns 1-3 in Table 4c).<sup>60</sup> Labor to electricity ratios decrease (Columns 4-6 in Table 4b) despite employment increases (Table 3). Importantly, I also find that machine to electricity ratios increase (Columns 7-8 in Table 4b). While these results corroborate all model predictions, confirming this last prediction is perhaps most surprising. In the model, this arises due to the discreteness in technological choices and complementarities in inputs. In a model without technological choices the machine to electricity ratio would instead unambiguously fall (see Lemma 2).

*Using baseline capitalization and FDI shocks to capital.*— Since machine capitalization from lower electricity prices appears to be such a central mechanism, I next provide two further pieces of model-consistent evidence showing that effects are stronger for plants with previously lower machinery to labor ratios.

First, in Figure 4a, I classify plants into low or high machinery capital to labor ratio based on whether they are above or below median ratio within their respective four digit industries in the previous period, and interact this classification with electricity prices, all appropriately instrumented. Consistent with the model, plants with higher relative baseline machinery capitalization, and thus possibly operating already with a more modern technology, see a less positive effect on electricity productivity from lower electricity prices, all differences being statistically significant. This implies that the pure substitution effect is stronger for relatively more capitalized firms, while the output and technology upgrading effect is relatively stronger for less capitalized firms, as shown in Table A.20.<sup>61</sup>

Second, while the previous categorization may be based on possibly endogenous machine to labor ratios, I next use a plausibly exogenous shock to machinery capitalization. Specifically, I use the roll out of financial trade liberalization in India for a subset of industries from 2006. While India underwent a substantial general trade liberalization in 1991, the 2006 policy allowed a subset of industries that were initially restricted to automatically approve foreign capital investments along with an increased maximum cap of foreign capital investments.<sup>62</sup> Bau and Matray (2023) argue that the policy timing for treated industries is plausibly exogenous and show in event studies that the liberalization increased revenues and capital in affected industries. I use a triple differences design based on treated/nontreated industries, pre/post the 2006 policy, and interact it with electricity prices all appropriately instrumented to analyze the differential effect of prices for firms that receive the exogenous shock to their capital.<sup>63</sup> This design is used to test whether firms with more capital show smaller electricity productivity responses from electricity prices. Figure 4b shows the coefficient on the triple interaction in an event study design with electricity productivity as outcome five years before and after the policy took effect. Indeed, after the

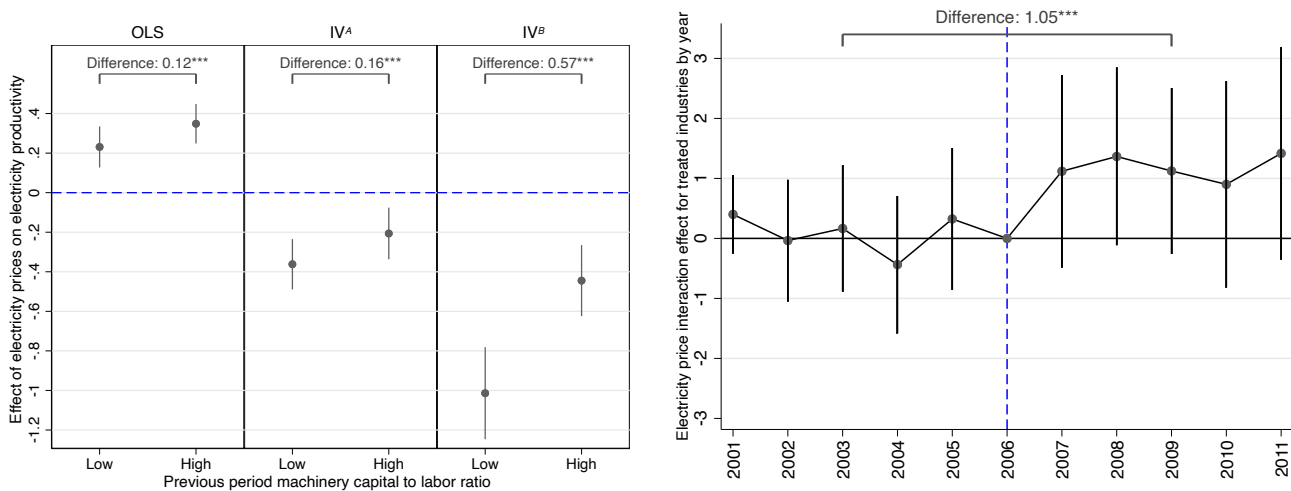
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<sup>60</sup>I use the inverse hyperbolic sine instead of the log of machinery investments to deal with zeros.

<sup>61</sup>This stronger effect also suggests that capital constraints cannot be too severe if we expect low capitalized firms to be more constrained (see Appendix A.2).

<sup>62</sup>See Bau and Matray (2023) for a detailed description. Table A.19 lists the treated industries.

<sup>63</sup>Note that my triple difference design allows me to account for additional unobserved factors by controlling for industry by year by region fixed effects, which would absorb the standard event study effect in Bau and Matray (2023).



(a) Electricity prices and previous machinery to labor ratio (b) Electricity prices and foreign capital access liberalization

**Figure 4:** Electricity price effects by previous machinery labor ratios and foreign capital access liberalization

Notes: Panel (a) shows the effect of electricity prices on electricity productivity by a median sample split within respective four digit industries for plants with a low or high machinery capital to labor ratio in the previous period. The results are reported for OLS and IV with 95% confidence intervals and pairwise tests for equality of coefficients. Panel (b) shows the triple difference coefficient and 95% confidence bands of the interaction of electricity prices, years, and treated industries under the 2006 FDI liberalization, instrumented with  $IV^A$  and electricity productivity as dependent variable. The triple difference coefficient using pre and post rather than individual years is reported above the graph. All regressions are weighted by the recorded sampling multiplier. Standard errors are two-way clustered at the plant and the state by year level.

policy took effect in 2006, the effect of electricity prices is higher for treated plants relative to non-treated plants. The triple difference using the post 2006 period instead of individual years is statistically significant at the 1% level (Table A.21). This means that the firms that received the boost in capital show no increased electricity productivity from lower electricity prices post 2006, while non-treated firms do.<sup>64</sup> While the parallel trends assumption cannot be tested directly, the pre-trends shown in Figure 4b are flat. Table A.21 shows additional results for labor productivity and output using the 2006 policy change.

*Lower electricity prices induce substitution from fossil fuels.*— It is likely that plants not only adjust their ratios between machinery, labor and electricity with different technologies, but also substitute more narrowly between electricity and other energy sources with lower electricity prices. This is important for calculating the impacts on emission later. Table 4c shows that lower prices induce substitution from fossil fuels to electricity. Using plants that report physical electricity and coal consumption, I estimate that the ratio between electricity to coal energy inputs increases with declining electricity prices in Columns 4-6, as plants substitute away from coal. Columns 7-9 show that the expenditure share of fuels other than electricity (i.e. coal, oil and gas) in output also decreases with declining electricity prices. Plants therefore not only electrify by becoming more machine intensive, they also electrify away from fossil fuels. One consequence of this substitution from fossil fuels to electricity is that *energy* productivity, that is output divided by all energy units not just electricity, increases even more than electricity productivity.

*Lower electricity prices increase electric equipment, wages, TFP, product lines, and markups.*— To end this

<sup>64</sup>The combined effect for treated firms is now slightly positive compared to negative for non-treated, see Table A.21.



section, I shed light on additional margins that help understand mechanisms. I first use the product level data on plant inputs that allow me to calculate *electric* equipment inputs as share of total inputs at the plant level. While this particular result should be interpreted somewhat cautiously, as many plants may not report equipment as part of their inputs but rather as part of their machinery capital, it provides an additional test of mechanism. Indeed, Appendix Table A.18 shows that lower electricity prices increase the share of electric equipment, such as powerlooms, consistent with a technology upgrading mechanism.

Second, lower electricity prices may also affect workers through wages, not just employment, particularly as I find increases in labor productivity (Bhagwati and Panagariya, 2014). Columns 1 to 3 in Table 4d show that lower electricity prices increase average wages per worker. This could be driven by either unit cost savings on other inputs (electricity), higher labor productivity due to more capital per worker (Table 4b), increased demand for workers due to upscaling (Table 4a), employing higher skilled workers, or a combination thereof. Taking the average of the two IV estimates of -0.1595, the 48% electricity price decline predicts a 11% increase in wages, explaining 20% of the 60% increase in wages (see Section III.C).

Third, upgrading to more modern capital intensive production processes could also have direct effects on plant TFP. I estimate that the effects on TFP are small (Columns 4-6 in Table 4d), but highly significant and robust to different methodologies of estimating TFP.<sup>65</sup> These results are consistent with firms using technologies that rely more on electricity but also improve performance. There is also evidence that lower electricity prices increase product variety measured as the number of plant product lines (Table A.18).

Finally I examine how electricity prices affect price over marginal cost markups  $\mu \equiv P/MC$  (see Section IV.D). Columns 7 to 9 in Table 4d show that markups increase with declining electricity prices. This implies that the improvement in firm profitability comes from both expansion and technology but also with an increase in markups. This adjustment in markups means that lower electricity prices are only imperfectly passed through to consumers, raising an important question of how the incidence of electricity price changes is distributed, which I analyze next.

#### D. The Incidence of Electricity Price Changes

The degree to which firms pass through changes in electricity prices to consumers determines the incidence of electricity price changes. As described in Section IV.D, I estimate pass-through elasticities by industry and report the cumulative distribution function of these pass-through elasticities as well as two example regressions in Figure A.30. The vast majority of pass-through elasticities is between 0.8 and 1.1. A pass-through elasticity greater than one means that costs are disproportionately passed through to consumers.<sup>66</sup> This can arise producers fail to previously collude in an oligopoly. An increase in costs can help to solve

<sup>65</sup>The main methodology to measure TFP is based on Wooldridge (2009) using deflated revenue data, so should be interpreted as revenue TFP. Since markups shrink, the impact on physical TFP could be slightly larger. Table A.16 reports effects when TFP is measured following Olley and Pakes (1996), Levinsohn and Petrin (2003) or Akerberg, Caves and Frazer (2015).

<sup>66</sup>While the pass-through *elasticity* is smaller than one for the five industries studied in Ganapati, Shapiro and Walker (2020), the pass-through *rate*  $\rho_{MC}$  is also greater than one for three of the five industries and in some of the studies cited therein.

**Table 5:** Electricity price changes and the share of incidence on consumers

<i>Incidence</i>	Oligopolistic competition	Monopoly	Perfect competition
Median	0.63	0.54	1.17
25th to 75th percentile	[0.53 - 0.79]	[0.50 - 0.59]	[0.99 - 1.45]
<i>Components</i>	$\hat{L}$	$\hat{\epsilon}_D$	$\hat{\rho}_{MC}$
Median	0.18	3.21	1.17
25th to 75th percentile	[0.03 - 0.34]	[2.48 - 4.34]	[0.99 - 1.45]

Notes: The table shows consumer incidence shares from electricity price changes, according to  $I^{share} = I/(1 + I)$ , as well as its components as described in Section IV.D. The quantiles are across all plants and all periods, using the sampling multipliers as frequency weights, where Lerner Index  $\hat{L}$  and pass through rates  $\hat{\rho}_{MC}$  vary at the plant-year level, and market demand elasticity  $\hat{\epsilon}_D$  at the industry-state-year level. The monopoly case corresponds to  $\hat{L}_{jisrt} = 1/\hat{\epsilon}_{D, isrt}$ , and the perfect competition case to  $\hat{L}_{jisrt} = 0$  which implies that the incidence share is equivalent to the pass-through rates.

the coordination problem of raising prices, one possible reason for pass-through rates greater than one.

The pass-through elasticities are combined with estimated plant level markups ( $\hat{\mu}$ ) into pass-through rates  $\hat{\rho}_{MC}$ . Table 5 shows the three components to calculate incidence: the Lerner index  $\hat{L}$ , the market demand elasticity  $\hat{\epsilon}_D$  and the marginal cost to price pass-through rate  $\hat{\rho}_{MC}$ , reporting the median, the 25th, and the 75th percentile of the distribution across plants, sectors and years. The median incidence share of consumer surplus  $I^{share}$  is 63%, indicating substantial benefits for consumers. There is some heterogeneity across industries and years; the 25th and 75th percentiles in consumer shares in Table 5 are 53% and 79% respectively, but even at the 5th percentile, the share of consumer incidence is a quarter of the total. Figure A.31 plots the incidence share over time for six aggregate industries, showing that there has been a small decline over time in consumer incidence share of a few percentage points. I also calculate the incidence under the extreme conduct assumptions of monopolies and perfect competition, where  $L = 1/\epsilon_D$  and  $L = 0$  respectively. As in Ganapati, Shapiro and Walker (2020), the monopoly estimate is below the oligopolistic estimate, while the perfect competition estimate is higher.

This implies that electricity pricing for industry is not only important for industrial development but also for consumer welfare. The reduction in cross-subsidization from industry to agriculture (Appendix A.5) has thus also benefited non-industrial consumers in the form of lower output prices. I next calculate the implications for aggregate welfare in terms of profits, consumer surplus and CO<sub>2</sub> emissions.

#### E. Aggregate Effects on Welfare and CO<sub>2</sub> Emissions

In this section I ask: how large was the monetary gain in producer surplus (profits) and consumer surplus net of government utility losses from the 48% price reduction, and what was the effect on aggregate CO<sub>2</sub> emissions? To this end, I use calculations based on the estimated parameters within the support of underlying electricity price changes, ignoring general equilibrium effects.

For the monetary gains, I use the semi-elasticity of profits to electricity prices to calculate that the 48% reduction of electricity prices led to an increase of ₹ 13.90 mil. for the average plant.<sup>67</sup> For the

<sup>67</sup>I take -21.25 as the average of the two estimates in Table 4a and calculate  $\log((1 - 0.48)^{-21.25}) = 13.90$ .

**Table 6:** Aggregate effects on CO<sub>2</sub> emissions from a 48% electricity price decline

<i>Additional emissions from (in Mt):</i>	Estimate	No substitution		
		No substitution	No productivity	& no productivity
Electricity use	29.4	29.4	65.3	65.3
Coal use	12.7	34.1	40.5	75.7
Oil use	-0.4	6.1	3.9	13.6
Total	41.7	69.6	109.7	154.6
Increase in %	31%	52%	82%	115%

Notes: The table shows the increases in emissions from a 48% decline in electricity prices. It is based on (i) the estimated effects on electricity use, electricity productivity, and the substitution between fuels, and on (ii) emission and conversion factors from (Minsitry of Coal, 2012; IPCC, 2006; Central Electricity Authority, 2006; IEA, 2013). The *Estimate* column shows the estimated effect on emissions. The three columns to the right show the effects when substitution between electricity and coal and oil is switched off, or when the productivity gains from lower prices are switched off, or both, all conditional on reaching the same output gains. Gas is omitted because its use is negligibly small in comparison.

entire manufacturing sector, this translates into profits of ₹ 1.69 trillion or US\$38 billion (in constant 2004 terms), equivalent to 2.8% of Indian real GDP in 2013.<sup>68</sup> The gains in consumer surplus have accordingly been US\$64 billion based on the incidence share estimated in Section V.D. The reduction in government profits from sale of electricity was ₹ 143 billion or US\$3 billion.<sup>69</sup> The US\$99 billion welfare gains imply annualized gains of US\$7.1 billion (from 1998-2000 to 2013), which in turn are equivalent to 0.5% of Indian GDP or 5.9% of manufacturing value added in 2013 (UNIDO, 2016). This demonstrates that the halving of industrial electricity prices from its comparatively high level had substantial effects on the Indian economy and welfare. It is worth noting that average wages (Table 4d) and employment also increased (Table 3) suggesting possible additional welfare increases for workers.

These welfare estimates do not yet include environmental damages. Therefore I next calculate the implications for aggregate CO<sub>2</sub> emissions by combining the estimated effects of electricity prices on consumption, productivity and fuel substitution with emission factors for specific fuels and the Indian power grid. I include emissions from electricity, coal and oil use and report the details of the calculation and data sources in Appendix A.15. From a baseline of 134.5Mt annual CO<sub>2</sub> emissions in manufacturing averaged across 1998-2000, the 48% decline in electricity prices increased emissions by 31% or 41.7Mt (Column 1 in Table 6).

This increase in emissions was entirely driven by firms scaling up.<sup>70</sup> In fact, Table 6 shows that the increase in emission would have been much larger if there was no electricity productivity enhancing effect from lower electricity prices, or no fuel substitution that induced coal and oil saving, all conditional on reaching the same output gains. Switching off fuel substitution effects, which forces firms to use

<sup>68</sup>Based on 121,825 manufacturing plants in the sampling frame in 1998, calculated by summing over the sampling multiplier.

<sup>69</sup>While profit per kWh fell with electricity prices, the quantity sold increased. I take -0.638 as the average of the two estimates on the impact on electricity consumption from Table 3 Columns 5-6, the average annual amount of electricity purchased from the grid in 1998-2000 in the sampling frame (53.5 billion kWh), the average cost of electricity supply in 2004 of 2.54 ₹ /kWh from the Ministry of Power (2009) and the average industrial electricity prices for 1998-2000 and 2013 (6.4 ₹ /kWh and 3.32 ₹ /kWh):  $(3.32 - 2.54) \cdot 53.5 \cdot (1 - 0.48)^{-0.638} - (6.4 - 2.54) \cdot 53.5 = 143$  billion ₹. Even if cost of supply was double and prices were below cost recovery, additional utility losses would only be slightly higher.

<sup>70</sup>That is if emissions are decomposed into output and emissions per output, the only reason emissions increased is because output increased, as emissions per output fell substantially.

even more coal and oil, would have produced a 52% increase in emissions (Column 2) instead of the 31%. Switching off the estimated effects on electricity productivity, i.e. setting Columns 2-3 in Table 2 to zero, would have produced a 82% increase in emissions (Column 3). Switching off both channels would have increased emissions by 115% (Column 4). While the secular decrease in industrial electricity prices increased CO<sub>2</sub> emissions, this increase is less than half of what we would expect in the absence of the electricity productivity enhancing effects from lower prices that I find.

Using a social cost of carbon of US\$100/tCO<sub>2</sub>, the costs from higher emissions are US\$4.2 billion. While this is sizable, it is small compared to the US\$99 billion welfare gains. The reduction in industrial electricity prices had substantial welfare benefits overall, even after accounting for damages from emissions.

#### F. The Contrary Effects of Coal Prices

The mechanisms discussed in this paper derive from the special role of electricity as a complementary input to modern capital intensive production processes. If this is the case, then we should not expect similar effects for coal prices, as fossil fuels are generally not broadly associated with modern industrial production. I next test this prediction using plant level coal prices for the roughly 45,000 observations of plant-years that use coal. As these suffer from similar endogeneity problems as electricity prices, I construct two instruments for coal prices for the coal used by manufacturing plants.

The first instrument,  $IV^E$  is an analogue to  $IV^A$ , using coal prices of manufacturing plants in the same state, but in different 2-digit industries, without the kernel weights. The second instrument,  $IV^F$ , is a shift-share instrument like  $IV^B$ . The shares are the logged distances of district centroids to the nearest coalfields, where distance captures increases in sourcing costs. The shifter is the nationally representative coal price at pit heads for industry (as opposed to power utilities).<sup>71</sup> When national average prices at the pit head rise, manufacturing plants further away from pit heads may see differential total price increases due to a differential size of the shipping costs components in total costs.

Table 7 shows the results. Indeed, in contrast to electricity prices, lower coal prices significantly *decrease* coal productivity (Table 7a). The IV coefficients are similar to each other, are of the same sign as the OLS coefficient and even slightly higher, in contrast to the results for electricity prices. While lower coal prices significantly increase coal consumption, they only have a small and insignificant effect on output or labor productivity in the IV specifications (Table 7a and 7b). Lower coal prices also have no significant effect on TFP (Table 7c).<sup>72</sup> There are small and insignificant effects on profits and revenues and an ambiguous effect on costs (Table 7c). Contrary to electricity, there is no similar scaling-up or technology effect with lower coal prices. This supports the notion that electricity is a special energy input complementary to modern production.

<sup>71</sup>The location of coalfields and power plants is illustrated in Figure A.6.

<sup>72</sup>This is in line with Cali et al. (2022) who even find positive effects on TFP from *higher* coal prices in Indonesia and Mexico.

**Table 7:** The contrary effects of coal prices on coal and labor productivity and firm performance

(a) Coal prices, coal productivity, and labor productivity

	Coal productivity (log)			Labor productivity (log)		
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(P^C)$	0.848*** (0.025)	1.484*** (0.179)	1.617*** (0.213)	0.0564*** (0.020)	-0.0251 (0.132)	0.300 (0.193)
OLS/IV	OLS	$IV^E$	$IV^F$	OLS	$IV^E$	$IV^F$
Observations	44968	44968	44968	44968	44968	44968
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes
First stage coef.	-	0.57***	0.01***	-	0.57***	0.01***
First stage SE	-	0.046	0.001	-	0.046	0.001
F-stat (Kleib.-Paap)	-	154.343	86.470	-	154.343	86.470
SE clustered by	Plant	Plant	Plant	Plant	Plant	Plant
No. of first clusters	16272	16272	16272	16272	16272	16272
SE clustered by	State-year	State-year	State-year	State-year	State-year	State-year
No. of second clusters	426	426	426	426	426	426

(b) Coal prices and output, coal use and employment

	Output (log)			Coal consumption (log)			Employees (log)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(P^C)$	0.0907*** (0.031)	-0.311 (0.248)	-0.135 (0.343)	-0.757*** (0.036)	-1.851*** (0.273)	-1.799*** (0.383)	0.0328 (0.021)	-0.320* (0.193)	-0.491* (0.252)
OLS/IV	OLS	$IV^E$	$IV^F$	OLS	$IV^E$	$IV^F$	OLS	$IV^E$	$IV^F$
Observations	44968	44968	44968	44968	44968	44968	44968	44968	44968

(c) Coal prices and profits, costs and TFP

	Profits (mil. ₹)			Total costs (mil. ₹)			TFP (log) (Wooldridge, 2009)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(P^C)$	-5.940*** (1.628)	-6.315 (15.050)	-7.393 (25.859)	-14.44** (6.592)	-29.82 (70.932)	3.729 (103.369)	-0.000544 (0.002)	-0.0198 (0.013)	-0.0306 (0.020)
OLS/IV	OLS	$IV^E$	$IV^F$	OLS	$IV^E$	$IV^F$	OLS	$IV^E$	$IV^F$
Observations	44965	44965	44965	44965	44965	44965	44582	44582	44582

Notes: Each column represents a separate regression at the plant level. The table shows results from OLS regression on logged coal prices, and IV regressions using  $IV^E$ , which is based on the coal prices of other plants, or the shift-share  $IV^F$ , as indicated. The dependent variables are indicated and described in Section III.B. In Panel (a), coal productivity is the value of output divided by the quantity of coal used in tonnes. In Panel (c), the regressions are reported in levels except for TFP because profits can be negative. The first stage statistics are reported. All regressions contain industry by year by region fixed effects. Regressions are weighted by the recorded sampling multiplier. Standard errors in parentheses are two-way clustered at the plant and the state by year level. Stars indicate p-values: \* < 0.1, \*\* < 0.05, \*\*\* < 0.01.

### G. Policy Implications

There are five policy implications I highlight based on the findings that are crucial for the context of industrial development and decarbonization. First, cross-subsidizing low agricultural and residential rates with high industrial rates can have negative externalities for both industrial development and electricity productivity. In the context of industrial development, lower electricity prices can achieve a win-win on both margins, and ultimately also benefit consumers.

Second, this does not imply that taxing carbon, which may increase electricity prices, is necessarily harmful, as such reasoning would conflate two types of externalities. The pure climate and pollution externalities from fossil fuel combustion can be internalized through pricing carbon. Simultaneously tackling excessively high industrial electricity prices through reduced electricity taxes or cross-subsidization,

or increased industrial electricity subsidies can address the electricity productivity externalities from technology upgrading and industrial development, especially in a setting of imperfect competition in the product market. The effect of these two instruments together could be comparable to subsidizing clean electricity generation, which can also reduce industrial electricity prices and incentivize lower fossil fuel use. However, in a setting of limited public budgets, it could be especially appealing that these instruments may be jointly budget neutral compared to expensive clean energy subsidies.

Third, as India and other low and middle income countries aim to transition to renewable energy, industrial electrification away from fossil fuels becomes essential in achieving climate goals to leverage electricity from renewables. This requires incentives for firms through lower relative prices between clean electricity and carbon intensive fuels to help direct investment in a clean transition as in [Acemoglu et al. \(2012, 2016\)](#). This strategy is even more appealing if lower electricity prices also improve electricity productivity and if taxing dirtier fuels has little direct effect on firm performance as shown in the previous section. Electrifying non-energy sectors also speaks to current challenges in transportation and industrial sectors of high income countries, where relatively lower electricity prices may incentivize such transitions.

Fourth, capital constraints could introduce frictions into the process of upgrading to modern technology as shown in Appendix A.2 in this model (see also [Lanteri and Rampini \(2023a,b\)](#); [Hawkins and Wagner \(2022\)](#)). The effects of lower electricity prices could be constrained in the presence of such capital constraints, and complementary policies that address capital frictions could fully unlock the technology upgrading mechanism. Finally, while industrial lobbying efforts in India may have been focused on securing import tariffs to boost competitiveness in output markets, the findings imply that focusing industrial lobbying efforts on lowering industrial electricity prices instead may be a promising alternative.

## VI. Conclusion

What is the role of industrial electricity prices in a context of industrial development? This paper shows that lower electricity prices can serve both environmental and developmental goals by improving electricity productivity and labor productivity in firms. As policy makers grapple with ambitious targets for improving energy efficiency, for example a doubling of the previous rate of improvements as agreed at COP28, these findings may be interpreted as a win-win in situations where trade-offs typically occur, particularly in lower income countries.

Using detailed data on electricity consumption and average prices at the plant level combined with instrumental variables to remove bias, I recover estimates at the micro level that help explain secular aggregate trends in electricity productivity and labor productivity at the macro level in India. I interpret the results through the lens of a model with discrete technological choices and complementarities between electricity and capital, and confirm model predictions with empirical tests. Lower electricity prices incentivize firms to use modern capital intensive and electricity-using production techniques. This boosts

output and overcompensates input substitution effects, which increases electricity and labor productivity through higher capital utilization. The underlying mechanism and resulting efficiency improvements therefore depend on context. They are likely to be most salient in the process of industrial development, rather than in advanced industrialized stages. Nevertheless, the broader implications of these findings, particularly the importance of electricity pricing in technology transitions, are also crucial for addressing current challenges of electrifying industry, transport, or residential heating in advanced economies as renewables ramp up.

The benefits of lower industrial electricity prices not only accrue to firms. Using data on output prices, I estimate how cost savings are passed through to consumers and find that almost two thirds of the welfare benefits accrue to consumers through lower output prices. While total carbon emissions increase from scaling up of industry, the boost in electricity productivity attenuates the additional emissions from scaling up by more than a half. The drop in industrial electricity prices in India led to substantial overall welfare benefits considering producers, consumers, utilities and environmental damages. Lower coal prices do not have such positive effects as electricity prices. This implies that policies that increase fossil fuel prices to internalize environmental and climate externalities, while addressing high industrial electricity prices such as reducing cross-subsidization to address the developmental and efficiency externalities may be particularly beneficial in a context of industrial development. Future research could extend the analysis to incorporate production networks and general equilibrium effects.<sup>73</sup>

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<sup>73</sup>Choi and Shim (2022), for example, show that there can be spillovers and general equilibrium effects from technology adoption in a context of industrialization.

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# APPENDIX FOR ONLINE PUBLICATION

## Complementary Inputs and Industrial Development: Can Lower Electricity Prices Improve Energy Efficiency?

by Gregor Singer  
LSE

### A.1. Model proofs

The firm's optimization problem is:

$$\max_{K,L,E,c} \Pi = PQ - p_K \cdot K - p_L \cdot L - p_E \cdot E - m \cdot c \quad (\text{A.1})$$

and for notational simplicity define  $Z$  and  $W$  as:

$$PQ = A(\alpha_l L^{\rho_l} + (1 - \alpha_l) X^{\rho_l})^{\frac{\phi}{\rho_l}} \equiv AZ^{\frac{\phi}{\rho_l}} \quad (\text{A.2})$$

$$X = (\alpha_e E^{\rho_e} + (1 - \alpha_e) K^{\rho_e})^{\frac{1}{\rho_e}} \equiv W^{\frac{1}{\rho_e}}$$

and

$$\alpha_l = \hat{\alpha}_l / c \quad (\text{A.3})$$

$$\rho_e = \hat{\rho}_e \cdot c$$

Conditional on technology choice  $c \in \{1, c'\}$ , where  $c' > 1$ , the first order conditions are:

$$\phi AZ^{*\frac{\phi}{\rho_l}-1} \alpha_l L^{*\rho_l-1} = p_L \quad (\text{A.4})$$

$$\phi AZ^{*\frac{\phi}{\rho_l}-1} (1 - \alpha_l) X^{*\rho_l-1} W^{*\frac{1}{\rho_e}-1} (1 - \alpha_e) K^{*\rho_e-1} = p_K \quad (\text{A.5})$$

$$\phi AZ^{*\frac{\phi}{\rho_l}-1} (1 - \alpha_l) X^{*\rho_l-1} W^{*\frac{1}{\rho_e}-1} \alpha_e E^{*\rho_e-1} = p_E \quad (\text{A.6})$$

Taking ratios of the first order conditions yields the input demands conditional on  $c$ :

$$K^* = \left( \frac{p_E(1 - \alpha_e)}{p_K \alpha_e} \right)^{\frac{1}{1 - \rho_e}} E \equiv \kappa_{KE} E^* \quad (\text{A.7})$$

$$X^* = (\alpha_e + (1 - \alpha_e) \kappa_{KE}^{\rho_e})^{\frac{1}{\rho_e}} E \equiv \kappa_{XE} E^* \quad (\text{A.8})$$

$$L^* = \left( \frac{(1 - \alpha_l) \alpha_e p_L}{\alpha_l p_E} \kappa_{XE}^{\rho_l - \rho_e} \right)^{\frac{1}{\rho_l - 1}} E \equiv \kappa_{LE} E^* \quad (\text{A.9})$$

$$E^* = \left[ \phi A \frac{\alpha_e (1 - \alpha_l)}{p_E} \kappa_{XE}^{\rho_l - \rho_e} (\alpha_l \kappa_{LE}^{\rho_l} + (1 - \alpha_l) \kappa_{XE}^{\rho_l})^{\frac{\phi}{\rho_l} - 1} \right]^{\frac{1}{1 - \phi}} \quad (\text{A.10})$$

Conditional on  $c$ , output and electricity productivity is:

$$PQ^* = A (\alpha_l \kappa_{LE}^{\rho_l} + (1 - \alpha_l) \kappa_{XE}^{\rho_l})^{\frac{\phi}{\rho_l}} E^{*\phi} \equiv \kappa_{PQE} E^{*\phi} \quad (\text{A.11})$$

$$\frac{PQ^*}{E^*} = \kappa_{PQE} E^{*\phi - 1} \quad (\text{A.12})$$

**Proof of Lemma 1.** Since  $c = 1$  in all cases, the conditional demands and output are also unconditional and continuous in factor prices. Therefore, we can derive the marginal effect  $\frac{\partial \frac{PQ^*}{E^*}}{\partial p_E} > 0$ , which is given by:

$$\frac{\partial \frac{PQ^*}{E^*}}{\partial p_E} = \frac{\partial \kappa_{PQE}}{\partial p_E} E^{*\phi - 1} + (\phi - 1) \kappa_{PQE} E^{*\phi - 2} \frac{\partial E^*}{\partial p_E} \quad (\text{A.13})$$

Note that prices and quantities as well as ratios of those are positive, i.e.

$$p_K, p_L, p_E, K, L, E, \kappa_{KE}, \kappa_{XE}, \kappa_{LE}, \kappa_{PQE} > 0$$

Next, I show that the following ratios are increasing in electricity prices:

$$\begin{aligned} \frac{\partial \kappa_{KE}}{\partial p_E} &= \underbrace{\frac{1}{1 - \rho_e}}_{>0} \underbrace{\left( \frac{p_E(1 - \alpha_e)}{p_K \alpha_e} \right)^{\frac{1}{1 - \rho_e} - 1}}_{>0} \underbrace{\frac{1 - \alpha_e}{p_K \alpha_e}}_{>0} > 0 \\ \frac{\partial \kappa_{XE}}{\partial p_E} &= \underbrace{(\alpha_e + (1 - \alpha_e) \kappa_{KE}^{\rho_e})^{\frac{1}{\rho_e} - 1}}_{>0} \underbrace{(1 - \alpha_e) \kappa_{KE}^{\rho_e - 1}}_{>0} \underbrace{\frac{\partial \kappa_{KE}}{\partial p_E}}_{>0} > 0 \\ \frac{\partial \kappa_{LE}}{\partial p_E} &= \underbrace{\frac{1}{\rho_l - 1}}_{<0} \underbrace{\left( \frac{(1 - \alpha_l) \alpha_e p_L}{\alpha_l p_E} \kappa_{XE}^{\rho_l - \rho_e} \right)^{\frac{1}{\rho_l - 1} - 1}}_{>0} \underbrace{\frac{(1 - \alpha_l) \alpha_e p_L \kappa_{XE}^{\rho_l - \rho_e}}{\alpha_l p_E}}_{>0} \underbrace{\left[ \frac{\rho_l - \rho_e}{\kappa_{XE}} \frac{\partial \kappa_{XE}}{\partial p_E} - \frac{1}{p_E} \right]}_{<0} > 0 \end{aligned}$$

For the last term  $\left[ \frac{\rho_l - \rho_e}{\kappa_{XE}} \frac{\partial \kappa_{XE}}{\partial p_E} - \frac{1}{p_E} \right] < 0$ , note that:

$$\left( \frac{\rho_l - \rho_e}{\kappa_{XE}} \frac{\partial \kappa_{XE}}{\partial p_E} \right) - \frac{1}{p_E} = \frac{1}{p_E} \left( \underbrace{\frac{\rho_l - \rho_e}{1 - \rho_e}}_{\substack{\leq 1 \text{ since} \\ \rho_l \leq 1 \ \& \ \rho_e < 0}} \underbrace{\left( \underbrace{\left( \frac{\alpha_e p_K}{(1 - \alpha_e) p_E} \right)^{\frac{\rho_e}{1 - \rho_e}} \frac{\alpha_e}{1 - \alpha_e} + 1}_{> 0} \right)^{-1}}_{> 0 \text{ and } < 1} - 1 \right) < 0$$

Next, note that:

$$\frac{\partial \kappa_{PQE}}{\partial p_E} = \underbrace{A \phi (\alpha_l \kappa_{LE}^{\rho_l} + (1 - \alpha_l) \kappa_{XE}^{\rho_l})^{\phi - 1}}_{> 0} \left( \underbrace{\alpha_l \kappa_{LE}^{\rho_l - 1} \frac{\partial \kappa_{LE}}{\partial p_E}}_{> 0} + \underbrace{(1 - \alpha_l) \kappa_{XE}^{\rho_l - 1} \frac{\partial \kappa_{XE}}{\partial p_E}}_{> 0} \right) > 0$$

Finally, note that the profit function  $\Pi^*$  is convex  $\frac{\partial^2 \Pi^*}{(\partial p_E)^2} \geq 0$ , and by Hotelling's lemma  $\frac{\partial \Pi^*}{\partial p_E} = -E^*$ .<sup>74,75</sup>

Taken together this implies that  $\frac{\partial E^*}{\partial p_E} \leq 0$ .

Therefore, since  $\phi < 1$ :

$$\frac{\partial \frac{PQ^*}{E^*}}{\partial p_E} = \underbrace{\frac{\partial \kappa_{PQE}}{\partial p_E} E^{*\phi - 1}}_{> 0} + \underbrace{(\phi - 1) \kappa_{PQE} E^{*\phi - 2}}_{< 0} \underbrace{\frac{\partial E^*}{\partial p_E}}_{< 0} > 0 \quad (\text{A.14})$$

**Proof of Proposition 1.** I first offer a simple proof by contradiction and then provide the necessary and sufficient conditions for the proposition to hold.

Suppose that on the contrary, electricity price decreases always decrease electricity productivity. Given the production decisions in Equations (A.1), (A.2) and (A.3), it is possible to find sets of parameter values  $\{p_K, p_L, p_E, c, \hat{\alpha}_l, \alpha_e, \rho_l, \hat{\rho}_e, \phi, A, m\}$  and electricity price decreases  $\Delta p_E$  for which electricity productivity is increasing, i.e.  $\frac{PQ^*}{E^*}|_{p_E} < \frac{PQ^*}{E^*}|_{p_E - \Delta p_E}$ . A proof of existence of such parameter values is the example

<sup>74</sup>For convexity: consider two prices  $p_E$  and  $p'_E$ , and define  $p''_E = \delta p_E + (1 - \delta)p'_E \forall \delta \in (0, 1)$ . Note that  $\Pi^*(p_E) \geq \Pi(p''_E, E^*(p_E))$  and  $\Pi^*(p'_E) \geq \Pi(p''_E, E^*(p'_E))$ . Multiplying the two inequalities by  $\delta$  and  $(1 - \delta)$ , summing and rearranging terms yields  $\delta \Pi^*(p_E) + (1 - \delta) \Pi^*(p'_E) \geq \Pi^*(p''_E)$ .

<sup>75</sup>For Hotelling's lemma apply the Envelope Theorem. Differentiating the profit function at the optimum,  $\frac{\partial \Pi^*}{\partial p_E} = (\frac{\partial PQ^*}{\partial E^*} - p_E) \frac{\partial E^*}{\partial p_E} + (\frac{\partial PQ^*}{\partial K^*} - p_K) \frac{\partial K^*}{\partial p_E} + (\frac{\partial PQ^*}{\partial L^*} - p_L) \frac{\partial L^*}{\partial p_E} - E^* = -E^*$ , where the terms in parentheses are zero because of the first order conditions.

in Figure A.3, which is a simulation based on the model in Equations (A.1), (A.2) and (A.3). In the neighborhood of the technology threshold, a decrease in the electricity price results in an increase in electricity productivity. This is not a unique example. It is straightforward to show additional examples by searching over parameter values that satisfy the below conditions. Indeed, Figure A.1 solves the model for a broad range of substitution elasticities including from strong complementarity up to substitutability between labor, capital and electricity, and shows there exist parameter sets where Proposition 1 holds for all combinations of substitution elasticities with reasonable values for all remaining parameters (see figure notes for details).

Finally, the necessary and sufficient conditions on parameter values and electricity price decreases for this proposition to hold are:

$$\begin{aligned} \Pi^*(p_E - \Delta_{p_E}, c = c') &> \Pi^*(p_E - \Delta_{p_E}, c = 1), \quad \text{i.e. prefer new technology with new prices} \\ \Pi^*(p_E, c = 1) &> \Pi^*(p_E, c = c'), \quad \text{i.e. prefer old technology with old prices} \\ \frac{PQ^*(p_E - \Delta_{p_E}, c = c')}{E^*(p_E - \Delta_{p_E}, c = c')} &> \frac{PQ^*(p_E, c = 1)}{E^*(p_E, c = 1)}, \quad \text{i.e. increased } PQ^*/E^* \text{ at new optimum} \end{aligned}$$

Because of Lemma 1, we know that this proposition can only hold in the presence of technology switches. The set of all possible parameter values that satisfy this proposition is given by these equations. Since this involves a non-linear combination of all parameters, the necessary and sufficient conditions are stated in general form with numerical example as in Figures A.1 and A.3 sufficient for a proof of existence. ■

**Proof of Lemma 2.** Since  $c = 1$  in all cases, the conditional demands and output are also unconditional and continuous in factor prices. Therefore, we can derive the marginal effect  $\frac{\partial \frac{K^*}{E^*}}{\partial p_E} > 0$ , which is given by:

$$\frac{\partial \frac{K^*}{E^*}}{\partial p_E} = \frac{\partial \kappa_{KE}}{\partial p_E} = \underbrace{\frac{1}{1 - \rho_e}}_{>0} \underbrace{\left( \frac{p_E(1 - \alpha_e)}{p_K \alpha_e} \right)^{\frac{1}{1 - \rho_e} - 1}}_{>0} \underbrace{\frac{1 - \alpha_e}{p_K \alpha_e}}_{>0} > 0 \quad (\text{A.15})$$

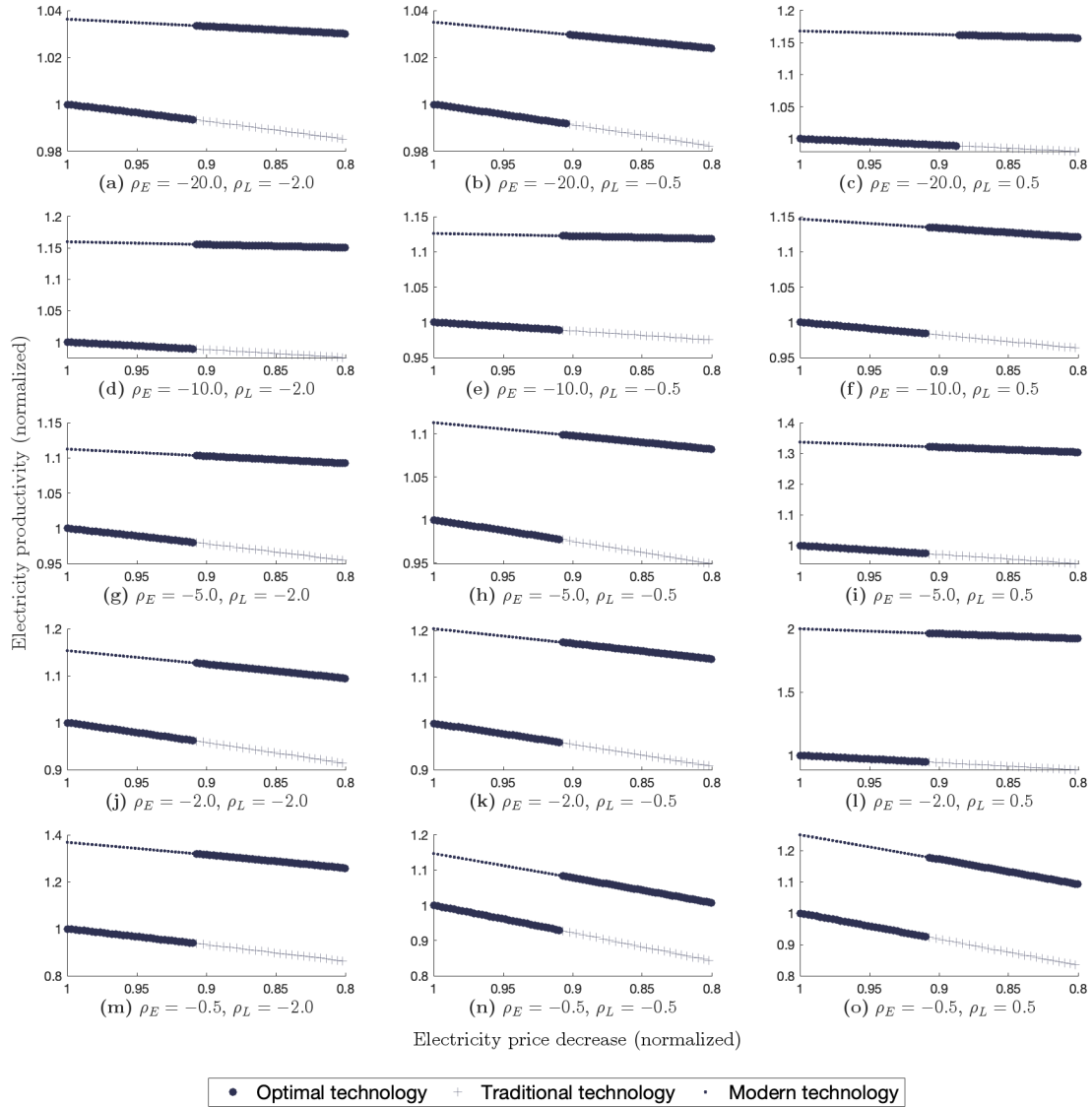
Again, note that prices and quantities as well as ratios of those are positive, i.e.

$$p_K, p_L, p_E, K, L, E, \kappa_{KE}, \kappa_{XE}, \kappa_{LE}, \kappa_{PQE} > 0$$

and observe directly that

$$\frac{\partial \kappa_{KE}}{\partial p_E} = \underbrace{\frac{1}{1 - \rho_e}}_{>0} \underbrace{\left( \frac{p_E(1 - \alpha_e)}{p_K \alpha_e} \right)^{\frac{1}{1 - \rho_e} - 1}}_{>0} \underbrace{\frac{1 - \alpha_e}{p_K \alpha_e}}_{>0} > 0$$

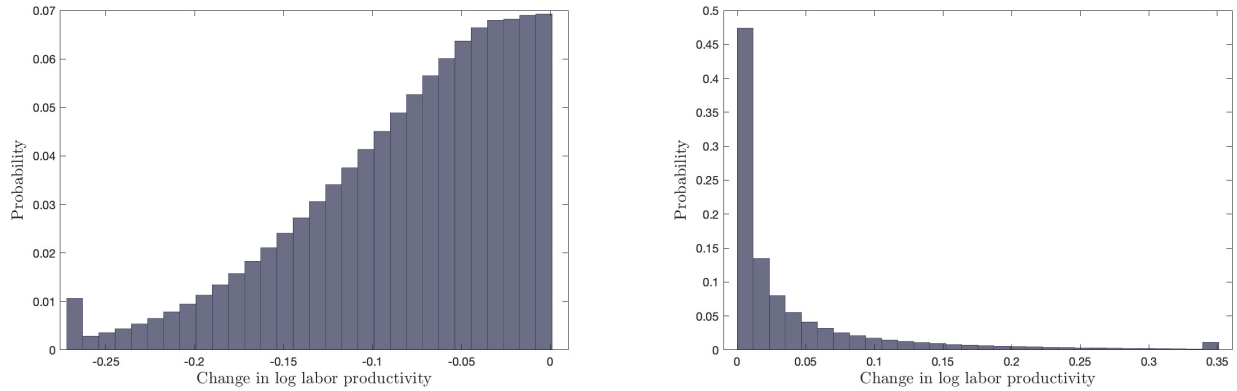
■



**Figure A.1:** Alternative substitution elasticities between labor, capital and electricity

Notes: The figures plot electricity productivity on the vertical axes (all normalized) against relative electricity price *decreases* on the horizontal axis. The panels vary the elasticity of substitution between capital and electricity ( $\hat{\rho}_e$ ) across rows from strong complementarities (-20) to weak complementarities (-0.5) for the traditional technology (with the modern technology appropriately more complementary) and the elasticity of substitution between capital services and labor ( $\hat{\rho}_l$ ) across columns from complementarities (-2) to substitutability (0.5). The figures show optimal choices both conditional on a specific technology as indicated, and the overall optimum (thick line). All outcomes are normalized by dividing by their value at the traditional technology ( $c = 1$ ) and original electricity price ( $\Delta_{PE} = 0$ ). These model simulations were generated by fixing the substitution elasticities as indicated and then searching for values of the other parameter to satisfy the implicit conditions given in the proof of Proposition 1, conditional on reasonable bounds  $\{p_K = (0.2, 20), p_L = (0.2, 20), c = (1.1, 10), \hat{\alpha}_l = (0.15, 0.75), \alpha_e = (0.1, 0.8), \phi = (0.75, 0.999), A = (1, 50), m = (0, 5)\}$ . There are many solution parameter that satisfy Proposition 1, and Panel (n), for example, shows a slightly different set than Figure 2.

Turning to labor productivity, in the absence of technology choices, i.e.  $c = 1$ , the effect of lower electricity prices on labor productivity depends on whether capital services  $X$  and labor  $L$  are complements ( $\rho_l < 0$ ) or substitutes ( $\rho_l > 0$ ). This is similar as in Acemoglu (2002), where factor specific technical change is either biased in the same factor or in another factor, depending on whether they are substitutes



(a) Capital services and labor complements ( $\rho_l < 0$ )

(b) Capital services and labor substitutes ( $\rho_l > 0$ )

**Figure A.2:** Labor productivity and electricity price decreases with constant technology: the role of complementarity vs substitutability between capital services and labor

Notes: Both panels show solutions of the model and histograms changes in log labor productivity after an electricity price decrease, both with constant technology  $c = 1$ . In particular, I draw 10 million values from independent uniform distributions for all parameters and prices. For prices I use support  $[1, 10]$ , for the shape parameters  $\alpha_e$   $\alpha_l$  I use  $[0, 1]$ , for the bundle of returns to scale in production and demand  $\phi$  I use  $[0.5, 0.99]$ , for fixed cost parameter  $m$  I use  $[0, 10]$  with  $c = 1$ , for total factor productivity  $A$  I use  $[0.1, 10]$  and for the complementarity parameter  $\rho_e$  I use support  $[-10, 0]$ . In Panel (a) the complementarity between labor and capital services  $\rho_l$  is drawn over support  $[-10, -0.001]$  implying complements. In Panel (b)  $\rho_l$  instead is drawn over support  $[0.001, 0.6]$  implying substitutes. I additionally draw electricity price decreases over support  $[0\%, 50\%]$  and calculate labor productivity before and after the price decrease for all 10 million draws in Panel (a) and Panel (b). Both histograms winsorize the change in log labor productivity at the 1 and 99 percentiles respectively (none of which induces a sign change).

or complements. Figure A.2 illustrates the role of this complementarity ( $\rho_l$ ) in the relationship between electricity price decreases and labor productivity in the absence of technology choices ( $c = 1$ ). Both panels show model based simulations. In particular, I draw 10 million values from independent uniform distributions for all parameters and prices.<sup>76</sup> In Panel (a) the complementarity between labor and capital services  $\rho_l$  is drawn over support  $[-10, -0.001]$  implying complements. In Panel (b)  $\rho_l$  instead is drawn over support  $[0.001, 0.6]$  implying substitutes. I additionally draw electricity price decreases over support  $[0\%, 50\%]$  and calculate labor productivity before and after the price decrease for all 10 million draws in Panel (a) and Panel (b). The panels show changes in log labor productivity after the price decrease, both with constant technology  $c = 1$ . Panel (a) shows that for all 10 million draws, the change is negative i.e. labor productivity decreases with an electricity price decrease when  $\rho_l < 0$  (complements), as in Figure 2 where  $\rho_l = -0.5$ . Intuitively, optimization requires using additional labor with increased capital services use, which together with decreasing returns implies lower labor productivity. Panel (b) shows that labor productivity increases with an electricity price decrease when  $\rho_l > 0$  (substitutes). The intuition is that optimization now requires higher substitution away from labor which increases labor productivity.

<sup>76</sup>For prices I use support  $[1, 10]$ , for the shape parameters  $\alpha_e$   $\alpha_l$  I use  $[0, 1]$ , for the bundle of returns to scale in production and demand  $\phi$  I use  $[0.5, 0.99]$ , for fixed cost parameter  $m$  I use  $[0, 10]$  with  $c = 1$ , for total factor productivity  $A$  I use  $[0.1, 10]$  and for the complementarity parameter  $\rho_e$  I use support  $[-10, 0]$ .

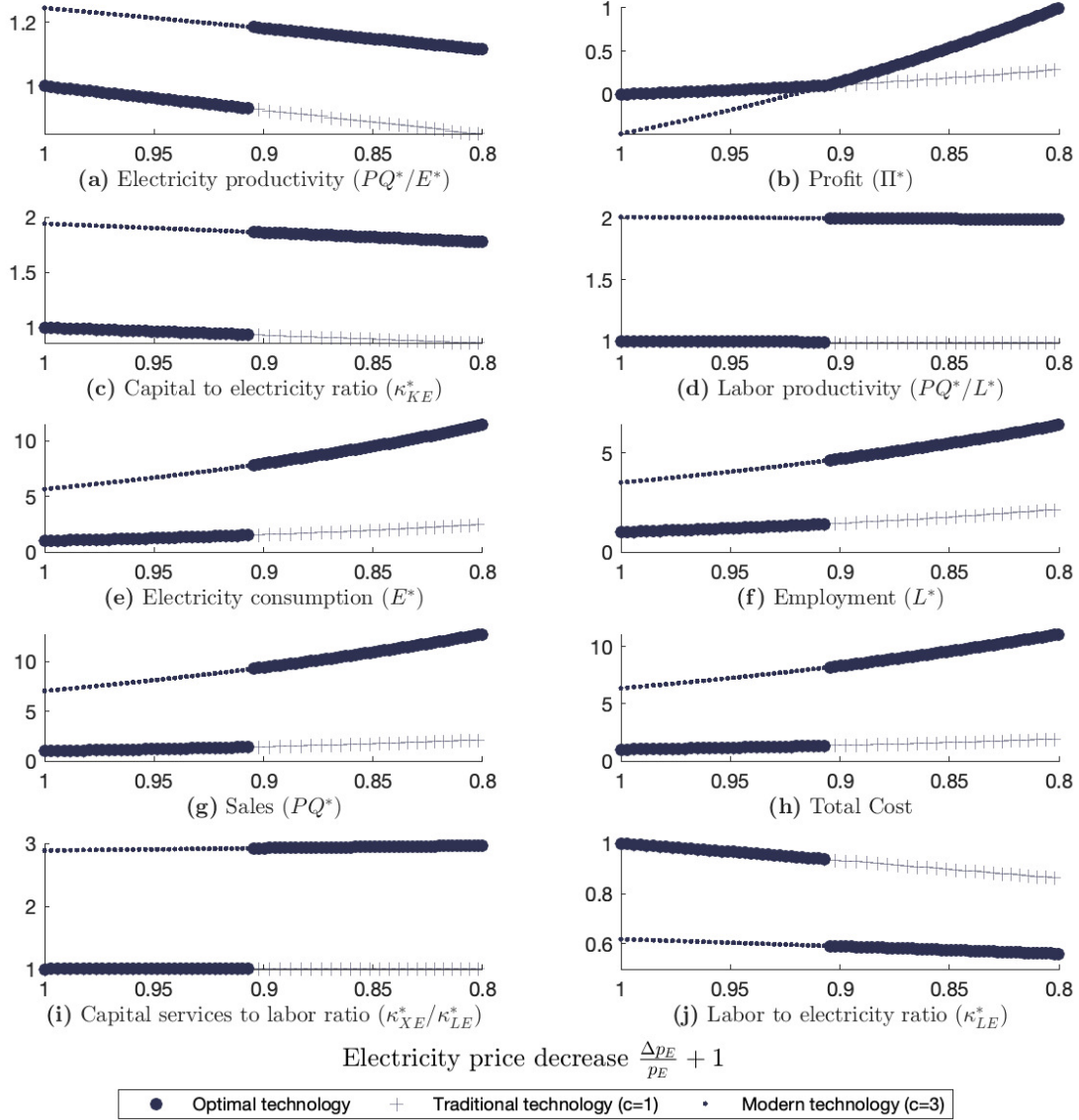


## A.2. Further model predictions and visualizations

Figure A.3 shows several margins of how a firm adjusts with the decline of electricity prices. Panel (a) to (d) in the first two rows repeat the graphs from Figure 2. After sufficient electricity price decreases  $\Delta_{PE}$ , the firm switches to the modern technology that is now more profitable (see Panel b), which brings about a step change in electricity productivity, the electricity to capital ratio (Panel c) and labor productivity (Panel d). When switching to the modern capital intensive and electricity-using technology, electricity use increases as illustrated in Panel (e). Employment also increases as shown in Panel (f). The fourth row shows that the switch to modern technology expands the firm: total sales in Panel (g) and total costs in Panel (h) increase at the threshold. The last row shows two further input ratios. Driven by substitution to the modern capital intensive technology, the capital services to labor ratio increases at the threshold in Panel (i), which allows both employment in Panel (f) and labor productivity in Panel (d) to also increase. The labor to electricity ratio falls (Panel j). Each of these predictions on input productivities, profits, sales, total costs and input ratios generated by the model are tested and confirmed in the empirical analysis.

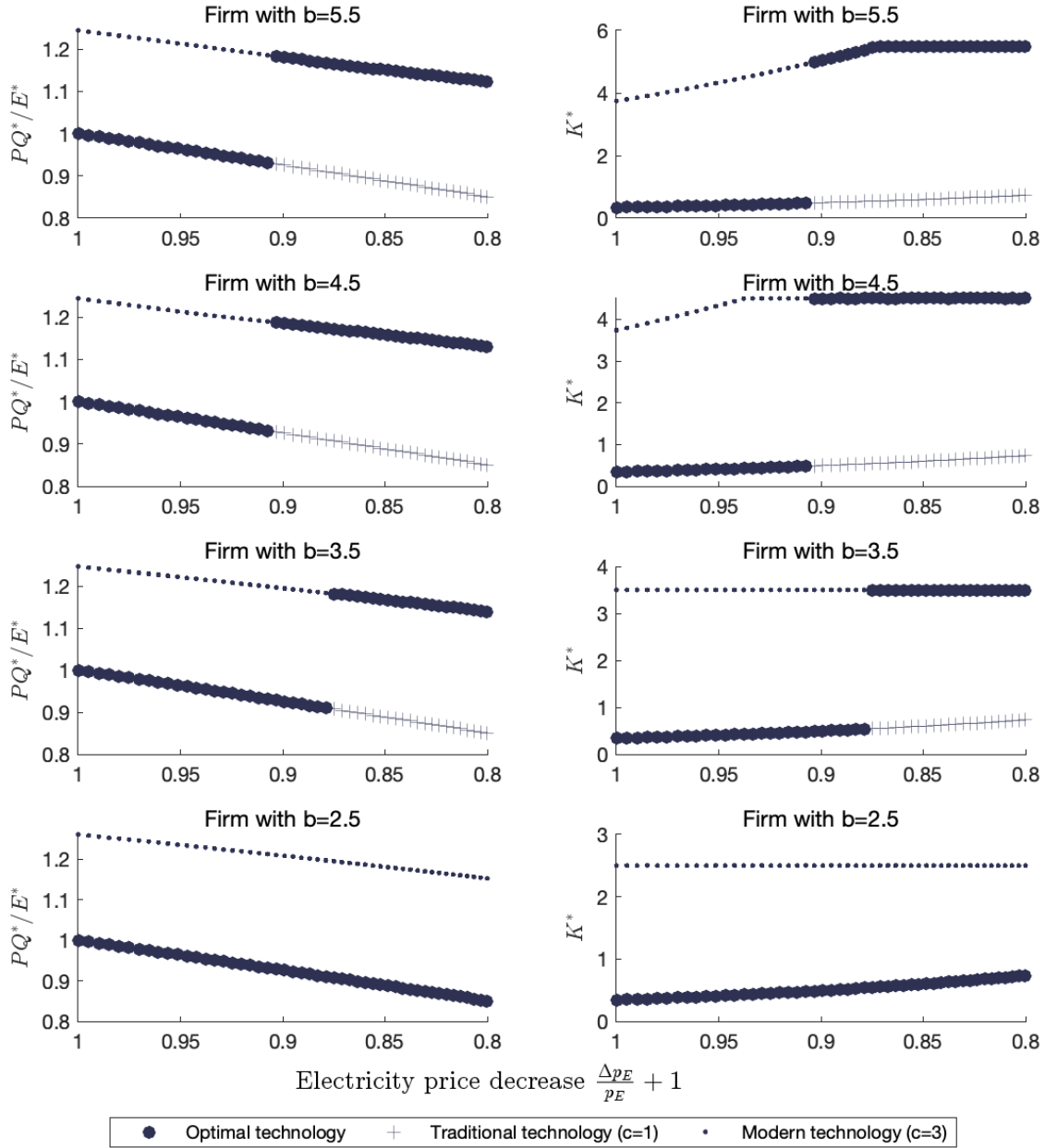
Figure A.4 shows the impact of introducing capital constraints  $K \leq b$ , which modifies the firm maximization problem. I plot the solutions to the problem, both in terms of electricity productivity in the plots on the left, and capital in the plots on the right. The rows from the top to the bottom successively tighten the capital constraint  $b$ . In the top row, the point of switching to the modern technology is equivalent to the baseline in Panel (a) of Figure 2 and A.3. As is visible on the right, the capital constraint only becomes binding when electricity prices fall even more, after the switch has become profitable already. In the second row, the constraint already binds for the modern technology before the point of switching to it, which, barely visible, slightly delays the optimal switch. In the third row, the constraint is even tighter, which significantly delays the optimal switching point. In the fourth row, with an even tighter constraint on capital, there is no optimal switch over the support of the 20% electricity price decrease, as it is more profitable to keep the traditional technology under such severe capital constraints.

Figure A.5 plots the same electricity productivity graphs as in Panel (a) of Figure 2 and A.3, but for heterogeneous firms. In particular, I use 100 firms, which vary in their total factor productivity  $A_i$  ranging from 9.1 to 9.25 in equal intervals. The graph shows 10 of these firms, and those with a higher  $A_i$  make the switch to the modern production technology earlier, i.e. with smaller electricity price decreases. Panel (b) of Figure A.5 plots aggregate electricity productivity ( $\sum PQ_i^* / \sum E_i^*$ ) across these 100 firms. It shows that *aggregate* electricity productivity can increase more smoothly over an extended range of electricity decreases as heterogeneous firms switch at different points. Similar graphs can be generated if firms are heterogeneous on other dimensions than total factor productivity. Once all firms have switched to the modern technology, aggregate electricity productivity is decreasing with further electricity price decreases (until a new more modern technology becomes available).



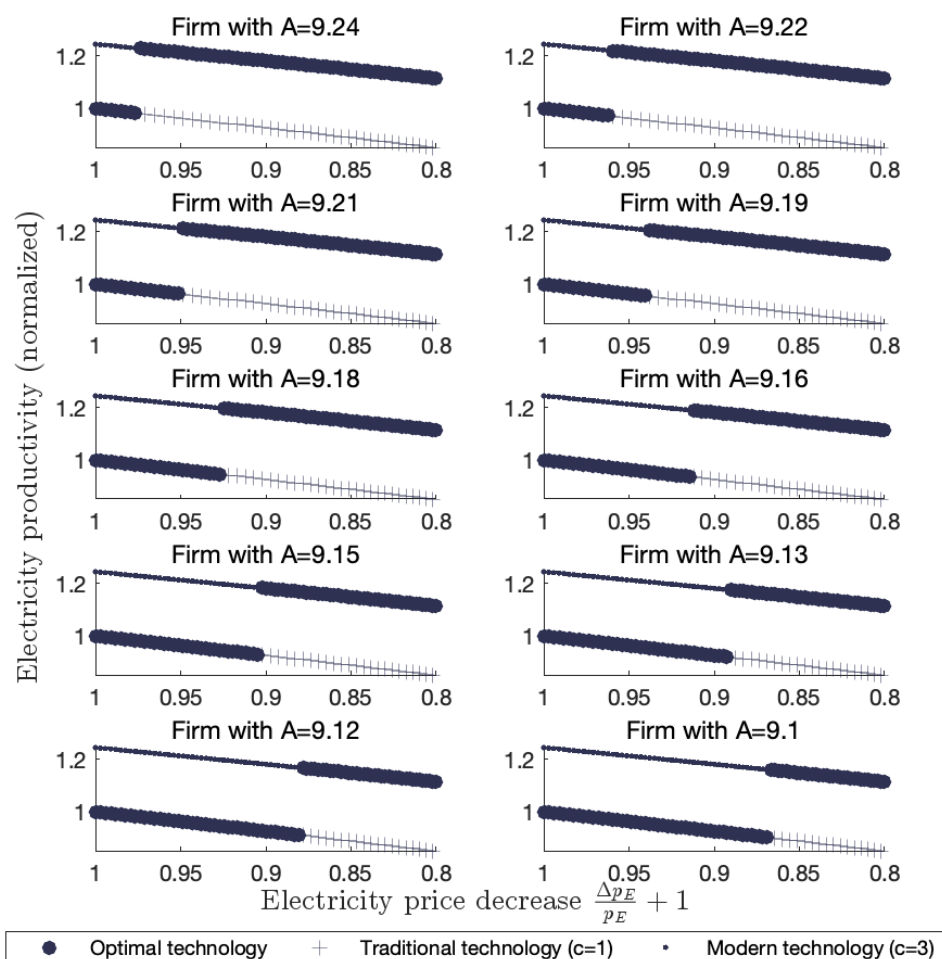
**Figure A.3:** Electricity price decreases and predictions for firm outcomes

Notes: The figures plot firm outcomes on the vertical axes (all normalized) against relative electricity price *decreases* on the horizontal axis. Panel (a) shows electricity productivity, Panel (b) firm profits, Panel (c) capital to electricity ratio, Panel (d) labor productivity, Panel (e) electricity consumption, Panel (f) employment, Panel (g) sales, Panel (f) total costs, Panel (i) capital services to labor ratio, and Panel (j) labor to electricity ratio. The figures show optimal choices both conditional on a specific technology as indicated, and the overall optimum (thick line). All outcomes are normalized by dividing by (for profits: subtracting) its value at the traditional technology ( $c = 1$ ) and original electricity price ( $\Delta_{PE} = 0$ ). The parameter values for this simulation are fixed at  $\{p_K = 6, p_L = 5, p_E = 0.5, c = 3, \hat{\alpha}_l = 1/3, \alpha_e = 0.5, \rho_l = -0.5, \hat{\rho}_e = -0.5, \phi = 0.95, A = 9.15, m = 1\}$  and  $\Delta_{PE}$  varies from 0 (corresponds to  $p_E = 0.5$ , and 1 on the horizontal axis) to  $1/12$  (corresponds to  $p_E = 0.4$ , and 0.8 on the horizontal axis).

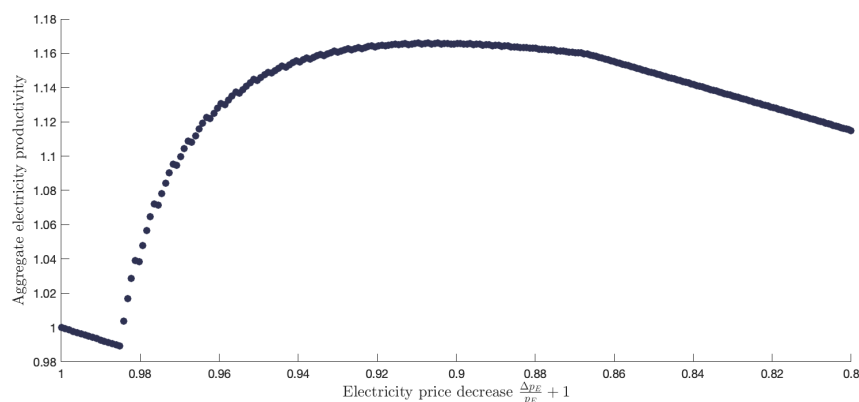


**Figure A.4:** Electricity price decreases in the presence of capital constraints

Notes: The figures plot electricity productivity (normalized) on the left and capital on the right (in levels) against electricity price *decreases* on the horizontal axis. The firm maximization problem is modified to include a capital constraint  $K \leq b$ . From the top to the bottom panels, each row has successively more stringent capital constraints as indicated. The figures show optimal choices both conditional on a specific technology as indicated, and the overall optimum (thick line). Electricity productivity is normalized by dividing by its value at the traditional technology ( $c = 1$ ) and original electricity price ( $\Delta p_E = 0$ ). The parameter values for this simulation are fixed at  $\{p_K = 6, p_L = 5, p_E = 0.5, c = 3, \hat{\alpha}_l = 1/3, \alpha_e = 0.5, \rho_l = -0.5, \hat{\rho}_e = -0.5, \phi = 0.95, A = 9.15, m = 1\}$  and  $\Delta p_E$  varies from 0 (corresponds to  $p_E = 0.5$ , and 1 on the horizontal axis) to  $1/12$  (corresponds  $p_E = 0.4$ , and 0.8 on the horizontal axis).



(a) Impact on electricity productivity of firms with different total factor productivity  $A_i$



(b) Impact on aggregate electricity productivity

**Figure A.5:** Electricity price decreases, heterogeneous firms and aggregate electricity productivity

Notes: Panel (a) plots electricity productivity for 10 selected firms that have heterogeneous total factor productivity  $A_i$  against relative electricity price decreases on the horizontal axis. The figures show optimal choices both conditional on a specific technology as indicated, and the overall optimum (thick line). The 10 firms that are displayed in Panel (a) are selected from the 100 firms for which  $A_i$  varies from 9.1 to 9.25, and have a value for  $A_i$  indicated above each graph. Panel (b) shows aggregate electricity productivity ( $\sum PQ_i^*/\sum E_i^*$ ) across all 100 firms. Electricity productivity in both panels is normalized by its value corresponding to the traditional technology ( $c = 1$ ) and original electricity price ( $\Delta p_E = 0$ ). The other parameter values for this simulation are fixed at  $\{p_K = 6, p_L = 5, p_E = 0.5, c = 3, \hat{\alpha}_l = 1/3, \alpha_e = 0.5, \rho_l = -0.5, \hat{\rho}_e = -0.5, \phi = 0.95, m = 1\}$  and  $\Delta p_E$  varies from 0 (corresponds to  $p_E = 0.5$ , and 1 on the horizontal axis) to  $1/12$  (corresponds to  $p_E = 0.4$ , and 0.8 on the horizontal axis).

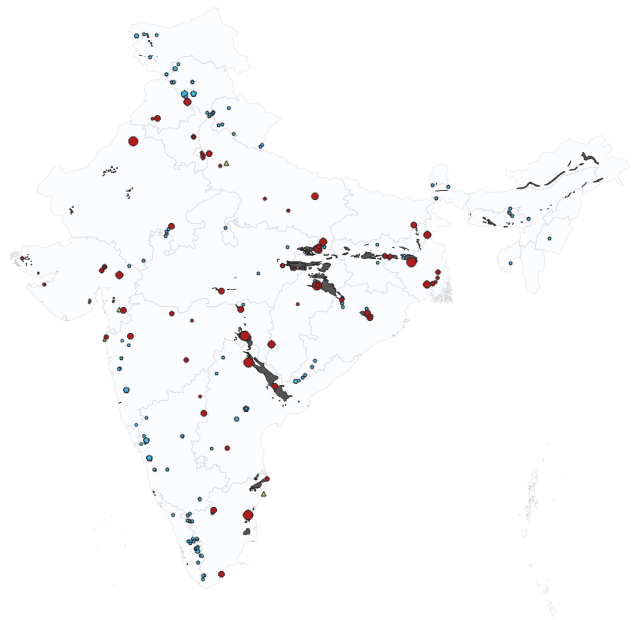
### A.3. Maps of power plants and coal reservoirs

Figure A.6 visualizes the location and growth of coal fired power plants near coalfields in maps using geo-located data on Indian coalfields and power plant characteristics. In 2013, a one percent increase in the distance of a district to the nearest coalfield is associated with a 2 MW lower coal power capacity. This is from a regression of installed coal capacity on logged distance to the nearest coalfield, all at the district level in 2013 with 594 Indian districts. The coefficient is  $-191.4$  with a robust t-statistic of 3.8 and  $R^2$  of 0.066.

Apart from demonstrating that coal plants are built near coalfields, the maps also show that hydro plants are near rivers especially in the mountainous region (mainly North-West), nuclear plants are typically built near the sea or rivers, and gas plants are built near ports and the major gas pipelines (e.g. in the North-East). Thermal plants accounted for 74% in 1998 and 68% in 2013, with the remainder produced by hydro (25% in 1998, 18% in 2013) and renewables (1% in 1998, 12% in 2013) (Ministry of Power, 1998a; Planning Commission, 2014). Of the thermal generation, the vast majority is made up of coal-based generation (around 85% throughout).

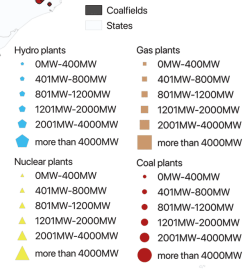
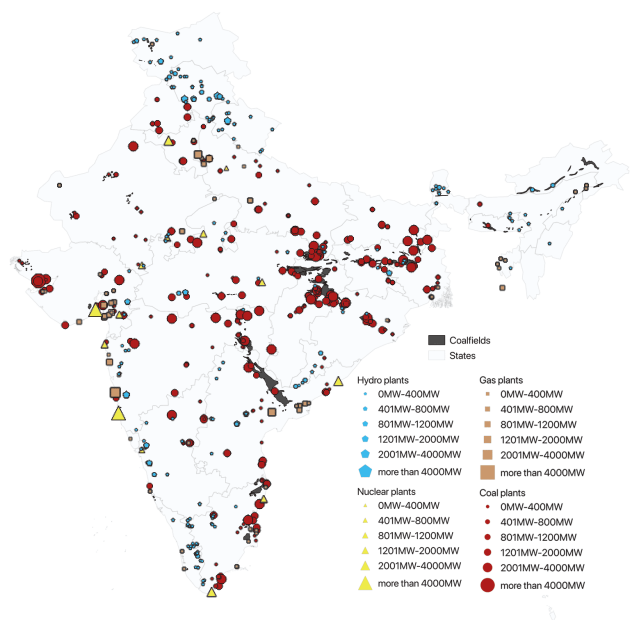
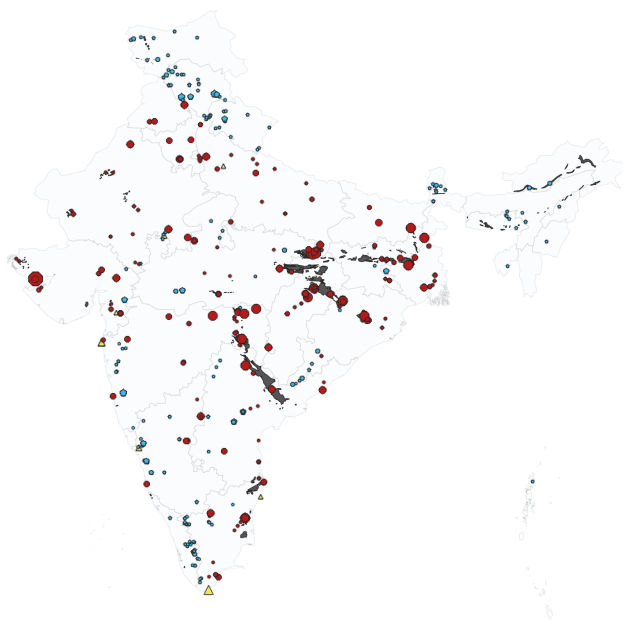
Coalfields

Power plants in 1998



Power plants in 2013

Power plants 2018 and under construction



**Figure A.6:** Maps of coalfields and power plants by year

Notes: The maps plot the coalfields (time invariant) and the stock of power plants in the corresponding years. The size of the markers corresponds to installed capacity. Data sources are described in Section III.B.

#### A.4. Electricity prices, the Electricity Act, and privately owned capacity near coalfields

This section provides further details on the ownership dynamics of Indian electricity generation, and the impact of the Electricity Act of 2003 on private ownership and electricity prices. In 1998, state and central government owned 65% and 30% of installed capacity respectively, with the remaining 5% owned privately (Ministry of Power, 1998a; Planning Commission, 2001). The Electricity Act of 2003 aimed to open this heavily regulated sector to more competition,<sup>77</sup> which led to more privately owned power plants entering. By 2013, the share of privately owned capacity rose to 31%, cutting mostly into the share of state-owned capacity (40%), while the centrally owned share remained at 29% (Planning Commission, 2014).<sup>78</sup> In February 2019, the share of the private sector (46%) was almost equal to the share of the combined government owned capacity (Central Electricity Authority, 2019).

The opening up of the power market after the Electricity Act of 2003 appears to have contributed to lower electricity prices. I examine the relationship between the median of the district level industrial electricity price and the share of installed coal fired capacity that is privately owned within a district. Table A.1 shows that the share of privately owned plants is significantly negatively associated with median electricity prices – but only after 2003.<sup>79</sup> A ten percentage point increase in the share of privately owned plants decreases median electricity prices by 0.24%. I use the timing of the Electricity Act to construct an instrument for prices for a robustness check of the analysis. Since the location choice of additional privately owned generating capacity is likely endogenous, I instead use the distance of districts to coalfields, which predicts the location of additional generating capacity (see Map A.6). Indeed, as Columns 4-6 of Table A.1 show, the share of private thermal capacity is predicted by the distance to coalfields.

Therefore, I construct a Bartik instrument ( $IV^{D1}$ ) based on the time-invariant distances to coalfields combined with the timing of the Electricity Act in 2003 to instrument for electricity prices as robustness check for the main analysis. I refine the instrument by using a triple interaction with a dummy that is one if a state has ever any coal fired generation power. This helps to increase power as states in the North-West near the Himalayas, for example, are heavily reliant on hydro power so distance to coalfields matters less and introduces noise. Columns 7-9 show that a 100 km decrease in the distance to the closest coalfield decreases electricity prices by 0.8%. Figure A.7 shows an event study version using the plant level data directly instead of district level median prices. From 2003, plants that are further away from coalfields experience a relative increase in electricity prices compared to those that are closer to coalfields.

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<sup>77</sup>The preamble states “An Act to consolidate the laws relating to generation [...] of electricity [...], promoting competition therein [...]”.

<sup>78</sup>From 1998 to 2013, total installed capacity rose by 143%.

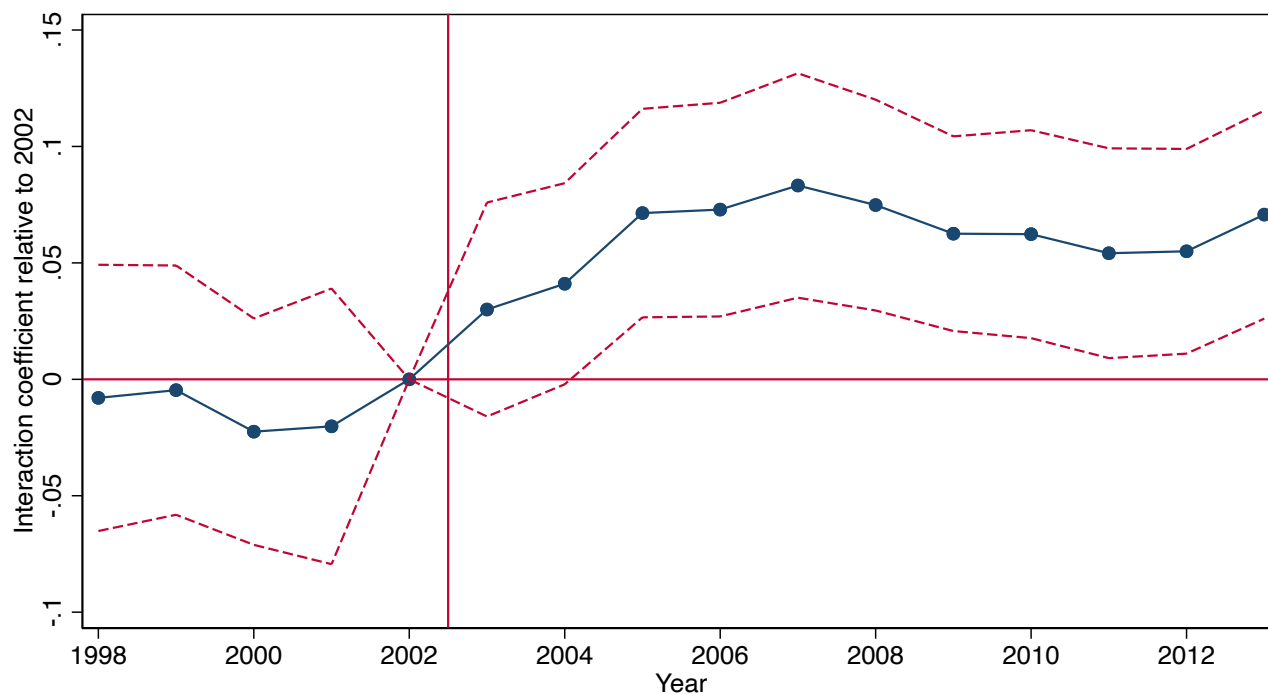
<sup>79</sup>This holds conditional on district and year fixed effects, and conditional on district and region by year fixed effects. I also control for time-varying total district level installed capacity.

**Table A.1:** Electricity prices, privately owned share in district installed capacity, and coalfields

	Electricity price (log)			Share private capacity			Electricity price (log)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Share private capacity	-0.0092 (0.015)	-0.0066 (0.018)	-0.0022 (0.014)						
Share private capacity x after 2003	-0.024** (0.012)	-0.024** (0.012)	-0.022*** (0.0025)						
Distance to coalfield ('00 km) x after 2003 x state w. coal power				-0.019*** (0.0071)	-0.014** (0.0067)	-0.016** (0.0073)	0.079*** (0.018)	0.079*** (0.018)	0.075*** (0.017)
N	7991	7991	7991	7991	7991	7991	7991	7991	7991
Total capacity	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-year FE	No	No	Yes	No	No	Yes	No	No	Yes

Notes: The table shows estimates from OLS regressions at the district-year level with the log median electricity price within a district as dependent variable in the first three columns and last three columns. The dependent variable in Columns 4-6 is the share of privately owned capacity in district level installed capacity and includes joint private/state and private/central ownership categories. The Indian Electricity Act was introduced in 2003 and the variable after 2003 indicates a dummy that is one from 2003. The distance to coalfields at the district level is in hundreds of km. The variable state w. coal power is a dummy that takes one if a state has ever had any coal power throughout the sample. The total capacity covariate controls for total installed capacity of any type and fuel at the district year level. District fixed effects absorb the distance to coalfields in levels. Regressions are weighted by the sampling multipliers and by the number of plants within a district-year cluster. Standard errors in parentheses are clustered two-way at the district and state by year level. Stars indicate p-values: \* < 0.1, \*\* < 0.05, \*\*\* < 0.01.

**Figure A.7:** Event study of impact of 2003 Electricity Act and distance to coalfields on electricity prices



Notes: The figure plots the coefficient on a triple interaction between district centroid distance to coalfields (in 100 km), year dummies, and a dummy that is one if there has ever been any coal fired power generation in a state. The regression is based on the plant level data as in the main paper with log electricity prices as dependent variable. All lower order interaction terms are included as well as industry by year by region fixed effects and district fixed effects. 95% confidence bands are based on standard errors that are two-way clustered at the plant and state by year level.



## A.5. Comparing India's high electricity prices across countries and users

Average electricity tariffs in India were the equivalent of 15.7 US cents (2004 US\$) for industrial users in 1998. As Figure A.8 and Table A.2 show, the G7 or OECD average was around 8.9 US cents in 1998, implying that the Indian industrial tariffs were around 80% higher. Adjusting for the difference in general price levels between India and G7 countries, Indian tariffs were 756% higher in 1998 based on purchasing power parity (PPP). Indian industrial tariffs were higher than G7 average prices until 2004 using market exchange rates. In PPP terms, Indian prices were still 140% higher than the G7 average in 2013. The Indian electricity price trends in the 2000s is in contrast to many other countries, where electricity prices instead increased as shown in Figure A.8. While electricity prices in India almost halved during the sample period, prices in OECD countries grew by roughly 40% (Table A.2).<sup>80</sup>

The high electricity prices in India for industrial users are in contrast to low electricity prices for agricultural and residential users, 2.6 and 6.8 US cents respectively in 1998, even though the cost of supply is usually lower for industrial users (Ministry of Power, 1998b).<sup>81</sup> This asymmetric price pattern leads to heavy cross-subsidization in Indian electricity. Industrial tariffs have typically been above the average cost of supply, but high subsidies are required for the agricultural sector. While agricultural consumers made up 32% of electricity consumption in 1998, they only accounted for 3.6% of revenues from electricity sales (Planning Commission, 2002). There was progress in reducing cross-subsidization, but it was not eliminated despite efforts to depoliticize tariffs based on the Electricity Act (2003). In 2013 industrial tariffs were still 7.6 US cents (2004 US\$) compared to 2.2 cents for agricultural tariffs (Ministry of Power, 2014). As a result, state electricity utilities have been loss-making almost across the board, recovering only between 73% and 89% of annual costs between 1998 and 2013 (Central Electricity Authority, 2006-2015).

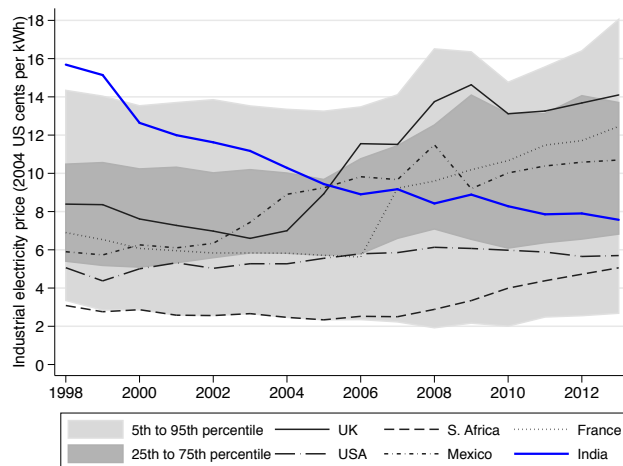
Figure A.9 compares industrial electricity prices across different consumption bands across Indian states in 2007, using manually collected data from government reports (Central Electricity Authority, 2006-2015). Industrial tariffs mostly follow increasing block tariffs, at least up to a point. On average, a higher band (of five bands) is associated with a 2.5 percent increase in the tariff.<sup>82</sup> Figure A.10 uses the plant level data and plots electricity prices against electricity purchased, both after partialing out state by year fixed effects, to recover an average slope of marginal prices. The figure confirms a slight increase in tariffs with consumption, except for the largest consumers. This is in contrast to European countries, where the tariff band for the largest consumers is on average less than half the band for the smallest consumers (Eurostat, 2016). Increasing or decreasing block tariffs are one of the challenges I take into account when identifying the effect of electricity prices.

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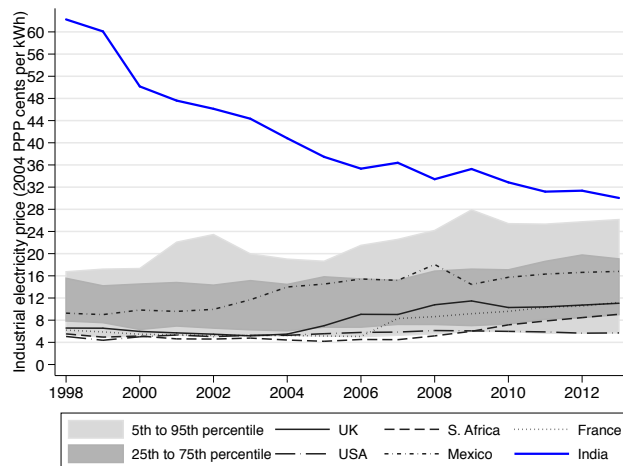
<sup>80</sup>See Sato et al. (2019) for more evidence on general price trends in various countries since 1995. They show that electricity is the most important fuel when accounting for overall energy prices.

<sup>81</sup>For the agricultural and residential tariffs, I calculated a simple average of state-wise average electricity tariffs, pooling consumption bands. The industrial tariffs are taken from the micro data and are comparable with reported simple averages.

<sup>82</sup>This is from a regression of manually collected log deflated electricity tariffs at the state-year-band level on consumption bands, accounting for state by year fixed effects.



(a) Industrial electricity prices (Market exchange rates)



(b) Industrial electricity prices (PPP)

**Figure A.8:** Industrial electricity prices in an international context (US\$ and PPP)

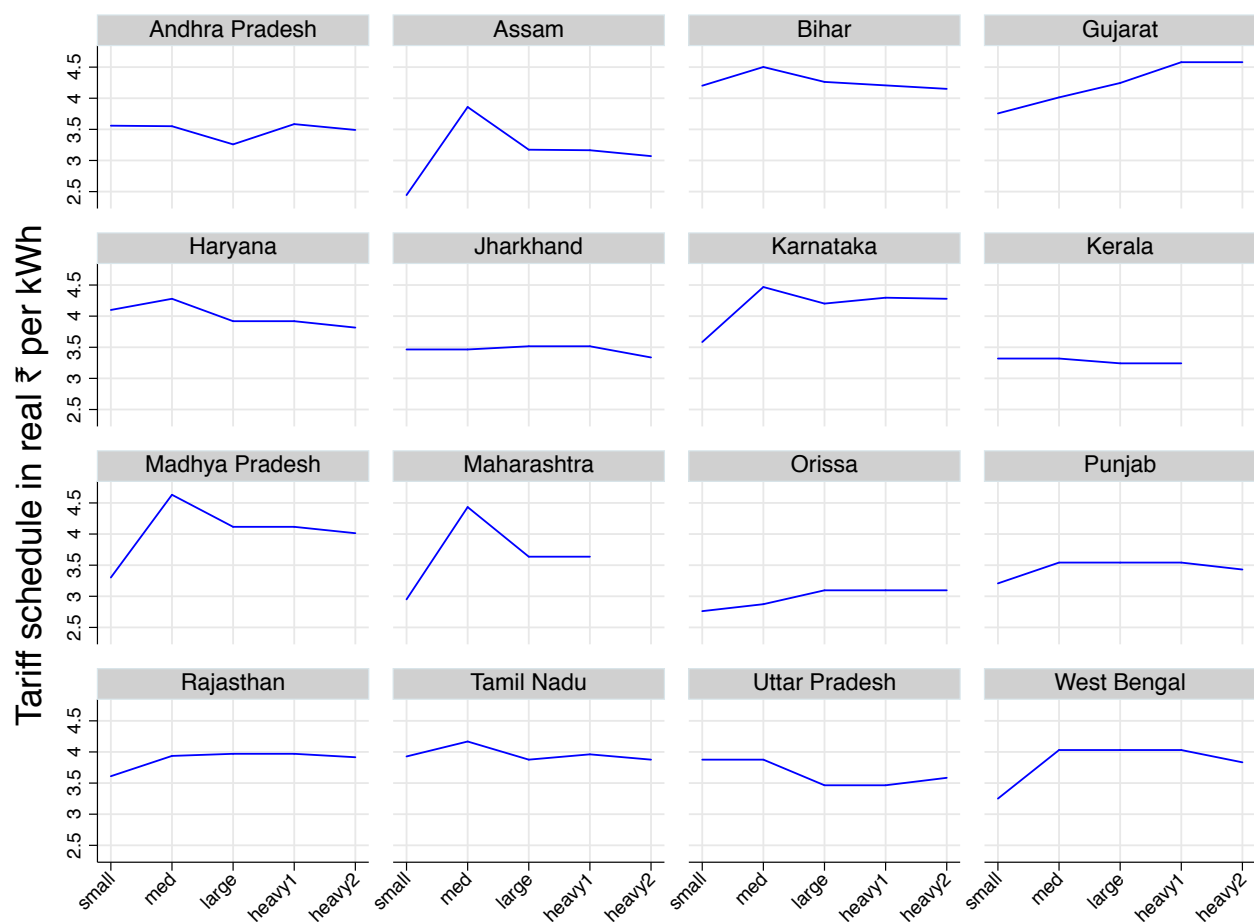
Notes: The figures plot real industrial electricity prices for six individual countries. Panel (a) is based on market exchange rates, and Panel (b) is based on PPP conversion factors. The shaded areas correspond to the interquartile range and the 5th to 95th percentile of a given year. This is based on a consistent set of 26 countries for which data for all years was available (see below). Raw price data comes from IEA (2018b), except for India, where the prices are based on the micro data in the main text. For India, IEA (2018b) data is only available from 2006, which is similar to the plotted data. Prices are deflated with national GDP deflators and turned into US\$ or PPP-US\$ with exchange rates and PPP conversion factors from the World Bank (2017). The base year for deflation is 2004 throughout this paper. The 26 countries used for the percentiles are: Algeria, Canada, Czech Republic, Denmark, France, Germany, Hungary, India, Ireland, Israel, Italy, Japan, Kazakhstan, Mauritius, Mexico, New Zealand, Paraguay, Poland, Portugal, Slovak Republic, South Africa, Spain, Switzerland, Turkey, United Kingdom, United States.

**Table A.2:** Industrial electricity prices in US-cents: India, OCEC and G7 averages (US\$ and PPP)

	Market exchange rates					PPP				
	India	G7	OECD	% of G7	% of OECD	India	G7	OECD	% of G7	% of OECD
1998	15.69	8.91	8.96	176	175	62.25	8.24	10.40	756	598
1999	15.14	8.42	8.57	180	177	60.09	7.76	10.03	774	599
2000	12.64	8.36	8.43	151	150	50.16	7.75	9.94	648	504
2001	12.00	8.97	8.81	134	136	47.61	8.36	10.40	570	458
2002	11.62	8.68	8.89	134	131	46.13	8.08	10.49	571	440
2003	11.17	9.01	9.11	124	123	44.34	8.41	10.78	527	411
2004	10.28	9.00	9.07	114	113	40.82	8.38	10.77	487	379
2005	9.44	9.55	9.43	99	100	37.46	8.88	11.16	422	336
2006	8.90	10.58	10.03	84	89	35.33	9.79	11.77	361	300
2007	9.17	11.25	10.30	82	89	36.39	10.41	12.11	350	301
2008	8.42	10.88	11.02	77	76	33.43	9.98	13.05	335	256
2009	8.89	11.59	11.46	77	78	35.27	10.61	13.70	332	257
2010	8.28	11.42	11.11	72	74	32.86	10.50	13.24	313	248
2011	7.86	12.20	11.50	64	68	31.18	11.24	13.60	278	229
2012	7.90	12.79	12.18	62	65	31.36	11.77	14.38	266	218
2013	7.57	13.53	12.43	56	61	30.04	12.45	14.56	241	206

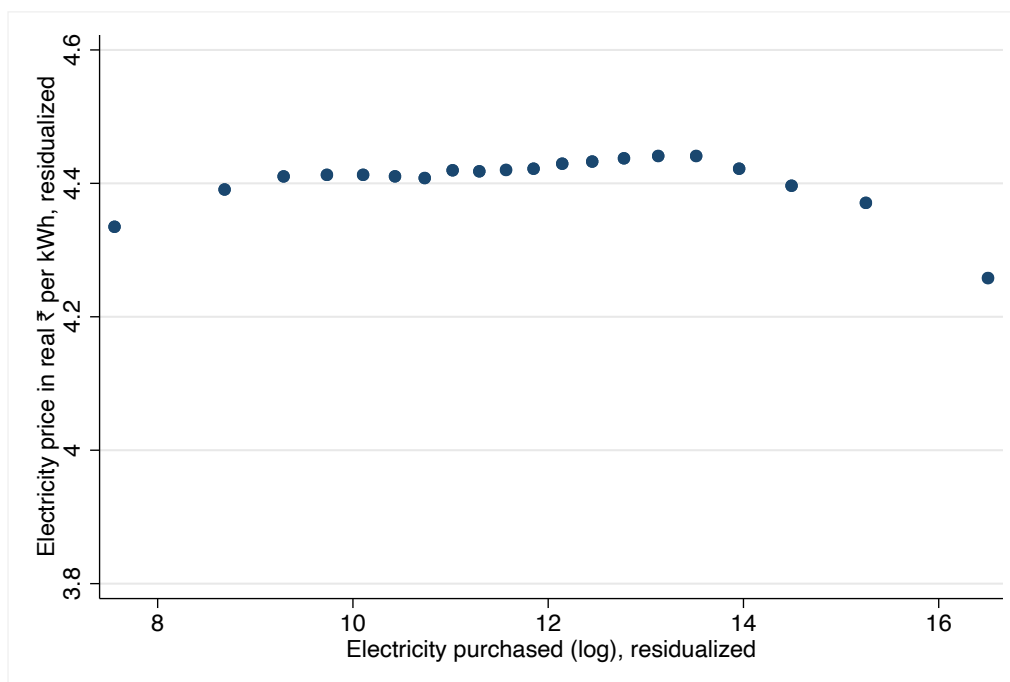
Notes: The table shows real industrial electricity prices for India, the simple average of the G7 nations, and the simple average of OECD countries, for which data in all years were available. The left part is based on market exchange rates, the right part is based on PPP conversion factors. Raw price data comes from IEA (2018b), except for India, where the prices are based on the micro data in the main text. For India, IEA (2018b) data is only available from 2006, which is similar to the reported data. Prices are deflated with national GDP deflators and turned into US\$ or PPP-US\$ with exchange rates and PPP conversion factors from World Bank (2017). The base year for deflation is 2004 throughout this paper. The included OECD countries are: Canada, Czech Republic, Denmark, France, Germany, Hungary, Ireland, Israel, Italy, Japan, Mexico, New Zealand, Poland, Portugal, Slovak Republic, Spain, Switzerland, Turkey, United Kingdom, United States.

**Figure A.9:** Reported industrial average tariff schedules in large states in 2007



Notes: Plotted are the average tariffs by state by size of industrial consumer. There are five categories increasing in electricity consumption from *small* to *heavy2*. The reported average tariffs are taken from the Indian [Central Electricity Authority \(2006-2015\)](#).

**Figure A.10:** Residualized electricity prices and quantity purchased



Notes: The figure shows a binned scatter plot where both plant level electricity prices, and log electricity purchased are pre-residualized by partialing out state by year fixed effects. This shows that marginal prices are fairly similar to average prices, and that tariffs are slightly increasing in quantity purchased except for the largest customers.

## A.6. No significant correlation between shortages and electricity prices

**Table A.3:** Electricity prices and power shortages

	Plant level			State level		
	(1)	(2)	(3)	(4)	(5)	(6)
Shortages	0.34 (1.59)	-0.02 (-0.19)	0.12 (0.95)	1.08 (1.02)	-0.01 (-0.02)	0.11 (0.64)
N	473866	473866	473866	458	458	458
Year FE	No	Yes	Yes	No	Yes	Yes
State FE	No	Yes	Yes	No	Yes	Yes
Region-year FE	No	No	Yes	No	No	Yes

Notes: The table shows estimates from OLS regressions of logged electricity price on shortages. The first three columns are using logged electricity prices at the plant level. The second three columns are regressions at the state year level with logged median electricity prices. Regressions are weighted by the sampling multipliers. The second three regressions are also weighted by the number of plants within a state year cluster. Shortages are at the state year level. Standard errors in parentheses are clustered at the state year level. Stars indicate p-values: \* < 0.1, \*\* < 0.05, \*\*\* < 0.01.

## A.7. Discussion of summary statistics Table 1

This section offers further description of the summary statistics shown in Table 1. First, there is considerable self-generation as the average amount of electricity self-generated is a quarter of the amount of electricity bought. This is driven by the 35% of plants that engage in self-generation, primarily to cope with outages as discussed in the main text. Second, average electricity productivity is lower when weighting by consumed

electricity, which suggests that larger electricity consumers are less electricity productive.<sup>83</sup> Third, on average, electricity has the largest share in fuel expenditure (0.63).<sup>84</sup> Fourth, electricity expenditure constitutes on average about 6% of total average costs. The average electricity price is around seven times higher than the coal price in kWh equivalent, as coal is a rarer form of energy. Fifth, machinery is the main type of capital and investment (as opposed to e.g. buildings). Sixth, the average variable cost markup (total revenues divided by total variable costs) is 20%, slightly lower than the marginal cost markup of 30%, where marginal cost markups are calculated following De Loecker and Warzynski (2012). Finally, plant TFP are similar for different methods, following Olley and Pakes (1996), Levinsohn and Petrin (2003) or Wooldridge (2009).

### A.8. Labor productivity, wages and electricity prices

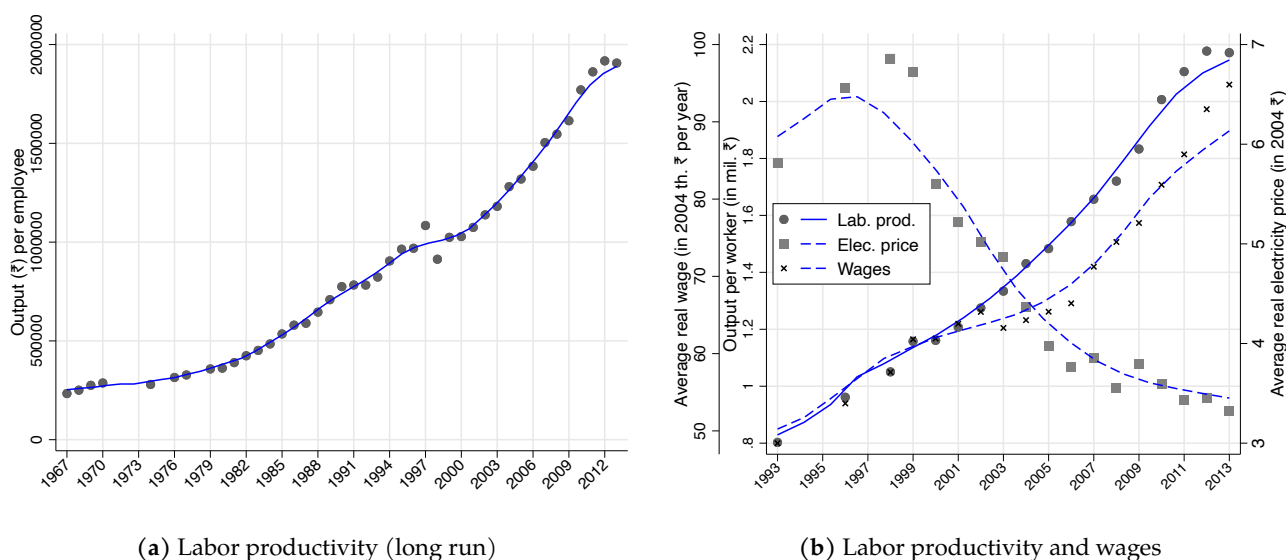


Figure A.11: Labor productivity and wages

Notes: Panel (a) plots annual labor productivity ratios (aggregate value of output divided by the number of employees) in Indian manufacturing over the long run. Output is deflated at the 2-digit industry level using 2-digit industry deflators before aggregating over industries. From 1967 to 1997 the raw ASI data in pre-aggregated form is used (at industry state year aggregation). From 1998 the raw plant level ASI data is used and aggregated with sampling multipliers. Panel (b) plots annual aggregate labor productivity ratios in the solid line (value of output divided by the number of employees) and real average wages in the dashed line. Aggregate labor productivity is calculated by first aggregating the value of output and the number of employees by plants, and then taking the ratio of the aggregates. Real average wages are calculated by first aggregating the wage bill of plants and the number of employees, and then taking the ratio of the aggregates. Plant output is deflated using 3-digit industry deflators before aggregating over industries. Wages are deflated using a state-wise deflator. All data points come from the raw plant level ASI data (from 711166 observations including years before 1998) and aggregated with sampling multipliers.

<sup>83</sup>Weighting by consumption maps plant level electricity productivity into aggregate electricity productivity, comparable with Figure 1.

<sup>84</sup>This is similar to the 60% that Marin and Vona (2021) report for France. Note that the share in raw energy is lower, because electricity prices are much higher per unit of energy than coal, gas or oil prices. As Figure A.19 in Appendix A.9 shows, the share of electricity in the energy mix in terms of energy units has risen from 16 to 20% since 1998.

## A.9. Additional electricity productivity and price graphs

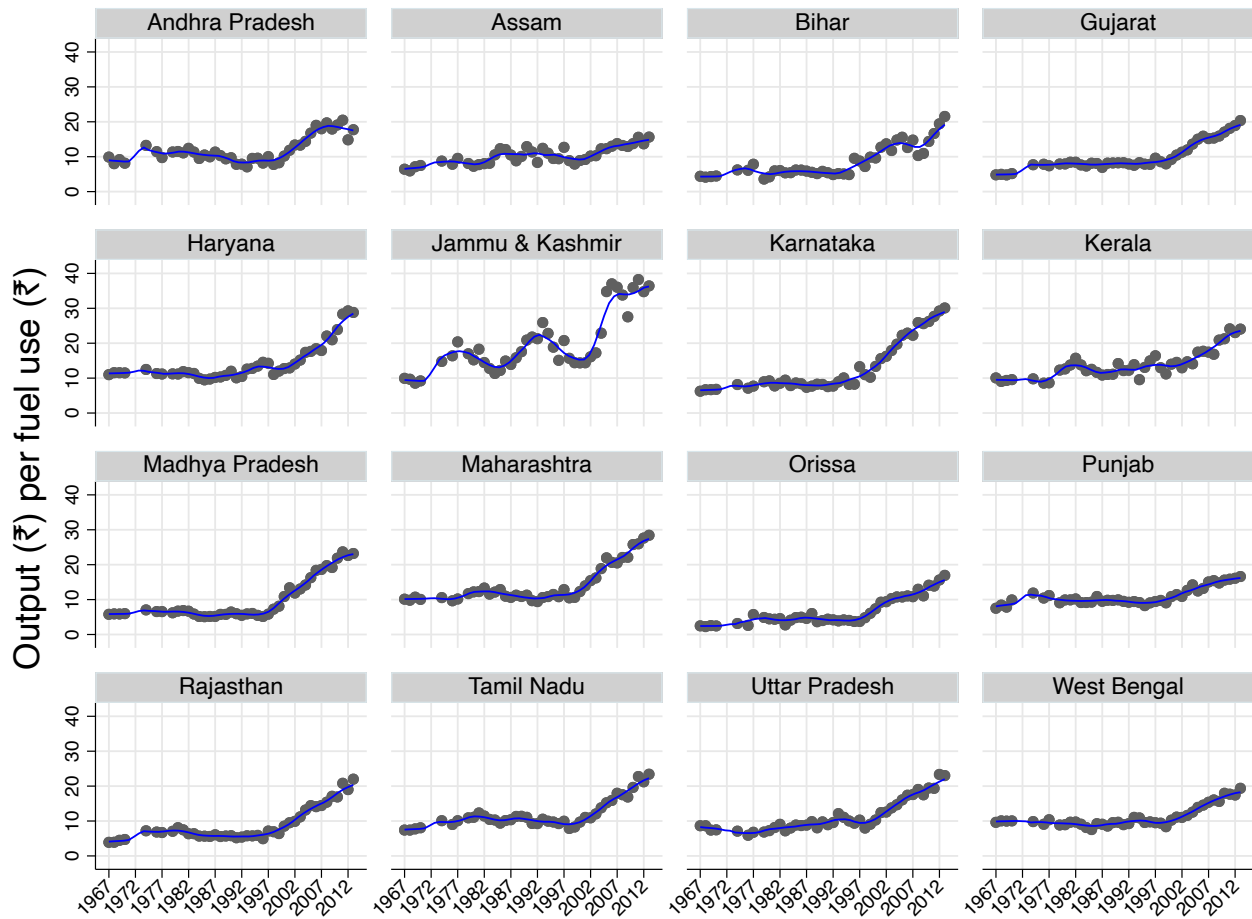
This section provides additional descriptive graphs. First, similar secular trends in energy productivity, electricity productivity and electricity prices can be observed across most states (Figures A.12 and A.13) and industries (Figures A.14 and A.15).<sup>85</sup> This suggests that the observed aggregate trends are not a story of mere reallocation across industries or states. Figure A.18 confirms the Indian trends in electricity productivity with alternative data from the IEA (2016) and UNIDO (2016), and also shows that electricity productivity did not increase nearly as much in OECD countries over the sample period.

Second, the patterns in electricity productivity and electricity prices are confirmed with alternative data sources. Figure A.18 uses (IEA, 2016; UNIDO, 2016) data for electricity productivity. Figure A.20 plots the electricity price index in real terms from the Office of the Economic Adviser (2019), and Figure A.21 plots the average of industrial electricity tariffs manually collected from the reports of the Central Electricity Authority (2006-2015) and from Indiastat (2019) through Lok Sabha and Rajya Sabha (Indian Parliament) questions. In summary, the trends are similar across different data sources, and the large Indian price decreases provide an ideal setting to study their relationship.

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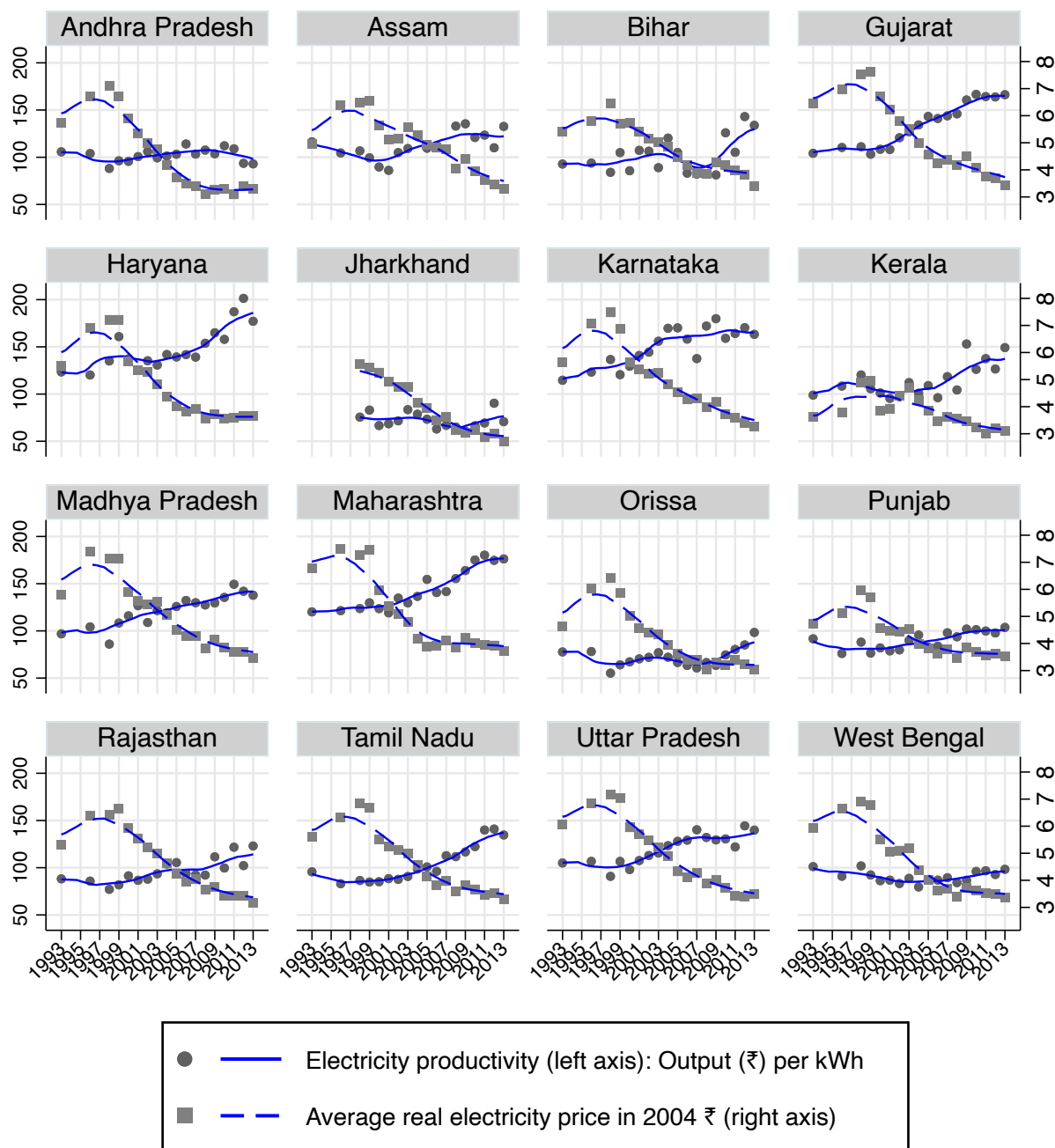
<sup>85</sup>Except for perhaps electricity productivity in metals and minerals (see Figure A.15).

Figure A.12: Energy productivity (per ₹) by state



Notes: The figure plots the annual energy productivity ratios (value of output divided by the value of fuel and electricity used). Sixteen of the largest states are displayed in this figure. Output is deflated at the 2-digit industry level using 2-digit industry deflators before aggregating over industries. Fuel and electricity use is deflated using a general fuel and electricity wholesale price deflator. The ratio of aggregate output to aggregate fuel and electricity consumption is displayed. From 1967 to 1997 the raw ASI data in pre-aggregated form is used (at industry state year aggregation). From 1998 the raw plant level ASI data is used and aggregated with sampling multipliers.

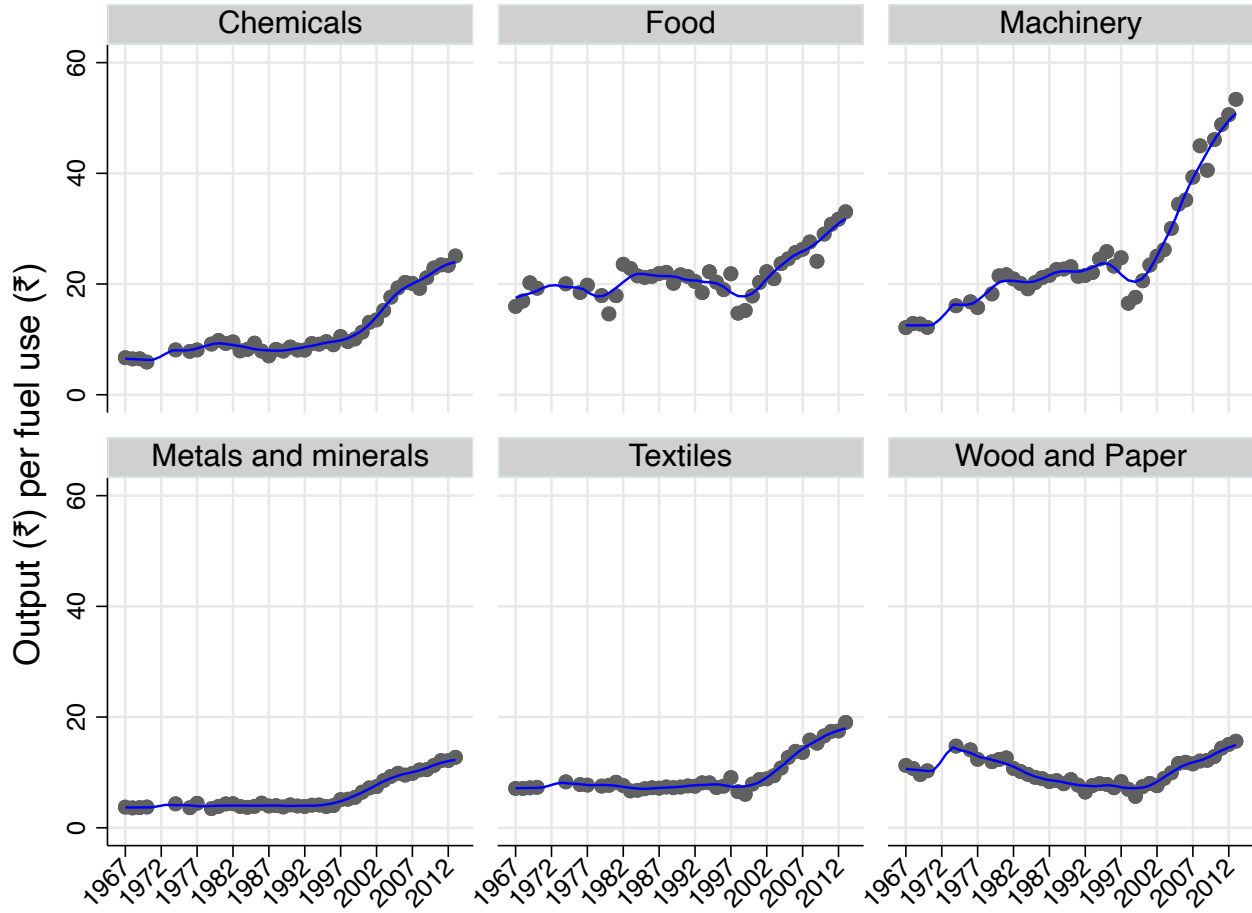
Figure A.13: Electricity productivity (per kWh) and prices by state



Notes: The figure plots the annual electricity productivity ratios by states (value of output divided by the quantity of electricity used in kWh) on the left axis and real average electricity prices on the right axis. Sixteen of the largest states are displayed in this figure. Plant output is deflated using 3-digit industry deflators before aggregating over industries and calculating aggregate output to aggregate electricity use (left axis). Real average electricity prices (right axis) are calculated by first aggregating the value of electricity bought by plants and the quantity bought, and then taking the ratio of the aggregates. All data points come from the raw plant level ASI data and aggregated with sampling multipliers.

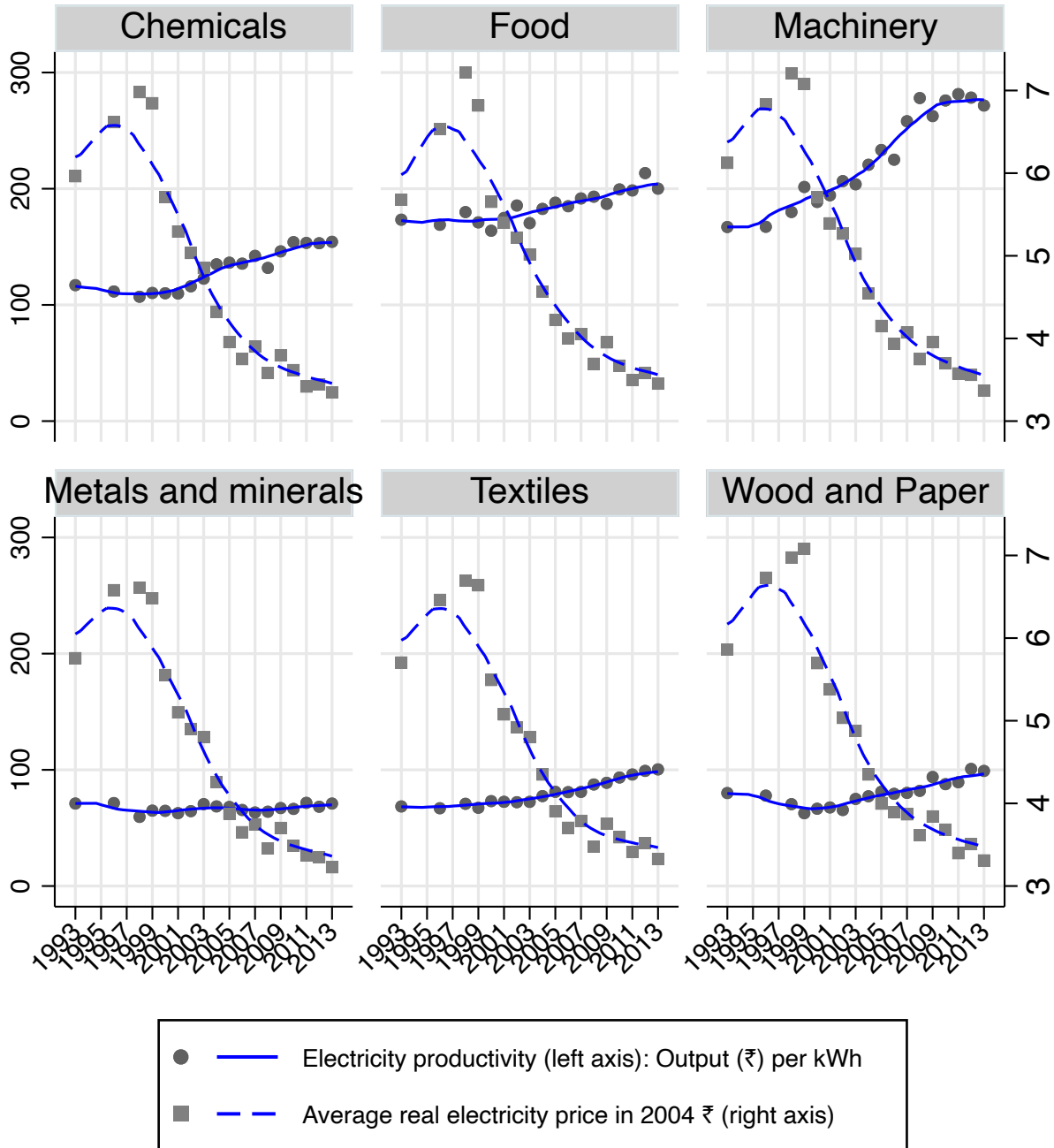


Figure A.14: Energy productivity (per ₹) by industry



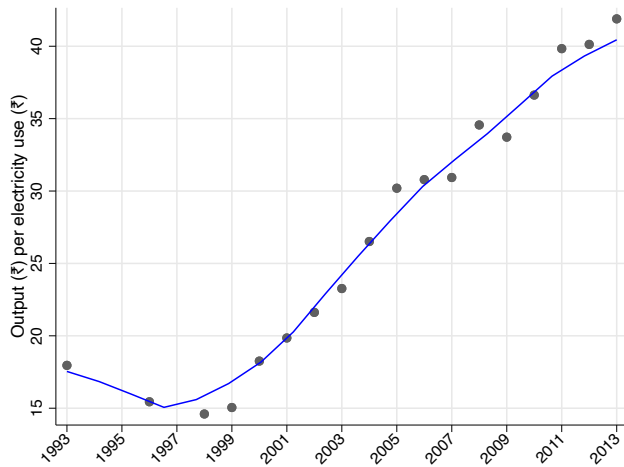
Notes: The figure plots the annual energy productivity ratios by industry (value of output divided by the value of fuel and electricity used). The industries are broad: chemicals includes rubber and plastics, machinery includes metal products, and textiles includes leather. Output is deflated at the 2-digit industry level using 2-digit industry deflators before aggregating over industries. Fuel and electricity use is deflated using a general fuel and electricity wholesale price deflator. The ratio of aggregate output to aggregate fuel and electricity consumption is displayed. From 1967 to 1997 the raw ASI data in pre-aggregated form is used (at industry state year aggregation). From 1998 the raw plant level ASI data is used and aggregated with sampling multipliers.

Figure A.15: Electricity productivity (per kWh) by industry

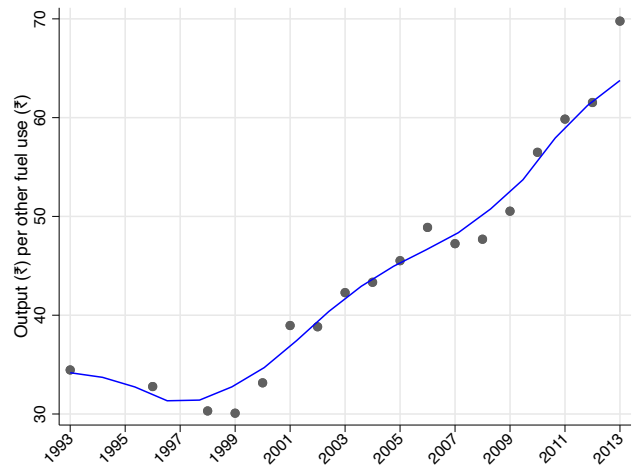


Notes: The figure plots the annual electricity productivity ratios by industry (value of output divided by the quantity of electricity used in kWh) on the left axis and real average electricity prices on the right axis. The industries are broad: chemicals includes rubber and plastics, machinery includes metal products, and textiles includes leather. Plant output is deflated using 3-digit industry deflators before aggregating over industries and calculating aggregate output to aggregate electricity use (left axis). Real average electricity prices (right axis) are calculated by first aggregating the value of electricity bought by plants and the quantity bought, and then taking the ratio of the aggregates. All data points come from the raw plant level ASI data and aggregated with sampling multipliers.

**Figure A.16: Electricity productivity (per ₹)**

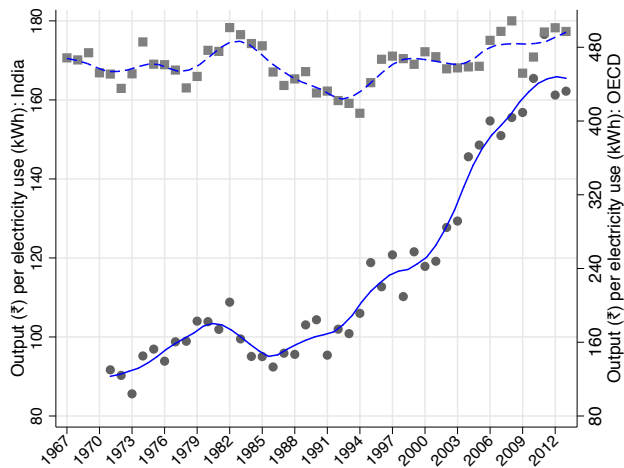


**Figure A.17: Other fuel productivity (per ₹)**

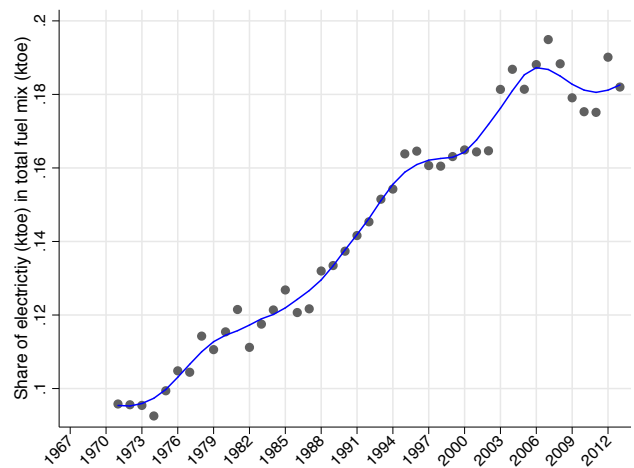


Notes: The figures plot the annual electricity productivity ratios (value of output divided by the value of electricity used) and the other fuel productivity ratios (value of output divided by the value of fuel other than electricity used). Plant output is deflated using 3-digit industry deflators before aggregating over industries. Electricity and fuel values are deflated using a general fuel and electricity wholesale price deflator. All data points come from the raw plant level ASI data and aggregated with sampling multipliers.

**Figure A.18: Electricity productivity (per kWh)**

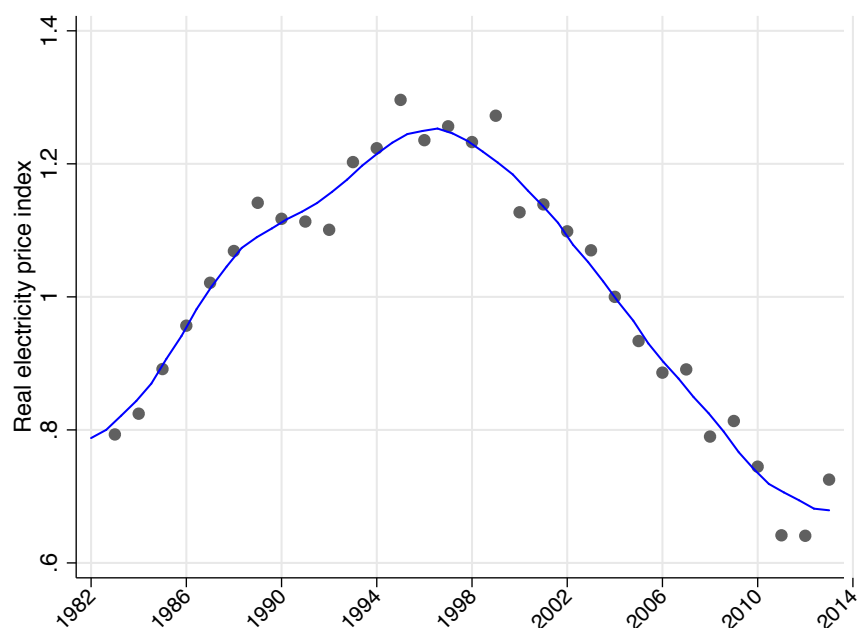


**Figure A.19: Share of electricity in fuel mix**



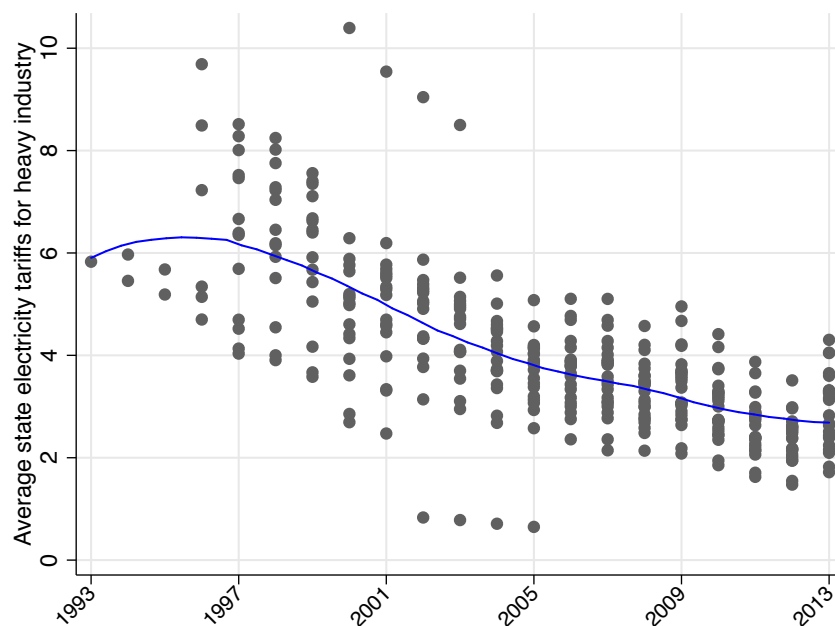
Notes: The left figure plots the annual electricity productivity ratios (value of output divided by the quantity of electricity used (in kWh)). Both quantities are for manufacturing only. Output is from [UNIDO \(2016\)](#), deflated with GDP deflators from [World Bank \(2017\)](#), and electricity consumption from the [IEA \(2016\)](#). Plotted are the values and kernel smoother for India with the solid line, corresponding to the left axis. The values and kernel smoother for OECD countries are the dashed lines, corresponding to the right axis. The right figure plots the share of electricity consumption in total fuel consumption in India (both in ktoe) using data from [IEA \(2016\)](#).

**Figure A.20: Real electricity price index**



Notes: The figure plots the real electricity price index for industry. It is based on the wholesale price index for electricity for industrial purposes.

**Figure A.21: Average real utility tariffs for heavy industry**



Notes: The figure plots the real electricity tariff for heavy industry. The tariffs are manually collected from publications of the Indian [Central Electricity Authority](#) (2006-2015) and from [Indiastat](#) (2019) through Lok Sabha and Rajya Sabha questions. Individual data points correspond to state level average tariffs for heavy industry.

## A.10. Variation in electricity and labor productivity, and electricity prices

Figures A.22, A.23 and A.24 plot the densities of logged electricity productivity, logged labor productivity and electricity prices for every year in the sample. The figures show the unconditional densities and the densities after partialing out state by industry (4 digit) fixed effects. They show that there remains substantial variation across plants even within these state by industry groups throughout the sample. The 90th to 10th percentile ratio drops from 3.5 to 2.7 for logged electricity productivity, from 3.5 to 2.6 for logged labor productivity and from ₹2.1 to 1.4 for electricity prices.

To more formally analyze the variation left across plants within industry, spatial or consumption size clusters, I decompose variances following Davis et al. (2013). I calculate the annual variance as  $V = \sum_e s_e (p_e - \bar{p})^2$ , where  $s_e$  are electricity purchase weights multiplied by the sample multiplier,  $p_e$  are logged electricity productivity, logged labor productivity, or prices, and  $\bar{p}$  the weighted average log productivity or price. I decompose total variance into a within “group” component  $V^W$ , and a component across “groups”  $V^G$ :

$$V = \sum_e s_e (p_e - \bar{p}_g)^2 + \sum_g s_g (\bar{p}_g - \bar{p})^2 = V^W + V^G$$

where  $s_g = \sum_{e \in g} s_e$  and  $\bar{p}_g$  the weighted average of log productivity or price within group  $g$ . I calculate the decomposition separately five times for five different groups, which are states, deciles of electricity purchase quantity, 4-digit industries, industry by states, and industry by states by deciles. Figure A.25 plots the total variance  $V$  and the across-group variances  $V^G$  to visualize the degree to which the groups can explain the variance across plants. The Figure also plots the share of  $V^G$  in  $V$  ( $V^G/V$ ) in the right panels where higher shares mean that the groups can explain more of the variation.

Figure A.25 shows that state-industry effects can only account for around 50% of the cross-sectional variance in electricity productivity, around 40% of the variation in labor productivity, and 60% of the variation in electricity prices.<sup>86</sup> For electricity and labor productivity, there is more variation across industries, while for electricity prices there is more variation across states. This is intuitive, as production techniques tend to vary more across industries, while electricity price-setting varies more across geography as explained in Section III.A.

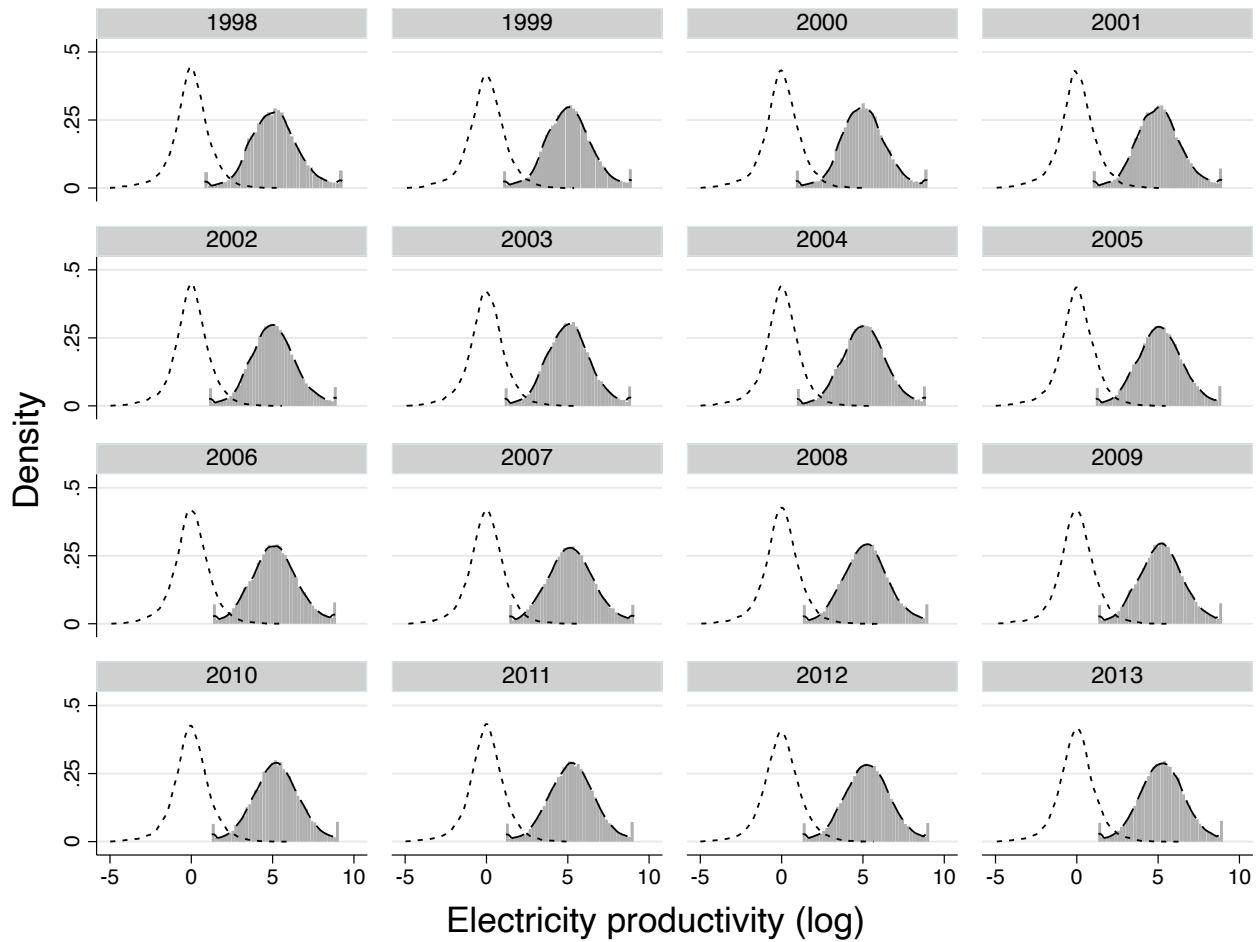
The variance in electricity prices has been decreasing from 1998 to 2013. Figure A.26 plots quantiles of the distribution over time and shows a convergence in electricity prices that accompanied the secular price decline. Comparing the decrease in the total variance of electricity prices and the shares that state by industry groups can explain in Figure A.25, we can conclude that the convergence has not been driven by reductions across industries or states alone, but by convergence within these clusters.

<sup>86</sup>Variation across districts (not plotted) can explain around 22% and 45% of electricity productivity and electricity prices respectively. Districts for the later years are not available for all observations.

The deciles of plants' electricity consumption cannot explain much of the variance. This is in contrast to the findings for the US (Davis et al., 2013) and France (Marin and Vona, 2021) and consistent with the observation in Section III.A that tariff schedules in India can be increasing or decreasing in consumption. The main analysis accounts for industry by year by region fixed effects to account for differences across industries. Importantly, we learn from these descriptives that there is substantial variation left after accounting for these fixed effects.

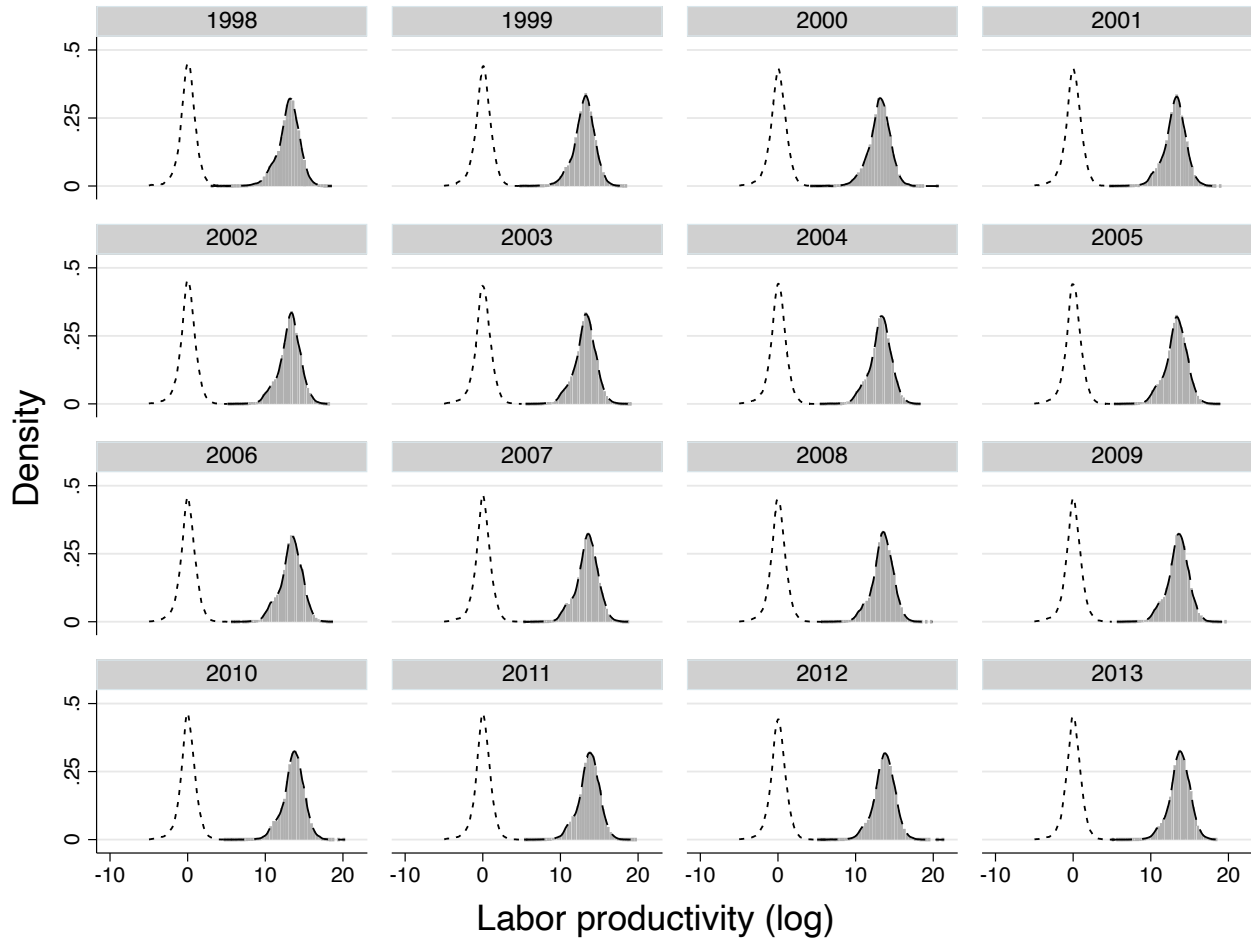
To study the persistence of electricity productivity, labor productivity and electricity prices within plants, I follow the approach of Farinas and Ruano (2005). I plot the CDF of logged electricity productivity, logged labor productivity and electricity prices for two separate years in Figure A.27, all conditional on previous period values. That is, I divide the sample into four quartiles based on previous period values and plot the four CDFs of the current period separately for these quartiles. As the CDF of the higher quartiles are to the right of the lower quartiles for every value, they first order stochastically dominate the distributions of plants ranked in lower previous period quartiles. Therefore, plants from a higher previous quartile are more likely to belong to the higher quartile in the current period. This implies that electricity productivity, labor productivity and electricity prices are all persistent. One important implication of this persistence is that I use variation within *and* across plants for the analysis.

Figure A.22: Heterogeneity in electricity productivity



Notes: The figure plots the histograms of plant level logged electricity productivity by year. The left kernel density plot shows the distribution of the residuals of logged electricity productivity after partialing out state by 4-digit industry by year fixed effects. Electricity productivity ratios are the value of output divided by the quantity of electricity used in kWh.

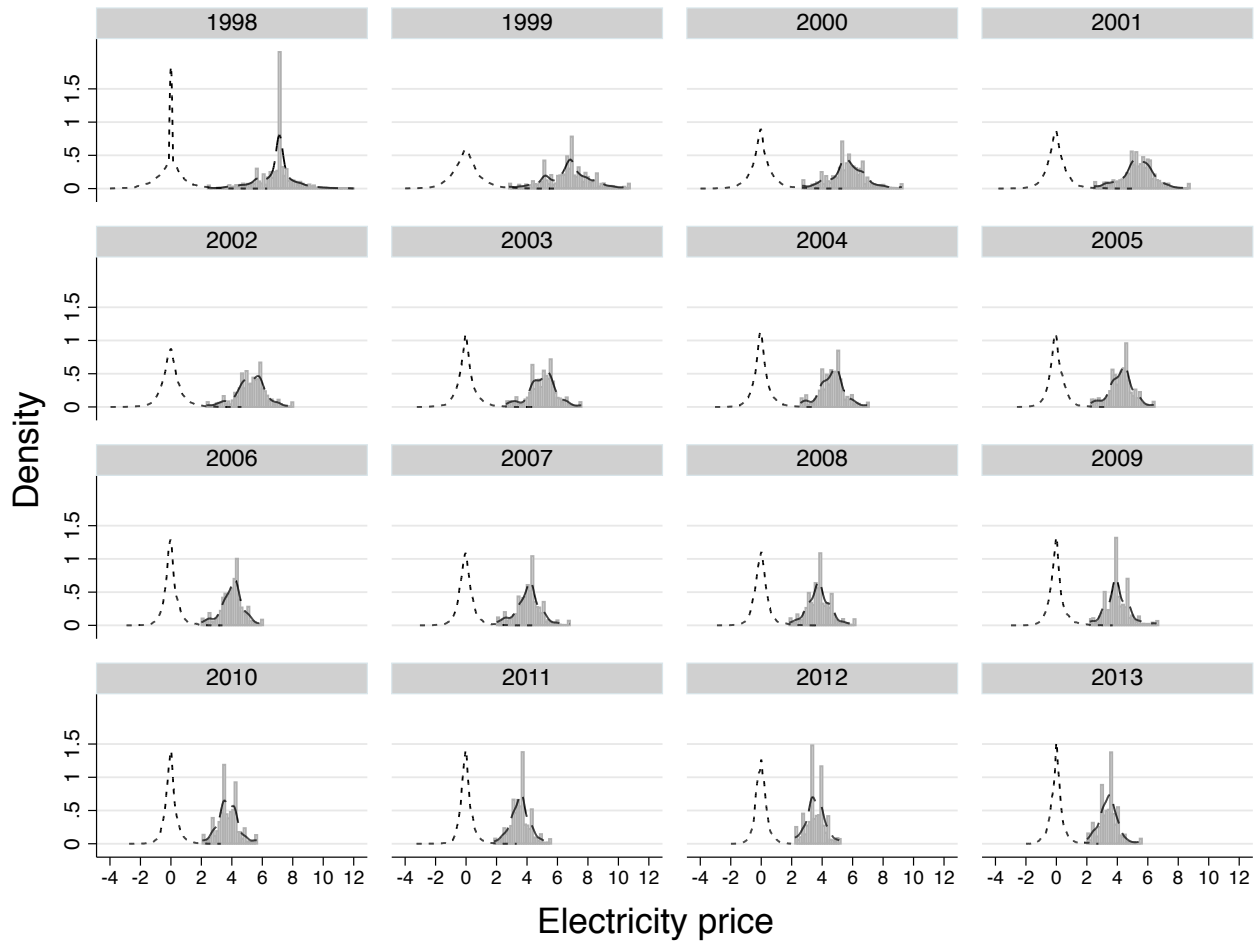
Figure A.23: Heterogeneity in labor productivity



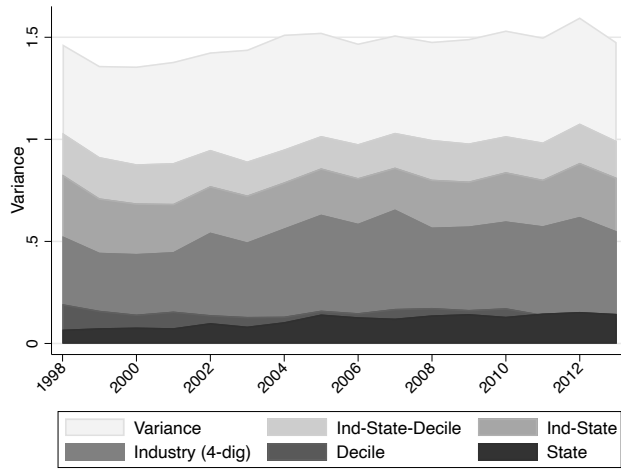
Notes: The figure plots the histograms of plant level logged labor productivity by year. The left kernel density plot shows the distribution of the residuals of logged labor productivity after partialing out state by 4-digit industry by year fixed effects. Labor productivity ratios are the value of output divided by the number of employees.



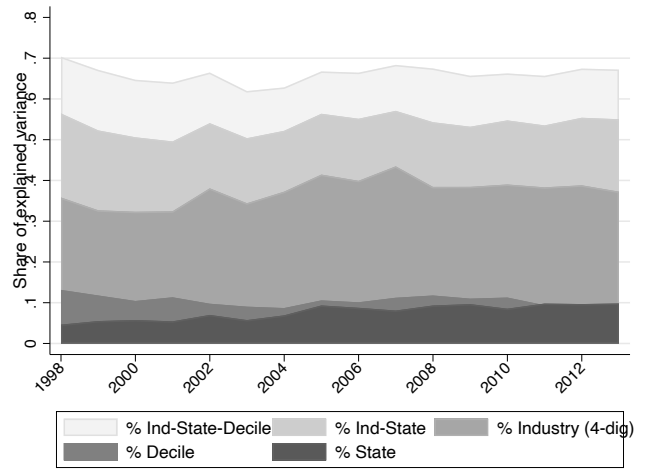
Figure A.24: Heterogeneity in electricity prices



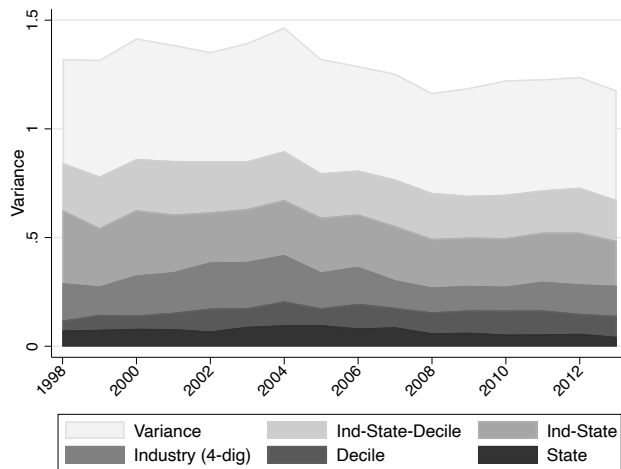
Notes: The figure plots the histograms of plant level electricity prices by year. The left kernel density plot shows the distribution of the residuals of electricity prices after partialing out state by 4-digit industry by year fixed effects.



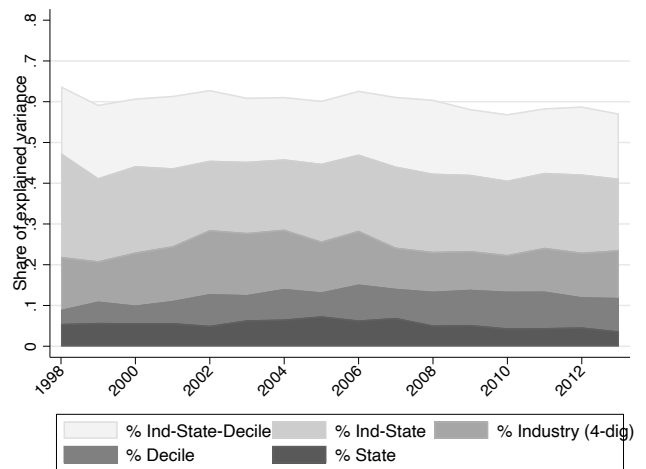
(a) Electricity productivity variance decomposition



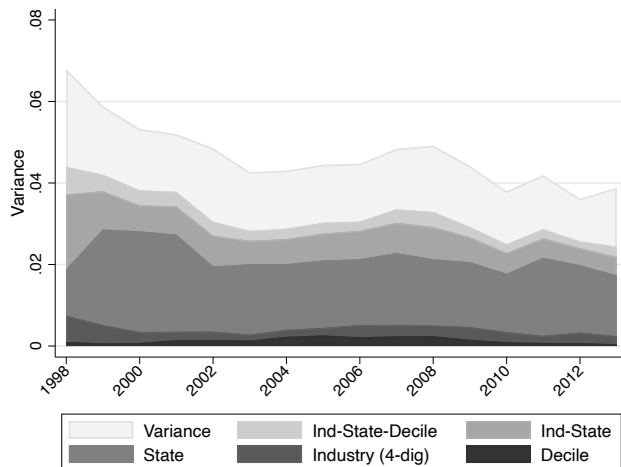
(b) Electricity productivity variance decomposition



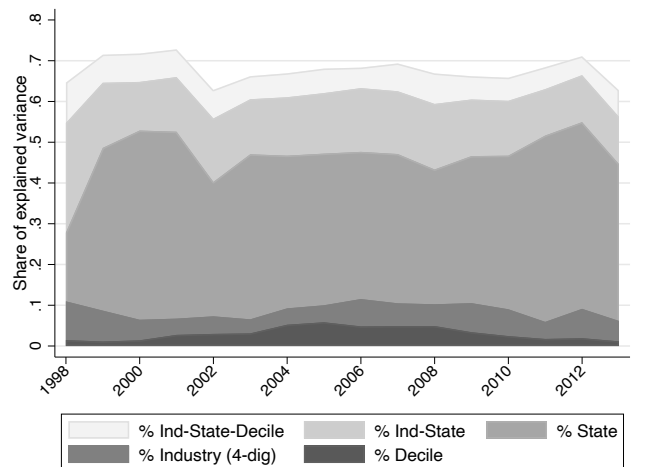
(c) Labor productivity variance decomposition



(d) Labor productivity variance decomposition



(e) Electricity price variance decomposition

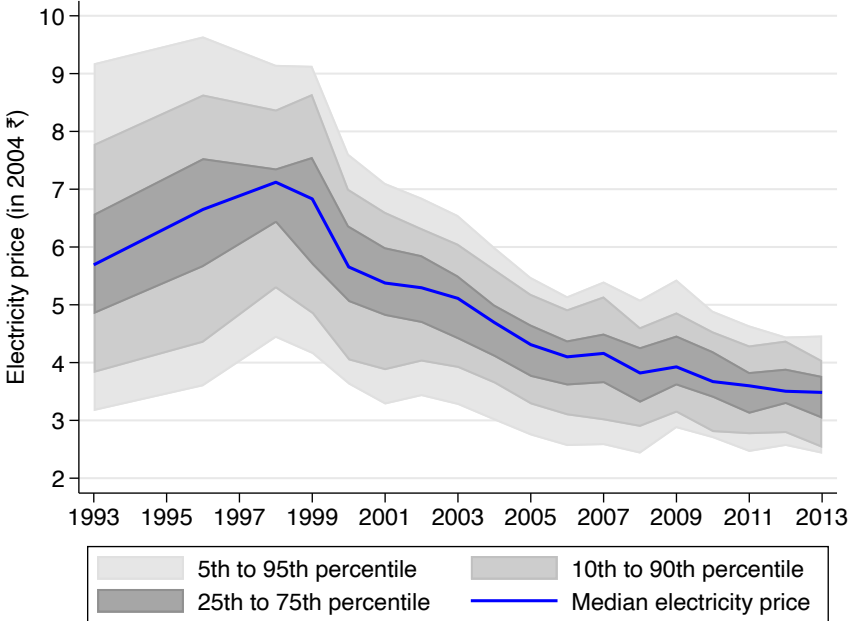


(f) Electricity price variance decomposition

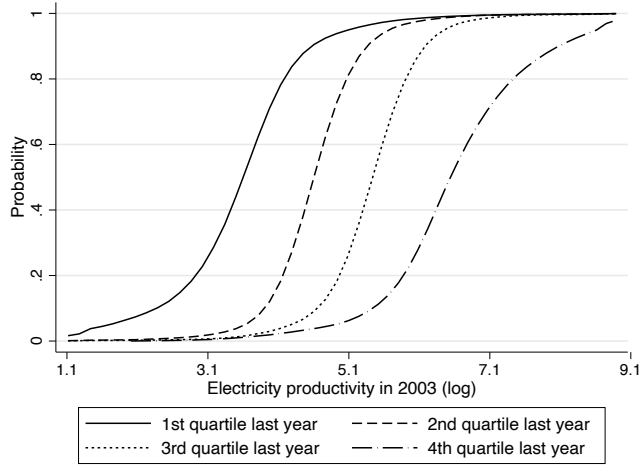
**Figure A.25:** Variance decompositions of electricity and labor productivities and electricity prices

Notes: The left Panels (a), (c) and (e) plot the annual total variance of logged electricity productivity, logged labor productivity and logged electricity prices respectively, and the variance explained by specified groups as described in the text. The right Panels (b), (d) and (f) plot the share of the variance explained by each group. Groups are deciles of electricity purchase quantity, 4-digit industries, states, and combinations thereof.

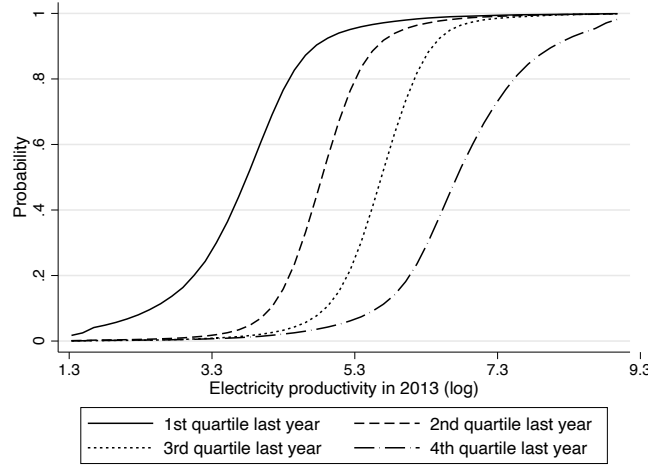
Figure A.26: Convergence in electricity prices



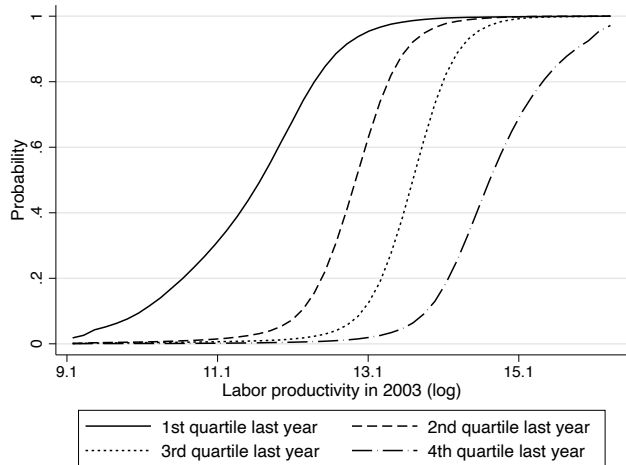
Notes: The figure plots the 5th, 10th, 25th, 50th, 75th, 90th and 95th percentile of real annual plant level electricity prices.



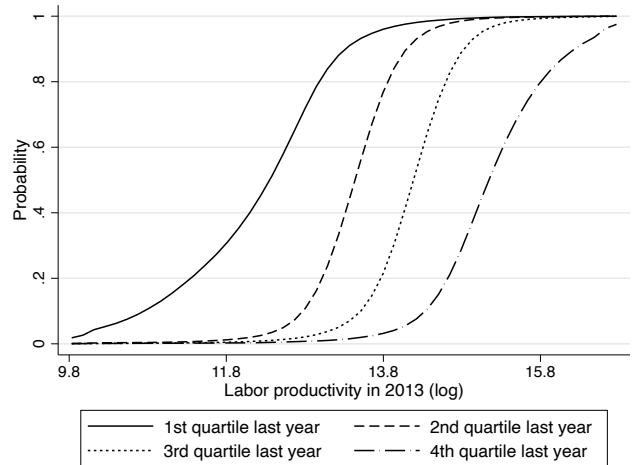
(a) Electricity productivity 2003 (CDF)



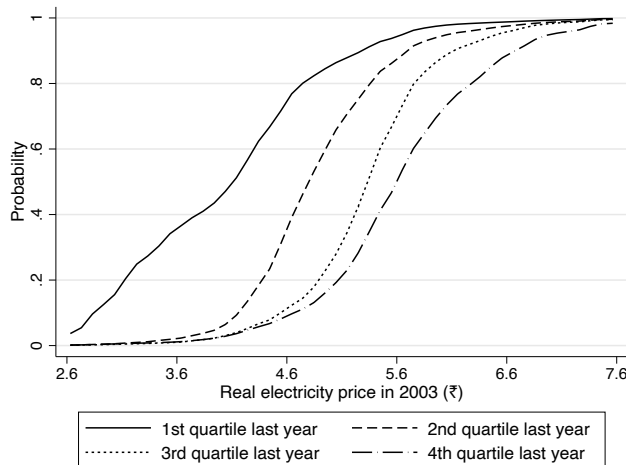
(b) Electricity productivity 2013 (CDF)



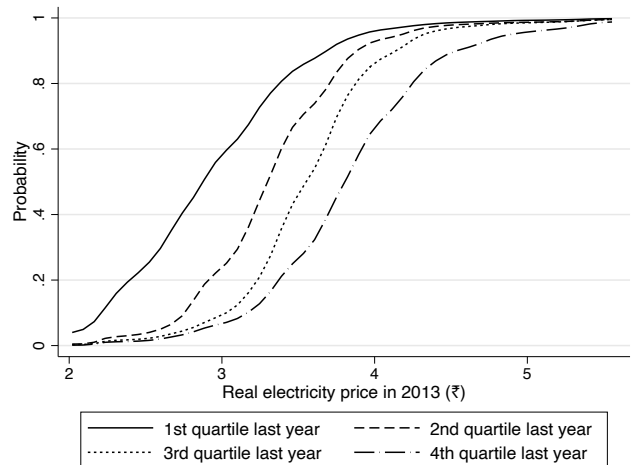
(c) Labor productivity 2003 (CDF)



(d) Labor productivity 2013 (CDF)



(e) Electricity prices 2003 (CDF)



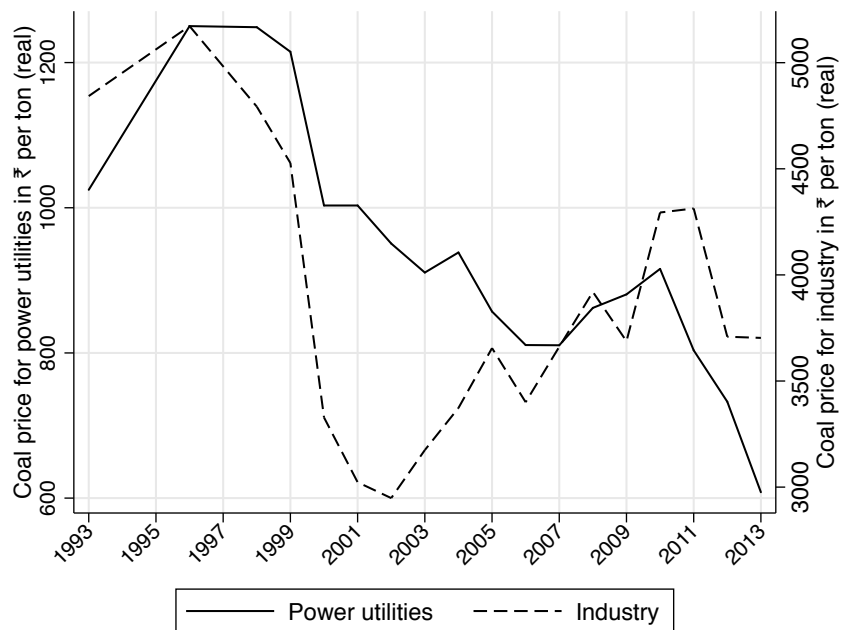
(f) Electricity prices 2013 (CDF)

**Figure A.27: Conditional CDFs of productivities and electricity prices**

Notes: The Panels (a), (c) and (e) plot the CDFs in 2003 separately for each quartile of the respective values in 2002, for logged electricity productivity, logged labor productivity, and electricity prices respectively. The Panels (b), (d) and (f) plot the same graphs for the CDFs in 2013 separately for each quartile of the respective values in 2012. The CDFs are empirical CDFs obtained through a Gaussian kernel smoother with bandwidth 0.1. The graphs show that each higher quartile first order stochastically dominates the lower quartiles. The conditional CDFs for other years look similar.

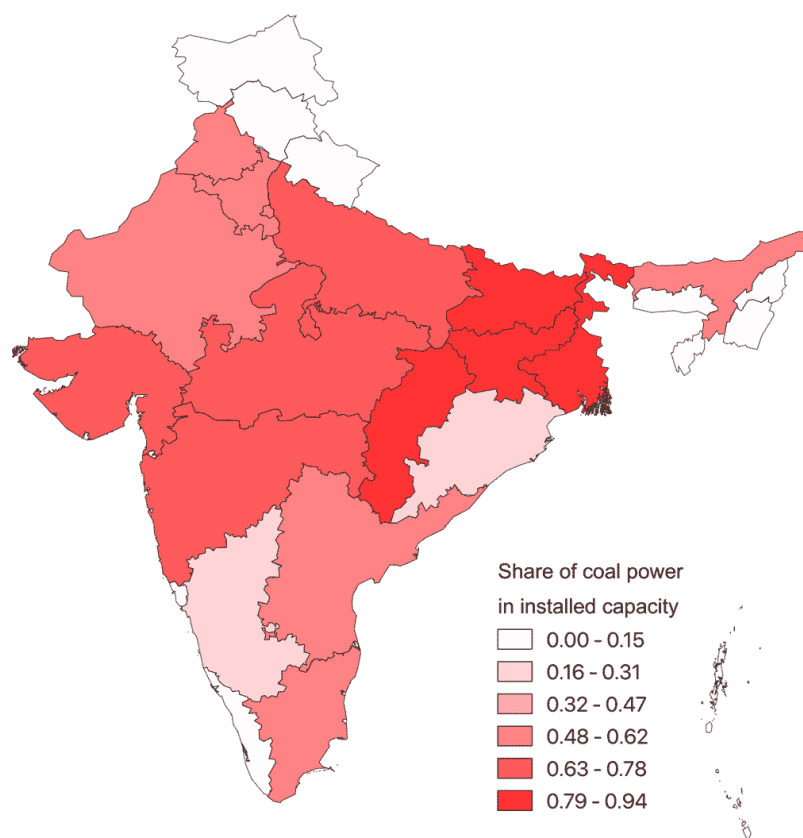
## A.11. Coal price for power utilities and industry, and coal share in installed capacity

Figure A.28: Coal price for power utilities versus coal price for industry



Notes: The solid line plots the coal price for thermal power plants and are from [Minsitry of Coal \(2012, 2015\)](#) as described in Section III.B. Prices for coal used in manufacturing industries are plotted with the dashed line. These are averages of the coal prices at the plant level in the ASI micro data (see Section III.B). All coal prices are in real terms and deflated using a general fuel and electricity wholesale price deflator. In nominal terms, coal prices have been mostly increasing.

**Figure A.29:** Share of coal power in total installed capacity



Notes: The shading indicates the share of coal fired thermal power generation capacity in total installed capacity at the state level in March 1998. Data comes from [Ministry of Power \(1998a, 2003\)](#).

**Table A.4:** Correlation of coal power shares with other predetermined variables

	Share rural (1)	Share domestic power (2)	Share power (3)	Labor productivity (log) (4)	Capital labor ratio (log) (5)	Share managerial wages (6)	Fuel share in output (7)	Wage share in output (8)
Coal power share	0.0216 (0.129)	0.181 (0.158)	-0.156 (0.153)	0.370 (0.300)	0.143 (0.318)	-0.0368 (0.035)	0.0183 (0.024)	-0.0141 (0.022)
Observations	31	31	31	31	31	28	26	26

Notes: The table shows state level regressions of the indicated outcome on the pre-sample coal power shares in generating capacity that is used in the construction of  $IV^B$ . Each column represents a separate regression controlling for region fixed effects as in the main analysis. The outcomes in Columns 1-3 come from the 91 Population Census from SHRUG. Share rural is the rural share in population. Share domestic power is the share of villages that have electricity for domestic use. Share power is the share of villages that have electricity for any use. The outcomes in Columns 4-5 are based on the 1998 version of the ASI microdata. Labor productivity is sales divided by number of employees. Capital labor ratio is total book value of capital divided by number of employees. The outcome in Column 6 is based on the 1996 version of the ASI microdata, and share managerial wages is the share of wages going to supervisors and managers in total wages. The outcomes in Columns 7-8 are based on the aggregate ASI data in 1997. Fuel share in output is total spending on fuel as share of output. Wage share in output is total emoluments as share of output. Robust standard errors are in parentheses.

## A.12. Additional regression results and robustness checks

**Table A.5:** Lagged electricity prices and electricity productivity

	Electricity productivity (log)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(P^E)$	0.295*** (0.049)	-0.273*** (0.062)	-0.735*** (0.087)			
Lagged $\log(P^E)$				0.0184 (0.042)	-0.275*** (0.060)	-0.727*** (0.086)
OLS/IV	OLS	$IV^A$	$IV^B$	OLS	$IV^A$ (lag)	$IV^B$ (lag)
Observations	225576	225576	225576	225576	225576	225576
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes
First stage coef.	-	0.98***	0.06***	-	0.98***	0.07***
First stage SE	-	0.005	0.003	-	0.005	0.003
F-stat (Kleib.-Paap)	-	46326.167	421.154	-	39799.891	405.397
SE clustered by	Plant	Plant	Plant	Plant	Plant	Plant
No. of first clusters	67789	67789	67789	67789	67789	67789
SE clustered by	State-year	State-year	State-year	State-year	State-year	State-year
No. of second clusters	469	469	469	469	469	469

Notes: See Table 2 for notes. The main difference is that the first three columns restrict the sample to the same observations as in the last three columns, where lagged logged electricity prices (and lagged instruments) are used.

**Table A.6:** Lagged electricity prices and labor productivity

	Labor productivity (log)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(P^E)$	-0.0412 (0.045)	-0.255*** (0.083)	-0.484*** (0.101)			
Lagged $\log(P^E)$				-0.0478 (0.045)	-0.251*** (0.083)	-0.478*** (0.100)
OLS/IV	OLS	$IV^A$	$IV^B$	OLS	$IV^A$ (lag)	$IV^B$ (lag)
Observations	225576	225576	225576	225576	225576	225576
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes
First stage coef.	-	0.98***	0.06***	-	0.98***	0.07***
First stage SE	-	0.005	0.003	-	0.005	0.003
F-stat (Kleib.-Paap)	-	46326.167	421.154	-	39799.891	405.397
SE clustered by	Plant	Plant	Plant	Plant	Plant	Plant
No. of first clusters	67789	67789	67789	67789	67789	67789
SE clustered by	State-year	State-year	State-year	State-year	State-year	State-year
No. of second clusters	469	469	469	469	469	469

Notes: See Table 2 for notes. The main difference is that the first three columns restrict the sample to the same observations as in the last three columns, where lagged logged electricity prices (and lagged instruments) are used.

**Table A.7:** Similar estimates with three alternative instruments  $IV^C$ ,  $IV^{D_1}$  and  $IV^{D_2}$ 

	Electricity productivity (log)					Labor productivity (log)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\log(P^E)$	0.37*** (0.044)	-0.27*** (0.071)	-0.50 (0.32)	-0.57*** (0.27)	-0.26 (0.18)	-0.028 (0.043)	-0.42*** (0.087)	-0.83** (0.35)	-0.95*** (0.25)	0.27 (0.19)
OLS/IV	OLS	$IV^C$	$IV^{D_1}$	$IV^{D_1}$	$IV^{D_2}$	OLS	$IV^C$	$IV^{D_1}$	$IV^{D_1}$	$IV^{D_2}$
Observations	485342	444428	444428	444424	485342	485342	444428	444428	444424	485342
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	No	No	No	Yes	No	No	No	No	Yes	No
Lower interactions	-	-	Yes	Yes	-	-	-	Yes	Yes	-
First stage coef.	-	0.97***	0.07***	0.07***	0.12***	-	0.97***	0.07***	0.07***	0.12***
First stage SE	-	0.005	0.017	0.011	0.014	-	0.005	0.017	0.011	0.014
F-stat (Kleib.-Paap)	-	37768.975	17.023	43.819	70.403	-	37768.975	17.023	43.819	70.403
Two-way clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: See Table 2 for notes. The main difference in this table is the use of alternative instruments,  $IV^C$ ,  $IV^{D_1}$ , and  $IV^{D_2}$ . Columns 3-4 and 8-9 also control for the lower order interactions between distance to coalfields, post 2003 Electricity Act, and a dummy if the state has ever coal power, as  $IV^{D_1}$  is based on the triple interaction between these variables (see also Section A.4). Columns 2-4 and 7-9 contain fewer observations due to some constraints in matching the ASI data versions with panel information and district information after 2009 for plants that do not appear before 2009.

**Table A.8:** Electricity prices and electricity productivity: controlling for distance to coalfields and shortages

	OLS			$IV^A$			$IV^B$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(P^E)$	0.343*** (0.045)	0.472*** (0.043)	0.459*** (0.044)	-0.256*** (0.071)	-0.131 (0.085)	-0.121 (0.088)	-0.828*** (0.102)	-0.940*** (0.149)	-0.980*** (0.148)
Distance to coalfield (in '00 km)	-0.0179** (0.007)		-0.0190*** (0.007)	-0.0138* (0.007)		-0.0176** (0.007)	-0.00996 (0.008)		-0.0154* (0.008)
Shortage		0.398* (0.226)	0.284 (0.239)		0.646*** (0.187)	0.517*** (0.192)		0.979*** (0.198)	0.862*** (0.201)
OLS/IV	OLS	OLS	OLS	$IV^A$	$IV^A$	$IV^A$	$IV^B$	$IV^B$	$IV^B$
Observations	444428	473433	432748	444428	473433	432748	444428	473433	432748
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First stage coef.	-	-	-	0.98***	0.97***	0.98***	0.06***	0.05***	0.05***
First stage SE	-	-	-	0.005	0.006	0.006	0.003	0.004	0.004
F-stat (Kleib.-Paap)	-	-	-	41074.924	25423.121	26129.044	307.814	173.595	176.737
Two-way clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: See Table 2 for notes. The main difference is that control variables are added as indicated.

**Table A.9:** Electricity prices and labor productivity: controlling for distance to coalfields and shortages

	OLS			$IV^A$			$IV^B$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(P^E)$	-0.0630 (0.044)	0.0866** (0.042)	0.0629 (0.042)	-0.466*** (0.084)	-0.151 (0.103)	-0.213** (0.100)	-1.043*** (0.097)	-1.089*** (0.159)	-1.012*** (0.144)
Distance to coalfield (in '00 km)	0.0362*** (0.007)		0.0399*** (0.007)	0.0389*** (0.008)		0.0406*** (0.008)	0.0428*** (0.008)		0.0426*** (0.009)
Shortage		-0.415* (0.229)	-0.562*** (0.216)		-0.318 (0.219)	-0.451** (0.198)		0.0679 (0.279)	-0.130 (0.237)
OLS/IV	OLS	OLS	OLS	$IV^A$	$IV^A$	$IV^A$	$IV^B$	$IV^B$	$IV^B$
Observations	444428	473433	432748	444428	473433	432748	444428	473433	432748
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First stage coef.	-	-	-	0.98***	0.97***	0.98***	0.06***	0.05***	0.05***
First stage SE	-	-	-	0.005	0.006	0.006	0.003	0.004	0.004
F-stat (Kleib.-Paap)	-	-	-	41074.924	25423.121	26129.044	307.814	173.595	176.737
Two-way clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: See Table 2 for notes. The main difference is that control variables are added as indicated.



**Table A.10:** Electricity prices and electricity and labor productivity in electricity intensive sectors

	Electricity productivity (log)			Labor productivity (log)		
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(P^E)$	0.323*** (0.047)	-0.210*** (0.074)	-0.585*** (0.102)	-0.168*** (0.047)	-0.545*** (0.085)	-1.049*** (0.103)
OLS/IV	OLS	$IV^A$	$IV^B$	OLS	$IV^A$	$IV^B$
Observations	260571	260571	260571	260571	260571	260571
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes
First stage coef.	-	0.97***	0.06***	-	0.97***	0.06***
First stage SE	-	0.005	0.004	-	0.005	0.004
F-stat (Kleib.-Paap)	-	32799.401	324.537	-	32799.401	324.537
Two-way clustered SE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: See Table 2 for notes. The main difference is that the sample is restricted to electricity intensive sectors only.

**Table A.11:** Electricity prices and electricity and labor productivity in plants that do not use coal

	Electricity productivity (log)			Labor productivity (log)		
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(P^E)$	0.372*** (0.047)	-0.244*** (0.072)	-0.840*** (0.107)	-0.0518 (0.045)	-0.407*** (0.087)	-1.086*** (0.104)
OLS/IV	OLS	$IV^A$	$IV^B$	OLS	$IV^A$	$IV^B$
Observations	435681	435681	435681	435681	435681	435681
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes
First stage coef.	-	0.97***	0.06***	-	0.97***	0.06***
First stage SE	-	0.005	0.003	-	0.005	0.003
F-stat (Kleib.-Paap)	-	44590.885	295.125	-	44590.885	295.125
Two-way clustered SE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: See Table 2 for notes. The main difference is that the sample is restricted to manufacturing plants that do not use coal directly.

**Table A.12: Electricity prices and electricity productivity by industry groups****(a) Electricity prices and electricity productivity (Chemicals, food, machinery))**

	Chemicals			Food			Machinery		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(P^E)$	0.139** (0.064)	-0.426*** (0.086)	-0.762*** (0.104)	0.608*** (0.073)	0.108 (0.168)	-1.636*** (0.447)	0.215*** (0.066)	-0.640*** (0.093)	-1.300*** (0.137)
OLS/IV	OLS	$IV^A$	$IV^B$	OLS	$IV^A$	$IV^B$	OLS	$IV^A$	$IV^B$
Observations	76574	76574	76574	92467	92467	92467	91156	91156	91156
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First stage coef.	-	0.98***	0.08***	-	0.90***	0.04***	-	1.01***	0.07***
First stage SE	-	0.007	0.003	-	0.014	0.003	-	0.006	0.004
F-stat (Kleib.-Paap)	-	17808.538	528.030	-	3940.605	105.141	-	24275.472	341.090
SE clustered by	Plant	Plant	Plant	Plant	Plant	Plant	Plant	Plant	Plant
No. of first clusters	27000	27000	27000	31608	31608	31608	29361	29361	29361
SE clustered by	State-year	State-year	State-year	State-year	State-year	State-year	State-year	State-year	State-year
No. of second clusters	472	472	472	500	500	500	440	440	440

**(b) Electricity prices and electricity productivity (Metals and minerals, textiles, wood and paper)**

	Metals and minerals			Textiles			Wood and Paper		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(P^E)$	0.486*** (0.053)	0.108 (0.104)	0.283 (0.197)	0.403*** (0.076)	-0.138 (0.158)	-1.013*** (0.266)	0.357*** (0.066)	-0.224** (0.096)	-0.695*** (0.137)
OLS/IV	OLS	$IV^A$	$IV^B$	OLS	$IV^A$	$IV^B$	OLS	$IV^A$	$IV^B$
Observations	102815	102815	102815	68878	68878	68878	38786	38786	38786
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First stage coef.	-	0.96***	0.05***	-	0.99***	0.07***	-	0.98***	0.06***
First stage SE	-	0.009	0.004	-	0.013	0.005	-	0.009	0.004
F-stat (Kleib.-Paap)	-	10644.302	175.524	-	5408.459	196.045	-	12000.421	261.732
SE clustered by	Plant	Plant	Plant	Plant	Plant	Plant	Plant	Plant	Plant
No. of first clusters	39326	39326	39326	21780	21780	21780	14084	14084	14084
SE clustered by	State-year	State-year	State-year	State-year	State-year	State-year	State-year	State-year	State-year
No. of second clusters	486	486	486	438	438	438	499	499	499

Notes: See Table 2 for notes. The main difference is that regressions are run individually by industry groups.

**Table A.13:** Electricity prices and labor productivity by industry groups

## (a) Electricity prices and labor productivity (Chemicals, food, machinery))

	Chemicals			Food			Machinery		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(P^E)$	-0.286*** (0.053)	-0.680*** (0.074)	-1.141*** (0.100)	0.454*** (0.074)	0.650*** (0.198)	-1.461*** (0.354)	-0.134** (0.059)	-0.673*** (0.101)	-1.235*** (0.124)
OLS/IV	OLS	$IV^A$	$IV^B$	OLS	$IV^A$	$IV^B$	OLS	$IV^A$	$IV^B$
Observations	76574	76574	76574	92467	92467	92467	91156	91156	91156
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First stage coef.	-	0.98***	0.08***	-	0.90***	0.04***	-	1.01***	0.07***
First stage SE	-	0.007	0.003	-	0.014	0.003	-	0.006	0.004
F-stat (Kleib.-Paap)	-	17808.538	528.030	-	3940.605	105.141	-	24275.472	341.090
SE clustered by	Plant	Plant	Plant	Plant	Plant	Plant	Plant	Plant	Plant
No. of first clusters	27000	27000	27000	31608	31608	31608	29361	29361	29361
SE clustered by	State-year	State-year	State-year	State-year	State-year	State-year	State-year	State-year	State-year
No. of second clusters	472	472	472	500	500	500	440	440	440

## (b) Electricity prices and labor productivity (Metals and minerals, textiles, wood and paper)

	Metals and minerals			Textiles			Wood and Paper		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(P^E)$	-0.142*** (0.052)	-0.443*** (0.109)	-1.480*** (0.167)	-0.106 (0.100)	-0.543** (0.229)	0.00768 (0.398)	0.174*** (0.060)	-0.0804 (0.101)	-0.645*** (0.146)
OLS/IV	OLS	$IV^A$	$IV^B$	OLS	$IV^A$	$IV^B$	OLS	$IV^A$	$IV^B$
Observations	102815	102815	102815	68878	68878	68878	38786	38786	38786
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First stage coef.	-	0.96***	0.05***	-	0.99***	0.07***	-	0.98***	0.06***
First stage SE	-	0.009	0.004	-	0.013	0.005	-	0.009	0.004
F-stat (Kleib.-Paap)	-	10644.302	175.524	-	5408.459	196.045	-	12000.421	261.732
SE clustered by	Plant	Plant	Plant	Plant	Plant	Plant	Plant	Plant	Plant
No. of first clusters	39326	39326	39326	21780	21780	21780	14084	14084	14084
SE clustered by	State-year	State-year	State-year	State-year	State-year	State-year	State-year	State-year	State-year
No. of second clusters	486	486	486	438	438	438	499	499	499

Notes: See Table 2 for notes. The main difference is that regressions are run individually by industry groups.

**Table A.14:** Electricity prices and electricity productivity in high price periods

	Electricity productivity (log)			Labor productivity (log)		
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(P^E)$	0.471*** (0.061)	0.00766 (0.094)	-0.737*** (0.168)	-0.0670 (0.057)	-0.430*** (0.105)	-1.066*** (0.149)
$\log(P^E) \cdot \mathbf{1}(year < 2006)$	-0.217** (0.084)	-0.531*** (0.128)	-0.0874 (0.193)	0.0796 (0.086)	0.0884 (0.170)	0.00701 (0.197)
OLS/IV	OLS	$IV^A$	$IV^B$	OLS	$IV^A$	$IV^B$
Observations	485342	485342	485342	485342	485342	485342
Ind by region by year FE	Yes	Yes	Yes	Yes	Yes	Yes
First stage coef. 1/1	-	0.96***	0.06***	-	0.96***	0.06***
First stage SE 1/1	-	0.006	0.005	-	0.006	0.005
First stage coef. 1/2	-	0.03***	0.01	-	0.03***	0.01
First stage SE 1/2	-	0.009	0.007	-	0.009	0.007
First stage coef. 2/1	-	-0.00	0.00	-	-0.00	0.00
First stage SE 2/1	-	0.000	0.000	-	0.000	0.000
First stage coef. 2/2	-	0.99***	0.06***	-	0.99***	0.06***
First stage SE 2/2	-	0.007	0.005	-	0.007	0.005
F-stat (Kleibergen-Paap)	-	11025.104	68.072	-	11025.104	68.072
Two-way clustered SE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: See Table 2 for notes. The main difference is that the independent variables are the logged electricity price and an interaction with a dummy that is one for all years before 2006. Instruments are interacted in the same way. The first stage statistics refer to variable 1 and corresponding instrument 1 etc. Note that mainly the corresponding instruments shift the variables (i.e. 1/1 and 2/2).

**Table A.15:** Electricity prices and electricity productivity: using both IVs

	Electricity productivity (log)			Labor productivity (log)		
	OLS (1)	IV <sup>A</sup> & IV <sup>B</sup> (2)	IV <sup>C</sup> & IV <sup>B</sup> (3)	OLS (4)	IV <sup>A</sup> & IV <sup>B</sup> (5)	IV <sup>C</sup> & IV <sup>B</sup> (6)
log( <i>P</i> <sup><i>E</i></sup> )	0.365*** (0.044)	-0.256*** (0.068)	-0.288*** (0.069)	-0.0282 (0.043)	-0.410*** (0.083)	-0.448*** (0.085)
IV 1	-	IV <sup>A</sup>	IV <sup>C</sup>	-	IV <sup>A</sup>	IV <sup>C</sup>
IV 2	-	IV <sup>B</sup>	IV <sup>B</sup>	-	IV <sup>B</sup>	IV <sup>B</sup>
Observations	485342	485342	444428	485342	485342	444428
Ind by region by year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	No	No	No	No	No
Plant FE	No	No	No	No	No	No
State trends	No	No	No	No	No	No
State by year FE	No	No	No	No	No	No
First stage coef. 1/1	-	0.94***	0.94***	-	0.94***	0.94***
First stage SE 1/1	-	0.007	0.008	-	0.007	0.008
First stage coef. 1/2	-	0.00***	0.00***	-	0.00***	0.00***
First stage SE 1/2	-	0.001	0.001	-	0.001	0.001
F-stat (Kleibergen-Paap)	-	23377.854	20445.636	-	23377.854	20445.636
Anderson-Rubin F	-	0.000	0.000	-	0.000	0.000
J-statistic	-	26.10	28.70	-	39.97	37.98
Two-way clustered SE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: See Table 2 for notes. The main difference is that both instruments are used simultaneously. The Sargan-Hansen J statistic is reported. The difference in the instrument is consistent with heterogeneous LATEs.

**Table A.16:** Electricity prices and productivity (TFP): alternative methodologies

	log(TFP) OP			log(TFP) LP			log(TFP) ACF		
	OLS (1)	IV <sup>A</sup> (2)	IV <sup>B</sup> (3)	OLS (4)	IV <sup>A</sup> (5)	IV <sup>B</sup> (6)	OLS (7)	IV <sup>A</sup> (8)	IV <sup>B</sup> (9)
log( <i>P</i> <sup><i>E</i></sup> )	-0.00735*** (0.002)	-0.0273*** (0.004)	-0.0387*** (0.005)	-0.000566 (0.002)	-0.0168*** (0.004)	-0.0321*** (0.007)	-0.00414** (0.002)	-0.00761*** (0.003)	-0.0233*** (0.006)
OLS/IV	OLS	IV <sup>A</sup>	IV <sup>B</sup>	OLS	IV <sup>A</sup>	IV <sup>B</sup>	OLS	IV <sup>A</sup>	IV <sup>B</sup>
Observations	378824	378824	378824	477697	477697	477697	477697	477697	477697
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First stage coef.	-	0.98***	0.06***	-	0.97***	0.06***	-	0.97***	0.06***
First stage SE	-	0.004	0.003	-	0.005	0.003	-	0.005	0.003
F-stat (Kleib.-Paap)	-	51023.623	390.549	-	44391.045	297.573	-	44391.045	297.573
Two-way clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: See Table 2 for notes. Different methods to recover TFP are used, and TFP used as dependent variable. OP refers to [Olley and Pakes \(1996\)](#), LP refers to [Levinsohn and Petrin \(2003\)](#) and ACF refers to [Akerberg, Caves and Frazer \(2015\)](#).

**Table A.17:** Electricity prices and electricity productivity: clustering at district and region year

	Electricity productivity (log)			Labor productivity (log)		
	(1)	(2)	(3)	(4)	(5)	(6)
log( <i>P</i> <sup><i>E</i></sup> )	0.340*** (0.117)	-0.265* (0.154)	-0.819*** (0.218)	-0.0563 (0.126)	-0.441* (0.242)	-1.084*** (0.229)
OLS/IV	OLS	IV <sup>A</sup>	IV <sup>B</sup>	OLS	IV <sup>A</sup>	IV <sup>B</sup>
Observations	444428	444428	444428	444428	444428	444428
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes
First stage coef.	-	0.98***	0.06***	-	0.98***	0.06***
First stage SE	-	0.018	0.010	-	0.018	0.010
F-stat (Kleib.-Paap)	-	3059.943	38.841	-	3059.943	38.841
SE clustered by	District	District	District	District	District	District
No. of first clusters	541	541	541	541	541	541
SE clustered by	Region-year	Region-year	Region-year	Region-year	Region-year	Region-year
No. of second clusters	96	96	96	96	96	96

Notes: See Table 2 for notes. The main difference is that the standard errors are clustered at a higher level, at the district level and the region-year level.

**Table A.18:** Electricity prices, product scope, and electric machinery equipment

	Number of products (log)			Share electric equipment		
	OLS (1)	$IV^A$ (2)	$IV^B$ (3)	OLS (4)	$IV^A$ (5)	$IV^B$ (6)
$\log(P^E)$	0.0455*** (0.012)	-0.00295 (0.023)	-0.0968*** (0.036)	-0.00283*** (0.001)	-0.00717*** (0.002)	-0.0143*** (0.002)
OLS/IV	OLS	$IV^A$	$IV^B$	OLS	$IV^A$	$IV^B$
Observations	484482	484482	484482	485338	485338	485338
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes
First stage coef.	-	0.97***	0.06***	-	0.97***	0.06***
First stage SE	-	0.005	0.003	-	0.005	0.003
F-stat (Kleib.-Paap)	-	43049.885	296.748	-	35167.892	340.075
Two-way clustered SE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: See Table 2 for notes. Dependent variables are different as indicated.

**Table A.19:** FDI liberalized industries in 2006

Manufacture of rubber tyres and tubes n.e.c.
Manufacture of essential oils; modification by chemical processes of oils and fats (e.g. by oxidation, polymerization etc.)
Manufacture of various other chemical products
Manufacture of rubber tyres and tubes for cycles and cycle-rickshaws
Manufacture of distilled, potable, alcoholic beverages such as whisky, brandy, gin, 'mixed drinks' etc.
Coffee curing, roasting, grinding blending etc. and manufacturing of coffee products
Retreading of tyres; replacing or rebuilding of tread on used pneumatic tyres
Manufacture of chemical elements and compounds doped for use in electronics
Manufacture of country liquor
Manufacture of matches
Manufacture of rubber plates, sheets, strips, rods, tubes, pipes, hoses and profile -shapes etc.
Distilling, rectifying and blending of spirits
Manufacture of bidi
Manufacture of catechu (katha) and chewing lime
Stemming and redrying of tobacco
Manufacture of other rubber products n.e.c.
Manufacture of rubber contraceptives
Manufacture of other tobacco products including chewing tobacco n.e.c.
Manufacture of pan masala and related products.

Notes: The table lists the industries that were liberalized for FDI in 2006.

**Table A.20:** Electricity prices and high baseline machinery to labor ratio

	Electricity productivity (log)			Output (log)		
	OLS (1)	$IV^A$ (2)	$IV^B$ (3)	OLS (4)	$IV^A$ (5)	$IV^B$ (6)
$\log(P^E)$	0.231*** (0.053)	-0.362*** (0.065)	-1.014*** (0.118)	0.142** (0.071)	-0.203* (0.121)	-0.429** (0.174)
$\log(P^E) \times \text{abovemed}$	0.117*** (0.036)	0.155*** (0.044)	0.569*** (0.124)	0.0475 (0.063)	0.191*** (0.071)	0.973*** (0.185)
OLS/IV	OLS	$IV^A$	$IV^B$	OLS	$IV^A$	$IV^B$
Observations	217773	217773	217773	217773	217773	217773
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes
F-stat (Kleib.-Paap)	-	24458.057	49.961	-	24458.057	49.961
Two-way clustered SE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: See Table 2 for notes. This table contains the interactions with an indicator of whether the plant was above the median in the machinery capital to labor ratio in the previous period ("abovemed"). Since spells of data are required, the sample size is lower. The interactions with treated industries are appropriately instrumented with interactions with  $IV^A$  and  $IV^B$  as indicated. The baseline variable "abovemed" is included but not reported.

**Table A.21:** Electricity prices and FDI-liberalized industries

	Electricity productivity (log)		Labor productivity (log)		Output (log)	
	OLS (1)	$IV^A$ (2)	OLS (3)	$IV^A$ (4)	OLS (5)	$IV^A$ (6)
$\log(P^E)$	0.278*** (0.060)	-0.504*** (0.087)	-0.0213 (0.065)	-0.528*** (0.144)	0.0236 (0.106)	-1.293*** (0.439)
$\log(P^E) \times treated$	-0.273** (0.123)	-0.686** (0.269)	0.391*** (0.113)	0.220 (0.206)	1.059*** (0.181)	0.570 (0.353)
$\log(P^E) \times post$	0.180** (0.083)	0.477*** (0.123)	-0.0672 (0.084)	0.0193 (0.179)	-0.285* (0.145)	-0.299 (0.590)
$\log(P^E) \times treated \times post$	0.448** (0.203)	1.052*** (0.382)	-0.121 (0.172)	-0.484* (0.281)	0.192 (0.216)	0.233 (0.619)
OLS/IV	OLS	$IV^A$	OLS	$IV^A$	OLS	$IV^A$
Observations	485342	485342	485342	485342	485342	485342
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes
F-stat (Kleib.-Paap)	-	476.538	-	476.538	-	476.538
Two-way clustered SE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: See Table 2 for notes. This table contains the interactions with indicators for treated industries liberalized for FDI in 2006 (treated) and post-2006 (post). The interactions with treated industries are appropriately instrumented with interactions with  $IV^A$ . Due to multiple endogenous variables, the F-stat for  $IV^B$  is low and results are not reported due to weak IV bias.

### A.13. Using nation-wide average product electricity intensities

Instead of examining plant level electricity productivities, I use constant product level electricity intensities following Abeberese (2017) in this section. Note that electricity intensity is simply the inverse of electricity productivity. For each product code, I calculate the average nation-wide electricity intensity in 2000. For each plant I apply the same nation-wide intensities to their product mix in every year, calculating the simple average of electricity intensities of their products, as well as the weighted average, weighted by the sales share of each product. As a result, these outcomes ignore any changes in electricity productivity of products through technology and inputs that I focus on, or any heterogeneity across time and across plants, which is, however, a feature of the data (see Figure 3).

Table A.22 shows the results using the average electricity intensity of the product mix. Since the product definition changed after 2009, I only run regression for a smaller sample until 2009. There is no significant relationship in the OLS or the IV regressions, which shows that accounting for heterogeneity and changes in electricity productivity across plants and time is crucial.

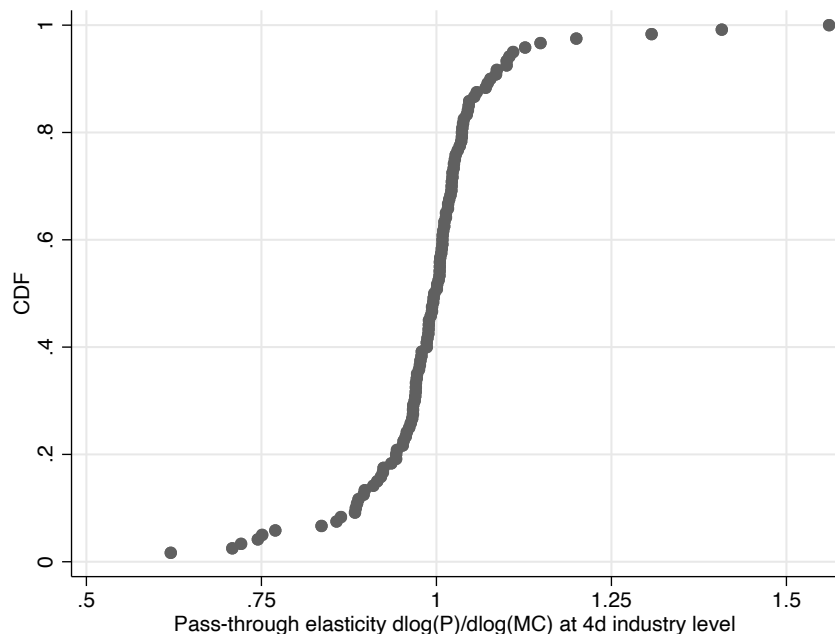
**Table A.22:** Electricity prices, and average product electricity intensity using nation-wide product averages

	Simple avg. product elec. int. (log)			Weighted avg. product elec. int. (log)		
	OLS (1)	$IV^A$ (2)	$IV^B$ (3)	OLS (4)	$IV^A$ (5)	$IV^B$ (6)
$\log(P^E)$	-0.0111 (0.024)	0.000471 (0.039)	0.0878 (0.062)	-0.0141 (0.024)	-0.0140 (0.039)	0.0777 (0.064)
OLS/IV	OLS	$IV^A$	$IV^B$	OLS	$IV^A$	$IV^B$
Observations	215151	215151	215151	215124	215124	215124
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes
First stage coef.	-	0.99***	0.06***	-	0.99***	0.06***
First stage SE	-	0.005	0.005	-	0.005	0.005
F-stat (Kleib.-Paap)	-	36700.369	194.976	-	36693.911	194.962
Two-way clustered SE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: See Table 2 for notes. The main difference is that the dependent variables are different as indicated.

## A.14. Pass-through elasticities and incidence on consumers over time for aggregated industries

Figure A.30: The distribution of pass-through elasticities

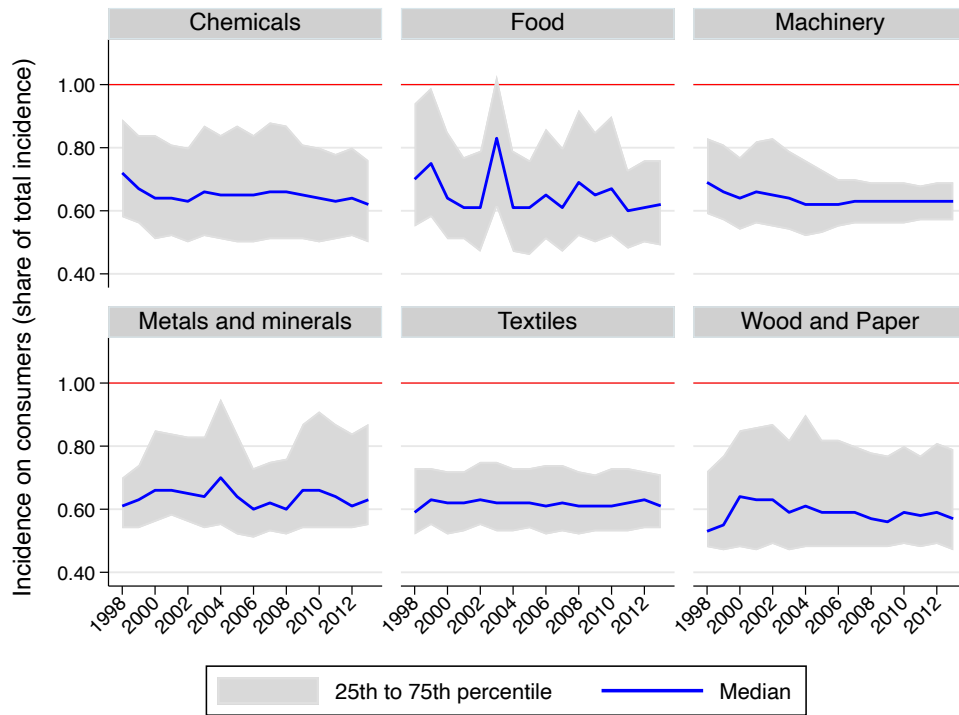


Notes: The figure plots the cumulative distribution function of the pass-through elasticities ( $d \log(P)/d \log(MC)$ ). The pass-through elasticities vary at the 4-digit industry level: there are 121 different pass-through elasticities. The pass-through elasticities are the coefficient on a regression of log prices on log marginal costs at the plant level for each 4-digit industry separately. Prices are calculated as average prices for the different products sold at the firm level, weighted by the quantity sold of each product. Marginal costs are recovered from the estimated markups and the average prices. The marginal costs in the regressions are instrumented with  $IV^A$  and  $IV^B$ , and regressions are weighted by the sampling weights. Therefore, there are two coefficients per pass-through elasticity per industry. The reported pass-through elasticities are weighted averages, for each pair of coefficients, where the weights are the t-statistics from the IV regression. Here are two example regressions for two different 4-digit industries of log prices on log marginal costs with different IVs:

	Manufacture of:	
	Grain mill products	Structural non-refractory clay and ceramic products
$\log(MC)$	0.997*** (0.0130)	0.730*** (0.0555)
OLS/IV	$IV^A$	$IV^B$
Observations	21812	6208
Region-year FE	Yes	Yes
F-stat (Kleib.-Paap)	35.65	28.98
SE clustered by	Plant	Plant
No. of first clusters	11707	3577
SE clustered by	State-year	State-year
No. of second clusters	435	220

Notes above table.

**Figure A.31:** Share of incidence on consumers from electricity price changes



Notes: The figure plots the median share of incidence on consumers  $I^{share}_t$  from electricity price changes for each year within each industry. The 25th and 75th percentiles are plotted as well. The industries are broad: chemicals includes rubber and plastics, machinery includes metal products, and textiles includes leather.



## A.15. Details on calculating aggregate effects on CO<sub>2</sub> emissions

I combine regression estimates with fuel use data and emission factors to calculate the effect on CO<sub>2</sub> emissions. The first step is to calculate the annual baseline CO<sub>2</sub> emission in the manufacturing ASI micro data from electricity, coal and oil averaged across 1998-2000:

**Electricity:** For electricity, I use the reported net consumption (adjusted for self generation and sale) in kWh and turn it into CO<sub>2</sub> emissions by taking the average emissions per kWh produced in the electricity generating sector (0.84 tCO<sub>2</sub>/MWh according to [Central Electricity Authority \(2006\)](#)).

**Coal:** For coal, I use the reported quantity in ton and turn it into CO<sub>2</sub> emissions by taking (i) the net calorific value per ton for Indian manufacturing (6350 kcal/kg according to [Minsitry of Coal \(2012\)](#)) (ii) and the average CO<sub>2</sub> emissions of 94.6 tCO<sub>2</sub> for coal use in industries according to the [IPCC \(2006\)](#).

**Oil:** For oil, only expenditure is available in 1998-2000. In 1996, however, there is detailed information on the quantities and types of oil used. I turn the quantities (liters) into energy units using [IEA \(2013\)](#) for the different oil types. I turn the energy units into CO<sub>2</sub> emissions using the [IPCC \(2006\)](#) tables for manufacturing industries. From the total CO<sub>2</sub> emissions from oil as well as the expenditure on oil (with real prices) in 1996, I take the ratio to calculate the CO<sub>2</sub> emissions per ₹ spent and apply this ratio to 1998-2000 to calculate the emissions from oil use.

I multiply all observations by the sampling multipliers to estimate the annual aggregate CO<sub>2</sub> emissions averaged across 1998-2000 from electricity (56.8Mt), coal (65.9Mt) and oil (11.8Mt), which are 134.5Mt combined. I omitted gas use as it is only responsible for a fraction of the CO<sub>2</sub> emissions (0.03Mt in 1996). In what follows, I assume that the emission intensity of a unit of electricity use, coal use or oil use is constant over the period 1998 to 2013.

The next step is to use regression estimates to calculate the impact of the electricity price decreases. I always use the average of the two elasticities obtained with  $IV^A$  and  $IV^B$ . Specifically, I use the elasticities in Columns 5-6 in Table 3 to calculate the impact of a 48% decrease in electricity prices on electricity consumption and therefore emissions. I combine these elasticities with those from a regression<sup>87</sup> of the logged ratio of electricity use to coal use on electricity prices to calculate the effect on coal use and therefore emissions from coal. I do something similar to calculate increased emissions from oil use, however, I rely on oil expenditure rather than quantities as for coal.<sup>88</sup> With these steps I obtain the estimates of Column 1 in Table 6.

The third step is to calculate the emission increases when switching off the substitution between fuels or the electricity productivity effect. To make these scenarios comparable I condition on reaching the same output gains. I switch off fuel substitution by requiring that the electricity price decline has no effect on fuel use ratios. That is, there is no saving of coal and oil use such that they need to increase by the

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<sup>87</sup>The average elasticity is -0.369.

<sup>88</sup>The average elasticity of the electricity to oil ratio is -0.688.

same percentage as electricity use as if they are Leontief. I switch off the electricity productivity effect by requiring that electricity use increases by the same percentage as output increases in the baseline scenario, but maintaining the fuel substitution effects through changes in fuel ratios. Finally, in the last column of Table 6 I switch off both substitution and electricity productivity effects.

### A.16. Holm-Bonferroni q-values for multiple hypothesis testing

Table A.23 applies the Holm (1979) Bonferroni correction to the p-values to adjust for multiple hypothesis testing.

**Table A.23: Holm (1979) Bonferroni correction for multiple hypotheses testing**

	OLS			$IV^A$			$IV^B$		
	Coef.	p-value	q-value (adj. pval)	Coef.	p-value	q-value (adj. pval)	Coef.	p-value	q-value (adj. pval)
<i>Independent variable: log(electricity price)</i>									
Electricity productivity (log)	0.365	9.0e-16***	2.0e-14***	-0.239	6.8e-04***	0.0034***	-0.777	5.2e-13***	6.3e-12***
Labor productivity (log)	-0.028	0.514	1	-0.389	5.7e-06***	4.6e-05***	-1.063	9.9e-23***	1.6e-21***
Output (log)	-0.027	0.715	1	-0.743	2.7e-07***	3.0e-06***	-1.600	3.0e-23***	5.2e-22***
Electricity consumption (log)	-0.385	3.1e-09***	6.5e-08***	-0.478	0.0021***	0.0083***	-0.797	1.2e-07***	5.8e-07***
Employees (log)	0.012	0.771	1	-0.339	1.1e-05***	7.6e-05***	-0.518	1.3e-10***	1.3e-09***
Profits	-5.037	9.5e-04***	0.0155**	-20.470	6.1e-10***	8.5e-09***	-22.034	5.7e-08***	3.4e-07***
Total revenues	-30.407	6.5e-04***	0.0117**	-132.317	5.5e-11***	8.7e-10***	-139.505	1.1e-10***	1.3e-09***
Total variable costs	-24.247	0.0011***	0.0165**	-109.058	1.1e-10***	1.6e-09***	-114.396	1.4e-10***	1.3e-09***
Ratio machinery to employees (log)	-0.160	0.0138**	0.124	-0.627	5.3e-08***	6.4e-07***	-1.517	8.3e-22***	1.2e-20***
Machinery to electricity ratio (log)	0.259	1.3e-06***	2.6e-05***	-0.467	7.0e-10***	9.1e-09***	-1.178	1.2e-19***	1.7e-18***
Employment to electricity ratio (log)	0.380	1.2e-18***	2.7e-17***	0.122	0.186	0.186	0.283	0.0062***	0.0124**
Investment in machinery (IHS)	0.158	0.439	1	-0.852	0.0295**	0.059*	-2.890	1.5e-10***	1.3e-09***
Ratio electricity to coal quantity	-10.188	0.0011***	0.0165**	-17.623	0.0025***	0.0083***	-22.088	0.0751*	0.0751*
Other fuels' share in output	0.004	9.1e-04***	0.0155**	0.013	1.3e-11***	2.2e-10***	0.023	5.0e-16***	6.5e-15***
Average wage per worker (log)	0.031	0.0266**	0.213	-0.142	4.6e-07***	4.6e-06***	-0.177	1.8e-07***	7.2e-07***
TFP (log)	-0.007	0.0031***	0.04**	-0.016	5.0e-06***	4.5e-05***	-0.033	2.9e-07***	8.6e-07***
Price marginal cost markup $\log(\mu)$	-0.018	0.0036***	0.0411**	-0.040	4.0e-04***	0.0024***	-0.106	3.2e-08***	2.3e-07***
<i>Independent variable: log(coal price)</i>									
Coal productivity (log)	0.848	0***	0***	1.484	1.7e-15***	1.3e-14***	1.617	1.8e-13***	1.4e-12***
Labor productivity (log)	0.056	0.0053***	0.0532*	-0.025	0.849	1	0.300	0.12	0.602
Output (log)	0.091	0.0034***	0.0411**	-0.311	0.21	0.842	-0.135	0.695	1
Coal consumption (log)	-0.757	0***	0***	-1.851	3.9e-11***	2.7e-10***	-1.799	3.6e-06***	2.5e-05***
Employees (log)	0.033	0.112	0.672	-0.320	0.0981*	0.589	-0.491	0.0517*	0.31
Profits	-5.940	3.0e-04***	0.0056***	-6.315	0.675	1	-7.393	0.775	1
Total variable costs	-14.435	0.0291**	0.213	-29.825	0.674	1	3.729	0.971	1
TFP (log)	-0.001	0.764	1	-0.020	0.124	0.622	-0.031	0.128	0.602

Notes: The table contains the coefficients and p-values from the original regressions in the main text. The q-values are the adjusted p-values for multiple hypothesis testing using the procedure outlined in Holm (1979). The correction procedures are separately applied by model (OLS,  $IV^A$ ,  $IV^B$ ) and by independent variable  $\log(\text{electricity price})$  and  $\log(\text{coal price})$ .