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

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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 benefited consumers, and the productivity improvements limited increases in carbon emissions.

JEL: Q41, D24, D22, O14

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 complementary 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.[1] 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.[2] 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 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 emissions in manufacturing industries as countries struggle to achieve climate goals (IEA, 2018*a*; Fowlie and Meeks, 2021), especially

[1] The effect on labor productivity depends on substitutability and returns to scale (e.g. Acemoglu, 2002).

[2] 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 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.

in developing countries where production capacity and energy demand are expanding fast.[3] In fact, many developing countries including India focus solely on energy and emission *intensity* rather than levels as policy objective under the Paris Agreement. 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, both of which are the case for India, the setting of this paper.[4] Although electricity prices are an equilibrium outcome, they serve as a sufficient statistic that nests any policy channel. The estimated price elasticities apply to any policy that shifts prices — deregulation, subsidy reform, grid investment, or fuel taxes—where the policy effect follows directly from combining these elasticities with the policy's effect on prices.

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.[5] 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.[6] Burgess et al. (2020) show that utilities are often caught in low cost-recovery and low reliability equilibria. I show that both shortages as well as overall utility cost-recovery are stable over time, because most electricity is supplied to residential and agricultural consumers who experienced relative price increases from low levels. In India, prices are therefore too low in the Burgess et al. (2020) sense for residential and agricultural consumers, but too high (above cost-recovery) for industry. Using multiple measures of shortages, I show that shortages are not correlated with industrial electricity prices.[7] 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 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 including a mixture decomposition that separates within-technology substitution from technology switching. 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

[3] Improvements in energy efficiency may in turn generate rebound effects in energy demand (Gillingham, Rapson and Wagner, 2016). Effects in this paper are inclusive of potential rebound effects.

[4] India's industrial electricity prices were around 70% higher than the G7 average in 1998, or six 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.

[5] Note that electricity productivity accounts for self-generated electricity as it is the ratio of deflated output to electricity consumed, i.e. purchased and generated electricity minus electricity sold.

[6] Fried and Lagakos (2023) show important long run effects in general equilibrium. 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. Ryan (2021) simulates the impact of transmission capacity improvements on the Indian electricity wholesale market.

[7] Note that Allcott, Collard-Wexler and O'Connell (2016) also argue that industrial electricity prices and shortages are not correlated in India, which allows them to focus on shortages while ignoring prices.

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 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 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.[8] 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 utility 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 dispersion across plants in terms of electricity and labor productivity as well as electricity prices, even within states and industries.

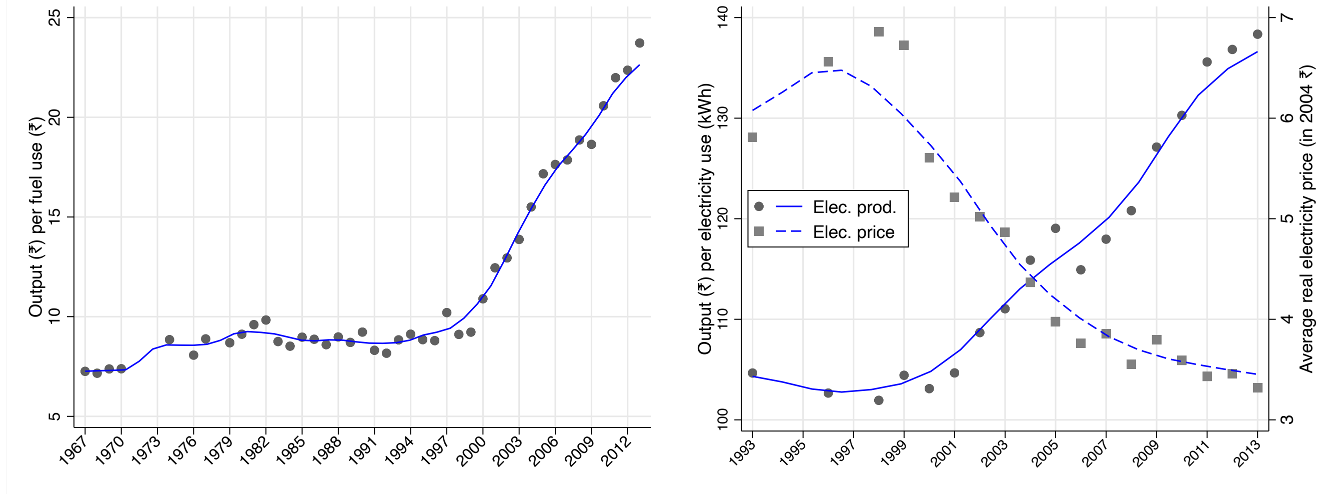
To estimate the effect of electricity prices at the micro level, I use a large panel data set of Indian manufacturing plants from 1998 to 2013, which includes annual information on the quantity and average price of electricity consumed at the plant level. Industry-by-region-by-year fixed effects allow 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 benefit from favorable relationships with state electricity providers, which could be correlated with their productivity.[9] 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 show that results are not driven by changes in the product mix, but by within-product technology differences across plants and time. I provide a range of robustness checks including additional price instruments based on policy shocks and an analysis of heterogeneous effects.

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

[8]The patterns in Figure 1 hold within industries and are therefore not driven by mere reallocation between sectors.

[9]Mahadevan (2023) shows Indian households in winning party constituencies were allowed to manipulate electricity bills.



(**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, i.e. aggregate real value of output divided by the aggregate value of fuel and electricity used, in Indian manufacturing over the longer run. Panel (b) plots annual aggregate electricity productivity ratios with the solid line, i.e. real value of output divided by the quantity of electricity consumed in kWh, including bought and generated. The dashed line plots real average electricity prices. Ratios in both panels are constructed by first aggregating numerator and denominator before taking the ratio. Output is deflated at the industry level before aggregation and fuel and electricity use or prices are deflated using a general fuel and electricity wholesale price deflator. The base year for deflation is 2004 throughout this paper.

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. To directly quantify within-technology substitution versus technology switching, I estimate a finite mixture decomposition that recovers positive substitution elasticities for both latent technologies, but shows that technology upgrading — the compositional shift toward machinery-intensive techniques — overwhelms the standard substitution effect. 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 and processes, 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 for firms, it is a priori unclear how much consumers are affected by pass-through of electricity costs to output prices, as well as direct losses for power utilities and consumers through decreased revenues and higher residential electricity tariffs. I exploit detailed information on output quantities and prices in the data to estimate 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. I account for industries serving final demand to varying degrees using input-output tables, and for utilities' deficit being covered by rate increases in the residential sector, which reduces consumer benefits. Total welfare gains from the 48% reduction in electricity prices are US$68 billion, which comprises US$37 billion gains for firms, and US$31 billion gains for consumers (45% share).

I end the paper by considering the environmental implications via CO_2 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_2 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_2. 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.[10] 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; Hassler, Krusell and Olovsson, 2021; Fried and Lagakos, 2023; Casey, 2024).[11] I show that cheaper access to a critical input for modern production, electricity, can increase capital investments and help transition to modern industrial technologies, while cheaper coal does not have the same benefits.[12] 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, where this is the first paper to show how lower electricity prices can improve labor *and* electricity productivity. Abeberese (2017) studies the effect of electricity prices on firm switching to

[10]Similarly, estimated firm fuel substitution from coal to electricity attenuated the increase in emissions.

[11]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.

[12]Calì 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. Casey (2024) does not distinguish between types of energy but shows how energy prices affect short and long run energy efficiency at an aggregate level. 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.

electricity intensive production in India, but there are important differences to this paper.[13] Her headline finding is that higher electricity prices induce firms to switch to less electricity intensive industries and product mixes, suggesting, contrary to here, that lower prices *decreased* electricity productivity in India. Importantly, this relies on pre-defined industry or product intensities which, however, ignore the salient improvements within industries or products by design. By instead measuring firm electricity productivity directly and using several instruments, I show that lower prices, in contrast, made firms more electricity productive (i.e less electricity intensive) despite using more electricity, and find no effects on the pre-defined product mix electricity intensity. I replicate Abeberese (2017) and show that the seemingly contradictory findings on product mix intensity are due to a partial omission of included fixed effects from a coding issue that once addressed, makes the relationship insignificant or reverses the sign of the effect, consistent with the findings here.[14] 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.[15] This comparison emphasizes that there are likely differential impact of electricity prices depending on the stage in industrial development.[16]

In the developing context, several studies report a positive elasticity of electricity productivity to electricity prices, but using OLS rather than instrumented prices, consistent with the OLS findings in this paper which are of opposite sign to 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) report, or use an index of all energy sources, not just electricity, conflating potentially opposite effects of electricity and fossil fuel prices. The findings in this paper also tie into the literature on effects of environmental policy and 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).[17] Finally, this paper 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), but in a developing country context.

[13] Similarly, Elliott, Sun and Zhu (2019) study the effect of electricity prices on industry switching in China.

[14] Apart from this crucial difference in the main finding, I also show (i) how this apparent puzzle can be rationalized with a model and testable predictions, (ii) along with evidence of mechanisms including additional exogenous variation (iii) using multiple instruments, (iv) a longer panel with three times the observations, (v) and analyzing impacts on consumers via pass-through into output prices and carbon emissions.

[15] 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.

[16] 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.

[17] The Porter and Van der Linde (1995) hypothesis, which postulates firm performance gains 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.

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:

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

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.[18] The elasticity of substitution between labor and capital services is governed by $\rho_l \leq 1$ and the labor share parameter is α_l. Capital services are produced in the inner nest combining machinery capital and electricity:

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

Capital K and electricity E are complementary inputs ($\rho_e < 0$) and α_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 produce the same output and 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. 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 (e.g. traditional vs modern textiles manufacturing). 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 ρ_e, and in fixed costs. The parameters are affected by technology choice $c \in \{1, c'\}$, 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 Π 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:

[18] The bundle consists of $\phi = \hat{\phi}(\eta + 1)$, where $\hat{\phi}$ are the returns to scale and η the inverse demand elasticity.

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 are 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, two otherwise identical firms may choose different technologies when facing lower electricity prices, which affects electricity productivity. This across-technology effect 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 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).

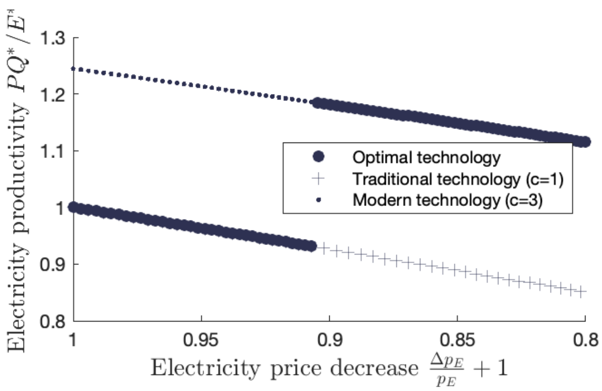
This increase in electricity productivity from lower electricity prices is driven by higher capital utilization required by the complementarity in the new technology. Panel (c) shows that the capital utilization effect can be so large that the capital to electricity ratio increases with the technology switch even though it is electricity that becomes cheaper, not capital. I will test this prediction of the model in the empirical part, by estimating the complementarity ρ_e by technology, including decomposing this overall effect into pure substitution and across technology effects. This also 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* $\frac{K^*}{E^*}$.

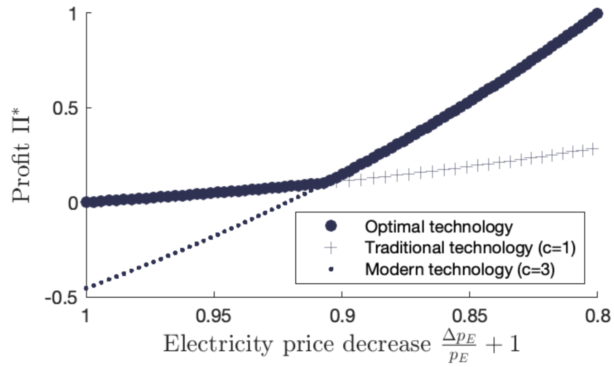
Proof. Appendix A.1 shows a proof. ■

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.

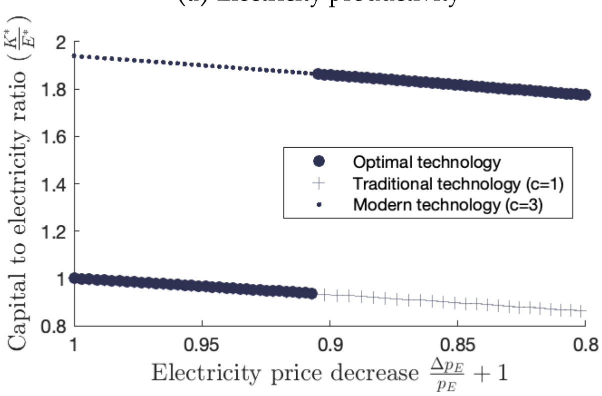
Appendix A.2 shows similar graphs for further firm outcomes and input ratios. This provides model predictions that are tested and corroborated in the empirical part of this paper. Appendix A.2 also shows how the introduction of capital constraints, if binding enough, can delay the switch to the modern



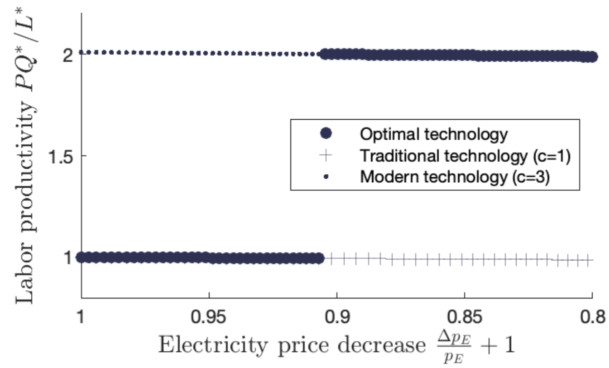
(**a**) Electricity productivity



(**b**) Profits



(**c**) Capital to electricity ratio



(**d**) Labor productivity

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 electricity 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 ($\Delta p_E = 0$). 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 Δp_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). As Appendix A.1 shows, these patterns are not unique to these parameter values, but instead exist for a broad range of values.

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 predominantly 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.11 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, with the remaining 5% owned privately (Ministry of Power, 1998*a*; Planning Commission, 2001-2002). The 2003 Electricity Act 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 Electricity Act has contributed to lower electricity prices.[19] Appendix A.12 provides details for how I combine the timing of the Electricity Act with location of coalfields to instrument for electricity prices in robustness checks.

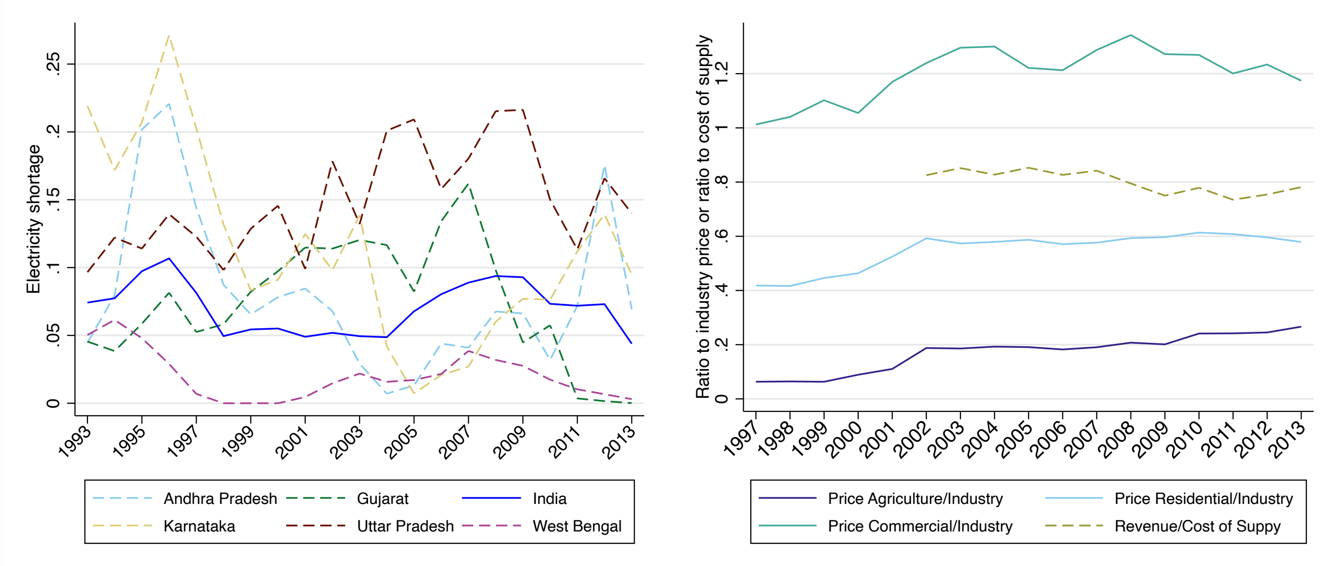
India's high industrial electricity prices in comparison.— The context of India's high industrial electricity prices is important for interpretation of the results. Average electricity tariffs in 1998, the beginning of the analysis period, were the equivalent of 15.1 US cents per kWh (2004 US$) for industrial users, around 70% higher than the G7 average in nominal terms, or six times as high in PPP terms, and continued to be higher in nominal terms until 2004 (see Appendix A.4 for more details). The industrial prices are significantly above cost-recovery, but in stark contrast to residential or agricultural prices (5.8 and 0.9 US cents per kWh in 1998). As a result, state electricity utilities have been loss-making almost across the board, despite the cross-subsidization from industrial electricity prices (Ministry of Power, 1998*b*). 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, determined by utility tariffs that are typically revised annually. The tariffs have generally been heavily regulated, with price levels tied to cost pressures for generators. Generation, transmission and distribution were largely vertically integrated before 2003 with individual State Electricity Boards setting tariffs for different end-users and locations within their jurisdiction.[20] 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, 2001-2002; 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 a 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 discussed below for identification with one of the instruments. Changes in coal prices for power generators are due to changes in regulatory processes or cost of mining (Minsitry of Coal, 2006, 2015).[21] Finally, the observed fall in industrial electricity prices over the sample period is

[19]See Cicala (2017) for how the introduction of market mechanisms reduced US electricity prices.

[20]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 (2001-2002); Cropper et al. (2011); IEA (2015); Ryan (2021); Preonas (2018); Mahadevan (2019).

[21]Since 2010, the coal price contains an additional tax of ₹50 per tonne (4% of the price), which also feeds into the coal cost



(**a**) Shortages over time

(**b**) Price ratios and cost-recovery

Figure 3: Electricity shortages, price ratios and cost of supply

Notes: Panel (a) plots electricity shortages over time, calculated as share of total required electricity using data from Central Electricity Authority (2006-2015) and Allcott, Collard-Wexler and O'Connell (2016). Panel (b) plots ratios of electricity prices in agriculture, residential or commercial over industrial electricity prices. These are calculated from publications of total revenue over total quantity of electricity delivered by sector from the Indian Planning Commission (2001-2002) and Ministry of Power (2002-2015). Panel (b) also shows the overall ratio of average rate of revenue (without subsidies) over the cost of supply available from 2002, both averaged across states.

due to a combination of lower generation costs (Figure A.28), deregulation and entry (Table A.4), and reductions in cross-subsidization (Figure A.13).[22]

Electricity prices, power shortages and self-generation.— India's generated electricity usually falls short of required electricity.[23] In the short run, distribution companies cannot adjust electricity pricing for end-users at high-frequency to clear markets as a response to shortages (Allcott, Collard-Wexler and O'Connell, 2016; Jha, Preonas and Burlig, 2022). In the longer run, one may be concerned that the decrease in industrial electricity prices affected the amount of electricity shortages. Burgess et al. (2020) show how many utilities in developing countries are stuck in a low reliability – low cost-recovery equilibrium, where low prices lead to more shortages. Yet, the degree of shortages was stable in India despite the fall in real industrial electricity prices over the sample period. Figure 3 Panel (a) plots shortage data as share of total required electricity from administrative reports for India overall and six major states over time. To explain the lack of correlation between industrial prices and shortages, it is key to note that industry is not the main consumer of electricity. As mentioned above, whereas industrial prices were above cost-recovery, residential and particularly agricultural prices were far below cost-recovery but consumed more electricity. Panel (b) plots the evolution of the price ratio of average agricultural and residential prices divided by industrial electricity prices using government publications.[24] While agricultural prices were only 6% of the industrial

shifting instrument.

[22]Three corresponding examples are in Figure A.28 that shows decreasing coal input costs for power plants, Table A.4 that shows lower prices from deregulation and entry following the 2003 Electricity act, and Figure A.13 that shows that residential and agricultural prices increased relative to industrial prices implying lower cross-subsidies.

[23]Total electricity shortages hovered around 4-11% during 1998-2013 (Ministry of Power (2018) and Figure 3) despite falling average plant load capacity factors. India has one of the highest rates of transmission losses in the world (IEA, 2015).

[24]All statistics in Panel (b) are calculated as weighted average across utilities and states, with weights based on the share of total electricity consumption by sector. Panel (b) of Figure A.13 shows simple averages instead.

price level at the beginning of the sample in 1998, they were 27% by the end of 2013. This is a four-fold increase in the relative price, showing a significant reduction in cross-subsidies. This in turn helped to stabilize cost-recovery for utilities despite falling industrial prices. Panel (b) also plots the cost-recovery where data is available from 2002. Cost-recovery is fairly stable around 80% helping explain the stability of shortages over time.[25]

Importantly, this institutional context implies that industrial electricity prices are not correlated with power shortages in India. Appendix A.6 shows this more formally using multiple types of data on shortages and electricity prices. First, shortages as measured by unmet electricity demand at the factory level from survey data is uncorrelated with electricity prices, both overall or at the intensive margin of unmet demand (Figure A.16 and Table A.2). Second, the correlation between state level power shortages from administrative data and industrial electricity prices is also insignificant and small (Table A.2). Using electricity price information from government reports instead also shows that shortages are uncorrelated with industrial electricity prices (Table A.3). By contrast, as Table A.3 shows, *overall* electricity prices based on all consumer sectors rather than industry alone, are indeed correlated with shortages. This is because, as Table A.3 also shows, the degree of cost-recovery drives electricity shortages and cost-recovery is in turn driven by these *overall* electricity prices, similar as in Burgess et al. (2020). This is consistent with the reasoning above based on Figure 3: due to reductions in cross-subsidies, lower industrial electricity prices do not lead to more shortages, as it is the overall electricity price that matters for cost-recovery and shortages. The fact that industrial electricity prices are not correlated with shortages allows me to focus on industrial electricity prices.[26] For the analysis, if anything, lower electricity prices would be expected to lead to more outages introducing a countervailing downward bias implying my estimates would be conservative. Nevertheless, I control for shortages in robustness checks in Appendix A.14.

Apart from the failure to account for supply and demand imbalances in the high frequency wholesale market (Jha, Preonas and Burlig, 2022), power outages are also driven by failures in technical equipment or networks (Allcott, Collard-Wexler and O'Connell, 2016). Coal supply issues, on the other hand, are only responsible for 0.2% to 3.3% of failures in thermal plants,[27] 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.[28]

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. Its long history since 1953 makes it a relatively reliable data source in the developing country context. The formal firms in the ASI are representative of

[25]Note that utilities cover the loss that they are making with government subsidies. So even if cost-recovery would decline, shortages can be stable if government tops up an increasing shortfall.

[26]This is in line with Allcott, Collard-Wexler and O'Connell (2016) who by the same logic can focus on shortages while ignoring industrial electricity prices. They also provide further evidence showing that a rainfall based instrument for hydro generation is also uncorrelated with electricity prices in India.

[27]Calculated as share of total annual outages using data from Allcott, Collard-Wexler and O'Connell (2016).

[28]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, 2023).

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.[29] 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.[30]

I use 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.[31]

I validate the quality of the derived ASI price data by comparing it to data from government publications in Figure A.6, by plotting it against manually collected tariff data mentioned below at the state by year level for large consumers in Figure A.9, and by showing results are robust when using this tariff data directly instead in Table A.7. Appendix A.3 shows further checks on the quality of the ASI-derived price data. Electricity productivity is deflated output divided by the quantity of electricity consumed, i.e. net purchases and self-generation. Labor productivity is deflated output divided by the number of employees. I also use plant level 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 use machinery capital (book value or investment), as it is the most relevant for this analysis. I measure firm-level capital rental rate as total capital charges (interest, plant rental expenses, and depreciation) divided by the gross book value of fixed assets. 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 pass-through and incidence, I exploit information on output sales and quantity at the plant-product level to construct 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.[32] 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.— 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).[33] Shares of coal fired power plants in state installed capacity in 1998 are from the Ministry of Power (1998*a*, 2003).[34]

[29]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.

[30]The accounting year in India runs from April to March, and I refer to it with the first year (i.e. 2006 is April 2006 to March 2007). 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 ASI data at the industry by state by year level from 1967 to 1997 for long run trends.

[31]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).

[32]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.

[33]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 used 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.

[34]Thermal shares as on 31st of March 1998, one day before the beginning of the sample. Chhattisgarh, Jharkhand and

Table 1: Summary statistics from plant level data

Main variables:

	Mean
Electricity bought (GWh)	1.84
Electricity generated (GWh)	0.63
Electricity sold (GWh)	0.09
Electricity consumed (GWh)	2.34
Electricity price (₹ per kWh)	4.44
Electricity share in total var cost	.054
Electricity productivity (₹ per kWh)	493.87
Electricity productivity (₹ per ₹)	121
Labor productivity (in mil. ₹)	1.5
Output (in mil. ₹)	280
Employees	162
Weighted by electricity consumed:	
Electricity productivity (₹ per kWh)	130
Electricity productivity (₹ per ₹)	33
Weighted by fuel consumed:	
Electricity share in fuel expenditure	0.63
Observations	485342
Firms	160836
Districts in sample	541
States in sample	32
Regions in sample	6
4-digit industries in sample	133
2-digit industries in sample	22

Additional variables:

	Mean	Obs.
Total capital (in mil. ₹)	36	482169
Mach. capital (in mil. ₹)	21	474372
Capital investment (in mil. ₹)	8.1	482621
Mach. investment (in mil. ₹)	4.1	475490
Capital rental rate (₹ per ₹)	.21	477316
Total revenue (in mil. ₹)	119	485263
Total variable costs (in mil. ₹)	101	485263
Total profit (in mil. ₹)	17	485263
AC-Markup (Price/AC)	1.2	485263
MC-Markup (Price/MC)	1.3	477710
TFP (Wooldridge)	7.3	477710
TFP (Levinsohn-Petrin)	9.8	477710
TFP (Olley-Pakes)	7	379038
Coal consumed (tonne)	383	485342
Coal price (₹ per tonne)	4153	49605
Coal price (₹ per kWh equivalent)	.64	49605
Coal productivity (₹ per th. tonne)	1077	49605
Coal productivity (₹ per ₹)	296	49605
Weighted by coal consumed:		
Coal productivity (₹ per th. tonne)	56	49605
Coal productivity (₹ per ₹)	23	49605

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.

Additional electricity tariff data and deflators.— I collect annual utility level average tariffs, revenues, and demand by sector as well as cost of supply from Planning Commission (2001-2002) and Ministry of Power (2002-2015). Additionally, I collect dated state level average tariffs by consumer type and consumer size from annual reports of the Central Electricity Authority (2006-2015) and from Indiastat (1998-2014) through Lok Sabha and Rajya Sabha (Parliament of India) questions. Data on international industrial energy prices is from IEA (2018*b*), and GDP deflators, exchange rates and 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

Uttarakhand were created in 2000, and shares correspond to Jan 2003 when data is first available.

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 (Figures A.18 and A.19), and consistent with other aggregate data sources and in contrast to the evolution in OECD countries (Figure A.10).[35] Figure A.17 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.[36] As noted in the beginning, this secular increase in electricity productivity occurred while real electricity prices fell by 48% during the same period.[37] 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 the productivity and price patterns are consistent across sectors and states, and not a story of mere across-sector or spatial reallocation.[38] The Appendix also confirms these patterns 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 (Figure A.17). 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.

Heterogeneity in electricity and labor productivity and prices.— Before setting up the econometric analysis at 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 4 plots the histograms of electricity productivity, labor productivity and electricity prices in 2003.[39] It shows that there remains substantial dispersion even after partialing out state by industry (4-digit) effects. Plants at the 90th percentile pay still around 33% 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 13 and 15 times higher than at the 10th percentile, similar or slightly higher than US productivity 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.[40] Finally, I show

[35]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).

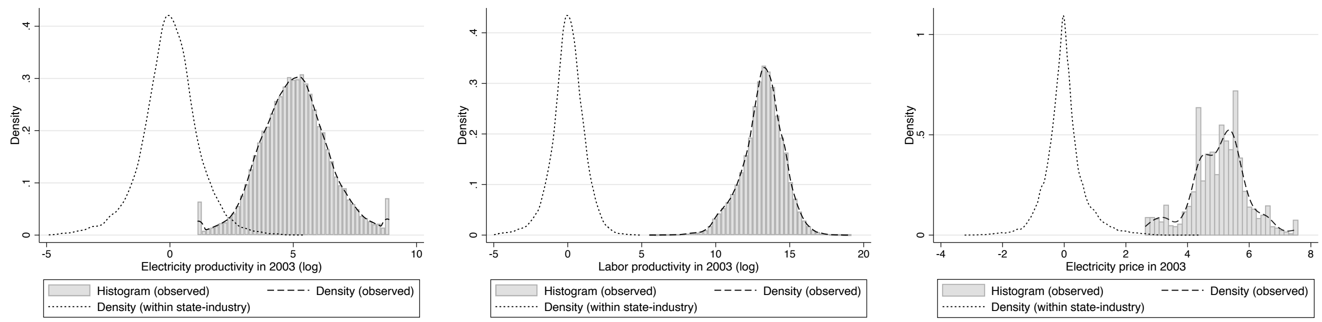
[36]The electricity share in the fuel mix grew from around 16 to 20% in energy units (Panel (b) of Figure A.10). The share of electricity in fuel expenditure was roughly constant at 65% from 2000-2013 implying higher quantity used as prices decreased substantially. Substitution to electricity meant that fuel productivity of other fuels increased considerably since 2000, as seen in Panel (b) of Figure A.11.

[37]Note that these are prices in real terms. In nominal terms prices may have risen over parts of the sample but are meaningless due to inflation. In the analysis, granular fixed effects absorb any difference in deflator choice due to prices being in logs.

[38]Ghani, Goswami and Kerr (2014) report an increase in electricity productivity mainly from within state-industry clusters.

[39]Figure A.21 shows a similar plot for the pooled sample across time after applying the same fixed effects as in the analysis below, and also shows the variation in prices that is predicted by the instruments. Figure A.20 shows the equivalent of Figure 4 for each year.

[40]The Appendix also shows that there has been some convergence in prices over time.



(**a**) Electricity productivity (**b**) Labor productivity (**c**) Electricity prices

Figure 4: 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 partialing 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 Figure A.20, and for the pooled sample with the same fixed effects used in the analysis (Figure A.21).

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:

$$y_{jisrt} = \beta \log(P^E_{jisrt}) + \alpha_{irt} + \epsilon_{jisrt} \tag{5}$$

where y_{jisrt} is in logs and P^E_{jisrt} is the electricity price for plant j in industry i in state s in region r in year t.[41] The analysis is conditional on 4-digit industry-by-region-by-year fixed effects α_{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, in part to control for Indian sectoral dereservation policy effects, 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). Importantly, the fixed effects preserve policy-relevant variation across states, districts and plants within the six regions that captures differences in tariff regulation and generation costs.

The above specification deliberately avoids plant fixed effects for three reasons.[42] First, between-plant variation likely captures a substantial amount of the key mechanism of technology differences and

[41]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.

[42]I rely on the plant identifiers for inference as discussed in Section IV.D. Including plant fixed effects in the main regression yields similar results, although with a loss of precision for one of the instruments. A Mundlak IV decomposition—after partialing out the baseline fixed effects, using both plant-mean prices and within-plant deviations (and instrumenting each with the corresponding components of IV^A or IV^B)—shows the between-plant component is stronger for both instruments than the within-plant component.

upgrading within industry-region-years, compared to mere within-plant variation. Machinery installation takes time and electricity prices are serially correlated, so responses to price changes can manifest gradually showing up between plants rather than within-plant changes alone, consistent with putty-clay models of energy adjustment (Atkeson and Kehoe, 1999; Hassler, Krusell and Olovsson, 2021; Casey, 2024). Therefore this approach exploits variation beyond the short-run as typical with plant fixed effects, including also longer-run variation manifesting between plants such as changes in production processes. As shown in Section III.C, there is much interesting variation between plants: A regression of logged electricity productivity on plant fixed effects can explain 80% of the variation (R^2). In Appendix Figure A.24, I show variations of popular Griliches and Regev (1995) decompositions that illustrate that the improvements in aggregate electricity productivity are driven by both within-plant and between-plant variation. Second, plant fixed effects require a strict exogeneity assumption, which is likely violated. Past shocks to output and productivity affect current electricity prices through block tariffs that vary with consumption, introducing bias.[43] Third, plant fixed effects fail to address time-varying endogeneity issues at the plant level. To tackle these concerns effectively, I instead use instrumental variable strategies as identifying variation.

The variation that remains after conditioning on industry-region-year effects reflects common state or local tariff or cost movements that shift plants' prices across space and time, as well as plant-level movements due to nonlinear tariffs or bargaining and discounts. This remaining variation is substantial as shown in Figures A.21 and 4, and I address next how I recover exogenous variation within these cells.

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 ξ_{jisrt} at the plant level and λ_{isrt} at the industry by state level. This allows me to rewrite the composite error ϵ_{jisrt} as sum of endogenous elements and true random error μ_{jisrt}:

$$\epsilon_{jisrt} = \xi_{jisrt} + \lambda_{isrt} + \mu_{jisrt}, \tag{6}$$

The nature of ξ_{jisrt} and λ_{isrt} comprises several factors, all conditional on controlling for 4-digit industry-by-region-by-year fixed effects α_{irt}. First, shocks to output and electricity demand (in ξ_{jisrt}) can also affect electricity prices due to different tariffs for different consumption bands (see Figures A.14 and A.15). Second, plants or groups of firms within an industry may negotiate or exert pressure for lower electricity prices (ξ_{jisrt} and λ_{isrt}). Their bargaining power and possible price corruption is likely related to their economic performance, which leads to reverse causality problems.[44] Third, there may be factors within regions and industries not captured by the fixed effects that jointly affect economic performance, electricity

[43] 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.

[44] 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 recorded quantities, so instrumenting for prices addresses remaining potential bias from this source.

productivity and electricity pricing (in λ_{isrt}).[45] 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 ξ_{jisrt} and λ_{isrt}). Finally, average electricity prices at the plant level may suffer from measurement error (in ξ_{jisrt}). I next turn to my two main 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.[46]

By construction, some average of electricity prices of other plants removes the idiosyncratic endogenous component ξ_{jisrt}. The validity of such types of instruments, however, depends on context Berry and Haile (2016), due to concerns with SUTVA and the exclusion restriction. To mitigate such concerns, my strategy is to construct IV^A only with plants outside the plant's own 2-digit industry, as both supply chains and output market competition occur predominantely within 2-digit industries. I therefore rely exclusively on information of plants in the same state, but in different 2-digit industries i^{2d}, removing the industry-level endgoenous component. The underlying assumption is that the endogenous components λ_{isrt} are not correlated across the 22 2-digit industries within a state, but are allowed to be correlated within 2-digit industries. Recall that industry-region-year effects are accounted for by α_{irt}, so the elements in λ_{isrt} that are common across regions are allowed to be correlated across 2-digit industries as well. Because remaining endogeneity could also reflect spatial rather than sectoral proximity (e.g., spatially organized bargaining or place-based political economy), I further 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:

$$w_{q^*}(q_j) = \begin{cases} \frac{b_{q^*} - |\log(q_j) - \log(q^*)|}{b_{q^*}^2} & \text{if: } \log(q_j) \in [\log(q^*) - b_{q^*}, \log(q^*) + b_{q^*}], \\ & \forall s_j = s_{j^*}, t_j = t_{j^*}, i_j^{2d} \neq i_{j^*}^{2d}. \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

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.[47] That is, the support of the kernel weights is

[45] 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.

[46] 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 Ackerberg and Devereux (2009), with highly similar results.

[47] The advantage of a flexible bandwidth is to ensure that enough observations are used for the construction of the instruments.

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:

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

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 and captures common state and local tariff shocks. 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).[48] 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:

$$IV_{srt}^B = \log(P_t^{CoalPower}) \frac{\text{coal-based installed capacity}_{sr_{1998}}}{\text{total installed capacity}_{sr_{1998}}} \tag{9}$$

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). For shifters, one initial 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. The two sectors require different types of coal, with thermal coal produced domestically by a national monopoly for power plants, and coking coal that is used by a subset of manufacturing industries is being largely imported from global markets, so coal prices for power plants do not directly affect coal prices for 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.[49] In a reassuring robustness check, I exclude all manufacturing plants that use coal directly, which are most likely to be affected by exclusion restriction violations if there are any, with similar results (Table A.15).

Regarding the shares, conditioning on industry-by-region-by-year fixed effects helps as exogeneity of

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

[48] 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).

[49] See also Abeberese (2017) for a subsample.

shares is only required within regions, and allows for trends and correlation of pre-sample shares with industrial structure (e.g. if heavier industry locates in coal regions). 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.5, 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 to measures of baseline industrial development, 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. To provide further support for this identification assumption, I show robustness of the IV^B estimates by including controls for these pre-determined variables interacted with the coal price in Table A.6, indicating that the coal shares are unlikely to spuriously correlate with future industrial development. 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.[50]

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. Specification Choice, Estimation and Inference

To estimate the reduced form regressions, 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.[51] 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.30. Finally, I use the two instruments separately to enable comparisons, but also provide results based on an over-identified IV-regression with both instruments.

E. A Mixture-Based Decomposition of Substitution and Technology in the Machinery-Electricity Bundle

To shed light on mechanisms, I estimate the structural complementarity in the inner nest of electricity and machinery use, based on the first order condition of the model in Section II. I focus on this equation for two reasons. First, it is particularly informative because the reduced-form result can overturn a sharp sign prediction from the CES benchmark with constant technology. The model predicts that the machinery to electricity ratio can increase with lower electricity prices through the technology channel. In a nested CES without technology choices, this sign would be unambiguously positive. Second, focusing on the inner nest allows me to sidestep other structural parameters such as returns to scale.

[50] 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.
[51] Including state fixed effects and state trends generates similar but slightly less precise estimates.

Conditional on technology c, the first order condition of (4) in logs (see Equation (A.7)), adding fixed effects α_{irt} and an error term ε_{jirst}, is[52]:

$$\log\left(\frac{K_{jirst}}{E_{jirst}}\right) \;=\; \alpha_c + \sigma_c \log\left(\frac{p^E_{jirst}}{p^K_{jirst}}\right) + \alpha_{irt} + \varepsilon_{jirst} \tag{10}$$

where $\sigma_c = \frac{1}{1-\rho_e(c)}$ is the technology-specific elasticity of substitution between machinery and electricity. It can be shown that even if the substitution elasticities vary across sectors or time, including the α_{irt} fixed effects recovers a consistent estimate of the weighted average substitution elasticity across sectors, regions and time. The key challenge is that the substitution parameter depends on technology, but we do not observe technology c directly. In reduced-form regressions as in (5), we capture the joint effect of technology differences and some average of substitution elasticities across technologies, assuming valid instruments for electricity prices. To recover structural parameters that capture average within-technology substitution, I separate the two effects, which then allows me to decompose the reduced-form elasticity.[53]

To do so, I introduce a parsimonious finite mixture model with two latent technology types $c \in \{1, 2\}$. Such models provide a standard way to represent unobserved heterogeneity with a small number of types in structural settings, and have been used to capture discrete differences in decision rules and technologies (Heckman and Singer, 1984; Keane and Wolpin, 1997; Kennan and Walker, 2011; Arcidiacono and Miller, 2011; Bonhomme, Lamadon and Manresa, 2022; Kasahara, Schrimpf and Suzuki, 2023). The idea is that each observation can be generated by one of two latent technologies with different machinery–electricity substitution elasticities, where technology membership is unobserved and statistically recovered, taking into account endogeneity of the relative prices.

I allow electricity prices to shift the probability of using a technology. Specifically, I model the prior probability of the modern technology π_{j2} as a logit function of log electricity prices $\widetilde{\log p^E_j}$, demeaned by industry-by-region-by-year averages to allow for correlation between electricity prices and these trends.[54] For exposition, let j index plant-year observations. The prior technology probabilities are:

$$\pi_{j2} \;\equiv\; \Pr(c = 2 \mid \widetilde{\log p^E_j}) \;=\; \Lambda\Big(\gamma_0 + \gamma_1 \widetilde{\log p^E_j}\Big), \qquad \pi_{j1} = 1 - \pi_{j2}, \tag{11}$$

where $\Lambda(\cdot)$ is the logistic CDF, and the above electricity price instruments will be used to construct moment conditions to identify γ_1. The priors in (11) map observables into *ex-ante* technology shares, describing how the probability of using the modern technology varies with electricity prices both within plants and across plants, before taking into account the plant's observed input mix. The posterior probabilities combine (i) the prior π_{jc} with (ii) a measure of fit of the technology-c specific relationship to the observed $\log(K_j/E_j)$. Define $u_{jc} \equiv \log(K_j/E_j) - (\alpha_c + \sigma_c \log(p^E_j/p^K_j) + \alpha_{irt(j)})$ as the residual implied separately by technology $c \in \{1, 2\}$ for each observation. Using Bayes' rule and a Gaussian likelihood with common variance s^2 and

[52]Note that the structural constant $\sigma_c \log\left(\frac{1-\alpha_e}{\alpha_e}\right)$ is absorbed in the technology-relative intercept and fixed effect $\alpha_c + \alpha_{irt}$.

[53]In the estimation, I pool plants across industries and absorb industry-by-region-by-year fixed effects, so the technology-specific slopes (σ_1, σ_2) are identified from within-cell variation and reflect an average machinery–electricity substitution elasticity in the estimation sample.

[54]This centering is not equivalent to including a set of fixed effects in a nonlinear logit, which would require solving for many more parameters, but it ensures that γ_1 is identified from within-cell price variation. I label technology 2 as the more machine-intensive modern technology.

$\varphi(\cdot)$ denoting the standard normal pdf, the posterior probabilities are:

$$r_{j2} = \frac{\pi_{j2}\,\varphi\big(u_{j2}/s\big)}{\pi_{j1}\,\varphi\big(u_{j1}/s\big) + \pi_{j2}\,\varphi\big(u_{j2}/s\big)}, \qquad r_{j1} = 1 - r_{j2}, \tag{12}$$

To estimate the model, I normalize $\alpha_1 \equiv 0$ as only the relative intercept is identified, and estimate the remaining parameters $(\alpha_2, \sigma_1, \sigma_2, \gamma_0, \gamma_1, s^2)$ by GMM, updating priors and posteriors at each optimization step. The advantage over the usual EM algorithm for mixture models is that GMM allows me to impose IV orthogonality conditions separately for each technology type as well as for the probability of technology use, allowing the different IVs to shift different subgroups and technology users. The estimator stacks three blocks of moments:

$$(i)\ \textit{Technology-specific mean IV moments:} \qquad \mathbb{E}\left[r_{jc}\,u_{jc}\begin{pmatrix}\widetilde{IV}_j^A\\ \widetilde{IV}_j^B\end{pmatrix}\right] = 0 \quad \text{for } c \in \{1,2\}, \tag{13}$$

$$(ii)\ \textit{Technology-choice moments:} \qquad \mathbb{E}\left[\big(r_{j2} - \pi_{j2}\big)\begin{pmatrix}1\\ \widetilde{IV}_j^A\\ \widetilde{IV}_j^B\end{pmatrix}\right] = 0, \tag{14}$$

$$(iii)\ \textit{Variance moments:} \qquad \mathbb{E}\left[\big(u_j^2 - v_j\big)\begin{pmatrix}1\\ \log\big(p_j^E/p_j^K\big)\end{pmatrix}\right] = 0, \tag{15}$$

where $\widetilde{IV}_j^A$ and $\widetilde{IV}_j^B$ are within-fixed effects demeaned versions of the excluded instruments. Moment block (i) estimates the analogue of equation (10) using the posterior weights to integrate out the unobserved technology type. Moment block (ii) imposes orthogonality of the difference between posterior and prior technology probabilities with the instruments. Moment block (iii) matches second moments implied by the mixture. Define the mixture residual as $u_j \equiv (1-\pi_{j2})u_{j1} + \pi_{j2}u_{j2}$, where u_{jc} is the residual under technology c defined above. Under the Gaussian likelihood, the model-implied conditional variance is $v_j \equiv s^2 + \pi_{j2}(1-\pi_{j2})\big(\alpha_2 + (\sigma_2 - \sigma_1)\log(p_j^E/p_j^K)\big)^2$.[55] I estimate the parameters by two-step GMM and compute standard errors from the covariance of the stacked moments that is two-way clustered on plants and state-years.

A key benefit of the mixture specification is that it yields a transparent decomposition of the marginal effect of electricity prices on the fitted $\log(K/E)$ relationship. Let the fitted value be $\widehat{\log(K_j/E_j)} = (1-\pi_{j2})a_{j1} + \pi_{j2}a_{j2} + \alpha_{irt(j)}$, where $a_{jk} = \alpha_k + \sigma_k \log(p_j^E/p_j^K)$. Holding p^K fixed implies $\partial \log(p_j^E/p_j^K)/\partial \log p_j^E = 1$, and $\alpha_{irt(j)}$ does not vary with $\log p_j^E$, so differentiating with respect to $\log p_j^E$ implies

$$\frac{\partial \widehat{\log(K_j/E_j)}}{\partial \log p_j^E} = \underbrace{(1-\pi_{j2})\sigma_1 + \pi_{j2}\sigma_2}_{\text{within-technology substitution}} + \underbrace{\frac{\partial \pi_{j2}}{\partial \log p_j^E}\Big(a_{j2} - a_{j1}\Big)}_{\text{technology differences}}, \tag{16}$$

[55] The first component of (15) pins down the overall variance level and therefore identifies s^2 (given the parameters that enter the between-technology term). The second component uses variation in relative prices to discipline the model-implied heteroskedasticity of $\log(K/E)$ induced by the mixture, since the between-technology gap depends on $\log(p_j^E/p_j^K)$.

where $\frac{\partial \pi_{j2}}{\partial \log p_j^E} = \gamma_1\, \pi_{j2}(1-\pi_{j2})$ in practice.[56] Equation (16) clarifies how the aggregate K/E response can flip sign even when both σ_1 and σ_2 are positive: if lower electricity prices increase the share of a more machinery-intensive technology, the average switching term can dominate the average within-technology substitution term. The decomposition into technology switching captures both within-plant adoption over time as well as technology differences across plants, without requiring a fully dynamic adoption model.

F. Recovering Pass-Through Rates and Consumer Incidence

To explore 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:

$$I \equiv \frac{dCS/dP^E}{dPS/dP^E} = \frac{\rho_{MC}}{1-(1-L\epsilon_D)\,\rho_{MC}} \tag{17}$$

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, ϵ_D and ρ_{MC}.

First, I draw on an established literature to recover markups μ from the production side using firm revenue and input data (Hall, 1988, 1990; Hall and Jones, 1999; De Loecker and Warzynski, 2012). The 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 ϵ_D as the median of the plant level demand elasticities within a 4-digit industry by year by state cluster.[57] 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.

[56] Because the technology adoption uses the within-fixed effect demeaned price $\widetilde{\log p_j^E}$, the chain rule gives $\frac{\partial \pi_{j2}}{\partial \log p_j^E} = \gamma_1\, \pi_{j2}(1-\pi_{j2}) \cdot \partial \widetilde{\log p_j^E} / \partial \log p_j^E$, where within-cell marginal changes holding the cell mean fixed implies $\partial \widetilde{\log p_j^E} / \partial \log p_j^E = 1$.

[57] 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).

Third, the main challenge is estimation of the pass-through parameter ρ_{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 μ, 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 (17). 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.[58] The pass-through elasticity is converted into the pass-through *rate* ρ_{MC} by multiplying it with the plant level markup μ. Pass-through is therefore allowed to differ across industries and plants, where heterogeneity could arise, for example, through market structure, concentration or market power. To summarize, the empirical components are:

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

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

$$I^{share} = I/(1+I) \tag{18}$$

When constructing consumer surplus below in Section V.E, I will address two further complications. First, not all firms sell directly to consumers, so consumer incidence shares are only relevant for output going to final demand. Second, electricity price reductions for industry might be financed through increases in residential prices, which affects consumers directly.

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

[58] 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.

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, or have lower block tariffs.[59] Figure 5 visualizes these results in a binscatter of electricity productivity on electricity prices conditional on industry-by-region-by-year fixed effects, following Cattaneo et al. (2024). Panel (a) shows the OLS relationship, while Panel (c) and (d) show the relationship with predicted electricity prices using IV^A and IV^B respectively. This shows that the results are not driven by outliers. Panel (b) uses electricity tariffs from Central Electricity Authority (2006-2015) and Indiastat (1998-2014) which are at the state by year level and therefore address a significant portion of the OLS bias in the plant level prices, resulting in the same sign as the two IV estimates. Table A.7 shows more results using these tariffs where the IV estimates are similar to those in Table 2, but the OLS is also negative and statistically significant.

The effect is stronger for IV^B than for IV^A. This could imply either treatment effects are heterogeneous and the instruments shift different subpopulations, or one of the instruments is not completely exogenous assuming homogeneous effects.[60] 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).[61] 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 stronger effect when using IV^B.[62] I exploit this below for estimating heterogeneous technologies in a mixture model more formally, allowing the two instruments to shift subpopulations with different technologies differentially.

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

[59]As a heuristic, I construct the difference between endogenous prices and prices predicted by the instrument. This difference is significantly correlated with size measured by sales, implying smaller, possibly less efficient firms are receiving a price discount corresponding to the endogeneity bias. See Bento and Restuccia (2017) or Hsieh and Klenow (2014) for the relationship between firm size, distortions and efficiency in India.

[60]Table A.19 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 homogeneous treatment assumption.

[61]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.

[62]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 2: Electricity prices and electricity productivity

	Electricity productivity (log)			Labor productivity (log)		
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(P^E)$	0.365***	-0.239***	-0.777***	-0.0282	-0.389***	-1.063***
	(0.044)	(0.070)	(0.105)	(0.043)	(0.085)	(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

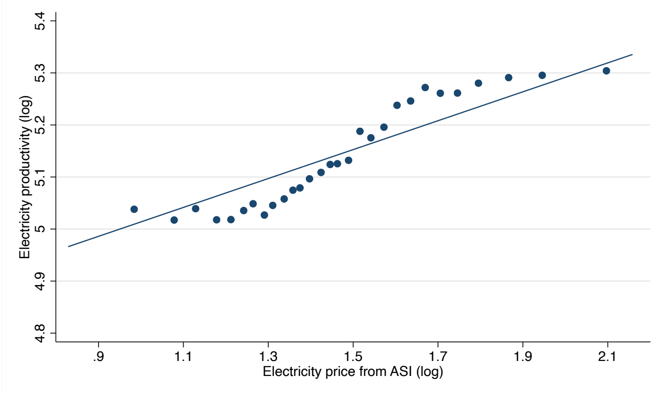
Notes: The dependent variable is log electricity productivity (value of output divided by the quantity of electricity used in kWh) for the first three columns and log labor productivity for the second three (value of output divided by employees). Each column represents a separate regression at the plant 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.

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. Note that these elasticities do not imply that arbitrarily low prices are optimal as I will later show diminishing returns with more plants mechanizing.

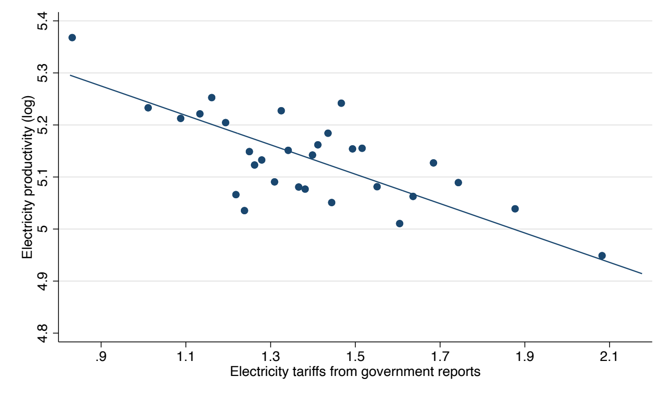
Technology or product mix?— It is possible that these improvements are driven by plants producing different sets of products, rather than with better technology. To test this, I first include product fixed effects (6145 products) and show in Table A.28 that estimates are similar and significant. This demonstrates that the improvements are not driven by changes in the product mix, but by within-product technology differences across plants and across time. Second, I map nation-wide average product level electricity intensities of 2000 to the evolving product mix as dependent variable to test if firms produce more electricity intensive products with lower prices. I find no evidence of this (see Table A.28). Since this outcome ignores the salient differences in electricity productivity within products, this again implies that the improvements are driven by within-product technology differences across plants and time that are crucial in a world of technology differences within industries and products. Third, this last finding appears to contradict Abeberese (2017), who using the latter outcome, finds that lower electricity prices increase the electricity intensity of the product mix, suggesting firms became less electricity productive.[63] I first replicate Abeberese (2017) in Appendix A.15 and then show that the results hinge on a coding issue that partially omits included fixed effects. Once this is fixed, the results turn insignificant or change sign, and are entirely consistent with the insignificant findings on product mix in this paper. Importantly, by instead analyzing firms' electricity productivity directly in my main results, I show that Indian firms became *more*, not less, electricity productive with lower prices.

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

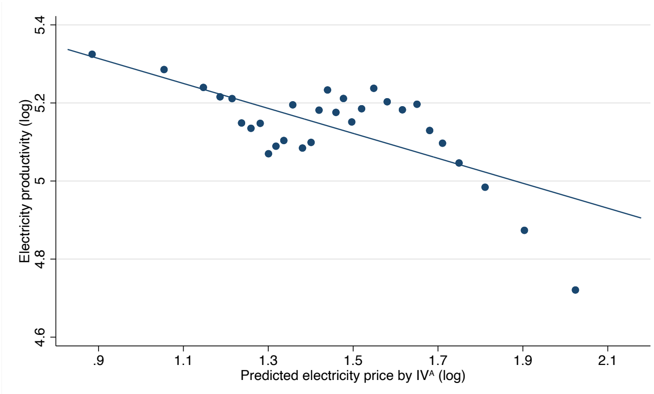
[63]The effects on electricity consumption, employment and output are comparable to the ones in Abeberese (2017).



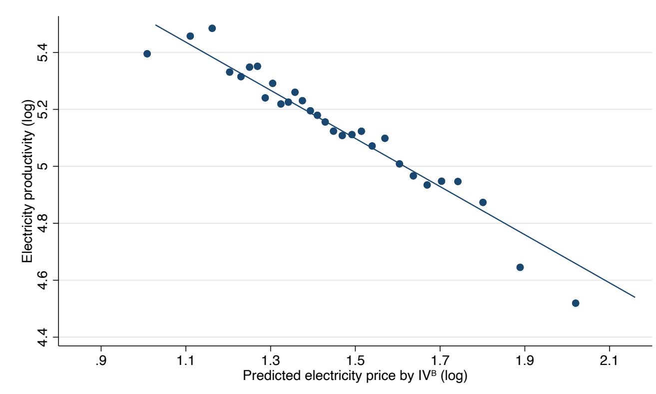
(**a**) Electricity prices from ASI



(**b**) Average utility tariffs from reports



(**c**) Electricity prices predicted by IV^A



(**d**) Electricity prices predicted by IV^B

Figure 5: Binscatter of electricity productivity and electricity prices

Notes: The figures show binscatter plots using Cattaneo et al. (2024) with plant level electricity productivity (log) on the vertical axis and with industry-by-region-by-year fixed effects. Panel (a) plots against log electricity prices at the plant level using ASI data. Panel (b) instead plots against utility tariffs at the state by year level from Central Electricity Authority (2006-2015) and Indiastat (1998-2014). Panel (c) and (d) plot against predicted electricity prices from IV^A and IV^B respectively, where predicted electricity prices are obtained by using fitted values from regressions on the respective instruments conditional on industry-by-region-by-year fixed effects. Results using labor productivity are in Figure A.30

substantially increase labor productivity, with an elasticity of -0.39 and -1.06 for IV^A and IV^B respectively.[64] 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.— To understand the channels for improved electricity and labor productivity, I start with the more proximate reasons by unpacking the ratios into its components. Table 3 shows regressions split up into the components of electricity and labor productivity, with logged electricity consumption (in kWh), employees, or output as dependent variables. Electricity is not a Giffen good. 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. Note that potential rebound effects on demand from increased electricity productivity (Gillingham, Rapson and Wagner, 2016) are included here and therefore also in the main estimates. The OLS estimate for employees is insignificant,

[64]Binscatters for labor productivity are in Figure A.30.

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	-0.743***	-1.600***	-0.385***	-0.478***	-0.797***	0.0119	-0.339***	-0.518***
	(0.073)	(0.143)	(0.153)	(0.064)	(0.155)	(0.148)	(0.041)	(0.076)	(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.

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. Effects on electricity consumption and employment (i.e. labor) are consistent with the model predictions in Section II and Appendix A.2.

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.

B. *Robustness*

Before moving to deeper mechanisms, I conduct a range of robustness checks, with most of the results in Appendix A.14. 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 alternative instruments yields similar estimate.— First, I use three alternative instruments. The first, IV^C, is similar to IV^A except that I exclude plants in the same district 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^{D_1}, 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.[65] The rationale for IV^{D_1} builds on the findings in Section III.A and Appendix A.12. 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 endogenous, I use the district distance to coalfields, as Table A.4 shows that this distance predicts shares in the private power capacity after 2003. Therefore, IV^{D_1} 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

[65] The triple interaction helps avoid capturing irrelevant states that rely on hydro power as the North-West (Appendix A.12).

A.27 shows how higher distance to coalfields increases electricity prices relatively from 2003. The third instrument, IV^{D_2} 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.8 shows that the estimates using these alternative instruments are similar to the main IV estimates.[66]

Using lagged prices.— Second, I use lagged prices and instruments to allow for more adjustment time to prices.[67] Using lags cuts the sample roughly in half as spells of plant observations are required. Tables A.9 and A.10 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.

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.11 and A.12. Note that the included industry-region-year fixed effects already account for a significant portion of power shortages, but directly controlling for these serves as an additional check. The estimates remain negative and are similar in magnitude.[68] This is somewhat expected as I already showed in Table A.2 that shortages are not associated with electricity prices. Both distance to coalfields and shortages, however, are significant in explaining electricity and to some extent labor productivity. Finally, if shortages do not affect electricity consumed and prices, but the ratio of electricity purchased to generated, we would expect a similar effect when using electricity purchased, rather than consumed, to construct electricity productivity. Reassuringly, this is corroborated in Table A.13.

Electricity intensive sectors, no direct coal users, and sector specific analysis.— Fourth, I restrict the sample to electricity intensive sectors, defined as 2-digit sectors with an above average electricity intensity with similar effect (Table A.14). Next, I restrict the sample to exclude all plants that use coal directly in their inputs in Table A.15 to show robustness to remaining concerns about the shifter based on coal prices for power utilities in IV^B. In addition, Table A.6 shows robustness to control interactions of the coal price with pre-sample state characteristics. I also run the analysis separately for six broad industry groups in Tables A.16 and A.17. The effects are broadly similar across sectors, except perhaps for metals and minerals, where estimates are insignificant, but still correct an upward bias in the OLS estimates.[69]

Controlling for input and output prices.— Fifth, electricity price changes may be correlated with electricity price changes for other plants, potentially affecting input or output prices through equilibrium adjustments. While the inclusion of industry-by-region-by-year fixed effects should largely account for these, I address remaining concerns about product market competition or supply chain effects by controlling for input and output price indices. These indices are specific to each plant's product and input mix, based on national median prices at the product level combined with within-plant sales and expenditure shares. Table A.22 shows that the estimates remain robust controlling for the input/output price indices.

[66]With the exception of IV^{D_2} and labor productivity as outcome, which, however, is a noisy estimate.

[67]This may also address potential remaining reverse causality concerns. Instead of lagged prices, Table A.18 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.

[68]Although somewhat noisier for IV^A.

[69]Since the basic metals industry relies predominantly on coal across many production techniques, there could be a null effect, with less complementarity between electricity and machines and less scope to move to electricity-based production. Figure A.19 supports 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***	-20.47***	-22.03***	-30.41***	-132.3***	-139.5***	-24.25***	-109.1***	-114.4***
	(1.515)	(3.243)	(3.999)	(8.863)	(19.734)	(21.182)	(7.405)	(16.537)	(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**	-0.627***	-1.517***	0.380***	0.122	0.283***	0.259***	-0.467***	-1.178***
	(0.065)	(0.114)	(0.151)	(0.041)	(0.092)	(0.103)	(0.053)	(0.074)	(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	-0.852**	-2.890***	-10.19***	-17.62***	-22.09*	0.00440***	0.0135***	0.0234***
	(0.204)	(0.390)	(0.441)	(3.103)	(5.800)	(12.383)	(0.001)	(0.002)	(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**	-0.142***	-0.177***	-0.00699***	-0.0156***	-0.0330***	-0.0183***	-0.0404***	-0.106***
	(0.014)	(0.028)	(0.033)	(0.002)	(0.003)	(0.006)	(0.006)	(0.011)	(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 (c), the ratio of electricity to coal is in quantity terms in MWh per tonne. Other fuels refer to gas, coal and oil. I take the inverse hyperbolic sine (IHS) of investment 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.

Alternative clustering of standard errors and multiple hypothesis testing.— Sixth, 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.21). Finally, I adjust all p-values upwards to account for multiple hypothesis testing in Table A.30. 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 impact 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 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).[70] 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, which I formalize next. In a model without technological choices the machine to electricity ratio would instead unambiguously fall (see Lemma 2).

Decomposing substitution elasticity and technology differences.— I implement the mixture decomposition in Section IV.E in Table 5 to separate within-technology substitution from price-induced technology differences in the machinery–electricity margin. Panel A reproduces the pooled IV sign reversal: the elasticity of $\log(K/E)$ with respect to $\log(p^E/p^K)$ is negative using either instrument (-0.37 with IV^A and -0.95 with IV^B), so plants raise K/E when electricity becomes cheaper.[71] Panel B shows that the sign reversal does not reflect "negative substitution": the estimated technology-specific substitution elasticities are both positive ($\hat{\sigma}_1 = 0.66$ and $\hat{\sigma}_2 = 0.11$), implying that within a given technique plants substitute toward electricity as it gets cheaper. The lower elasticity for the modern technology 2 implies stronger complementarity in that technology, consistent with the model. Panel C shows why the aggregate flips sign: the average within-technology component is $+0.41$, but the technology-switching component is -0.98, yielding a total elasticity of about -0.56. Thus, the dominant channel is technology upgrading—electricity prices shift plants toward more machinery-intensive techniques. This extensive-margin response reflects compositional shifts across technologies both within plants over time and across plants, and overwhelms the standard within-technology substitution effect.

Using baseline capitalization and FDI shocks to capital.— Since machine capitalization from lower electricity prices appears to be the 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 6a, 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

[70] I use the inverse hyperbolic sine instead of the log of machinery investments to deal with zeros. Note that the bias for the ratios, the difference between OLS and IV, depends on the bias in the numerator and denominator. For machinery to labor, the sign does not flip, but the size of the bias is roughly similar as for the machinery to electricity ratio.

[71] These estimates are close to the reduced-form regressions in Table 4b (Columns 7–8), where $\log(K/E)$ is regressed on electricity prices alone. Reassuringly, the results are unchanged when controlling directly for the user cost of capital in that table, suggesting that the reduced-form estimates are not driven by omitted movements in capital costs.

Table 5: Decomposing machinery–electricity substitution and technology switching

	Panel A. IV		*Panel B. Structural GMM-IV*		*Panel C. Decomposition*	
	(1)	(2)	(3)	(4)	(5)	
$\log(p^E/p^K)$	-0.382***	-0.991***	0.670***	0.106***	**Within-tech:**	**0.419**
	(0.080)	(0.153)	(0.031)	(0.038)	**Across-tech:**	**-0.927**
Structural parameter	–	–	σ_1	σ_2	**Total:**	**-0.508**
Observations	465886	465886	465886	465886	465886	
Estimator (IV/GMM)	IV^A	IV^B	GMM-IV	GMM-IV	GMM-IV	

Notes: Panel A reports pooled IV estimates of $\log(K/E)$ on $\log(p^E/p^K)$ with industry-by-region-by-year fixed effects, using IV^A and IV^B separately as indicated. Panel B reports structural GMM estimates of the technology-specific substitution elasticities ($\hat{\sigma}_1, \hat{\sigma}_2$) from the two-technology mixture IV–GMM estimator (using both instruments). Panel C shows, based on Panel B, the implied within-technology versus across-technology decomposition, averaging the marginal effects across all observations. Standard errors in parentheses are two-way clustered at the plant and the state-year level. Stars indicate p-values: * < 0.1, **< 0.05, ***< 0.01.

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.25.[72]

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.[73] 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.[74] This design is used to test whether firms with more capital show smaller electricity productivity responses from electricity prices. Figure 6b 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 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.26). 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.[75] While the parallel trends assumption cannot be tested directly, the pre-trends shown in Figure 6b are flat. Table A.26 shows additional results for labor productivity and output using the 2006 policy change.

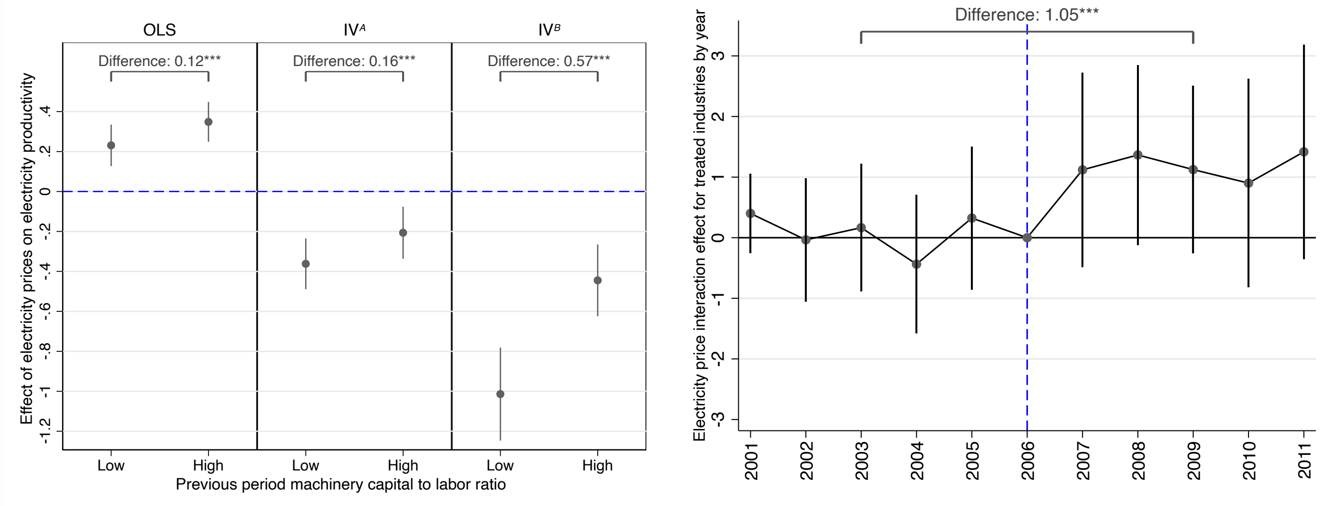
Lower electricity prices induce substitution from fossil fuels.— It is likely that plants not only adjust their

[72]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).

[73]See Bau and Matray (2023) for a detailed description. Table A.24 lists the treated industries.

[74]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).

[75]The combined effect for treated firms is now slightly positive compared to negative for non-treated, see Table A.26.



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

Figure 6: 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.

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 import 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* efficiency, 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 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.23 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

Table 6: Electricity price changes and the share of incidence on consumers

Incidence	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]
Components	$\widehat{L}$	$\widehat{\epsilon}_D$	$\widehat{\rho}_{MC}$
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.F. The quantiles are across all plants and all periods, using the sampling multipliers as frequency weights, where Lerner Index $\widehat{L}$ and pass through rates $\widehat{\rho}_{MC}$ vary at the plant-year level, and market demand elasticity $\widehat{\epsilon}_D$ at the industry-state-year level. The monopoly case corresponds to $\widehat{L}_{jisrt} = 1/\widehat{\epsilon}_{D,isrt}$, and the perfect competition case to $\widehat{L}_{jisrt} = 0$ which implies that the incidence share is equivalent to the pass-through rates.

predicts an 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.[76] 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.23).

Finally I examine how electricity prices affect price over marginal cost markups $\mu \equiv P/MC$ (see Section IV.F). 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.F, 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.31. The vast majority of pass-through elasticities are between 0.8 and 1.1. A pass-through elasticity greater than one means that costs are disproportionately passed through to consumers.[77] This can arise if producers fail to previously collude in an oligopoly. An increase in costs can help to solve 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 ($\widehat{\mu}$) into pass-through rates $\widehat{\rho}_{MC}$. Table 6 shows the three components to calculate incidence: the Lerner index $\widehat{L}$, the market demand elasticity $\widehat{\epsilon}_D$ and the marginal cost to price pass-through rate $\widehat{\rho}_{MC}$, reporting the median, the 25th, and the 75th percentile of the distribution across plants, sectors and years. The median incidence share I^{share} across all plants is 63%. There is some heterogeneity across industries and years; the 25th and 75th percentiles are 53% and 79% respectively, even at the 5th percentile, the share of consumer incidence

[76]The main methodology to measure TFP is based on Wooldridge (2009) using deflated revenue data, so should be interpreted as revenue TFP. Since markups increase, the impact on physical TFP could be slightly smaller. Table A.20 reports effects when TFP is measured following Olley and Pakes (1996), Levinsohn and Petrin (2003) or Ackerberg, Caves and Frazer (2015).

[77]While the pass-through *elasticity* is smaller than one for the five industries studied in Ganapati, Shapiro and Walker (2020), the pass-through *rate* ρ_{MC} is also greater than one for three of the five industries and in some of the studies cited therein.

is a quarter of the total. Figure A.32 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, with lower and higher incidence estimates than in the benchmark oligopoly case. The next section calculates aggregate consumer surplus that takes into account that industries sell to final demand in varying degrees which determines the overall consumer welfare share, in addition to calculating total profits and CO_2 emissions.

E. Aggregate Effects on Welfare and CO_2 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_2 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 producer gains, I use the semi-elasticity of variable 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.[78] For the entire manufacturing sector, this translates into profits of ₹ 1.69 trillion or US$ 37.4 billion (in constant 2004 terms), equivalent to 2.8% of Indian real GDP in 2013.[79]

For consumer gains, there are two steps: First, since a subset of firms in the sample may not sell to consumers directly, I am using input-output tables to obtain the share of output going to final demand by industry with details in Section A.17. Using this data along with incidence shares estimated in Section V.D, the first component of change in consumer surplus is US$ 34.4 billion. Second, the reduction in government profits from sale of electricity was ₹ 143 billion or US$3.5 billion.[80] If utilities financed this deficit through a rate increase for the residential sector, consumer surplus gains would be reduced directly by US$ 3.4 billion to US$31 billion, based on demand elasticities for the residential sector with details in Section A.17.

Using this figure, the share of consumer surplus in total welfare gains is 45%, which is lower than average plant level incidence shares in Table 6, as the denominator of total welfare also includes profits of firms that may contribute little to final demand. Importantly, this implies that electricity pricing for industry is not only relevant for industrial development but also for consumers. The reduction in cross-subsidization from industry (Appendix A.5) has thus also generated sizable net benefits to consumers through lower output prices. The US$ 68.4 billion total welfare gains imply annualized gains of US$ 4.9 billion that are equivalent to 0.36% of Indian GDP or 4% of manufacturing value added in 2013 (UNIDO,

[78] I take -21.25 as the average of the two estimates in Table 4a and calculate $\log((1-0.48)^{-21.25}) = 13.90$. Note that this is an 80% increase in profits over the mean (Table 1) and represents 19% of the increase in variable costs similar to average markup estimates. The increase in variable profits is incentive consistent. First, note that capital expenditure increases by ₹ 6.6 mil, using the elasticity of overall book value of capital and the 15% depreciation rate from the Indian Income Tax Rules, so profits net of capital costs increase by ₹ 7.3 mil. Second, in the absence of electricity price reductions, if producers still decided to produce exactly like in the factual with modern technology, the additional increase in variable costs would have been ₹ 8.2 mil, larger than variable profits net of investment costs implying that producers would not have chosen this in the absence of price changes.

[79] Based on 121,825 manufacturing plants in the sampling frame in 1998, calculated by summing over the sampling multiplier.

[80] 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 across the sample of 3.14 ₹ /kWh (6.9 US cents) from the Planning Commission (2001-2002); Ministry of Power (2002-2015) and the average industrial electricity prices for 1998-2000 and 2013 (6.4 ₹ /kWh and 3.32₹ /kWh): $(3.32-3.14)\cdot 53.5\cdot(1-0.48)^{-0.638} - (6.4-3.14)\cdot 53.5 = 160$ billion ₹ . Note that this implied loss for utilities is conservative by using an average cost of supply. Even if cost of supply was double and prices were below cost-recovery, additional utility losses would only be slightly higher.

Table 7: Aggregate effects on CO_2 emissions from a 48% electricity price decline

Additional emissions from (in Mt):	Estimate	No substitution	No productivity	No substitution & 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.

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 benefits for workers.

These welfare estimates do not include environmental damages yet. I next calculate the implications for aggregate CO_2 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 and report the details of the calculation and data sources in Appendix A.18. From a baseline of 134.5Mt annual CO_2 emissions in manufacturing (1998-2000 average), the 48% decline in electricity prices increased emissions by 31% or 41.7Mt (Column 1 in Table 7).

This increase in emissions was entirely driven by firms scaling up.[81] In fact, Table 7 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 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 an 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_2 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_2, the costs from higher emissions are US\$4.2 billion. While this is sizable, it is small compared to the US\$67.3 billion welfare gains, so the reduction in industrial electricity prices had substantial welfare benefits 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

[81] 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.

Table 8: The contrary effects of coal prices on coal and labor productivity and firm performance

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

	Coal productivity (log)			Labor productivity (log)			Profit		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(P^C)$	0.848***	1.484***	1.617***	0.0564***	-0.0251	0.300	-5.940***	-6.315	-7.393
	(0.025)	(0.179)	(0.213)	(0.020)	(0.132)	(0.193)	(1.628)	(15.050)	(25.859)
OLS/IV	OLS	IV^E	IV^F	OLS	IV^E	IV^F	OLS	IV^E	IV^F
Observations	44968	44968	44968	44968	44968	44968	44965	44965	44965

(**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***	-0.311	-0.135	-0.757***	-1.851***	-1.799***	0.0328	-0.320*	-0.491*
	(0.031)	(0.248)	(0.343)	(0.036)	(0.273)	(0.383)	(0.021)	(0.193)	(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

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, and profits are in levels as they can be negative. The first stage coefficients are 0.57 for IV^E with a KP F-stat of 154 and 0.01 for IV^F with an F-stat of 86. 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.

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.[82] The shifter is the nationally representative coal price at pit heads for industry (as opposed to power utilities) of the appropriate coal grades from Minsitry of Coal (2012, 2015). When national average prices at the pit head rise, manufacturing plants further away from pit heads may see differential total price increases due to the differential size of shipping cost components in total costs.

Table 8 shows the results. Indeed, in contrast to electricity prices, lower coal prices significantly *decrease* coal productivity. 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. Lower coal prices also have no significant effect on TFP (Table A.27).[83] There are small and insignificant effects on profits and revenues and an ambiguous effect on costs (Table 8a and A.27). 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.

G. *Policy Implications*

I highlight five policy implications from these findings that are crucial for the context of industrial development and decarbonization. First, cross-subsidizing low agricultural and residential rates with high

[82]The location of coalfields and power plants is illustrated in Figure A.26.

[83]This is in line with Calì et al. (2022) who even find positive effects on TFP from *higher* coal prices in Indonesia and Mexico.

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 conflates two types of market failures. The pure climate and pollution externalities from fossil fuel combustion can be internalized by pricing carbon. Simultaneously tackling excessive industrial electricity prices through reduced electricity taxes or cross-subsidization, or increased industrial electricity subsidies can address the industrial development market failure that generates lower electricity productivity from too little technology upgrading, 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 decarbonization 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 (2023*a*,*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. Note, however, that if we think that capital frictions especially affect less capitalized firms, the results in Figure 6 showing stronger effects for less capitalized firms suggest that frictions are not dominating the effect. 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, e.g. doubling the previous rate of improvements agreed at COP28, these findings could be interpreted as win-win in lower income country settings where trade-offs often occur.

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 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, and I show diminishing returns as the economy mechanizes. These effects are likely to be most salient in the process of industrial development, rather than at advanced industrialized stages. Nevertheless, the broader implications of these findings of electricity pricing in technology transitions are also crucial for addressing current decarbonization 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 around one half 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 market failures may be particularly beneficial in a context of industrial development. Future research could extend the analysis to incorporate production networks and general equilibrium effects.[84]

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[84] 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?

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Contents

A.1 Model proofs

The firm's optimization problem is:

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

and for notational simplicity define Z and W as:

$$\begin{aligned} PQ &= A(\alpha_l L^{\rho_l} + (1-\alpha_l) X^{\rho_l})^{\frac{\phi}{\rho_l}} \equiv AZ^{\frac{\phi}{\rho_l}} \\ X &= (\alpha_e E^{\rho_e} + (1-\alpha_e) K^{\rho_e})^{\frac{1}{\rho_e}} \equiv W^{\frac{1}{\rho_e}} \end{aligned} \tag{A.2}$$

and

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

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

$$\phi A Z^{*\frac{\phi}{\rho_l}-1} \alpha_l L^{*\rho_l - 1} = p_L \tag{A.4}$$

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

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

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

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

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

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

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

Conditional on c, output and electricity productivity is:

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

$$\frac{PQ^*}{E^*} = \kappa_{PQE} E^{*\phi - 1} \tag{A.12}$$

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:

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

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:

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

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

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

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:

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

Next, note that:

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

Finally, note that the profit function Π^* is convex $\frac{\partial^2 \Pi^*}{(\partial p_E)^2} \geq 0$, and by Hotelling's lemma $\frac{\partial \Pi^*}{\partial p_E} = -E^*$.[85,86] Taken together this implies that $\frac{\partial E*}{\partial p_E} \leq 0$.

Therefore, since $\phi < 1$:

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

■

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 Δp_P 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 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:

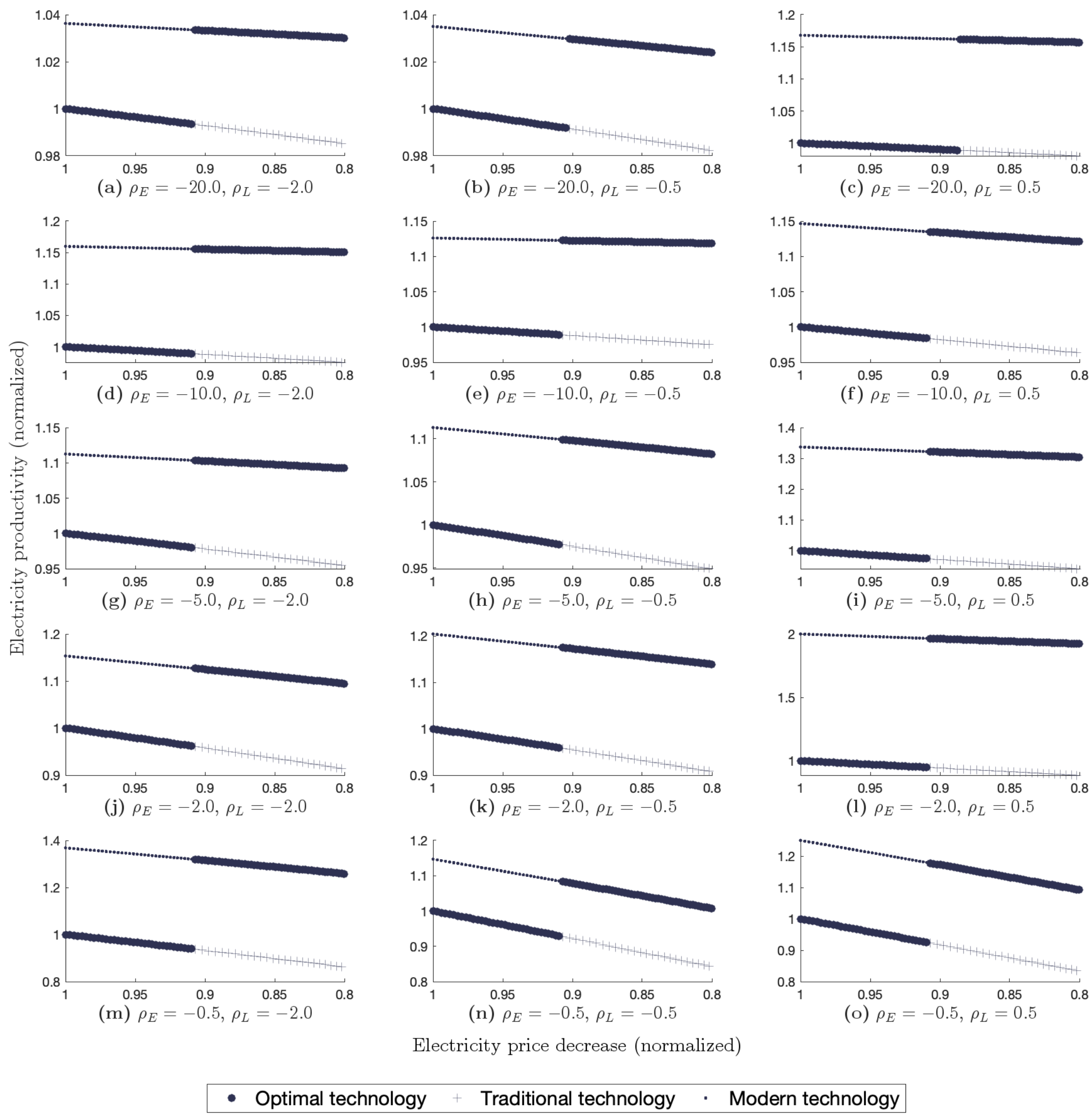
$$\begin{aligned}
\Pi^*(p_E - \Delta_{p_E}, c = c') &> \Pi^*(p_E - \Delta_{p_E}, c = 1), \quad \text{i.e. prefer new technology with new prices} \\
\Pi^*(p_E, c = 1) &> \Pi^*(p_E, c = c'), \quad \text{i.e. prefer old technology with old prices} \\
\frac{PQ^*(p_E - \Delta_{p_E}, c = c')}{E^*(p_E - \Delta_{p_E},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

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. ■

[85] 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 δ and $(1-\delta)$, summing and rearranging terms yields $\delta \Pi^*(p_E) + (1-\delta)\Pi^*(p_E) \geq \Pi^*(p_E'')$.

[86] 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.

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

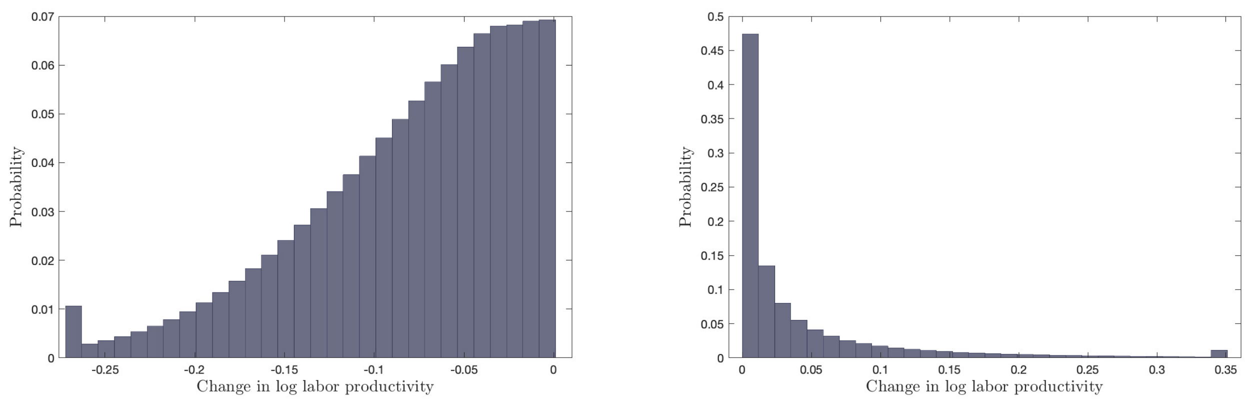


Notes: The figures plot electricity productivity on the vertical axes (all normalized) against relative electricity price *decreases* on the horizontal axis. The panels vary the elasticity of substitution between capital and electricity ($\hat{\rho}_e$) across rows from strong complementarities (-20) 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 ($\Delta p_E = 0$). 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.

Proof of Lemma 2. Since $c = 1$ in all cases, the conditional demands and output are also unconditional

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

(**a**) Capital services and labor complements ($\rho_l < 0$) (**b**) Capital services and labor substitutes ($\rho_l > 0$)



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 α_e α_l I use $[0, 1]$, for the bundle of returns to scale in production and demand ϕ 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 ρ_e I use support $[-10, 0]$. In Panel (a) the complementarity between labor and capital services ρ_l is drawn over support $[-10, -0.001]$ implying complements. In Panel (b) ρ_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).

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:

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

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

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

■

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 or complements. Figure A.2 illustrates the role of this complementarity (ρ_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.[87] In Panel (a) the complementarity between labor and capital services ρ_l is drawn over support $[-10, -0.001]$ implying complements. In Panel (b) ρ_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.

[87] For prices I use support $[1, 10]$, for the shape parameters α_e α_l I use $[0, 1]$, for the bundle of returns to scale in production and demand ϕ 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 ρ_e I use support $[-10, 0]$.

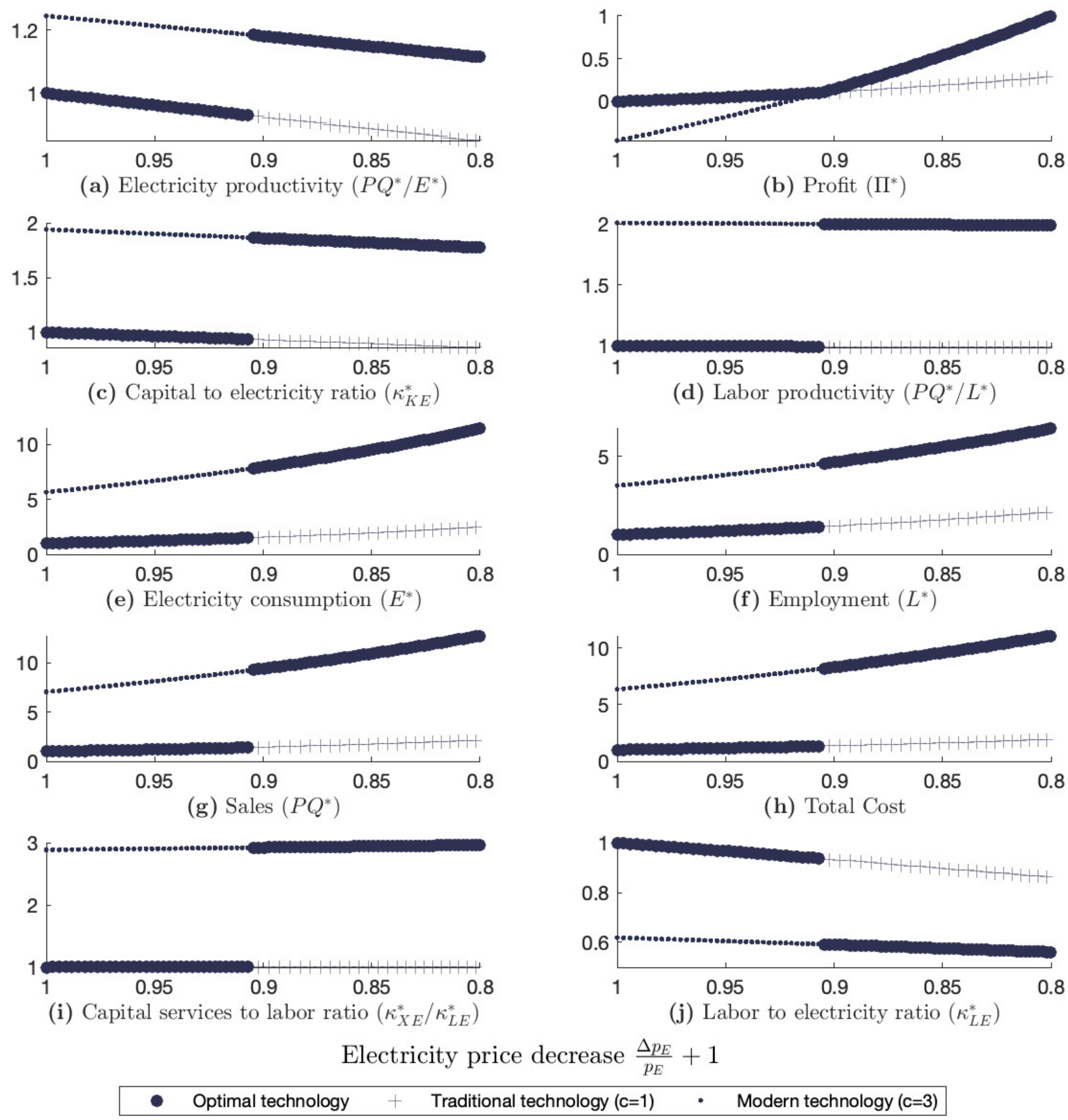
A.2 Further model predictions and visualizations

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 Δp_E, 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 capital to electricity 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 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.

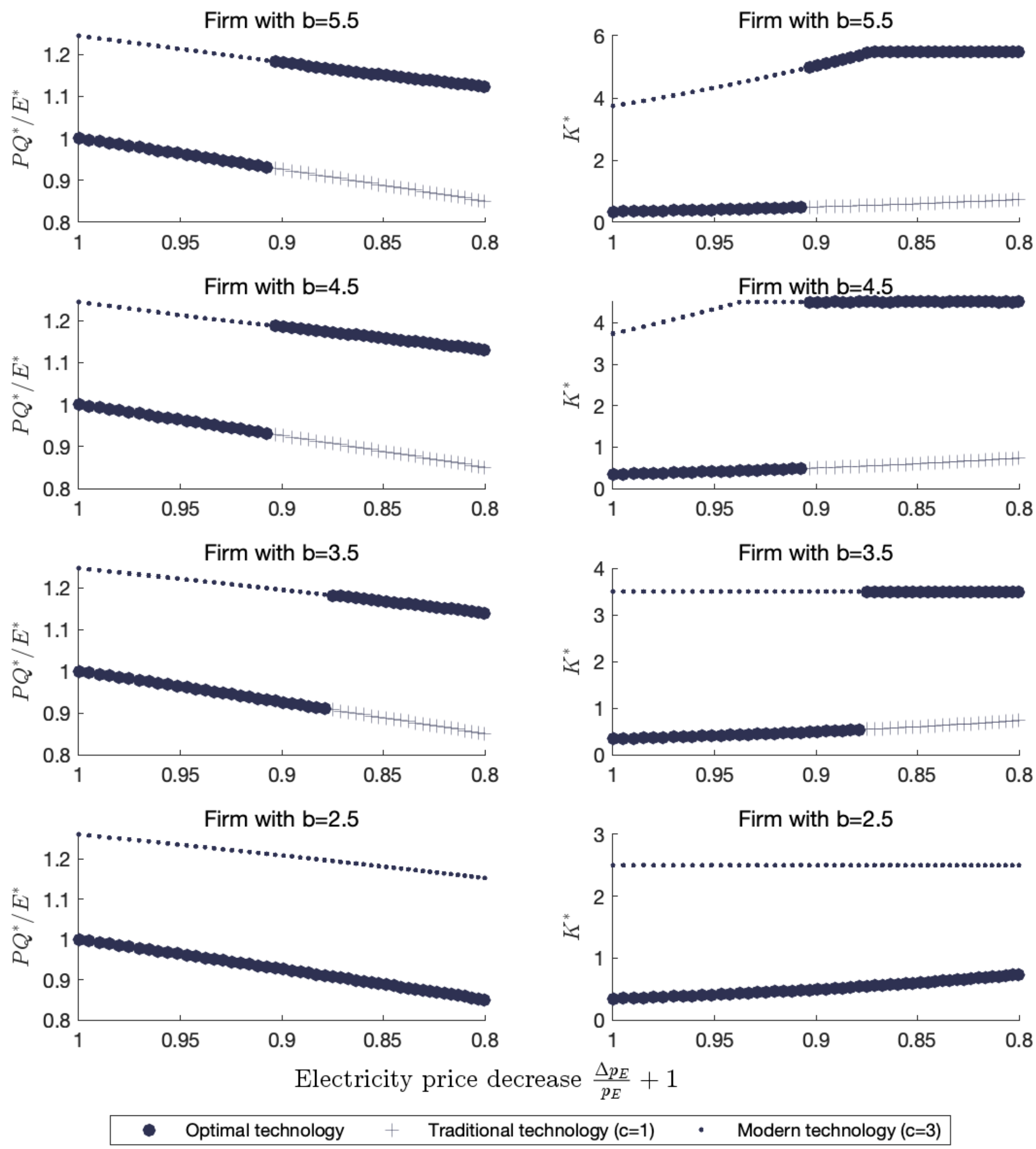
Figure A.5 plots the same electricity productivity graphs as in Panel (a) of Figure 2 and A.3, but for heterogeneous firms. In particular, I use 100 firms, which vary in their total factor productivity A_i ranging from 9.1 to 9.25 in equal intervals. The graph shows 10 of these firms, and those with 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 increases 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 (h) 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 ($\Delta p_E = 0$). 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 Δp_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).

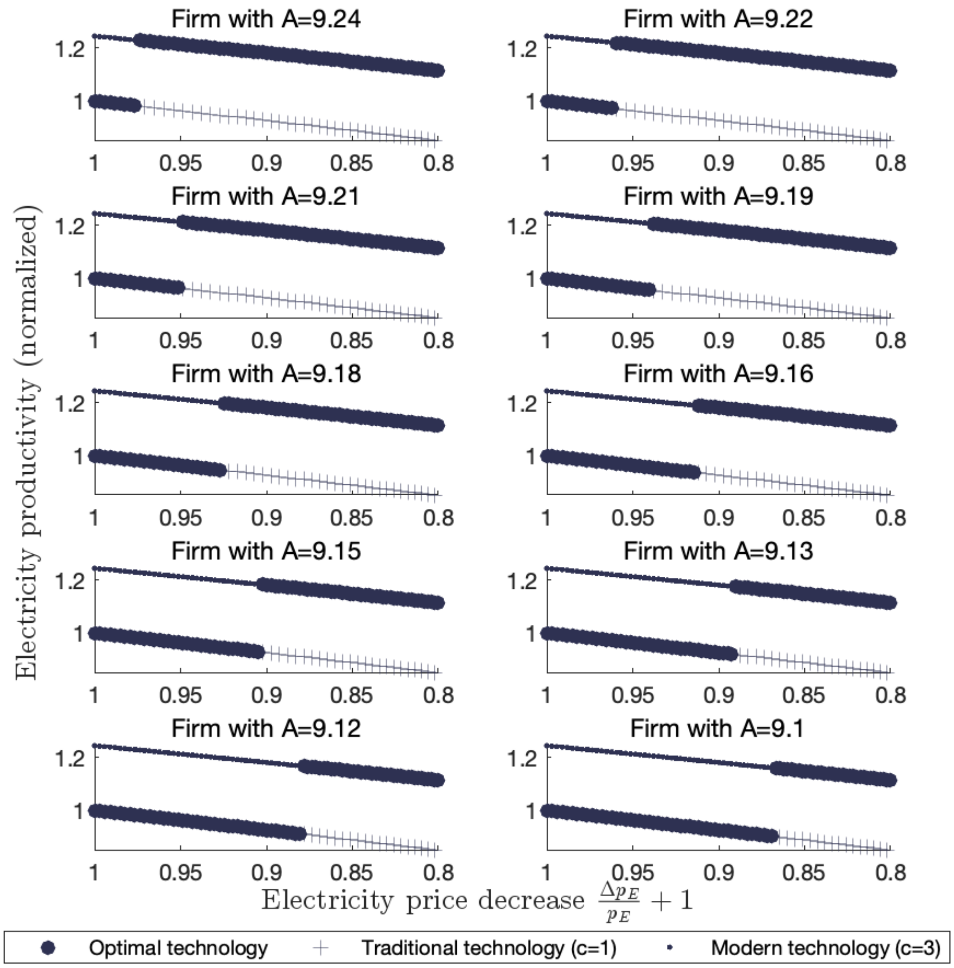
Figure A.4: Electricity price decreases in the presence of capital constraints



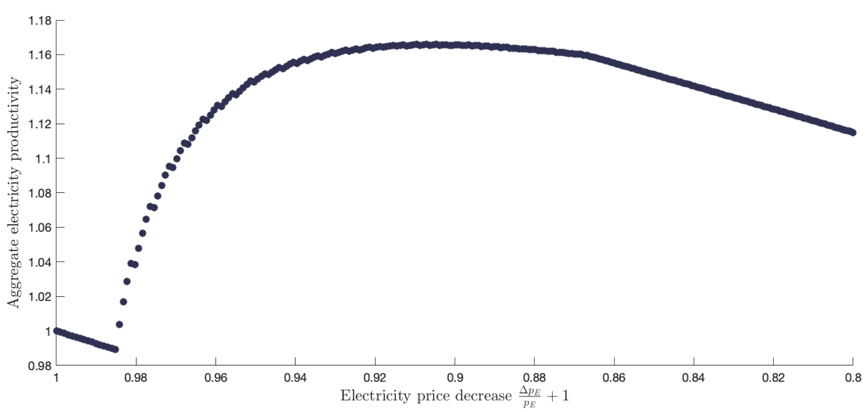
Notes: The figures plot electricity productivity (normalized) on the left and capital on the right (in levels) against electricity price *decreases* on the horizontal axis. The firm maximization problem is modified to include a capital constraint $K \leq b$. From the top to the bottom panels, each row 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 Δp_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).

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

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



(**b**) Impact on 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 Δp_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 Comparing electricity prices and productivities using alternative data sources

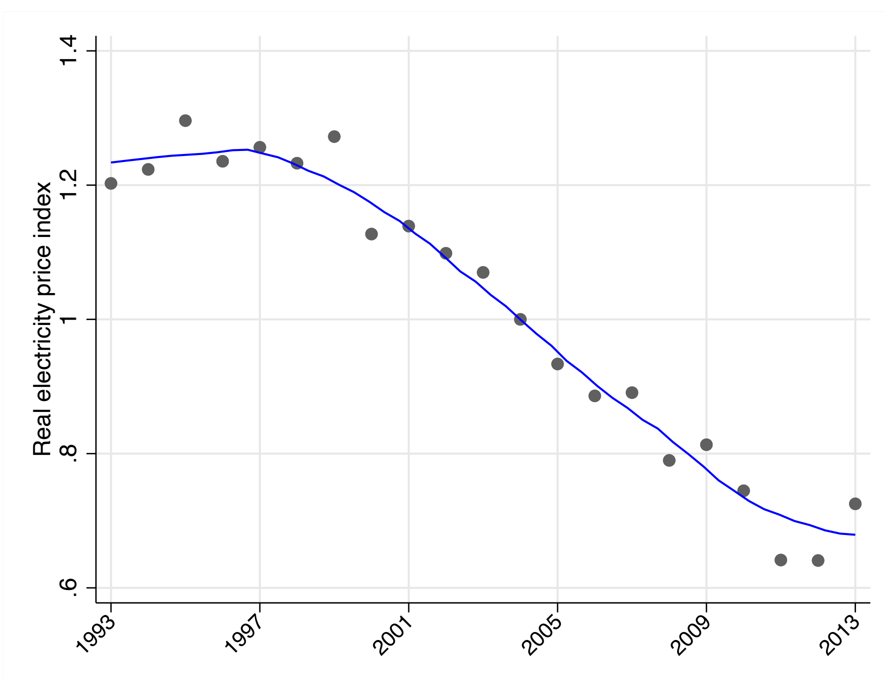
This section provides additional descriptive graphs. First, the patterns in electricity prices and electricity productivity are confirmed with alternative data sources. Figure A.6 shows the evolution of the industrial electricity price in real terms from three different sources. The solid line is the ASI-derived price as in Figure 1. The dashed line is the average price derived from publications of the Planning Commission (2001-2002) and Ministry of Power (2002-2015) dividing total utility revenues (summed across all utilities) by total kWh supplied for the industrial sector. The dotted line is a weighted average of industrial electricity tariffs manually collected from the reports of the Indian Central Electricity Authority (2006-2015) and from Indiastat (1998-2014), weighted by supplied kWh across states. All three sources show a similar pattern of decreasing prices. Figure A.7 plots the electricity price index in real terms from the Office of the Economic Adviser (2019) corroborating this pattern. Figure A.8 plots the average of industrial electricity tariffs specifically for heavy industry, one of several size bins within industry. Figure A.9 compares the ASI-derived electricity prices and the collected average industrial electricity tariffs for large industry across state-year clusters and shows that they are highly correlated, but can deviate due to some firms not being categorized as large industry or due to different tariffs within states that are captured by the ASI data.

Figure A.10 uses (IEA, 2016; UNIDO, 2016) data for electricity productivity showing a consistent pattern. Panel (a) also shows that electricity productivity did not increase nearly as much in OECD countries over the sample period. Panel (b) shows that the share of electricity in the energy mix has increased. Figure A.11 shows electricity productivity per ₹ rather than per kWh, and other fuel productivity per ₹. The figure shows that electricity productivity is increasing even more when measured in ₹ terms, which is consistent with the decreasing electricity prices.

Figure A.6: Comparing industrial electricity prices from three alternative sources

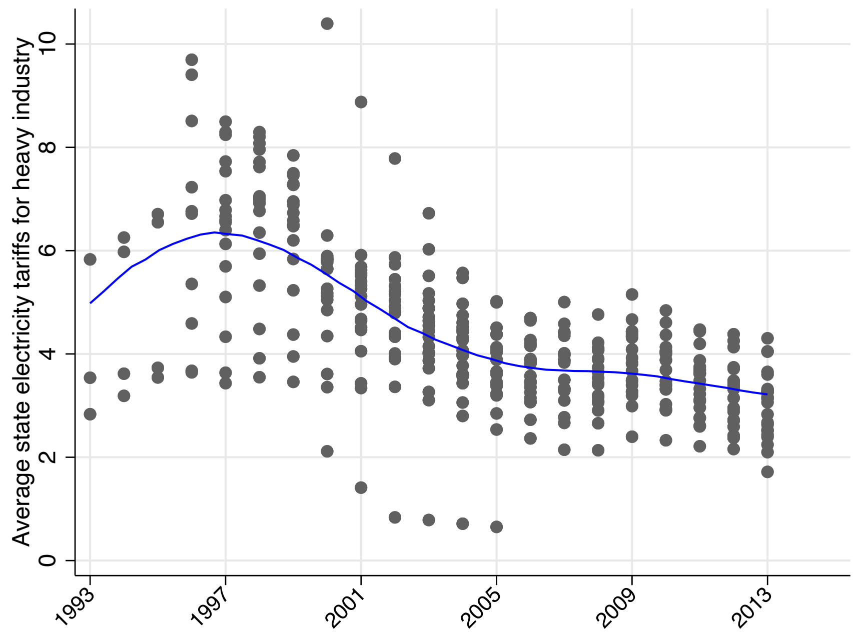
Notes: The figure plots industrial electricity prices from three sources. The solid blue line is the ASI-derived price as in Figure 1. The dashed red line is the average price derived from publications of the Planning Commission (2001-2002) and Ministry of Power (2002-2015) dividing total utility revenues (summed across all utilities) by total kWh supplied for the industrial sector. The dotted orange line is weighted average of industrial electricity tariffs manually collected from the reports of the Indian Central Electricity Authority (2006-2015) and from Indiastat (1998-2014) through Lok Sabha and Rajya Sabha questions, weighted by supplied kWh across states.

Figure A.7: Real electricity price index



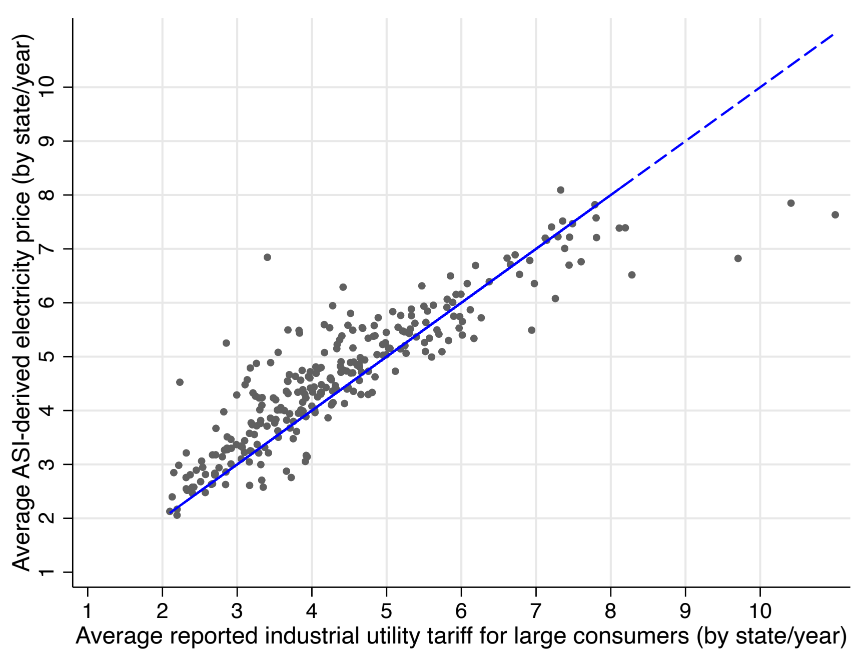
Notes: The figure plots the real electricity price index for industry. It is based on the deflated wholesale price index for electricity for industrial purposes.

Figure A.8: 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 (1998-2014) through Lok Sabha and Rajya Sabha questions. Individual data points correspond to state level average tariffs for heavy industry.

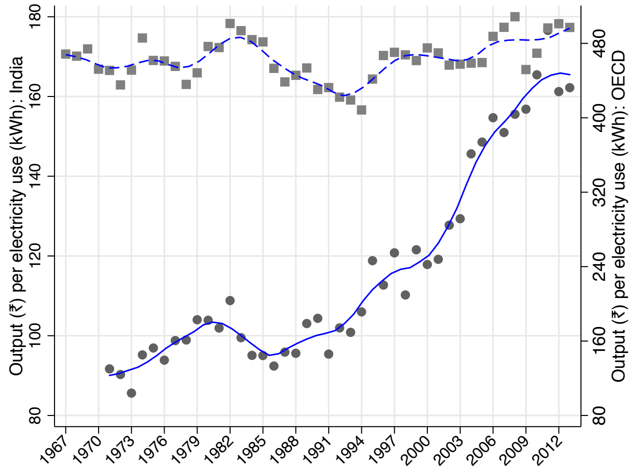
Figure A.9: Comparing ASI-derived electricity prices and published average industrial electricity tariffs



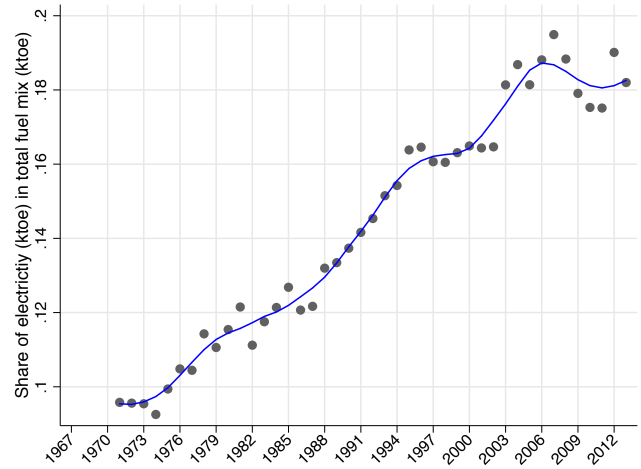
Notes: The figure plots ASI-derived real electricity prices aggregated to the state by year level against published real electricity tariffs for large industry averaged at the state by year level. The tariffs are manually collected from publications of the Indian Central Electricity Authority (2006-2015) and from Indiastat (1998-2014) through Lok Sabha and Rajya Sabha questions. Individual data points correspond to state level average tariffs for heavy industry.

Figure A.10: Electricity productivity and share in fuel mix using data from IEA (2016) and UNIDO (2016)

(**a**) Electricity productivity (per kWh)



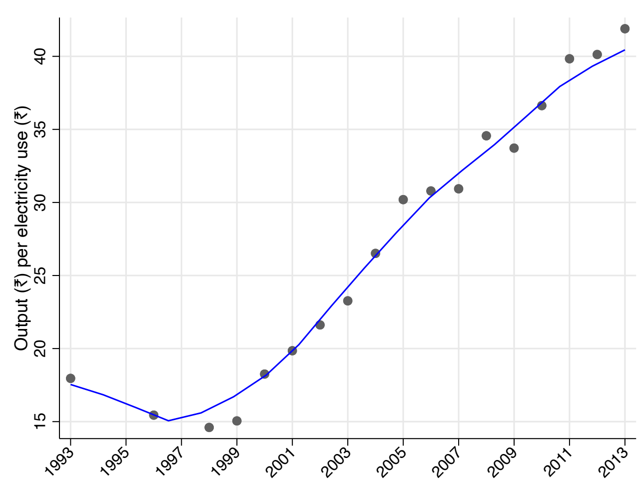
(**b**) Share of electricity in fuel mix



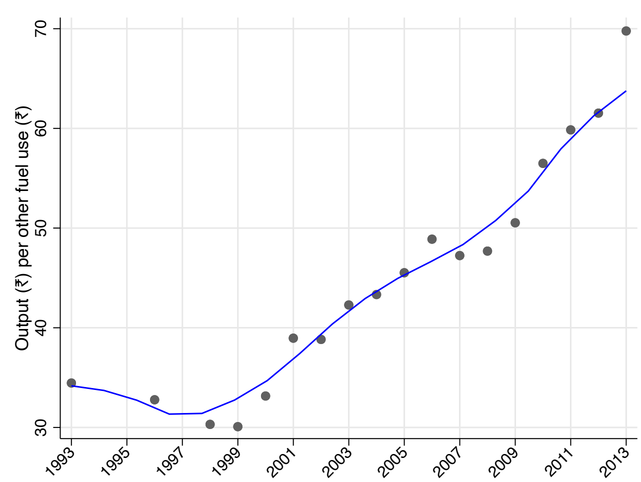
Notes: Panel (a) plots the annual electricity productivity ratios (value of output divided by the quantity of electricity used (in kWh)). Both quantities are for manufacturing only. Output is from UNIDO (2016), deflated with GDP deflators from World Bank (2017), and electricity consumption from the IEA (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. Panel (b) plots the share of electricity consumption in total fuel consumption in India (both in ktoe) using data from IEA (2016).

Figure A.11: Electricity productivity and other fuel productivity (per ₹)

(**a**) Electricity productivity (per ₹)



(**b**) Other fuel productivity (per ₹)



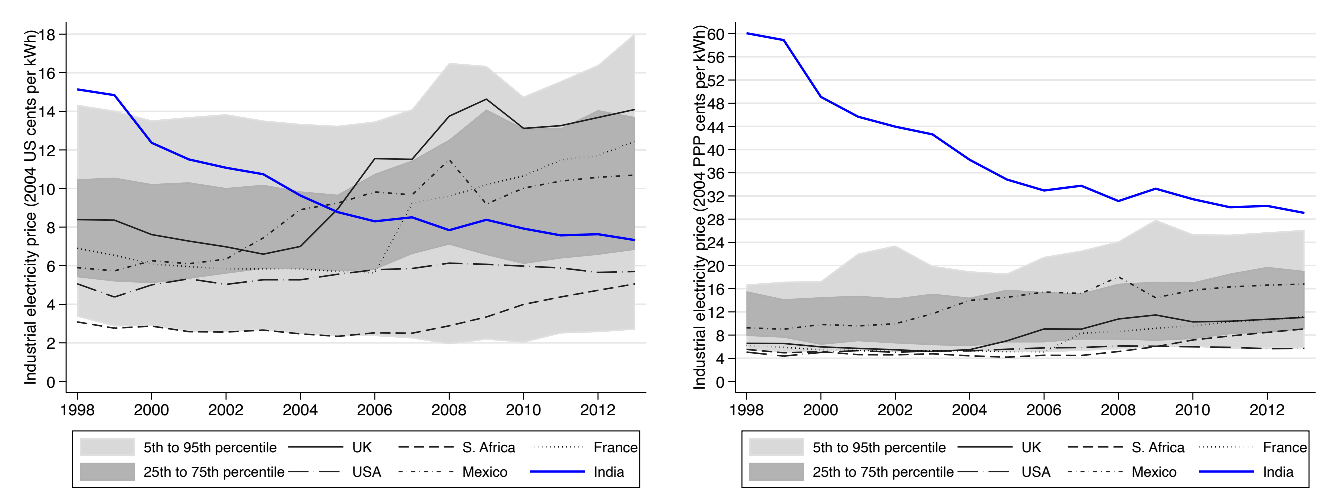
Notes: Panel (a) plots the annual electricity productivity ratios (value of output divided by the value of electricity used). Panel (b) plots the other fuel productivity ratios (value of output divided by the value of fuel other than electricity used). Plant output is deflated using 3-digit industry 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.

A.4 India's high electricity prices in international comparison

Average electricity tariffs in India were the equivalent of 15.1 US cents (2004 US$) for industrial users in 1998. As Figure A.12 and Table A.1 show, the G7 or OECD average was around 8.9 US cents in 1998, implying that the Indian industrial tariffs were around 70% higher. Adjusting for the difference in general price levels between India and G7 countries, Indian tariffs were 630% 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 133% 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.12. While electricity prices in India almost halved during the sample period, prices in OECD countries grew by roughly 40% (Table A.1).[88]

Figure A.12: Industrial electricity prices in an international context (US$ and PPP)

(**a**) Industrial electricity prices (Market exchange rates) (**b**) Industrial electricity prices (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 (2018*b*), except for India, where the prices are based on the micro data in the main text. For India, IEA (2018*b*) 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.

[88] 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.

Table A.1: Industrial electricity prices in US-cents: India, OECD 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	15.14	8.91	8.96	170	169	60.08	8.24	10.40	730	578
1999	14.84	8.42	8.57	176	173	58.89	7.76	10.03	759	587
2000	12.37	8.36	8.43	148	147	49.09	7.75	9.94	634	494
2001	11.51	8.97	8.81	128	131	45.67	8.36	10.40	547	439
2002	11.08	8.68	8.89	128	125	43.96	8.08	10.49	544	419
2003	10.74	9.01	9.11	119	118	42.63	8.41	10.78	507	395
2004	9.64	9.00	9.07	107	106	38.24	8.38	10.77	456	355
2005	8.78	9.55	9.43	92	93	34.84	8.88	11.16	393	312
2006	8.30	10.58	10.03	78	83	32.94	9.79	11.77	336	280
2007	8.51	11.25	10.30	76	83	33.76	10.41	12.11	324	279
2008	7.84	10.88	11.02	72	71	31.12	9.98	13.05	312	239
2009	8.38	11.59	11.46	72	73	33.26	10.61	13.70	313	243
2010	7.92	11.42	11.11	69	71	31.44	10.50	13.24	299	238
2011	7.57	12.20	11.50	62	66	30.05	11.24	13.60	267	221
2012	7.63	12.79	12.18	60	63	30.29	11.77	14.38	257	211
2013	7.33	13.53	12.43	54	59	29.07	12.45	14.56	233	200

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 (2018*b*), except for India, where the prices are based on the micro data in the main text. For India, IEA (2018*b*) 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.

A.5 Electricity prices across user groups, cross-subsidization and block tariffs

The high electricity prices in India for industrial users are in contrast to low electricity prices for agricultural and residential users, 0.9 and 5.8 US cents respectively in 1998 (Planning Commission, 2001-2002), even though the cost of supply is usually lower for industrial users (Ministry of Power, 1998*b*).[89] 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, 2001-2002). 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 2.0 cents for agricultural tariffs (Ministry of Power, 2002-2015). 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).

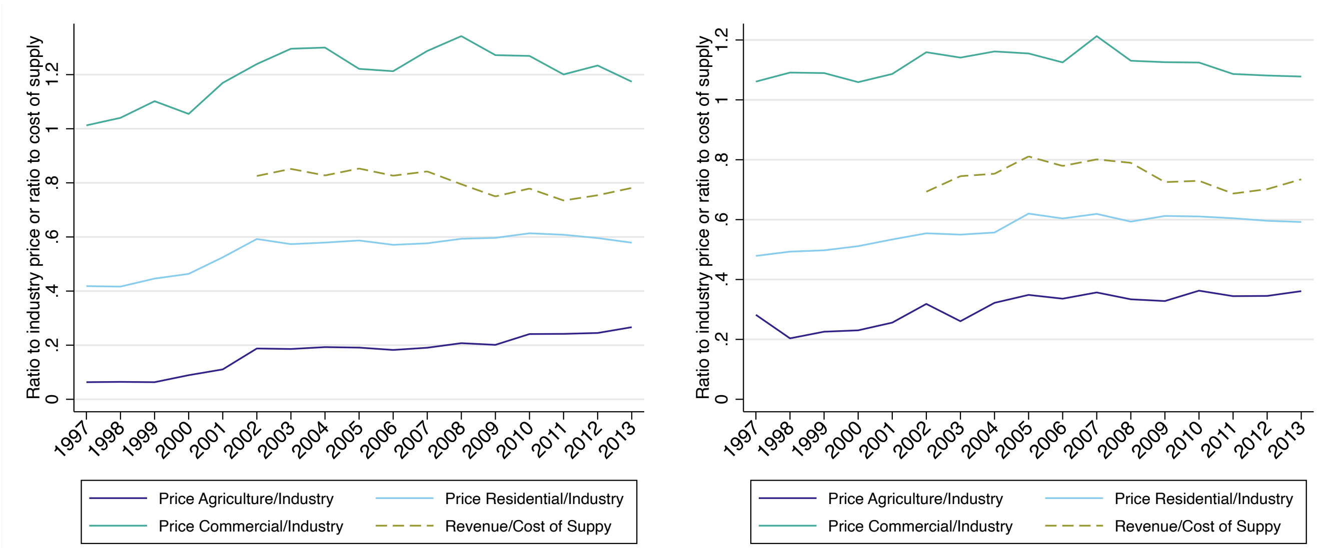
Figure A.14 compares industrial electricity prices across different consumption bands across Indian states in 2007, using manually collected data from government reports (Central Electricity Authority, 2006-2015). Industrial tariffs mostly follow increasing block tariffs, at least up to a point. On average, a higher band (of five bands) is associated with a 1.8 percent increase in the tariff.[90] Figure A.15 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.

[89] For the agricultural and residential tariffs, I divided total revenues by total kWh supplied for each sector across all utilities and states using data from Planning Commission (2001-2002), which is effectively a weighted average tariff. The simple average tariff in 1998 across states is 2.2 and 5.3 for agricultural and residential respectively. The implied industrial tariff from these publications would be 13.9 in 1998, similar to the ASI reported average.

[90] 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.

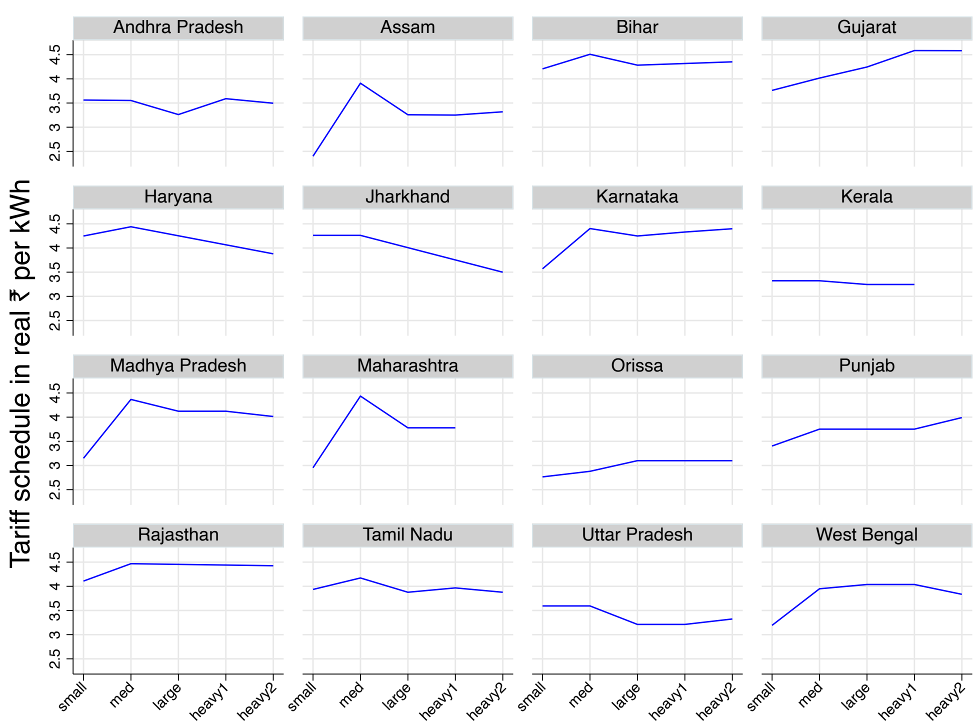
Figure A.13: Price ratios by user groups and cost of supply (weighted and simple average)

(**a**) Price ratios and cost-recovery (weighted average) (**b**) Price ratios and cost-recovery (simple average)



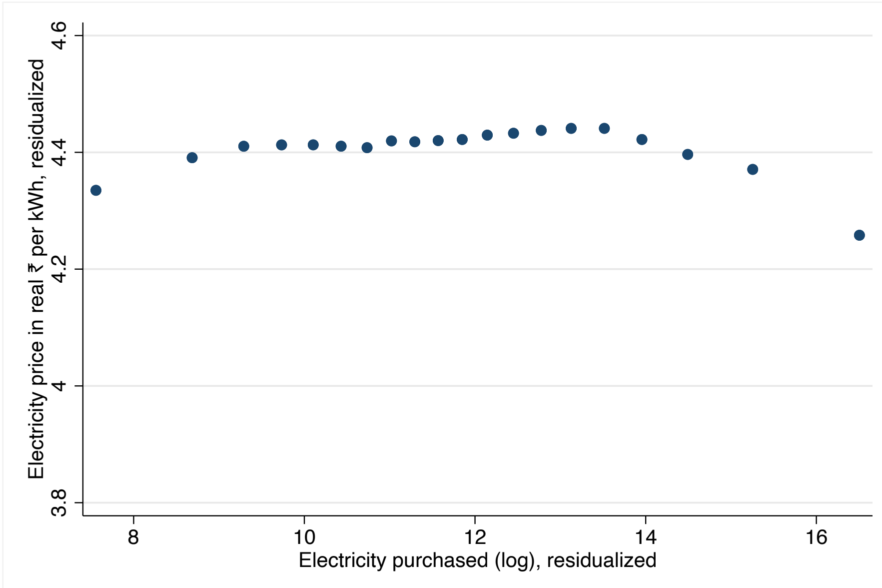
Notes: Both panels plot ratios of electricity prices in agriculture, residential or commercial over industrial electricity prices. In Panel (a), these are effectively calculated as weighted average over utilities and states using total revenue over total quantity of electricity delivered by sector. In Panel (b) these are simple averages across all utilities and states ignoring the size of utilities. The panels also show the overall ratios of average rate of revenue (without subsidies) over the cost of supply, averaged across utilities weighted by kwh of supply in Panel (a) and as simple average in Panel (b). Data is from Planning Commission (2001-2002) and Ministry of Power (2002-2015).

Figure A.14: 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.15: Residualized electricity prices and quantity purchased



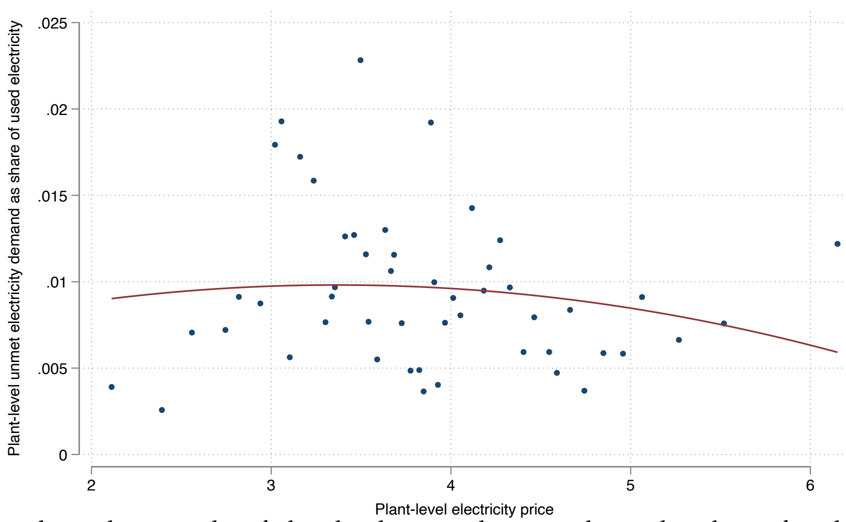
Notes: The figure shows a binned scatter plot where both plant level electricity prices, and log electricity purchased are pre-residualized by partialing out state by year fixed effects. This shows that marginal prices are fairly similar to average prices, and that tariffs are slightly increasing in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

A.6 Electricity shortages and electricity prices

To explore the relationship between electricity prices and power shortages, I use two measures of shortages. First, I construct a manufacturing plant level measure by using the data on unmet electricity demand at the plant level available in years 2004-2013 (with the exception of year 2006-2007). I calculate the share of unmet electricity demand as a share of total electricity consumed by the plant. Figure A.16 plots unmet demand against plant level electricity prices and shows no significant correlation between the two. Columns 1-6 of Table A.2 more formally show that there is no significant correlation with electricity prices, where even columns focus on the intensive margin of shortages dropping all observations with zero unmet demand. Second, I construct a state level measure by using the administrative data on state level shortages reported by utilities as a share of total required electricity at the state by year level as in Figure 3. Columns 7-9 of Table A.2 shows that the correlation is, again, small and insignificant.

In Table A.3, I instead use electricity prices from the Planning Commission (2001-2002) and Ministry of Power (2002-2015) publications, which are based on utility revenues divided by total kWh supplied. I calculate average industrial electricity prices and average *overall* electricity prices at the state by year level. I also calculate the share of costs recovered by utilities, which is the ratio of average revenues over average cost of supply, available from 2002. I use the same data on state level shortages as in Columns 7-9 of Table A.2 and Figure 3. In Panel (a) of Table A.3 I show OLS estimates based on the levels of prices and shortages. In Panel (b) I show elasticity estimates based on PPML regressions and logged independent variables. The first two columns confirm that there is no correlation between industrial electricity prices and shortages. However, Columns 3-4 show that *overall* electricity prices are predicting shortages. This is, as Columns 5-6 show, because shortages are strongly correlated with cost-recovery, and cost-recovery in turn is driven by *overall* electricity prices (Columns 7-8).

Figure A.16: Unmet electricity demand and electricity prices



Notes: The figure shows a binned scatter plot of plant level unmet electricity demand as share of total electricity used against plant level electricity prices. The data is from the ASI for the years 2004-2013, excluding 2006-2007. The figure shows that there is no significant correlation between unmet demand and electricity prices.

Table A.2: Electricity prices and two measures of power shortages

	Share plant level unmet electricity demand						State level shortages		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Electricity price (log)	-0.0057	-0.042	-0.0055	-0.082	-0.0053	-0.042	0.014	-0.0028	0.0025
	(0.0061)	(0.12)	(0.0042)	(0.090)	(0.0038)	(0.075)	(0.0090)	(0.0067)	(0.0034)
N	338140	12219	338140	12218	338140	12218	589459	589459	589459
Year FE	No	No	Yes	Yes	Yes	Yes	No	Yes	Yes
State FE	No	No	Yes	Yes	Yes	Yes	No	Yes	Yes
Region-year FE	No	No	No	No	Yes	Yes	No	No	Yes
Int. marg. unmet	No	Yes	No	Yes	No	Yes	No	No	No

Notes: The table shows estimates from OLS regressions on logged electricity price. In Columns 1-6 the dependent variable is manufacturing plant level unmet electricity demand as share of total electricity consumed by the plant. Columns 2, 4 and 6 focus on the intensive margin unmet electricity by dropping all observations where the dependent variable is zero. In Columns 7-8, the dependent variable are state by year level electricity shortages reported by the utilities as share of total required electricity at the state by year level. Regressions are weighted by the sampling multipliers. Standard errors in parentheses are clustered at the state year level. Stars indicate p-values: * < 0.1, **< 0.05, ***< 0.01.

Table A.3: State power shortages, cost-recovery and utility electricity prices

(a) Levels: OLS regressions in levels

	State level shortages						State level cost-recovery	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Industry electricity price	-0.00058	-0.0014						
	(0.0022)	(0.0034)						
Overall electricity price			-0.0075*	-0.012***			0.15***	0.16***
			(0.0039)	(0.0043)			(0.024)	(0.025)
Cost-recovery					-0.091***	-0.13***		
					(0.016)	(0.019)		
N	419	419	420	420	327	327	327	327
Year FE	No	Yes	No	Yes	No	Yes	No	Yes
State FE	No	Yes	No	Yes	No	Yes	No	Yes
Region-year FE	No	Yes	No	Yes	No	Yes	No	Yes

(b) Elasticities: PPML regressions with log independent variables

	State level shortages						State level cost-recovery	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Industry electricity price (log)	-0.12	-0.27						
	(0.14)	(0.18)						
Overall electricity price (log)			-0.42**	-0.85***			0.64***	0.72***
			(0.18)	(0.19)			(0.078)	(0.080)
Cost-recovery (log)					-0.64***	-1.09***		
					(0.13)	(0.15)		
N	416	416	416	416	327	327	324	324
Year FE	No	Yes	No	Yes	No	Yes	No	Yes
State FE	No	Yes	No	Yes	No	Yes	No	Yes
Region-year FE	No	Yes	No	Yes	No	Yes	No	Yes

Notes: The table shows estimates from OLS regressions using variables in levels in Panel (a) and elasticity estimates from PPML regressions using independent variables in logs, all at the state by year level. In Columns 1-6 the dependent variable are state by year level electricity shortages reported by the utilities as share of total required electricity at the state by year level. In Columns 7-8 the dependent variable is the share of utility costs that are recovered through revenues at the state level. The electricity price for industry and the overall electricity price is from Planning Commission (2001-2002) and Ministry of Power (2002-2015). Standard errors in parentheses are clustered at the state by 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.[91] Third, on average, electricity has the largest share in fuel expenditure (0.63).[92] 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 rawer 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).

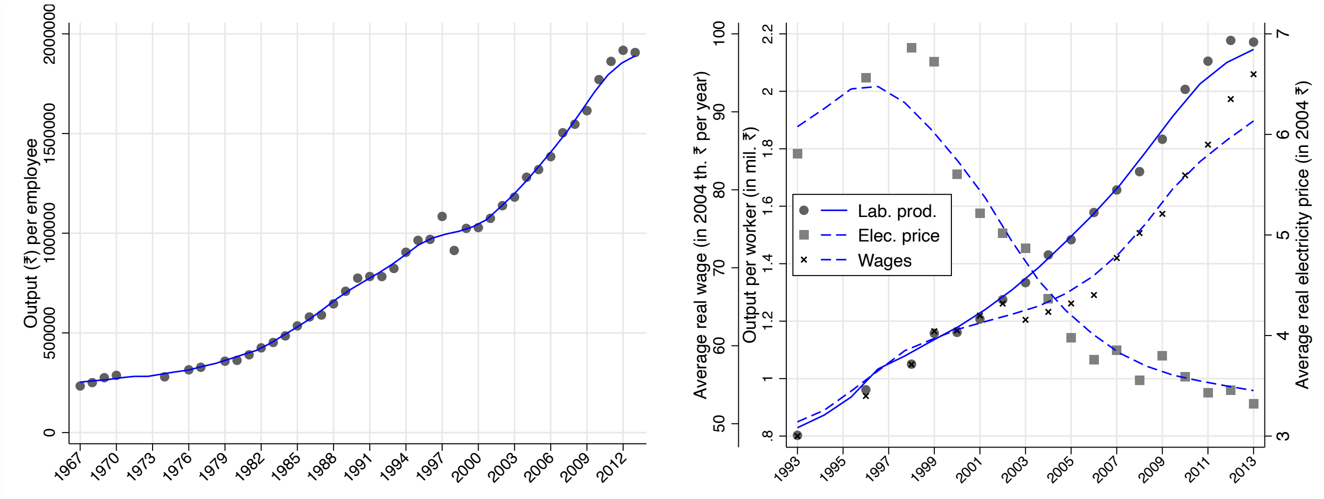
[91] Weighting by consumption maps plant level electricity productivity into aggregate electricity productivity, comparable with Figure 1.

[92] 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 Panel (b) in Figure A.10 shows, the share of electricity in the energy mix in terms of energy units has risen from 16 to 20% since 1998.

A.8 Labor productivity, wages and electricity prices

Figure A.17: Labor productivity and wages

(**a**) Labor productivity (long run) (**b**) Labor productivity and wages



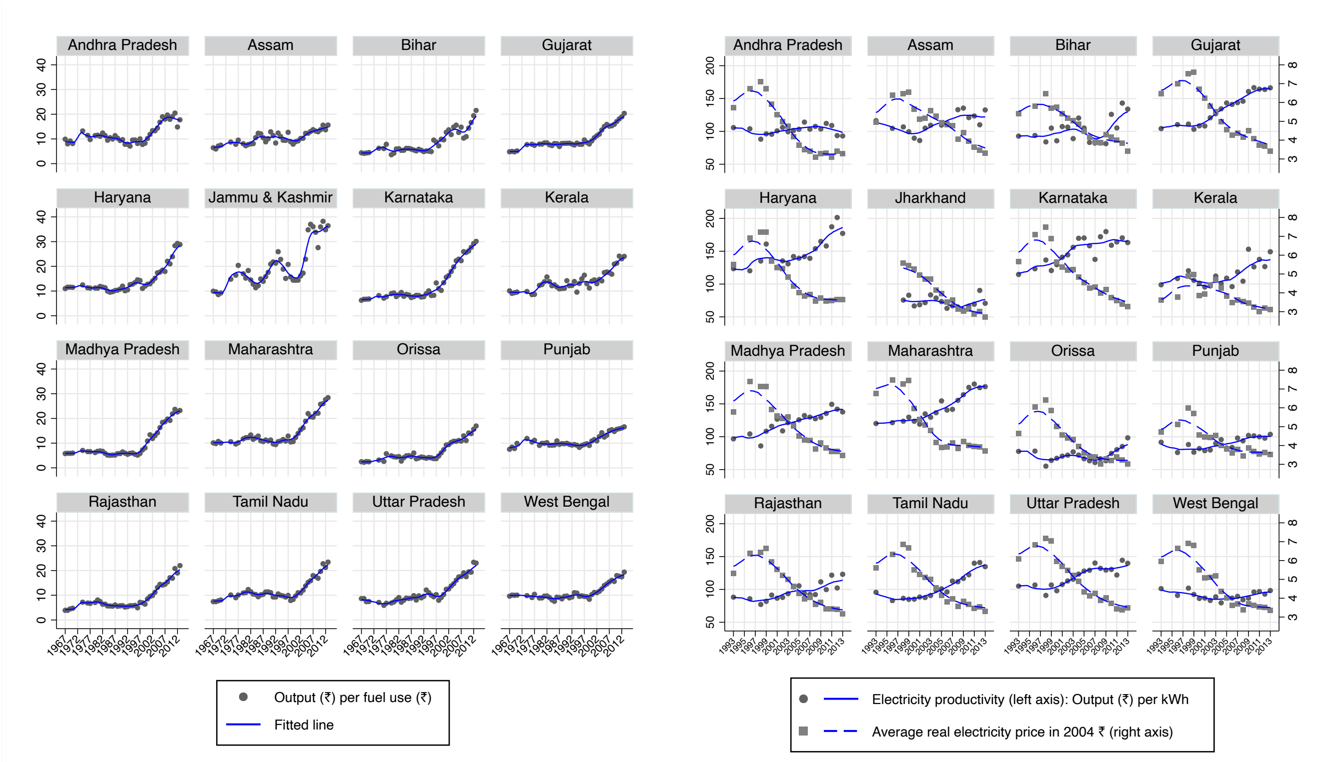
Notes: Panel (a) plots annual labor productivity ratios (aggregate value of output divided by the number of employees) in Indian manufacturing over the long run. Output is deflated at the 2-digit industry level using 2-digit industry deflators before aggregating over industries. From 1967 to 1997 the 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.

A.9 Electricity price and productivity graphs across states or sectors

Second, similar secular trends in energy productivity, electricity productivity and electricity prices can be observed across most states (Figures A.18) and industries (Figures A.19).[93] This suggests that the observed aggregate trends are not a story of mere reallocation across industries or states.

Figure A.18: Energy productivity (per ₹), electricity productivity (per kWh) and prices by state

(**a**) Energy productivity (per ₹) by state (**b**) Electricity productivity (per kWh) and prices by state

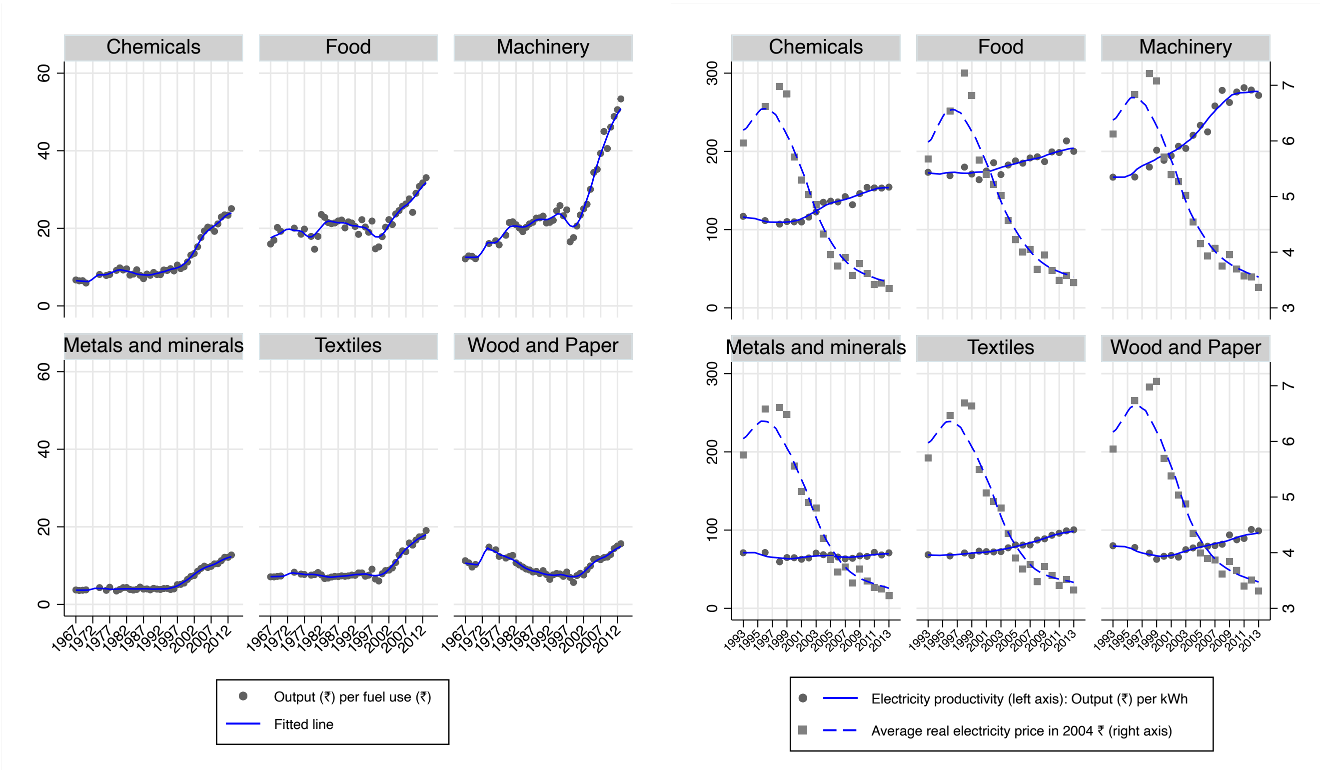


Notes: The figure shows sixteen of the largest states. Panel (a) plots the annual energy productivity ratios (value of output divided by the value of fuel and electricity used). Output is deflated at the 2-digit industry level using 2-digit industry deflators before aggregating over industries. Fuel 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. Panel (b) 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. 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.

[93] Except for perhaps electricity productivity in metals and minerals (see Panel (b) of Figure A.19).

Figure A.19: Energy productivity (per ₹), electricity productivity (per kWh) and prices by industry

(**a**) Energy productivity (per ₹) by industry (**b**) Electricity productivity (per kWh) and prices by industry



Notes: The figure shows six broad industries: chemicals includes rubber and plastics, machinery includes metal products, and textiles includes leather. Panel (a) plots the annual energy productivity ratios by industry (value of output divided by the value of fuel and electricity used). 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. Panel (b) 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. 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.

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

Figure A.20 plots the densities of logged electricity productivity, logged labor productivity and electricity prices for every year in the sample. The figure 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. Figure A.21 instead shows the variation pooled across years, and applying the same industry-by-region-by-year fixed effects as in the main analysis. It also shows the variation in electricity prices that is predicted by the two instruments.

To more formally show the substantial 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 $V = \sum_e s_e \left(p_e - \overline{p}\right)^2$, where s_e are electricity purchase weights multiplied by the sample multiplier, p_e are logged electricity productivity, logged labor productivity, or prices, and $\overline{p}$ 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:

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

where $s_g = \sum_{e \in g} s_e$ and $\overline{p}_g$ 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.22 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.22 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.[94] 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.23 plots quantiles of the distribution over time and shows a convergence in electricity prices that accompanied the secular price decline. 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.

In Figure A.24 (a), I use a Griliches and Regev (1995)-style decomposition of changes in electricity productivity, using electricity quantity as the activity weight (adjusted by the sampling multiplier). For each endpoint year t on the x-axis, outcomes are averaged within two adjacent 3-year windows, $A = \{t-5, \dots, t-3\}$ and $B = \{t-2, \dots, t\}$. The window-to-window decomposition is computed on plants observed at least once in both windows ("continuers"), and, to address rotating-sample variability, continuers are reweighted in each window via calibration so that their weighted electricity totals match the full-sample totals in that window. Both within improvement and between-plant reallocation contribute to the aggregate change. The gap between the black (full-sample aggregate) and dashed series reflects plants not linkable

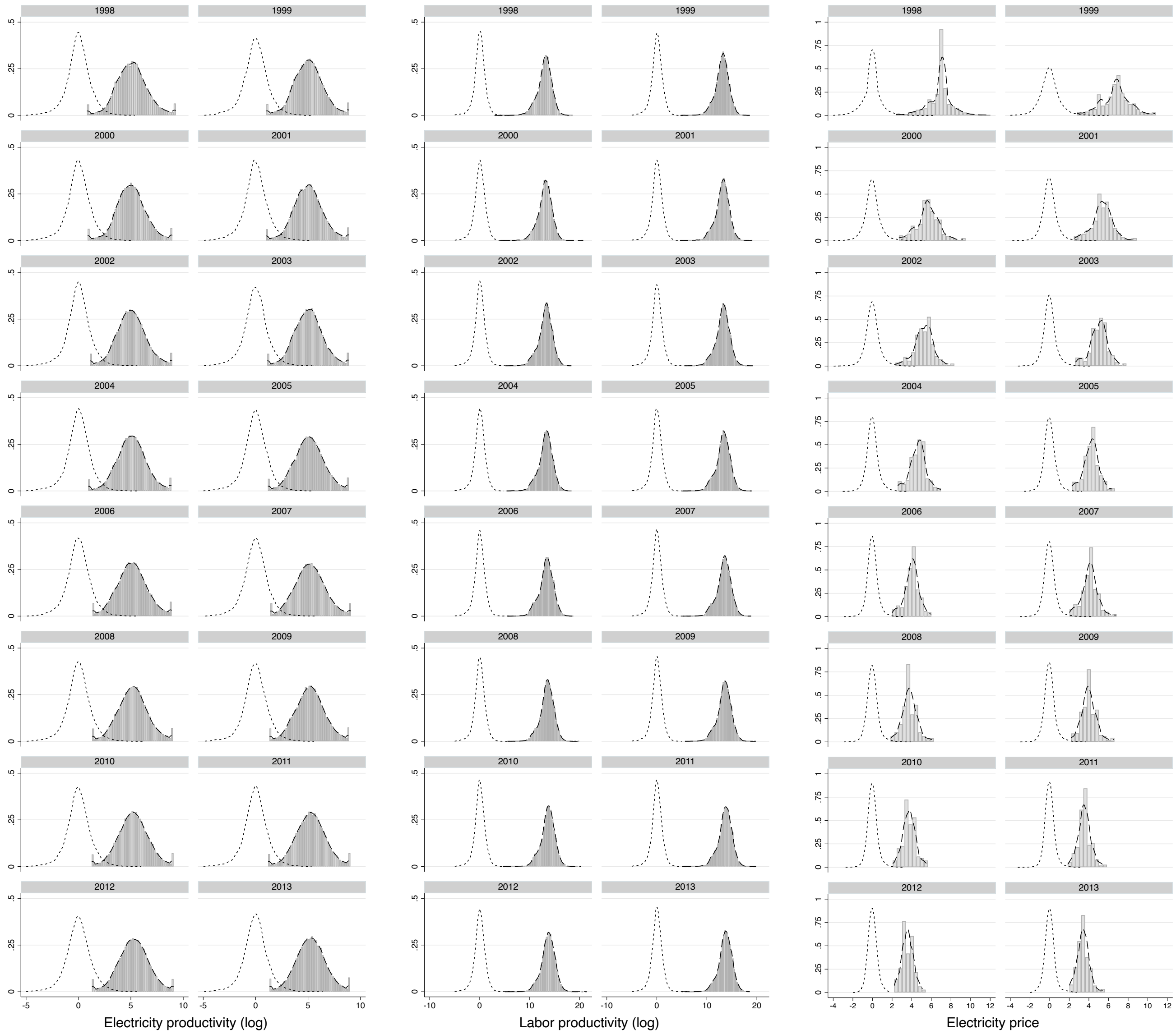
[94] Variation across districts (not plotted) can explain around 22% and 45% of electricity productivity and electricity prices respectively. Districts for the later years are not available for all observations.

across both windows (sampling rotation and true entry/exit), which are not separately decomposed. As a complementary approach that does not require plants to be observed in consecutive years, I also report a within/between decomposition computed year-by-year, leveraging long-term averages within plants in Figure A.24 (b). Let p_{it} denote electricity productivity and let $s_{it} = Q_{it}/\sum_j Q_{jt}$ be the electricity-quantity share (adjusted by sampling multipliers). Define each plant's long-run component as an electricity-weighted mean $\mu_i = \sum_t Q_{it}p_{it}/\sum_t Q_{it}$ and deviations $\tilde{p}_{it} = p_{it} - \mu_i$. Then the aggregate $P_t = \sum_i s_{it}p_{it}$ can be decomposed as $P_t = \sum_i s_{it}\mu_i + \sum_i s_{it}\tilde{p}_{it}$, so changes satisfy $\Delta P_t = \Delta(\sum_i s_{it}\mu_i) + \Delta(\sum_i s_{it}\tilde{p}_{it})$. The first term captures reallocation toward plants with higher permanent productivity, while the second captures within-plant movements relative to each plant's long-run level.

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.25, 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.20: Heterogeneity in electricity and labor productivity, and electricity prices within years

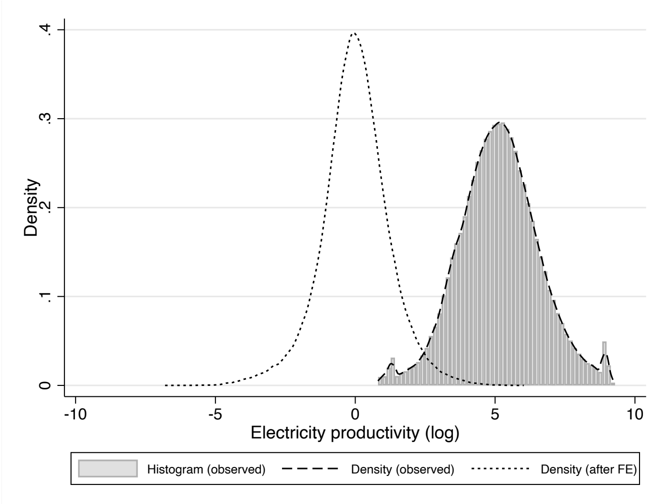
(**a**) Electricity productivity (**b**) Labor productivity (**c**) Electricity prices



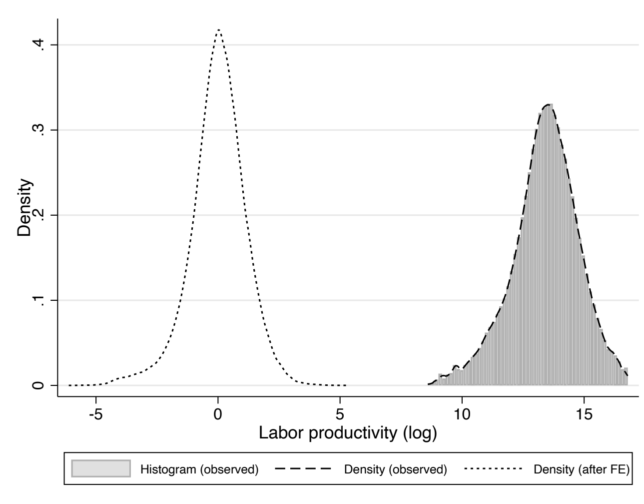
Notes: The figure plots the histograms of a plant level variable by year. The grey shaded areas are the observed histograms. The left kernel density plot shows the distribution of the residuals after partialing out state by 4-digit industry by year fixed effects. Panel (a) plots electricity productivity in logs, which is the value of output divided by the quantity of electricity used in kWh. Panel (b) plots logged labor productivity, which is the value of output divided by the number of employees. Panel (c) plots logged electricity prices, which are the value of electricity divided by the quantity of electricity used in kWh.

Figure A.21: Heterogeneity in electricity and labor productivity, and electricity prices in pooled sample after FE

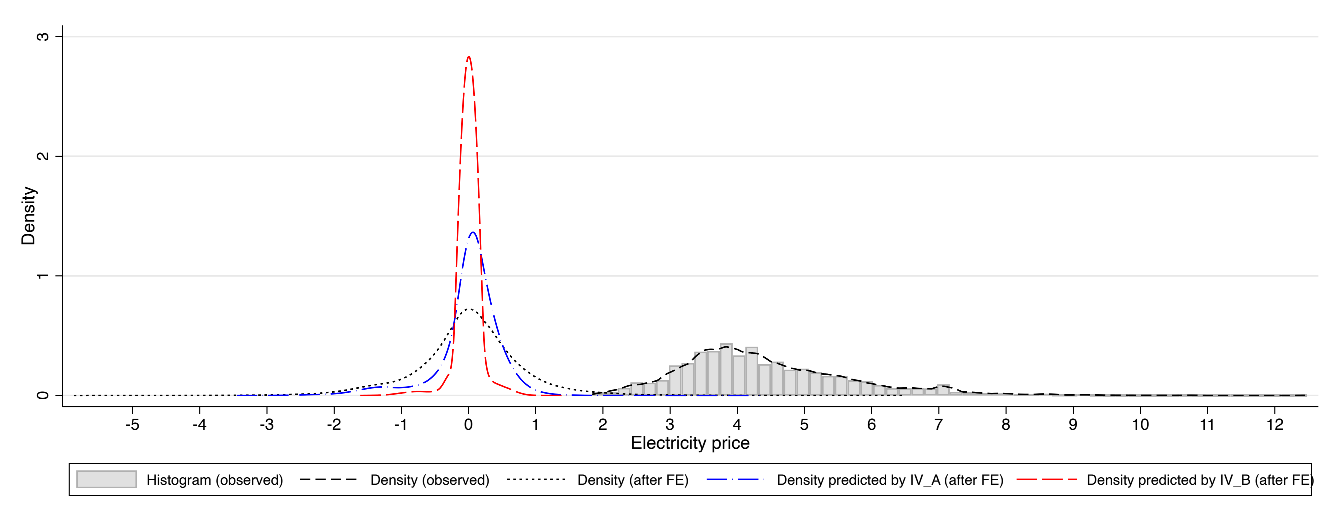
(**a**) Electricity productivity



(**b**) Labor productivity



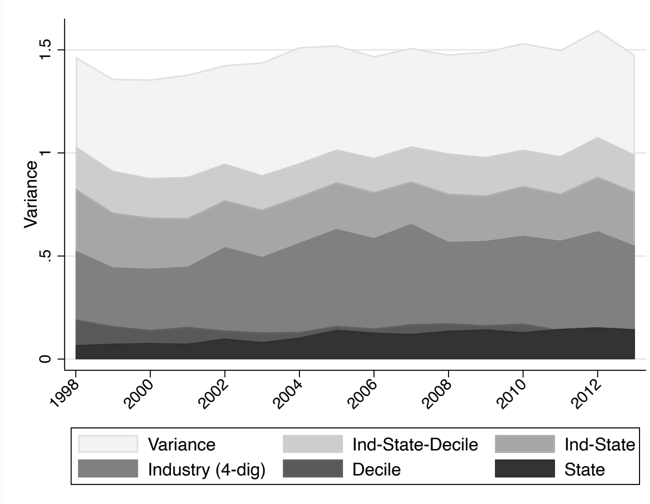
(**c**) Electricity prices



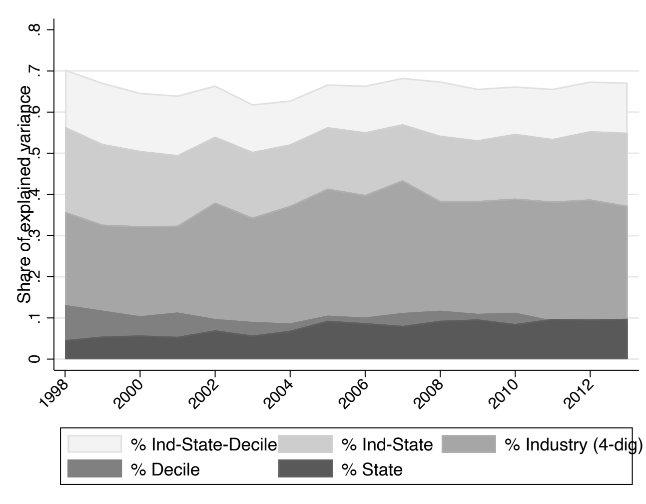
Notes: Panel (a) plots the histogram of plant level logged electricity productivity in the pooled sample. Electricity productivity ratios are the value of output divided by the quantity of electricity used in kWh. The kernel density plot to the left shows the distribution of the residuals of logged electricity productivity after partialing out by 4-digit industry-by-region-by-year fixed effects. Panel (b) and Panel (c) show the same plots for labor productivity and electricity prices in 2003. Additionally Panel (c) plots the density in electricity prices predicted by IV^A and IV^B.

Figure A.22: Variance decompositions of electricity and labor productivities and electricity prices

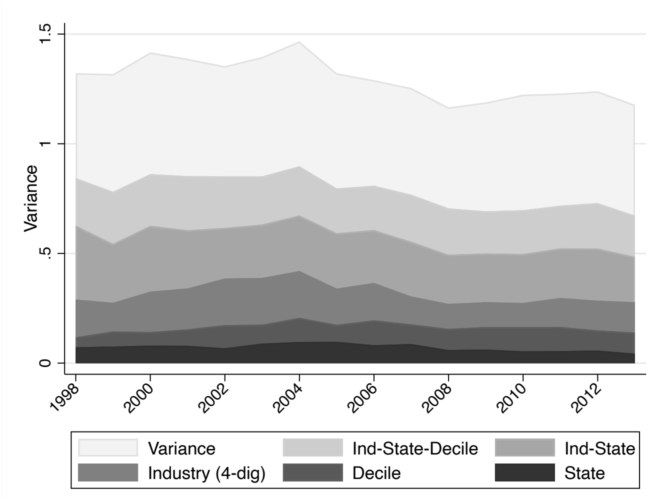
(**a**) Electricity productivity variance decomposition



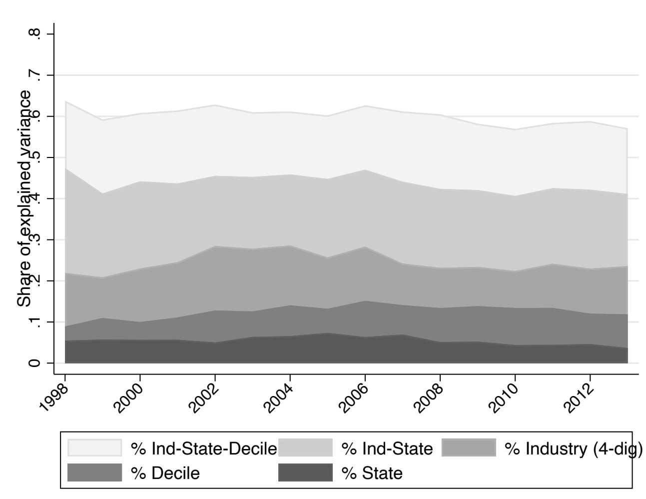
(**b**) Electricity productivity variance decomposition



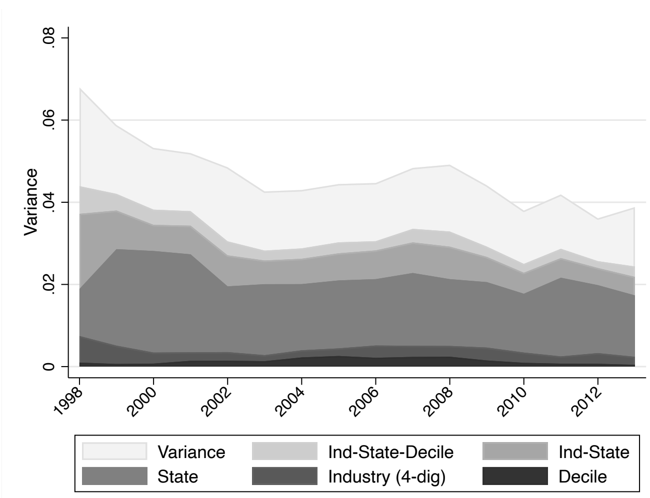
(**c**) Labor productivity variance decomposition



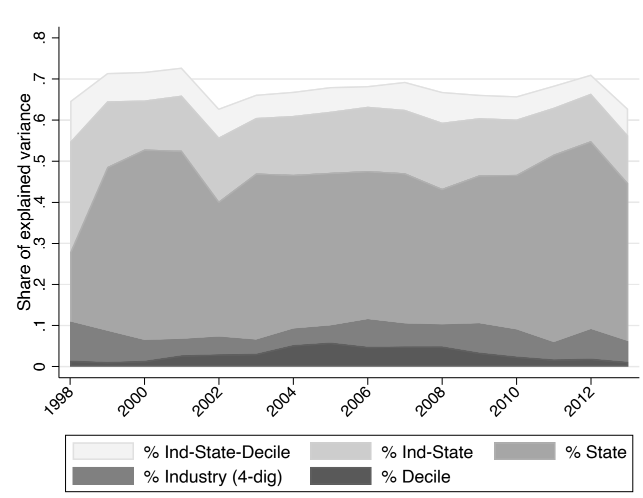
(**d**) Labor productivity variance decomposition



(**e**) Electricity price variance decomposition

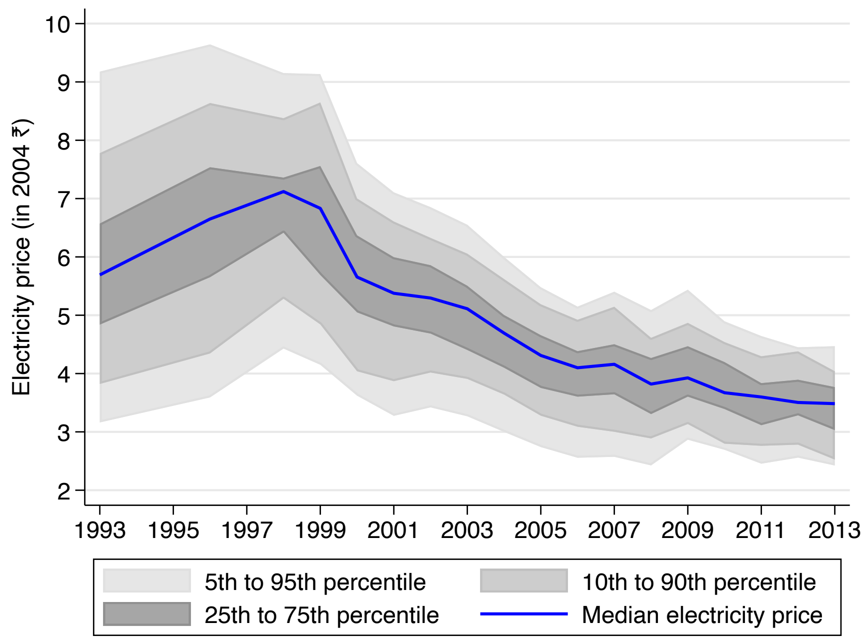


(**f**) Electricity price variance decomposition



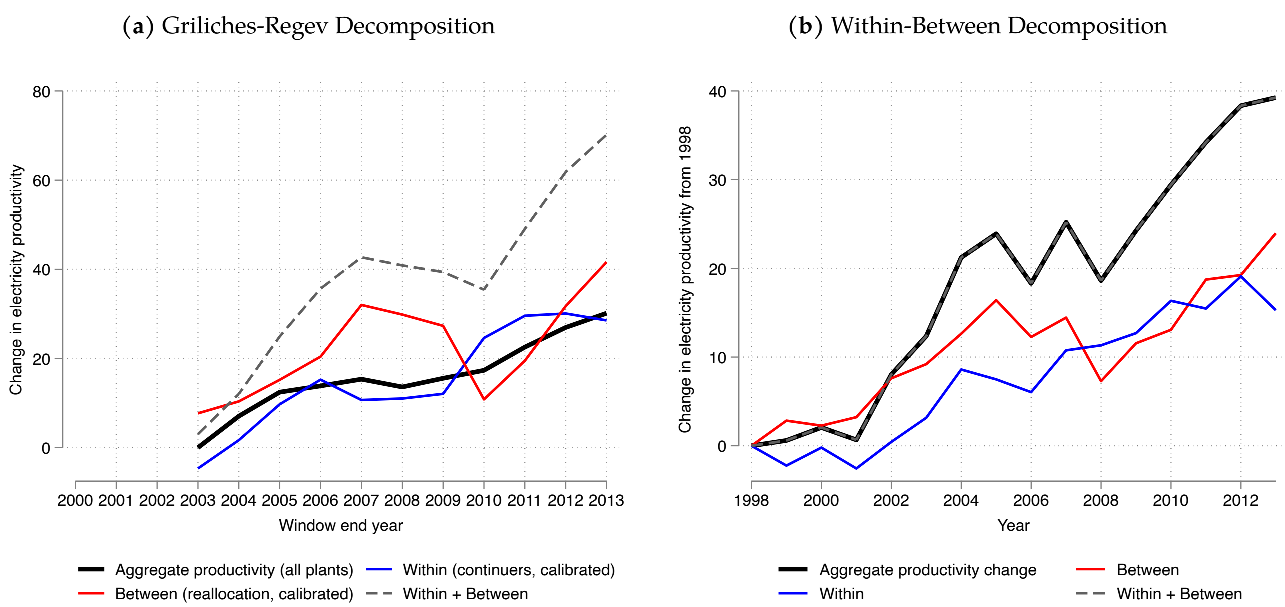
Notes: The left Panels (a), (c) and (e) plot the annual total variance of logged electricity productivity, logged labor productivity and logged electricity prices respectively, and the variance explained by specified groups as described in the text. The right Panels (b), (d) and (f) plot the share of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

Figure A.23: 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.

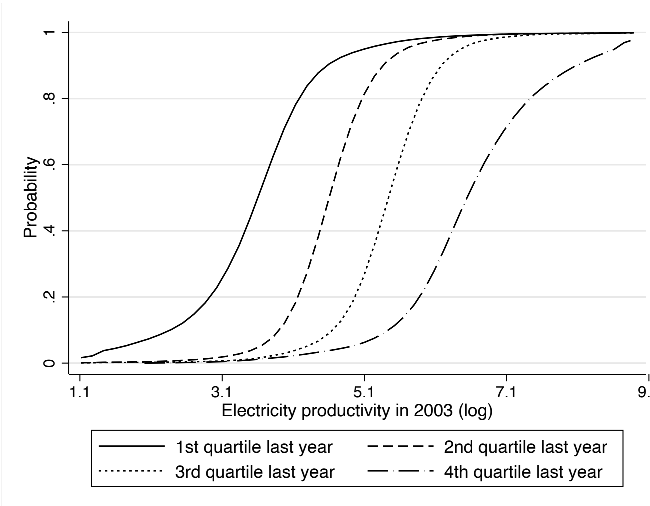
Figure A.24: Decomposing Aggregate Electricity Productivity



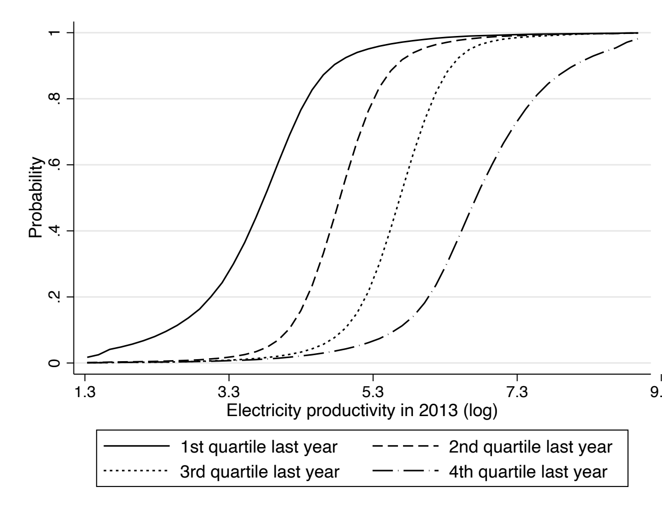
Notes: Panel (a) shows a Griliches-Regev decomposition of changes in aggregate electricity productivity into within-plant improvements and between-plant reallocation effects, using 3-year windows as described in the text. Panel (b) shows a within/between decomposition of annual changes in aggregate electricity productivity, as described above in the Appendix text.

Figure A.25: Conditional CDFs of productivities and electricity prices

(**a**) Electricity productivity 2003 (CDF)

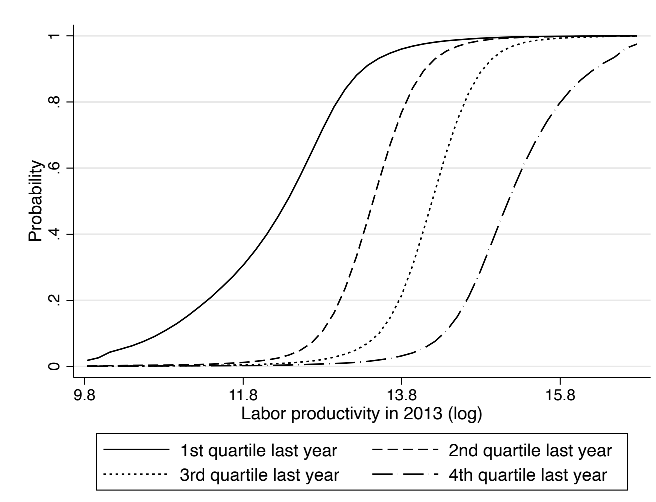


(**b**) Electricity productivity 2013 (CDF)

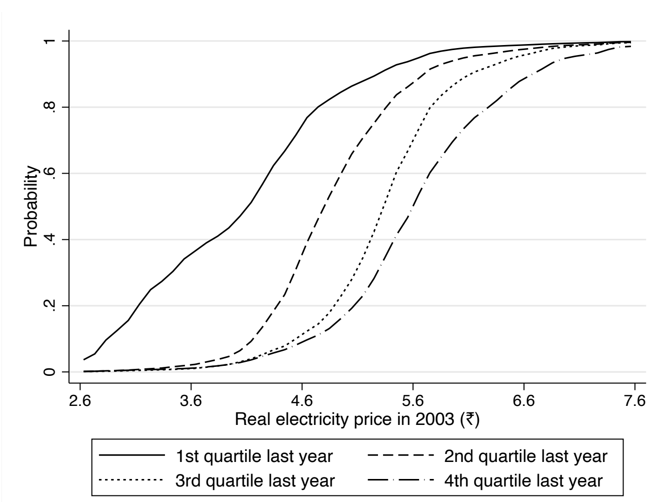


(**c**) Labor productivity 2003 (CDF)

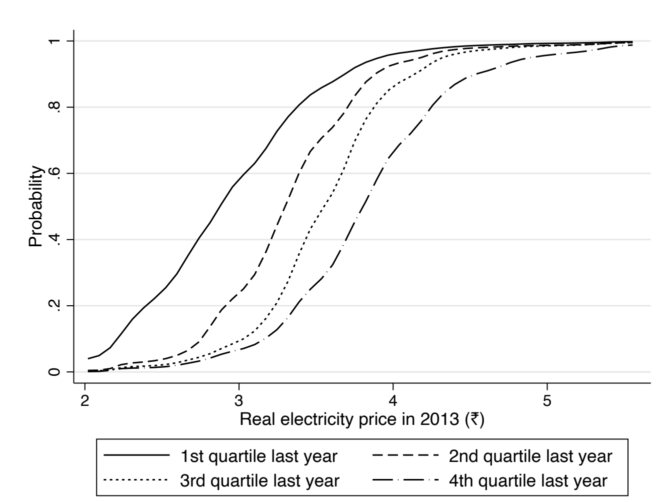
(**d**) Labor productivity 2013 (CDF)



(**e**) Electricity prices 2003 (CDF)



(**f**) Electricity prices 2013 (CDF)



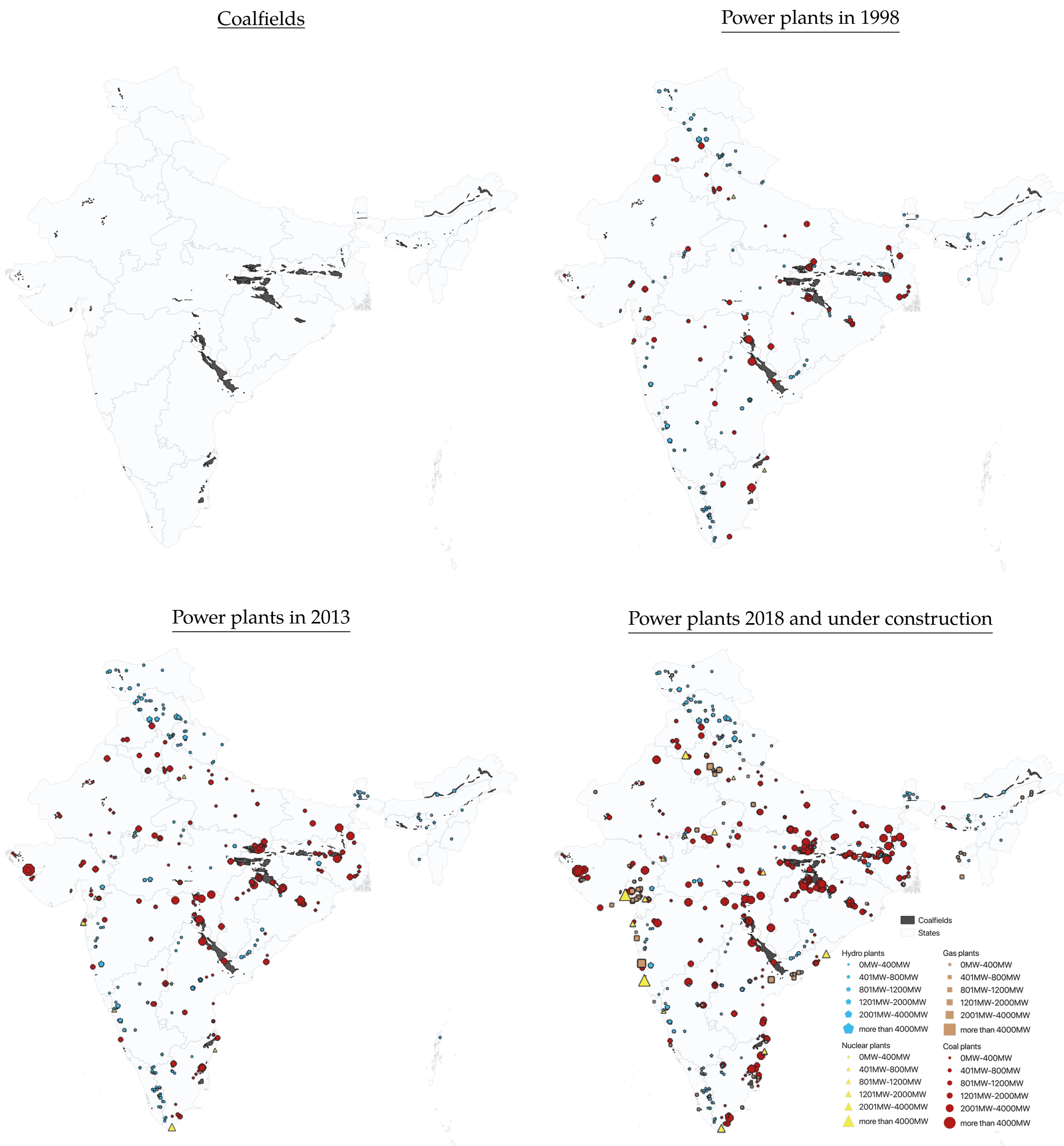
Notes: The Panels (a), (c) and (e) plot the CDFs in 2003 separately for each quartile of the respective values in 2002, for logged electricity productivity, logged labor productivity, and electricity prices respectively. The Panels (b), (d) and (f) plot the same graphs for the CDFs in 2013 separately 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 Maps of power plants and coal reservoirs

Figure A.26 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, 1998*a*; Planning Commission, 2014). Of the thermal generation, the vast majority is made up of coal-based generation (around 85% throughout).

Figure A.26: 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.12 The Electricity Act and entry of private power plants 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, 1998*a*; Planning Commission, 2001-2002). The Electricity Act of 2003 aimed to open this heavily regulated sector to more competition,[95] 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).[96] 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.4 shows that the share of privately owned plants is significantly negatively associated with median electricity prices – but only after 2003.[97] 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.26). Indeed, as Columns 4-6 of Table A.4 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.27 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.

[95]The preamble states "An Act to consolidate the laws relating to generation [...] of electricity [...], promoting competition therein [...].".

[96]From 1998 to 2013, total installed capacity rose by 143%.

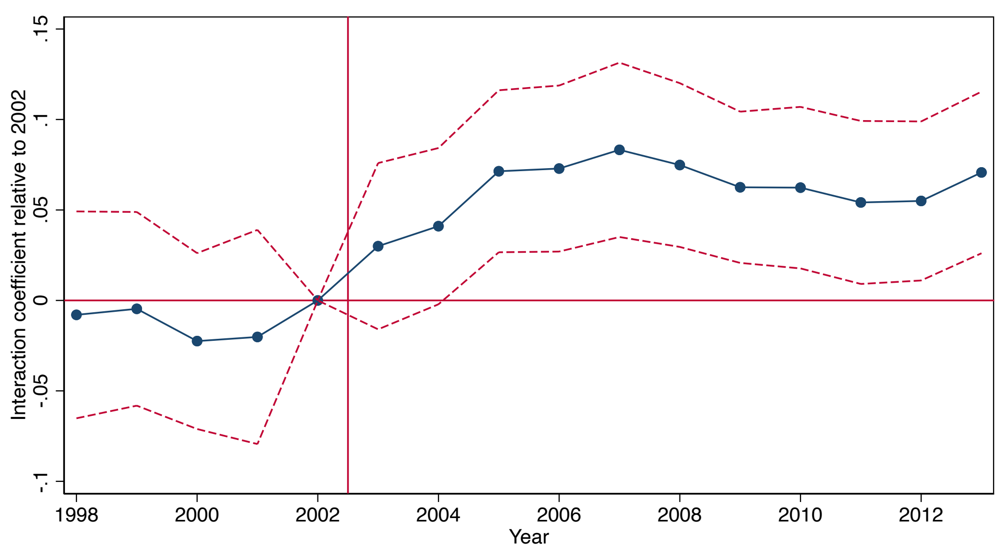
[97]This holds conditional on district and year fixed effects, and conditional on district and region by year fixed effects. I also control for time-varying total district level installed capacity.

Table A.4: 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	-0.0066	-0.0022						
	(0.015)	(0.018)	(0.014)						
Share private capacity x after 2003	-0.024**	-0.024**	-0.022***						
	(0.012)	(0.012)	(0.0025)						
Distance to coalfield ('00 km) x after 2003 x state w. coal power				-0.019***	-0.014**	-0.016**	0.079***	0.079***	0.075***
				(0.0071)	(0.0067)	(0.0073)	(0.018)	(0.018)	(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.

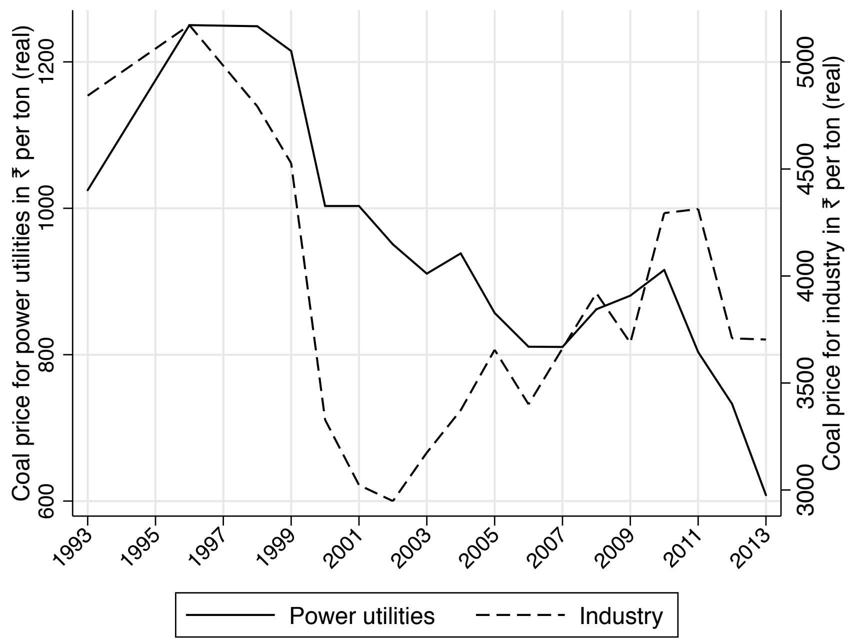
Figure A.27: Event study of impact of 2003 Electricity Act and distance to coalfields on electricity prices



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.

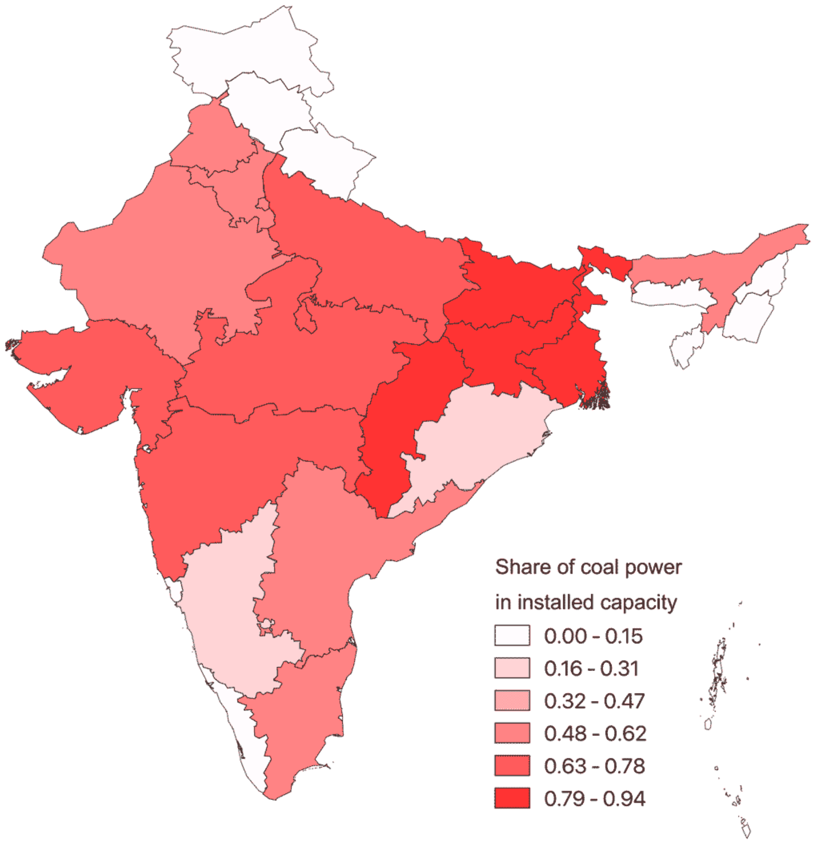
A.13 Coal price for power utilities and industry, and coal share in installed capacity

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 (1998*a*, 2003).

Table A.5: 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	0.181	-0.156	0.370	0.143	-0.0368	0.0183	-0.0141
	(0.129)	(0.158)	(0.153)	(0.300)	(0.318)	(0.035)	(0.024)	(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.

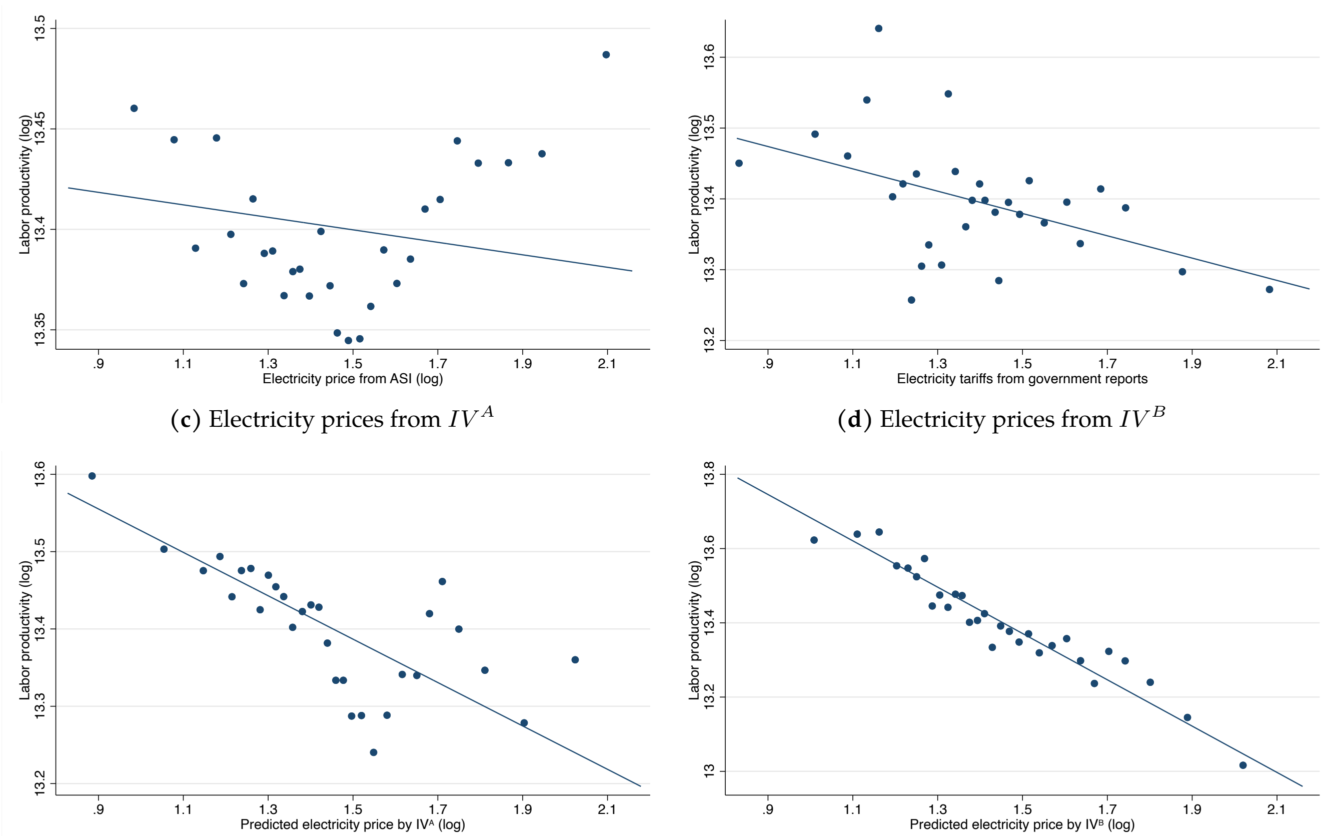
Table A.6: Electricity prices and electricity productivity: controlling for interacted presample shares for IV^B

	IV^B							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\log(P^E)$	-0.796***	-0.539***	-0.559***	-0.781***	-0.819***	-0.562***	-0.384***	-0.931***
	(0.118)	(0.096)	(0.092)	(0.105)	(0.101)	(0.114)	(0.105)	(0.156)
Share rural X CP	-0.0149*							
	(0.009)							
Share domestic power X CP		-0.0317***						
		(0.006)						
Share power X CP			0.0281***					
			(0.006)					
log(Labor productivity) X CP				-0.0129**				
				(0.005)				
log(Capital labor ratio) X CP					-0.0267***			
					(0.005)			
Share managerial wages X CP						0.153***		
						(0.039)		
Fuel share in output X CP							-0.609***	
							(0.051)	
Wage share in output X CP								0.403***
								(0.099)
OLS/IV	IV^B	IV^B	IV^B	IV^B	IV^B	IV^B	IV^B	IV^B
Observations	481164	481164	481164	485115	485115	462049	455584	455584
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First stage coef.	0.06***	0.06***	0.07***	0.06***	0.06***	0.07***	0.06***	0.05***
First stage SE	0.004	0.003	0.003	0.003	0.003	0.005	0.004	0.004
F-stat (Kleib.-Paap)	244.509	359.692	399.509	327.169	283.964	214.346	228.501	145.095
Two-way clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: See Table 2 for notes. The main difference is that each regression contains a control variable that is a pre-sample state level variable interacted with the log coal price (CP) used in construction of IV^B. See Table A.5 for explanation of interacted control variables.

A.14 Additional regression results and robustness checks

Figure A.30: Binscatter of labor productivity and electricity prices



(**a**) Electricity prices from ASI

(**b**) Electricity prices from government

(**c**) Electricity prices from IV^A

(**d**) Electricity prices from IV^B

Notes: The figures show binscatter plots using Cattaneo et al. (2024) with plant level labor productivity (log) on the vertical axis and with industry-by-region-by-year fixed effects. Panel (a) plots against log electricity prices at the plant level using ASI data. Panel (b) instead plots against utility tariffs at the state by year level from Central Electricity Authority (2006-2015) and Indiastat (1998-2014). Panel (c) and (d) plot against predicted electricity prices from IV^A and IV^B respectively, where predicted electricity prices are obtained by using fitted values from regressions on the respective instruments conditional on industry-by-region-by-year fixed effects. Results using electricity productivity are in Figure 5.

Table A.7: Using published average electricity tariff data instead of ASI derived plant level prices

	Electricity productivity (log)			Labor productivity (log)		
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(P^E)$	-0.203***	-0.273***	-0.772***	-0.212***	-0.411***	-1.047***
	(0.045)	(0.072)	(0.100)	(0.056)	(0.091)	(0.117)
OLS/IV	OLS	IV^A	IV^B	OLS	IV^A	IV^B
Observations	478910	478910	478910	478910	478910	478910
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes
First stage coef.	-	0.93***	0.06***	-	0.93***	0.06***
First stage SE	-	0.037	0.004	-	0.037	0.004
F-stat (Kleib.-Paap)	-	649.603	263.237	-	649.603	263.237
Two-way clustered SE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: See Table 2 for notes. The main difference is that the manually collected utility tariffs are used for the endogenous electricity price variable instead of ASI-derived prices. The utility tariffs are at the state by year level and averaged across industrial consumer bands, taken from Central Electricity Authority (2006-2015) and Indiastat (1998-2014). Reassuringly, even using OLS with this average tariff measure already removes a lot of the plant-level OLS bias present in the OLS estimates in main Table 2. The IV estimates between this table and the main Table 2 are statistically indistinguishable.

Table A.8: 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***	-0.27***	-0.50	-0.57**	-0.26	-0.028	-0.42***	-0.83**	-0.95***	0.27
	(0.044)	(0.071)	(0.32)	(0.27)	(0.18)	(0.043)	(0.087)	(0.35)	(0.25)	(0.19)
OLS/IV	OLS	IV^C	IV^{D1}	IV^{D1}	IV^{D2}	OLS	IV^C	IV^{D1}	IV^{D1}	IV^{D2}
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.12). 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.9: Lagged electricity prices and electricity productivity

	Electricity productivity (log)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(P^E)$	0.295***	-0.273***	-0.735***			
	(0.049)	(0.062)	(0.087)			
Lagged $\log(P^E)$				0.0184	-0.275***	-0.727***
				(0.042)	(0.060)	(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.10: Lagged electricity prices and labor productivity

	Labor productivity (log)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(P^E)$	-0.0412	-0.255***	-0.484***			
	(0.045)	(0.083)	(0.101)			
Lagged $\log(P^E)$				-0.0478	-0.251***	-0.478***
				(0.045)	(0.083)	(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.11: 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***	0.472***	0.459***	-0.256***	-0.131	-0.121	-0.828***	-0.940***	-0.980***
	(0.045)	(0.043)	(0.044)	(0.071)	(0.085)	(0.088)	(0.102)	(0.149)	(0.148)
Distance to coalfield	-0.0179**		-0.0190***	-0.0138*		-0.0176**	-0.00996		-0.0154*
(in '00 km)	(0.007)		(0.007)	(0.007)		(0.007)	(0.008)		(0.008)
Shortage		0.398*	0.284		0.646***	0.517***		0.979***	0.862***
		(0.226)	(0.239)		(0.187)	(0.192)		(0.198)	(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.12: 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	0.0866**	0.0629	-0.466***	-0.151	-0.213**	-1.043***	-1.089***	-1.012***
	(0.044)	(0.042)	(0.042)	(0.084)	(0.103)	(0.100)	(0.097)	(0.159)	(0.144)
Distance to coalfield	0.0362***		0.0399***	0.0389***		0.0406***	0.0428***		0.0426***
(in '00 km)	(0.007)		(0.007)	(0.008)		(0.008)	(0.008)		(0.009)
Shortage		-0.415*	-0.562***		-0.318	-0.451**		0.0679	-0.130
		(0.229)	(0.216)		(0.219)	(0.198)		(0.279)	(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.13: Electricity prices and electricity productivity using only purchased electricity

	Electricity productivity (log)		
	(1)	(2)	(3)
$\log(P^E)$	0.434***	-0.157**	-0.731***
	(0.046)	(0.076)	(0.110)
OLS/IV	OLS	IV^A	IV^B
Observations	485342	485342	485342
Ind-region-year FE	Yes	Yes	Yes
First stage coef.	-	0.97***	0.06***
First stage SE	-	0.005	0.003
F-stat (Kleib.-Paap)	-	43194.635	296.507
Two-way clustered SE	Yes	Yes	Yes

Notes: See Table 2 for notes. The main difference is that the dependent variable is constructed using only electricity purchased instead of electricity consumed.

Table A.14: 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***	-0.210***	-0.585***	-0.168***	-0.545***	-1.049***
	(0.047)	(0.074)	(0.102)	(0.047)	(0.085)	(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.15: 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***	-0.244***	-0.840***	-0.0518	-0.407***	-1.086***
	(0.047)	(0.072)	(0.107)	(0.045)	(0.087)	(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.16: 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**	-0.426***	-0.762***	0.608***	0.108	-1.636***	0.215***	-0.640***	-1.300***
	(0.064)	(0.086)	(0.104)	(0.073)	(0.168)	(0.447)	(0.066)	(0.093)	(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***	0.108	0.283	0.403***	-0.138	-1.013***	0.357***	-0.224**	-0.695***
	(0.053)	(0.104)	(0.197)	(0.076)	(0.158)	(0.266)	(0.066)	(0.096)	(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.17: 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***	-0.680***	-1.141***	0.454***	0.650***	-1.461***	-0.134**	-0.673***	-1.235***
	(0.053)	(0.074)	(0.100)	(0.074)	(0.198)	(0.354)	(0.059)	(0.101)	(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***	-0.443***	-1.480***	-0.106	-0.543**	0.00768	0.174***	-0.0804	-0.645***
	(0.052)	(0.109)	(0.167)	(0.100)	(0.229)	(0.398)	(0.060)	(0.101)	(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.18: 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***	0.00766	-0.737***	-0.0670	-0.430***	-1.066***
	(0.061)	(0.094)	(0.168)	(0.057)	(0.105)	(0.149)
$\log(P^E) \cdot \mathbf{1}(year < 2006)$	-0.217**	-0.531***	-0.0874	0.0796	0.0884	0.00701
	(0.084)	(0.128)	(0.193)	(0.086)	(0.170)	(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.19: Electricity prices and electricity productivity: using both IVs

	Electricity productivity (log)			Labor productivity (log)		
	OLS	IV^A & IV^B	IV^C & IV^B	OLS	IV^A & IV^B	IV^C & IV^B
	(1)	(2)	(3)	(4)	(5)	(6)
log(P^E)	0.365***	-0.256***	-0.288***	-0.0282	-0.410***	-0.448***
	(0.044)	(0.068)	(0.069)	(0.043)	(0.083)	(0.085)
IV 1	-	IV^A	IV^C	-	IV^A	IV^C
IV 2	-	IV^B	IV^B	-	IV^B	IV^B
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.20: Electricity prices and productivity (TFP): alternative methodologies

	log(TFP) OP			log(TFP) LP			log(TFP) ACF		
	OLS	IV^A	IV^B	OLS	IV^A	IV^B	OLS	IV^A	IV^B
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
log(P^E)	-0.00735***	-0.0273***	-0.0387***	-0.000566	-0.0168***	-0.0321***	-0.00414**	-0.00761***	-0.0233***
	(0.002)	(0.004)	(0.005)	(0.002)	(0.004)	(0.007)	(0.002)	(0.003)	(0.006)
OLS/IV	OLS	IV^A	IV^B	OLS	IV^A	IV^B	OLS	IV^A	IV^B
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 Ackerberg, Caves and Frazer (2015).

Table A.21: Electricity prices and electricity productivity: clustering at district and region year

	Electricity productivity (log)			Labor productivity (log)		
	(1)	(2)	(3)	(4)	(5)	(6)
log(P^E)	0.340***	-0.265*	-0.819***	-0.0563	-0.441*	-1.084***
	(0.117)	(0.154)	(0.218)	(0.126)	(0.242)	(0.229)
OLS/IV	OLS	IV^A	IV^B	OLS	IV^A	IV^B
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.22: Controlling for product and input mix specific input and output price indices

	Electricity productivity (log)			Labor productivity		
	OLS	IV^A	IV^B	OLS	IV^A	IV^B
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(P^E)$	0.400***	-0.132*	-0.737***	-0.0569	-0.405***	-1.072***
	(0.047)	(0.070)	(0.114)	(0.046)	(0.086)	(0.110)
Output price index (log)	0.0263***	0.0263***	0.0264***	0.0312***	0.0312***	0.0313***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Input price index (log)	-0.0121***	-0.0119***	-0.0117***	0.0144***	0.0145***	0.0148***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
OLS/IV	OLS	IV^A	IV^B	OLS	IV^A	IV^B
Observations	425458	425458	425458	425458	425458	425458
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)	-	41171.284	249.307	-	41171.284	249.307
Two-way clustered SE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variables are indicated at the top. Additional control variables are included compared to Table 2 as indicated. The output price index is constructed at the plant by year level by assigning to each produced product the national median product level price from the ASI data, and then aggregating across products produced within each plant using sales shares. The input price index is constructed at the plant by year level by assigning to each input product the national median input level price from the ASI data, and then aggregating across inputs used within a plant using expenditure shares. See Table 2 for additional notes.

Table A.23: Electricity prices, product scope, and electric machinery equipment

	Number of products (log)			Share electric equipment		
	OLS	IV^A	IV^B	OLS	IV^A	IV^B
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(P^E)$	0.0455***	-0.00295	-0.0968***	-0.00283***	-0.00717***	-0.0143***
	(0.012)	(0.023)	(0.036)	(0.001)	(0.002)	(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.24: 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.25: Electricity prices and high baseline machinery to labor ratio

	Electricity productivity (log)			Output (log)		
	OLS	IV^A	IV^B	OLS	IV^A	IV^B
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(P^E)$	0.231***	-0.362***	-1.014***	0.142**	-0.203*	-0.429**
	(0.053)	(0.065)	(0.118)	(0.071)	(0.121)	(0.174)
$\log(P^E) \times abovemed$	0.117***	0.155***	0.569***	0.0475	0.191***	0.973***
	(0.036)	(0.044)	(0.124)	(0.063)	(0.071)	(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.26: Electricity prices and FDI-liberalized industries

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

Table A.27: Coal prices and revenues, costs, and TFP

	Revenues (mil. ₹)			Total costs (mil. ₹)			TFP (log) (Wooldridge, 2009)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(P^C)$	-20.09**	-21.31	-2.026	-14.44**	-29.82	3.729	-0.000544	-0.0198	-0.0306
	(8.002)	(85.610)	(128.414)	(6.592)	(70.932)	(103.369)	(0.002)	(0.013)	(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: See Table 8a for notes.

A.15 Using product fixed effects or nation-wide average product electricity intensities

To test whether it is the product mix that drives the results of higher electricity productivity, I first include additional product fixed effects (6145 products). For each plant-year observation, the dummy for a particular product is one if the plant produces this product in this year.[98] The results are shown in Columns 1-3 of Table A.28, and are similar to the baseline results in Table 2. Importantly, this implies that the results are not driven by changes in product mix but indeed by product technology. Note that I only use observations until 2009, as the product identification system changed in 2010.

Next, instead of examining plant level electricity productivities as outcome, I use constant product level electricity intensities following Abeberese (2017). 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 these constant nation-wide intensities to their evolving product mix, calculating the simple average of electricity intensities of their products, as well as the average weighted by the sales share of each product.[99] Crucially, as a result, these outcomes ignore any changes in electricity productivity of products through technology, and any heterogeneity across time and across plants, which is, however, a feature of the data and variation I capture in the main text (see Figure 4). Columns 4-9 in Table A.28 show the results using these average electricity intensities of the product mix. There is no significant relationship in the OLS or the IV regressions, which demonstrates that accounting for heterogeneity and changes in electricity productivity across plants and time are key for capturing the relationship between electricity prices and productivity, and that results are not driven by changes in the product mix.

Finally, the last result may seem at odds with the headline result in Table 3 of Abeberese (2017), who shows the opposite results, i.e. lower prices increase electricity intensity of the product mix, which would correspond to a *decrease* in electricity productivity (there are no results about electricity productivity per se). I first replicate the results using the same specification and replication archive from Abeberese (2017), as well as the corresponding shorter sample from 2000/01 to 2007/08.[100] Table A.29 shows the results. There are three different dependent variables corresponding to Panel B, C and D of Table 3 in Abeberese (2017) respectively. The first four columns use the dummy for switching to a less electricity-intensive five-digit industry, the second four columns are the log of the simple average productivity intensity of the product mix, and the last four columns are the log of the weighted average productivity intensity of the product mix, all constructed using the replication code. The specification in the paper includes firm fixed effects and uneven columns include additional controls, corresponding to Columns 5 and 6 of Table 3 of Abeberese (2017) respectively.

The number of observations (72,987 and 107,891) are close to her reported number of observations (73,387 and 108,402).[101] The reported coefficients and standard errors in Abeberese (2017) are in the first row and almost identical replicated coefficients and standard errors in the second row. All of these are,

[98]This is the extensive margin of switching products, but it can also be shown using weights between zero and one that replace the binary product dummies with continuous product indicators that correspond to the share of a particular product in sales per plant-year, capturing both extensive and intensive margin product mix changes.

[99]Again focusing on the sample up until 2009 as product definitions changed thereafter.

[100]I thank Ama Baafra Abeberese for correspondence and sharing the industry crosswalk used for this exercise.

[101]The small difference likely arises from updates to the ASI data versions, where I am using a more recent version. With the exception of the ASI raw data, I use all other data and deflators from her replication package. I can almost exactly replicate all summary statistic.

Table A.28: Product FE, or average product electricity intensity using nation-wide product averages

	Electricity productivity (log)			Simple avg. product elec. int. (log)			Weigh. avg. prod. elec. int. (log)		
	OLS	IV^A	IV^B	OLS	IV^A	IV^B	OLS	IV^A	IV^B
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(P^E)$	0.310***	-0.387***	-0.672***	-0.0111	0.000471	0.0878	-0.0141	-0.0140	0.0777
	(0.047)	(0.068)	(0.096)	(0.024)	(0.039)	(0.062)	(0.024)	(0.039)	(0.064)
OLS/IV	OLS	IV^A	IV^B	OLS	IV^A	IV^B	OLS	IV^A	IV^B
Observations	342659	342659	342659	215151	215151	215151	215124	215124	215124
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	No	No	No	No	No	No
F-stat (Kleib.-Paap)	-	32270.752	244.033	-	36700.369	194.976	-	36693.911	194.962
Two-way clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is indicated at the top. Columns 1-3 include product fixed effects. See Table 2 for further notes.

however, only significant due to a coding issue. The region by year fixed effects are only partially included, due to being pre-generated in the replication code and how Stata generates fixed effects.[102] As Columns 3-4, 7-8, and 11-12 show, all the relationships turn insignificant, and sometimes the coefficients change sign, once the fixed effects are included as intended in Abeberese (2017). Importantly, this is entirely consistent with my findings in Table A.28 that there is no decrease in electricity productivity coming from the product mix i.e. from what firms produce.

[102] This error is generated by the Stata command *xi i.region*i.t* (line 796) to generate the fixed effects, which should instead be *xi i.region*i.t, noomit*, as otherwise Stata also expects the uninteracted region and time fixed effects to be separately included in the regression, which they are not.

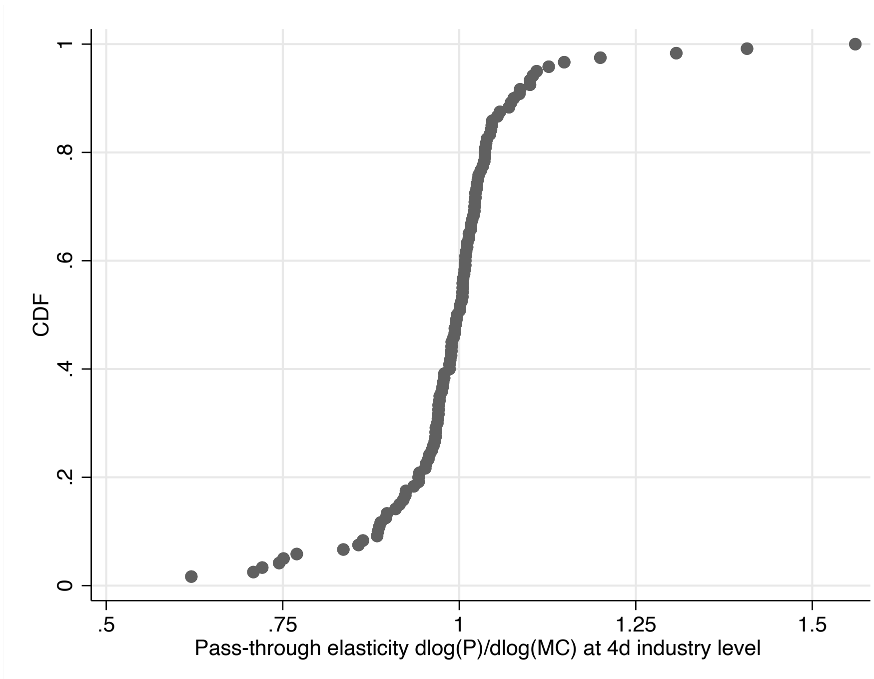
Table A.29: Comparison to Table 3 of Abeberese (2017): Including partially omitted fixed effects

	Dummy for switching to less electricity-intensive				Simple avg. product elec. int. (log)				Weighted avg. product elec. int. (log)			
	Partial omission		No omission		Partial omission		No omission					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\log(P^E)$ [Reported]	1.462**	1.510*	-	-	-0.859***	-0.975***	-	-	-0.788***	-0.906***	-	-
	(0.673)	(0.767)			(0.279)	(0.324)			(0.301)	(0.327)		
$\log(P^E)$	1.561**	1.616**	-0.119	-0.405	-0.873***	-0.985***	0.210	-0.126	-0.810**	-0.925***	-0.398	-0.575
	(0.675)	(0.781)	(0.650)	(0.719)	(0.300)	(0.342)	(0.605)	(0.536)	(0.322)	(0.346)	(0.595)	(0.586)
Region1_Time2			0.0472**	0.0563**			-0.0236	-0.0131			0.00593	0.0121
			(0.021)	(0.024)			(0.024)	(0.023)			(0.025)	(0.025)
Region1_Time3			0.0900**	0.103**			-0.0372	-0.0219			0.00136	0.00842
			(0.041)	(0.044)			(0.038)	(0.032)			(0.038)	(0.034)
Region1_Time4			0.0827**	0.0958**			-0.0497	-0.0306			0.0190	0.0264
			(0.041)	(0.044)			(0.047)	(0.041)			(0.048)	(0.045)
Region1_Time5			0.123***	0.136***			-0.0706*	-0.0493			-0.0160	-0.00666
			(0.034)	(0.035)			(0.043)	(0.036)			(0.043)	(0.040)
Region1_Time6			-0.0107	-0.000343			-0.0784***	-0.0626**			-0.0411	-0.0339
			(0.025)	(0.027)			(0.029)	(0.026)			(0.031)	(0.030)
Region1_Time7			0.00972	0.00631			-0.0676***	-0.0690***			-0.0644***	-0.0659***
			(0.007)	(0.008)			(0.017)	(0.019)			(0.018)	(0.019)
Region2_Time2	-0.0632	-0.0637	0.00826	0.0220	0.0341	0.0384*	0.00362	0.0150	0.0351	0.0378*	0.0235	0.0293
	(0.047)	(0.050)	(0.033)	(0.036)	(0.021)	(0.021)	(0.026)	(0.024)	(0.022)	(0.023)	(0.026)	(0.026)
Region2_Time3	-0.0253	-0.0258	0.0712*	0.0931**	0.0687***	0.0830***	0.0204	0.0438	0.0716***	0.0815***	0.0533*	0.0661**
	(0.051)	(0.056)	(0.040)	(0.045)	(0.020)	(0.022)	(0.032)	(0.030)	(0.021)	(0.023)	(0.031)	(0.032)
Region2_Time4	-0.0615	-0.0612	0.0724	0.102*	0.0648**	0.0836***	-0.0147	0.0205	0.0626**	0.0753**	0.0324	0.0512
	(0.061)	(0.068)	(0.054)	(0.061)	(0.027)	(0.030)	(0.048)	(0.044)	(0.030)	(0.033)	(0.048)	(0.049)
Region2_Time5	-0.0575	-0.0570	0.101	0.139*	0.104***	0.134***	0.000208	0.0496	0.107***	0.128***	0.0682	0.0951
	(0.070)	(0.080)	(0.067)	(0.077)	(0.033)	(0.039)	(0.059)	(0.055)	(0.037)	(0.041)	(0.059)	(0.062)
Region2_Time6	-0.158***	-0.153***	-0.0559	-0.0268	0.0452**	0.0722**	-0.0214	0.0184	0.0385	0.0545*	0.0132	0.0347
	(0.046)	(0.051)	(0.043)	(0.050)	(0.023)	(0.030)	(0.039)	(0.040)	(0.025)	(0.030)	(0.038)	(0.042)
Region2_Time7	-0.0599**	-0.0525	-0.0251	-0.00879	-0.00322	0.0168	-0.0195	0.00382	-0.00745	0.00136	-0.0137	-0.00109
	(0.030)	(0.034)	(0.016)	(0.019)	(0.020)	(0.023)	(0.017)	(0.021)	(0.026)	(0.030)	(0.025)	(0.028)
Region3_Time2	-0.0835**	-0.0841*	-0.00971	0.00674	0.0372	0.0491*	-0.00942	0.0109	0.0245	0.0334	0.00679	0.0178
	(0.040)	(0.044)	(0.031)	(0.035)	(0.025)	(0.027)	(0.031)	(0.029)	(0.031)	(0.032)	(0.037)	(0.038)
Region3_Time3	-0.107*	-0.107*	0.0269	0.0564	0.0442	0.0656*	-0.0450	-0.00669	0.0364	0.0524	0.00246	0.0232
	(0.055)	(0.063)	(0.055)	(0.063)	(0.031)	(0.034)	(0.050)	(0.045)	(0.034)	(0.037)	(0.052)	(0.053)
Region3_Time4	-0.109	-0.116	0.0764	0.108	0.0867**	0.104**	-0.0299	0.00980	0.0720*	0.0885**	0.0276	0.0492
	(0.079)	(0.091)	(0.075)	(0.083)	(0.036)	(0.041)	(0.064)	(0.058)	(0.039)	(0.042)	(0.065)	(0.065)
Region3_Time5	-0.0663	-0.0770	0.110	0.136*	0.0640	0.0752	-0.0705	-0.0334	0.0634	0.0787	0.0122	0.0323
	(0.073)	(0.086)	(0.070)	(0.077)	(0.041)	(0.048)	(0.075)	(0.068)	(0.045)	(0.050)	(0.076)	(0.076)
Region3_Time6	-0.189***	-0.197***	-0.0475	-0.0231	0.0549	0.0692	-0.0430	-0.0114	0.0395	0.0548	0.00224	0.0198
	(0.059)	(0.071)	(0.057)	(0.063)	(0.044)	(0.049)	(0.061)	(0.058)	(0.044)	(0.048)	(0.061)	(0.062)
Region3_Time7	-0.104***	-0.107**	-0.0180	-0.00370	0.0252	0.0293	-0.0326	-0.0160	0.0103	0.0149	-0.0117	-0.00313
	(0.037)	(0.042)	(0.035)	(0.039)	(0.030)	(0.034)	(0.040)	(0.039)	(0.031)	(0.033)	(0.040)	(0.041)
Region4_Time2	0.00626	0.00667	0.00590	0.00895	0.00307	0.00921	0.00342	0.00804	-0.00573	-0.00173	-0.00560	-0.00268
	(0.024)	(0.026)	(0.013)	(0.016)	(0.031)	(0.032)	(0.025)	(0.026)	(0.027)	(0.028)	(0.025)	(0.025)
Region4_Time3	0.0325	0.0334	0.0319**	0.0381**	-0.0101	0.00170	-0.00468	0.00315	-0.00369	0.00386	-0.00162	0.00349
	(0.023)	(0.024)	(0.014)	(0.016)	(0.029)	(0.030)	(0.021)	(0.022)	(0.030)	(0.031)	(0.026)	(0.028)
Region4_Time4	0.0804***	0.0799***	0.0481*	0.0478*	-0.000657	0.00914	0.00875	0.0127	-0.00535	0.00233	-0.00177	0.00158
	(0.025)	(0.025)	(0.025)	(0.024)	(0.046)	(0.045)	(0.035)	(0.035)	(0.039)	(0.040)	(0.035)	(0.035)
Region4_Time5	0.102**	0.0980**	0.0560***	0.0496**	-0.0314	-0.0269	-0.00860	-0.0135	-0.0281	-0.0225	-0.0194	-0.0206
	(0.046)	(0.046)	(0.021)	(0.021)	(0.041)	(0.046)	(0.024)	(0.031)	(0.034)	(0.038)	(0.028)	(0.033)
Region4_Time6	0.00531	0.00138	-0.0377**	-0.0405**	-0.0180	-0.00608	-0.00582	-0.00262	-0.0161	-0.00507	-0.0114	-0.00783
	(0.032)	(0.031)	(0.018)	(0.019)	(0.029)	(0.034)	(0.019)	(0.023)	(0.023)	(0.027)	(0.019)	(0.023)
Region4_Time7	-0.0140	-0.0142	-0.0197***	-0.0238**	-0.0320	-0.0386	-0.0252	-0.0318	-0.0147	-0.0194	-0.0121	-0.0161
	(0.020)	(0.022)	(0.007)	(0.009)	(0.026)	(0.028)	(0.018)	(0.021)	(0.022)	(0.025)	(0.020)	(0.022)
Region5_Time2	-0.0967***	-0.0984***	-0.0267	-0.0115	0.0243	0.0338	-0.00749	0.00721	0.0357*	0.0431**	0.0236	0.0319
	(0.032)	(0.038)	(0.029)	(0.033)	(0.024)	(0.023)	(0.029)	(0.027)	(0.020)	(0.021)	(0.025)	(0.025)
Region5_Time3	-0.0306	-0.0339	0.0372	0.0518	0.0273	0.0377	-0.0139	0.00278	0.0332*	0.0426**	0.0176	0.0271
	(0.031)	(0.038)	(0.028)	(0.033)	(0.025)	(0.024)	(0.031)	(0.029)	(0.019)	(0.020)	(0.024)	(0.025)
Region5_Time4	-0.0288	-0.0315	0.0413	0.0600	0.0194	0.0359*	-0.0173	0.00318	0.0425**	0.0555***	0.0285	0.0405
	(0.033)	(0.041)	(0.030)	(0.037)	(0.019)	(0.020)	(0.027)	(0.026)	(0.017)	(0.019)	(0.024)	(0.025)
Region5_Time5	-0.0393	-0.0433	0.0571	0.0762*	0.0371*	0.0476*	-0.0253	-0.00361	0.0554**	0.0655**	0.0317	0.0437
	(0.042)	(0.049)	(0.037)	(0.043)	(0.022)	(0.026)	(0.038)	(0.034)	(0.022)	(0.026)	(0.035)	(0.035)
Region5_Time6	-0.116***	-0.123**	-0.0249	-0.00898	-0.0103	-0.00355	-0.0649*	-0.0492	0.0128	0.0218	-0.00791	0.00100
	(0.037)	(0.048)	(0.036)	(0.040)	(0.021)	(0.023)	(0.034)	(0.030)	(0.025)	(0.026)	(0.035)	(0.034)
Region5_Time7	-0.0453**	-0.0473**	-0.00386	-0.000347	-0.0000711	-0.00412	-0.0256	-0.0229	0.00799	0.00644	-0.00171	-0.000839
	(0.019)	(0.021)	(0.017)	(0.017)	(0.017)	(0.017)	(0.022)	(0.019)	(0.020)	(0.021)	(0.023)	(0.022)
Region6_Time2	-0.0725**	-0.0721**	-0.00559	0.00963	-0.0597***	-0.0529**	-0.0654***	-0.0578***	0.00865	0.0121	0.00648	0.0106
	(0.031)	(0.034)	(0.028)	(0.032)	(0.022)	(0.024)	(0.018)	(0.019)	(0.020)	(0.021)	(0.017)	(0.018)
Region6_Time3	-0.0825	-0.0993	0.0426	0.0446	0.0458*	0.0204	-0.00628	-0.0190	0.0402*	0.0315	0.0204	0.0127
	(0.053)	(0.065)	(0.050)	(0.052)	(0.026)	(0.037)	(0.034)	(0.036)	(0.022)	(0.032)	(0.032)	(0.034)
Region6_Time4	-0.177*	-0.194*	0.0538	0.0776	0.0599	0.0483	-0.0660	-0.0500	0.0874**	0.0895*	0.0396	0.0472
	(0.093)	(0.111)	(0.090)	(0.096)	(0.041)	(0.051)	(0.073)	(0.066)	(0.041)	(0.047)	(0.070)	(0.068)
Region6_Time5	-0.212*	-0.228*	0.0592	0.0937	0.0200	0.0167	-0.126	-0.0982	0.0689	0.0760	0.0133	0.0275
	(0.110)	(0.129)	(0.105)	(0.114)	(0.042)	(0.051)	(0.082)	(0.073)	(0.045)	(0.051)	(0.081)	(0.079)
Region6_Time6	-0.235**	-0.248**	0.00184	0.0345	0.0484	0.0499	-0.0852	-0.0553	0.0640	0.0725	0.0132	0.0286
	(0.096)	(0.112)	(0.092)	(0.100)	(0.042)	(0.049)	(0.078)	(0.069)	(0.045)	(0.049)	(0.077)	(0.075)
Region6_Time7	-0.139**	-0.147**	0.00255	0.0228	0.0426	0.0450	-0.0406	-0.0206	0.0578*	0.0638*	0.0261	0.0365
	(0.057)	(0.067)	(0.055)	(0.060)	(0.030)	(0.033)	(0.049)	(0.044)	(0.030)	(0.033)	(0.048)	(0.047)
Observations	72987	72987	72987	72987	107891	107891	107891	107891	107891	107891	107891	107891
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Notes: These regressions follow the methodology and replication package of Abeberese (2017). Standard errors are clustered at the state by year level. Columns 3-4, 7-8, and 11-12 show the change in results without the partial omission of region by year fixed effects.

A.16 Pass-through elasticities and incidence on consumers over time for aggregated industries

Figure A.31: The distribution of pass-through elasticities

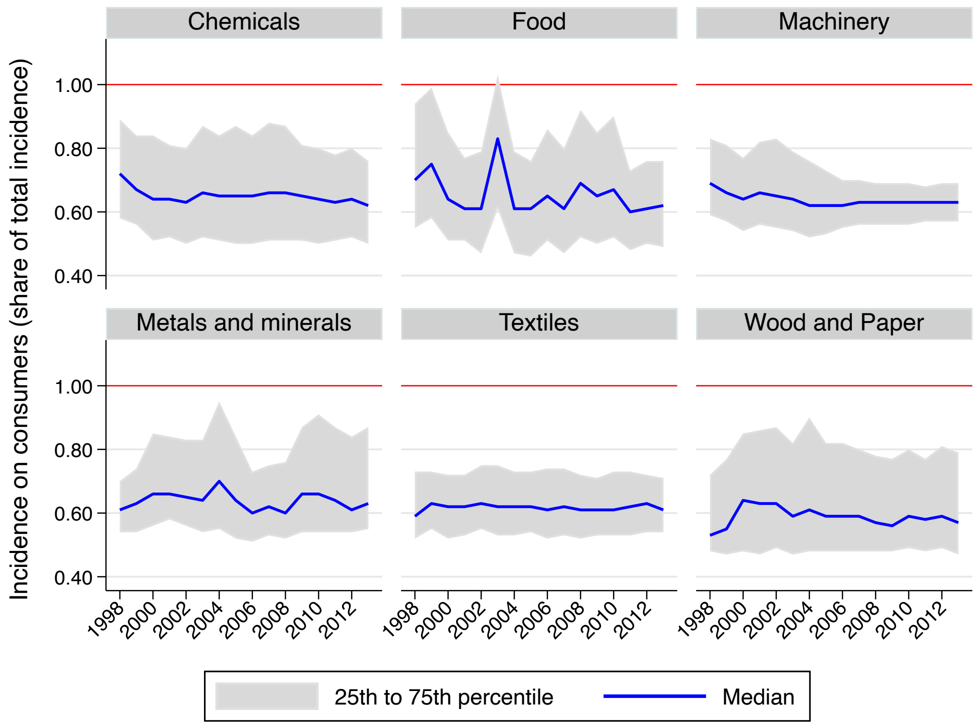


Notes: The figure plots the cumulative distribution function of the pass-through elasticities $(d\log(P)/d\log(MC))$. The pass-through elasticities vary at the 4-digit industry level: there are 121 different pass-through elasticities. The pass-through elasticities are the coefficient on a regression 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***	0.730***
	(0.0130)	(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.32: Share of incidence on consumers from electricity price changes



Notes: The figure plots the median share of incidence on consumers I^{share} 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.17 Consumer welfare changes accounting for non-final demand and for financing through residential tariff increases

Consumer surplus changes accounting for non-final demand: The degree to which industries sell to consumers (final demand) varies. To account for this, I use the 2007-08 input-output tables from the Central Statistics Office (2012) that also contain information of the share of each industry's output going to final demand. These IO industry categories are slightly coarser (58 industries) than 4-digit (133 industries). I manually create a crosswalk to map the 4-digit industries to the 58 IO industries. Recall incidence and incidence shares at the plant level are a function of estimated parameters ρ_{MC}, L, and ϵ_D that vary at industry or plant level:

$$I(\rho_{MC}, L, \epsilon_D) = dCS/dPS \tag{A.16}$$

$$I^{share}(\rho_{MC}, L, \epsilon_D) = dCS/(dCS + dPS) = I/(1+I) \tag{A.17}$$

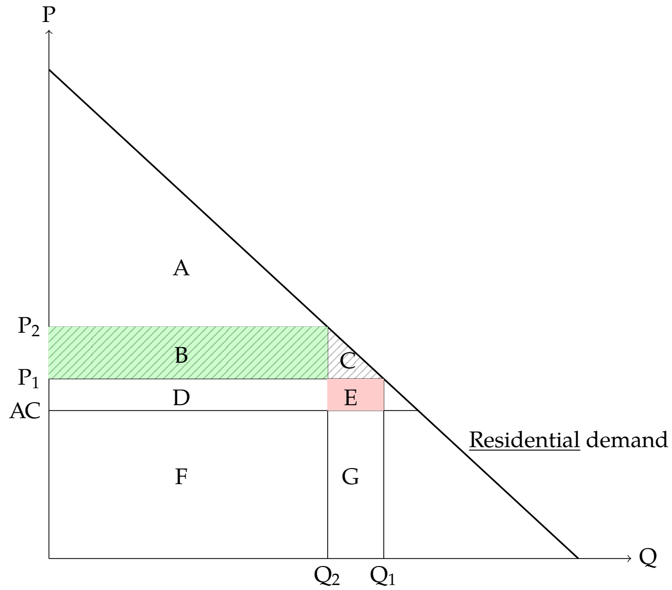
To calculate change in total consumer surplus, I use the observed share of output by IO industries going to final demand (s_{IOind}).[103] I first take the median estimated consumer incidence within each IO industry (I_{IOind}). I then combine this with the portion of output going to final demand in each IO industry and the estimated change in total producer surplus by industry dPS_{IOind} based on the sampling frame and the profit semi-elasticity from Table 4a. Change in total consumer surplus dCS is the sum over IO industries:

$$dCS = \sum_{IOind} dPS_{IOind} \cdot s_{IOind} \cdot I_{IOind}(\rho_{MC}, L, \epsilon_D) \tag{A.18}$$

Change in total consumer surplus is US$ 34.4 billion. The adjustment taking into account final demand only is important, as the unadjusted figure would amount to US$ 64 billion.[104] As a robustness check, I also estimate profit semi-elasticities by IO industry to construct dPS_{IOind}, instead of using the overall semi-elasticity from Table 4a. This could in principle increase or decrease dCS, depending on whether producers with a higher share going to final demand have higher or lower profit semi-elasticities. The results are similar with a total adjusted consumer surplus of US$ 29.8 billion.

[103] Change in producer surplus is change in profits, irrespective of whether output is going to final demand.
[104] To calculate change in total unadjusted consumer surplus dCS, I set s_{IOind} to 1 and use median incidence I across all plants.

Figure A.33: Changes in consumer surplus from residential electricity tariff changes



Notes: The figure depicts the schematic of a simple demand curve for residential electricity. P_1 and P_2 denote the price increase, and AC constant average cost of electricity supply.

Financing through residential tariff increases: If the electricity price reduction for industry is financed entirely through increased rates for residential users, consumers have consumer surplus reductions from paying higher tariffs directly. The deficit for utilities from lower industrial prices amounts to US$ 3.53 billion as shown in Section V.E. I next calculate the welfare losses for residential consumers if this deficit is financed through tariff increases in the residential sector.

Figure A.33 depicts a simple demand curve for residential electricity with prevailing prices P_1 and electricity purchased Q_1. To finance the deficit, utilities increase residential rates to P_2 which generates additional revenue B, forgone sales $E+G$, and lower costs G since less electricity is sold at higher residential rates, assuming constant average cost of supply AC. Overall the utility makes additional profits $B - E$ from this residential rate increase. The corresponding loss in consumer surplus is $B + C$.

To quantify these changes, I am using residential $P_1 = 4.9$ US cents per kWh and $AC = 6.9$ US cents per kWh from the Planning Commission (2001-2002); Ministry of Power (2002-2015), and $Q_1 = 125.447$ TWh residential electricity consumption from the Central Statistics Office (2016), all averaged across the sample period.[105] I use an elasticity of demand for the Indian residential electricity sector of -0.41 (average between urban and rural) from Table A.8 in Mahadevan (2023). This allows me to solve a system of equations for the new prices and quantities given by:

$$\text{Elasticity of residential demand} = \frac{(Q_2 - Q_1) * P_1}{(P_2 - P_1) * Q_1} = -0.41 \tag{A.19}$$

$$\text{Required additional profit} = B - E = (P_2 - P_1) * Q_2 - (P_1 - AC) * (Q_1 - Q_2) = 3.5 \text{ billion} \tag{A.20}$$

The solution is $P_2 = 8.0$ cents per kWh, which implies a required 63% increase in residential utility tariffs to finance the reduction in industrial tariffs. The resulting loss in consumer surplus in the residential

[105]Using residential prices and cost of supply values from different fixed years rather than averages does not change the resulting change in consumer surplus much.

sector is US$ 3.4 billion, which amounts to overall net gains for consumers of US$31 billion.

A.18 Details on calculating aggregate effects on CO_2 emissions

I combine regression estimates with fuel use data and emission factors to calculate the effect on CO_2 emissions. The first step is to calculate the annual baseline CO_2 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_2 emissions by taking the average emissions per kWh produced in the electricity generating sector (0.84 tCO_2/MWh according to Central Electricity Authority (2006)).
Coal: For coal, I use the reported quantity in ton and turn it into CO_2 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_2 emissions of 94.6 tCO_2 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_2 emissions using the IPCC (2006) tables for manufacturing industries. From the total CO_2 emissions from oil as well as the expenditure on oil (with real prices) in 1996, I take the ratio to calculate the CO_2 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_2 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_2 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[106] 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.[107] With these steps I obtain the estimates of Column 1 in Table 7.

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 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

[106]The average elasticity is -0.369.
[107]The average elasticity of the electricity to oil ratio is -0.688.

Table 7 I switch off both substitution and electricity productivity effects.

A.19 Holm-Bonferroni q-values for multiple hypothesis testing

Table A.30 applies the Holm (1979) Bonferroni correction to the p-values to adjust for multiple hypothesis testing.

Table A.30: 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)
Independent variable: log(electricity price)									
Electricity productivity (log)	0.365	9.0e-16***	2.1e-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***	6.8e-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***	0.0164**	-20.470	6.1e-10***	8.5e-09***	-22.034	5.7e-08***	3.4e-07***
Total revenues	-30.407	6.5e-04***	0.0124**	-132.317	5.5e-11***	8.7e-10***	-139.505	1.1e-10***	1.3e-09***
Total variable costs	-24.247	0.0011***	0.0176**	-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***	2.7e-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***	2.8e-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***	0.0176**	-17.623	0.0025***	0.0083***	-22.088	0.0751*	0.0751*
Other fuels' share in output	0.004	9.1e-04***	0.0164**	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***	0.0431**	-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***	0.0445**	-0.040	4.0e-04***	0.0024***	-0.106	3.2e-08***	2.3e-07***
Independent variable: log(coal price)									
Coal productivity (log)	0.848	0***	0***	1.484	1.7e-15***	1.5e-14***	1.617	1.8e-13***	1.6e-12***
Labor productivity (log)	0.056	0.0053***	0.0586*	-0.025	0.849	1	0.300	0.12	0.723
Profits	-5.940	3.0e-04***	0.0059***	-6.315	0.675	1	-7.393	0.775	1
Output (log)	0.091	0.0034***	0.0445**	-0.311	0.21	1	-0.135	0.695	1
Coal consumption (log)	-0.757	0***	0***	-1.851	3.9e-11***	3.1e-10***	-1.799	3.6e-06***	2.9e-05***
Employees (log)	0.033	0.112	0.672	-0.320	0.0981*	0.687	-0.491	0.0517*	0.362
Total revenues	-20.092	0.0124**	0.124	-21.315	0.803	1	-2.026	0.987	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	0.747	-0.031	0.128	0.723

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(electricity price) and log(coal price).