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 benefitted 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 complementarity input to run machines. The price of electricity, conditional on physical access to power, can therefore play an important role in how countries and sectors upgrade to modern capital intensive and electricity-using production (Atkeson and Kehoe, 1999). In this paper, I show that lower electricity prices, as a result, not only improve labor productivity, but can surprisingly also improve electricity productivity (output per unit of electricity) through this mechanism. While energy prices are usually thought to involve trade-offs between developmental and environmental goals in highly industrialized countries (e.g. Marin and Vona, 2021), lower industrial electricity prices could deliver on both dimensions in a context of industrial development.

The findings in this paper can explain a puzzling pattern in Indian aggregate manufacturing data, where electricity prices fell substantially while electricity productivity increased at the same time. Intuition from standard models would predict the opposite: substitution towards the cheaper input, electricity, together with an unambiguous decrease in electricity productivity.[1] The key insight to resolve this apparent puzzle is that in the presence of non-convex 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 use 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).

Apart from these broader implications for industrial development, the finding that lower electricity

[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 a typical putty-clay models optimize by investing in complementary machines with changes in energy prices, which in turn magnifies positive effects on output and capital utilization compared to clay-clay models (Pindyck and Rotemberg, 1983). Abeberese (2017) provides evidence on changes in production processes due to electricity prices in India. Ravago et al. (2019) find that higher electricity prices amplified premature deindustrialization and shifts towards more labor intensive manufacturing in the Philippines.

prices can induce energy conservation per unit of output is important in its own right. Energy efficiency receives much policy interest as one of the principal ways to reduce carbon intensity in manufacturing industries as countries struggle to achieve climate goals (IEA, 2018*a*; Fowlie and Meeks, 2021), especially in developing countries where production capacity and energy demand is expanding fast. While policy makers may fear that low industrial electricity prices could fail to provide sufficient incentives to improve energy efficiency, we have surprisingly little causal evidence on its effect on electricity productivity. I emphasize that the results in this paper are likely to be especially relevant in contexts of industrial development and where industrial electricity prices are cut from comparatively high levels, which is both the case for India, the setting of this paper.[3]

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

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

I begin the paper by developing a nested constant elasticity of substitution (CES) production model with the innovation of non-convex discrete technology choices that have different degrees of complementarities across inputs. The purpose of the model is to illustrate how lower electricity prices can improve both electricity and labor productivity through more capital intensive technology adoption. The model generates a set of testable predictions I later take to the data, some of which are opposite predictions 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 patterns in the data. Figure 1 presents puzzling

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

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

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

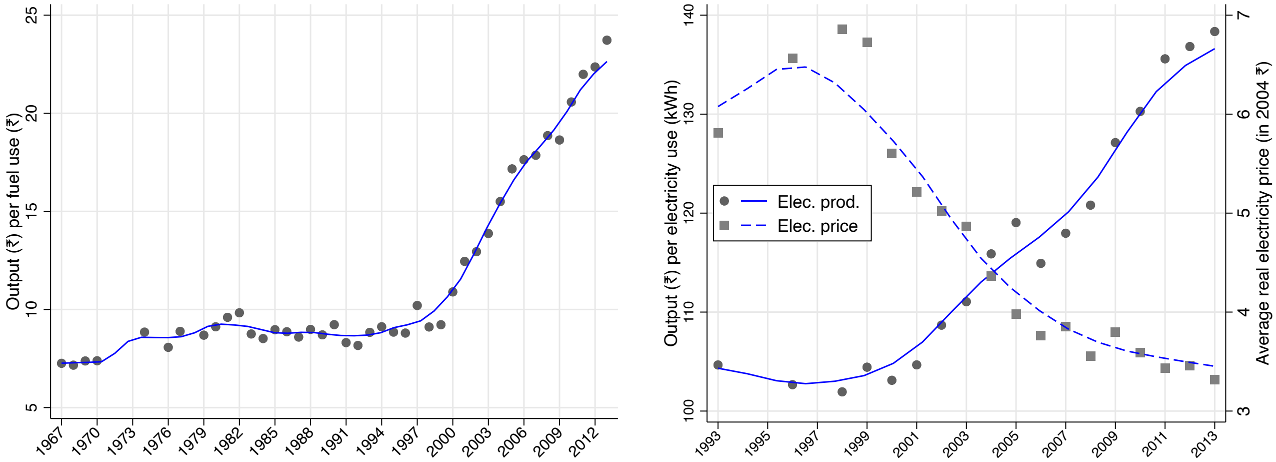
trends at the aggregate level. First, Panel (a) shows a secular increase in India's manufacturing all-fuel energy productivity in the 2000s after remaining mostly flat for several decades since the 1960s. Panel (b) focuses on electricity and the period with more detailed data used for analysis. It shows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

To estimate the effect of electricity prices at the micro level, I use a large panel data set of Indian manufacturing plants from 1998 to 2013, which includes annual information on the quantity and the 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 to set up my empirical framework. For example, most Indian states have increasing block tariffs for industry such that plants with higher consumption pay higher prices, or plants may negotiate discounts or enjoy favorable relationships with state electricity providers, which could be correlated with their productivity.[7] 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. The IV estimates from the micro data can explain the secular increase in *aggregate* electricity productivity in Figure 1 remarkably well. To my knowledge, these are the first plausibly causal estimates to show that lower electricity prices can increase both labor and electricity productivity. I provide a range of robustness checks including additional instruments based on policy

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

[7] Mahadevan (2019*a*) shows that household consumers in the constituencies of the winning party were allowed to manipulate electricity bills in India.



(**a**) Energy productivity (long run)

(**b**) Electricity productivity and prices

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

Notes: The left figure plots annual energy productivity ratios (aggregate value of output divided by the aggregate value of fuel and electricity used) 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. Fuel and electricity use is deflated using a general fuel and electricity wholesale price deflator. From 1967 to 1997 the raw ASI data in pre-aggregated form is used (at industry state year aggregation). From 1998 the raw plant level ASI data is used and aggregated with sampling multipliers. The right figure plots annual aggregate electricity productivity ratios in the solid line (value of output divided by the quantity of electricity used in kWh) and real average electricity prices in the dashed line. Aggregate electricity productivity is calculated by first aggregating the value of output and the quantity of electricity consumed (bought and generated) by plants, and then taking the ratio of the aggregates. Real average electricity prices are calculated by first aggregating the value of electricity bought by plants and the quantity bought, and then taking the ratio of the aggregates. Plant output is deflated using 3-digit industry deflators before aggregating over industries. Electricity values are deflated using a general fuel and electricity wholesale price deflator. All data points come from the raw plant level ASI data (from 711166 observations including years before 1998) and aggregated with sampling multipliers. The base year for deflation is 2004 throughout this paper. Wholesale price deflators are from the Office of the Economic Adviser from the Government of India.

shocks and an analysis of heterogeneous effects by industry.

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

I then estimate effects on welfare. While there are clear positive effects on firms, consumers can be affected by pass-through of electricity costs to output prices, while power utilities can be affected through decreased revenues.[8] 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, and combine these with my estimates of plant level market power and estimates of demand elasticities to recover plant level pass-through rates and consumer and producer incidence shares under imperfect competition in a generalized oligopoly. On average, two thirds of the incidence of lower electricity prices fell on consumers. Total welfare gains from the 48% reduction in electricity prices are 99 billion USD, which comprises 38 billion USD gains for firms, 64 billion USD gains for consumers, and 3 billion USD losses for utilities.

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 4.2 billion USD at a social cost of carbon of 100 USD per tCO_2. This increase in emissions is driven purely by scale, and I show that without the estimated improvement of electricity productivity the emission increases would have been more than double.[9] Second, the effect of coal prices on firms 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.[10]

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 before I offer a conclusion 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, 2021; Aghion et al., 2022),

[8]The degree to which consumers and producers share surplus is determined by how well producers can substitute to electricity, by their market power and demand elasticities, and how marginal costs are passed-through to prices. Ganapati, Shapiro and Walker (2020) show how incidence can be expressed as a function of these parameters in a generalized oligopoly.

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

[10]Depending on the fuel mix of electricity generation, reducing industrial electricity prices relative to coal prices could deliver both, substitution from fossil fuels to electricity, and despite increasing electricity use, improving electricity productivity.

especially with complementarity between energy and capital (Berndt and Wood, 1979; Pindyck and Rotemberg, 1983; Atkeson and Kehoe, 1999).[11] This paper shows 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 increasing electrical machines has a labor replacing effect, this is overcompensated by labor demand increases through the associated boost in productivity and scale, similar to the two opposing effects of automation through direct labor replacement and indirect employment increases through productivity (Acemoglu and Restrepo, 2018; Aghion et al., 2022).

This paper also contributes to the literature on impacts of energy, and electricity prices in particular, on firm outcomes. Abeberese (2017) studies the effect of electricity prices on firm performance and industry switching in India, but there are important differences to this paper.[13] Her main finding is that higher electricity prices induce firms to switch to less electricity intensive industries and products, suggesting lower prices *decreased* electricity productivity in India, using (pre-defined) industry intensities. By instead measuring firm electricity productivity directly and using multiple instruments, I show that lower prices, on the contrary, made firms more electricity productive (i.e less electricity intensive) despite using more electricity, and show how this apparent puzzle can be rationalized with a model and testable predictions.[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 potentially differential impact of electricity prices depending on the stage in industrial development.[16]

In the developing context, there are several studies that find a positive elasticity of electricity productivity to electricity prices, but using OLS rather than instrumenting for prices, consistent with the OLS findings in this paper which are of opposite sign as the IV estimates (Fisher-Vanden et al., 2004; Hang and Tu, 2007; Fisher-Vanden et al., 2016; Rentschler and Kornejew, 2017). A range of studies analyze

[11]See Acemoglu et al. (2012) on how this matters for the direction of technical change, Goldberg et al. (2010); 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 (2021) provides a recent literature review.

[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. 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.

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

[14]I also use a longer panel with three times the observations to corroborate some of the findings on other firm outcomes.

[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 a recent 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.

the impact of energy prices on outcomes other than electricity productivity, mainly on employment or output (Deschenes, 2011; Kahn and Mansur, 2013; Cox et al., 2014; Aldy and Pizer, 2015; Sadath and Acharya, 2015; Popp, 2002; Marin and Vona, 2021). Most of these estimates, however, either rely on state level prices that ignore the substantial heterogeneity in electricity prices across plants that this paper or Davis et al. (2013) reports, or use an index of all energy sources, not just electricity, mixing the potentially opposite effects of electricity and fossil fuel prices. The findings in this paper also tie into the literature of the effects of environmental policy, especially carbon pricing, on firm performance (Martin, De Preux and Wagner, 2014; Martin, Muûls and Wagner, 2015; Calel and Dechezlepretre, 2016; Dechezleprêtre and Sato, 2017). Carbon pricing tends to lower electricity prices relative to fossil fuel prices, and as in Acemoglu et al. (2012), it is the relative price between clean and dirty energy that matters for directing investment and sustainable growth.[17] Finally, this paper also contributes to the literature on energy cost pass-through and incidence shares between firms and consumers (Weyl and Fabinger, 2013; Fabra and Reguant, 2014; Ganapati, Shapiro and Walker, 2020; De Loecker et al., 2016; Miller, Osborne and Sheu, 2017; Hausman, 2018).

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

The purpose of this section is to show 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. The outer 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 total factor productivity, L 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 share parameter of labor is α_l. Capital services are produced using the inner nest of 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, i.e. $\rho_e < 0$, and α_e is the shape parameter. There are two discrete (i.e. non-convex) types of technology c available, both of which require all three inputs. The first type ($c = 1$) is a traditional technology which is more labor intensive, and capital relies to a

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

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

smaller degree on electricity (e.g. traditional textiles manufacturing). The second type ($c = c' > 1$) is a modern technology, which is capital service intensive, and uses modern machinery that relies to a larger degree on electricity as complementary input. The key differences between the two technologies can be captured by distinct values for two parameters in the production function, the capital service intensity $(1 - \alpha_l)$ and the complementarity between capital and electricity ρ_e. Both parameters are affected by technology choice $c \in \{1, c'\}$, where $c' > 1$:

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

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 share parameter of labor to $\hat{\alpha}_l/c'$. The modern technology also increases the complementarity between capital and electricity to $\hat{\rho}_e c'$ (since $\hat{\rho}_e < 0$ the absolute value of $\hat{\rho}_e$ is increased).

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 higher for the modern electricity-using production process. A firm maximizes profits Π:

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

where p_K, p_L and p_E are the factor prices. It is useful to recall the effect of prices in a standard set-up with only one technology choice. In particular, the effect of an electricity price decrease on electricity productivity is unambiguously negative:

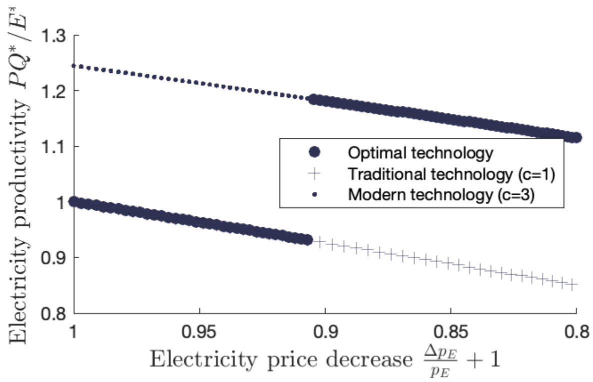
Lemma 1. *Without discrete technology choices ($c = c' = 1$), an electricity price decrease from p_E to $p_E - \Delta_{p_E}$ always decreases electricity productivity $\frac{PQ^*}{E^*}$.*

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

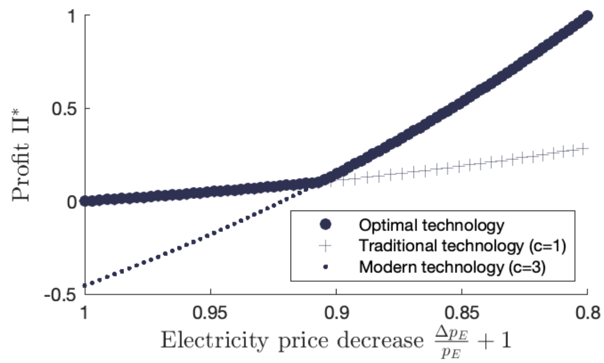
Once we allow for non-convex production technologies, the firm can decide whether to switch technologies when prices decrease, which in turn also affects electricity productivity. This across-technology effect of a price decrease can be larger than the pure within-technology effect of Lemma 1.

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 $\frac{PQ^*}{E^*}$.*

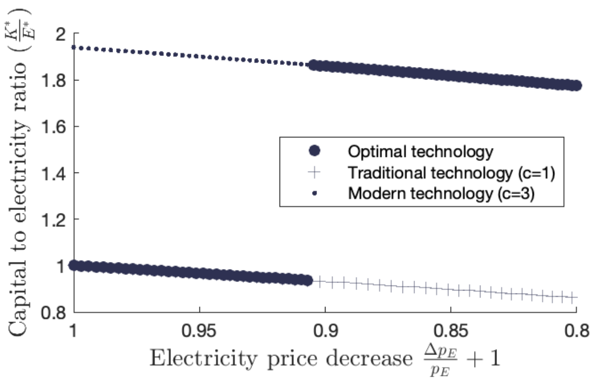
Proof. Appendix A.1 provides a proof. ■



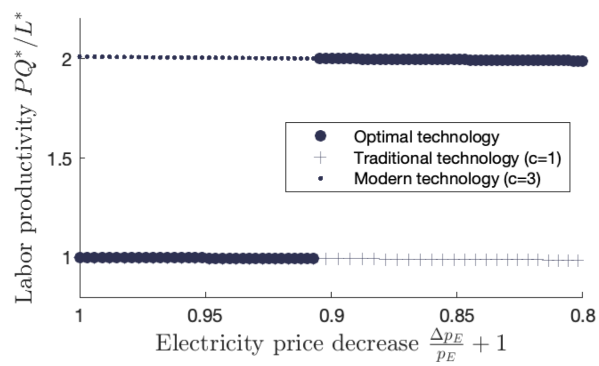
(**a**) Electricity productivity



(**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) capital to labor ratio and Panel (d) labor productivity. The figures show optimal choices both conditional on a specific technology as indicated, and the overall optimum (thick line). All outcomes are normalized by dividing by (for profits: subtracting) its value at the traditional technology ($c = 1$) and original electricity price ($\Delta_{PE} = 0$). The parameter values for this simulation are 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 Δ_{PE} varies from 0 (corresponds to $p_E = 0.5$, and 1 on the horizontal axis) to $1/12$ (corresponds $p_E = 0.4$, and 0.8 on the horizontal axis).

Figure 2 provides a visualisation of Proposition 1 based on simulation. For a given parameter set, 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 normalised 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 due to lower electricity prices is driven by higher capital utilization required by the new technology. Panel (c) of Figure 2 shows that the capital utilization effect can be so large that the capital to electricity ratio increases with the technology switch even though it is electricity that becomes cheaper, not capital. I will test this prediction of the model in the empirical part, which allows distinguishing the model from a standard model 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 the proof. ■

Turning to labor productivity, without discrete technologies, an electricity price decrease can increase or decrease labor productivity, depending on whether labor and capital services (X) are complements or substitutes (similar as in Acemoglu (2002)). This is further illustrated in Figure A.1 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. This increase in labor productivity is 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. The Appendix also shows how the introduction of capital constraints, if binding enough, can delay the switch to the modern technology. Finally, for heterogeneous firms the thresholds for switching technologies are at different values of electricity prices. Appendix A.2 shows that this is one way electricity productivity aggregated across firms can increase more smoothly with electricity price decreases.

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

This section first describes the relevant institutional context, followed by an analysis of the trends and variation in the data to guide empirical identification and interpretation of results.

A. India's Electricity Sector

The key contextual features are that (i) electricity is predominately produced by coal fired plants, (ii) generation is mainly state owned with increasing private ownership after deregulation in 2003, (iii) industrial electricity prices came down from a high level, (iv) industrial prices are to be set according to cost pressures and usually follow block tariffs, and (v) power shortages and electricity prices are uncorrelated.

Fuel mix of power generation.— Most of India's electricity is generated by coal fired power plants (roughly 60%), followed by hydro. The share of coal fired plants in generation across states forms part of one of the shift-share instruments in the analysis. Variation in coal fired share in generation is mainly determined by the presence of coalfields, as coal accounts for up to two-thirds of production costs in these plants (IEA, 2015; Abeberese, 2017). Appendix A.3 shows supporting evidence by visualizing the location of coal fired power plants and coalfields in maps and showing regression results.

Ownership and deregulation.— India's electricity generation is dominated by state and central governments. In 1998, they owned 65% and 30% of installed capacity respectively, with the remaining 5% owned privately (Ministry of Power, 1998*a*; Planning Commission, 2001). The Electricity Act of 2003 aimed to open the heavily regulated sector to more competition, which led to an increase in the share of privately owned capacity to 31% by 2013. The opening up of the power market following the 2003 Electricity Act appears to have contributed to lower electricity prices.[19] Appendix A.4 provides more details and how I use the timing of the Electricity Act together with the location of coalfields to instrument for electricity prices in robustness checks.[20]

India's high industrial electricity prices.— The context of India's high industrial electricity prices is important for interpretation of the results. Average electricity tariffs in 1998, the beginning of the analysis period, were the equivalent of 15.7 US cents per kWh (2004 USD) for industrial users, around 80% higher than the G7 average in nominal terms, or six times as high in PPP terms (see Appendix A.5), and continued to be higher in nominal terms until 2004. This is in stark contrast to residential or agricultural prices (6.8 and 2.6 US cents per kWh in 1998). As a result, state electricity utilities have been loss-making almost across the board, despite industrial electricity prices being above cost recovery (Ministry of Power, 1998*b*) (Appendix A.5 provides more details). The main reason for the heavy cross-subsidisation across sectors is political as farmers form important voting blocs that governments try to cater to (Abeberese, 2017). Finally, unlike in many European countries, industrial electricity tariffs mostly follow flat or slightly increasing block tariffs, as I show in Appendix A.5 with manually collected data from government reports and by plotting plant average prices against quantity to recover changes in marginal electricity prices.

Electricity price setting.— Electricity prices in India have generally been heavily regulated, with price levels tied to cost pressures for generators. Generation, transmission and distribution was largely vertically integrated before 2003 with individual State Electricity Boards setting tariffs for different end-users and locations within their jurisdiction. Prices remained heavily regulated after the Electricity Act of 2003 despite some unbundeling (Planning Commission, 2001; IEA, 2015).[21] The cost pressures for coal-fired generators are determined by coal prices. The largest public coal production company, Coal India Limited, acts as quasi-monopoly (81% market share in 1998) and supplies most power plants (Preonas, 2018). Coal prices for power generators and industry are set independently and often move in opposite directions (see Figure A.28 in Appendix A.11), important context for identification with one of the instruments. Coal price adjustments for power generators are mainly due to changes in international coal prices and the cost of production (Minsitry of Coal, 2006, 2015; Abeberese, 2017).[22] A combination of changes in

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

[20]In a further robustness check, I use the staggered implementation of unbundling utilities following the Electricity Act (Cropper et al., 2011; Mahadevan, 2019*b*).

[21]Regional trading of electricity is highly limited. The networks across regions are in the process of getting better integrated (IEA, 2015). For additional information on unbundling and spot vs. longer term electricity markets see Planning Commission (2001); Cropper et al. (2011); IEA (2015); Ryan (2021); Abeberese (2017); Preonas (2018); Mahadevan (2019*b*).

[22]Since 2010, the coal price contains an additional tax of 50 ₹ /tonne (4% of the price). This policy change also feeds into the

generation costs, deregulation and entry, and reductions in cross-subsidization has contributed to the observed fall in electricity prices over the sample period.

Electricity prices and power shortages.— India's generated electricity usually falls short of required electricity.[23] Distribution companies, however, are generally not allowed to adjust electricity pricing for end-users to clear markets as a response to shortages (Allcott, Collard-Wexler and O'Connell, 2016; Jha, Preonas and Burlig, 2022). Importantly, this institutional context implies that changes in electricity prices are not correlated with changing patterns of power shortages in India. Indeed, the correlation between annual state level power shortages and industrial electricity prices is insignificant and small (see Appendix A.6).[24] For the analysis, if anything, lower electricity prices would be expected to lead to more outages introducing a bias towards zero. Nevertheless, I control for shortages in robustness checks in Appendix A.12. One reason for power outages are failures in technical equipment or networks (Allcott, Collard-Wexler and O'Connell, 2016). Another reason is the failure of electricity prices in the wholesale market to account for supply and demand imbalances across hours and days (Jha, Preonas and Burlig, 2022). Coal supply issues are only responsible for 0.2% to 3.3% of failures in thermal plants,[25] so while coal supply affects electricity prices, it is unlikely to affect outages. Power outages led to adoption of electricity generators by larger industrial plants. Importantly, the adoption of electricity generators is mainly driven by smoothing over outages and not by electricity prices, since self-generation is typically more expensive than buying electricity from the grid.[26]

B. Data

Manufacturing plant level data.— The main data source is the Annual Survey of Industries (ASI), India's mandatory annual establishment level manufacturing survey since 1953. Its long history makes it a relatively reliable data source in the development country context. The formal firms contained in the ASI are representative of two-thirds of manufacturing output (Allcott, Collard-Wexler and O'Connell, 2016), with the remaining one-third made up by informal firms or firms with less than 10 employees.[27] By combining the panel and the cross-sectional editions of the ASI, I retrieve panel identifiers as well as

coal cost shifting instrument.

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

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

[25]Calculated as share of total planned and unplanned outages, annually from 1998 to 2009 using data from Allcott, Collard-Wexler and O'Connell (2016).

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

[27]The survey divides plants into a census sector, where all plants are sampled that have ≥ 100 employees (until 2004 ≥ 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 ≥ 10 employees with electricity and all plants with ≥ 20 employees without electricity.

district codes, which are only available in the respective editions. I use an annual panel from 1998 to 2013 for the main analysis.[28]

I use the quantity and value of electricity purchased, generated, and sold. By dividing the value of electricity purchased by its quantity, I can calculate the average price paid for electricity at the plant level.[29] Electricity productivity is (deflated) output divided by the quantity of electricity consumed (net purchases and generated). Labor productivity is (deflated) output divided by the number of employees. I use further plant level data on output (sales), employees, wages, the book value of capital, investment in and the book value of machinery, intermediate inputs, and other fuel expenditures and quantities (coal, gas and oil). I construct total variable costs as the sum of wages, input costs, and other variable expenses, and total revenues as the sum of sales and other receipts. The difference is total profits. For the analysis of cost pass-through and incidence, I exploit the information of output sales and output quantity at the plant-product level to construct a measure of output prices and quantity.[30]

I winsorize the lowest and highest percentile of each variable within each year to reduce the sensitivity to outliers.[31] All monetary values from all sources are deflated into a common base year 2004 throughout this paper.[32] I drop observations in non-manufacturing industries and those with a missing electricity price, electricity productivity or output. All regressions are weighted by the included sampling multiplier. Table 1 shows that after the cleaning steps, there are 485,948 plant year observations from 160,955 plants, and Appendix A.7 provides a brief discussion of the summary statistics.[33]

Coal prices for thermal power plants and for industry.— Coal prices for thermal power plants (as opposed to manufacturing plants) are from the Minsitry of Coal (2012, 2015). I use the published annual pit-head prices specifically for power utilities customers and inclusive of royalties and taxes, based on a representative Coal India Limited (CIL) mine and grade selected by the Minsitry of Coal (2012).[34] Shares of coal fired power plants in state installed capacity in 1998 are from the Ministry of Power (1998*a*, 2003).[35] For the instrument for manufacturing plant level coal prices in Section IV.D., I use the pit-head

[28]The accounting year in India is from April to March. Throughout the paper, I refer to the first year of the accounting year for ASI data and Government reports. So for example, year April 2006 to March 2007 is referred to as 2006.

[29]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). Furthermore, firms may react to average rather than marginal prices (Ito, 2014).

[30]Output prices are the average of product prices, weighted by their quantities.

[31]I winsorize final variables only. That is electricity productivity (sales divided by electricity use) is winsorized before sales and electricity use are individually winsorized to avoid double winsorization.

[32]I deflate outputs and inputs using 3-digit industry deflators, investment and installed capital and machinery 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]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.

[34]These are the ones of Eastern Coalfields Limited of Coal India Limited, Rajmahal field, Grade E. These are also 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). Figure A.28 in Appendix A.11 plots these prices in real terms.

[35]Thermal shares as on 31st of March 1998, one day before the beginning of the sample, following Abeberese (2017). Chhattisgarh, Jharkhand and Uttarakhand were created in 2000, and shares correspond to Jan 2003 when data is first available.

Table 1: Summary statistics from plant level data

Main variables:

	Mean
Electricity bought (GWh)	0.82
Electricity generated (GWh)	0.21
Electricity sold (GWh)	0.03
Electricity consumed (GWh)	0.99
Electricity price (₹ per kWh)	4.57
Electricity share in total var cost	.058
Electricity productivity (₹ per kWh)	448.52
Electricity productivity (₹ per ₹)	107
Labor productivity (in mil. ₹)	1.3
Output (in mil. ₹)	119
Employees	72
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
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 table shows the sample means based on the pooled plant level data from 1998-2013. The means are calculated using the sampling multiplier as weights. Were 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 total factor productivities (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 the TFP estimation using Wooldridge (2009) in the Indian context).

prices specifically for industry with the appropriate coal grades (Minsitry of Coal, 2012, 2015).

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

Power shortages.— 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.

Coalfields and power plants.— 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).

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

This section presents key empirical patterns to motivate the econometric analysis.

Industrial energy and labor productivity over 50 years.— Panel (a) of Figure 1 shows that there was a remarkable increase in energy productivity, more than doubling from 2000 until 2013, after staying roughly constant between 1967 and 1999. This was not driven by a particular industry or state alone (see Figures A.18 and A.10 in Appendix A.9), and is in contrast to the evolution in OECD countries, as Figure A.18 in Appendix A.9 shows.[36] Figure A.8 in Appendix A.8 shows that labor productivity increased more steadily during those 47 years.

Industrial electricity and labor productivity, and prices and wages 1993-2013.— Panel (b) of Figure 1 shows that electricity productivity increased by 34% from 2000 to 2013.[37] This trend did not occur because of substitution away from electricity. If anything, there was substitution away from other fuels to electricity.[38] Surprisingly, this secular increase in electricity productivity occurred while electricity prices fell by 48% during the same period. This paper offers evidence to explain these at first puzzling curves. Indeed, simply taking the aggregate data points of Panel (a) in Figure 1 yields an elasticity of -0.4, remarkably close to the plant level IV estimates in the main analysis (but of opposite sign to the plant level OLS estimates). Appendix A.9 shows that this pattern is consistent across sectors and states, and not a story of mere across-sector or spatial reallocation.[39] The Appendix also confirms the trends using alternative production and price data sources (IEA, 2016; UNIDO, 2016; Office of the Economic Adviser, 2019), including manually collected tariffs from publications by the electricity regulator, and contrast the electricity price decline with the 40% price increase in OECD countries. Finally, during the electricity price decline of 2000-2013, labor productivity and wages increased by around 90% and 60% respectively (see Figure A.9 in Appendix A.8). The IV results below suggest that the electricity price decline explains a sizeable portion of the increase in labor productivity and to a smaller extent in wages.[40]

Heterogeneity in labor and electricity productivity and prices.— How much variation in prices and input productivity is there left within industries and states for a plant level analysis? Figure 3 plots the histogram of electricity productivity, labor productivity and electricity prices in 2003.[41] The Figure shows that there remains substantial variation even after partialing out state-by-industry (4-digit) effects. Plants at the 90th percentile pay still around 50% higher electricity prices than those at the 10th percentile

[36]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).

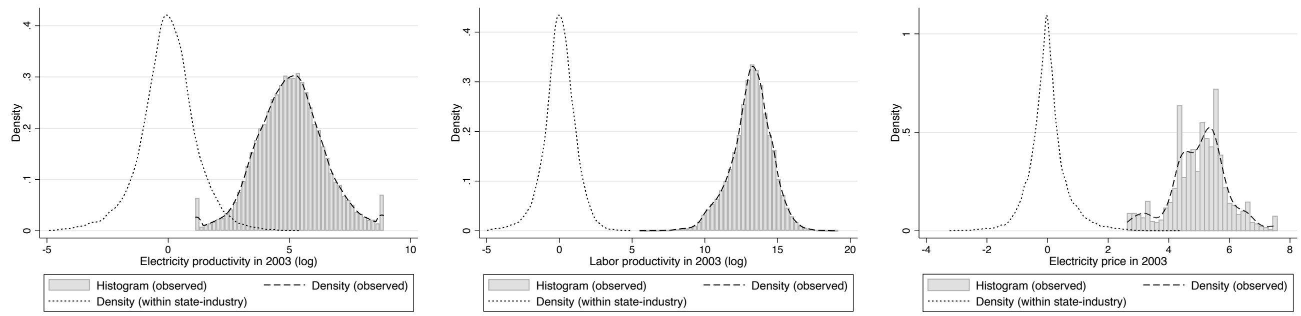
[37]This is the increase from the 1998-2000 average. Also the fuel productivity of fuels other than electricity increased considerably since 2000, as Figure A.17 in Appendix A.9 shows.

[38]The electricity share in the fuel mix grew from around 16 to 20% in energy units, as Figure A.19 in Appendix A.9 shows. The share of electricity in fuel expenditure was roughly constant at 65% in 2000 and 63% in 2013 implying higher quantity used under the large price decreases.

[39]Ghani, Goswami and Kerr (2014) report an increase in electricity productivity in the 2000s which was mainly through improvements in existing state-industry clusters.

[40]Note that a pure substitution towards electricity would decrease labor use and wages, absent increases in scale.

[41]Similar plots are shown in Figure A.22 and Figure A.24 in Appendix A.10 for all years.



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

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

Notes: Panel (a) plots the histogram of plant level logged electricity productivity in 2003. Electricity productivity ratios are the value of output divided by the quantity of electricity used in kWh. The kernel density plot to the left shows the distribution of the residuals of logged electricity productivity after partialing out state by 4-digit industry by year fixed effects. Panel (b) and Panel (c) show the same plots labor productivity and electricity prices in 2003. The patterns are similar for all years as shown in Figure A.22 and Figure A.24 in Appendix A.10. Plant output is deflated using 3-digit industry deflators. Electricity prices are deflated using a general fuel and electricity wholesale price deflator. The base year for deflation is 2004 throughout this paper. Wholesale price deflators are from the Office of the Economic Adviser from the Government of India.

within state-by-industry clusters within the same year. Plant labor and electricity productivity at the 90th percentile is 160% and 170% higher than at the 10th percentile, larger than some TFP dispersions found in the literature (Bartelsman and Doms, 2000; Syverson, 2004, 2011). Appendix A.10 presents a more formal variance decomposition following Davis et al. (2013), showing that state-industry effects can only account for about half the variation in input productivities or electricity prices.[42] Finally, I show in Appendix A.10 that plant electricity prices and productivity are persistent by showing first order stochastic domination through time following Farinas and Ruano (2005). This persistence within plants, together with the substantial variation across plants, suggests an empirical strategy that also leverages across plant variation.

IV. Empirical Strategy

Using micro-data at the plant level, 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. The analysis is conditional on 4-digit industry by region by year fixed effects α_{irt}. This accounts for all aggregate technology, TFP, demand, and price trends that are allowed to be differentiated by industry. Furthermore, α_{irt} allows these unobserved trends to be regionally differentiated as there is poor integration of electricity markets across regions in India (IEA, 2015; Ryan, 2021; Ministry of Power,

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

2018).[43]

The above specification deliberately avoids plant fixed effects for three reasons.[44] First, both within and between-plant variation together are more likely to capture the mechanism of technology differences and upgrading within industry-region-years, as compared to mere within-plant variation.[45] As shown in Section III.C., there is much interesting variation between plants that plant fixed effects would eliminate due to persistency within plants. A regression of logged electricity productivity on plant fixed effects can explain 80% of the variation (R^2). Second, plant fixed effects require a strict exogeneity assumption which is likely to be violated, and can introduce further bias. Past shocks to output and electricity or labor productivity are likely correlated with current electricity prices, as block tariffs can change with consumption.[46] Third, plant fixed effects are unable to address time-varying endogeneity concerns at the plant level which I discuss next, and which I address with an instrumental variable strategy.

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 $\log(P^E)_{jisrt}$, which I call μ_{jisrt}, are likely to vary mostly at the state-year or district-year level as discussed in Section III.A., determined by changes in costs of electricity generation or policies that are orthogonal to plant level shocks. Suppose the endogenous elements contained in the price can be expressed as ξ_{jisrt} at the plant level and λ_{isrt} at the industry level within states. This allows us to define the composite error term as:

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

The nature of ξ_{jisrt} and λ_{isrt} consists of 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}) also affect electricity prices due to different tariffs for different consumption bands (see Figures A.7 and A.8). 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 the possibility of price corruption is likely

[43] 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 around six regions in national accounts.

[44] I rely on the plant identifiers for inference as discussed in Section IV.F.. Including plant fixed effects in the main regression yields similar results, although with a loss of precision for one of the instruments.

[45] Including plant fixed effect can be thought of using short-run variation, while excluding plant fixed effects also exploits variation relevant for the medium or longer run, such as changes in production processes (Ganapati, Shapiro and Walker, 2020). Atkeson and Kehoe (1999) show that responses to energy price changes may not show up in the very short run in typical putty-clay models (see also Hassler, Krusell and Olovsson (2021) or Hawkins and Wagner (2022)).

[46] 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.

related to their economic performance, which leads to reverse causality problems.[47] Third, there may be shocks to industries within regions that jointly affect economic performance, electricity productivity and electricity pricing (in λ_{isrt}).[48] Fourth, even within states, plants may locate where electricity prices are low and that may be correlated to their electricity productivity and consumption (in ξ_{jisrt}). Finally, average electricity prices at the plant level may suffer from measurement error (in ξ_{jisrt}). I next turn to my two instrumental variable strategies aimed at isolating the exogenous components of the price variation.

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

The main idea of the first instrument is that other plants nearby should also be affected by exogenous changes in electricity prices. Some weighted average of other plants could therefore extract the common exogenous signal such as changes in generation costs.[49] In order to avoid capturing endogenous components λ_{isrt} in the instrument, I rely on information of plants in the same state, but in different industries. Specifically, I use prices of plants with similar purchase quantities in the same year, in the same state, but in different 2-digit industries i^{2d}. The underlying assumption is that the endogenous components λ_{isrt} are not correlated across 2-digit industries within a state, but are allowed to be correlated within 2-digit industries, e.g. through competition in the output market or supply chains.[50] Recall that industry by region by 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. By construction, the plant specific ξ_{jisrt} are not correlated with the (weighted) average of ξ_{jisrt} of plants in other industries.

I use plants with similar purchase quantities to smooth over block tariffs that are based on purchase quantities. The instrument is a weighted average of prices of other plants, weighted by the distance in their purchase quantities. I use a triangular kernel function with weights $w_{q^*}(q_j)$ to smooth over possible discontinuities in tariff bands:

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

where q^* is the electricity quantity purchased in kWh by plant j^* that we want to create the instrument

[47] Furthermore, while manipulation of recorded electricity quantities is primarily an issue at the household level (Mahadevan, 2019*a*), instrumenting for prices that are derived through expenditures and recorded quantities also addresses this source of bias.

[48] Prices may also response to changes in aggregate electricity productivity and electricity demand from firms. In a robustness check, I use lagged (instrumented) electricity prices to address reverse causality issues at the more aggregate level and find similar results.

[49] The instrument is similar to the 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).

[50] There are 22 2-digit industries and 133 4-digit industries in the final sample.

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.[51] That is, the support of the kernel weights is 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 $i_j^{2d} \neq i_{j^*}^{2d}$, and the weight decreases linearly in the distance of logged purchase quantity. The first instrument IV^A for the electricity price of plant j^* is then the average of the electricity prices of other plants P_{jisrt}^E, weighted by the triangular kernel weights:

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

Identification requires that there are no endogenous factors that are common across plants from *different* (2-digit) industries that affect their electricity productivity and the pricing of electricity simultaneously, conditional on the industry-by-region-by-year fixed effects. In a robustness check, I construct an instrument IV^C that also excludes plants in the IV that are based in the same district. This allows for endogenous components in prices that are spatially correlated within districts. The results are quantitatively very similar. Under the identification assumption, the instrument addresses the endogeneity concerns layed out above in Section IV.A.. The advantage of this instrument is that it can be readily calculated in other settings. This can facilitate comparable analyses and further explorations 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 main idea for the second instrument is to use a cost shifter for electricity generation directly, following Abeberese (2017).[52] Since coal is the largest cost factor in electricity generation (see Section III.A.), the price of coal shifts electricity generation costs, and therefore 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 installed 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

[51] The advantage of a bandwidth that is flexible rather than fixed is to ensure that enough observations are used for the construction of the instruments. I also tried the 10th and the 50th percentile, as well as a fixed cutoff based on the average 25th percentile with similar results.

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

(Borusyak, Hull and Jaravel, 2022) or exogenous weights (Goldsmith-Pinkham, Sorkin and Swift, 2020). As for shifters, one concern is that coal prices for power generation may also impact firms that use coal directly. As discussed in Section III.A. and III.B., in India's case the coal price for power utilities is set independently to the coal price for industry, and is thus unlikely to directly affect manufacturing plants. Indeed, Figure A.28 in Appendix A.11 plots both coal prices in real terms, and shows that often one decreases while the other increases at the same time.[53] While the coal prices for power utilities and industries are set independently, excluding all plants that use coal directly yields very similar results. As for the shares, conditioning on industry-by-region-by-year fixed effects helps as exogeneity of shares is only required within regions, and allows for correlation of pre-sample shares with industrial structure. I provide a map of the pre-sample thermal shares in Figure A.29 in Appendix A.11. I present some evidence of exogeneity of shares in Appendix Table A.4 where I show state-level regressions of shares on several pre-determined variables to show that they are uncorrelated, such as share of rural population, access to electricity, labor productivity, capital labor ratio, share of wages spent on skilled workers, or fuel share in output. Finally, Adao, Kolesár and Morales (2019) show that standard errors may need adjustment for shift-share designs. Following their procedure, I recover standard errors that would be similar or slightly smaller after adjustment, likely due to negative correlation of residuals within clusters that are based on thermal shares.[54]

The instrument isolates exogenous movements in electricity prices driven by cost pressures from coal prices for generation. An advantage of instrument IV^B is that it might be less susceptible to specific types of common shocks that 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. *Two Similar Instruments for Industrial Coal Prices* (IV^E *and* IV^F)

In Section V.F., I compare the effect of electricity prices with the effect of coal prices. Specifically, I ask whether declining electricity prices have more positive effects than declining coal prices. Coal prices suffer from similar endogeneity concerns as electricity prices. I construct two instruments for industrial coal prices that are similar to the ones above. The first instrument, IV^E is the analogue to IV^A, using coal prices of plants in the same state, but from different 2-digit industries, without the kernel weights. The second instrument, IV^F, is a shift-share instrument like IV^B. The shares are the logged distances of district centroids to the nearest coalfields, where distance captures increases in sourcing costs. The shifter is the nationally representative coal price (at pit heads) for industry (as opposed to power utilities), taken from the Minsitry of Coal (2012, 2015). The location of coalfields and power plants is illustrated in

[53] See also Abeberese (2017) for more discussion.

[54] 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.

Figure A.5 in Appendix A.3.

E. Recovering Pass-Through Rates and Consumer Incidence

To shed light on how the change in electricity prices affects consumers and the resulting incidence shares between producers and consumers, I need to identify several additional parameters. Incidence shares depend on how electricity prices affect marginal costs through input substitution ($\gamma \equiv dMC/dP^E$), and on the pass-through rate of marginal costs to output prices through 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, under the assumption that average variable costs are equal to marginal costs ($AVC = MC$) incidence on consumers in a generalized oligopoly, where CS and PS are consumer and producer surplus, is:

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

where $\rho_{MC} \equiv dP/dMC$ 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, and ϵ_D and ρ_{MC}.

There is an established literature recovering 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 minimising, 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 (μ) using materials as variable input, which determine the plant level Lerner index L together with observed output prices. I estimate the output elasticity along with TFP using Wooldridge (2009) building on Levinsohn and Petrin (2003).

It is well know that for standard oligopolistic environments, the first order conditions of firm profit maximisation imply a mapping between markups and demand elasticities. For the market level demand elasticities ϵ_D, I take the median of the plant level demand elasticities within a 4-digit industry by year by state cluster.[55] Market demand conditions are thus allowed to vary across industries, time and space.[56]

The main challenge is estimation of the pass-through parameter ρ_{MC}, which requires data on revenues and output quantity. The most direct way is to regress prices on marginal cost. Revenues and quantities

[55]Plant level markups (and demand elasticities) can diverge from the market demand elasticities due to distortions for example. 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). The median is more robust to outliers.

[56]This different to Ganapati, Shapiro and Walker (2020), who estimate demand functions instead. The two alternative approaches require different assumptions. Since we need to estimate markups and production functions in any case and assume oligopolistic competition and cost minimisation already, the additional profit maximisation assumption required here to recover demand elasticities appears innocuous. Regardless of how demand elasticities are recovered, the main challenge is to get estimates for the pass-through.

are separately reported for most plants in the data, which allows me to calculate average sales prices at the plant-product level. I calculate the plant level average price across products, 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 with these prices. I recover prices and marginal costs for 87% of the 485948 observations, covering 121 of the 133 4-digit industries. Since I also construct total variable cost (see Section III.B.), I can recover AVC by dividing total variable costs by quantity. This allows me to examine the validity of the underlying assumption ($AVC = MC$) for Equation (10). A regression of logged AVC on logged MC yields a coefficient of 0.98 and an R^2 of 0.95, which suggests that the assumption is reasonable.

The pass-through parameter ρ_{MC} is likely to differ by industry and firms, depending for example on the market structure, concentration or market power. I estimate a pass-through *elasticity* for each 4-digit industry separately, regressing prices ($\log(P)$) on marginal costs ($\log(MC)$). I instrument for the endogenous marginal costs using the two instruments for the electricity price IV^A and IV^B described above.[57] The pass-through elasticity is converted into the pass-through rate ρ_{MC} by multiplying it with the plant level markup μ. To summarise, the empirical components are:

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

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

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

F. Specification Choice, Estimation and Inference

I conclude this section by making a few remarks about model specifications and estimation. First, I do not include state by year effects for the baseline specification. This is because IV^B only varies at the state by year level and much of the exogenous variation is also at the state by year level.[58] Second, I exploit the panel structure for calculation of standard errors in all specifications. I two-way cluster standard 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 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 Table A.23 in Appendix A.16. Finally, I use the two instruments separately to enable comparisons, but also provide additional results based on an over-identified IV-regression with two instruments.

[57] Endogeneity concerns arise for example because marginal costs are estimated leading to measurement error. I use the instruments separately. For each industry, I take the weighted average of the two IV coefficients, where the weights are the t-statistics. Note that average electricity prices are similar to marginal electricity prices in this context (see Footnote 29).

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

V. Results

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

A. Electricity Productivity, Labor Productivity, and Their Components

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

Lower electricity prices improve electricity productivity.— The OLS correlation between electricity prices and electricity productivity is positive with an elasticity of 0.37 (Column 1 in Table 2). The endogeneity bias in this estimate is large, however. The more causal 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. The positive bias in the OLS estimates suggests that less efficient plants manage to obtain lower electricity prices through, e.g., exemptions, negotiations, corruption or location choices.

The effect is more strongly negative for IV^B than for IV^A. This could be due to heterogeneous local average treatment effects. Following Imbens and Angrist (1994) and Imbens and Rubin (1997), I discretize both electricity prices and both instruments by their median sample split after partialing out fixed effects to shed light on possible heterogeneous treatment 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 instruments estimates are likely two different local heterogeneous treatment effects and both instruments shift slightly different subpopulations (Imbens and Rubin, 1997).[59]

How well can the causal estimates from micro data explain the aggregate puzzling trends of increasing electricity productivity (34%) while electricity prices fell by 48%, as documented in Section III.C.? Taking the average of local treatment effects of IV^A and IV^B as -0.508 in a back of the envelope calculation, the reduction in electricity prices predicts a $(1-0.48)^{-0.508}-1 = 39\%$ increase in electricity productivity. The IV estimates can therefore explain the aggregate secular trends remarkably well, especially considering that the simple OLS correlation at the micro level is of opposite sign.

Lower electricity prices improve labor productivity.— Columns 5 and 6 of Table 2 show that lower electricity prices also substantially increase labor productivity, with an elasticity of -0.39 and -1.06 for IV^A and

[59] In particular, for IV^A, the outcome is 23% lower for never-takers than for compliers, while it is 55% for IV^B. The outcome is 15% higher for always-takers than for compliers for IV^A, and 38% for IV^B.

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 logged electricity productivity (value of output divided by the quantity of electricity used in kWh). 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 IV^A based on the electricity prices of similar 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. Plant output is deflated using 3-digit industry deflators and electricity prices are deflated using a general fuel and electricity wholesale price deflator. Stars indicate p-values: * < 0.1, **< 0.05, ***< 0.01.

IV^B respectively. There is a significant 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, the 48% electricity price decline predicts a $(1-0.48)^{-0.725} - 1 = 61\%$ increase in labor productivity, which can explain two thirds of the 90% increase in labor productivity during the same time as documented in Section III.C..

Electricity prices affect electricity consumption, employment, and output.— Why have lower electricity prices improved electricity productivity and labor productivity in India? I find that lower electricity prices still increase electricity consumption and employment, consistent with intuition and the model predictions in Section II. and Appendix A.2. Table 3 presents the regressions split up into the components of electricity productivity and labor productivity, with logged electricity consumption (in kWh), employees, or logged output as dependent variables. In both the OLS and IV regressions, lower electricity prices increase electricity consumption, with the causal effect being slightly larger. A one percent decrease in electricity prices increases physical electricity consumption by 0.48 to 0.80 percent. The OLS estimate for employees is insignficant, but the IV estimates are significant, with a one percent decrease in electricity prices increasing number of employees by 0.34 to 0.52 percent.

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

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 logged output or logged electricity consumption (in kWh) as indicated. Each column represents a separate regression at the plant level. 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. The rest of the table layout follows the same structure as the main Table 2.

error as well as endogeneity bias from increasing tariff schedules where shocks to electricity consumption are positively correlated with electricity prices.

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

B. *Robustness*

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

Using lagged prices.— First, I use lagged prices and instruments to allow for more time to adjust to prices.[60] Using lags cuts the sample in around a half as spells of firm observations are required. Tables A.5 and A.6 in Appendix A.12 first show the contemporaneous effects for the reduced sample and then the lagged effects for electricity and labor productivity respectively. Reassuringly, the IV estimates for electricity productivity and labor productivity hardly change. The positive bias in the OLS estimates, however, is substantially reduced when using lags.

Using alternative instruments yields similar estimate.— Second, I use three alternative instruments. The first, IV^C, is similar to IV^A except that I exclude plants in the same districts for the construction of the

[60]This may also addresses potential remaining reverse causality concerns.

instrument. The second one, IV^{D_1}, is similar to IV^{B} in that it is also a shift-share instrument. The shift uses the timing of the 2003 Electricity Act and the shares are the calculated distance of district centroids to coalfields. The rationale for the second instruments builds on the finding in Section III.A. and Table A.1 in Appendix A.4 that the share of private power capacity can explain lower electricity prices, but only after 2003. Since local changes in private power share are likely to be endogenous, I use the distance to coalfields. Table A.1 shows that the distance of districts to coalfields predicts shares in the private power capacity. Therefore, I use the distance to coalfields interacted with the post 2003 dummy as an instrument, controlling for the distance to coalfields. The third instrument, IV^{D_2} uses the staggered unbundeling of generation, transmission and distribution by states identified by Cropper et al. (2011). Mahadevan (2019*b*) uses the staggered implementation of unbundeling in an event study and finds an effect on electricity prices. Table A.7 in Appendix A.12 shows that the estimates using these alternative instruments are similar to the main IV estimates.[61]

Controlling for power shortages and distance to coalfields.— Third, I control for the distance from districts to coalfields, for state-year level power shortages, and for both simultaneously in Tables A.8 and A.9 in Appendix A.12. Note that the included industry by region by year fixed effects in the main specification may already control for a significant portion of power shortages, but directly controlling for these serves as an additional robustness check. The estimates remain negative and are similar in magnitude. I already showed in Table A.3 in Appendix A.6 that shortages are not associated with electricity prices. Both, the distance to coalfields and shortages are significant when explaining electricity productivity, however.

Electricity intensive sectors and sector specific analysis.— Fourth, I restrict the sample to electricity intensive sectors, loosely defined as the 2-digit sectors with an above average electricity intensity. Effects are similar as Table A.10 in Appendix A.12 shows. I also run the analysis separately for six broad industry groups in Table A.11 and Table A.12. The effects are broadly similar across sectors, except perhaps for metals and minerals, where estimates are insignificant, but still correcting an upward bias in the OLS estimates. Since the basic metals industry relies predominantly on coal across many production techniques, there could be a null effect, as that there is less scope to move to electricity based production. Figures A.13 and A.14 in Appendix A.9 support this hypothesis. While energy productivity rose in this sector, electricity productivity remained fairly stable.

Stronger effect during earlier high price periods.— Fifth, I examine whether the effect was stronger for the earlier high price period in India. In the framework of the model, it is plausible that decreasing electricity prices have particularly strong effects on output at earlier stages of industrial upgrading and when electricity prices are at high levels discouraging plants from using electricity associated with modern productive production processes. The nature of comparatively high Indian electricity prices (see Appendix A.5) and the subsequent halving of prices during the sample period (Figure 1) lend itself to

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

test this hypothesis. I interact the electricity price with an indicator for the first eight years of the sample periods in Table A.13 in Appendix A.12.[62] At least for electricity productivity as outcome, the interaction term is negative for both IV and the OLS specifications. This suggests that the negative implications of high electricity prices on output and electricity productivity are particularly relevant in contexts with high electricity prices.

Overidentified IV.— Sixth, I run an over-identified model using both IV^A and IV^B simultaneously in Table A.15 in Appendix A.12. The effects are similar to the main results, mainly driven by the stronger instrument IV^A. The Sargan-Hansen J-test rejects that both instruments have the same effect. While this could imply that one of the instruments is not completely exogenous under the assumption that treatment effects are constants, it could also imply evidence of heterogeneous treatment effects, which is also supported by the analysis above based on Imbens and Rubin (1997).

Alternative clustering of standard errors and multiple hypothesis testing.— Seventh, I two-way cluster at the district and the region year level, allowing more generously for arbitrary correlation in errors, with slightly larger standard errors but still significant results (Table A.17 in Appendix A.12). Finally, I adjust all p-values upwards to account for multiple hypothesis testing in Table A.23 in Appendix A.16. Almost all estimates remain statistically significant at conventional levels.

C. Mechanisms

I next explore the impacts of electricity prices on a range of outcomes and interaction effects to shed more light on deeper mechanisms of how electricity and labor productivity are affected, and test the predictions of the model in Section II..

Testing model predictions: scaling up, investment and input ratios.— Electricity is complementary to modern production techniques in the model in Section II.. Lower electricity prices can incentivize to switch to these more modern capital production techniques which generates the increase in electricity and labor productivity. I next test all predictions of the model in Figure 2 and Figure A.2 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. I have already shown that lower electricity prices increase output. Table 4a shows the effect on profits, total revenues and total variable costs (in levels).[63] A one percent decrease in electricity prices increases total profits by 0.21-0.22 million ₹ (4,800US$) per plant, increases revenues by 1.3-1.4 million ₹ (30,000US$), but also *increases* total variable costs by 1.1 million ₹ (24,000US$). The

[62]The average real price in the first eight years was 5.5 ₹ per kWh compared to 3.8 ₹ per kWh in the second eight years. For the IV^A, the entire effect is driven by the period where electricity prices were high. For IV^B, the interaction effect is negative as well, but insignificant. The conclusions are similar when looking at three periods as in Table A.14 in Appendix A.12.

[63]See Section III.B. for variable descriptions.

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 employment (log)			Employment 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**) 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

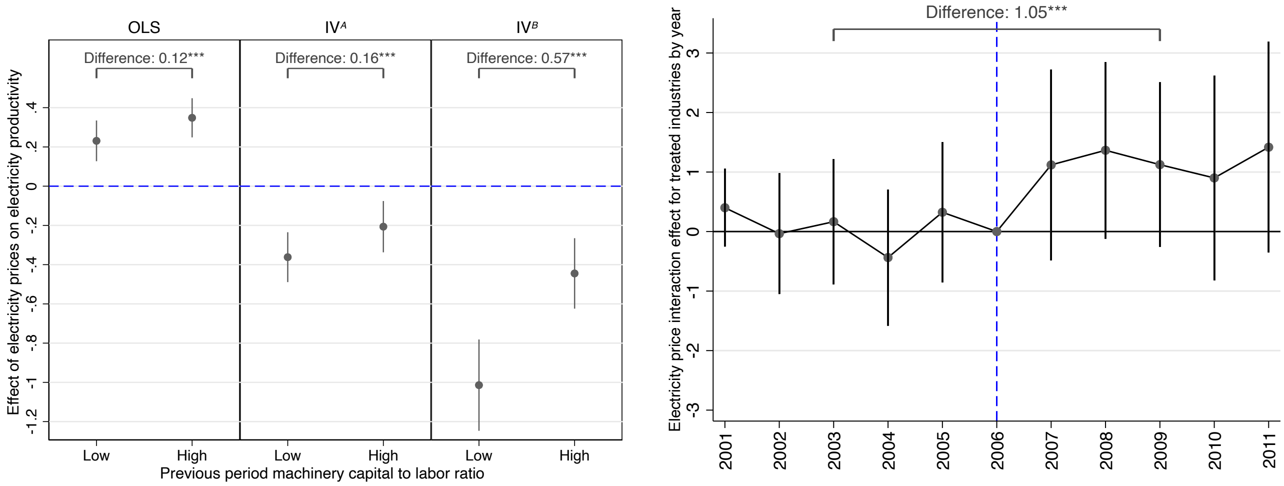
	Average wage per worker (log)			TFP (log) (Wooldridge, 2009)			Price-MC markups $\log(\mu)$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(P^E)$	0.0314**	-0.142***	-0.177***	-0.00699***	-0.0156***	-0.0330***	-0.0183***	-0.0404***	-0.106***
	(0.014)	(0.028)	(0.033)	(0.002)	(0.003)	(0.006)	(0.006)	(0.011)	(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 first 9 columns are based on regressions in levels because profits can be negative. In panel (b), the ratio of electricity to coal is in quantity terms in MWh per tonne. Other fuels refer to gas, coal and oil. The inverse hyperbolic sine (IHS) of investment is taken to deal with zeros in investment. 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. The rest of the table layout follows the same structure as the main Table 2.

increase in variable costs from a decrease of electricity prices is consistent with the prediction of the model in Section II., and strongly suggests that plants scale up with declining electricity prices. The increase in employment confirms this scaling up effect (Columns 8-9 in Table 3).

Second, the machine to employment ratio increases as shown in Columns 1-3 in Table 4b, driven by an increase in investment in machinery (Columns 1-3 in Table 4c).[64] Third, the employment to electricity ratio decreases (Columns 4-6 in Table 4b), while employment increases (Column 7-8 in Table 3). Fourth, the machine to electricity ratio increases (Columns 7-8 in Table 4b). This prediction is perhaps the most surprising and arises due to the discreteness in technological choices and complementarities in inputs. In a simple model without technological choices the machine to electricity ratio would unambiguously

[64] I use the inverse hyperbolic sine instead of the log of machinery investments to deal with zeros. The effects can be interpreted as elasticity.



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

Figure 4: Electricity price effect, foreign capital access liberalization, and existing machinery labor ratio

Notes: Panel (a) shows the effect of electricity prices on electricity productivity by a median sample split for plants with a low or high machinery capital to labor ratio based on the previous period median within respective four digit industries. 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 in parentheses are two-way clustered at the plant and the state by year level.

fall (see Lemma 2 in Section II.).

Using baseline capitalization and FDI shocks to capital.— I next provide two further pieces of model-consistent evidence for the relative machine capitalization as a central mechanisim by showing that the effects mainly operate through firms with a lower machinery to labor ratio.

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

Second, for an exogenous shock to machinery capitalization, 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 investments into capital as well as an increased maximum cap of foreign capital investments.[65] 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 using treated industries, pre and post the 2006

[65]See Bau and Matray (2023) for a detailed description. Table A.19 lists the treated industries.

policy, and interact it with electricity prices all appropriately instrumented to analyse the differential effect of prices for firms that receive an arguably exogenous shock to their capital.[66] This design is used to test whether firms with more capital show smaller electricity productivity responses from electricity prices. Figure 4b shows the coefficient on the triple interaction in an event study design with electricity productivity as outcome five years before and after the policy took effect, using instruments and corresponding interactions based on IV^A. Indeed, after the policy took effect in 2006, the effect of electricity prices is positive for treated plants relative to non-treated plants. The triple difference using the post 2006 period instead of individual years is statistically significant at the 1% level (Table A.21). This means that the firms that received the boost in capital show no increased electricity productivity from lower electricity prices, while non-treated firms do.[67] While the parallel trends assumption cannot be tested directly, the pre-trends shown in Figure 4b are flat. Table A.21 shows additional results for labor productivity and output using the 2006 policy change.

Lower electricity prices induce substitution from fossil fuels.— Table 4c shows that lower prices induced substitution from fossil fuels to electricity, a result that I will use below when calculating impacts on emission. Using plants that report physical electricity and coal consumption, 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. The consequence of this substitution from fossil fuels to electricity is that energy productivity (output divided by all energy units) increases even more than electricity productivity.

Lower electricity prices increase electric equipment, wages, TFP, product lines, and markups.— Using detailed data on plant inputs allows me to calculate electric equipment as share of total inputs at the plant level. Appendix Table A.18 shows that lower electricity prices increase the share of electric equipment, such as powerlooms, consistent with mechanisims presented above.[68]

Apart from improving profitability for the firm, increases in labor productivity can also help increase worker wages (Bhagwati and Panagariya, 2014). Columns 1 to 3 in Table 4d shows that lower electricity prices increased average wages per worker. This is likely 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, the 48% electricity price decline predicts a $(1-0.48)^{-0.1595}-1=11\%$ increase in wages, which can explain around 20% of the 60% increase in wages during this period as documented in Section III.C..

[66] 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).

[67] The combined effect for treated firms is now slightly positive compared to negative for non-treated, see Table A.21.

[68] Since many plants may not report equipment as part of their inputs, and rather as part of their machinery capital, this result should be interpreted somewhat cautiously.

Upgrading to more modern capital intensive production processes could also have direct effects on plant total factor productivity. I estimate that the effects on TFP are small (Columns 4-6 in Table 4d), but highly significant and robust to different methodologies to estimate TFP.[69] These results are consistent with firms switching to products that require more electricity but also improve performance.[70] There is also evidence that lower electricity prices increase product variety produced measured as the number of product lines a plant has (Table A.18 in Appendix A.12).

Finally I examine how electricity prices affect price over marginal cost markups $\mu \equiv P/MC$.[71] Columns 7 to 9 in Table 4d show that markups increase with declining electricity prices. The improvement in profitability comes not only with firm expansion but also with an increase in markups. The adjustment of markups suggests that there is imperfect pass-through of declining costs to consumers raising an important question of how the incidence of electricity price changes is distributed, which I analyse next.

D. The Incidence of Electricity Price Changes

The degree to which firms pass on increases or reductions in electricity prices to consumers determines the incidence of electricity price changes. As described in Section IV.E. I estimate pass-through elasticities by industry. The cumulative distribution function of these pass-through elasticities, as well as two example regressions are presented in Figure A.30 in Appendix A.14. The vast majority of pass-through elasticities is between 0.8 and 1.1. A pass-through elasticity of greater than one means that costs are disproportionately passed through to consumers.[72] This can be the case if producers fail to collude in an oligopoly at baseline. An increase in costs can help to solve the coordination problem of raising prices, which can explain pass-through rates greater than one.

The pass-through elasticities are combined with the plant level markups ($\widehat{\mu}$) into the pass-through rates $\widehat{\rho}_{MC}$. The three components to calculate incidence I^{share}, the Lerner index $\widehat{L}$, the market demand elasticity $\widehat{\eta}_D$ and the marginal cost to price pass-through rate $\widehat{\rho}_{MC}$ are reported in Table 5. The estimates shown are the median, the 25th and 75th percentile of the distribution across plants, sectors and years.[73]

Table 5 reports a 63% median incidence share of consumer surplus I^{share} over all sectors and the whole sample period, indicating substantial benefits for consumers. This implies that electricity pricing for industry is important for industrial development and consumer welfare alike. The reduction in cross-subsidisation from industry to agriculture (see Section A.5) may thus have also benefited non-

[69] The baseline effects are on TFP measured via Wooldridge (2009) using deflated revenue data, so should be interpreted as revenue TFP. Since markups shrink, we would expect the impact on physical TFP to be larger. Table A.16 in Appendix A.12 provide the effects on TFP measured via Olley and Pakes (1996), Levinsohn and Petrin (2003) or Ackerberg, Caves and Frazer (2015).

[70] This is in line with Abeberese (2017) who found improvements in TFP, employment and investment.

[71] See Section IV.E. for how I estimate markups.

[72] 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.

[73] $\widehat{L}$ and $\widehat{\rho}_{MC}$ vary at the plant-year level, and $\widehat{\eta}_D$ varies at the industry-state-year level. The estimates for the Lerner index are in line with the descriptive statistics of markups reported in Table 1.

Table 5: Electricity prices 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	$\widehat{L}$	$\widehat{\eta}_D$	$\widehat{\rho}_{MC}$
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 the share of incidence on consumers from electricity price changes, according to $I^{share} = I/(1+I)$. The quantiles are across all plants and all periods, using the sampling multipliers as frequency weights. The reported components ($\widehat{L}_{jisrt}$, $\widehat{e}_{D,isrt}$ and $\widehat{\rho}_{MC,jirst}$) for the calculation are described in the text. The monopoly case corresponds to $\widehat{L}_{jisrt} = 1/\widehat{e}_{D,isrt}$, and the perfect competition case to $\widehat{L}_{jisrt} = 0$.

industrial consumers. In the next Section V.E. I calculate the aggregate effects on welfare in terms of profits, consumer surplus and CO_2 emissions.

There is some heterogeneity across industries and years. The 25th and 75th percentiles in consumer shares in Table 5 are 53% and 79% respectively. Even at the 5th percentile, the share of consumer incidence is a quarter of the total. Figure A.31 in Appendix A.14 plots the incidence share over time for six aggregate industries, showing that there has been a few percentage points decline in consumer incidence share over time. I also calculate the incidence under the extreme conduct assumptions of monopolies and perfect competition, where $L = 1/\epsilon_D$ and $L = 0$ respectively. As in Ganapati, Shapiro and Walker (2020), the monopoly estimate is below the oligopolistic estimate, and the perfect competition higher than the oligopoly counterpart.[74]

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 governments receipts through utilities from the 48% price reduction, and what was the effect on aggregate CO_2 emissions? These are back of the envelope calculations, and I ignore general equilibrium effects.

For the monetary gains, I use the semi-elasticity of profits to electricity prices to calculate that a 48% reduction of electricity prices led to an increase of 14.08 mil. ₹ for the average plant.[75] This translates into aggregate gains in profits for the entire manufacturing sector of 1.69 trillion ₹ or 38 billion USD (in constant 2004 terms), equivalent to 2.8% of Indian real GDP in 2013.[76] The gains in consumer surplus have accordingly been 64 billion USD based on the incidence share estimated in Section V.D.. The reduction in government profits from sale of electricity was 143 billion ₹ or 3 billion USD.[77] The 99 billion

[74] For the perfect competition case, the incidence share is equivalent to the pass-through rate as $L = 0$ (see Equation (10)).

[75] I take -21.25 as the average of the two estimates (-20.47 and -22.03) in Table 4a. A 48% reduction corresponds to $\log((1-0.48)^{-21.25}) = 13.90$ mil. ₹.

[76] There were 121,825 plants in the manufacturing sector sampling frame in 1998, calculated by summing over the sampling multiplier.

[77] While profit per kWh fell with electricity prices, the quantity sold increased. I take -0.638 as 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

Table 6: 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, all conditional on reaching the same output gains. Gas is omitted because its use negligibly small in comparison.

USD welfare gains imply annualized gains of 7.1 billion USD (from 1998-2000 to 2013), which in turn are equivalent to 0.5% of Indian GDP or 5.9% of manufacturing value added in 2013 (UNIDO, 2016). The halving of industrial electricity prices from its comparatively high level had substantial effects on welfare and the Indian economy. Note that average wages (Table 4d) and employment also increased (Table 3) leading to potential additional welfare increases through workers.

Next, I calculate the effects on 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 use and report the details of the calculation and data sources in Appendix A.15. From a baseline of 134.5Mt CO_2 emissions in manufacturing averaged across 1998-2000, the 48% decline in electricity prices increased emissions by 31% or 41.7Mt (Column 1 in Table 6). This was driven by the scaling up of firms. The effect of prices on improving electricity productivity as well as substitution from coal and oil had a large attenuating effect on this emissions increase.

Table 6 shows how large the emission increases had been if we switch off these channels, 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 productivity effects, i.e. setting the effect in Column 1 in Table 2 to zero, would have produced a 82% increase in emissions. Switching off both channels would have increased emissions by 115%. While the secular decrease in industrial electricity prices increased CO_2 emissions, this increase is less than half of what we would expect had there not been the effect of electricity prices on electricity productivity.

Using a social cost of carbon of 100USD per tCO_2, the costs from higher emissions are 4.2 billion USD. While this is sizeable, it is small compared to the welfare gains of 99 billion USD. From this point of view, the reduction in industrial electricity prices was welfare enhancing, even accounting for damages from

purchased from the grid in 1998-2000 in the sampling frame (53.5 billion kWh), the average cost of electricity supply in 2004 of 2.54 ₹ /kWh from the Ministry of Power (2009) and the average industrial electricity prices for 1998-2000 and 2013 (6.4 ₹ /kWh and 3.32₹ /kWh): $(3.32 - 2.54) \cdot 53.5 \cdot (1 - 0.48)^{-0.638} - (6.4 - 2.54) \cdot 53.5 = 143$ billion ₹.

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

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

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

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

	Output (log)			Coal consumption (log)			Employment (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

(**c**) Coal prices and profits, costs and TFP

	Profits (mil. ₹)			Total costs (mil. ₹)			TFP (log) (Wooldridge, 2009)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(P^C)$	-5.940***	-6.315	-7.393	-14.44**	-29.82	3.729	-0.000544	-0.0198	-0.0306
	(1.628)	(15.050)	(25.859)	(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: Each column represents a separate regression at the plant level. Reported are results from OLS regression on logged coal prices, and IV regressions. The IV^E is based on the coal prices of similar plants. In the shift-share IV^F, the share is the logged distance of a district to the nearest coal mine and the shift is the logged raw coal price for industry at a representative mine. The dependent variables are indicated and described in Section III.B.. In panel (a), coal productivity is the value of output divided by the quantity of coal used in tonnes. In panel (b), the regressions are reported in levels except for TFP because profits can be negative. The first stage statistics are reported. All regressions contain industry by year by region fixed effects. Regressions are weighted by the recorded sampling multiplier. Standard errors in parentheses are two-way clustered at the plant and the state by year level. Plant output is deflated using 3-digit industry deflators and coal prices are deflated using a general fuel and electricity wholesale price deflator.

emissions. A reduction in industrial coal prices, on the other hand, would have had very different effects to which I turn next.

F. The Contrary Effects of Coal Prices

The mechanisms discussed in this paper are based on 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 associated with more modern industrial production equipment. I next test this prediction using plant level coal prices for the roughly 45,000 observations of plant-years that use coal. As these suffer from similar endogeneity problems as electricity prices, I construct two instruments as described in Section IV.D..

Indeed, in contrast to electricity prices, lower coal prices significantly *decrease* coal productivity and have no significant effect on labor productivity as shown in Table 7a. While lower coal prices significantly increase coal consumption, they only have a small and insignificant effect on output in the IV specifications, as shown in Table 7b. The impact on electricity use is either insignificant or negative. There is a small insignificant effect on profits and revenues and an ambiguous effect on costs (Table 7c). There is no similar scaling up effect with lower coal prices as there is with higher electricity prices. Contrary to electricity prices, higher coal prices also have no significant effect on TFP (Table 7c).[78]

G. Policy Implications

There are five policy implications to highlight in the context of industrial development that follow from the findings. First, cross-subsidizing low agricultural and residential rates with high industrial rates has 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 is harmful, as it may increase electricity prices, since this reasoning conflates two types of externalities. The climate and pollution externalities from fossil fuel can be internalized through pricing carbon while subsidizing industrial electricity prices at the same time to address the industrial development and efficiency externality. This would be similar to subsidzing clean electricity generation, as long as lower prices are passed through to industry. Third, and relatedly, with India and many other low and middle income countries aiming to move to renewable electricity generation, electrification of industry is essential to reaching climate goals. This requires incentives for firms through lower relative prices between clean electricity and carbon intensive fossil fuels, which can help direct investment in a clean transition as in Acemoglu et al. (2012, 2016), especially given the results in the previous section that taxing dirtier fuels has little direct effect on firm performance. Fourth, capital constraints could introduce frictions into the upgrading to modern technology as shown in Appendix A.2 (see also Lanteri and Rampini (2023*a*,*b*); Hawkins and Wagner (2022)). The reported estimates would be even larger in the presence of such capital constraints, and complementary policies that address capital frictions could fully unlock the technology upgrading mechanism. Finally, while industrial lobbying efforts may have been focused on securing tariffs to restrict competition on output markets, the findings imply that focusing efforts on lowering industrial electricity prices in the context of political constraints may be a promising alternative.

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

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 environmental and developmental goals by improving electricity productivity and labor productivity in firms. Policy makers might regard this as a win-win in a situation where trade-offs typically occur, particularly in lower income countries.

Using instrumental variables to remove bias and detailed data on electricity consumption and average prices at the plant level, I recover estimates at the micro level that help explain secular aggregate trends in electricity productivity and labor productivity at the macro level in India. I interpret the results through the lens of a model with discrete technological choices and complementarities between electricity and capital and test model predictions. Firms are incentivized to use modern capital intensive and electricity-using production techniques with lower electricity prices. This boosts output and overcompensates input substitution effects, which increases electricity and labor productivity through higher capital utilization.

The benefits of lower 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 just over half of the welfare benefits accrue to consumers through lower output prices. While total carbon emissions increase through the scaling up of industry, the electricity efficiency increase reduces the emission increase by more than a half. The drop in industrial electricity prices in India led to significant overall welfare benefits across producers, consumers, utilities and environmental damages. Lower coal prices have no such positive effects as electricity prices. This implies that policies that increase fossil fuel prices to internalize environmental and climate externalities, while addressing high industrial electricity prices such as reducing cross-subsidization to address the developmental and efficiency externalities may be particularly beneficial.

While the price of electricity for industry is important and can affect technological choices and capital accumulation, the reliability of electricity supply has been shown to be similarly important in a separate literature. Prices and shortages are not related in India due to the institutional context, and I use data on electricity shortages in the analysis to test robustness. Future research could analyses the effect of prices and shortages in a unified framework to integrate two related strands of the literature, as well as consider production networks and general equilibrium effects.[79]

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[79] Choi and Shim (2022) show that there can be spillovers and general equilibrium effects from technology adoption in a context of industrialization.

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APPENDIX FOR ONLINE PUBLICATION

Complementary inputs and industrial development:
Can lower electricity prices improve energy efficiency?

by Gregor Singer
LSE

A.1 Model proofs

The firm's optimization problem is:

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

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 these 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:

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

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 $\frac{\partial\Pi^*}{\partial p_E}=-E^*$.[80,81] Taken together this implies that $\frac{\partial E*}{\partial p_E}\leq 0$.

Therefore, since $\phi<1$:

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

■

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 Δ_{PE} for which electricity productivity is increasing, i.e. $\frac{PQ^*}{E^*}|_{p_E}<\frac{PQ^*}{E^*}|_{p_E-\Delta_{PE}}$. A proof of existence of such parameter values is the example in

[80] 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 $\delta\Pi^*(p_E)+(1-\delta)\Pi^*(p_E)\geq\Pi^*(p''_E)$.

[81] 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.2, which is a simulation based on the model in Equations (A.1), (A.2) and (A.3). Choosing an initial p_E close to the technology threshold results in an increase of electricity productivity from an electricity price decrease. It is possible to select additional examples by repeatedly drawing parameter values and price decreases from independent uniform distributions and filtering by the below conditions.

Because of Lemma 1, we know that this proposition can only hold in the presence of a technology switch. The necessary and sufficient conditions on parameter values and electricity price decreases for this proposition and technology switch to hold are:

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

The set of all possible parameter values that fulfil 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. A numerical example as in Figure A.2 is sufficient for a proof of existence. ■

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

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

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

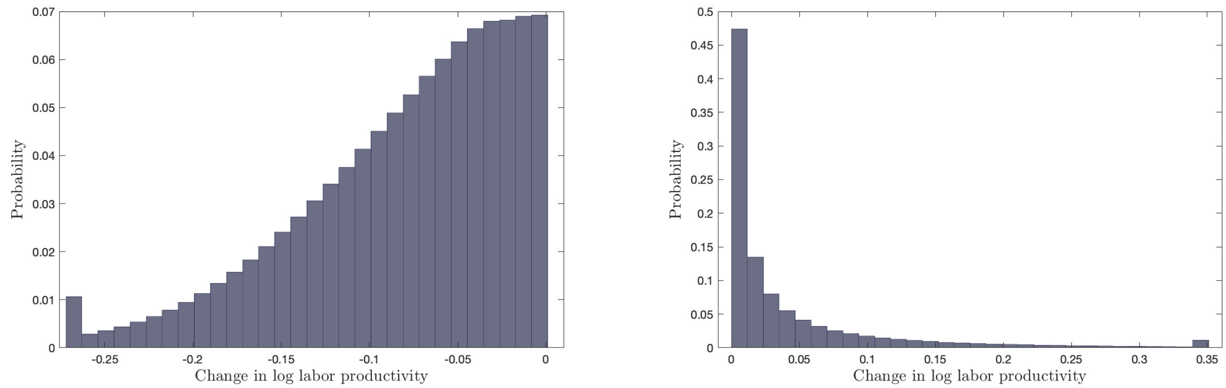
$$p_K, p_L, p_E, K, L, E, \kappa_{KE}, \kappa_{XE}, \kappa_{LE}, \kappa_{PQE} > 0$$

Observe directly that

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

■

In the absence of technology choices, i.e. $c = 1$, the effect of electricity price decreases 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.



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

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

Figure A.1: Labor productivity and electricity price decreases with constant technology: the role of complementarity between capital services and labor

Notes: Both panels show histograms of model based simulations of 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.

Figure A.1 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.[82] 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.

[82]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.2 shows several margins of how a firm adjusts with the decline of electricity prices. Panel (a) to (d) in the first two row repeat the graphs from Figure 2. After a certain threshold of electricity price decreases Δ_{PE}, the firm switches to the more profitable (Panel b) modern technology which brings about a step change in electricity productivity, the electricity to capital ratio (Panel c) and labor productivity (Panel d). When switching to the modern capital intensive and electricity-using technology, electricity use increases as illustrated in Panel (e). Employment also increases as shown in Panel (f). The fourth row shows that the switch to modern technology expands the firm: total sales in Panel (g) and total costs in Panel (h) increase at the threshold. The last row shows two further input ratios. Driven by substitution to the modern capital intensive technology, the capital services to labor ratio increases at the threshold in Panel (i), which allows both employment in Panel (f) and labor productivity in Panel (d) to also increase. Each of these predictions on input productivities, profits, sales, total costs and input ratios generated by the model are tested and corroborated in the empirical analysis.

Figure A.3 shows the impact of introducing capital constraints $K \leq b$, which modifies the firm maximisation problem. Figure A.3 plots 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 A.2. 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.

Figure A.4 plots the same electricity productivity graphs as in Panel (a) of Figure A.2, 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.4 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 even more modern technology becomes available).

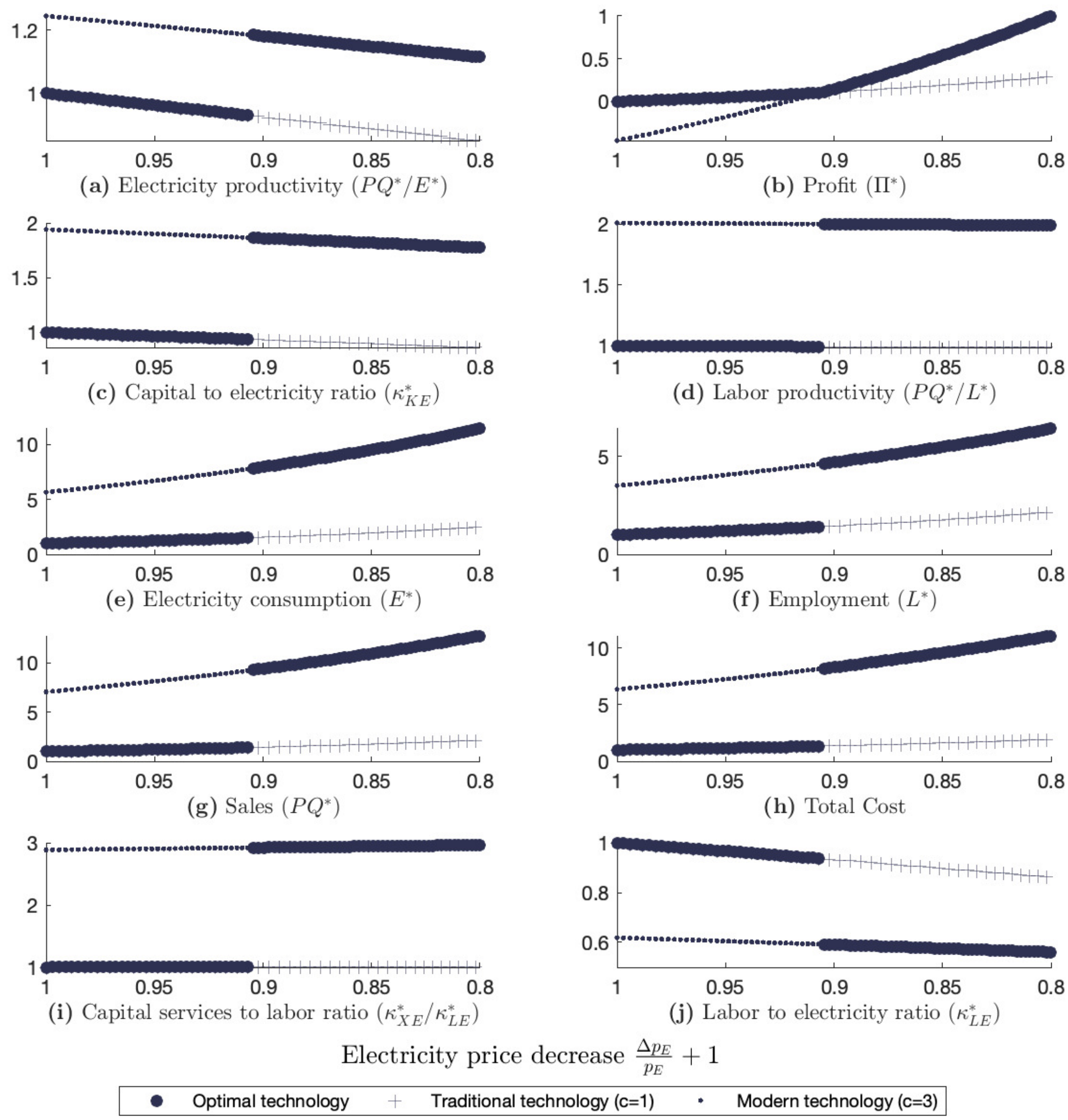


Figure A.2: Electricity price decreases, total revenue, costs and input ratios

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

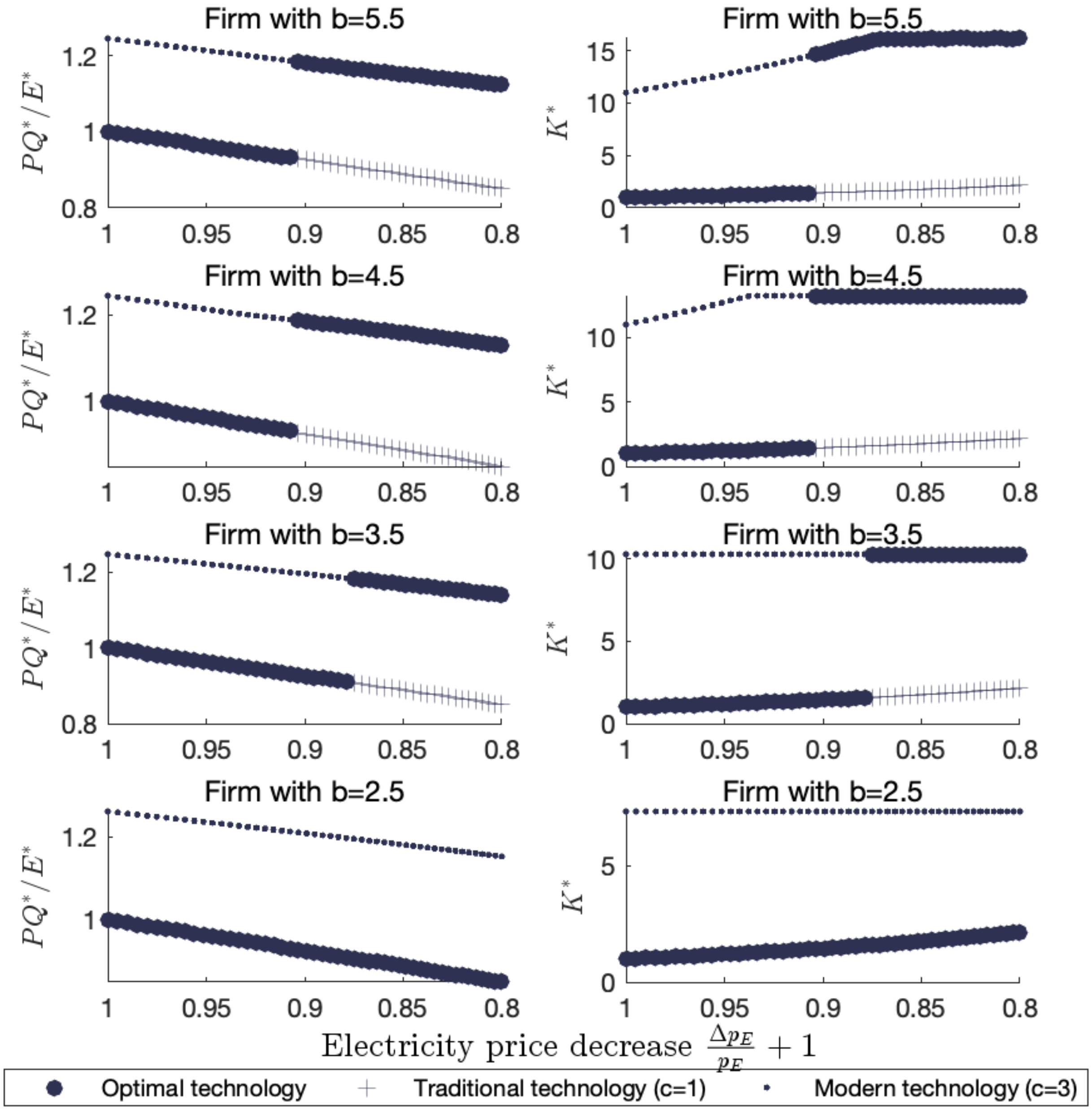
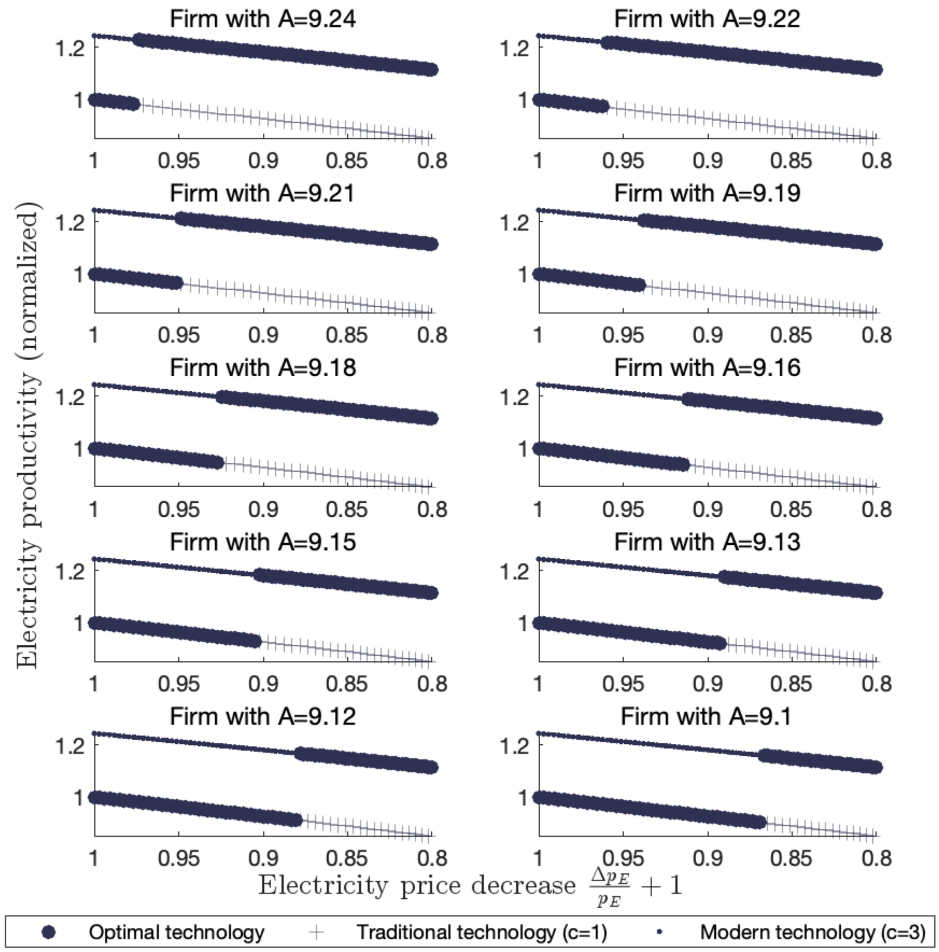
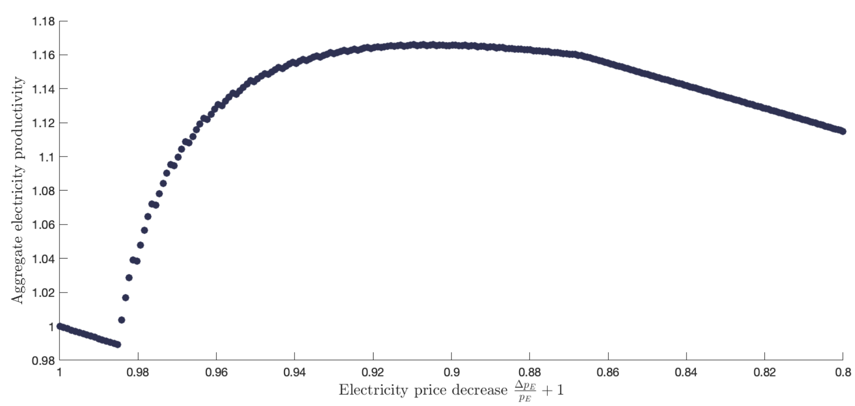


Figure A.3: Electricity price decreases, total revenue, costs and input ratios

Notes: The figures plot electricity productivity on the right and capital on the left (all normalized) relative 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). All outcomes are normalized by dividing by its value at the traditional technology ($c = 1$) and original electricity price ($\Delta_{PE} = 0$). The parameter values for this simulation are fixed at $\{p_K = 6, p_L = 5, p_E = 0.5, c = 3, \hat{\alpha}_l = 1/3, \alpha_e = 0.5, \rho_l = -0.5, \hat{\rho}_e = -0.5, \phi = 0.95, A = 9.15, m = 1\}$ and Δ_{PE} varies from 0 (corresponds to $p_E = 0.5$, and 1 on the horizontal axis) to $1/12$ (corresponds $p_E = 0.4$, and 0.8 on the horizontal axis).



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



(**b**) Impact on aggregate electricity productivity

Figure A.4: Electricity price decreases, heterogeneous firms and aggregate electricity productivity

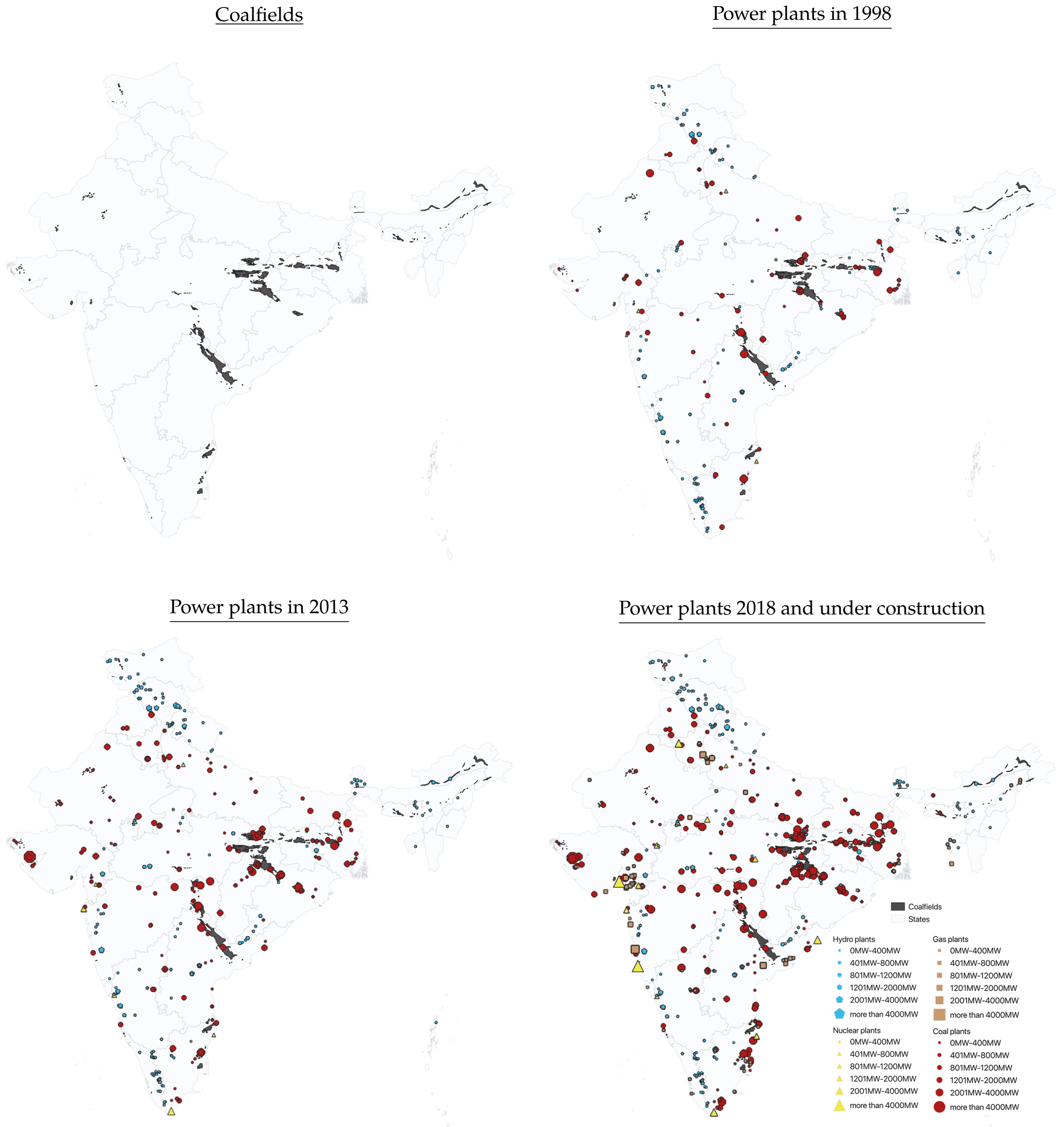
Notes: Panel (a) plots electricity productivity for 10 selected firms that have heterogeneous total factor productivity A_i against relative electricity price *decreases* on the horizontal axis. The figures show optimal choices both conditional on a specific technology as indicated, and the overall optimum (thick line). The 10 firms that are displayed in Panel (a) are selected from the 100 firms for which A_i varies from 9.1 to 9.25, and have a value for A_i indicated above each graph. Panel (b) hows 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 ($\Delta_{PE} = 0$). 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 Δ_{PE} varies from 0 (corresponds to $p_E = 0.5$, and 1 on the horizontal axis) to 1/12 (corresponds $p_E = 0.4$, and 0.8 on the horizontal axis).

A.3 Maps of power plants and coal reservoirs

Figure A.5 visualizes the levels and increases of coal fired power plants near coalfields in maps using geo-located data on Indian coalfields and power plant characteristics. Indeed, 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. This is based on 594 Indian districts. The coefficient is -191.4 with a robust t-statistic of 3.8 and R^2 of 0.066.

Apart from showing that coal plants are built near coalfields, the maps also shows that hydro plants are near rivers especially in the mountainous region, 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 lion's share is borne by coal-based generation (around 85% throughout).

Figure A.5: Maps of coalfields and powerplants by year



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

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

This section provides further details on the ownership dynamics of Indian electricity generation, and the impact of the Electricity Act of 2003 on private ownership and electricity prices. In 1998, state and central government owned 65% and 30% of installed capacity respectively, with the remaining 5% owned privately (Ministry of Power, 1998*a*; Planning Commission, 2001). The Electricity Act of 2003 aimed to open this heavily regulated sector to more competition,[83] 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).[84] In February 2019, the share of the private sector (46%) was almost equal to the share of the combined government owned capacity (Central Electricity Authority, 2019).

The opening up of the power market after the Electricity Act of 2003 appears to have contributed to lower electricity prices. I examine the relationship between the median of the district level industrial electricity price and the share of installed coal fired capacity that is privately owned within a district. Table A.1 shows that the share of privately owned plants is significantly negatively associated with median electricity prices – but only after 2003.[85] A one percentage point increase in the share of privately owned plants decreases median electricity prices by 2.4%. This suggest using 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, likely predicting the location of additional generating capacity (see Map A.5). Indeed, as Columns 4-6 of Table A.1 show, the share of private thermal capacity is predicted by the distance to coalfields. Therefore, I construct a Bartik instrument 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.

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

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

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

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

	Electricity price			Share private capacity			Electricity price		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Share private capacity	0.09	0.11	0.06						
	(0.96)	(1.18)	(0.64)						
Share private capacity	-0.24***	-0.24***	-0.20**						
x After 2003	(-2.94)	(-2.94)	(-2.36)						
Distance to coalfield ('00 km)				-0.02***	-0.02**	-0.03***	-0.07**	-0.08***	-0.09***
x After 2003				(-2.69)	(-2.42)	(-2.85)	(-2.47)	(-2.64)	(-3.04)
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 median electricity price within a district as dependent variable in the first three columns and last three columns. The Indian Electricity Act was introduced in 2003. The share of privately owned capacity in district level installed capacity includes private/state and private/central ownership categories. The total capacity covariate controls for total installed capacity at the district year level. The distance to coalfields at the district level is in hundreds of km. Columns 4-6 have the share of privately owned capacity as dependent variable. District fixed effects control for 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 at the district level. The coefficients on the interaction in column (1) and (2) correspond to a semi-elasticity of 0.03. Stars indicate p-values: * < 0.1, **< 0.05, ***< 0.01.

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

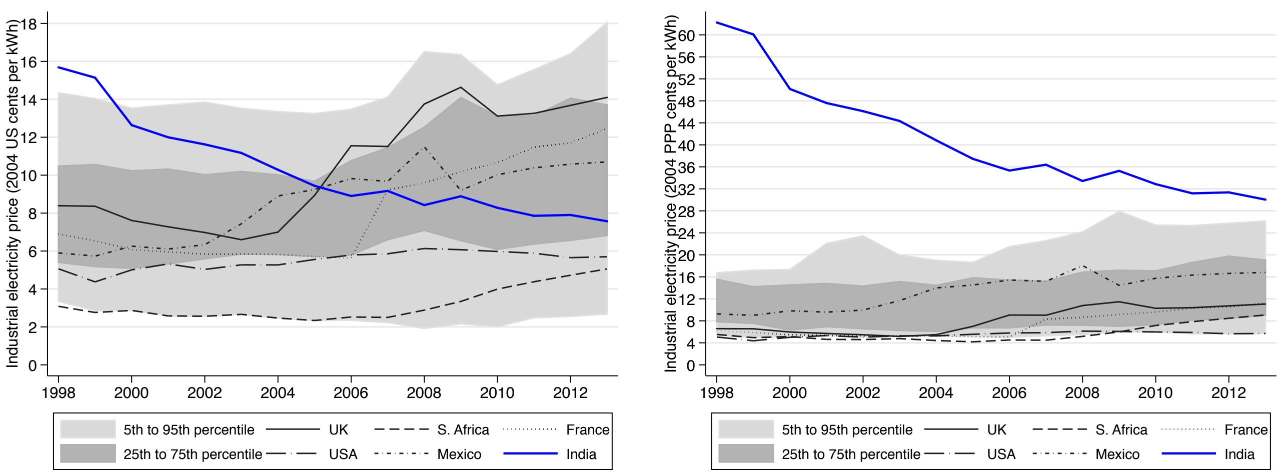
Average electricity tariffs in India were the equivalent of 15.7 US cents (2004 USD) for industrial users in 1998. As Figure A.6 and Table A.2 show, the G7 or OECD average was around 8.9 US cents in 1998, implying that the Indian industrial tariffs were around 80% higher. Adjusting for the difference in general price levels between India and G7 countries, Indian tariffs were around 756% higher in 1998 based on purchasing power parity (PPP). As Figure A.6 and Table A.2 show, Indian industrial tariffs were higher than G7 average prices until 2004 using market exchange rates. In PPP terms Indian prices were still 140% higher than the G7 average in 2013.

The high electricity prices in India for industrial users are in contrast to low electricity price for agricultural and residential users, 2.6 and 6.8 US cents respectively in 1998, even though the cost of supply is usually lower for industrial users (Ministry of Power, 1998*b*).[86] This asymmetric price pattern leads to heavy cross-subsidization in Indian electricity. Industrial tariffs have typically been above the average cost of supply, but high subsidies are required for the agricultural sector. While agricultural consumers made up 32% of electricity consumption in 1998, they only accounted for 3.6% of revenues from electricity sales (Planning Commission, 2002). Despite efforts to reduce cross-subsidization and depoliticize tariffs based on the Electricity Act (2003), industrial tariffs were still 7.6 US cents (2004 USD) compared to 2.2 cents for agricultural tariffs in 2013 (Ministry of Power, 2014). As a result, state electricity utilities have been loss-making almost across the board, recovering only between 73% and 89% of annual

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

costs between 1998 and 2013 (Central Electricity Authority, 2006-2015).

Figure A.7 compares industrial electricity prices across different consumption bands across Indian states in 2007, using manually collected data from government reports (Central Electricity Authority, 2006-2015). Industrial tariffs mostly follow increasing block tariffs, at least up to a point. On average, a higher band (of five bands) is associated with a 2.5 percent increase in the tariff.[87] Figure A.8 uses the plant level data and plots electricity prices against electricity purchased, both after partialling 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 are take into account when identifying the effect of electricity prices.



(**a**) Industrial electricity prices (Market exchange rates)

(**b**) Industrial electricity prices (PPP)

Figure A.6: Industrial electricity prices in an international context (USD and PPP)

Notes: The figures plot real industrial electricity prices for six individual countries. Panel (a) is based on market exchange rates, and Panel (b) is based on PPP conversion factors. The shaded areas correspond to the interquartile range and the 5th to 95th percentile of a given year. This is based on a consistent set of 26 countries for which data for all years was available (see below). Raw price data comes from IEA (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 USD or PPP-USD with exchange rates and PPP conversion factors from World Bank (2017). For India, prices are deflated using a general fuel and electricity wholesale price deflator as in the main text. The base year for deflation is 2004 throughout this paper. Wholesale price deflators are from the Office of the Economic Adviser from the Government of India. 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.

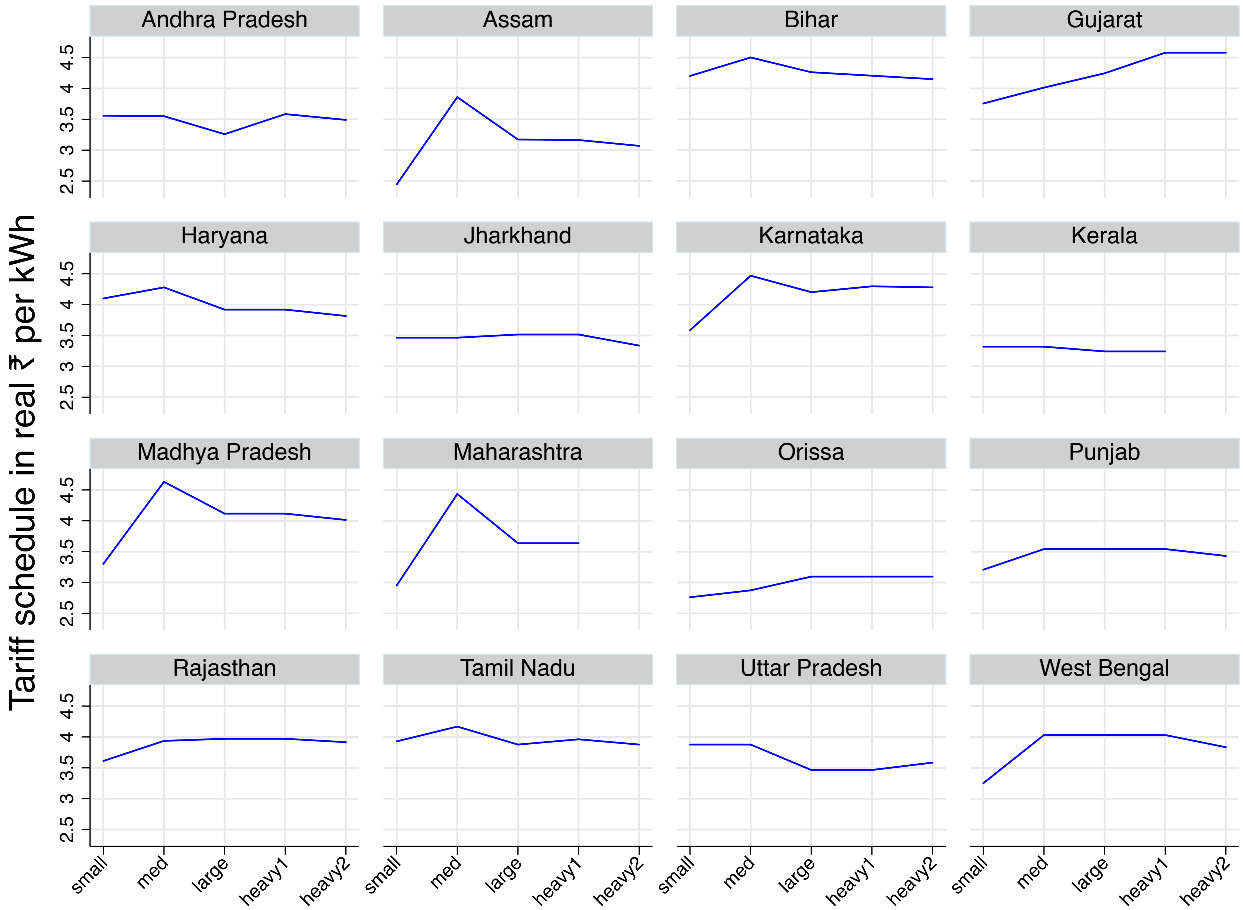
[87] This is from a regression of manually collected log deflated electricity tariffs at the state-year-band level on consumption bands, accounting for state-by-year fixed effects.

Table A.2: Industrial electricity prices in US-cents: India and G7 average (USD and PPP)

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

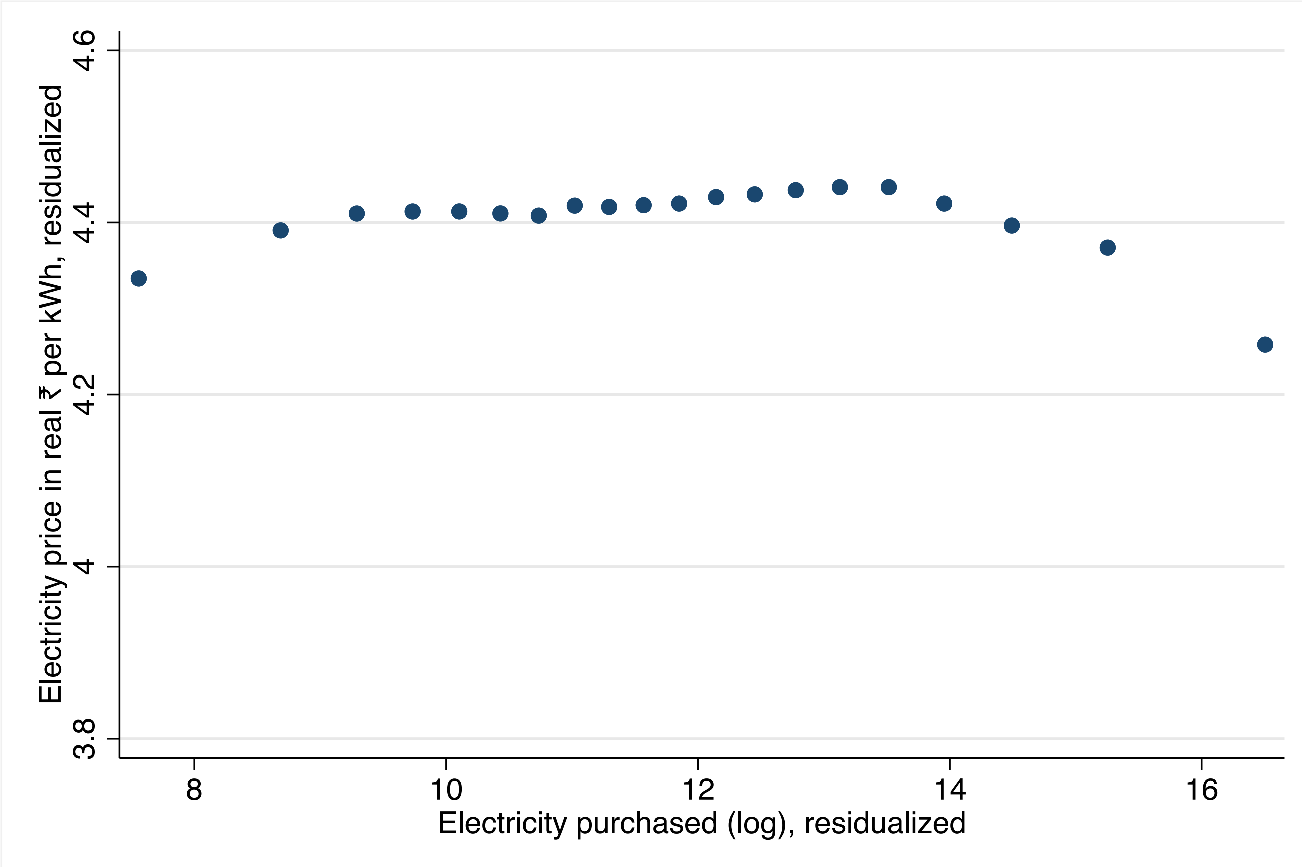
Notes: The table shows the real industrial electricity prices for India, the simple average of the G7 nations, and the simple average of OECD countries, for which data in all years were available. The left part is based on market exchange rates, the right part is based on PPP conversion factors. Raw 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 USD or PPP-USD with exchange rates and PPP conversion factors from World Bank (2017). For India prices are deflated using a general fuel and electricity wholesale price deflator as in the main text. The base year for deflation is 2004 throughout this paper. Wholesale price deflators are from the Office of the Economic Adviser from the Government of India. The included OECD countries are: Canada, Czech Republic, Denmark, France, Germany, Hungary, Ireland, Israel, Italy, Japan, Mexico, New Zealand, Poland, Portugal, Slovak Republic, Spain, Switzerland, Turkey, United Kingdom, United States.

Figure A.7: 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). The tariffs are deflated with the general fuel and electricity wholesale price deflator. The base year for deflation is 2004 throughout this paper. Wholesale price deflators are from the Office of the Economic Adviser from the Government of India.

Figure A.8: Residualized electricity prices and quantitiy purchased



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

A.6 No significant correlation between shortages and electricity prices

Table A.3: Electricity prices and power shortages

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

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

A.7 Discussion of summary statistics Table 1

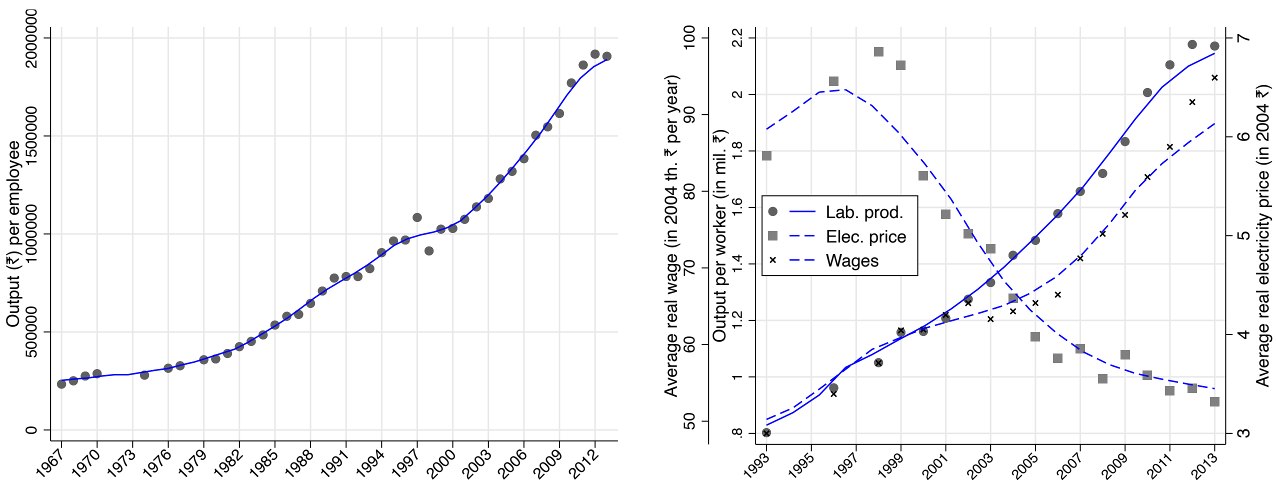
This section briefly describes the summary statistics shown in Table 1. First, there is considerable self-generation as the average amount of electricity self-generated is a quarter of the amount of electricity bought. This is driven by the 35% of plants that engage in self-generation, primarily to cope with outages as discussed in the previous section. Second, average electricity productivity is lower when weighting by consumed electricity, which suggests that larger electricity consumers are less electricity productive.[88] Third, on average, electricity has the largest share in fuel expenditure (0.63).[89] 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%. Marginal cost markups are calculated following De Loecker and Warzynski (2012). Finally, plant total factor productivity (TFP) are similar for different methods, following Olley and Pakes (1996), Levinsohn and Petrin (2003) or Wooldridge (2009).[90]

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

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

[90] Markups are calculated following De Loecker and Warzynski (2012) after estimating production functions following Wooldridge (2009).

A.8 Labor productivity, wages and electricity prices



(**a**) Labor productivity (long run)

(**b**) Labor productivity and wages

Figure A.9: 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. The base year for deflation is 2004 throughout this paper. Wholesale price deflators are from the Office of the Economic Adviser from the Government of India.

A.9 Additional electricity productivity and price graphs

This section provides additional descriptive graphs that the main text refers to. First, similar secular trends in energy productivity, electricity productivity and electricity prices can be observed across most industries (Figures A.13, A.14 and A.15) and states (Figures A.10, A.11 and A.12).[91] This suggest that the observed aggregate trends are not a story of mere reallocation across industries or states.

Second, the patterns in electricity productivity and electricity prices are confirmed with alternative data sources. Figure A.18 uses (IEA, 2016; UNIDO, 2016) data for electricity productivity. Figure A.20 plots the electricity price index in real terms from the Office of the Economic Adviser (2019), and Figure A.21 plots the average of industrial electricity tariffs manually collected from the reports of the Central Electricity Authority (2006-2015) and from Indiastat (2019) through Lok Sabha and Rajya Sabha (Indian Parliament) questions.

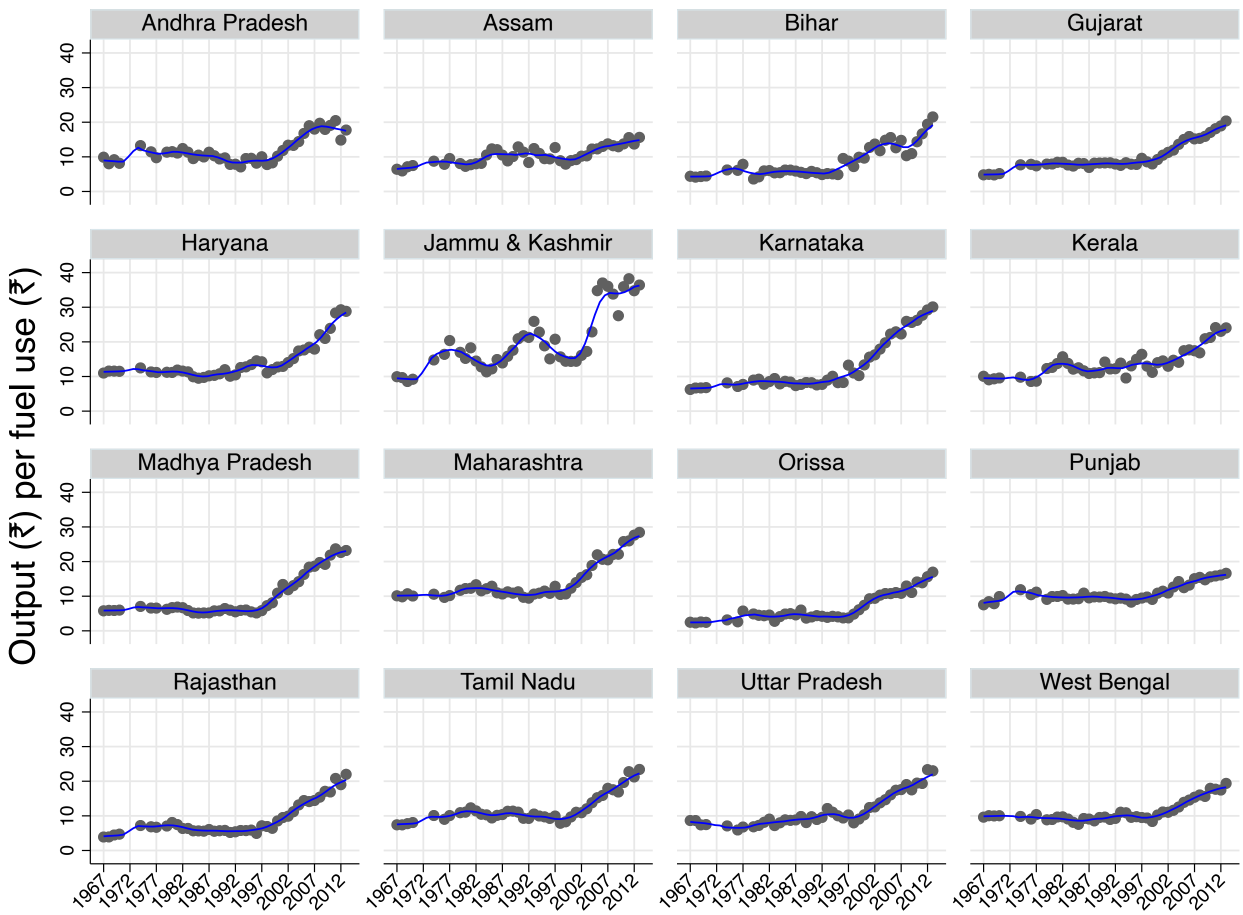
Third, the electricity price trend in the 2000s is in contrast to many other countries, where electricity prices rather increased. Figure A.6 plots industrial electricity prices for a range of OECD and non-OECD

[91] Except for perhaps electricity productivity in metals and minerals (see Figure A.14).

countries. While electricity prices in India almost halved during the sample period, prices in OECD countries grew by roughly 40% (see also Table A.2).[92]

In summary, the trends are similar across different data sources, and the large Indian price decreases provide a rather unique setting to study their relationship.

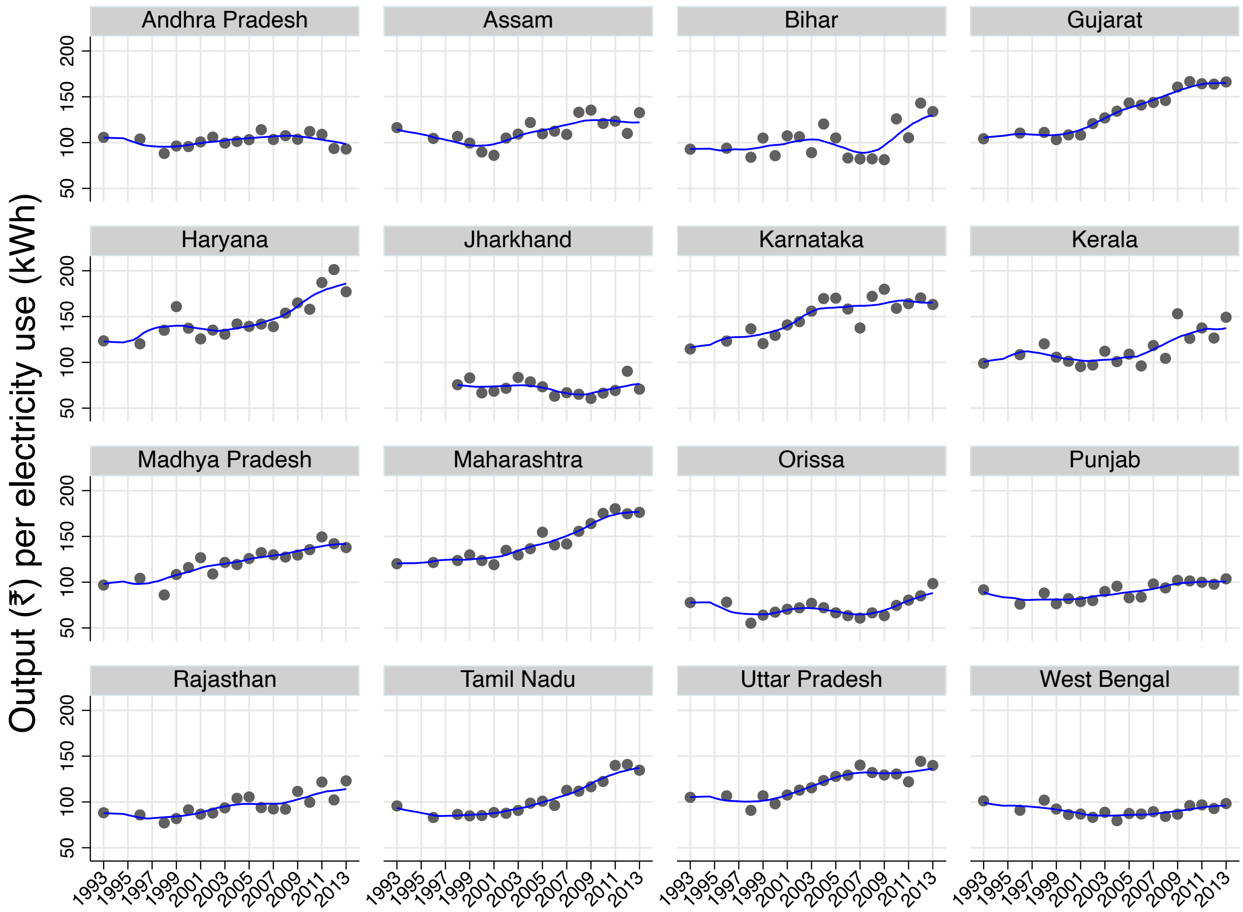
Figure A.10: Energy productivity (per ₹) by state



Notes: The figure plots the annual energy productivity ratios (value of output divided by the value of fuel and electricity used). Sixteen of the largest states are displayed in this figure. Output is deflated at the 2-digit industry level using 2-digit industry deflators before aggregating over industries. Fuel and electricity use is deflated using a general fuel and electricity wholesale price deflator. The ratio of aggregate output to aggregate fuel and electricity consumption is displayed. The base year for deflation is 2004 throughout this paper. Wholesale price deflators are from the Office of the Economic Adviser from the Government of India. 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.

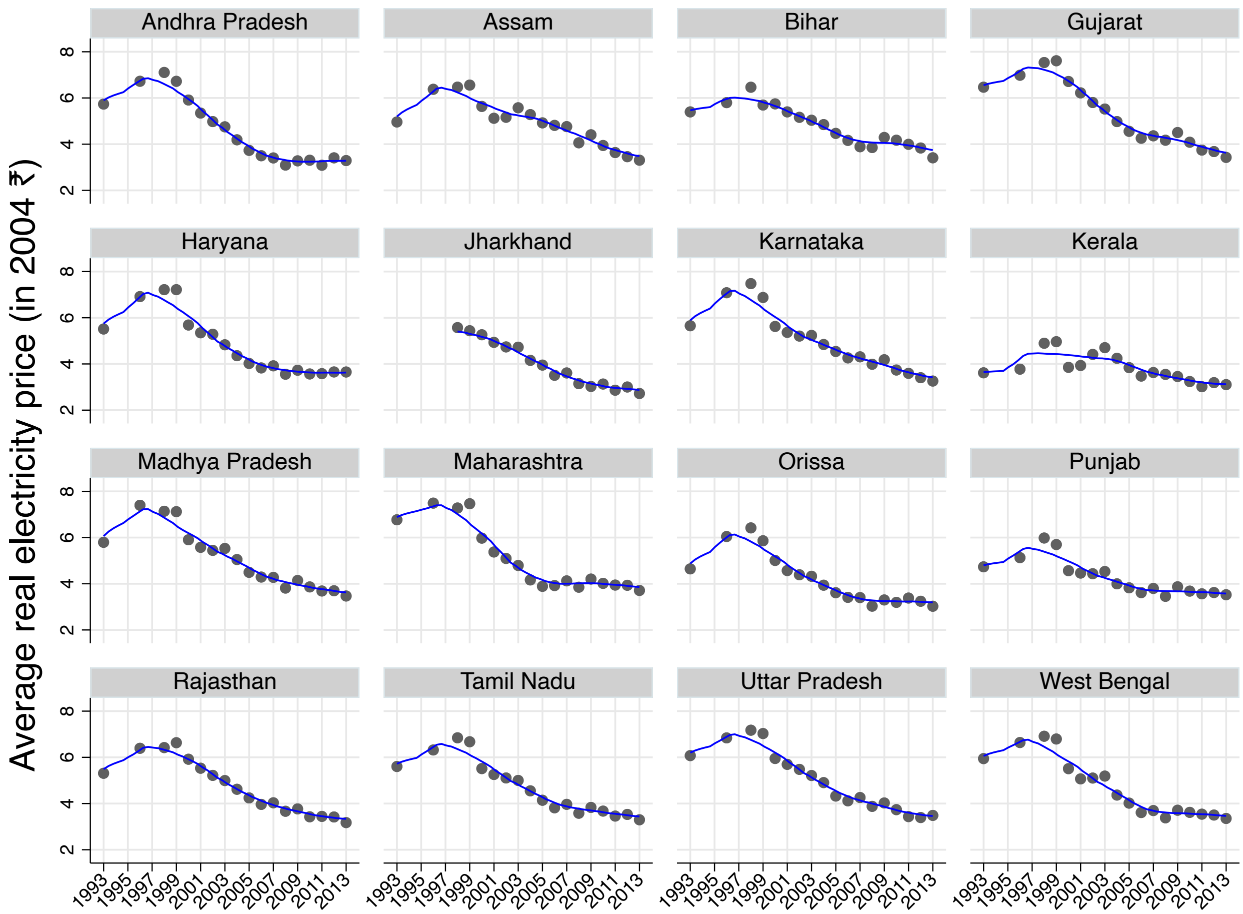
[92]See Sato et al. (2019) for more evidence on general price trends in various countries since 1995. They show that electricity is the most important fuel when accounting for overall energy prices.

Figure A.11: Electricity productivity (per kWh) by state



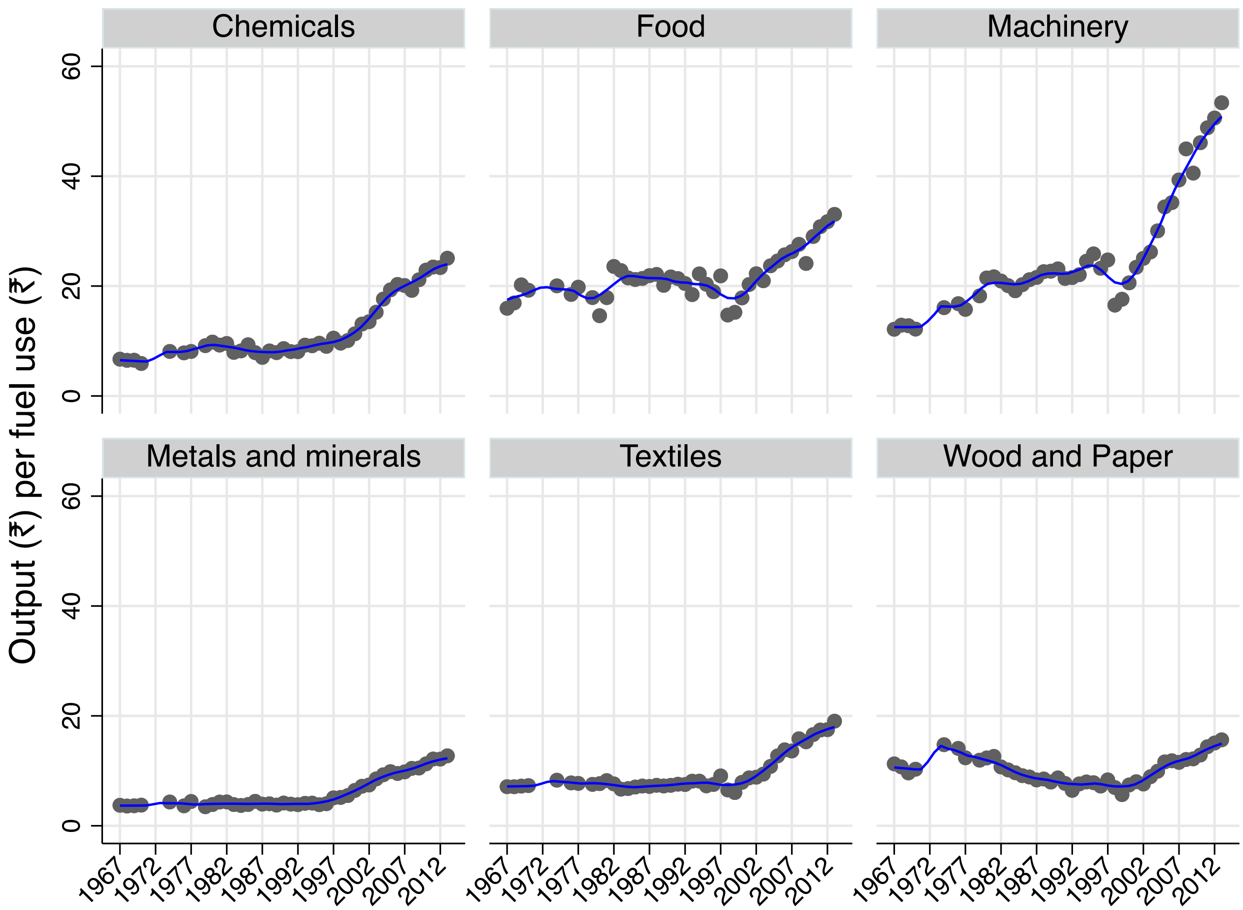
Notes: The figure plots the annual electricity productivity ratios by states (value of output divided by the quantity of electricity used in kWh). Sixteen of the largest states are displayed in this figure. Plant output is deflated using 3-digit industry deflators before aggregating over industries. The ratio of aggregate output to aggregate electricity use is displayed. The base year for deflation is 2004 throughout this paper. Wholesale price deflators are from the Office of the Economic Adviser from the Government of India. All data points come from the raw plant level ASI data and aggregated with sampling multipliers.

Figure A.12: Electricity prices by state



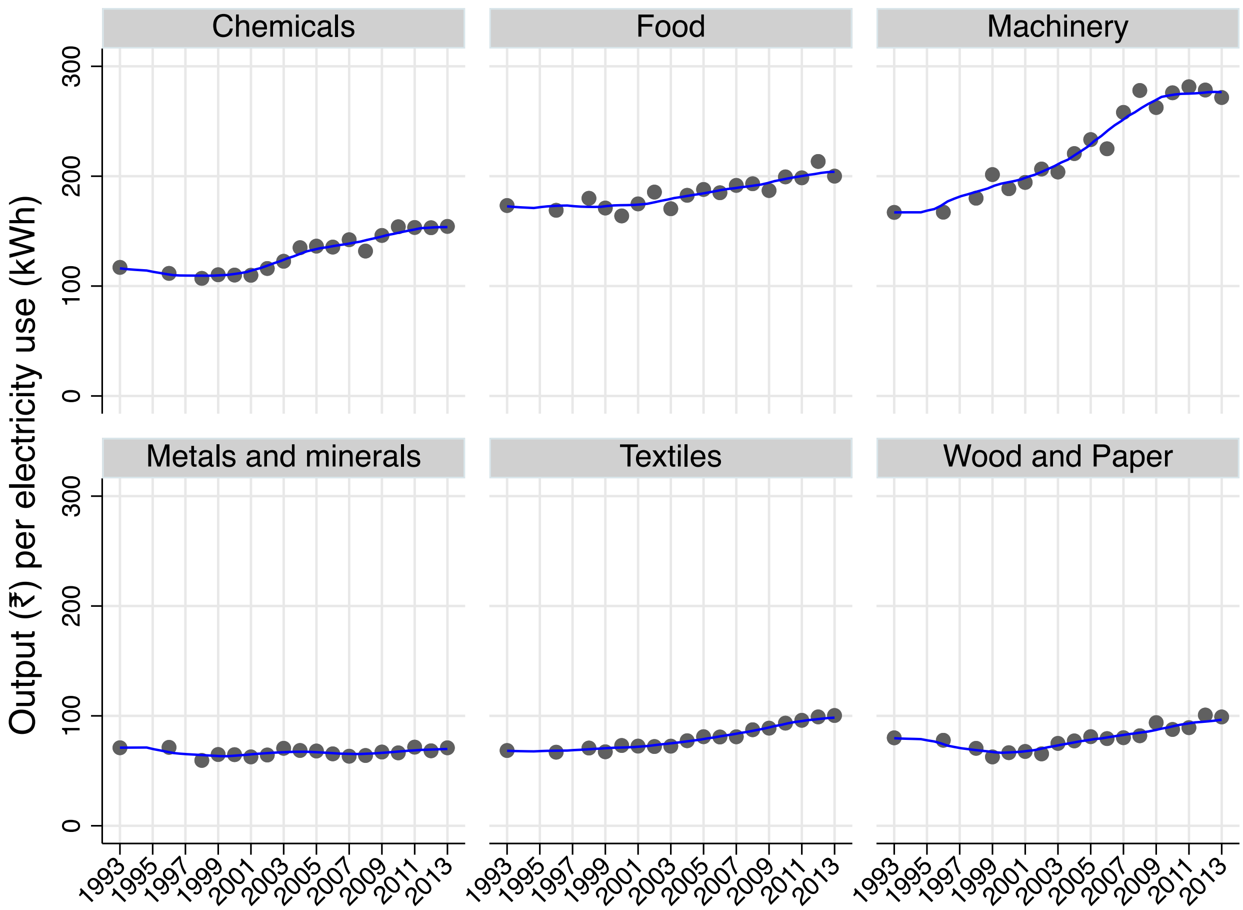
Notes: The figure plots the real average electricity prices by states. Sixteen of the largest states are displayed in this figure. They are calculated by first aggregating the value of electricity bought by plants and the quantity bought, and then taking the ratio of the aggregates. Electricity values are deflated using a general fuel and electricity wholesale price deflator. The base year for deflation is 2004 throughout this paper. Wholesale price deflators are from the Office of the Economic Adviser from the Government of India. All data points come from the raw plant level ASI data and aggregated with sampling multipliers.

Figure A.13: Energy productivity (per ₹) by industry



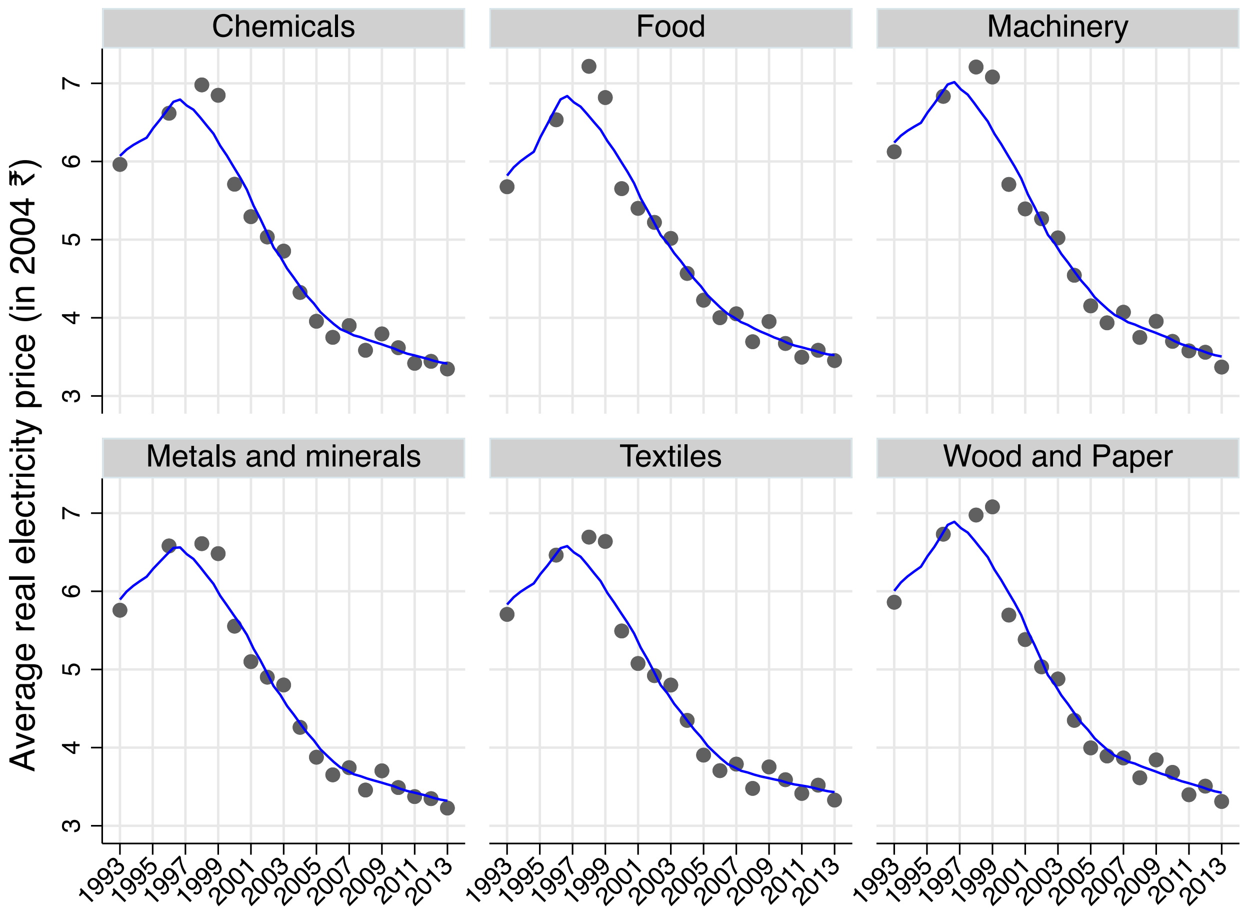
Notes: The figure plots the annual energy productivity ratios by industry (value of output divided by the value of fuel and electricity used). The industries are broad: chemicals includes rubber and plastics, machinery includes metal products, and textiles includes leather. Output is deflated at the 2-digit industry level using 2-digit industry deflators before aggregating over industries. Fuel and electricity use is deflated using a general fuel and electricity wholesale price deflator. The ratio of aggregate output to aggregate fuel and electricity consumption is displayed. The base year for deflation is 2004 throughout this paper. Wholesale price deflators are from the Office of the Economic Adviser from the Government of India. From 1967 to 1997 the raw ASI data in pre-aggregated form is used (at industry state year aggregation). From 1998 the raw plant level ASI data is used and aggregated with sampling multipliers.

Figure A.14: Electricity productivity (per kWh) by industry



Notes: The figure plots the annual electricity productivity ratios by industry (value of output divided by the quantity of electricity used in kWh). The industries are broad: chemicals includes rubber and plastics, machinery includes metal products, and textiles includes leather. Plant output is deflated using 3-digit industry deflators before aggregating over industries. The ratio of aggregate output to aggregate electricity use is displayed. The base year for deflation is 2004 throughout this paper. Wholesale price deflators are from the Office of the Economic Adviser from the Government of India. All data points come from the raw plant level ASI data and aggregated with sampling multipliers.

Figure A.15: Electricity prices by industry



Notes: The figure plots the real average electricity prices by industry. The industries are broad: chemicals includes rubber and plastics, machinery includes metal products, and textiles includes leather. They are calculated by first aggregating the value of electricity bought by plants and the quantity bought, and then taking the ratio of the aggregates. Electricity values are deflated using a general fuel and electricity wholesale price deflator. The base year for deflation is 2004 throughout this paper. Wholesale price deflators are from the Office of the Economic Adviser from the Government of India. All data points come from the raw plant level ASI data and aggregated with sampling multipliers.

Figure A.16: Electricity productivity (per ₹)

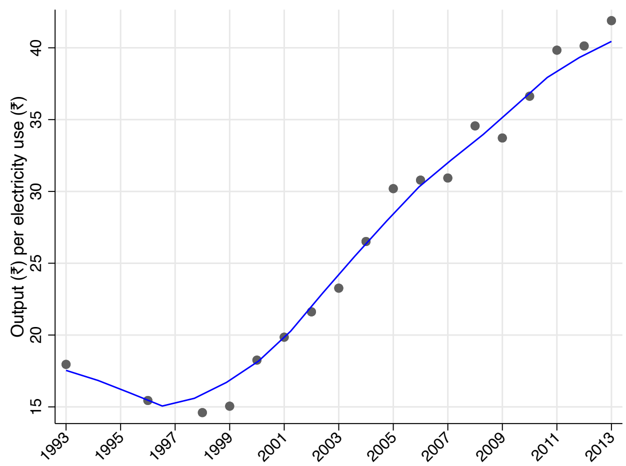
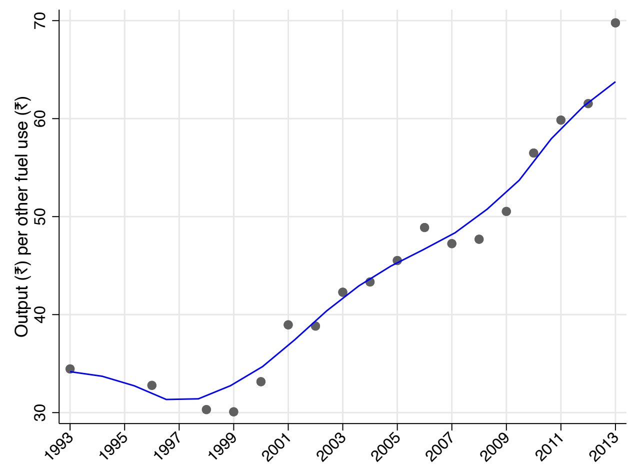


Figure A.17: Other fuel productivity (per ₹)



Notes: The figure plots the annual electricity productivity ratios (value of output divided by the value of electricity used) and the other fuel productivity ratios (value of output divided by the value of fuel other than electricity used). Plant output is deflated using 3-digit industry deflators before aggregating over industries. Electricity and fuel values are deflated using a general fuel and electricity wholesale price deflator. The base year for deflation is 2004 throughout this paper. Wholesale price deflators are from the Office of the Economic Adviser from the Government of India. All data points come from the raw plant level ASI data and aggregated with sampling multipliers.

Figure A.18: Electricity productivity (per kWh)

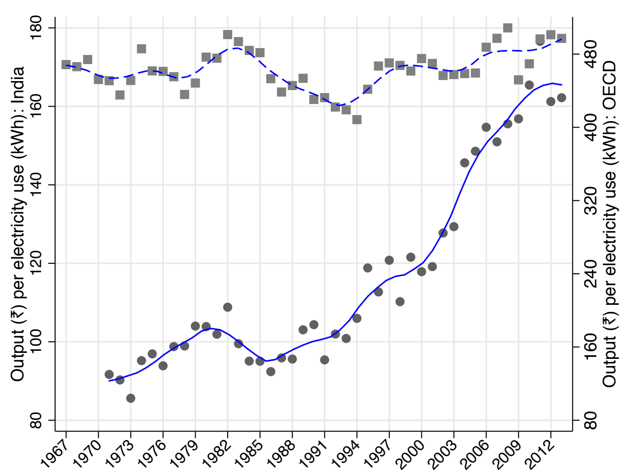
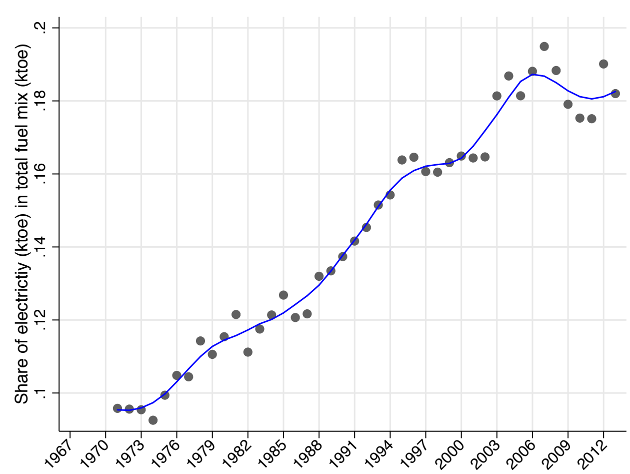
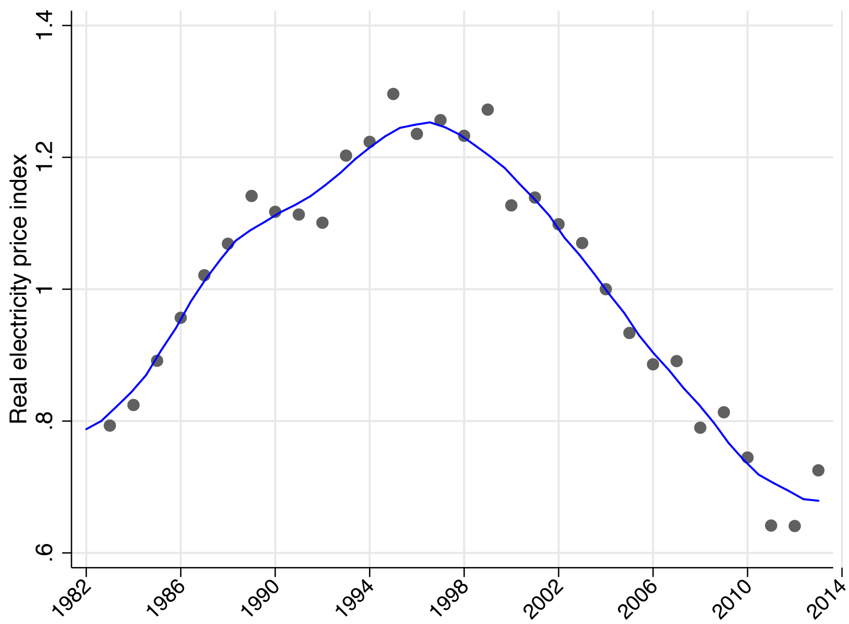


Figure A.19: Share of electricity in fuel mix



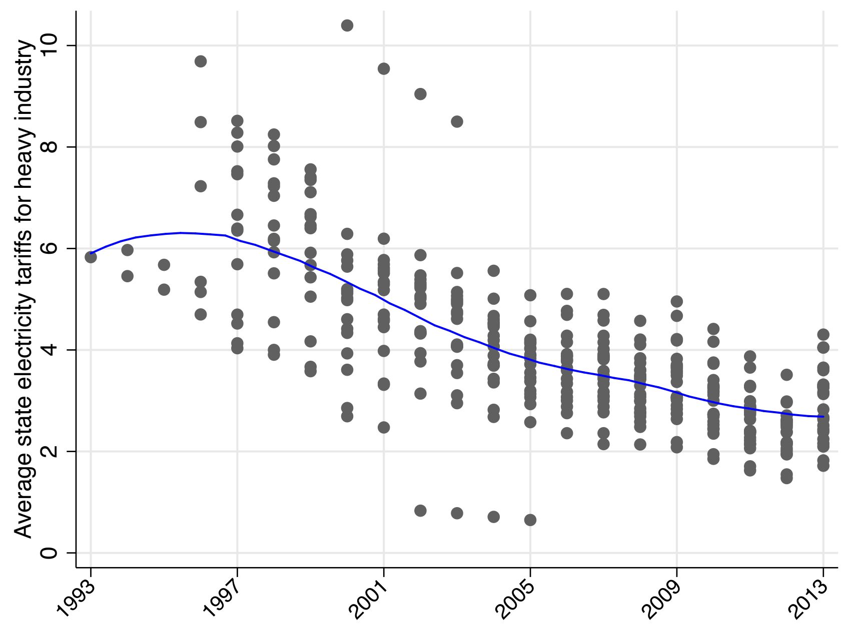
Notes: The left figure plots the annual electricity productivity ratios (value of output divided by the quantity of electricity used (in kWh)). Both quantities are for manufacturing only. Output is from UNIDO (2016), deflated with GDP deflators from World Bank (2017), and electricity consumption from the IEA (2016). The base year for deflation is 2004 throughout this paper. Plotted are the values and kernel smoother for India with the solid line, corresponding to the left axis. The values and kernel smoother for OECD countries are the dashed lines, corresponding to the right axis. The right figure plots the share of electricity consumption in total fuel consumption in India (both in ktoe) using data from IEA (2016).

Figure A.20: Real electricity price index



Notes: Plotted is the real electricity price index for industry. It is based on the wholesale price index for electricity for industrial purposes. The wholesale price index for electricity is deflated with the general fuel and electricity wholesale price deflator. The base year for deflation is 2004 throughout this paper. Wholesale price deflators are from the Office of the Economic Adviser from the Government of India.

Figure A.21: Average real state tariffs for heavy industry



Notes: Plotted is the real electricity tariff for heavy industry. The tariffs are manually collected from publications of the Indian Central Electricity Authority (2006-2015) and from Indiastat (2019) through Lok Sabha and Rajya Sabha questions. Individual data points correspond to state level average tariffs for heavy industry. Tariffs are deflated using a general fuel and electricity wholesale price deflator. The base year for deflation is 2004 throughout this paper. Wholesale price deflators are from the Office of the Economic Adviser from the Government of India.

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

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

To more formally analyse the variation left across plants within industry, spatial or consumption size clusters, I decompose variances following Davis et al. (2013). I calculate the annual variance as $V = \sum_e s_e \left(p_e - \overline{p}\right)^2$, 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:

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

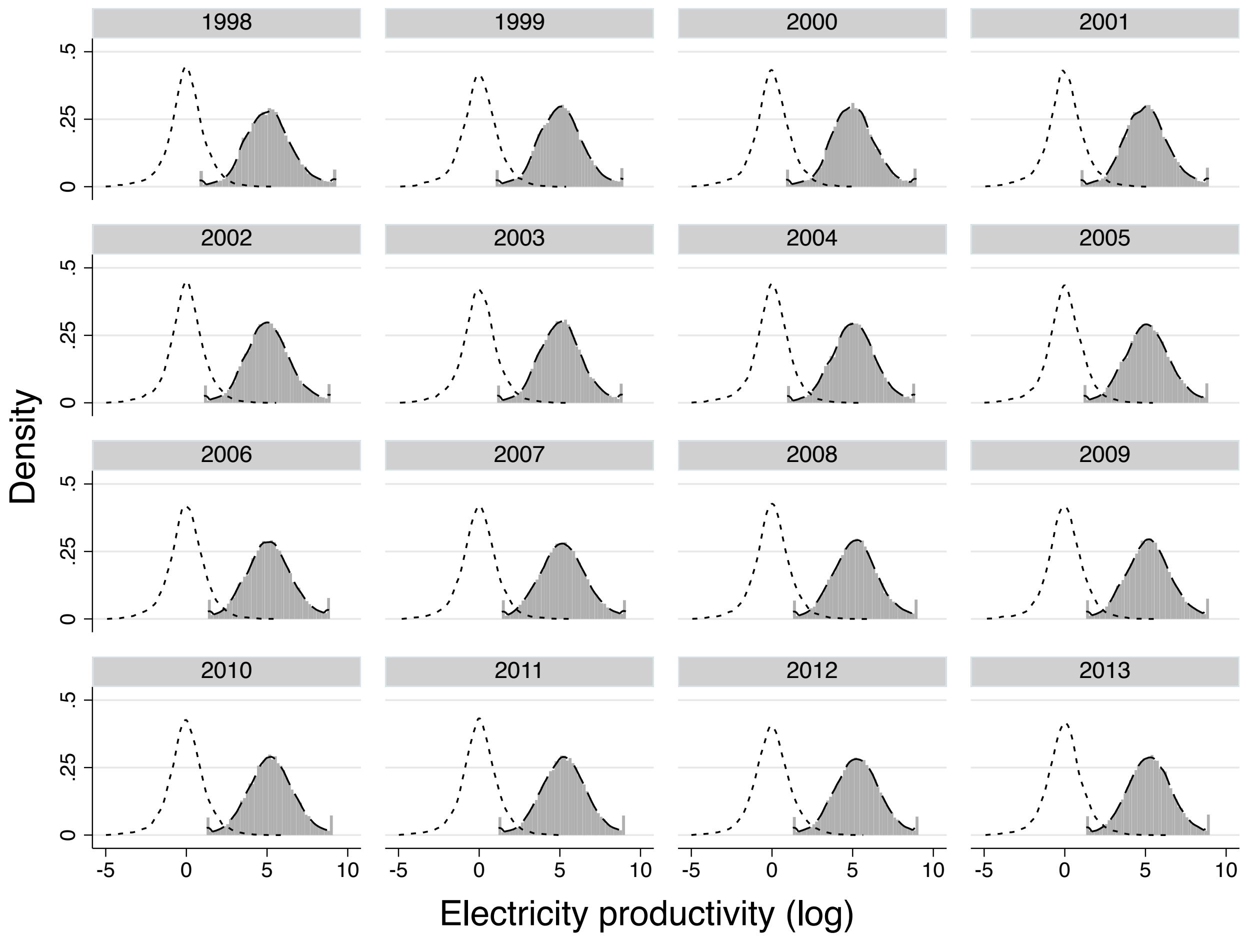
where $s_g = \sum_{e \in g} s_e$ and $\overline{p}_g$ the weighted average of log productivity or price within group g. I calculate the decomposition separately five times for five different groups, which are states, deciles of electricity purchase quantity, 4-digit industries, industry-by-states, and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

Figure A.25 shows that state-industry effects can only account for around 50% of the cross-sectional variance in electricity productivity, around 40% of the variation in labor productivity, and 60% of the variation in electricity prices.[93] For electricity and labor productivity, there is more variation across industries, while for electricity prices there is more variation across states. This is intuitive, as production techniques tend to vary more across industries, while electricity price-setting varies more across geography as explained in Section III.A.. The variance in electricity prices has been decreasing from 1998 to 2013. Figure A.26 plots quantiles of the distribution over time and shows a convergence in electricity prices that accompanied the secular price decline. Comparing the decrease in the total variance of electricity prices and the shares that state-by-industry groups can explain in Figure A.25, we can conclude that the convergence has not been driven by reductions across industries or states alone, but by convergence within these clusters. The deciles of plants' electricity consumption cannot explain much of the variance. This is in contrast to the findings for the US (Davis et al., 2013) and France (Marin and Vona, 2021) and consistent with the observation in Section III.A. that tariff schedules in India can be increasing or decreasing in consumption. The main analysis accounts for industry by year by region fixed effects to account for differences across industries. Importantly, we learn from these descriptives that there is substantial variation left after accounting for these fixed effects.

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

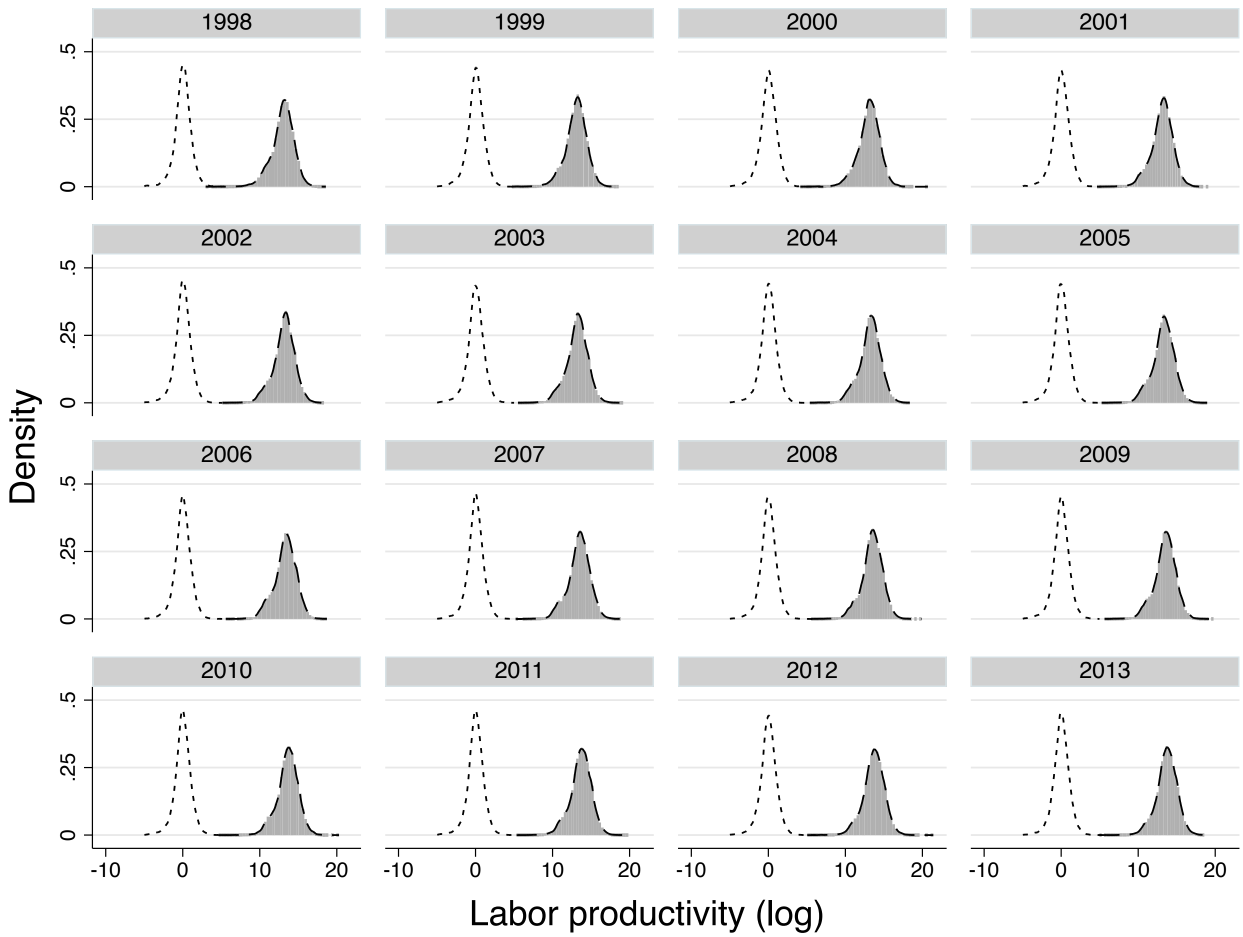
[93]Variation across districts (not plotted) can explain around 22% and 45% of electricity productivity and electricity prices respectively. Districts for the later years are not available for all observations.

Figure A.22: Heterogeneity in electricity productivity



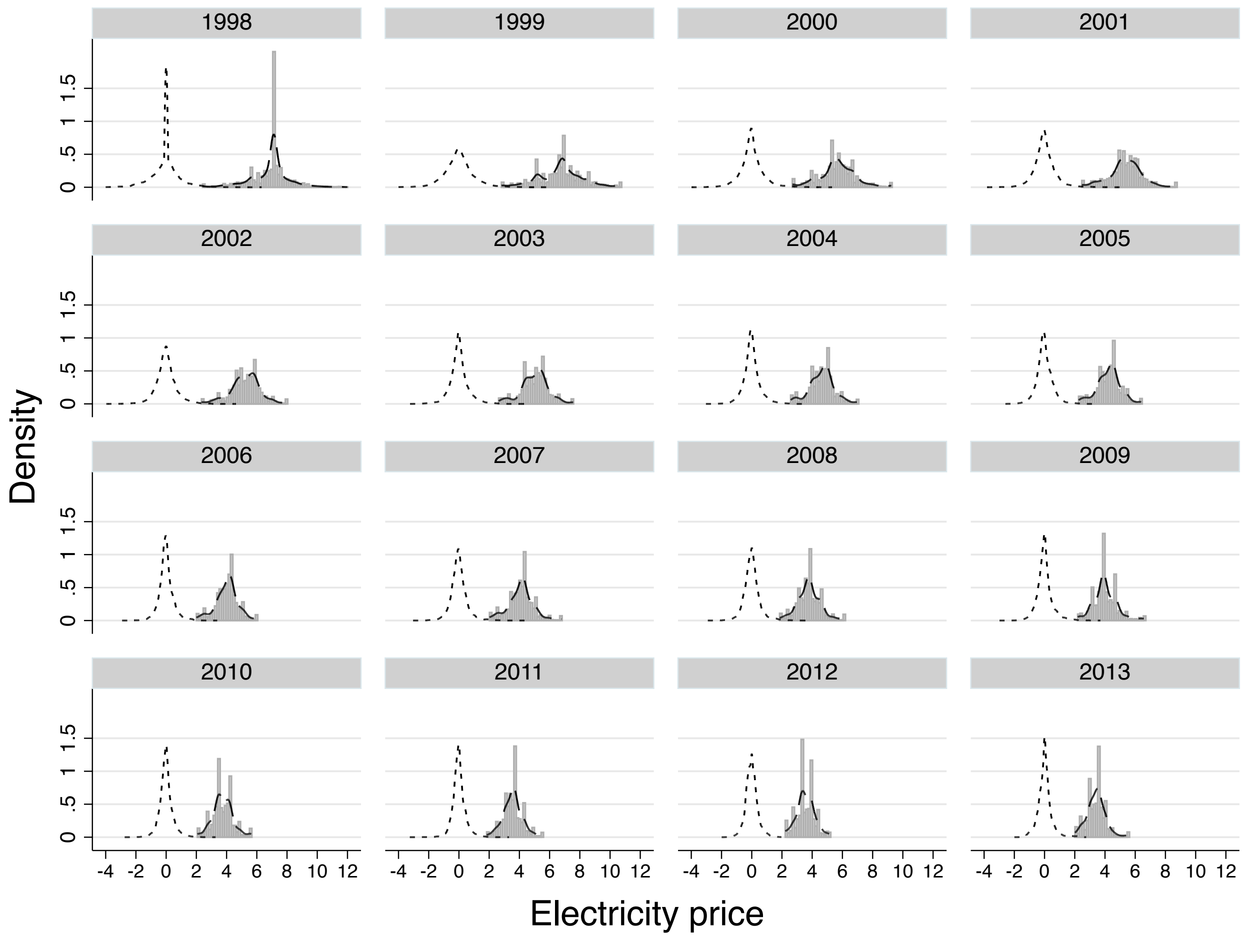
Notes: The figure plots the histograms of plant level logged electricity productivity by year. The left kernel density plot shows the distribution of the residuals of logged electricity productivity after partialing out state by 4-digit industry by year fixed effects. Electricity productivity ratios are the value of output divided by the quantity of electricity used in kWh. Plant output is deflated using 3-digit industry deflators. The base year for deflation is 2004 throughout this paper. Wholesale price deflators are from the Office of the Economic Adviser from the Government of India.

Figure A.23: Heterogeneity in labor productivity

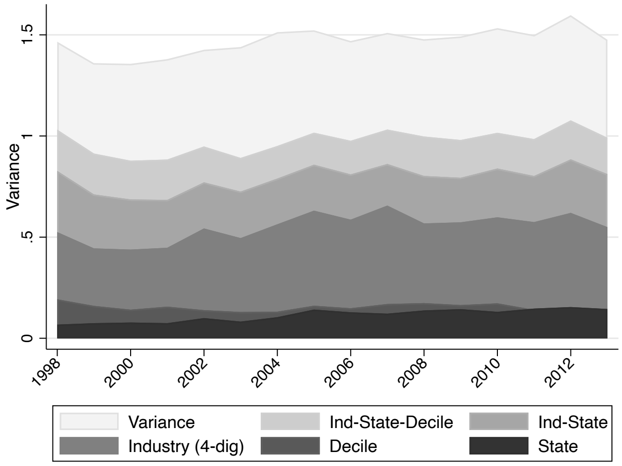


Notes: The figure plots the histograms of plant level logged labor productivity by year. The left kernel density plot shows the distribution of the residuals of logged labor productivity after partialing out state by 4-digit industry by year fixed effects. Labor productivity ratios are the value of output divided by the number of employees. Plant output is deflated using 3-digit industry deflators. The base year for deflation is 2004 throughout this paper. Wholesale price deflators are from the Office of the Economic Adviser from the Government of India.

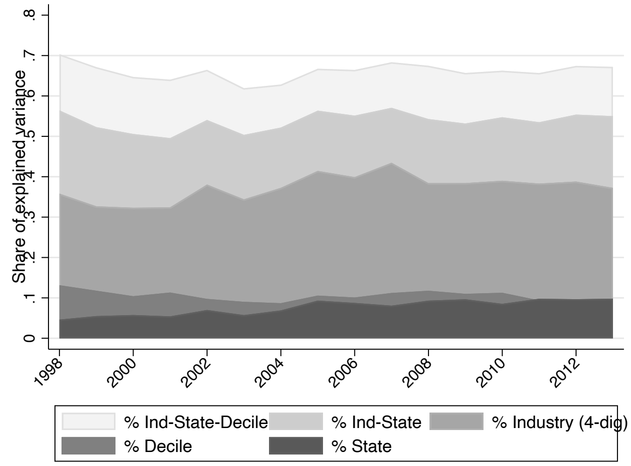
Figure A.24: Heterogeneity in electricity prices



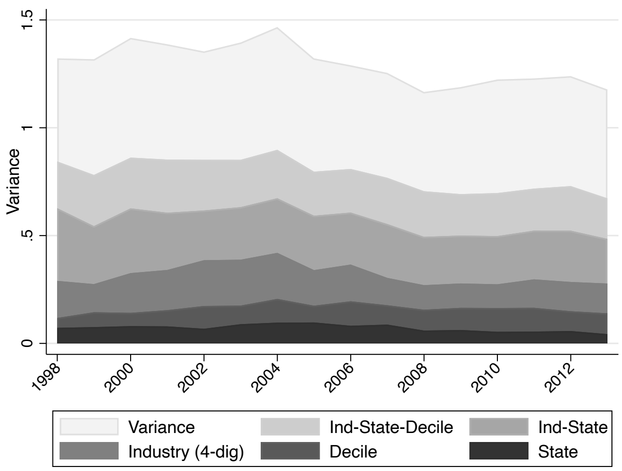
Notes: The figure plots the histograms of plant level electricity prices by year. The left kernel density plot shows the distribution of the residuals of electricity prices after partialing out state by 4-digit industry by year fixed effects. Electricity prices are deflated using a general fuel and electricity wholesale price deflator. The base year for deflation is 2004 throughout this paper. Wholesale price deflators are from the Office of the Economic Adviser from the Government of India.



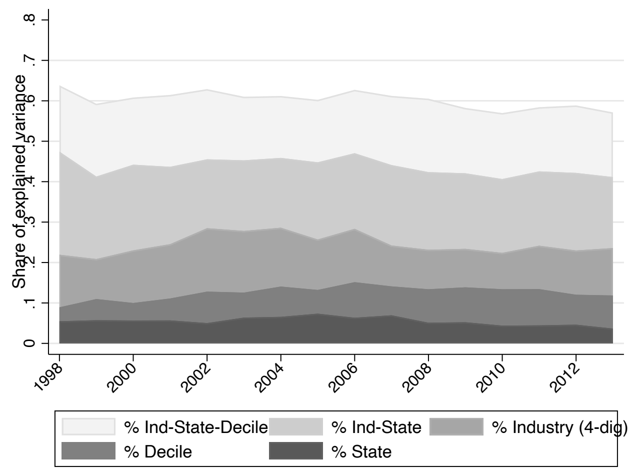
(**a**) Electricity productivity variance decomposition



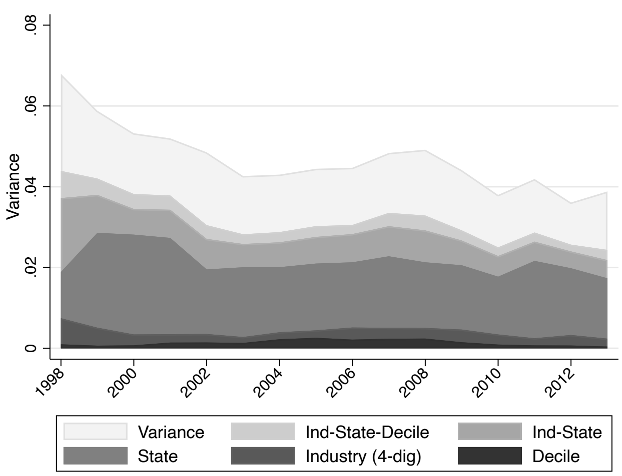
(**b**) Electricity productivity variance decomposition



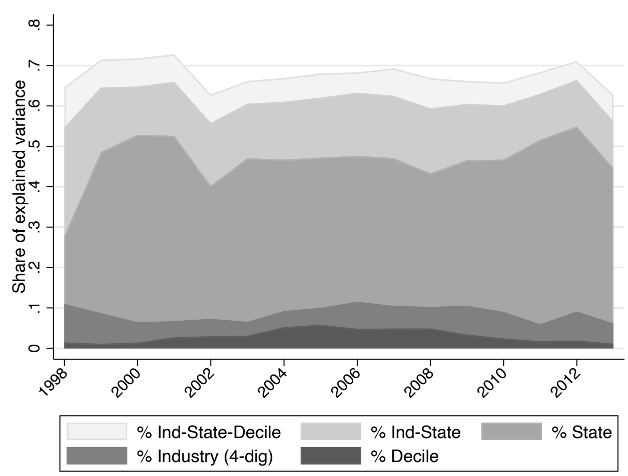
(**c**) Labor roductivity variance decomposition



(**d**) Labor roductivity variance decomposition



(**e**) Electricity price variance decomposition

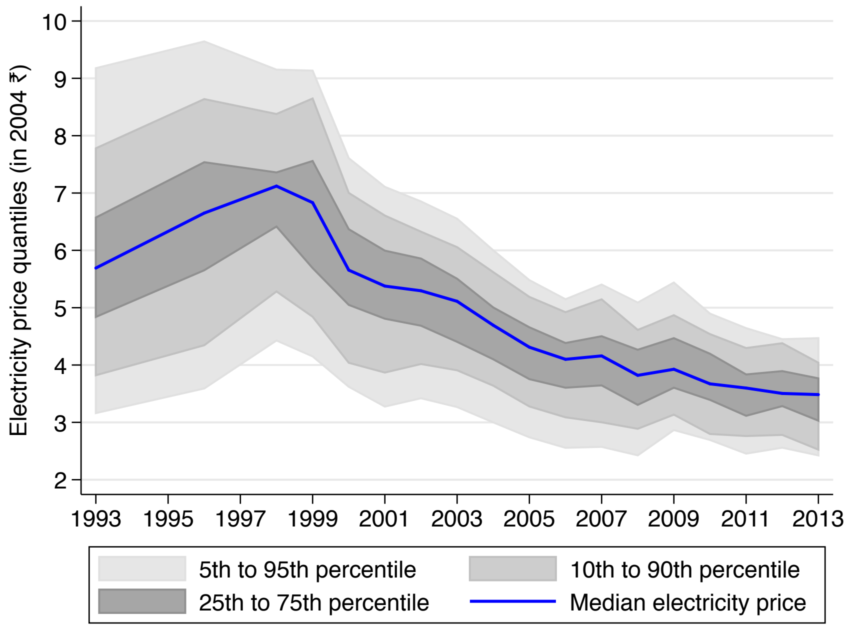


(**f**) Electricity price variance decomposition

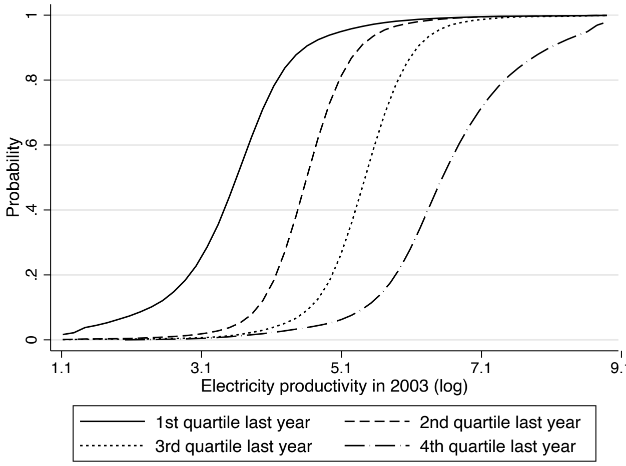
Figure A.25: Variance decompositions of electricity and labor productivities and electricity prices

Notes: The left Panels (a), (c) and (e) plot the annual total variance of logged electricity productivity, logged labor productivity and logged electricity prices respectively, and the variance explained by specified groups as described in the text. The right Panels (b), (d) and (f) plot the share of the variance explained by each group. Groups are deciles of electricity purchase quantity, 4-digit industries, states, and combinations. Plant output is deflated using 3-digit industry deflators. Electricity prices are deflated using a general fuel and electricity wholesale price deflator. The base year for deflation is 2004 throughout this paper. Wholesale price deflators are from the Office of the Economic Adviser from the Government of India.

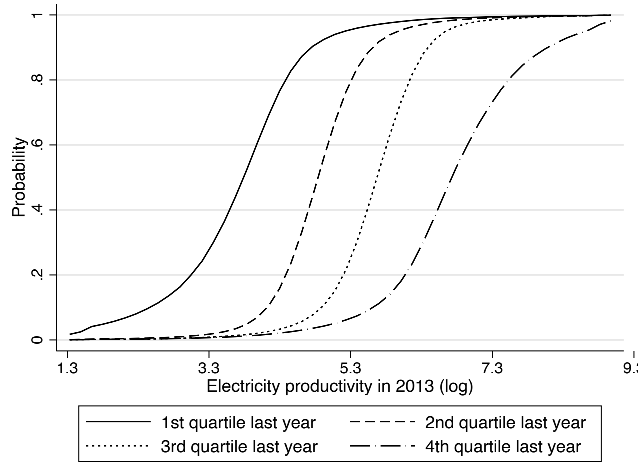
Figure A.26: Convergence in electricity prices



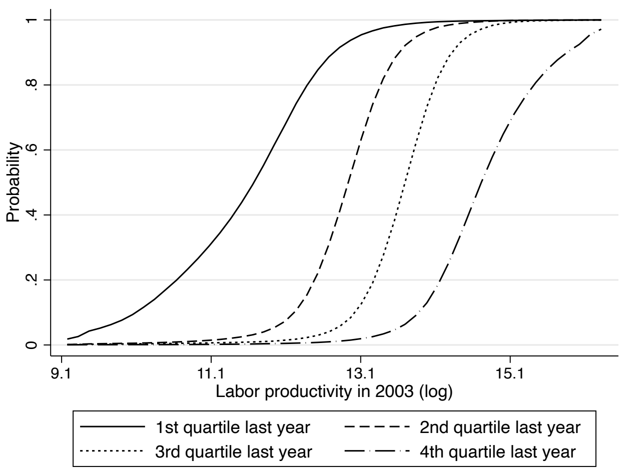
Notes: Plotted are the 5th, 10th, 25th, 50th, 75th, 90th and 95th percentile of the annual plant level electricity prices. Electricity prices are deflated using a general fuel and electricity wholesale price deflator. The base year for deflation is 2004 throughout this paper. Wholesale price deflators are from the Office of the Economic Adviser from the Government of India.



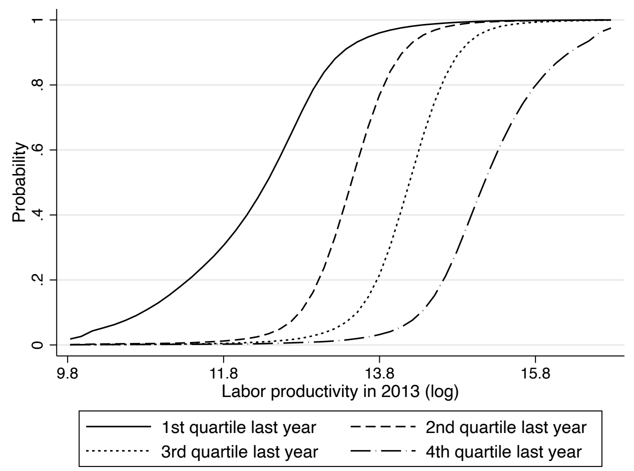
(**a**) Electricity productivity 2003 (CDF)



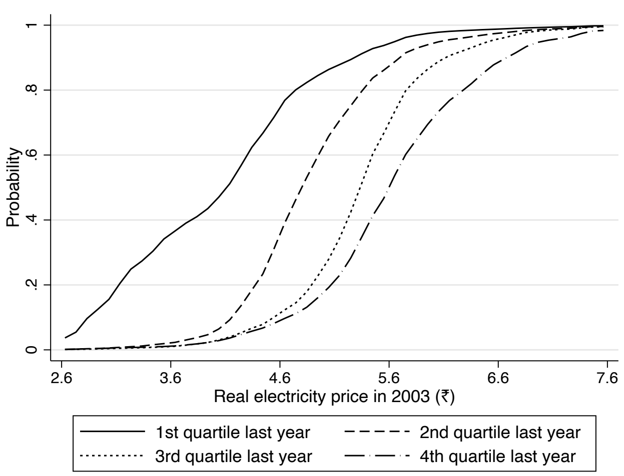
(**b**) Electricity productivity 2013 (CDF)



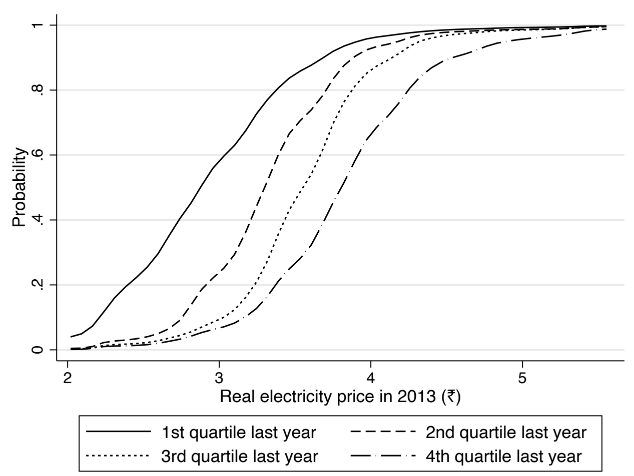
(**c**) Labor productivity 2003 (CDF)



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



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



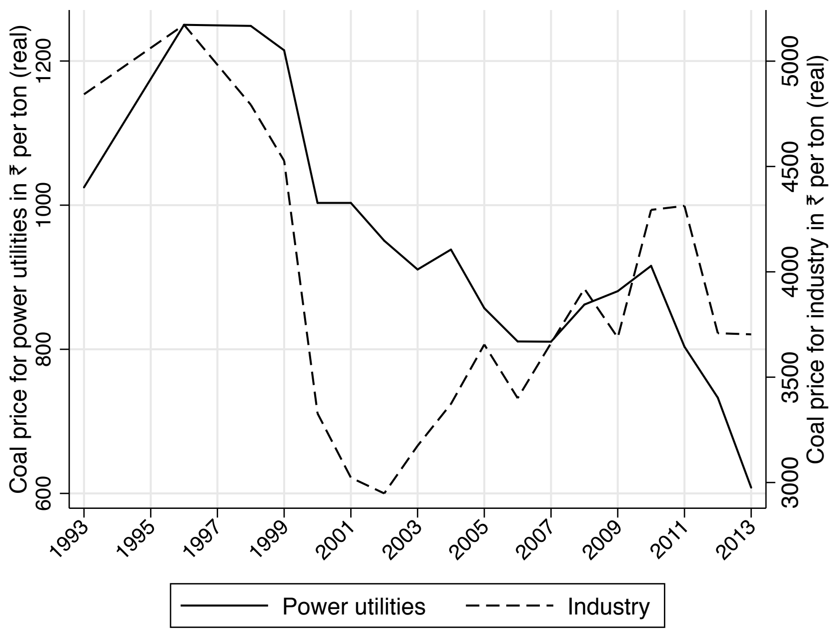
(**f**) Electricity prices 2013 (CDF)

Figure A.27: Variance decompositions and conditional CDFs of productivities and electricity prices

Notes: The Panels (a), (c) and (e) plot the CDFs in 2003 separately for each quartile of the respective values in 2002, for logged electricity productivity, logged labor productivity, and electricity prices respectively. The Panels (b), (d) and (f) plot the same graphs for the CDFs in 2013 separately for each quartile of the respective values in 2012.The CDFs are empirical CDFs obtained through a Gaussian kernel smoother with bandwidth 0.1. The graphs show that each higher quartile first order stochastically dominates the lower quartiles. The conditional CDFs for other years look similar. Plant output is deflated using 3-digit industry deflators. Electricity prices are deflated using a general fuel and electricity wholesale price deflator. The base year for deflation is 2004 throughout this paper. Wholesale price deflators are from the Office of the Economic Adviser from the Government of India.

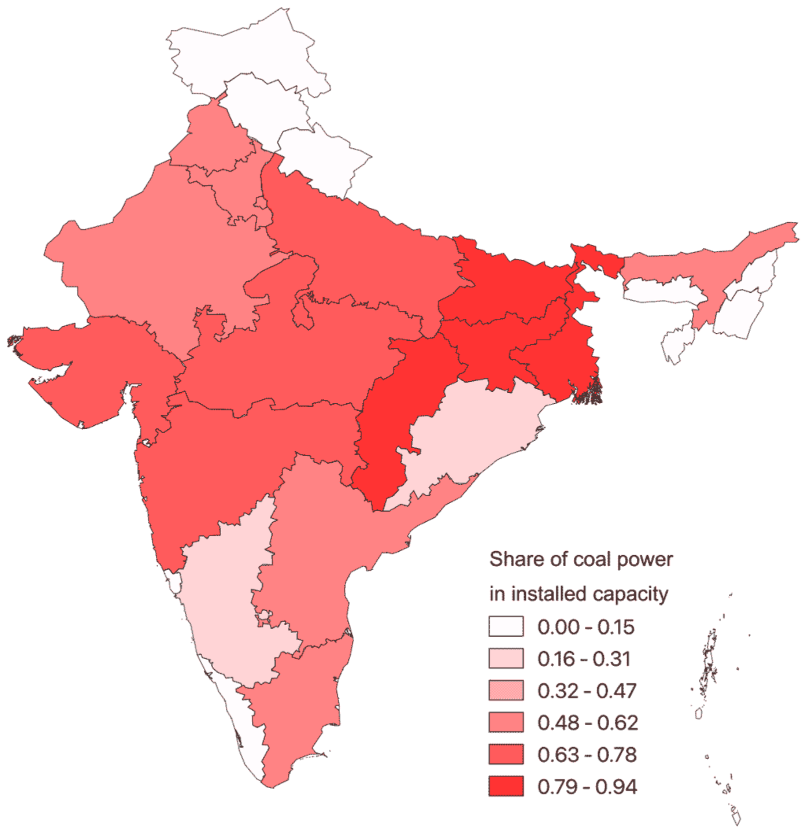
A.11 Coal share in installed capacity and coal price for power utilities and industry

Figure A.28: Coal price for power utilities and industry



Notes: The solid line plots the coal prices 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. The base year for deflation is 2004 throughout this paper. Wholesale price deflators are from the Office of the Economic Adviser from the Government of India.

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

	Share rural (1)	Share domestic power (2)	Share power (3)	Labor productivity (log) (4)	Capital-labor Ratio (log) (5)	Share managerial wages (6)	Fuel share in output (7)	Wage share in output (8)
Coal power share	0.0216	0.181	-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 Columns 6 is based on the 1996 version of the ASI microdata. Share managerial wages is the share of wages going to supervisors and managers in total wages. The outcomes in Columns 7-8 are based on the aggregate ASI data in 1997. Fuel share in output is total spending on fuel as share of output. Wage share in output is total emoluments as share of output. Robust standard errors are in parentheses.

A.12 Additional regression results and robustness checks

Table A.5: Lagged electricity prices and electricity productivity

	Electricity productivity (log)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(P^E)$	0.295***	-0.273***	-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: The dependent variable is logged electricity productivity (value of output divided by the quantity of electricity used in kWh). Each column represents a separate regression at the plant level. 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. 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. The rest of the table layout follows the same structure as the main Table 2.

Table A.6: 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: The dependent variable is logged electricity productivity (value of output divided by the quantity of electricity used in kWh). Each column represents a separate regression at the plant level. 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. 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. The rest of the table layout follows the same structure as the main Table 2.

Table A.7: Electricity prices and electricity productivity 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)
$\log(P^E)$	0.365***	-0.268***	-0.525	-0.262	-0.0282	-0.424***	-1.934*	0.270
	(0.044)	(0.071)	(0.782)	(0.182)	(0.043)	(0.087)	(1.110)	(0.190)
OLS/IV	OLS	IV^C	IV^{D1}	IV^{D2}	OLS	IV^C	IV^{D1}	IV^{D2}
Observations	485342	444428	444428	485342	485342	444428	444428	485342
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Distance to coalfield	No	No	Yes	No	No	No	Yes	No
First stage coef.	-	0.97***	-0.02**	0.12***	-	0.97***	-0.02**	0.12***
First stage SE	-	0.005	0.008	0.014	-	0.005	0.008	0.014
F-stat (Kleib.-Paap)	-	37768.975	5.359	70.403	-	37768.975	5.359	70.403
Two-way clustered SE	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}. Column 3 and 7 also control for the level of the distance to coalfields as IV^{D_1} contains the interaction with the post 2003 Electricity Act.

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

	OLS			IV^A			IV^B		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(P^E)$	0.343***	0.472***	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.9: Electricity prices and labor productivity: controlling for distance to coalfields and shortages

	OLS			IV^A			IV^B		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(P^E)$	-0.0630	0.0866**	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.10: Electricity prices and electricity and labor productivity in electricity intensive sectors

	Electricity productivity (log)			Labor productivity (log)		
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(P^E)$	0.323***	-0.210***	-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.11: 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.12: 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.13: 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: The dependent variable is logged electricity productivity (value of output divided by the quantity of electricity used in kWh) in Columns 1 to 3 and logged labor productivity in Columns 4 to 6. Each column represents a separate regression at the plant level. 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). 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. The rest of the table layout follows the same structure as the main Table 2.

Table A.14: Electricity prices and electricity productivity interacted with three periods

	Electricity productivity (log)			Labor productivity (log)		
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(P^E)$	0.506***	0.0555	-0.725***	-0.0202	-0.400***	-1.062***
	(0.067)	(0.111)	(0.200)	(0.064)	(0.120)	(0.171)
$\log(P^E) \cdot \mathbf{1}(year < 2003)$	-0.275***	-0.728***	-0.117	0.103	0.172	0.0999
	(0.098)	(0.163)	(0.235)	(0.100)	(0.221)	(0.239)
$\log(P^E) \cdot \mathbf{1}(year \geq 2003 \text{ or } year \leq 2007)$	-0.176*	-0.270*	-0.0618	-0.140	-0.113	-0.0962
	(0.104)	(0.147)	(0.248)	(0.101)	(0.182)	(0.242)
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	-	0.95***	0.05***	-	0.95***	0.05***
First stage SE 1/1	-	0.007	0.005	-	0.007	0.005
First stage coef. 1/2	-	0.04***	0.01	-	0.04***	0.01
First stage SE 1/2	-	0.012	0.008	-	0.012	0.008
First stage coef. 1/3	-	0.03***	0.01	-	0.03***	0.01
First stage SE 1/3	-	0.010	0.008	-	0.010	0.008
First stage coef. 2/1	-	-0.00***	-0.00	-	-0.00***	-0.00
First stage SE 2/1	-	.	0.000	-	.	0.000
First stage coef. 2/2	-	0.99***	0.06***	-	0.99***	0.06***
First stage SE 2/2	-	0.009	0.006	-	0.009	0.006
First stage coef. 2/3	-	0.00***	0.00	-	0.00***	0.00
First stage SE 2/3	-	.	0.000	-	.	0.000
First stage coef. 3/1	-	0.00	-0.00	-	0.00	-0.00
First stage SE 3/1	-	0.000	0.000	-	0.000	0.000
First stage coef. 3/2	-	0.00	0.00	-	0.00	0.00
First stage SE 3/2	-	0.000	0.000	-	0.000	0.000
First stage coef. 3/3	-	0.98***	0.06***	-	0.98***	0.06***
First stage SE 3/3	-	0.007	0.007	-	0.007	0.007
F-stat (Kleibergen-Paap)	-	3860.844	35.817	-	3860.844	35.817
Two-way clustered SE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: See Table A.13 for notes. The main difference is that prices are interacted with three different periods (one baseline omitted).

Table A.15: 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.16: 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: OP refers to Olley and Pakes (1996), LP refers to Levinsohn and Petrin (2003) and ACF refers to Ackerberg, Caves and Frazer (2015). See Table 2 for notes. The main difference is that different methods to recover TFP are used, and TFP used as dependent variable.

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

	Electricity productivity (log)			Labor productivity (log)		
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(P^E)$	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.18: 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. The main difference is that the dependent variables are different as indicated.

Table A.19: FDI liberalized industries in 2006

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

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

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

	Electricity productivity (log)			Output (log)		
	OLS	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.21: 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)
$\log(P^E) \times treated \times post$	0.448**	1.052***	-0.121	-0.484*	0.192	0.233
	(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.

A.13 Using nation-wide average product electricity intensities

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

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

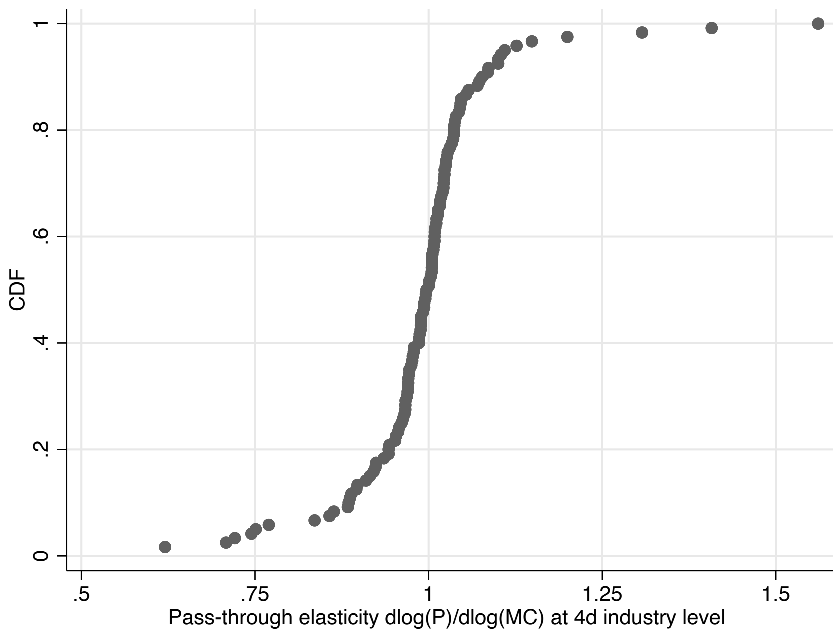
Table A.22: Electricity prices, and average product electricity intensity using nation-wide product averages

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

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

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

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

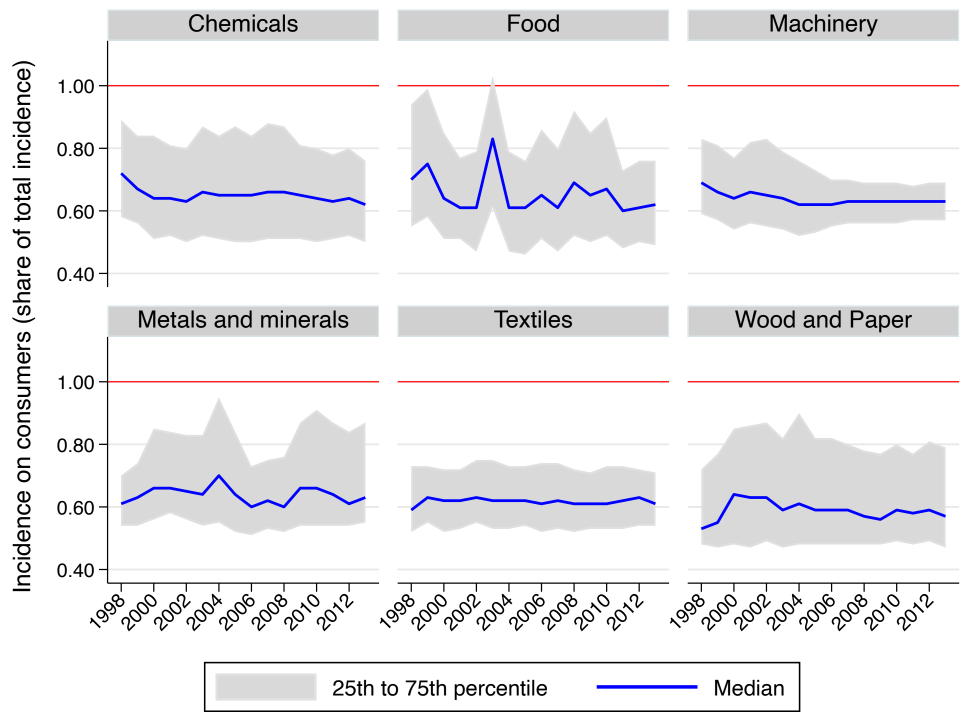


Notes: The figure plots the cumulative distribution function of the pass-through elasticities $(d\log(P)/d\log(MC))$. The pass-through elasticities vary at the 4-digit industry level: there are 121 different pass-through elasticities. The pass-through elasticities are the coefficient on a regression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

	Manufacture of:	
	Grain mill products	Structural non-refractory clay and ceramic products
$\log(MC)$	0.997***	0.730***
	(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.31: 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.15 Details on calculating aggregate effects on CO_2 emissions

In a back of the envelope calculation, I combine regression estimates with the fuel use data and emission factors I 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 specific 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[94] 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.[95] With these steps I obtain the estimates of Column (1) in Table 6.

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

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

use. I switch off the electricity productivity effect by requiring that electricity use increases by the same percentage as output increase in the baseline scenario. Finally, in the last column of Table 6 I switch off both substitution and electricity productivity effects.

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

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

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

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

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