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Gregor Singer

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

Gregor Singer[‡]
LSE

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Abstract

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

JEL: Q41, D24, D22, O14

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

[‡]London School of Economics. E-mail: g.a.singer@lse.ac.uk. I thank Nicolas Astier, Lint Barrage, Geoff Barrows, Judson Boomhower, Robin Burgess, Fiona Burlig, Tatyana Deryugina, Natalia Fabra, Stephie Fried, Teevrat Garg, Lawrence Goulder, Josh Graff Zivin, Ben Groom, Bard Harstad, Koichiro Ito, Kelsey Jack, Mark Jacobsen, Seema Jayachandran, Akshaya Jha, Diego Känzig, Namrata Kala, Ryan Kellogg, David Lagakos, Erin Mansur, Leslie Martin, Kyle Meng, Antony Millner, Giordano Mion, Mar Reguant, Joseph Shapiro, Anant Sudarshan, Catherine Thomas, Kathrine Wagner, Ulrich Wagner, Shuang Zhang, and participants at the 2020 UCSD Environmental Economics seminar, the 2020 UCSD GPS junior faculty seminar, the 2020 EAERE conference, the 2020 AERE conference, the 2020 LSE and Imperial College Workshop in Environmental Economics, the 2022 Queen Mary Centre for Globalisation Research seminar, the 2022 European Winter Meetings of the Econometric Society, the 2023 ASSA AEA meetings, the 2023 CESifo Conference on Energy and Climate Economics, the 2023 NBER Summer Institute (DEV), the 2023 LSE Environment Week, the 2023 Yale-Rise conference, the 2024 Mannheim Conference on Energy and the Environment, the 2024 Maastricht Workshop on Applied Economics of the Environment, the 2024 SED Annual Conference, the 2024 PSE Regulation and Environment Seminar, the 2024 Oxford Environment and Resource Economics Seminar, the 2025 Potsdam Research Seminar in Economics, and the 2025 NBER Economics of Decarbonizing Industrial Production Workshop for valuable comments and discussions. I thank Mehak Vohra for excellent research assistance. I gratefully acknowledge support from the Grantham Research Institute on Climate Change and the Environment at the London School of Economics. This research is based on a chapter of my 2019 PhD thesis.

I. Introduction

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

The findings in this paper explain a puzzling pattern in Indian aggregate manufacturing data, where electricity prices fell substantially as electricity productivity increased. Intuition from standard models would predict the opposite: substitution towards the cheaper input, electricity, with an unambiguous decrease in electricity productivity.[1] The key insight to resolve this apparent puzzle is that in the presence of discrete technological choices and complementarities, the substitution effect can be overturned by a technology upgrading effect. Lower 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 increases both electricity consumption and employment, output can increase disproportionately due to more capital intensive production. As a result, lower electricity prices increase both labor and electricity productivity by speeding up the transition to 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 itself (Aghion et al., 2022) or through changing labor costs, e.g. from migration patterns (Imbert et al., 2022). This is also relevant for the broader electrification debate: in highly industrialized countries lower electricity prices for industry or transport may primarily facilitate a shift from fossil fuel to electric technologies, whereas in developing countries electrification from lower electricity prices may extend beyond switching fuel sources, encompassing a more fundamental transition from labor intensive to capital intensive technologies.

Beyond 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 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).

prices can induce energy conservation per unit of output is important in its own right. Energy efficiency receives much policy interest as a principal way to reduce carbon emissions in manufacturing as countries struggle to achieve climate goals (IEA, 2018*a*; Fowlie and Meeks, 2021), especially in developing countries where production capacity and energy demand are growing rapidly.[3] In fact, many developing countries including India focus solely on energy and emission *intensity* rather than levels under the Paris Agreement. While policy makers may fear that low industrial electricity prices provide insufficient incentives to improve energy efficiency, we have surprisingly little causal evidence of their effect on electricity productivity. This paper provides, to my knowledge, the first plausibly causal evidence that lower electricity prices can increase both labor and electricity productivity. I emphasize that this result is likely more relevant in contexts of industrial development and where electricity prices are cut from comparatively high levels, both of which apply to India, the setting of this paper.[4] Although electricity prices are an equilibrium outcome, they are a sufficient statistic for the price channel through which many policies affect firms. For policies that shift electricity prices—such as deregulation, subsidy reform, grid investment, or fuel taxes—the estimated elasticities can be applied to a policy-induced price change to quantify their effects on firms through prices.

While this paper focuses on the effects of electricity prices, a related literature focuses on the *reliability* of electricity and its implications. This is important in a developing country context where shortages are frequent.[5] Allcott et al. (2016) show that power shortages in India reduce revenues by about 5% on average, and distort the plant size distribution due to returns to scale in self-generation.[6] Burgess et al. (2020) show that utilities are often caught in low cost-recovery and low reliability equilibria. I show that both shortages as well as overall utility cost-recovery are stable over time, because most electricity is supplied to residential and agricultural consumers who experienced relative price increases from low levels. In India, prices are therefore too low in the Burgess et al. (2020) sense for residential and agricultural consumers, but too high (above cost-recovery) for industry. Using multiple measures of shortages, I show that shortages are not correlated with industrial electricity prices.[7] Nevertheless, I provide robustness analyses for my estimates controlling for power shortages.

This paper proceeds in five steps. First, I set up a model to illustrate how such counter-intuitive effects of electricity prices are possible and generate testable predictions from these mechanisms. Second, I motivate the empirical analysis with trends in the data and the Indian institutional set-up. Third, I estimate the effects of electricity price reductions on industrial plants and test mechanisms including a mixture decomposition that separates within-technology substitution from technology

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

[4]India's industrial electricity prices were around 70% higher than the G7 average in 1998, or six times as high in PPP terms. For highly industrialized contexts, see Davis et al. (2008) for the US, Marin and Vona (2021) for France, or von Graevenitz and Rottner (2022) for Germany.

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

[6]Fried and Lagakos (2023) show important long run effects in general equilibrium. See also Alam (2013); Rud (2012); Jha et al. (2022) for further evidence on India. Ryan (2021) simulates the impact of transmission capacity improvements on the Indian electricity wholesale market.

[7]Note that Allcott et al. (2016) also argue that industrial electricity prices and shortages are not correlated in India, which allows them to focus on shortages while ignoring prices.

switching. Fourth, I estimate pass-through to calculate incidence on consumers and welfare. Fifth, I estimate environmental implications, and contrast my results with coal price reductions.

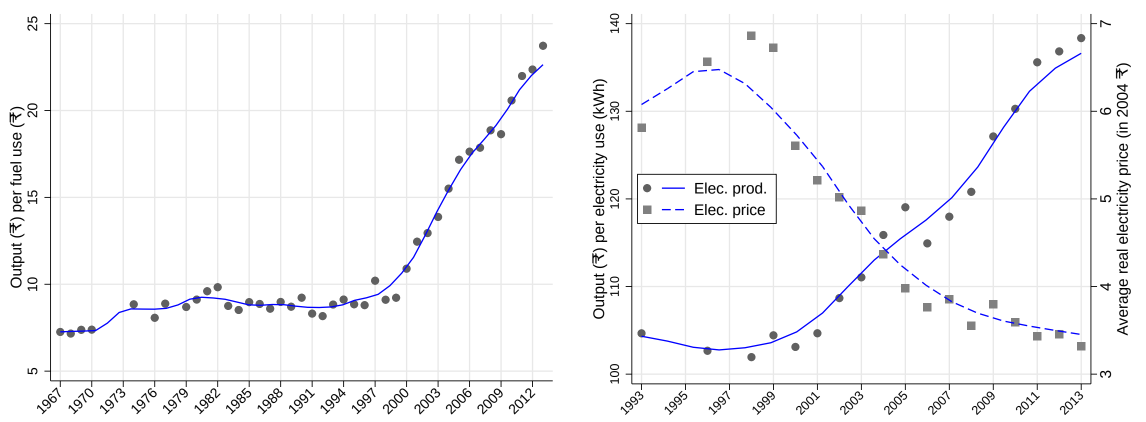
I begin the paper by developing a nested constant elasticity of substitution (CES) production model with the innovation of non-convex discrete technology choices that have different degrees of complementarities across inputs. The purpose of the model is to illustrate how lower electricity prices can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

To motivate the empirical analysis and identification, I discuss price setting and other structural features of India's electricity sector and document key data patterns. Figure 1 presents trends at the aggregate level. Panel (a) shows a secular increase in India's manufacturing all-fuel energy productivity in the 2000s after remaining mostly flat since the 1960s. Panel (b) focuses on electricity and the period with more detailed data used for analysis showing aggregate electricity productivity improved by 34% from 1998-2000 to 2013.[8] Surprisingly, this improvement happened during a time when electricity became substantially cheaper. Real average industrial electricity prices fell by 48% during the same time (right axis), a pattern robust across various data sources including plant-level data, official price indices and manually collected utility tariffs. It turns out that these initially counter-intuitive aggregate trends can be well explained by the empirical IV estimates from the micro data. To justify an analysis at the plant level, I document significant dispersion across plants in terms of electricity and labor productivity as well as electricity prices, even within states and industries.

To estimate the effect of electricity prices at the micro level, I use a large panel data set of Indian manufacturing plants from 1998 to 2013, with annual information on the quantity and average price of electricity consumed at the plant level. Industry-by-region-by-year fixed effects allow for flexible and unobserved aggregate trends in productivity, demand, and prices, differentiated by industry and region, but several identification challenges remain that I discuss for my empirical framework. For example, most Indian states have increasing block tariffs for industry such that plants with higher consumption pay higher prices, or plants may negotiate discounts or benefit from ties to state electricity providers, which could be correlated with their productivity.[9] To address these endogeneity concerns, I use two different instruments based on the institutional context of Indian electricity pricing. The first uses electricity prices paid by other plants in the same state but different industry, kernel-weighted by distance in 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 0.40-1.06 and electricity productivity by 0.25-0.78 percent for each instrument. The endogeneity bias in the OLS estimates, however, is large. While the OLS elasticity of labor productivity to electricity prices is near zero, the OLS elasticity of electricity productivity is of opposite sign to the IV elasticity and

[8] The patterns in Figure 1 hold within industries and are therefore not driven by mere reallocation between sectors.
[9] Mahadevan (2023) shows Indian households in winning party constituencies were allowed to manipulate electricity bills.



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

(**b**) Electricity productivity and prices

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

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

statistically significant. I show that results are not driven by changes in the product mix, but by within-product technology differences across plants and time. I provide several robustness checks including additional price instruments based on policy shocks and analysis of heterogeneous effects.

The proximate mechanism is that the effect of prices on output outweighs the effect on electricity consumption or employment. I find that, as total variable costs increase, plants scale up with lower electricity prices. To explore deeper mechanisms, I test predictions of the nested CES production model, use exogenous shocks to machinery capital for a subset of plants from India's FDI liberalization in 2006, and examine plant decisions and outcomes. I present evidence that lower electricity prices significantly increase profits, plant total factor productivity (TFP), wages, investment in machinery, labor, machine to labor ratios, machine to electricity ratios, and markups. To directly quantify within-technology substitution versus technology switching, I estimate a finite mixture decomposition that recovers separate structural substitution elasticities within both latent technologies, but shows that technology upgrading—the compositional shift toward machinery-intensive techniques—overwhelms the standard substitution effect. These results corroborate all model predictions including those that distinguish it from standard CES models, and are consistent with a setting where electricity prices influence investment and technological decisions. Lower prices can incentivize firms to invest in modern electricity-using machinery and processes, especially for plants with initially low machinery penetration. This, in turn, improves productivity and output more than labor and electricity use.

I then estimate welfare effects. While there are clear positive effects for firms, it is a priori unclear how much consumers are affected by pass-through of electricity costs to output prices and losses through higher residential electricity tariffs from utilities financing deficits. I exploit detailed output quantity and price data to estimate pass-through elasticities by industry using the above instruments for marginal costs. I then combine these with my estimates of plant-level market power and demand elasticities to recover plant-level pass-through rates and consumer and producer incidence shares under imperfect competition in a generalized oligopoly. I account for industries serving final demand to varying degrees using input-output tables, and for utility deficit offsets by residential rate increases, which reduce consumer benefits. Total welfare gains from the 48% electricity price reduction are US$77 billion, comprising US$44 billion for firms and US$33 billion for consumers (43%).

I end the paper by considering environmental implications via CO_2 emissions and contrasting the findings of electricity price effects with coal price effects on industries, providing an additional test of mechanisms. First, using emission factors for specific fuels and the Indian grid, I estimate a 42.8Mt increase in CO_2 emissions from the 48% price reduction, equivalent to an additional welfare loss of US$4.3 billion at a social cost of carbon of US$100 per tCO_2. This increase is driven solely by scale as efficiency increased, and I show that without the estimated improvement in electricity productivity, emission increases would have been over double.[10] Second, coal price effects are opposite to electricity price effects. I estimate that lower coal prices *decrease* coal productivity and have no significant effect on labor productivity or other measures of firm performance. Comparing the effects of electricity and coal prices provides further evidence on the mechanism that electricity, unlike coal, has a special role in industrial modernization as complementary input. This finding is also relevant for climate policy, particularly regarding relative taxation of fossil fuels and electricity in developing countries.

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

A. Related Literature

This paper contributes to the broader literature on industrial development and the importance of capital intensive production technologies (Caselli, 2005), and how some cheaper inputs can help in this process (Acemoglu et al., 2012; Goldberg et al., 2010; Verhoogen, 2023; Aghion et al., 2022), especially given complementarity between energy and capital (Berndt and Wood, 1979; Pindyck and Rotemberg, 1983; Atkeson and Kehoe, 1999; Ryan, 2018; Hassler et al., 2021; Fried and Lagakos, 2023; Casey, 2024).[11] I show that cheaper access to a critical input for modern production, electricity, can affect capital investments and help firms transition to modern industrial technologies, while cheaper coal lacks these benefits.[12] While electrical machines have a labor replacing effect, I find that this is

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

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

[12] Calì et al. (2022) show that lower coal prices can lead to productivity losses. Macher et al. (2021) show that cement plants adopt efficiency enhancing technology when fossil fuel prices are high. Casey (2024) does not distinguish between types of

overcompensated by labor demand increases through associated input productivity and scale gains, 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 how energy, and electricity prices in particular, affect firm outcomes, showing how lower electricity prices can improve labor *and* electricity productivity. Four insights from the analysis are key. First, accounting for heterogeneity across firms is essential. Studies that assign fixed electricity intensities at the industry or product level, such as Abeberese (2017) for India or Elliott et al. (2019) for China, cannot capture technology differences and improvements in electricity productivity that occur within products and industries.[13] Abeberese (2017)'s headline finding suggests that lower prices decreased electricity productivity, but this relies on pre-defined intensities that ignore within-product technology differences. I find no significant effect on the product mix intensity, but instead show that firms are more electricity productive with lower prices when measured directly, using multiple instruments.[14] Beyond this finding, this paper rationalizes these patterns with a model of technology choices, decomposes the effect into within-technology substitution and across-technology differences, brings additional exogenous variation from India's FDI liberalization, and estimates consumer welfare and carbon externalities.

Second, the sign of the effect likely depends on the stage of industrial development. Davis et al. (2008), one of the first plant-level studies of electricity productivity and prices, find a positive elasticity in the US, a context of already highly mechanized production.[15] I present evidence that the effect moves closer to the industrialized counterpart as firms mechanize, suggesting the mechanism is most salient during industrial development. Third, addressing endogeneity is critical. Several developing-country studies report a positive OLS elasticity of electricity productivity to prices (Fisher-Vanden et al., 2004; Hang and Tu, 2007; Fisher-Vanden et al., 2016; Rentschler and Kornejew, 2017), consistent with my OLS estimates of opposite sign to the IV estimates. Fourth, conflating electricity with other energy sources may be problematic. As I show, coal prices have opposite effects to electricity prices (lower coal prices decrease coal productivity), so a composite index risks commingling offsetting effects, relevant for the broader firm energy price literature(Deschenes, 2011; Kahn and Mansur, 2013; Aldy and Pizer, 2015; Sadath and Acharya, 2015; Popp, 2002). This also connects to environmental policy (Martin et al., 2015; Calel and Dechezleprêtre, 2016; Dechezleprêtre and Sato, 2017), as carbon pricing lowers electricity relative to fossil fuel prices, redirecting investment as in Acemoglu et al. (2012).[16] Finally, this paper contributes to the literature on energy cost pass-through and incidence

energy but shows how energy prices affect short and long run aggregate energy efficiency. Hawkins and Wagner (2022) show energy price impacts on efficiency also depend on capital adjustment frictions preventing firms from updating technology.

[13]Aggregate prices, e.g. at the state level, also risk missing the substantial plant-level heterogeneity in electricity prices documented in this paper and in Davis et al. (2008).

[14]I replicate Abeberese (2017) in Table A.18 and show that the seemingly contradictory findings on product mix intensity are due to a partial omission of included fixed effects from a software issue that once addressed, makes the relationship insignificant or reverses the sign of the effect, consistent with the findings here.

[15]Their period featured rising prices rather than declining prices from high levels as in India, so effects on production technologies may also be asymmetric. Using sectoral price data, Linn (2008) also finds a positive elasticity of electricity productivity to energy prices in the US. His findings suggest that entrants' energy efficiency respond more to energy prices than that of incumbents. See also Hawkins and Wagner (2022) for an analysis of persistent effects of electricity prices on entrants in the US, and Pizer et al. (2002) who study technology adoption, energy prices and aggregate energy efficiency.

[16]The Porter and Van der Linde (1995) hypothesis, which postulates firm performance gains from environmental regulation,

shares between firms and consumers (Weyl and Fabinger, 2013; Fabra and Reguant, 2014; Ganapati et al., 2020; De Loecker et al., 2016; Miller et al., 2017; Hausman, 2018), but in a developing country context.

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

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

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

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

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

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

$$\alpha_l = \hat{\alpha}_l / c \qquad \textit{and} \qquad \rho_e = \hat{\rho}_e \cdot c$$

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 labor share to $\hat{\alpha}_l/c'$, capturing more capital intensive production. For example, a handloom in textiles uses more labor per machine bundle than a powerloom, but a powerloom cannot function without electricity. Therefore, it also increases the complementarity between capital and electricity to $\hat{\rho}_e c'$ (as $\hat{\rho}_e < 0$ the absolute value of $\hat{\rho}_e$ is increased), as modern machines are more reliant on electricity to produce.

There are fixed costs $m \cdot c$ associated with choosing a particular technology $c \in \{1, c'\}$, where $m \geq 0$ such that fixed costs are allowed to be higher for the modern electricity-using production

may apply to fossil fuels, but not necessarily to electricity. See Lu and Pless (2021) for a fossil fuel example.

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

process (e.g. electrical wiring). A firm maximizes profits Π given input prices p_K, p_L and p_E:

$$\max_{K,L,E,c} \Pi = PQ - p_K \cdot K - p_L \cdot L - p_E \cdot E - m \cdot c \tag{3}$$

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

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

However, once we allow for non-convex production technologies, two otherwise identical firms may choose different technologies when facing lower electricity prices, resulting in:

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 $\frac{PQ^*}{E^*}$. Appendix A.1 provides a proof.*

The across-technology effect can therefore be larger than the pure within-technology effect of Lemma 1. The proof characterizes this result further. It shows that the level of electricity use is higher in the modern technology, which benefits more from the price drop. The increase in output scale is even higher, however, driven by greater machinery adoption required by the complementarity in the new technology, raising electricity productivity. Figure 2 visualizes Proposition 1 by solving the model for a given parameter set. These patterns are not unique to this specific parameter set. Indeed, they arise for a broad range of substitution elasticities between labor, capital and electricity as illustrated in Figure A.1, and the proof shows the exact interval conditions. Figure 2a shows optimal electricity productivity $\frac{PQ^*}{E^*}$ against electricity price decreases. The upper line plots conditional on the modern technology $c = 3$, and the lower line for the traditional technology $c = 1$, both normalized. 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 fall enough to yield higher overall profits. This technology adoption leads to a step change in electricity productivity as shown in Panel (a).

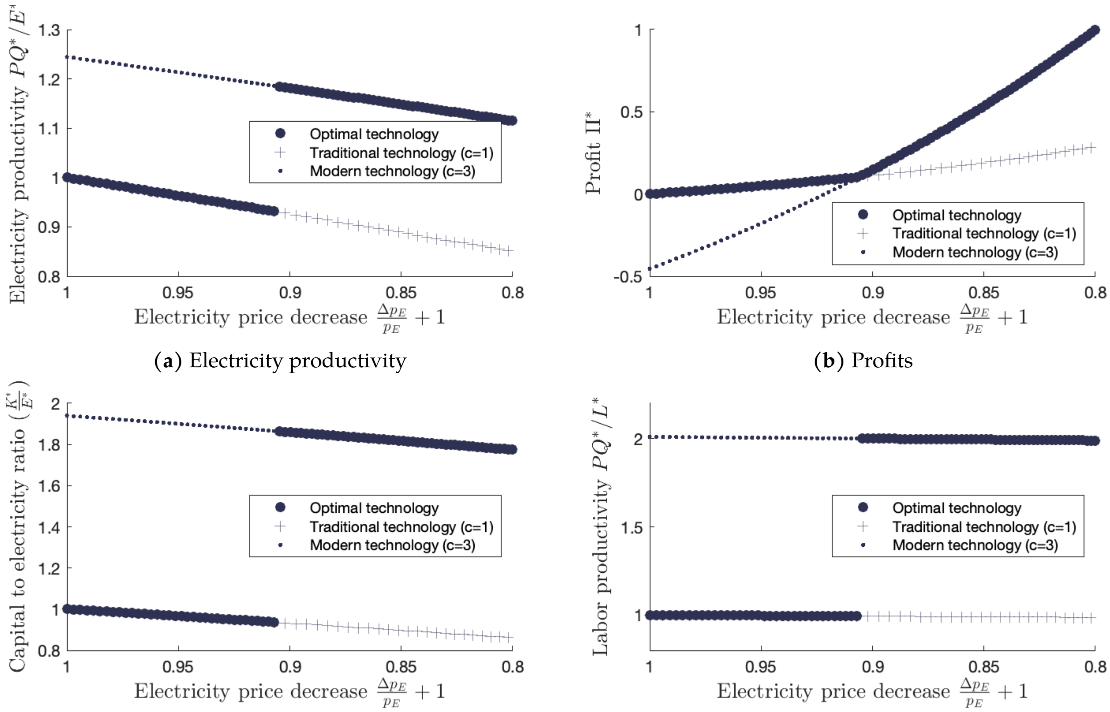
Panel (c) shows that the capital utilization effect across technologies is so large that the capital to electricity ratio increases with the technology switch, even though it is electricity that becomes cheaper, not capital. This is not possible without technology choices, as:

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 $\frac{K^*}{E^*}$. Appendix A.1 shows a proof.*

However, in this model, the only way Proposition 1 can arise is:

Corollary 1. *With discrete technologies, an electricity price decrease that also increases electricity productivity $\frac{PQ^*}{E^*}$ as in Proposition 1 must also increase the capital to electricity ratio $\frac{K^*}{E^*}$. Appendix A.1 shows a proof.*

This is a sharp distinction from standard models without discrete technologies. I will test this prediction of the model in the empirical part, and will estimate the complementarity ρ_e by technology, including decomposing this overall effect into pure substitution and across technology effects.



(**a**) Electricity productivity

(**b**) Profits

(**c**) Capital to electricity ratio

(**d**) Labor productivity

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

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

Turning to labor productivity, without technology choices, an electricity price decrease can increase or decrease labor productivity, depending on whether labor and capital services are complements or substitutes, similar as in Acemoglu (2002).

Lemma 3. *Without discrete technology choices, an electricity price decrease from p_E to $p_E - \Delta_{p_E}$ decreases labor productivity if $\rho_l < 0$ and increases it if $\rho_l > 0$. Appendix A.1 shows a proof.*

However, the switch to modern technology unambiguously increases labor productivity in this model, as Panel (d) of Figure 2 shows, driven by a higher utilization of capital services:

Corollary 2. *With discrete technologies, an electricity price decrease that also increases electricity productivity $\frac{PQ^*}{E^*}$ as in Proposition 1 must also increase labor productivity $\frac{PQ^*}{L}$. Appendix A.1 shows a proof.*

Figure A.2a shows similar graphs for further firm outcomes and input ratios. These model predictions are tested and corroborated empirically below. Figure A.2b shows how the introduction of capital constraints, if binding enough, can delay the switch to the modern technology. Finally, Figure A.2c shows how the adoption threshold varies for heterogeneous firms, and how this maps into aggregate electricity productivity that increases more smoothly with electricity price decreases.

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

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

A. India's Electricity Sector

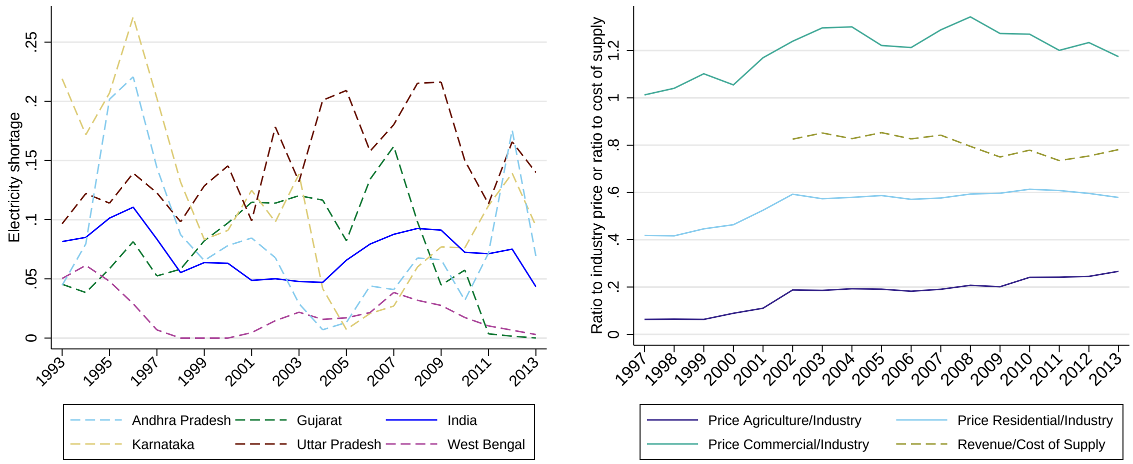
Where does electricity come from and how do prices come about? I next highlight five key contextual features: (i) electricity is predominantly produced by coal-fired plants, (ii) generation is mainly state owned with increasing private ownership after deregulation in 2003, (iii) industrial electricity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

Fuel mix of generation and ownership.— Electricity is mainly purchased from the grid and most of it is generated by coal-fired power plants (roughly 60%), followed by hydro. The variation in the coal share in generating capacity across states contributes to one of the shift-share instruments in the analysis. This variation is mainly determined by the presence of coalfields, as coal accounts for up to two-thirds of production costs in coal plants (IEA, 2015). Figure A.12 maps the geography of coal power plants and coalfields. India's electricity generation is dominated by state and central governments, owning 65% and 30% of installed capacity in 1998, with the remaining 5% privately owned (Planning Commission, 2001-2002). The 2003 Electricity Act aimed to open the heavily regulated sector to more competition, raising the private capacity share to 31% by 2013. This market opening contributed to lower electricity prices, which I exploit for additional identification in robustness checks.[18]

India's high industrial electricity prices in comparison.— India's high industrial electricity prices are important context for interpreting the results. Average electricity tariffs in 1998, at the beginning of the analysis period, were equivalent to 15.1 US cents per kWh (2004 US$) for industrial users, around 70% higher than the G7 average in nominal terms, or six times as high in PPP terms, and remained higher in nominal terms until 2004 (Figure A.5). Importantly, industrial prices are significantly above cost-recovery, in stark contrast to residential or agricultural prices (5.8 and 0.9 US cents per kWh in 1998). While agricultural consumers made up 32% of electricity consumption in 1998, they accounted for only 3.6% of sales revenue (Planning Commission, 2001-2002). As a result, state electricity utilities have been loss-making almost across the board, despite cross-subsidization from industrial users (Ministry of Power, 1998*b*). The main reason for the heavy cross-subsidization across sectors is political as farmers form important voting blocs that governments aim to cater to (Abeberese, 2017).

Electricity pricing.— Electricity prices vary locally across manufacturing plants, determined by utility tariffs that are typically revised annually. Tariffs have been heavily regulated, with prices tied to cost pressures for generators. Generation, transmission and distribution were largely vertically integrated before 2003 with individual State Electricity Boards setting tariffs for different end-users

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



(**a**) Shortages over time

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

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

Notes: Panel (a) plots electricity shortages over time, calculated as share of total required electricity using data from Central Electricity Authority (2006-2015) and Allcott et al. (2016). Panel (b) plots ratios of electricity prices in agriculture, residential or commercial over industrial electricity prices. These are calculated as total revenue over total quantity of electricity delivered by sector from the Indian Planning Commission (2001-2002) and Ministry of Power (2002-2015). These are weighted averages across states and utilities based on the share of total electricity consumption, but using simple averages yields the same conclusions. Panel (b) also shows the overall ratio of average rate of revenue (without subsidies) over the cost of supply available from 2002.

and locations within their jurisdiction.[19] Unlike in many European countries, industrial tariffs mostly follow flat or slightly increasing block tariffs, as I show in Figure A.6 using manually collected tariff data and by plotting plant average prices against quantities to visualize marginal prices. Prices remained heavily regulated after the Electricity Act of 2003 despite some unbundling (IEA, 2015). Coal prices are the main cost pressure for coal-fired generators and thus electricity prices. The largest coal producer, government owned Coal India Limited, is a quasi-monopoly (81% market share in 1998) supplying most power plants (Preonas, 2018). Coal prices for power generators and industry are set independently and often move in opposite directions (see Figure A.13a), important context for identification for one of the instruments discussed below. Changes in coal prices for power generators reflect regulatory shifts or cost of mining (Ministry of Coal, 2006, 2015).[20] Finally, the observed fall in industrial electricity prices over the sample period is due to a combination of lower generation costs (Figure A.13a), deregulation and entry (Table A.3), and reduced cross-subsidization (Figure 3b).

Electricity prices, power shortages and self-generation.— India's electricity generation usually falls short of demand.[21] In the short run, distribution companies cannot adjust pricing for end-users at high-frequency to clear markets as a response to shortages (Allcott et al., 2016; Jha et al., 2022). In the longer run, one may be concerned that the decrease in industrial electricity prices affected shortages directly. Burgess et al. (2020) show how many utilities in developing countries are stuck

[19] Regional electricity trading is highly limited. Networks across regions are in the process of getting better integrated (IEA, 2015). For additional information on unbundling and spot vs. longer term electricity markets see Planning Commission (2001-2002); Cropper et al. (2011); IEA (2015); Ryan (2021); Preonas (2018); Mahadevan (2019).

[20] Since 2010, the coal price has an additional tax of ₹50 per tonne (4% of the price), feeding into the cost shifting instrument.

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

in a low reliability – low cost-recovery equilibrium, where low prices lead to more shortages. Yet, the degree of shortages was stable in India despite falling real industrial electricity prices over the sample period. Figure 3 Panel (a) plots shortage data as share of total required electricity from administrative reports for India overall and six major states over time. The key to explain this lack of correlation between industrial prices and shortages is that industry is not the main consumer of electricity. While industrial prices were above cost-recovery, residential and particularly agricultural prices were far below cost-recovery but consumed more electricity. Panel (b) plots the price ratio of average agricultural and residential prices to industrial prices using government publications. While agricultural prices were only 6% of the industrial price level at the beginning of the sample in 1998, they were 27% by the end of 2013. This is a four-fold increase in the relative price, showing a significant reduction in cross-subsidies. This in turn helped stabilize cost-recovery for utilities despite falling industrial prices. Panel (b) also plots cost-recovery where data is available from 2002. Cost-recovery is fairly stable around 80% helping explain the stability of shortages over time.[22]

Importantly, this institutional context implies that industrial electricity prices are not correlated with power shortages in India. I show this more formally using multiple types of data on shortages and electricity prices. First, shortages as measured by unmet electricity demand at the factory level from survey data are uncorrelated with electricity prices, both overall or at the intensive margin of unmet demand (Figure A.7 and Table A.1). Second, the correlation between state-level power shortages from administrative data and industrial electricity price from government reports is also insignificant and small (Table A.2). By contrast, as Table A.2 shows, *overall* electricity prices based on all consumer sectors rather than industry alone, are indeed correlated with shortages. This is because, as Table A.2 also shows, the degree of cost-recovery drives electricity shortages and cost-recovery is in turn driven by these *overall* electricity prices, as in Burgess et al. (2020). This is consistent with Figure 3: due to reductions in cross-subsidies, lower industrial electricity prices do not lead to more shortages, as it is the overall electricity price that matters for cost-recovery and shortages. The fact that industrial electricity prices are not correlated with shortages allows me to focus on industrial electricity prices.[23] For the analysis, if anything, lower electricity prices would lead to more outages, introducing a countervailing downward bias making my estimates conservative. Nevertheless, I control for shortages in robustness checks in Table A.7.

Apart from the failure to account for supply and demand imbalances in the high frequency wholesale market (Jha et al., 2022), power outages are also driven by technical equipment or network failures (Allcott et al., 2016). Coal supply issues, on the other hand, are only responsible for 0.2% to 3.3% of failures in thermal plants,[24] so while coal supply affects electricity prices, it is unlikely to affect outages. Finally, power outages led to adoption of electricity generators by a few larger industrial plants. Importantly, generator adoption is driven by insuring against outages and not by electricity

[22]Note that utilities cover their losses with government subsidies. So even if cost-recovery would decline, shortages can be stable if government tops up an increasing shortfall.

[23]This is in line with Allcott et al. (2016), who by the same logic focus on shortages while ignoring industrial electricity prices. They provide evidence that a rainfall instrument for hydro power is also uncorrelated with electricity prices in India.

[24]Calculated as share of total annual outages using data from Allcott et al. (2016).

prices, since self-generation is typically more expensive than buying electricity from the grid.[25]

B. Data

Manufacturing plant-level data.— The main data source is the Annual Survey of Industries (ASI), India's mandatory establishment level survey. Its long history since 1953 makes it relatively reliable in a developing-country context. Formal firms in the ASI represent two-thirds of manufacturing output (Allcott et al., 2016), with the remainder comprising informal and sub-10 employees firms.[26] By matching panel and cross-sectional ASI editions, I retrieve panel identifiers and district codes only available in each edition, and use an annual panel from 1998 to 2013 for the main analysis.[27]

I use quantity and value of electricity purchased, generated, and sold. By dividing the value of electricity purchased by its quantity, I can calculate the average price paid for electricity at the plant level. I validate the quality of the derived prices below. In this context, average electricity prices are similar to marginal prices.[28] Electricity productivity is deflated output divided by the quantity of electricity consumed, i.e. net purchases and self-generation.[29] Labor productivity is deflated output per employee. I also use plant-level output (sales), employees, wages, intermediate inputs, and other fuel expenditures and quantities (coal, gas and oil). Importantly, I distinguish between different types of capital and use machinery capital (book value or investment), as it is the most relevant for this analysis. I measure firm-level capital rental rates as total capital charges (interest, plant rental expenses, and depreciation) divided by the gross book value of fixed assets. I construct total variable costs as the sum of wages, input costs, and other variable expenses, and total revenues as the sum of sales and other receipts. The difference is total profits. To analyze pass-through and incidence, I use both output sales and quantity at the plant-product level to construct output prices and quantities. I drop non-manufacturing observations, winsorize the top and bottom percentile of each variable within each year to reduce sensitivity to outliers, and deflate all monetary values to a common base year 2004 throughout the paper.[30] I weight all regressions by the included sampling multiplier. Table 1 shows that after the cleaning steps, there are 485,342 plant-year observations from 160,836 plants.

Additional data.— I manually collect annual utility level average tariffs, revenues, demand by sector, and cost of supply and cost-recovery from Planning Commission (2001-2002) and Ministry of Power (2002-2015). Additionally, I collect dated state average tariffs by consumer type and consumer size

[25] Bhattacharya and Patel (2008) estimate self-generation to be at least 25% more expensive than buying electricity. In other developing countries, the price ratio between self-generated and grid electricity is even larger (Fried and Lagakos, 2023).

[26] The survey divides plants into a census sector, where all plants with ≥ 100 employees (≥ 200 until 2004) are sampled, 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.

[27] The accounting year in India runs from April to March, and I refer to it by the first year (i.e. 2006 is April 2006 to March 2007). For robustness checks and trends, I add the 1993 and 1996 cross-sectional ASI micro data editions. I also use industry-state-year ASI aggregates from 1967-1997 for long-run trends.

[28] This is because marginal prices are relatively flat i.e. pricing is fairly linear (Figure A.6a). Note that firms may also react to average rather than marginal prices (Ito, 2014).

[29] Around a quarter of consumed electricity is self-generated.

[30] I winsorize final variables only to avoid double winsorization. I deflate outputs and inputs using 3-digit industry deflators, investment and installed machinery capital using a machinery deflator, wages, total revenues, total costs and total profits using a state deflator, and fuels and manually collected tariffs and prices (electricity, coal, gas, oil) using a fuel and electricity deflator (Office of the Economic Adviser, 2019; Reserve Bank of India, 2019).

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)	448.5
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
Capital rental rate (₹ per ₹)	.36	472503
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. Where indicated, the means are additionally weighted by the consumed electricity, fuel or coal to make the means more representative of aggregate productivities. Marginal cost (MC) markups are calculated following De Loecker and Warzynski (2012), and plant TFP are calculated using Wooldridge (2009), Levinsohn and Petrin (2003), or Olley and Pakes (1996) as indicated. See Singer (2019) for a detailed example of TFP estimation using Wooldridge (2009) in the Indian context.

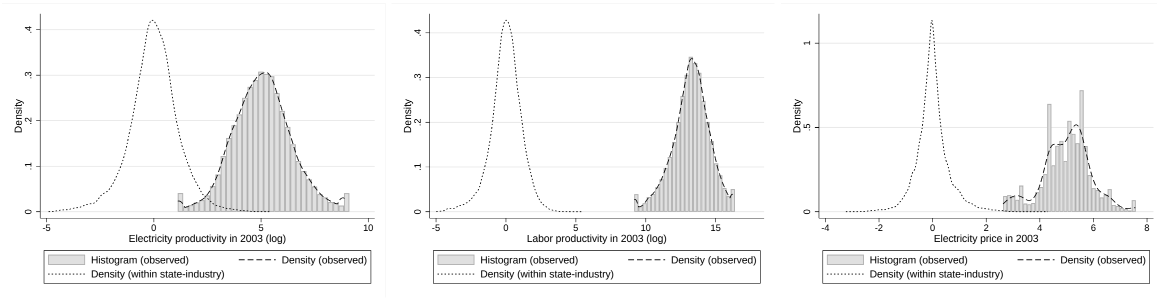
from annual reports of the Central Electricity Authority (2006-2015) and from Indiastat (1998-2014) through Lok Sabha and Rajya Sabha (Parliament of India) questions. For coal prices for thermal power plants (as opposed to manufacturing plants), I use the published annual pit-head prices specifically for power utilities and inclusive of royalties and taxes, based on a representative Coal India Limited (CIL) mine and grade (Figure A.13a). Shares of coal-fired power plants in state installed capacity in 1998 are shown in Figure A.13b. Data on state-level power shortages are from the Central Electricity Authority (2006-2015), and from Allcott et al. (2016) for before 2005. Data for additional analysis, such as the location of coalfields and power plants, are described in respective figure and table notes.

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

To motivate the main analysis I next present key empirical patterns. Both the doubling in energy productivity from 2000 to 2013, after remaining constant in previous decades, as well as the increase in electricity productivity while electricity prices fell (Figure 1) also hold within sectors or states (Figure A.8), ruling out mere across-sector or spatial reallocation. These patterns are also not driven by substitution away from electricity. If anything, there was substitution away from other fuels towards electricity.[31] Alternative data sources confirm these patterns in electricity productivity and show that this is in contrast to the evolution of electricity productivity in OECD countries (Figure A.4a).[32]

[31]The share of electricity in fuel expenditure was roughly constant at 65% from 2000-2013 implying higher quantity used as prices decreased substantially. Substitution to electricity meant that fuel productivity of other fuels increased even more since 2000, as seen in Figure A.4b.

[32]See also Barrows and Ollivier (2018) and Ghani et al. (2014) for emission and electricity productivity in India.



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

Figure 4: Heterogeneity in electricity and labor productivity and in electricity prices

Notes: Panel (a) plots the histogram of plant-level logged electricity productivity in 2003. The kernel density plot to the left shows the distribution of the residuals of logged electricity productivity after partialing out state by 4-digit industry by year fixed effects. Panel (b) and Panel (c) show the same plots for labor productivity and electricity prices in 2003. The patterns are similar for each year, or for the pooled sample with the same fixed effects used in the analysis (Figure A.10).

Figure A.9 shows that labor productivity increased more steadily over these five decades. Labor productivity and wages increased by around 90% and 60% respectively from 1998-2013 (Figure A.9). The IV results below can explain the increase in electricity productivity from electricity prices well, and to a slightly smaller degree also the increase in labor productivity and wages.

Importantly, I validate the reliability of the derived ASI price data against administrative tariff data from several government publications and official real price indices in Figure A.3a, against manually collected tariff data at the state by year level for large consumers in Figure A.3b, and by showing results are robust when using this tariff data instead (Table A.6).[33] Figure A.5 contrasts the price trends with OECD countries, where industrial electricity prices have been increasing.

Before setting up the econometric analysis at the plant level, it is crucial to ask how much variation in prices and productivities is left when looking *within* industries or regions. Figure 4 plots histograms of electricity productivity, labor productivity and electricity prices in 2003.[34] It shows that there remains substantial dispersion even after partialing out state-industry (4-digit) effects. Plants at the 90th percentile still pay around 33% higher electricity prices than those at the 10th percentile within state-industry-year clusters. Plant labor and electricity productivity at the 90th percentile is 13 and 15 times higher than at the 10th percentile, similar or slightly higher than US productivity dispersions in the literature (Syverson, 2004, 2011). Figure A.11a presents a formal variance decomposition following Davis et al. (2013), showing that about half the variation in prices or input productivities is *within* states and industries. Finally, Figure A.11b shows that plant electricity prices are persistent through first order stochastic dominance across periods. The persistence within plants and the substantial variation across plants suggests an empirical strategy that also includes between-plant variation.

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

[34] The same pattern holds in other years. Figure A.10 shows a similar plot for the pooled sample across time after applying the same fixed effects as in the analysis below, and also shows the variation in prices that is predicted by the instruments.

IV. Empirical Strategy

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

$$y_{jisrt} = \beta \log(P^E_{jisrt}) + \alpha_{irt} + \epsilon_{jisrt} \tag{4}$$

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.[35] The analysis is conditional on 4-digit industry-by-region-by-year fixed effects α_{irt}. The fixed effects account for confounding aggregate trends that may be correlated with electricity prices and outcomes, such as technology and productivity, demographics, demand for manufacturing products, or industry structure and product prices. These unobserved trends are allowed to vary by 4-digit industry, in part to control for Indian sectoral dereservation policy effects, as well as by region, in part because of poor electricity market integration across Indian regions (IEA, 2015; Ryan, 2021; Ministry of Power, 2018). Importantly, the fixed effects preserve policy-relevant variation across states, districts and plants within the six regions that captures differences in tariff regulation and generation costs.

The above specification deliberately avoids plant fixed effects for three reasons.[36] First, between-plant variation likely captures much of the key mechanism of technology differences and upgrading within industry-region-years, compared to mere within-plant variation. Machinery installation takes time and electricity prices are serially correlated, so responses to price changes can manifest gradually showing up between plants rather than within-plant changes alone, consistent with putty-clay models of energy adjustment (Atkeson and Kehoe, 1999; Hassler et al., 2021; Casey, 2024). Therefore, this approach exploits not only short-run variation, as typical with plant fixed effects, but also longer-run between-plant variation such as changes in production processes. As shown in Section III.C, there is much interesting variation between plants: A regression of logged electricity productivity on plant fixed effects can explain 80% of the variation (R^2). In Appendix Figure A.11, I show variations of popular Griliches and Regev (1995) decompositions, illustrating that the improvements in aggregate electricity productivity are driven by both within-plant and between-plant variation. Second, plant fixed effects require a strict exogeneity assumption, which is likely violated. Past shocks to output and productivity affect current electricity prices through block tariffs that vary with consumption, introducing bias.[37] Third, plant fixed effects fail to address time-varying endogeneity at the plant level. To address these concerns effectively, I instead use instrumental variables for identifying variation.

The variation that remains after conditioning on industry-region-year effects reflects common state or local tariff or cost movements that shift plants' prices across space and time, and plant-level

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

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

[37] 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.

movements from nonlinear tariffs, bargaining or discounts. This remaining variation is substantial as shown in Figures A.10 and 4, and I address next how I recover exogenous variation within these cells.

A. Endogeneity Concerns

To structure the discussion about endogeneity concerns, it helps to think about the exogenous and endogenous components in $\log(P^E_{jisrt})$ within industry-region-year groups in Equation (4).

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

$$\epsilon_{jisrt} = \xi_{jisrt} + \lambda_{isrt} + \mu_{jisrt}, \tag{5}$$

The nature of ξ_{jisrt} and λ_{isrt} comprises several factors, all conditional on controlling for 4-digit industry-by-region-by-year fixed effects α_{irt}. First, shocks to output and electricity demand (in ξ_{jisrt}) can affect electricity prices through tariff variation across different consumption bands (Figures A.6b and A.6a). Second, plants or groups of firms within an industry may negotiate or exert pressure for lower prices (ξ_{jisrt} and λ_{isrt}). Their bargaining power likely relates to their economic performance, leading to reverse causality problems.[38] Third, there may be factors within regions and industries not captured by the fixed effects that jointly affect economic performance, electricity productivity and electricity pricing (in λ_{isrt}).[39] 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} and λ_{isrt}). Finally, plant-level electricity prices may suffer from measurement error (in ξ_{jisrt}). I next turn to two instrumental variable strategies to isolate exogenous components of the price variation.

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

The idea of the first instrument (IV^A) is that any exogenous components in the electricity price should also affect other plants nearby. Some weighted average of other plants, for example in the same state, could therefore extract the common exogenous signal while being agnostic about the specific source of the signal that could stem from changes in electricity generation costs or differences in regulation.[40]

By construction, some average of electricity prices of other plants removes the idiosyncratic endogenous component ξ_{jisrt}. The validity of these types of instruments, however, depends on context

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

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

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

(Berry and Haile, 2016), due to concerns with SUTVA and the exclusion restriction. To mitigate these concerns, I construct IV^A only with plants outside the plant's own 2-digit industry, as both supply chains and output market competition occur predominantly within 2-digit industries. I therefore rely exclusively on plants in the same state, but in different 2-digit industries i^{2d}, removing the industry-level endogenous component. The underlying assumption is that the endogenous components λ_{isrt} are not correlated across the 22 2-digit industries within a state, but allowed to be correlated within them. Recall that industry-region-year effects are accounted for by α_{irt}, so elements in λ_{isrt} common across regions can be correlated across 2-digit industries as well. Because remaining endogeneity could also reflect spatial rather than sectoral proximity (e.g., spatially organized bargaining or place-based political economy), I further relax Equation (5) in a robustness check by additionally excluding same district plants when constructing a version of this instrument (IV^C), with very similar results.

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

$$w_{q^*}(q_j) = \begin{cases} \frac{b_{q^*} - |\log(q_j) - \log(q^*)|}{b_{q^*}^2} & \text{if: } \log(q_j) \in [\log(q^*) - b_{q^*}, \log(q^*) + b_{q^*}], \\ & \forall s_j = s_{j^*}, t_j = t_{j^*}, i_j^{2d} \neq i_{j^*}^{2d}. \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

where q^* is the electricity quantity purchased in kWh by plant j^* that we want to create the instrument for, and q_j is the electricity quantity purchased by other plants j. The cutoff b_{q^*} is the 25th percentile of the distribution of the logged ratio of the purchase quantities in absolute terms $|\log(q_j) - \log(q^*)|$, and is thus allowed to vary by plant j^* that we want to instrument for.[41] 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 $i_j^{2d} \neq i_{j^*}^{2d}$. The weight decreases linearly in the distance of logged purchase quantity. The first instrument IV^A for the electricity price of plant j^* is then the average of the electricity prices of other plants P_{jisrt}^E, weighted by the triangular kernel weights:

$$IV_{j^*isrt}^A = \sum_{j \neq j^*} P_{jisrt}^E \frac{w_{q^*}(q_j)}{\sum_{j \neq j^*} w_{q^*}(q_j)} \tag{7}$$

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

[41] The advantage of a flexible bandwidth 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.

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

The second instrument is a cost shifter for electricity generation, following Abeberese (2017).[42] Since coal is the largest cost factor in electricity generation (see Section III.A), the price of coal shifts electricity generation costs for power plants, and therefore downstream electricity prices. The instrument is based on a shift-share structure as in Bartik (1991). The shifters are nationally representative coal prices specifically for power utilities (see Section III.B). These shifters are weighted by the pre-sample (March 1998) shares of thermal coal-fired capacity in total installed capacity at the state level:

$$IV_{srt}^{B} = \log(P_t^{CoalPower}) \frac{\text{coal-based installed capacity}_{sr_{1998}}}{\text{total installed capacity}_{sr_{1998}}} \tag{8}$$

Recent advances show that identification in shift-share designs requires only either exogenous shifters (Borusyak et al., 2022) or exogenous shares (Goldsmith-Pinkham et al., 2020). A concern for shifters is that coal prices may also affect firms using coal directly. In India, however, coal prices for power utilities are set independently from those for industry (Section III.A). The two sectors require different types of coal. Thermal coal used by power plants is produced domestically by a national monopoly. Coking coal used by a subset of manufacturing plants is largely imported from global markets, so coal prices for power plants are not tied to coal prices for industry. Indeed, Figure A.13a plots both coal prices in real terms showing that often one falls while the other rises at the same time. In a reassuring robustness check, I exclude all manufacturing plants that use coal directly, which are most likely to be affected by such exclusion restriction violations, with similar results (Table A.10).

Regarding the shares, conditioning on industry-by-region-by-year fixed effects helps as shares exogeneity is only required within regions, and allows for trends and correlation of pre-sample shares with industrial structure (e.g. if heavier industry locates in coal regions). Figure A.13b shows a map of pre-sample thermal shares. I present additional evidence of exogeneity of shares in Table A.5a, showing state-level regressions of shares on several pre-determined variables using data from Asher et al. (2020). The shares are uncorrelated with measures of baseline industrial development, such as rural population share, electricity access, labor productivity, capital labor ratio, skilled wage share, or fuel share in output. To further support this identification assumption, Table A.5b shows robustness of the IV^B estimates by including controls for these pre-determined variables interacted with the coal shifter, indicating that shares are unlikely to correlate spuriously with future industrial development. Finally, Adao et al. (2019) show standard errors may need adjustment for shift-share designs. Following their procedure, I recover adjusted standard errors that are similar or even smaller, likely due to negative correlation of residuals within clusters that are based on thermal shares.[43]

Instrument IV^B isolates exogenous movements in electricity prices driven by cost pressures in upstream generation. Its advantage is that it could be less susceptible to specific correlated shocks that may threaten the validity of instrument IV^A, if they exist. Disadvantages of IV^B are that it tends

[42] A similar shift-share instrument for energy prices relying on thermal shares in generation has also been used in Ganapati et al. (2020) or Elliott et al. (2019).

[43] In Table 2, the standard error falls from 0.105 to 0.028 (Column 3) and slightly increases from 0.103 to 0.112 (Column 6).

to be much weaker than IV^A and harder to replicate in other contexts as it relies on external data.

D. Specification Choice, Estimation and Inference

The baseline reduced-form specifications exclude state by year effects, as IV^B only varies at the state by year level and much of the exogenous variation operates at the state by year level.[44] I exploit the panel structure for standard errors in all specifications. I two-way cluster errors at the plant level, and at the state by year level, since one of the instruments varies at that level. As a robustness check, I two-way cluster 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.19. Finally, I use the two instruments separately to enable comparisons, but also provide results based on an over-identified IV-regression with both instruments.

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

To shed light on mechanisms, I estimate the structural complementarity in the inner nest of electricity and machinery, motivated by the model first order condition in Section II. I focus on this equation for two reasons. First, it is particularly informative because the reduced-form result can overturn a sharp sign prediction from the CES benchmark with constant technology. Corollary 1 predicts that the machinery to electricity ratio increases with lower electricity prices under Proposition 1. This must come from technology differences, as this sign is unambiguously positive within technology by Lemma 2. Second, focusing on the inner nest lets me sidestep estimating other structural parameters such as returns to scale. Conditional on technology c, the first order condition of (3) in logs (see Equation (A.4)), adding fixed effects α_{irt} and an error term ε_{jirst}, is[45]:

$$\log\left(\frac{K_{jirst}}{E_{jirst}}\right) \;=\; \alpha_c + \sigma_c \log\left(\frac{p^E_{jirst}}{p^K_{jirst}}\right) + \alpha_{irt} + \varepsilon_{jirst} \tag{9}$$

where $\sigma_c = \frac{1}{1-\rho_e(c)}$ is the technology-specific elasticity of substitution between machinery and electricity. It can be shown that even if the substitution elasticities vary across sectors or time, including the α_{irt} fixed effects recovers a consistent estimate of the weighted average substitution elasticity across sectors, regions and time. The key challenge is that σ_c depends on unobserved technology c. Reduced-form regressions as in (4) capture the joint effect of technology differences and some within-technology average of substitution elasticities, assuming valid instruments for electricity prices. To recover structural parameters for within-technology substitution, I separate the two effects, allowing me to decompose the reduced-form elasticity.[46]

To do so, I introduce a parsimonious finite mixture model with two latent technology types $c \in \{1, c'\}$ as empirical analogues of the theory model. Such models provide a way to represent unobserved

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

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

[46] I pool plants across industries and absorb industry-by-region-by-year fixed effects, so the technology-specific slopes $(\sigma_1, \sigma_{c'})$ are identified from within-cell variation and reflect an average machinery-electricity substitution elasticity.

heterogeneity with a small number of types in structural settings, and have been used to capture discrete differences in decision rules and technologies (Heckman and Singer, 1984; Keane and Wolpin, 1997; Kennan and Walker, 2011; Arcidiacono and Miller, 2011; Bonhomme et al., 2022; Kasahara et al., 2023). The idea is that each observation can be generated by one of two latent technologies with different machinery–electricity substitution elasticities, where technology membership is unobserved and statistically recovered, taking into account endogeneity of the relative prices.

I allow electricity prices to shift the probability of using a technology. Specifically, I model the prior probability of the modern technology $\pi_{jc'}$ as a logit function of log electricity prices $\widetilde{\log p_j^E}$, demeaned by industry-by-region-by-year averages to allow for correlation between electricity prices and these trends.[47] For exposition, let j index plant-year observations. The prior technology probabilities are:

$$\pi_{jc'} \;\equiv\; \Pr(c = c' \mid \widetilde{\log p_j^E}) \;=\; \Lambda\left(\gamma_0 + \gamma_1 \widetilde{\log p_j^E}\right), \qquad \pi_{j1} = 1 - \pi_{jc'}, \tag{10}$$

where $\Lambda(\cdot)$ is the logistic CDF, and the electricity price instruments will provide moment conditions identifying γ_1. The priors in (10) map observables into *ex-ante* technology shares, describing how the probability of using the modern technology varies with electricity prices both within and across plants, before taking into account the plant's observed input mix. The posterior probabilities combine (i) the prior π_{jc} with (ii) a measure of fit of the technology-c specific relationship to the observed $\log(K_j/E_j)$. Define $u_{jc} \equiv \log(K_j/E_j) - (\alpha_c + \sigma_c \log(p_j^E/p_j^K) + \alpha_{irt(j)})$ as the residual implied separately by technology $c \in \{1, c'\}$ for each observation. Using Bayes' rule and a Gaussian likelihood with common variance s^2 and $\varphi(\cdot)$ denoting the standard normal pdf, the posterior probabilities are:

$$r_{jc'} = \frac{\pi_{jc'}\, \varphi\big(u_{jc'}/s\big)}{\pi_{j1}\, \varphi\big(u_{j1}/s\big) + \pi_{jc'}\, \varphi\big(u_{jc'}/s\big)}, \qquad r_{j1} = 1 - r_{jc'}, \tag{11}$$

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

$$(i)\ \textit{Technology-specific mean IV moments:} \qquad \mathbb{E}\left[r_{jc}\, u_{jc} \begin{pmatrix} \widetilde{IV}_j^A \\ \widetilde{IV}_j^B \end{pmatrix} \right] = 0 \quad \text{for } c \in \{1, c'\}, \tag{12}$$

$$(ii)\ \textit{Technology-choice moments:} \qquad \mathbb{E}\left[\big(r_{jc'} - \pi_{jc'}\big) \begin{pmatrix} 1 \\ \widetilde{IV}_j^A \\ \widetilde{IV}_j^B \end{pmatrix} \right] = 0, \tag{13}$$

$$(iii)\ \textit{Variance moments:} \qquad \mathbb{E}\left[\big(u_j^2 - v_j\big) \begin{pmatrix} 1 \\ \log\big(p_j^E/p_j^K\big) \end{pmatrix} \right] = 0, \tag{14}$$

[47]This differs from including fixed effects in a nonlinear logit, which would require solving for many parameters, but it ensures that γ_1 is identified from within-cell price variation. I label technology c' as the machine-intensive modern technology.

where $\widetilde{IV}_j^A$ and $\widetilde{IV}_j^B$ are within-fixed effects demeaned versions of the excluded instruments. Moment block (i) estimates the analogue of (9) using the posterior weights to integrate out the unobserved technology type. Moment block (ii) imposes orthogonality of the difference between posterior and prior technology probabilities with the instruments. Moment block (iii) matches second moments implied by the mixture. The mixture residual is $u_j \equiv (1-\pi_{jc'})u_{j1} + \pi_{jc'}u_{jc'}$, where u_{jc} is the above residual under technology c. Under Gaussian likelihood, the model-implied conditional variance is $v_j \equiv s^2 + \pi_{jc'}(1-\pi_{jc'})\big(\alpha_{c'} + (\sigma_{c'} - \sigma_1)\log(p_j^E/p_j^K)\big)^2$.[48] I estimate parameters by two-step GMM with two-way clustered standard errors (plants and state-years) based on the stacked moments covariance.

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

$$\frac{\partial \widehat{\log(K_j/E_j)}}{\partial \log p_j^E} = \underbrace{(1-\pi_{jc'})\sigma_1 + \pi_{jc'}\sigma_{c'}}_{\text{within-technology substitution}} + \underbrace{\frac{\partial \pi_{jc'}}{\partial \log p_j^E}\Big(a_{jc'} - a_{j1}\Big)}_{\text{technology differences}}, \tag{15}$$

where $\frac{\partial \pi_{jc'}}{\partial \log p_j^E} = \gamma_1\, \pi_{jc'}(1-\pi_{jc'})$ in practice.[49] Equation (15) clarifies how the aggregate K/E response can flip sign even when both σ_1 and $\sigma_{c'}$ are positive: if lower electricity prices increase the share of a more machinery-intensive technology, the average switching term can dominate the average within-technology substitution term. The decomposition captures both within-plant adoption over time as well as cross-plant technology differences, without requiring a fully dynamic adoption model.

F. Recovering Pass-Through Rates and Consumer Incidence

Exploring how electricity price changes affect downstream consumers requires several additional parameters. The incidence of electricity price changes depends on how electricity prices affect marginal costs (MC) through input substitution ($\gamma \equiv dMC/dP^E$), and the pass-through rate of marginal costs to output prices (P) determined by market structure and power ($\rho_{MC} \equiv dP/dMC$). I employ a partial equilibrium analysis following Ganapati et al. (2020) allowing for factor substitution, incomplete pass-through and imperfect competition. As they show, in a generalized oligopoly under the assumption that average variable costs equal marginal cost ($AVC = MC$), incidence is defined as:

$$I \equiv \frac{dCS/dP^E}{dPS/dP^E} = \frac{\rho_{MC}}{1-(1-L\epsilon_D)\,\rho_{MC}} \tag{16}$$

[48] The first component of (14) pins down the overall variance level and therefore identifies s^2 (given the parameters that enter the between-technology term). The second component uses variation in relative prices to discipline the model-implied heteroskedasticity of $\log(K/E)$ induced by the mixture, since the between-technology gap depends on $\log(p_j^E/p_j^K)$.

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

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

First, I draw on the literature recovering markups μ from the production side using firm revenue and input data (Hall, 1988; De Loecker and Warzynski, 2012). Cost minimization and the first order condition of a variable input yield markups as a function of the output elasticity and revenue share of that input. I estimate plant-level markups ($\mu = P/MC$) using materials as variable input, which determine the plant-level Lerner index L together with observed output prices.[50]

Second, I use the well-known mapping between markups and demand elasticities implied by first order conditions of profit maximization in oligopolistic environments. I define the market level demand elasticities ϵ_D as the median of the plant-level demand elasticities within a 4-digit industry by year by state cluster.[51] Market demand structure is thus allowed to vary across industries, time and space. This approach differs from Ganapati et al. (2020), who instead estimate demand functions, which requires additional assumptions. The only additional assumption I need is profit maximization, which appears innocuous given the existing assumptions of cost minimization and competition.

Third, the main challenge is estimation of the pass-through parameter ρ_{MC}. The most direct way is to regress prices on marginal cost, which requires output prices and marginal cost at the plant level. I leverage the detailed data on plant by product level revenues and quantities that are separately reported for most plants, which allows me to calculate average sales prices at the plant-product level. I construct a plant-level average price across products (P), weighted by the quantity of each product. From the estimated plant-level price marginal cost markups μ, I can back out plant-level marginal costs MC with these prices. I recover prices and marginal costs for 88% of the 485,342 observations, covering 121 of the 133 4-digit industries. Since I also construct total variable cost (Section III.B), I can recover AVC by dividing total variable costs by quantity sold. This allows me to examine the validity of the underlying assumption ($AVC = MC$) for Equation (16). A regression of log AVC on log MC yields a coefficient of 1.03 and an R^2 of 0.99, indicating that the assumption is reasonable.

With prices and marginal costs in hand, I estimate pass-through *elasticities* for each 4-digit industry separately, regressing prices ($\log(P)$) on marginal costs ($\log(MC)$). Crucially, I already have constructed instruments for electricity prices, so these instruments also shift marginal costs. This allows me to instrument for endogenous marginal costs using IV^A and IV^B.[52] The pass-through elasticity is converted into the pass-through *rate* ρ_{MC} by multiplying it with the plant-level markup μ. Pass-through is therefore allowed to differ across industries and plants, where heterogeneity could

[50] I estimate the output elasticity and plant TFP using Levinsohn and Petrin (2003) and Wooldridge (2009).

[51] plant-level markups (and demand elasticities) can diverge from the market demand elasticities, for example, due to distortions. Singer (2019) provides some examples of such distortions in the Indian context. Taking the median or mean of production or demand elasticities is common in the literature, see e.g. Asker et al. (2014).

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

arise, for example, through market structure, concentration or market power. The components are:

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

Finally, the incidence of consumer surplus as share of total incidence is $I^{share} = I/(1+I)$. In Section V.E, I address two complications for consumer surplus. First, not all firms sell directly to consumers, so I adjust incidence shares for final-demand output. Second, electricity price reductions for industry may be financed through higher residential prices, which directly affects consumers.

V. Results

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

A. Electricity Productivity, Labor Productivity, and Their Components

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

Lower electricity prices improve electricity productivity.— The OLS elasticity between electricity prices and electricity productivity is positive (0.37), in line with common intuition (Column 1 in Table 2). However, the endogeneity bias in this estimate is large. The IV estimates in Columns 2 and 3 are of opposite sign and highly significant, with an elasticity of -0.25 and -0.78 for the two instruments IV^A and IV^B respectively. This positive OLS bias suggests that less efficient plants manage to obtain lower electricity prices through exemptions, negotiations, corruption or location choices, or have lower block tariffs.[53] Figure 5 visualizes these results in a binscatter of electricity productivity on electricity prices conditional on industry-by-region-by-year fixed effects, following Cattaneo et al. (2024). Panel (a) shows the OLS relationship, while Panel (c) and (d) show the relationship using predicted prices from IV^A and IV^B, confirming results are not outlier-driven. Panel (b) uses the administrative average electricity tariffs at the state by year level, addressing a significant portion of the OLS bias in plant-level prices, resulting in the same sign as the IV estimates. Table A.6 shows results using these tariffs with similar IV estimates as in Table 2, but the OLS is also negative and significant.

The effect is stronger for IV^B than for IV^A. This implies either heterogeneous IV treatment effects across subpopulations, or a failure of exogeneity for one instrument under homogeneous effects.[54]

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

[54] Table A.11 shows an over-identified model using both IV^A and IV^B simultaneously. The Sargan-Hansen J-test rejects that both instruments have the same effect under homogeneous treatment assumption.

Table 2: Electricity prices, electricity productivity and labor productivity

	Electricity productivity (log)			Labor productivity (log)		
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(P^E)$	0.365***	-0.251***	-0.777***	-0.0282	-0.400***	-1.063***
	(0.044)	(0.072)	(0.105)	(0.043)	(0.086)	(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)	-	45263.8	296.5	-	45263.8	296.5

Notes: The dependent variable is log electricity productivity (value of output divided by the quantity of electricity used in kWh) for the first three columns and log labor productivity for the last three (value of output divided by employees). Each column represents a separate regression at the plant level. As indicated, they either are OLS regression or IV regressions, using IV^A based on the electricity prices of other plants, or the shift-share IV^B. The first stage coefficients and SE 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 (160836 clusters) and the state by year level (501 clusters). Stars indicate p-values: * < 0.1, **< 0.05, ***< 0.01.

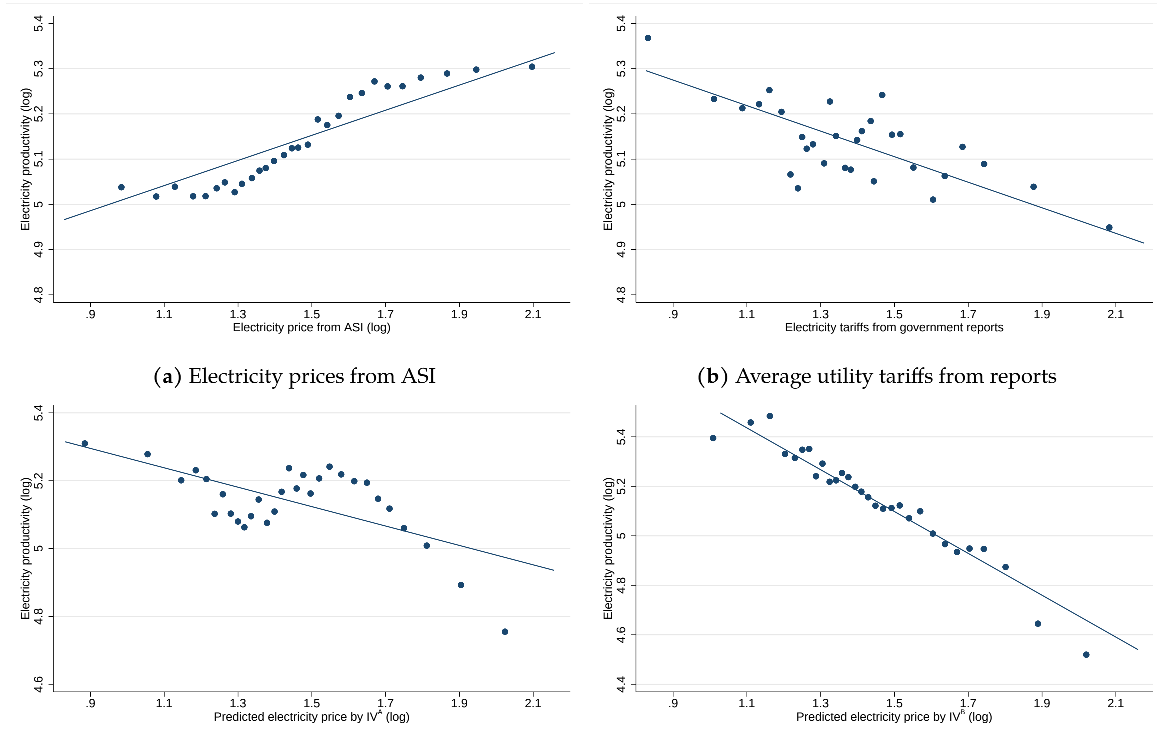
To assess whether treatment effects are heterogeneous, I follow Imbens and Angrist (1994) and Imbens and Rubin (1997) and discretize prices and both instruments at their median sample split after partialing out fixed effects. Under the monotonicity assumption, I can distinguish between compliers, observations for which the instrument affects treatment (electricity price), as well as never-takers and always-takers, which have a low and high electricity price irrespective of the instrument. Comparing outcome levels of electricity productivity between these three groups for both instruments suggests that the two IV estimates are two different local heterogeneous treatment effects, as they shift different subpopulations (Imbens and Rubin, 1997).[55] Importantly, the characteristics of the subpopulations shifted by the two IVs is in line with mechanisms analyzed below, where we would expect differential effects: IV^B shifts plants with relatively lower baseline machinery to labor ratios than IV^A, producing a stronger effect.[56] I exploit this below to estimate heterogeneous technologies in a mixture model, allowing the two instruments to shift subpopulations with different technologies differentially.

The causal estimates from micro data offer a compelling explanation of the aggregate electricity productivity and prices trends in Figure 1. With a 48% decline in electricity prices, taking the average local treatment effects between IV^A and IV^B of -0.51 predicts a 40% rise in electricity productivity (calculated as $(1\text{-}0.48)^{-0.51}$-1). This closely matches the observed 34% aggregate increase. The IV estimates can therefore explain the secular trends remarkably well, especially given the simple OLS correlation at the micro level is of opposite sign. These elasticities do not imply arbitrarily low prices are optimal, as I later show diminishing returns with more plants mechanizing.

Technology or product mix?— These improvements may be driven by plants producing different sets of products, rather than with better technology. To test this, I first include product fixed effects (6145 products) and show in Table A.17 that estimates are similar. This demonstrates that the improvements are not driven by product-mix changes, but by within-product technology differences across plants

[55] Electricity productivity is 22% higher for low-price compliers than for never-takers under IV^A, while it is 62% under IV^B. It is 14% lower for high-price compliers than for always-takers under IV^A (and 32% under IV^B).

[56] Against an overall mean machinery to labor ratio of 0.17, IV^B low-price compliers have a 0.06 lower previous period ratio than never-takers (0.05 higher for IV^A), whereas the difference between compliers and always takers is near zero for both IVs.



(**a**) Electricity prices from ASI

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

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

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

Figure 5: Binscatter of electricity productivity and electricity prices

Notes: The figures show binscatter plots using Cattaneo et al. (2024) with plant-level electricity productivity (log) on the vertical axis and with industry-by-region-by-year fixed effects. Panel (a) plots against log electricity prices using plant-level ASI data. Panel (b) instead plots against utility tariffs at the state by year level from Central Electricity Authority (2006-2015) and Indiastat (1998-2014). Panel (c) and (d) plot against electricity prices predicted by IV^A and IV^B respectively, where predicted electricity prices are obtained by using fitted values from regressions on the respective instruments conditional on industry-by-region-by-year fixed effects. Results using labor productivity are in Figure A.15

and time.[57] Second, I map nation-wide average product-level electricity intensities fixed in 2000 to the evolving product mix as dependent variable to test if firms shift to more electricity intensive products with lower prices. I find no evidence in Table A.17. Since this outcome ignores the salient differences in electricity productivity within products, it implies that the improvements are driven by within-product technology differences across plants and time, crucial to account for in a world with technology differences. Third, this last finding appears to contradict Abeberese (2017), who, using the latter outcome, finds that lower prices increase the electricity intensity of the product mix, suggesting firms became less electricity productive. I first replicate Abeberese (2017) in Table A.18 and then show that the results hinge on a coding issue that partially omits included fixed effects. Once fixed, the results turn insignificant or change sign, and are entirely consistent with my insignificant findings on product mix. Importantly, by instead analyzing firms' electricity productivity directly in my main results, I show that Indian firms became *more*, not less, electricity productive with lower prices.

Lower electricity prices improve labor productivity.— Columns 5 and 6 of Table 2 show that lower electricity prices substantially increase labor productivity, with elasticities of -0.40 and -1.06 for

[57] This controls for extensive margin product switching, but results are similar replacing the binary dummies with continuous weights corresponding to each product's share of plant-year sales that capture both extensive and intensive margin changes.

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)
$\log(P^E)$	-0.027	-0.83***	-1.60***	-0.39***	-0.55***	-0.80***	0.012	-0.41***	-0.52***
	(0.073)	(0.15)	(0.15)	(0.064)	(0.17)	(0.15)	(0.041)	(0.080)	(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
F-stat (Kleib.-Paap)	-	45263.8	296.5	-	45263.8	296.5	-	45263.8	296.5

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

IV^A and IV^B (binscatters are in Figure A.15). There is a significant bias in the OLS estimates in Column 4 that are close to zero, and the above LATE analysis for IV^A and IV^B applies here as well. Averaging the two IV estimates at -0.73, the 48% electricity price decline predicts a 61% increase in labor productivity, explaining two thirds of the 90% aggregate increase documented in Section III.C. Lower industrial electricity prices have thus also contributed towards developmental goals.

Electricity consumption, employment, and output.— To better understand underlying channels, I start with proximate reasons in Table 3 by unpacking the electricity and labor productivity ratios into their components: electricity consumption (in kWh), employees, and output. Electricity is not a Giffen good. In both OLS and IV regressions, lower electricity prices increase electricity consumption, with slightly larger causal effects. A one percent price decrease raises electricity consumption by 0.55 to 0.80 percent. Note that potential demand rebound effects from increased electricity productivity (Gillingham et al., 2016) are absorbed here and in the main estimates. The OLS estimate for employees is insignificant, but the IV estimates are significant, with a one percent price decrease increasing employees by 0.41 to 0.52 percent. Effects on electricity consumption and employment are consistent with the model predictions in Figure A.2a. The OLS effect of prices on output is close to zero. In contrast, the IV estimates are large and negative (-0.83 and -1.60). While the positive OLS bias operates through all three variables, it is most pronounced in output. This implies the bias comes primarily from output shocks correlated with electricity prices, e.g. through exemptions due to negative output shocks or because favorable prices may reduce competitive pressure to perform. It is also consistent with attenuation bias from measurement error or endogeneity bias from increasing tariff schedules where consumption shocks correlate positively with prices.

B. Robustness

Before moving to deeper mechanisms, I conduct a range of robustness checks. They reinforce the above conclusions about OLS bias and lower electricity prices increasing electricity and labor productivity.

Alternative instruments yield similar estimates.— First, I use three alternative instruments. The first, IV^C, resembles IV^A but excludes plants in the same district in the instrument. This allows for endogeneity in electricity prices based on spatial proximity, including political economy considerations such as corruption or lobbying within districts across industries. The second instrument, IV^{D_1}, is also a shift-share instrument. The shift is the timing of the 2003 Electricity Act and the shares are the distance of district centroids to coalfields, interacted with a dummy for states with any coal power over the sample period.[58] The rationale for IV^{D_1} builds on the insight that the share of private power capacity can explain lower electricity prices, but only from 2003 as the Electricity Act opened the power sector (Table A.3a). Since local changes in private power share are likely endogenous, I use district distance to coalfields, which Table A.3b shows predicts private power capacity shares after 2003. Therefore, IV^{D_1} leverages distance to coalfields interacted with the timing of the 2003 Act, controlling for lower order terms. The event study in Figure A.14 shows greater distance to coalfields increases prices relatively from 2003. The third instrument, IV^{D_2} uses the staggered unbundling of generation, transmission and distribution by states identified by Cropper et al. (2011). Mahadevan (2019) uses the staggered unbundling in an event study and finds an effect on electricity prices. Appendix Table A.4 shows that estimates using these instruments are all similar to the main IV estimates.[59]

Controlling for input and output prices.— Second, electricity price changes may be correlated with electricity price changes for other plants, potentially affecting input or output prices through equilibrium adjustments. While the inclusion of industry-by-region-by-year fixed effects should largely account for these, I address remaining concerns about product market competition or supply chain effects by controlling for input and output price indices. These indices are specific to each plant's product and input mix, based on national median prices at the product level combined with plant product/input mix. Table A.6 shows estimates are robust to the input/output price index controls.

Controlling for power shortages and distance to coalfields.— Third, I control for state-year power shortages, district distance to coalfields, or both in Table A.7. Note that the included industry-region-year fixed effects already absorb much of the variation in shortages, but controlling for them serves as additional check. The estimates remain significantly negative and similar in magnitude. This is expected as Tables A.1 and A.2 already showed that shortages are not associated with electricity prices. Both control variables, however, significantly explain electricity and to some extent labor productivity. Finally, if shortages do not affect consumed electricity and prices, but the ratio of purchased to self-generated electricity, we would expect similar effects when using purchased rather than consumed electricity to construct electricity productivity. Reassuringly, this is corroborated in Table A.9.

Electricity intensive sectors, no direct coal users, and sector specific analysis.— Fourth, in Table A.10, I show robustness to restricting the sample to electricity intensive sectors, i.e. 2-digit sectors with above average intensity, or excluding all plants that use coal directly as input to address remaining concerns about the coal price shifter for power utilities in IV^B. Table A.5b shows robustness to control interactions of the coal shifter with pre-sample state characteristics. A separate analysis for six broad industry groups in Table A.12 yields broadly similar effects across sectors, except perhaps for metals and minerals, where estimates are insignificant but still correct an upward bias in the OLS estimates.[60]

[58]The triple interaction helps avoid capturing irrelevant states that rely on hydro power such as the North-West.

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

[60]Since basic metals industries rely predominantly on coal across many production techniques, there could be a null effect, with less complementarity between electricity and machines and less scope to move to electricity-based production. Figure A.8 supports this hypothesis. While energy productivity rose in this sector, electricity productivity remained fairly stable.

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

Outcome	OLS	IV^A	IV^B	N	Outcome	OLS	IV^A	IV^B	N
(**a**) *Profitability and scale*					(**c**) *Investment and fuel substitution*				
Profits (mil. ₹)	-5.04***	-27.9***	-22.0***	485263	Investment in	-0.28***	-1.25***	-0.71***	474910
	(1.51)	(3.66)	(4.00)		machinery (PPML)	(0.089)	(0.17)	(0.18)	
Total revenues	-30.4***	-184.0***	-139.5***	485263	Electricity to coal	-10.2***	-23.6***	-22.1*	47968
(mil. ₹)	(8.86)	(22.9)	(21.2)		quantity ratio	(3.10)	(5.77)	(12.4)	
Total variable	-24.2***	-152.6***	-114.4***	485263	Other fuels' share	0.0044***	0.013***	0.023***	485342
costs (mil. ₹)	(7.41)	(19.2)	(17.5)		in output	(0.0013)	(0.0019)	(0.0028)	
(**b**) *Input ratios*					(**d**) *Average wages, TFP and markups*				
Machinery to	-0.16**	-0.67***	-1.52***	467686	Average wage	0.030**	-0.16***	-0.18***	445903
labor (log)	(0.065)	(0.12)	(0.15)		per worker (log)	(0.014)	(0.030)	(0.033)	
Labor to	0.38***	0.12	0.28***	485342	TFP (log)	-0.0070***	-0.019***	-0.033***	477697
electricity (log)	(0.041)	(0.099)	(0.10)			(0.0024)	(0.0034)	(0.0063)	
Machinery to	0.26***	-0.50***	-1.18***	467686	Price-MC	-0.018***	-0.045***	-0.11***	484943
electricity (log)	(0.053)	(0.074)	(0.12)		markups $\log(\mu)$	(0.0063)	(0.011)	(0.019)	

Notes: Each row reports a regression at the plant level for the listed dependent variable. The OLS, IV^A, and IV^B columns report the coefficient on logged electricity prices, with two-way clustered standard errors in parentheses. Observations correspond to the sample used for that dependent variable. The dependent variables are indicated and described in Section III.B. Profits, revenues and total variable costs are in levels because profits can be negative. The ratio of electricity to coal is in quantity terms in MWh per tonne. Other fuels refer to gas, coal and oil. I use PPML with IVs via GMM for investment to deal with zeros. Wages are residualized by district. All regressions contain industry by year by region fixed effects. Regressions are weighted by the recorded sampling multiplier. Stars indicate p-values: * < 0.1, **< 0.05, ***< 0.01.

Lagged prices and inference.— Fifth, I use lagged prices and instruments to allow for more adjustment time.[61] Reassuringly, the IV estimates for electricity and labor productivity hardly change. The positive OLS bias, however, substantially falls when using lags (Table A.8). Sixth, I two-way cluster at the district and the region year level to allow for more arbitrary correlation in errors, with slightly larger standard errors but still significant results (Table A.11). I adjust all p-values upwards to account for multiple hypothesis testing in Table A.19. Almost all estimates remain statistically significant.

C. *Mechanisms*

I next explore deeper mechanisms by testing model predictions, estimating the structural complementarity, using additional exogenous variation, and showing the impact on several outcomes.

Testing model predictions: scaling up, investment and input ratios.— In the model in Section II, electricity is a complementary input to modern production techniques. Lower electricity prices can incentivize more modern capital intensive production techniques, generating higher electricity and labor productivity. I test all predictions of the model visualized in Figure 2 and Figure A.2a using reduced-form regressions without restricting 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 from lower prices. Table 4a shows effects on profits, total revenues and total variable costs (in levels). A one percent decrease in electricity prices increases total profits by ₹0.22-0.28 million (US$5,500) per plant, increases revenues by ₹1.4-1.8 million (US$36,000), but also *increases* total variable costs by ₹1.1-1.5 million (US$30,000). This is consistent with the model: plants scale up as

[61]This may also address potential remaining reverse causality concerns. Using lags cuts the sample roughly in half as spells of plant observations are required. There is also evidence (available upon request) that effects on electricity productivity were stronger in the first half of the sample period when prices were relatively higher, consistent with the notion that positive implications of decreasing electricity price are particularly beneficial when baseline prices are high.

Table 5: Decomposing machinery–electricity substitution and technology switching

	Panel A. IV		*Panel B. Structural GMM-IV*		*Panel C. Decomposition*	
	(1)	(2)	(3)	(4)	(5)	
$\log(p^E/p^K)$	-0.388***	-0.893***	0.675***	0.085**	**Within-tech:**	**0.398**
	(0.081)	(0.137)	(0.035)	(0.037)	**Across-tech:**	**-0.948**
Structural parameter	–	–	σ_1	$\sigma_{c'}$	**Total:**	**-0.550**
Observations	460835	460835	460835	460835	460835	
Estimator (IV/GMM)	IV^A	IV^B	GMM-IV	GMM-IV	GMM-IV	

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

electricity prices fall, also echoed by rising employment (Columns 8-9 in Table 3). Second, turning to input ratios in Table 4b, lower electricity prices increase machine to labor ratios, driven by investment in machinery (Table 4c).[62] Labor to electricity ratios decrease despite employment increases (Table 3). Importantly, I also find that machine to electricity ratios increase. These results corroborate all model predictions, but confirming this last prediction is perhaps most surprising. In the model, this arises from the discreteness in technological choices and input complementarities, which I turn to next. In a world without technological choices the machine to electricity ratio unambiguously falls (Lemma 2).

Decomposing substitution elasticities and technology differences.— In Table 5, I implement the mixture decomposition (Section IV.E) to separate within-technology substitution from price-induced technology differences in the machinery–electricity margin. Panel A reproduces the pooled IV sign reversal: the elasticity of $\log(K/E)$ with respect to $\log(p^E/p^K)$ is negative (-0.39 with IV^A and -0.89 with IV^B), so plants raise K/E when electricity becomes cheaper (Corollary 1).[63] Panel B shows that the sign reversal does not reflect "negative substitution": the estimated technology-specific substitution elasticities are both positive ($\hat{\sigma}_1 = 0.68$ and $\hat{\sigma}_{c'} = 0.09$), implying that within a given technique plants substitute toward electricity as it gets cheaper (Lemma 2). The lower elasticity for modern technology c' implies stronger complementarity in that technology, consistent with the model. Panel C shows why the aggregate flips sign: the average within-technology component is $+0.40$, but the technology-switching component is -0.95, yielding a total elasticity of about -0.55. Thus, the dominant channel is technology upgrading—electricity prices shift plants toward more machinery-intensive techniques. This extensive-margin response reflects compositional shifts across technologies both within plants over time and across plants, and overwhelms the standard within-technology substitution effect.

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

First, in Figure 6a, I classify plants as above or below the median machinery capital-to-labor

[62] Note that the bias for the ratios, the OLS-IV difference, depends on the bias in the numerator and denominator. For machinery to labor, the sign does not flip, but the size of the bias is roughly similar to that for the machinery to electricity ratio.

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

ratio within their four-digit industry in the previous period and interact this classification with electricity prices, all appropriately instrumented. Consistent with the model, plants with higher baseline capitalization, possibly already operating with a more modern technology, see a weaker response of electricity productivity from lower prices, all differences being statistically significant. This implies that the pure substitution effect is stronger for relatively more capitalized firms, while the technology and output effect is relatively stronger for less capitalized firms, as shown in Table A.15.[64]

Second, while the previous categorization may be based on endogenous machine to labor ratios, I next use a plausibly exogenous shock to machinery capitalization: the rollout of financial trade liberalization in India for a subset of industries from 2006. While India underwent a substantial general trade liberalization in 1991, the 2006 policy allowed a subset of industries that were initially restricted to automatically approve foreign capital investments and increased the foreign-capital investment cap.[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 based on treated/nontreated industries x pre/post the 2006 policy x electricity prices, all appropriately instrumented, to analyze the differential effect of prices for firms receiving the capital shock.[66] I use this design to test whether firms with more capital show smaller electricity productivity responses to prices. The event study in Figure 6b plots the triple-interaction coefficient five years before and after the policy. Indeed, after the 2006 policy, the electricity price response in treated plants becomes significantly less negative relative to untreated plants. The triple difference is statistically significant at the 1% level (Table A.15), and the implied treated group elasticity shifts from strongly negative before 2006 to slightly positive after 2006 from the capital boost. While the parallel trends assumption cannot be tested directly, the pre-trends shown in Figure 6b are flat. Table A.15 shows additional triple difference results for labor productivity and output.

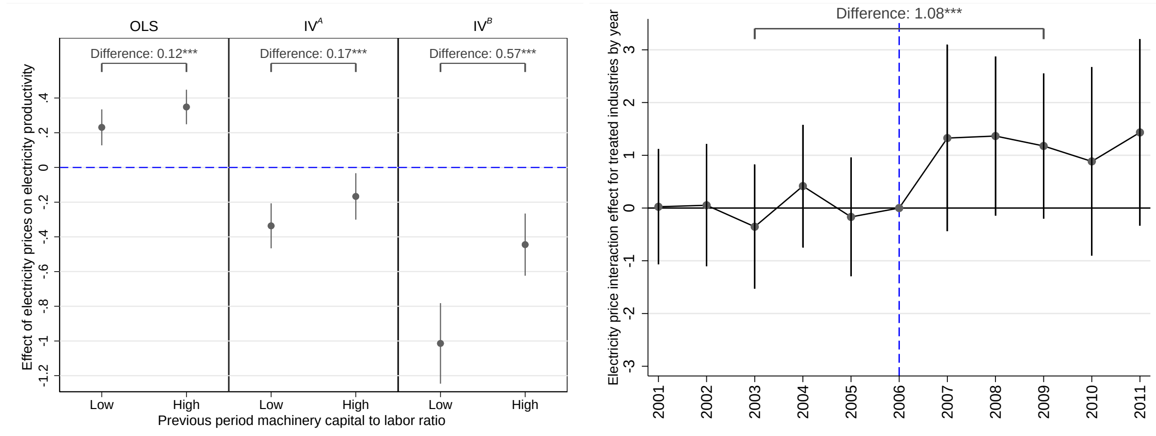
Lower electricity prices induce substitution from fossil fuels.— Plants likely not only adjust their machinery-labor-electricity ratios with different technologies, but also substitute more narrowly between electricity and other energy sources. This matters for estimating the impacts on emissions below. Table 4c shows that lower prices induce substitution from fossil fuels to electricity. Among plants reporting physical coal consumption, the electricity to coal ratio increases with declining electricity prices, as plants substitute away from coal. The expenditure share of non-electric fuels (i.e. coal, oil and gas) in output also decreases. Plants therefore not only electrify by becoming more machine intensive, but also electrify away from fossil fuels. Consequently, *energy* efficiency, i.e. output per unit of all energy not just electricity, rises even more than electricity productivity.

Lower electricity prices increase electric equipment, wages, TFP, product lines, and markups.— To end this section, I examine further margins that help understand mechanisms. First, I use the product-level input data to calculate *electric* equipment inputs as share of total inputs at the plant level. While this result should be interpreted cautiously, as many plants may report equipment under capital rather

[64] This also suggests capital constraints cannot be too severe if low capitalized firms are more constrained (Figure A.2b).

[65] See Bau and Matray (2023) for a detailed description. Table A.14 lists the treated industries.

[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).



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

Figure 6: Electricity price effects by previous machinery labor ratios and foreign capital access liberalization

Notes: The dependent variable in both panels is electricity productivity. Panel (a) shows the effect of electricity prices for plants split by a median machine-labor ratio within four digit industries in the previous period. Shown are 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. The pre-post triple difference coefficient is reported above the graph. All regressions are sampling multiplier weighted and standard errors are two-way clustered at the plant and the state by year level.

than inputs, it provides an additional test of mechanism. Indeed, Table A.9 shows that lower electricity prices increase the share of electric equipment, such as powerlooms, consistent with a technology mechanism. Second, lower electricity prices may also affect workers through wages given increases in labor productivity (Bhagwati and Panagariya, 2014). Table 4d shows lower prices increase average wages per worker. This could be driven by unit cost savings from cheaper electricity, higher labor productivity from more capital per worker (Table 4b), increased worker demand from upscaling (Table 4a), or shifts towards higher skilled workers. Averaging the two IV estimates (-0.17), the 48% electricity price decline predicts a 12% wage increase, explaining 20% of the observed 60% increase. Third, I estimate small but significant effects on TFP (Table 4d).[67] Lower electricity prices also increase product variety measured as the number of plant product lines (Table A.9). Finally I examine effects on markups $\mu \equiv P/MC$ (see Section IV.F). Markups increase with declining electricity prices (Table 4d), implying that gains in firm profitability come from both expansion and technology but also from higher markups. Lower electricity prices are therefore only imperfectly passed through to consumers, raising an important question about the distribution of incidence, which I analyze next.

D. Pass-through and Incidence of Electricity Price Changes

The degree to which firms pass through electricity price changes to consumers determines incidence. As described in Section IV.F, I estimate pass-through elasticities by industry and report their CDF and two example regressions in Figure A.16. The vast majority of pass-through elasticities are between 0.8

[67]TFP is measured following Wooldridge (2009) using deflated revenue data, so should be interpreted as revenue TFP. Since markups increase, the impact on physical TFP could be slightly smaller. Table A.13 shows robustness when TFP is measured following Olley and Pakes (1996), Levinsohn and Petrin (2003) or Ackerberg et al. (2015).

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

Incidence	Oligopolistic competition	Monopoly	Perfect competition
Median	0.62	0.54	1.18
25th to 75th percentile	[0.52 - 0.76]	[0.50 - 0.59]	[1.01 - 1.45]
Components	$\widehat{L}$	$\widehat{\epsilon}_D$	$\widehat{\rho}_{MC}$
Median	0.18	3.19	1.18
25th to 75th percentile	[0.03 - 0.34]	[2.25 - 4.55]	[1.01 - 1.45]

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

and 1.1. Elasticities above one imply costs are more than fully passed through to consumers.[68] This can arise if producers previously failed to collude in an oligopoly, as higher costs can help to solve the coordination problem of raising prices. The pass-through elasticities are combined with estimated plant-level markups ($\widehat{\mu}$) into pass-through rates $\widehat{\rho}_{MC}$. Table 6 shows the three incidence components: Lerner index $\widehat{L}$, market demand elasticity $\widehat{\epsilon}_D$ and pass-through rate $\widehat{\rho}_{MC}$, reporting the median, the 25th, and the 75th percentiles across plants, sectors and years. The median incidence share I^{share} is 62%, but there is heterogeneity across industries and years; the 25th and 75th percentiles are 52% and 76% respectively, and the 5th percentile is at 26% consumer share. Figure A.16c plots consumer incidence shares for six aggregate industries, showing a small decline over time. I also calculate incidence under extreme conduct assumptions of monopoly ($L = 1/\epsilon_D$) and perfect competition ($L = 0$), yielding lower and higher estimates than in the benchmark oligopoly case. The next section calculates total consumer surplus accounting for industries' varying final-demand shares.

E. Aggregate Effects on Welfare and CO_2 Emissions

I now ask: how large was the gain in producer and consumer surplus net of government utility losses from the 48% price reduction, and what was the effect on aggregate CO_2 emissions? To this end, I use the estimated parameters within the support of underlying electricity price changes, ignoring general equilibrium effects. For the producer gains, I apply the semi-elasticity of variable profits to electricity prices, implying that the 48% reduction of electricity prices led to an increase of ₹16.32 mil. for the average plant.[69] Across the entire manufacturing sector, this amounts to ₹1.99 trillion or US$ 43.9 billion in profits (in constant 2004 terms), equivalent to 3.2% of Indian real GDP in 2013.[70]

For consumer gains, I proceed in two steps: First, since a subset of firms may not sell to consumers directly, I am using input-output tables to obtain the share of output going to final demand by industry

[68] While the pass-through *elasticity* is below one for the five industries studied in Ganapati et al. (2020), the pass-through *rate* ρ_{MC} also exceeds one for many of their industries and in some studies cited therein.

[69] I take -24.95 as the average of the two estimates in Table 4a and calculate $\log((1-0.48)^{-24.95}) = 16.32$. Note that this is a 99% increase in profits over the mean (Table 1) and represents 19% of the increase in variable costs similar to average markup estimates. The increase in variable profits is incentive consistent. First, note that capital expenditure increases by ₹6.79 mil, using the elasticity of overall book value of capital and the 15% depreciation rate from the Indian Income Tax Rules, so profits net of capital costs increase by ₹9.52 mil. Second, absent electricity price reductions, if producers had still produced exactly as in the factual with modern technology, the additional increase in variable costs would have been ₹9.74 mil, larger than variable profits net of investment costs, implying that producers would not have chosen this in the absence of price changes.

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

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

Additional emissions from (in Mt):	Estimate	No substitution	No productivity	No substitution & no productivity
Electricity use	31.5	31.5	68.9	68.9
Coal use	11.4	36.5	44.1	79.9
Oil use	-0.1	6.5	4.9	14.3
Total	42.8	74.5	117.9	163.0
Increase in %	32%	55%	88%	121%

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 (Ministry of Coal, 2012; IPCC, 2006; Central Electricity Authority, 2006; IEA, 2013). The *Estimate* column shows the estimated effect on emissions. The three columns to the right show the effects when substitution between electricity and coal and oil is switched off, or when the productivity gains from lower prices are switched off, or both, all conditional on reaching the same output gains. Gas is omitted because its use is negligibly small in comparison.

(details in Section A.3). Using this data along with incidence shares estimated from Section V.D, the first component of consumer surplus change is US$ 36.2 billion. Second, the reduction in government profits from lower electricity sales prices was ₹ 159 billion or US$3.5 billion.[71] If utilities financed this deficit via higher rates in the residential sector affecting consumers directly, consumer surplus falls by US$3.4 billion down to US$33 billion, based on residential demand elasticities (details in Section A.3).

The consumer surplus share in total welfare gains is 43%, lower than average plant-level incidence shares in Table 6, as the denominator also includes profits of firms that contribute little to final demand. Importantly, electricity pricing for industry therefore matters for consumers, not only for producers. Reductions in cross-subsidization (Figure 3b) also generated sizable net consumer benefits through lower output prices. The US$ 76.7 billion total welfare gains imply annualized gains of US$ 5.5 billion, equivalent to 0.41% of Indian GDP or 5% of manufacturing value added in 2013 (UNIDO, 2016). The substantial decrease in industrial electricity prices from their comparatively high levels had substantial effects on welfare and Indian industrial development. It is worth noting that average wages and employment also increased (Tables 4d and 3) suggesting additional benefits for workers.

I next include environmental damages in the welfare estimates by estimating effects on aggregate CO_2 emissions. I combine the estimated effects of electricity prices on electricity demand, productivity and fuel substitution with emission factors for specific fuels and the Indian power grid. I include emissions from electricity, coal and oil and report details and data sources in Appendix A.4. From a baseline of 134.5Mt annual CO_2 emissions in manufacturing (1998-2000 average), the 48% decline in electricity prices increased emissions by 32%, or 42.8Mt (Column 1 in Table 7). This increase in emissions was entirely driven by firms scaling up.[72] In fact, Table 7 shows that emissions would have risen far more without the electricity productivity gains from lower prices or the fuel substitution away from coal and oil, conditional on achieving the same output gains. Switching off fuel substitution effects forcing firms to use more coal and oil would have produced a 55% increase in emissions

[71] Although profit per kWh fell, quantity sold increased. I take -0.674 as average quantitiy elasticity from Table 3, annual electricity purchased from the grid in 1998-2000 in the sampling frame (53.5 billion kWh), average cost of electricity supply across the sample of 3.14 ₹ /kWh (6.9 US cents) from the Planning Commission (2001-2002); Ministry of Power (2002-2015), and the average industrial electricity prices in 1998-2000 and 2013 (6.4 ₹ /kWh and 3.32₹ /kWh): $(3.32 - 3.14) \cdot 53.5 \cdot (1 - 0.48)^{-0.674} - (6.4 - 3.14) \cdot 53.5 = 159$ billion ₹ . This implied loss for utilities is conservative because it uses an average cost of supply. Even if supply costs were double and prices below cost-recovery, additional utility losses would only be slightly higher.

[72] Decomposing emissions into output and emissions per output, emissions only increased due to output as intensity fell.

(Column 2) instead of the 32%. Switching off the estimated effects on electricity productivity, i.e. setting Columns 2-3 in Table 2 to zero, would have produced an 88% increase in emissions (Column 3). Switching off both channels would have increased emissions by 121% (Column 4). While the secular decrease in industrial electricity prices increased CO_2 emissions, the increase is less than half of what we would expect absent the electricity productivity effects that I find. Using a social cost of carbon of US$100/t$CO_2$, the costs from higher emissions are US$4.3 billion. While sizable, it is small compared to the US$76.7 billion welfare gains, so the reduction in industrial electricity prices had substantial welfare benefits even after accounting for emissions externalities.

F. The Contrary Effects of Coal Prices

The mechanisms discussed above derive from the special role of electricity as a complementary input to modern capital intensive production. If so, we should not expect similar effects for coal prices, as fossil fuels are generally not associated with modern industrial production. I test this using plant-level coal prices for roughly 45,000 coal using plant-years. As these suffer from similar endogeneity problems, I construct two instruments for coal prices paid by manufacturing plants. The first, IV^E, is analogous to IV^A, using coal prices paid by plants in the same state, but in different 2-digit industries, without the kernel weights. The second, IV^F, is a shift-share instrument. The shares are logged distances of district centroids to the nearest coalfields, capturing variation in sourcing costs.[73] The shifter is the nationally representative coal price at pit heads for industry (as opposed to power utilities) of the appropriate coal grades from Ministry of Coal (2012, 2015). When average pit head prices rise, plants further away from coalfields see differential price increases due to varying shipping cost shares in total costs. Table A.16 shows that, indeed, lower coal prices significantly *decrease* coal productivity, in contrast to the electricity pattern. Here, the IV coefficients also have the same sign as the OLS and are actually higher. While lower coal prices increase coal consumption, they only have small and insignificant IV effects on output and labor productivity. Lower coal prices also have no significant effect on TFP[74], profits or costs. Contrary to electricity, there is no scaling-up or technology effect, supporting the view that electricity is a special energy input complementary to modern production.

G. Policy Implications

I highlight five policy implications crucial for industrial development and decarbonization. First, cross-subsidizing low agricultural and residential rates with high industrial rates harms both labor and electricity productivity. Lower industrial electricity prices can achieve a win-win on both development and decarbonization margins, and through cost pass-through, benefit consumers as well.

Second, this does not imply that carbon pricing, which may raise electricity costs, is necessarily harmful, as such reasoning conflates two inefficiencies. Carbon pricing internalizes the pure climate externality from fossil fuel combustion. Decreasing excessively high industrial electricity prices at

[73] The location of coalfields and power plants is illustrated in Figure A.12.
[74] This is in line with Calì et al. (2022) who even find positive effects on TFP from *higher* coal prices in Indonesia and Mexico.

the same time, whether by reducing cross-subsidy distortions or electricity taxes, or as deliberate industrial policy via electricity price subsidies, can address the industrial development failure in which high electricity costs suppress technology upgrading and electricity productivity, particularly under imperfect product-market competition. The combined effect of these two policies resembles a subsidy to clean electricity generation, which also lowers industrial electricity prices and curbs fossil fuel use. The key advantage in a setting of limited public budgets is that the two instruments can be jointly budget neutral, unlike expensive clean-energy subsidies.

Third, as India and other low- and middle-income countries transition to renewables in generation, industrial electrification is essential for leveraging cleaner electricity supply. Directing investment toward electrification requires lower relative prices of clean electricity versus carbon-intensive fuels as in Acemoglu et al. (2012, 2016). This strategy is even more appealing given the finding that lower electricity prices improve electricity productivity while taxing dirtier fuels has little direct effect on firm performance. The same logic applies to current decarbonization challenges in transport, industry and residential heating in high-income countries, where relatively lower electricity prices may incentivize clean transitions. Fourth, capital constraints can create frictions in adopting modern technology as shown in Figure A.2b (see also Lanteri and Rampini (2023*a*,*b*); Hawkins and Wagner (2022)), and require complementary policies addressing capital frictions to fully unlock the technology-upgrading mechanism. That said, the results in Figure 6 showing stronger effects for less-capitalized firms suggest that capital frictions do not dominate the overall effect. Fifth, while industrial lobbying in India often focused on securing import tariffs, the findings suggest that lobbying for lower industrial electricity prices may be a more effective route to competitiveness on the output market.

VI. Conclusion

What is the role of industrial electricity prices in a context of industrial development? This paper shows that lower electricity prices can serve both environmental and developmental goals by improving electricity and labor productivity in firms. As policy makers grapple with ambitious targets for improving energy efficiency, e.g. doubling the rate of improvement agreed at COP28, these findings suggest a win-win in lower income countries where trade-offs are common.

Using detailed plant-level data on electricity consumption and prices combined with instrumental variables to remove bias, I recover estimates at the micro level that help explain secular trends in electricity and labor productivity at the macro level in India. I interpret the results through the lens of a model with discrete technological choices and complementarities between electricity and capital, and confirm model predictions empirically. Lower electricity prices incentivize firms to adopt modern capital intensive and electricity-using production techniques. This boosts output, overcompensating input substitution effects, which raises electricity and labor productivity through higher capital utilization. The mechanism therefore depends on context, and I show diminishing returns as the economy mechanizes. These effects are likely to be most salient in the process of industrial development, rather than at advanced industrialized stages. Nevertheless, the broader implications for electricity pricing in technology transitions extend to current decarbonization challenges of electrifying industry, transport, or residential heating in advanced economies as renewables ramp up.

The benefits of lower industrial electricity prices accrue not only to firms. Using data on output prices, I find that roughly half of the welfare benefits accrue to consumers through lower output prices, even if residential rates compensate for utility losses. While carbon emissions increase with industrial upscaling, the electricity productivity boost attenuates additional emissions from scaling by more than half. Lower coal prices lack comparable effects. This implies that policies that increase fossil fuel prices to internalize environmental externalities, while reducing industrial electricity prices, for example by eliminating distortions from cross-subsidization, may be particularly beneficial in a context of industrial development. Future research could extend the analysis to incorporate production networks and general equilibrium effects.[75]

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APPENDIX FOR ONLINE PUBLICATION

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

by Gregor Singer, London School of Economics: g.a.singer@lse.ac.uk

A.1 Model proofs and visualizations

For fixed c and interior optimum (K^*, L^*, E^*), define Z and W as the upper- and inner-nest CES terms, so $PQ = AZ^{\frac{\phi}{\rho_l}}$ and $X = W^{\frac{1}{\rho_e(c)}}$. The FOCs are:

$$\phi A Z^{\frac{\phi}{\rho_l}-1}\alpha_l(c)L^{\rho_l-1} = p_L, \tag{A.1}$$

$$\phi A Z^{\frac{\phi}{\rho_l}-1}\big(1-\alpha_l(c)\big)X^{\rho_l-1}W^{\frac{1}{\rho_e(c)}-1}\big(1-\alpha_e\big)K^{\rho_e(c)-1} = p_K, \tag{A.2}$$

$$\phi A Z^{\frac{\phi}{\rho_l}-1}\big(1-\alpha_l(c)\big)X^{\rho_l-1}W^{\frac{1}{\rho_e(c)}-1}\alpha_e E^{\rho_e(c)-1} = p_E. \tag{A.3}$$

Define $\sigma_e(c) := \frac{1}{1-\rho_e(c)} > 0$, $\kappa_{KE} := K^*/E^*$, $\kappa_{XE} := X^*/E^*$, and $\kappa_{LE} := L^*/E^*$. Taking ratios:

$$\kappa_{KE} = \Big(\frac{p_E(1-\alpha_e)}{p_K\alpha_e}\Big)^{\sigma_e(c)}, \quad \kappa_{XE} = \Big(\alpha_e + (1-\alpha_e)\kappa_{KE}^{\rho_e(c)}\Big)^{1/\rho_e(c)}, \quad \kappa_{LE} = \left(\frac{(1-\alpha_l(c))\alpha_e}{\alpha_l(c)}\frac{p_L}{p_E}\kappa_{XE}^{\rho_l-\rho_e(c)}\right)^{\frac{1}{\rho_l-1}}, \tag{A.4}$$

By Euler's theorem with homogeneity degree ϕ, $p_K K^* + p_L L^* + p_E E^* = \phi PQ^*$, hence

$$\frac{PQ^*}{E^*} =: \eta_c(p_E) = \frac{1}{\phi}\big(p_E + p_K\kappa_{KE} + p_L\kappa_{LE}\big), \qquad \frac{PQ^*}{L^*} =: \lambda_c(p_E) = \frac{1}{\phi}\Big(p_L + \frac{p_K\kappa_{KE} + p_E}{\kappa_{LE}}\Big), \tag{A.5}$$

Within-technology optimality

Lemma 1 (Within a fixed technology, cheaper electricity lowers electricity productivity)**.** *Fix technology c. Then $\eta_c(p_E) = PQ^*/E^*$ is strictly increasing in p_E, and $p_E \downarrow$ strictly lowers PQ/E.*

Proof. From (A.5), it is enough to show $\kappa'_{KE}(p_E, c) > 0$ and $\kappa'_{LE}(p_E, c) > 0$. The first is shown below for Lemma 2. For the second, log-differentiate the κ_{LE} expression in (A.4): $\frac{d\log\kappa_{LE}}{d\log p_E} = \frac{1}{\rho_l-1}\Big[-1 + (\rho_l - \rho_e(c))\frac{d\log\kappa_{XE}}{d\log p_E}\Big]$. Using the κ_{XE} and κ_{KE} formulas in (A.4), $\frac{d\log\kappa_{XE}}{d\log p_E}$ equals $\frac{d\log\kappa_{KE}}{d\log p_E}$ times the CES share multiplier $\frac{(1-\alpha_e)\kappa_{KE}^{\rho_e(c)}}{\alpha_e+(1-\alpha_e)\kappa_{KE}^{\rho_e(c)}} \in (0,1)$, so $0 < \frac{d\log\kappa_{XE}}{d\log p_E} < \frac{d\log\kappa_{KE}}{d\log p_E} = \frac{1}{1-\rho_e(c)}$. Hence if $\rho_l \leq \rho_e(c)$ the bracket is negative; if $\rho_l > \rho_e(c)$ then $(\rho_l - \rho_e(c))\frac{d\log\kappa_{XE}}{d\log p_E} < \frac{\rho_l-\rho_e(c)}{1-\rho_e(c)} < 1$ (since $\rho_l < 1$), so the bracket is again negative. Because $\rho_l - 1 < 0$, $\frac{d\log\kappa_{LE}}{d\log p_E} > 0$. Therefore both κ_{KE} and κ_{LE} increase in p_E, and (A.5) implies $\eta'_c(p_E) > 0$. ■

Lemma 2 (Within a fixed technology, cheaper electricity lowers K/E)**.** *Fix technology c. Then $\kappa_{KE}(p_E, c) = K^*/E^*$ is strictly increasing in p_E; equivalently, $p_E \downarrow$ strictly lowers K/E.*

Proof. From (A.4), $\kappa_{KE} = \big(\frac{p_E(1-\alpha_e)}{p_K\alpha_e}\big)^{\sigma_e(c)}$ with $\sigma_e(c) = \frac{1}{1-\rho_e(c)} > 0$, so for $p_E > 0$, $\frac{\partial\kappa_{KE}}{\partial p_E} = \frac{\sigma_e(c)}{p_E}\kappa_{KE}(p_E, c) > 0$ and hence κ_{KE} is strictly increasing in p_E. ■

Lemma 3 (Within a fixed technology: labor productivity λ_c)**.** *Fix technology c. For $\lambda_c(p_E)$ as defined in (A.5): if $\rho_l < 0$, λ_c is increasing in p_E (so $p_E \downarrow$ lowers PQ/L); if $\rho_l = 0$, λ_c is constant; if $\rho_l > 0$, λ_c is decreasing in p_E (so $p_E \downarrow$ raises PQ/L).*

Proof. Let $s_L := \frac{p_L L^*}{p_K K^* + p_L L^* + p_E E^*}$. Euler and interior FOCs imply $\lambda_c = \frac{p_L}{\phi s_L}$, so $\operatorname{sign}(d\lambda_c/dp_E) = -\operatorname{sign}(ds_L/dp_E)$. Let $p_X(p_E, c)$ be the CES unit cost of the inner K–E aggregate; standard duality gives $p'_X(p_E, c) > 0$. With $\sigma_l := \frac{1}{1-\rho_l}$ and $\Gamma(c) := \left(\frac{1-\alpha_l(c)}{\alpha_l(c)}\right)^{\sigma_l} > 0$, the upper-nest CES share formula is $s_L = \left[1 + \Gamma(c)\left(\frac{p_X(p_E,c)}{p_L}\right)^{1-\sigma_l}\right]^{-1}$. If $\rho_l < 0$ (so $\sigma_l < 1$), s_L decreases in p_X, hence $ds_L/dp_E < 0$ and $d\lambda_c/dp_E > 0$. If $\rho_l > 0$ (so $\sigma_l > 1$), s_L increases in p_X, hence $ds_L/dp_E > 0$ and $d\lambda_c/dp_E < 0$. If $\rho_l = 0$ (so $\sigma_l = 1$), s_L is constant, so λ_c is constant. ■

Across-technology optimality

Proposition 1. (Part A) *There exists a nonempty open set of primitives and prices $p_E^H > p_E^L$ such that $\Pi_1(p_E^H) > \Pi_{c'}(p_E^H)$, $\Pi_{c'}(p_E^L) > \Pi_1(p_E^L)$, and $\eta_{c'}(p_E^L) > \eta_1(p_E^H)$; thus a fall in p_E induces adoption of c' and raises realized electricity productivity across the switch.*

(Part B) *Let p_0 be a threshold electricity price satisfying $\Delta\Pi(p_0) = 0$, where $\Delta\Pi(p_E) := \Pi_{c'}(p_E) - \Pi_1(p_E)$. Let $p_Z(p_E; c)$ denote the unit cost of one unit of the upper CES aggregate under technology c. Define $q := \frac{\phi}{1-\phi}$ and electricity's variable-cost share $s_E(c, p_E)$. Then a marginal fall in p_E at p_0 both induces switching $(1 \to c')$ and raises realized electricity productivity iff $\left(\frac{p_Z(p_0;c')}{p_Z(p_0;1)}\right)^q < \frac{s_E(c',p_0)}{s_E(1,p_0)} < 1$.*

Proof part A: by construction and continuity. Using the numerical parameterization underlying Figure 2, solving the problem gives $\Pi_1(0.50) > \Pi_{c'}(0.50)$, $\Pi_{c'}(0.40) > \Pi_1(0.40)$, $\eta_1(0.50) \approx 2.865$, and $\eta_{c'}(0.40) \approx 3.194$; setting $p_E^H = 0.5$ and $p_E^L = 0.4$ gives the three strict inequalities. Under interior solutions, (Π_c, η_c) are continuous in $(p_E, \text{primitives})$, so these strict inequalities persist on an open neighborhood of that parameter vector; hence the relevant set of primitives is nonempty and open. ■

Proof part B: switching threshold and interval characterization. Let $p_X(p_E; c) := \left(\alpha_e^{\sigma_e(c)} p_E^{1-\sigma_e(c)} + (1-\alpha_e)^{\sigma_e(c)} p_K^{1-\sigma_e(c)}\right)^{\frac{1}{1-\sigma_e(c)}}$ denote the inner-nest unit cost and let $p_Z(p_E; c) := \left(\alpha_l(c)^{\sigma_l} p_L^{1-\sigma_l} + (1-\alpha_l(c))^{\sigma_l} p_X(p_E; c)^{1-\sigma_l}\right)^{\frac{1}{1-\sigma_l}}$ denote the unit cost of one unit of the upper aggregate under technology c. Define $s_E(c, p_E) := \frac{p_E E^*(p_E,c)}{p_K K^*(p_E,c) + p_L L^*(p_E,c) + p_E E^*(p_E,c)}$ and write variable profits as $V(p_E, c) := \Pi_c(p_E) + mc$. For fixed c, the one-dimensional problem over the upper aggregate implies $V(p_E, c) = \kappa\, p_Z(p_E; c)^{-q}$ with $\kappa > 0$ common across technologies and $q = \frac{\phi}{1-\phi}$. At an indifference point p_0 with $\Delta\Pi(p_0) = 0$, a marginal fall in p_E induces switching iff $\Delta\Pi'(p_0) < 0$. By envelope, $\Pi'_c(p_E) = -E^*(p_E, c)$, so this is equivalent to $E^*(p_0, c') > E^*(p_0, 1)$.

Using Shephard's lemma and $V \propto p_Z^{-q}$, $E^*(p_E, c) = -\frac{dV(p_E,c)}{dp_E} = \frac{q}{p_E} V(p_E, c)\, s_E(c, p_E)$, hence the switching condition becomes $\frac{s_E(c',p_0)}{s_E(1,p_0)} > \left(\frac{p_Z(p_0;c')}{p_Z(p_0;1)}\right)^q$. Next, Euler gives $p_K K^* + p_L L^* + p_E E^* = \phi P Q^*$, so $\eta_c(p_E) = \frac{PQ^*}{E^*} = \frac{p_E}{\phi\, s_E(c,p_E)}$. Therefore at common price p_0, $\eta_{c'}(p_0) > \eta_1(p_0)$ iff $\frac{s_E(c',p_0)}{s_E(1,p_0)} < 1$. By continuity the strict inequality implies the same ranking for a small price decrease around p_0. Combining the two inequalities yields exactly the stated interval condition.

Finally, the threshold condition is $\Delta\Pi(p_0) = 0 \iff m(c' - 1) = V(p_0, c') - V(p_0, 1)$, so for any candidate p_0 the implied fixed cost is uniquely $m^*(p_0) := \frac{V(p_0,c') - V(p_0,1)}{c'-1}$. Under the band, $\frac{s_E(c',p_0)}{s_E(1,p_0)} < 1$ and $\left(\frac{p_Z(p_0;c')}{p_Z(p_0;1)}\right)^q < \frac{s_E(c',p_0)}{s_E(1,p_0)}$ imply $\left(\frac{p_Z(p_0;c')}{p_Z(p_0;1)}\right)^q < 1$, hence $p_Z(p_0; c') < p_Z(p_0; 1)$ and so

$V(p_0,c') > V(p_0,1)$. Therefore $m^*(p_0) > 0$. Hence if the interval holds at candidate p_0, there exists a unique positive fixed cost that makes p_0 the switching threshold. Fixed costs pin down the threshold level, while the interval is the local switching/productivity condition at that threshold. ■

Interpretation. Equivalently, the threshold condition is $1 < \frac{\eta_{c'}(p_0)}{\eta_1(p_0)} < \left(\frac{p_Z(p_0;1)}{p_Z(p_0;c')}\right)^q$. Modern technology must therefore be more electricity-productive at the threshold, but not so electricity-saving that a marginal fall in p_E raises profits less under modern than under the old technology to incentivize switching. More precisely, modern's scale advantage more than offsets its lower electricity share for electricity demand in levels, so $E^*(p_0,c') > E^*(p_0,1)$ even though $\eta_{c'}(p_0) > \eta_1(p_0)$. Since $s_E = s_X s_{E|X}$, modern's greater X-intensity tends to raise s_X, so for total electricity share to fall it must reduce the within-X electricity share $s_{E|X}$ by even more. If $\frac{p_Z(p_0;c')}{p_Z(p_0;1)} \approx 1$, the lower bound is close to the upper bound 1, so the feasible interval is tight; if modern has a larger variable-cost advantage, the interval is easier to satisfy. Since modern is more X-intensive, lower p_E or p_K relative to p_L tends to lower $\frac{p_Z(p_0;c')}{p_Z(p_0;1)}$ and relax the condition. Corollary 1 implies the necessary condition $B(p_0) := \frac{p_0(1-\alpha_e)}{p_K\alpha_e} < 1$, so electricity must already be cheap enough relative to capital at the switching threshold. Because $q = \frac{\phi}{1-\phi}$, higher ϕ widens the feasible region on the left side of the interval by making a given variable cost advantage translate into a larger scale response. Fixed costs do not determine whether the mechanism is feasible, but the location of the threshold. Under the switching condition, $m^{*\prime}(p_0) = -\frac{E^*(p_0,c')-E^*(p_0,1)}{c'-1} < 0$, so the value of m consistent with a switching threshold is decreasing in p_0. That is a larger fixed-cost gap $m(c'-1)$ typically requires a lower threshold electricity price. ■

Corollary 1 (Proposition 1 implies a K/E jump)**.** *Let p_0 satisfy $\Delta\Pi(p_0) = 0$. Under maintained assumptions, if at p_0 a marginal fall in p_E both induces switching $1 \to c'$ and raises realized electricity productivity (Proposition 1), then the capital–electricity ratio rises across technologies: $\kappa_{KE}(p_0,c') > \kappa_{KE}(p_0,1)$.*

Proof. Define $B(p_0) := \frac{p_0(1-\alpha_e)}{p_K\alpha_e}$ and shares $s_L(c,p_0) := \frac{p_L L^*}{p_K K^*+p_L L^*+p_0E^*}$, $s_X(c,p_0) := 1 - s_L(c,p_0)$, and $s_{E|X}(c,p_0) := \frac{p_0E^*}{p_0E^*+p_K K^*}$, all at (p_0,c), so $s_E = s_X s_{E|X}$. From Proposition 1, $(\frac{p_Z(p_0;c')}{p_Z(p_0;1)})^q < \frac{s_E(c',p_0)}{s_E(1,p_0)} < 1$, hence $s_E(c',p_0) < s_E(1,p_0)$. Corollary 2 proves $s_L(c',p_0) < s_L(1,p_0)$, so $s_X(c',p_0) > s_X(1,p_0)$. Since $s_E(c',p_0) < s_E(1,p_0)$ and $s_E = s_X s_{E|X}$, we get $s_{E|X}(c',p_0) < s_{E|X}(1,p_0)$. If $B(p_0) \geq 1$, then $s_{E|X}(c,p_0) = \left[1 + \frac{1-\alpha_e}{\alpha_e}B(p_0)^{\sigma_e(c)-1}\right]^{-1}$ with $\sigma_e(c') < \sigma_e(1)$ implies $s_{E|X}(c',p_0) \geq s_{E|X}(1,p_0)$, a contradiction. Hence $B(p_0) < 1$. Finally, (A.4) gives $\kappa_{KE}(p_0,c) = B(p_0)^{\sigma_e(c)}$; with $B(p_0) < 1$ and $\sigma_e(c') < \sigma_e(1)$, $\kappa_{KE}(p_0,c') > \kappa_{KE}(p_0,1)$. ■

Corollary 2 (Proposition 1 implies a PQ/L jump)**.** *Let p_0 satisfy $\Delta\Pi(p_0) = 0$. Under maintained assumptions, if at p_0 a marginal fall in p_E both induces switching $1 \to c'$ and raises realized electricity productivity (Proposition 1), then labor productivity rises across technologies: $\lambda_{c'}(p_0) > \lambda_1(p_0)$.*

Proof. Define $s_L(c,p_0) := \frac{p_L L^*}{p_K K^*+p_L L^*+p_0E^*}$ at (p_0,c). By Euler, $\lambda_c(p_0) = \frac{p_L}{\phi\, s_L(c,p_0)}$, so it is enough to prove $s_L(c',p_0) < s_L(1,p_0)$. Proposition 1 implies $p_Z(p_0;c') < p_Z(p_0;1)$. To compare s_L, let $\sigma_l := \frac{1}{1-\rho_l} > 0$. For $\rho_l = 0$, $s_L(c,p_0) = \alpha_l(c)$, so $\alpha_l(c') < \alpha_l(1)$ implies $s_L(c',p_0) < s_L(1,p_0)$. For $\rho_l > 0$, $\sigma_l > 1$ and the dual share formula gives $s_L(c,p_0) = \alpha_l(c)^{\sigma_l} p_L^{1-\sigma_l}/p_Z(p_0;c)^{1-\sigma_l}$, hence

$\frac{s_L(c',p_0)}{s_L(1,p_0)} = \left(\frac{\alpha_l(c')}{\alpha_l(1)}\right)^{\sigma_l}\left(\frac{p_Z(p_0;1)}{p_Z(p_0;c')}\right)^{1-\sigma_l} < 1$ because $\alpha_l(c') < \alpha_l(1)$, $p_Z(p_0;c') < p_Z(p_0;1)$, and $1-\sigma_l < 0$. For $\rho_l < 0$, first note that $p_X(p_0,c') \geq p_X(p_0,1)$, because at fixed positive prices the inner CES unit cost is weakly decreasing in the elasticity $\sigma_e(c)$. Let $\omega_c := s_L(c,p_0)/(1-s_L(c,p_0))$; then $\omega_c = \left(\frac{\alpha_l(c)}{1-\alpha_l(c)}\right)^{\sigma_l}\left(\frac{p_L}{p_X(p_0,c)}\right)^{1-\sigma_l}$ with $\sigma_l < 1$, so $\alpha_l(c') < \alpha_l(1)$ and $p_X(p_0,c') \geq p_X(p_0,1)$ imply $\omega_{c'} < \omega_1$, hence $s_L(c',p_0) < s_L(1,p_0)$ since $s_L = \omega/(1+\omega)$ is increasing in ω. Thus $s_L(c',p_0) < s_L(1,p_0)$ for all $\rho_l < 1$, implying $\lambda_{c'}(p_0) > \lambda_1(p_0)$. ■

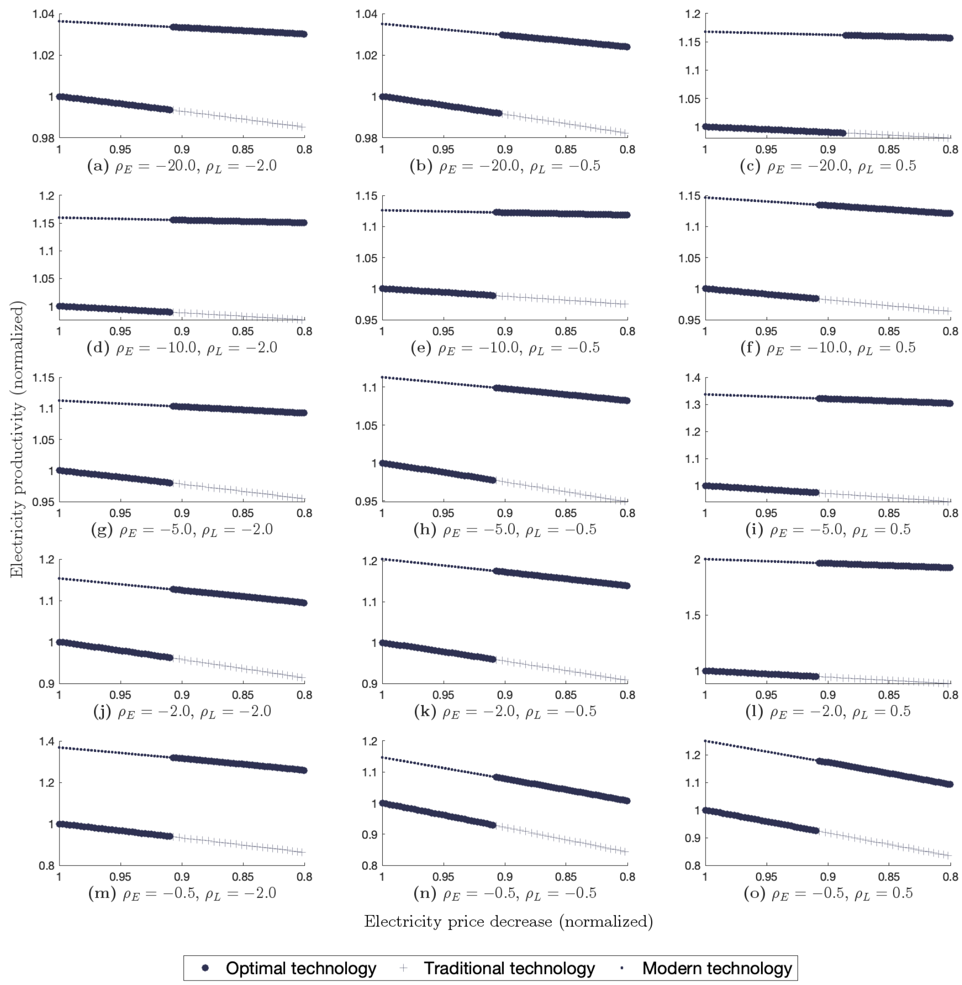
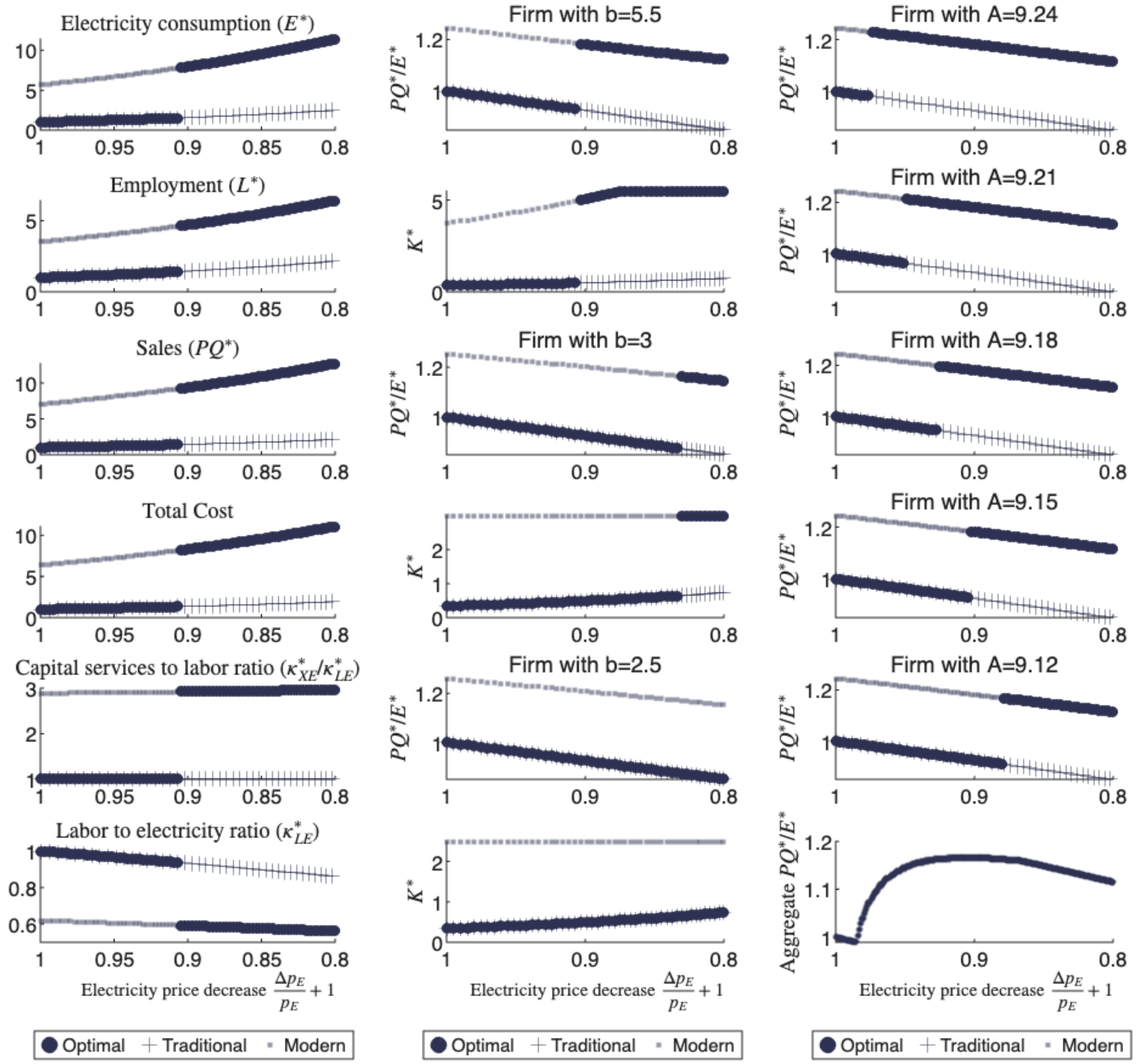


Figure A.1: Alternative substitution elasticities between labor, capital and electricity

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

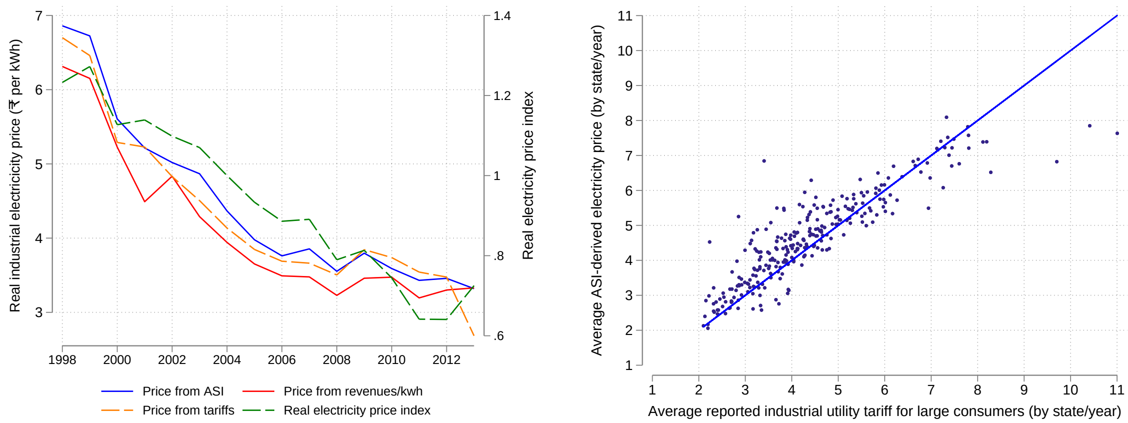


(**a**) Other outcomes (**b**) Capital constraints (**c**) Heterogeneity and aggregate

Figure A.2: Electricity price decreases and predictions for firm outcomes, capital constraints, heterogeneous firms and aggregate electricity productivity

Notes: All 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 ($\Delta p_E = 0$). The parameter values for this simulation are fixed at $\{p_K = 6, p_L = 5, p_E = 0.5, c' = 3, \hat{\alpha}_l = 1/3, \alpha_e = 0.5, \rho_l = -0.5, \hat{\rho}_e = -0.5, \phi = 0.95, A = 9.15, m = 1\}$ and Δp_E varies from 0 (corresponds to $p_E = 0.5$, and 1 on the horizontal axis) to $1/12$ (corresponds to $p_E = 0.4$, and 0.8 on the horizontal axis). Panel (a) plots firm outcomes on the vertical axes (all normalized) against relative electricity price *decreases* on the horizontal axis. Panel (b) shows the impact of capital constraints by modifying the firm maximization problem to include a capital constraint $K \leq b$. In the first two figures the constraint is slack and does not affect the switching threshold. In the second two figures, K is binding for modern, and the switching threshold is when prices are cheaper. In the last two figures, the constaint is so binding that there is no switch to modern over the displayed price range. Panel (c) plots electricity productivity for 5 simulated firms that have heterogeneous total factor productivity A_i against relative electricity price *decreases* on the horizontal axis. The bottom of Panel (c) shows aggregate electricity productivity ($\sum PQ^*_i / \sum E^*_i$) across 100 firms that have A_i varying from 9.1 to 9.25.

A.2 Additional results

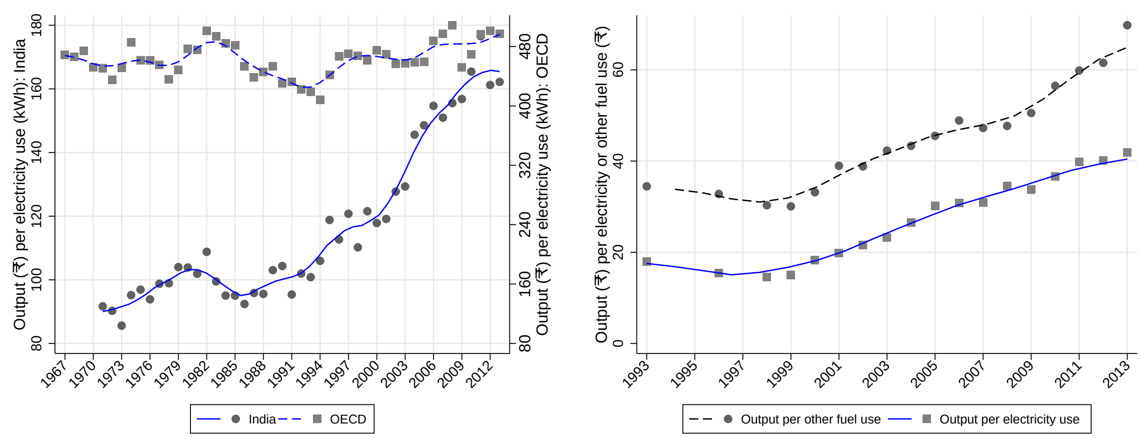


(**a**) Comparing industrial electricity prices from four alternative sources

(**b**) Comparing ASI-derived with published electricity prices

Figure A.3: Comparing electricity prices from different sources

Notes: Panel (a) plots industrial electricity prices from four sources. The solid blue line is the ASI-derived price as in Figure 1. The solid red line is the average price derived from publications of the Planning Commission (2001-2002) and Ministry of Power (2002-2015) dividing total utility revenues (summed across all utilities) by total kWh supplied for the industrial sector. The dashed orange line is weighted average of industrial electricity tariffs manually collected from the reports of the Indian Central Electricity Authority (2006-2015) and from Indiastat (1998-2014) through Lok Sabha and Rajya Sabha questions, weighted by supplied kWh across states. The dashed green line plots the real electricity price index for industry from the Office of the Economic Adviser (2019). It is based on the deflated wholesale price index for electricity for industrial purposes. Panel (b) plots ASI-derived real electricity prices aggregated to the state by year level against published real electricity tariffs for large industry averaged at the state by year level, with sources as above. They are highly correlated, but can deviate due to some firms not being categorized as large industry or due to different tariffs within states that are captured by the ASI data.

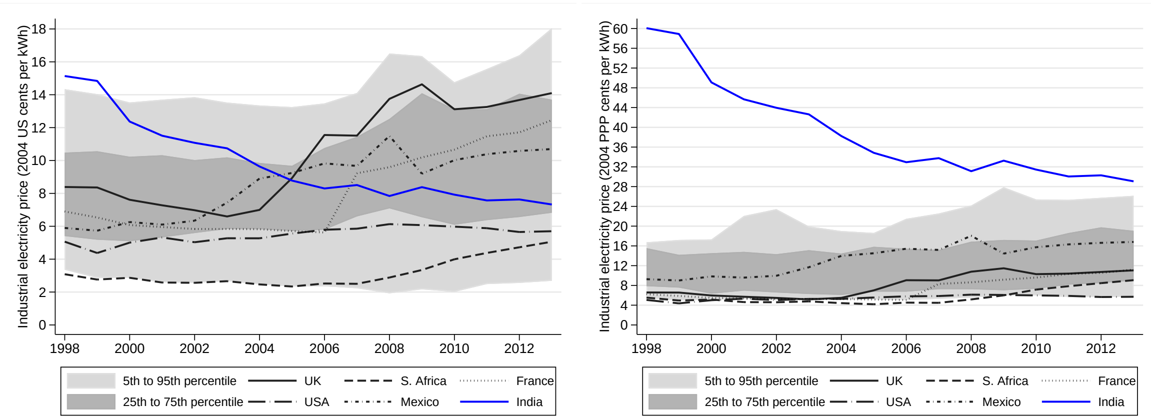


(**a**) Electricity productivity (per kWh)

(**b**) Electricity and other fuel productivity (per ₹)

Figure A.4: Electricity productivity comparisons

Notes: Panel (a) plots the annual electricity productivity ratios (value of output divided by the quantity of electricity used (in kWh)). Both quantities are for manufacturing only. Output is from UNIDO (2016), deflated with GDP deflators from World Bank (2017), and electricity consumption from the IEA (2016). Plotted are the values and kernel smoother for India with the solid line, corresponding to the left axis. The values and kernel smoother for OECD countries are the dashed lines, corresponding to the right axis, showing that electricity productivity did not increase nearly as much in OECD countries over the sample period. Panel (b) plots the annual electricity productivity ratios using costs rather than kwh (value of output divided by the value of electricity used) as well as other fuel productivity ratios (value of output divided by the value of fuel other than electricity used), both using ASI data and deflated revenues and costs.

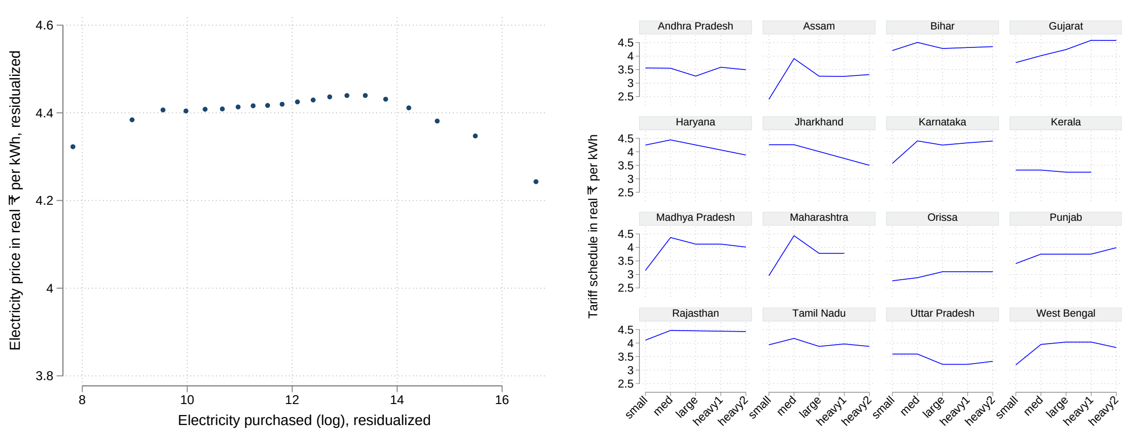


(**a**) Industrial electricity prices (Market exchange rates)

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

Figure A.5: Industrial electricity prices in an international context (US$ and PPP)

Notes: The figures plot real industrial electricity prices for six individual countries. Panel (a) is based on market exchange rates, and Panel (b) is based on PPP conversion factors. The shaded areas correspond to the interquartile range and the 5th to 95th percentile of a given year. This is based on a consistent set of 26 countries for which data for all years was available (see below). Raw price data comes from IEA (2018*b*), except for India, where the prices are based on the micro data in the main text. For India, IEA (2018*b*) data is only available from 2006, which is similar to the plotted data. Prices are deflated with national GDP deflators and turned into US$ or PPP-US$ with exchange rates and PPP conversion factors from the World Bank (2017). The base year for deflation is 2004 throughout this paper. The 26 countries used for the percentiles are: Algeria, Canada, Czech Republic, Denmark, France, Germany, Hungary, India, Ireland, Israel, Italy, Japan, Kazakhstan, Mauritius, Mexico, New Zealand, Paraguay, Poland, Portugal, Slovak Republic, South Africa, Spain, Switzerland, Turkey, United Kingdom, United States. In 1998, India's price was 170% (169%) the average G7 (OECD) price in MER, and 730% (578%) in PPP terms. In 2013, India's price was 54% (59%) the average G7 (OECD) price in MER, and 233% (200%) in PPP terms.



(**a**) Residualized electricity prices and quantity purchased

(**b**) Reported industrial average tariff schedules in large states in 2007

Figure A.6: Minor non-linearities in electricity tariffs across user groups and consumption levels

Notes: Panel (a) shows a binned scatter plot where both plant-level electricity prices, and log electricity purchased are pre-residualized by partialing out state by year fixed effects. This shows that marginal prices are fairly similar to average prices, and that tariffs are slightly increasing in quantity purchased except for the largest customers (note the y-scale). Panel (b) shows the average tariffs by state by size of industrial consumer in 2007 only for major states. There are five categories increasing in electricity consumption from *small* to *heavy2*. The reported average tariffs are collected from the Indian Central Electricity Authority (2006-2015). On average, a higher band (of five bands) is associated with a 1.8 percent increase in the tariff.

Figure A.7: Unmet electricity demand and prices

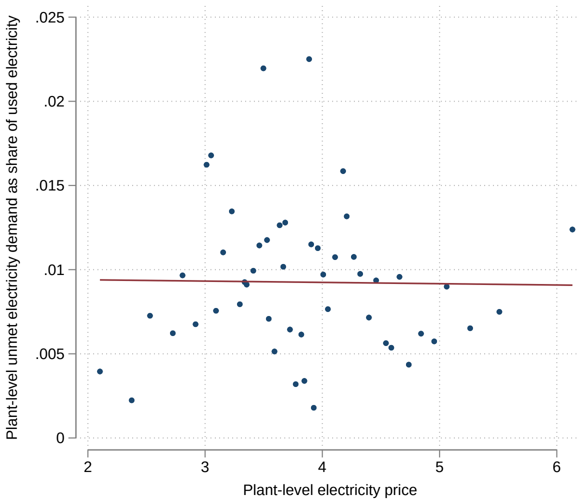


Table A.1: Electricity prices and unmet demand

(**a**) Plant-level share unmet demand

	(1)	(2)	(3)
Electricity price (log)	-0.0015	-0.0026	-0.0026
	(0.0039)	(0.0038)	(0.0035)
N	269075	269075	269075

(**b**) Plant-level unmet intensive margin

	(1)	(2)	(3)
Electricity price (log)	0.065	-0.042	0.0043
	(0.063)	(0.079)	(0.067)
N	10430	10429	10429

Notes: The Figure shows a binned scatter plot of manufacturing plant-level unmet electricity demand as share of total electricity used against plant-level electricity prices, showing no correlation. The data is from the ASI for the years 2004-2013, excluding 2006-2007. The Table shows estimates from OLS regressions on logged electricity price. The dependent variable is plant-level unmet electricity demand as share of total electricity consumed. Panel (b) focuses on the intensive margin unmet electricity by dropping all observations where the dependent variable is zero. Regressions are weighted by the sampling multipliers. Standard errors in parentheses are clustered at the state year level. Stars indicate p-values: $^* < 0.1$, $^{**} < 0.05$, $^{***} < 0.01$.

Table A.2: State power shortages, cost-recovery and utility electricity prices

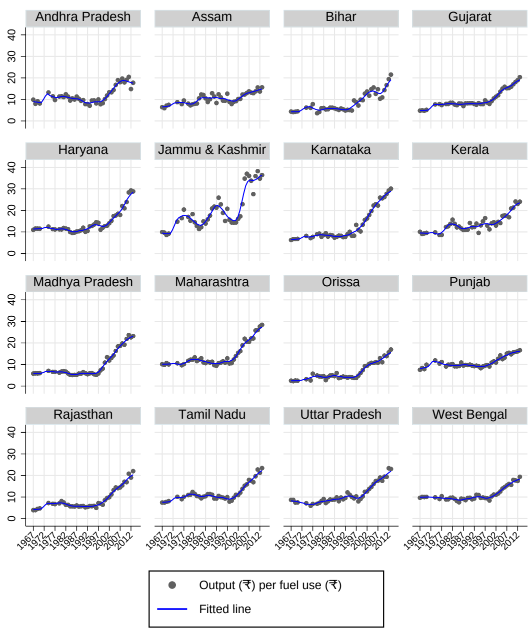
(**a**) Levels: OLS regressions in levels

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

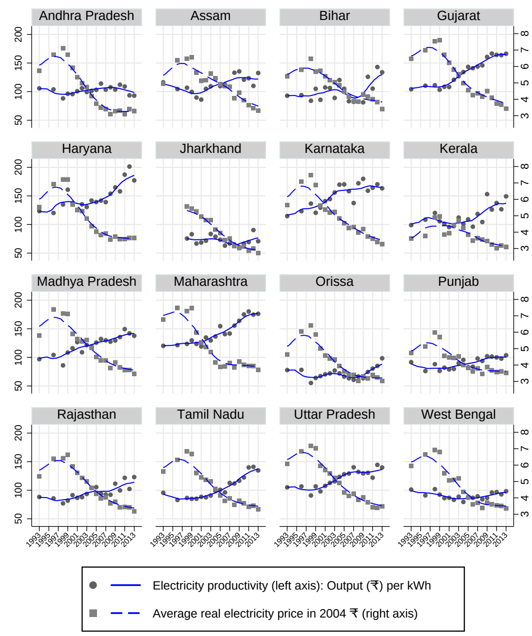
(**b**) Elasticities: PPML regressions with log independent variables

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

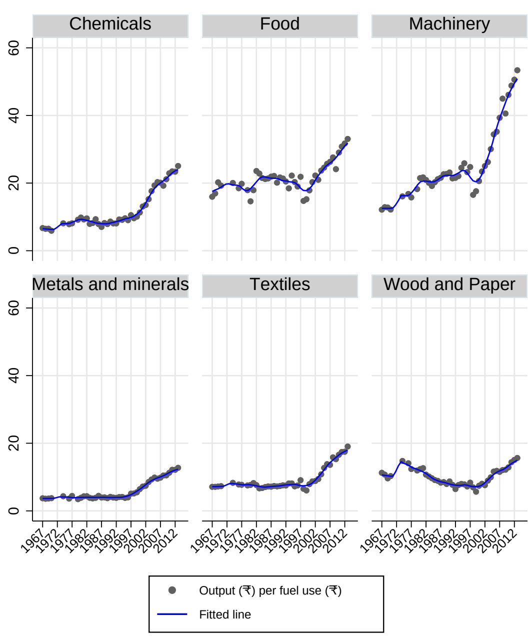
Notes: The table shows estimates from OLS regressions using variables in levels in Panel (a) and elasticity estimates from PPML regressions using independent variables in logs in Panel (b), all at the state by year level. In Columns 1-6 the dependent variable are state by year level electricity shortages reported by the utilities as share of total required electricity at the state by year level. In Columns 7-8 the dependent variable is the share of utility costs that are recovered through revenues at the state level. The electricity price for industry and the overall electricity price is from Planning Commission (2001-2002) and Ministry of Power (2002-2015). Standard errors in parentheses are clustered at the state by year level. Stars indicate p-values: $^* < 0.1$, $^{**} < 0.05$, $^{***} < 0.01$.



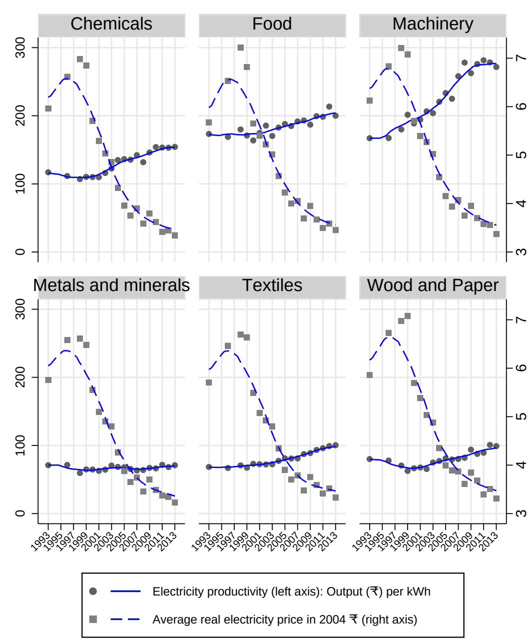
(**a**) Energy productivity (per ₹) by state



(**b**) Electricity prod. (per kWh) and prices by state



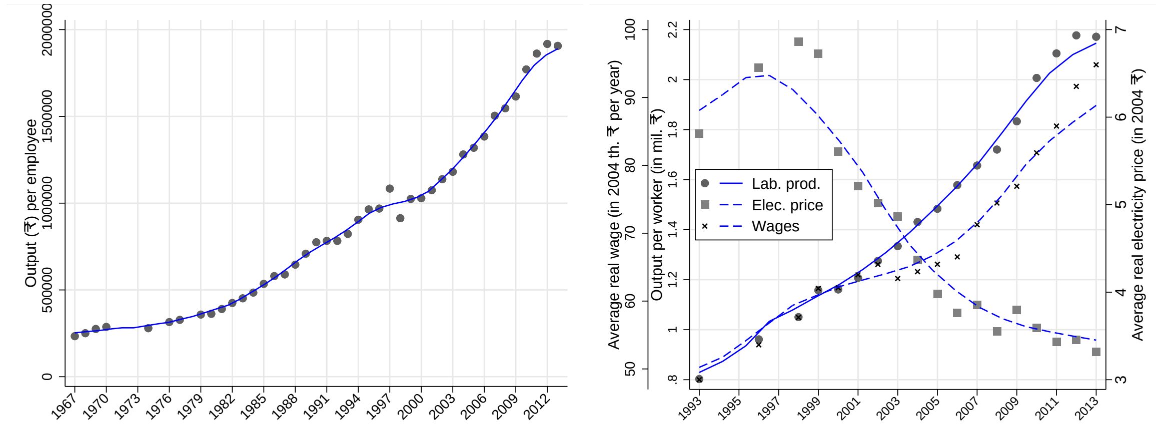
(**c**) Energy productivity (per ₹) by industry



(**d**) Electricity prod. (per kWh) and prices by industry

Figure A.8: Energy productivity (per ₹), electricity productivity (per kWh) and prices by state and industry

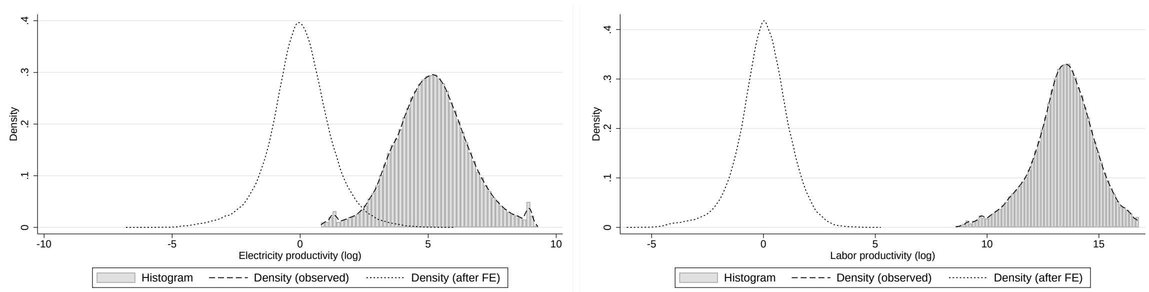
Notes: Panel (a) and (b) plot trends by state and Panel (c) and (d) by industry aggregates. Panels (a) and (c) plot the annual energy productivity ratios (value of output divided by the value of fuel and electricity used) from industry -evel data. Output is deflated at the 2-digit industry level using 2-digit industry deflators before aggregating over industries. Fuel and electricity use is deflated using a general fuel and electricity wholesale price deflator. Panels (b) and (d) plot the annual electricity productivity ratios from plant data (deflated value of output divided by the quantity of electricity used in kWh) on the left axis and real average electricity prices on the right axis.



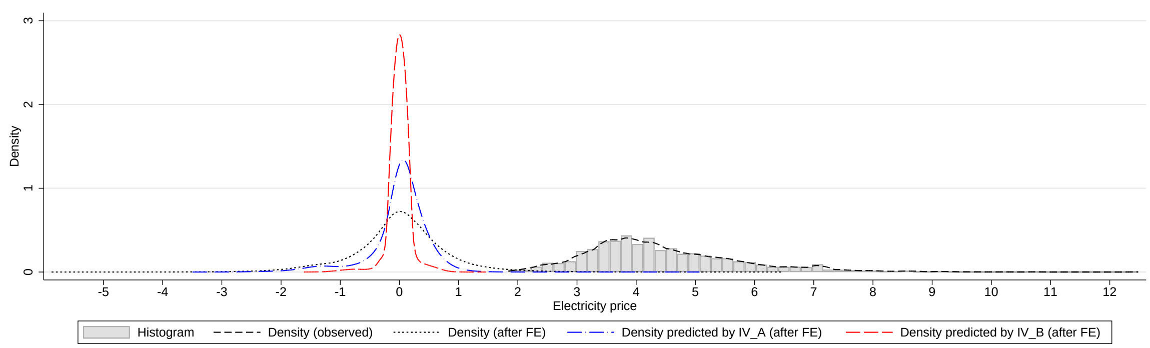
(**a**) Labor productivity (long run) (**b**) Labor productivity and wages

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 from industry-level data. Output is deflated at the 2-digit industry level before aggregating over industries. 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 from plant-level data. Aggregate labor productivity is calculated by first aggregating the value of output and the number of employees across 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.



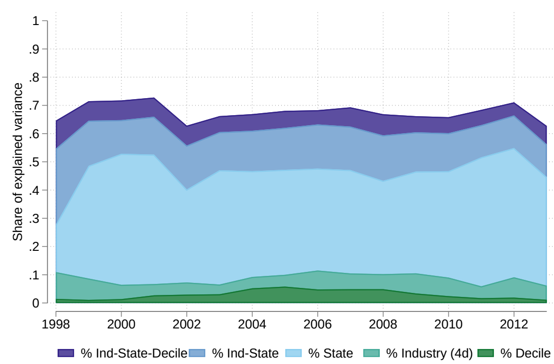
(**a**) Electricity productivity (**b**) Labor productivity



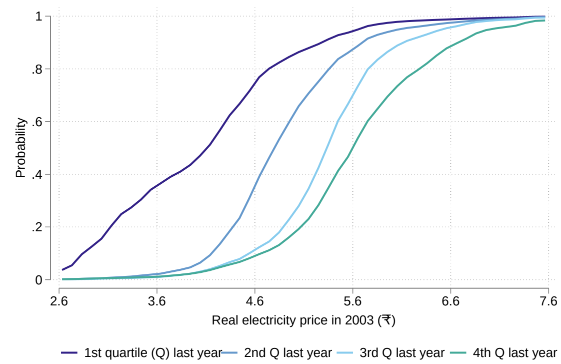
(**c**) Electricity prices

Figure A.10: Heterogeneity in electricity and labor productivity, and electricity prices in pooled sample after FE

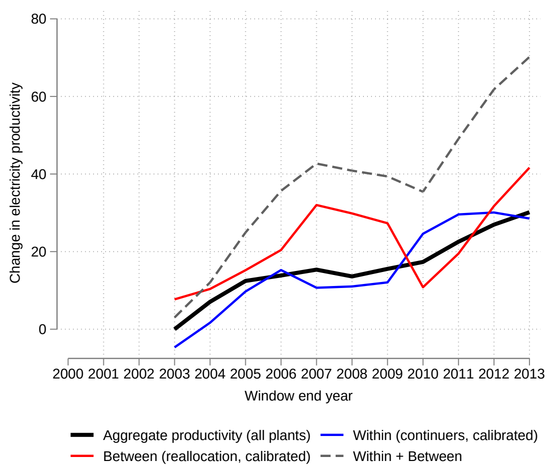
Notes: Panel (a) plots the histogram of plant-level logged electricity productivity in the pooled sample. Electricity productivity ratios are the value of output divided by the quantity of electricity used in kWh. The kernel density plot to the left shows the distribution of the residuals of logged electricity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



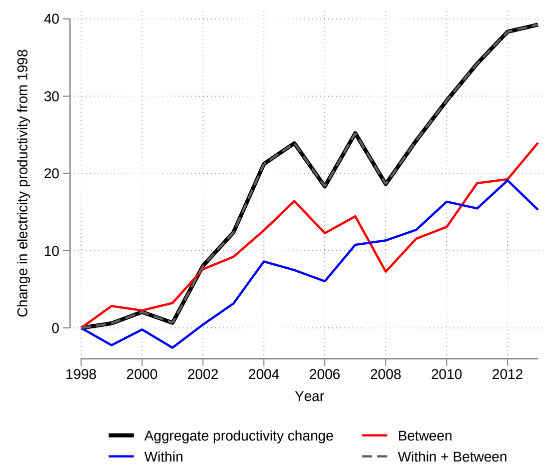
(a) Electricity price variance decomposition



(b) Electricity prices 2003 (CDF)



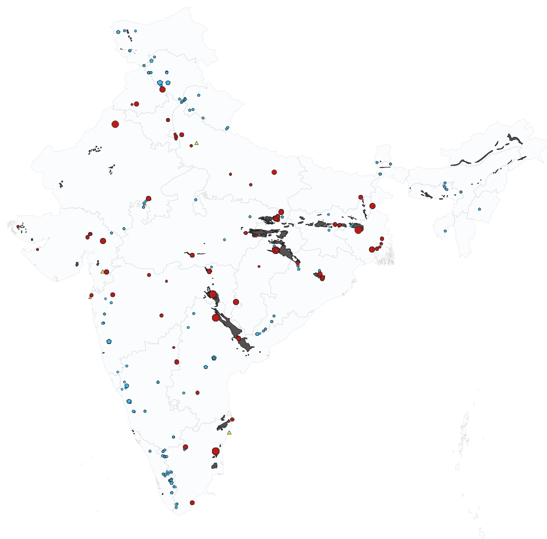
(c) Griliches-Regev Decomposition



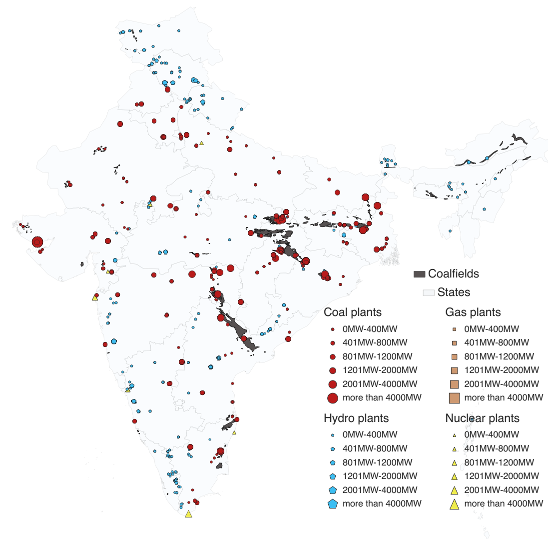
(d) Within-Between Decomposition

Figure A.11: Decomposing Electricity Price Variance and Aggregate Electricity Productivity

Notes: Panel (a) shows a variance decomposition of electricity prices 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 prices, and $\overline{p}$ the weighted average log 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 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. The figure plots the share of V^G in total variance V (V^G/V) where higher shares mean that the groups can explain more of the variation. About 60% of the variation in electricity prices is across state by industry groups (mostly across states), but a substantial 40% is not explained by these groups so vary within. Only a small share is explained by deciles of consumption size consistent with fairly flat tariffs.. For electricity and labor productivity, there is more variation across industries than across states (results available upon request), as production techniques vary more across industries while electricity prices vary more across space. Panel (b) plots the CDF of electricity prices across plants in 2003 conditional on previous period values of the same plants following Farinas and Ruano (2005). 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. The CDF of the higher quartiles are to the right of the lower quartiles for every value, so they first order stochastically dominate the distributions of plants ranked in lower previous period quartiles indicating persistence of electricy prices. This also holds for the other years (and similarly for electricity and labor productivity). Panel (c) shows a Griliches and Regev (1995)-style decomposition of changes in electricity productivity, using electricity quantity as the activity weight (adjusted by the sampling multiplier). For each endpoint year t on the x-axis, outcomes are averaged within two adjacent 3-year windows, $A = \{t-5, \ldots, t-3\}$ and $B = \{t-2, \ldots, t\}$. The window-to-window decomposition is computed on plants observed at least once in both windows ("continuers"), and, to address rotating-sample variability, continuers are reweighted in each window via calibration so that their weighted electricity totals match the full-sample totals in that window. Both within improvement and between-plant reallocation contribute to the aggregate change. The gap between the black (full-sample aggregate) and dashed series reflects plants not linkable across both windows (sampling rotation and true entry/exit), which are not separately decomposed. Panel (d) shows a complementary approach that does not require plants to be observed in consecutive years. The figure shows a within/between decomposition computed year-by-year, leveraging long-term averages within plants. Let p_{it} denote electricity productivity and let $s_{it} = Q_{it}/\sum_j Q_{jt}$ be the electricity-quantity share (adjusted by sampling multipliers). I define each plant's long-run component as an electricity-weighted mean $\mu_i = \sum_t Q_{it} p_{it} / \sum_t Q_{it}$ and deviations are $\tilde{p}_{it} = p_{it} - \mu_i$. Then the aggregate $P_t = \sum_i s_{it} p_{it}$ can be decomposed as $P_t = \sum_i s_{it}\mu_i + \sum_i s_{it}\tilde{p}_{it}$, so changes satisfy $\Delta P_t = \Delta\left(\sum_i s_{it}\mu_i\right) + \Delta\left(\sum_i s_{it}\tilde{p}_{it}\right)$. The first term captures reallocation toward plants with higher permanent productivity, while the second captures within-plant movements relative to each plant's long-run level.



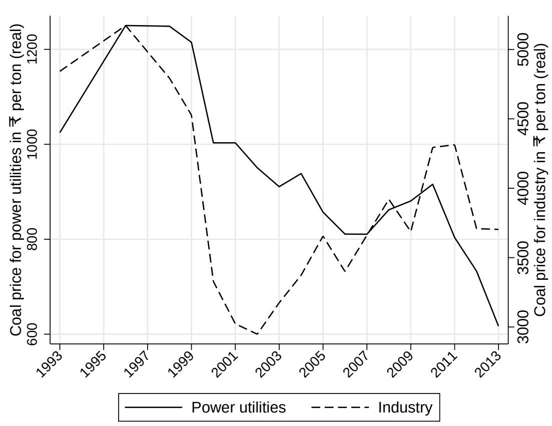
(**a**) Power plants and coalfields 1998



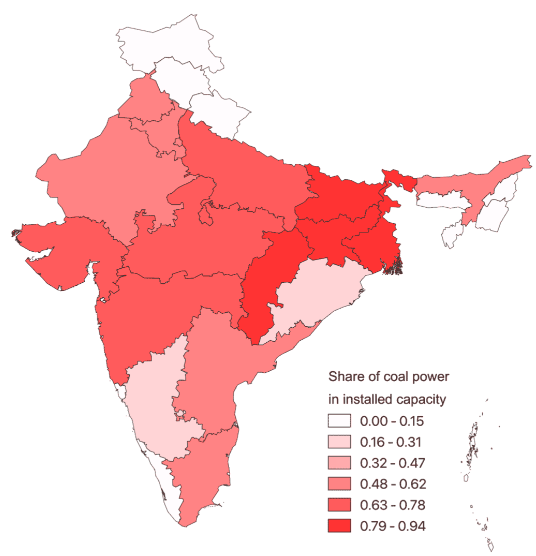
(**b**) Power plants and coalfields 2013

Figure A.12: Maps of coalfields and power plants by year

Notes: The maps plot the coalfields (time invariant) and the stock of power plants in the corresponding years. The size of the markers corresponds to installed capacity. Geo-located data on Indian coalfields is from Trippi and Tewalt (2011). 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). The maps visualize the growth of coal-fired power plants near coalfields. 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 (t-statistic of 3.8 and R^2 of 0.066). Apart from demonstrating that coal plants are built near coalfields, the maps also show that hydro plants are near rivers especially in the mountainous region (mainly North-West), nuclear plants are typically built near the sea or rivers, and gas plants are built near ports and the major gas pipelines (e.g. in the North-East).



(**a**) Coal prices for power utilities versus industry



(**b**) Share of coal power in total installed capacity

Figure A.13: Shifter and shares for IV^B

Notes: In Panel (a) the solid line plots the real coal price for thermal power plants from Ministry of Coal (2012, 2015). These are the ones of Eastern Coalfields Limited of Coal India Limited, Rajmahal field, Grade E, in line with those used by Abeberese (2017) and Ministry of Coal (2012). 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 Ministry of Coal (2013). 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. Both coal prices are in real terms. In nominal terms, coal prices have been mostly increasing. Panel (b) shows the share of coal-fired thermal power generation capacity in total installed capacity at the state level as on 31st of March 1998 from Ministry of Power (1998*a*, 2003), one day before the beginning of the sample. Chhattisgarh, Jharkhand and Uttarakhand were created in 2000, and shares correspond to Jan 2003 when data is first available.

Table A.3: Electricity prices, privately owned share in district installed capacity, and coalfields

(**a**) Electricity price (log)

	(1)	(2)
Share private capacity	-0.0067	0.0005
	(0.015)	(0.014)
Share private capacity x after 2003	-0.025**	-0.023***
	(0.012)	(0.0044)

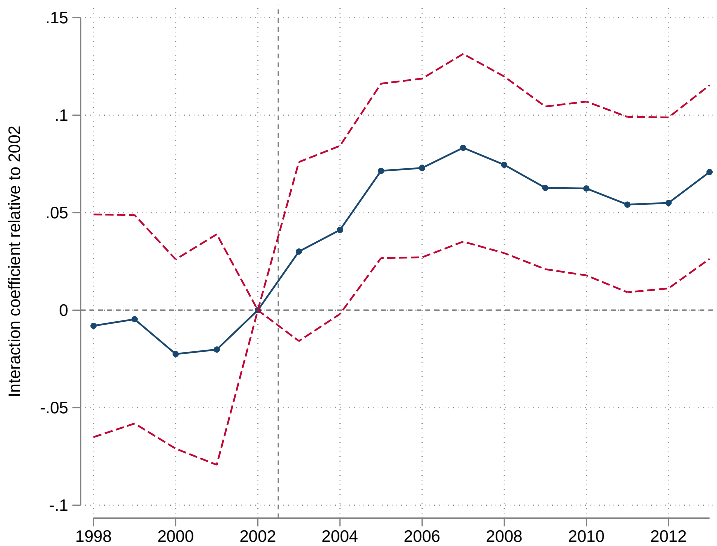
(**b**) Share private capacity

	(1)	(2)
Distance to coalfield ('00 km) x after 2003 x state w. coal power	-0.019***	-0.016**
	(0.0071)	(0.0073)

(**c**) Electricity price (log)

	(1)	(2)
Distance to coalfield ('00 km) x after 2003 x state w. coal power	0.079***	0.076***
	(0.019)	(0.017)
Observations	8007	8007
Total capacity	No	Yes
Year FE	Yes	Yes
District FE	Yes	Yes
Region-year FE	No	Yes

Figure A.14: Event study of impact of 2003 Electricity Act and distance to coalfields on electricity prices



Notes: The table shows estimates from OLS regressions at the district-year level with the log median electricity price within a district as dependent variable in Panel (a) and (c). The dependent variable in Panel (b) is the share of privately owned capacity in district level installed capacity and includes joint private/state and private/central ownership categories. The Indian Electricity Act was introduced in 2003 and the variable after 2003 indicates a dummy that is one from 2003. The distance to coalfields at the district level is in hundreds of km. 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. The variable state w. coal power is a dummy that takes one if a state has ever had any coal power throughout the sample. The total capacity covariate controls for total installed capacity of any type and fuel at the district year level. District fixed effects absorb the distance to coalfields in levels. Regressions are weighted by the sampling multipliers and by the number of plants within a district-year cluster. Standard errors in parentheses are clustered two-way at the district and state by year level. Stars indicate p-values: * < 0.1, ** < 0.05, *** < 0.01. The figure plots the coefficient on a triple interaction between district centroid distance to coalfields (in 100 km), year dummies, and a dummy that is one if there has ever been any coal fired power generation in a state. The regression is based on the plant-level data as in the main paper with log electricity prices as dependent variable. All lower order interaction terms are included as well as industry by year by region fixed effects and district fixed effects. 95% confidence bands are based on standard errors that are two-way clustered.

Table A.4: Similar estimates with three alternative instruments IV^C, IV^{D_1} and IV^{D_2}

	Electricity productivity (log)					Labor productivity (log)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\log(P^E)$	0.37***	-0.25***	-0.50	-0.57**	-0.26	-0.028	-0.35***	-0.85**	-0.96***	0.27
	(0.044)	(0.089)	(0.32)	(0.27)	(0.18)	(0.043)	(0.11)	(0.35)	(0.25)	(0.19)
OLS/IV	OLS	IV^C	IV^{D1}	IV^{D1}	IV^{D2}	OLS	IV^C	IV^{D1}	IV^{D1}	IV^{D2}
Observations	485342	444937	446268	446264	485342	485342	444937	446268	446264	485342
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	No	No	No	Yes	No	No	No	No	Yes	No
Lower interactions	-	-	Yes	Yes	-	-	-	Yes	Yes	-
First stage coef.	-	0.90***	0.07***	0.07***	0.12***	-	0.90***	0.07***	0.07***	0.12***
First stage SE	-	0.016	0.017	0.011	0.014	-	0.016	0.017	0.011	0.014
F-stat (Kleib.-Paap)	-	3365.2	17.2	43.9	70.4	-	3365.2	17.2	43.9	70.4
Two-way clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

Table A.5: Robustness of IV^B to controlling for interacted predetermined variables

(**a**) Correlation of coal power shares with other predetermined variables

	Share rural	Share domestic power	Share power	Labor productivity (log)	Capital labor ratio (log)	Share managerial wages	Fuel share in output	Wage share in output
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Coal power share	0.0215	0.181	-0.156	0.231	0.0487	-0.0368	0.0183	-0.0141
	(0.129)	(0.158)	(0.153)	(0.292)	(0.326)	(0.035)	(0.024)	(0.022)
Observations	31	31	31	31	31	28	26	26

(**b**) Electricity prices and electricity productivity: controlling for interacted presample shares for IV^B

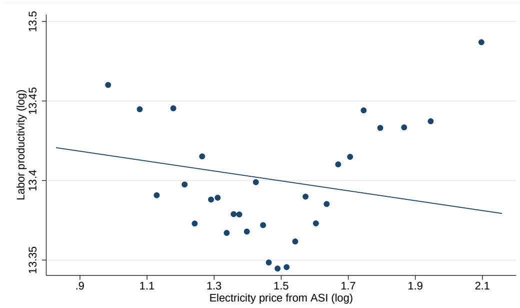
	Dependent Variable: Electricity Productivity (log)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\log(P^E)$	-0.796***	-0.539***	-0.559***	-0.803***	-0.824***	-0.562***	-0.384***	-0.931***
	(0.118)	(0.096)	(0.092)	(0.116)	(0.105)	(0.114)	(0.105)	(0.156)
Control X Price shifter	-0.0149*	-0.0317***	0.0281***	-0.0082	-0.0209***	0.153***	-0.609***	0.403***
	(0.009)	(0.006)	(0.006)	(0.006)	(0.005)	(0.039)	(0.051)	(0.099)
OLS/IV	IV^B	IV^B	IV^B	IV^B	IV^B	IV^B	IV^B	IV^B
Observations	481164	481164	481164	485115	485115	462049	455584	455584
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-stat (Kleib.-Paap)	244.5	359.7	399.5	270.6	278.0	214.3	228.5	145.1

Notes: Panel (a) shows state-level regressions of the indicated outcome on the pre-sample coal power shares in generating capacity that is used in the construction of IV^B. Each column represents a separate regression controlling for region fixed effects as in the main analysis. The outcomes in Columns 1-3 come from the 91 Population Census from SHRUG. Share rural is the rural share in population. Share domestic power is the share of villages that have electricity for domestic use. Share power is the share of villages that have electricity for any use. The outcomes in Columns 4-5 are based on the 1998 version of the ASI microdata. Labor productivity is sales divided by number of employees. Capital labor ratio is total book value of capital divided by number of employees. The outcome in Column 6 is based on the 1996 version of the ASI microdata, and share managerial wages is the share of wages going to supervisors and managers in total wages. The outcomes in Columns 7-8 are based on the aggregate ASI data in 1997. Fuel share in output is total spending on fuel as share of output. Wage share in output is total emoluments as share of output. Panel (b) shows the same regressions as in Table 2 using IV^B, but with an additional control variable that is a pre-sample state-level variable indicated at top of Panel (a) interacted with the log coal price (CP) used in construction of IV^B.

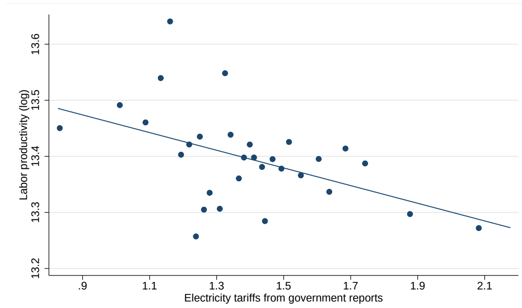
Table A.6: Using published average electricity tariff data instead of ASI derived plant-level prices, or controlling for product and input mix specific input and output price indices

	Using published tariffs						Controlling for input and output prices					
	Electricity productivity (log)			Labor productivity (log)			Electricity productivity (log)			Labor productivity (log)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\log(P^E)$	-0.20***	-0.29***	-0.77***	-0.21***	-0.42***	-1.05***	0.40***	-0.14*	-0.74***	-0.057	-0.42***	-1.07***
	(0.045)	(0.075)	(0.10)	(0.056)	(0.094)	(0.12)	(0.047)	(0.072)	(0.11)	(0.046)	(0.087)	(0.11)
Output price index (log)							0.026***	0.026***	0.026***	0.031***	0.031***	0.031***
							(0.0017)	(0.0017)	(0.0017)	(0.0018)	(0.0018)	(0.0019)
Input price index (log)							-0.012***	-0.012***	-0.012***	0.014***	0.015***	0.015***
							(0.0024)	(0.0024)	(0.0024)	(0.0023)	(0.0023)	(0.0023)
OLS/IV	OLS	IV^A	IV^B	OLS	IV^A	IV^B	OLS	IV^A	IV^B	OLS	IV^A	IV^B
Observations	478910	478910	478910	478910	478910	478910	425458	425458	425458	425458	425458	425458
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-stat (Kleib.-Paap)	-	652.9	263.2	-	652.9	263.2	-	43309.3	249.3	-	43309.3	249.3

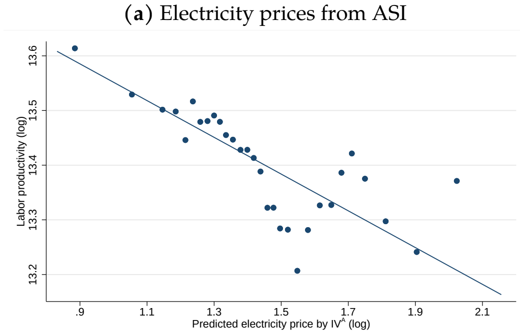
Notes: See Table 2 for notes. In Columns 1-6 the difference is that the manually collected utility tariffs are used for the endogenous electricity price variable instead of ASI-derived prices. The utility tariffs are at the state by year level and averaged across industrial consumer bands, taken from Central Electricity Authority (2006-2015) and Indiastat (1998-2014). Reassuringly, even using OLS with this average tariff measure already removes a lot of the plant-level OLS bias present in the OLS estimates in main Table 2. The IV estimates between this table and the main Table 2 are statistically indistinguishable. In Columns 7-12 the difference is that plant-level output and input price indices are added as control variables. The output price index is constructed at the plant by year level by assigning to each produced product the national median product level price from the ASI data, and then aggregating across products produced within each plant using sales shares. The input price index is constructed at the plant by year level by assigning to each input product the national median input level price from the ASI data, and then aggregating across inputs used within a plant using expenditure shares.



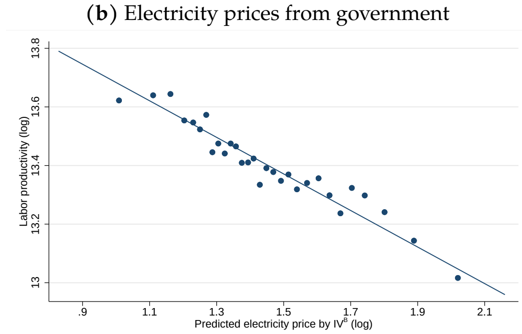
(**a**) Electricity prices from ASI



(**b**) Electricity prices from government



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



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

Figure A.15: Binscatter of labor productivity and electricity prices

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

Table A.7: Electricity prices and electricity productivity: controlling for distance to coalfields and shortages

(**a**) Electricity productivity (log)

	OLS			IV^A			IV^B		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(P^E)$	0.35***	0.39***	0.38***	-0.26***	-0.24***	-0.23***	-0.81***	-0.88***	-0.90***
	(0.045)	(0.044)	(0.045)	(0.072)	(0.078)	(0.079)	(0.10)	(0.12)	(0.11)
Distance to coalfield	-0.018***		-0.018***	-0.014**		-0.016**	-0.010		-0.014*
(in ’00 km)	(0.0070)		(0.0070)	(0.0071)		(0.0070)	(0.0080)		(0.0080)
Shortage		0.21	0.083		0.59***	0.46**		0.97***	0.87***
		(0.23)	(0.24)		(0.18)	(0.19)		(0.19)	(0.19)

(**b**) Labor productivity (log)

	OLS			IV^A			IV^B		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(P^E)$	-0.060	0.025	-0.0001	-0.48***	-0.30***	-0.36***	-1.04***	-1.03***	-0.97***
	(0.044)	(0.040)	(0.041)	(0.086)	(0.088)	(0.087)	(0.096)	(0.13)	(0.11)
Distance to coalfield	0.036***		0.039***	0.038***		0.040***	0.042***		0.042***
(in ’00 km)	(0.0073)		(0.0074)	(0.0076)		(0.0076)	(0.0084)		(0.0084)
Shortage		-0.52**	-0.67***		-0.33	-0.46**		0.11	-0.082
		(0.22)	(0.21)		(0.21)	(0.19)		(0.26)	(0.23)
OLS/IV	OLS	OLS	OLS	IV^A	IV^A	IV^A	IV^B	IV^B	IV^B
Observations	446268	482764	443690	446268	482764	443690	446268	482764	443690
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-stat (Kleib.-Paap)	-	-	-	42385.8	35456.6	35005.3	308.4	236.5	245.8

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

Table A.8: Lagged electricity prices, electricity and labor productivity

	Electricity productivity (log)						Labor productivity (log)					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\log(P^E)$	0.30***	-0.24***	-0.73***				-0.041	-0.32***	-0.48***			
	(0.049)	(0.065)	(0.087)				(0.045)	(0.083)	(0.10)			
Lagged $\log(P^E)$				0.018	-0.23***	-0.73***				-0.048	-0.31***	-0.48***
				(0.042)	(0.062)	(0.086)				(0.045)	(0.083)	(0.10)
OLS/IV	OLS	IV^A	IV^B	OLS	IV^A(lag)	IV^B(lag)	OLS	IV^A	IV^B	OLS	IV^A(lag)	IV^B(lag)
Observations	225576	225576	225576	225576	225576	225576	225576	225576	225576	225576	225576	225576
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-stat (Kleib.-Paap)	-	50578.8	421.2	-	44102.4	405.4	-	50578.8	421.2	-	44102.4	405.4

Notes: See Table 2 for notes. The main difference is that the columns 1-3 and 7-9 restrict the sample to the same observations as in the following three columns, where lagged logged electricity prices (and lagged instruments) are used.

Table A.9: Purchased electricity in electricity productivity only, product scope, and electric machinery equipment

	Elec prod. purch. only (log))			Number of products (log)			Share electric equipment		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(P^E)$	0.43***	-0.18**	-0.73***	0.045***	-0.013	-0.097***	-0.0028***	-0.0056***	-0.012***
	(0.046)	(0.077)	(0.11)	(0.012)	(0.023)	(0.036)	(0.0007)	(0.0014)	(0.0020)
OLS/IV	OLS	IV^A	IV^B	OLS	IV^A	IV^B	OLS	IV^A	IV^B
Observations	485342	485342	485342	484482	484482	484482	485338	485338	485338
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-stat (Kleib.-Paap)	-	45263.8	296.5	-	45114.0	296.7	-	45257.5	296.5

Notes: See Table 2 for notes. The main difference is that the dependent variable is constructed using only electricity purchased instead of electricity consumed in Columns 1-3, and other dependent variables as indicated in Columns 4-9.

Table A.10: Focusing on electricity intensive sectors or on plants that do not use coal

	Electricity intensive sectors						Plants that do not use coal					
	Electricity productivity (log)			Labor productivity (log)			Electricity productivity (log)			Labor productivity (log)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\log(P^E)$	0.32***	-0.20***	-0.58***	-0.17***	-0.58***	-1.05***	0.37***	-0.26***	-0.84***	-0.052	-0.41***	-1.09***
	(0.047)	(0.076)	(0.10)	(0.047)	(0.085)	(0.10)	(0.047)	(0.074)	(0.11)	(0.045)	(0.088)	(0.10)
OLS/IV	OLS	IV^A	IV^B	OLS	IV^A	IV^B	OLS	IV^A	IV^B	OLS	IV^A	IV^B
Observations	260571	260571	260571	260571	260571	260571	435681	435681	435681	435681	435681	435681
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-stat (Kleib.-Paap)	-	35179.0	324.5	-	35179.0	324.5	-	46172.2	295.1	-	46172.2	295.1

Notes: See Table 2 for notes. The main difference is that the sample is restricted to electricity intensive sectors only in Columns 1-6 and to manufacturing plants that do not use coal directly in Columns 7-12.

Table A.11: Different clustering or using both IVs simultaneously

	Clustering on district and region-year						Using both IVs simultaneously					
	Electricity productivity (log)			Labor productivity (log)			Electricity productivity (log)			Labor productivity (log)		
	OLS	IV^A	IV^B	OLS	IV^A	IV^B	OLS	IV^A & IV^B	IV^C & IV^B	OLS	IV^A & IV^B	IV^C & IV^B
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\log(P^E)$	0.35***	-0.27*	-0.80***	-0.054	-0.45*	-1.08***	0.37***	-0.27***	-0.38***	-0.028	-0.42***	-0.52***
	(0.12)	(0.15)	(0.22)	(0.13)	(0.24)	(0.23)	(0.044)	(0.070)	(0.074)	(0.043)	(0.084)	(0.094)
OLS/IV	OLS	IV^A	IV^B	OLS	IV^A	IV^B	OLS	IV^A	IV^C	OLS	IV^A	IV^C
Observations	446268	446268	446268	446268	446268	446268	485342	485342	444937	485342	485342	444937
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-stat (Kleib.-Paap)	-	3175.1	39.0	-	3175.1	39.0	-	24639.9	2229.5	-	24639.9	2229.5
J-statistic	-	-	-	-	-	-	-	23.8	20.2	-	37.3	34.5

Notes: See Table 2 for notes. In Columns 1-6, the difference is that the standard errors are clustered at a higher level, at the district level and the region-year level. In Columns 7-12 the 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.12: Electricity prices, electricity and labor productivity by industry groups

(**a**) Chemicals, Food

	Chemicals						Food					
	Electricity productivity (log)			Labor productivity (log)			Electricity productivity (log)			Labor productivity (log)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\log(P^E)$	0.14**	-0.42***	-0.76***	-0.29***	-0.70***	-1.14***	0.61***	0.017	-1.64***	0.45***	0.79***	-1.46***
	(0.064)	(0.086)	(0.10)	(0.053)	(0.075)	(0.100)	(0.073)	(0.17)	(0.45)	(0.074)	(0.21)	(0.35)
OLS/IV	OLS	IV^A	IV^B	OLS	IV^A	IV^B	OLS	IV^A	IV^B	OLS	IV^A	IV^B
Observations	76574	76574	76574	76574	76574	76574	92467	92467	92467	92467	92467	92467
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-stat (Kleib.-Paap)	-	18463.3	528.0	-	18463.3	528.0	-	3908.0	105.1	-	3908.0	105.1

(**b**) Machinery, Metals and Minerals

	Machinery						Metals and Minerals					
	Electricity productivity (log)			Labor productivity (log)			Electricity productivity (log)			Labor productivity (log)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\log(P^E)$	0.22***	-0.66***	-1.30***	-0.13**	-0.70***	-1.23***	0.49***	0.12	0.28	-0.14***	-0.53***	-1.48***
	(0.066)	(0.094)	(0.14)	(0.059)	(0.10)	(0.12)	(0.053)	(0.11)	(0.20)	(0.052)	(0.11)	(0.17)
OLS/IV	OLS	IV^A	IV^B	OLS	IV^A	IV^B	OLS	IV^A	IV^B	OLS	IV^A	IV^B
Observations	91156	91156	91156	91156	91156	91156	102815	102815	102815	102815	102815	102815
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-stat (Kleib.-Paap)	-	22634.0	341.1	-	22634.0	341.1	-	11410.8	175.5	-	11410.8	175.5

(**c**) Textiles, Wood and Paper

	Textiles						Wood and Paper					
	Electricity productivity (log)			Labor productivity (log)			Electricity productivity (log)			Labor productivity (log)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\log(P^E)$	0.40***	-0.15	-1.01***	-0.11	-0.54**	0.0077	0.36***	-0.22**	-0.70***	0.17***	-0.094	-0.65***
	(0.076)	(0.16)	(0.27)	(0.10)	(0.23)	(0.40)	(0.066)	(0.097)	(0.14)	(0.060)	(0.10)	(0.15)
OLS/IV	OLS	IV^A	IV^B	OLS	IV^A	IV^B	OLS	IV^A	IV^B	OLS	IV^A	IV^B
Observations	68878	68878	68878	68878	68878	68878	38786	38786	38786	38786	38786	38786
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-stat (Kleib.-Paap)	-	5639.7	196.0	-	5639.7	196.0	-	11619.7	261.7	-	11619.7	261.7

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

Table A.13: 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)
$\log(P^E)$	-0.0073***	-0.032***	-0.039***	-0.0006	-0.021***	-0.032***	-0.0041**	-0.0099***	-0.023***
	(0.0025)	(0.0044)	(0.0045)	(0.0024)	(0.0039)	(0.0072)	(0.0017)	(0.0028)	(0.0063)
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
F-stat (Kleib.-Paap)	-	54447.2	390.5	-	46574.8	297.6	-	46574.8	297.6

Notes: See Table 2 for notes. Different methods to recover TFP are used, and TFP used as dependent variable. OP refers to Olley and Pakes (1996), LP refers to Levinsohn and Petrin (2003) and ACF refers to Ackerberg et al. (2015).

Table A.14: 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.15: Electricity prices, high baseline machinery to labor ratio, and FDI-liberalized industries

	Electricity productivity (log)			Output (log)			Elec. prod. (log)		Labor prod. (log)		Output (log)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\log(P^E)$	0.23***	-0.34***	-1.01***	0.14**	-0.35***	-0.43**	0.26***	-0.36***	-0.16*	-0.54***	-0.26*	-1.06***
	(0.053)	(0.066)	(0.12)	(0.071)	(0.12)	(0.17)	(0.083)	(0.11)	(0.084)	(0.16)	(0.13)	(0.25)
$\log(P^E) \times abovemed$	0.12***	0.17***	0.57***	0.048	0.12	0.97***						
	(0.036)	(0.044)	(0.12)	(0.063)	(0.074)	(0.18)						
$\log(P^E) \times treated$							-0.35**	-0.67***	0.54***	0.44**	1.35***	1.22***
							(0.16)	(0.22)	(0.12)	(0.19)	(0.18)	(0.32)
$\log(P^E) \times post$							0.21**	0.38**	0.040	0.011	-0.072	-0.33
							(0.11)	(0.15)	(0.10)	(0.19)	(0.17)	(0.32)
$\log(P^E) \times treated \times post$							0.59**	1.08***	-0.29	-0.56**	-0.15	-0.15
							(0.25)	(0.37)	(0.20)	(0.29)	(0.22)	(0.42)
OLS/IV	OLS	IV^A	IV^B	OLS	IV^A	IV^B	OLS	IV^A	OLS	IV^A	OLS	IV^A
Observations	217773	217773	217773	217773	217773	217773	347398	347398	347398	347398	347398	347398
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-stat (Kleib.-Paap)	-	26643.7	50.0	-	26643.7	50.0	-	407.0	-	407.0	-	407.0

Notes: See Table 2 for notes. Columns 1-6 contain 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. Columns 7-12 contain the interactions with indicators for treated industries liberalized for FDI in 2006 (treated) and post-2006 (post). The interactions with treated industries are appropriately instrumented with interactions with IV^A. Due to multiple endogenous variables, the F-stat for IV^B is low and results are not reported due to weak IV bias.

Table A.16: The contrary effects of coal prices on coal and labor productivity and firm performance

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

	Coal productivity (log)			Labor productivity (log)			Profit (mil. ₹)			TFP (log) (Wooldridge, 2009)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\log(P^C)$	0.85***	1.45***	1.61***	0.055***	-0.021	0.31	-5.30***	-4.15	-6.81	-0.0007	-0.021	-0.031
	(0.025)	(0.18)	(0.21)	(0.020)	(0.13)	(0.19)	(1.76)	(15.8)	(25.8)	(0.0018)	(0.013)	(0.020)
OLS/IV	OLS	IV^E	IV^F	OLS	IV^E	IV^F	OLS	IV^E	IV^F	OLS	IV^E	IV^F
Observations	45126	45126	45126	45126	45126	45126	45123	45123	45123	44740	44740	44740
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-stat (Kleib.-Paap)	-	153.5	86.8	-	153.5	86.8	-	153.5	86.8	-	152.2	89.1

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

	Output (log)			Coal consumption (log)			Employees (log)			Total costs (mil. ₹)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\log(P^C)$	0.091***	-0.31	-0.13	-0.76***	-1.82***	-1.79***	0.035*	-0.32*	-0.50**	-14.6**	-38.1	-2.47
	(0.031)	(0.25)	(0.34)	(0.035)	(0.27)	(0.38)	(0.021)	(0.19)	(0.25)	(6.53)	(71.4)	(102.7)
OLS/IV	OLS	IV^E	IV^F	OLS	IV^E	IV^F	OLS	IV^E	IV^F	OLS	IV^E	IV^F
Observations	45126	45126	45126	45126	45126	45126	45126	45126	45126	45123	45123	45123
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-stat (Kleib.-Paap)	-	153.5	86.8	-	153.5	86.8	-	153.5	86.8	-	153.5	86.8

Notes: Each column represents a separate regression at the plant level with dependent variables as indicated. The table shows results from OLS regression on logged coal prices, and IV regressions using IV^E, which is based on the coal prices of other plants, or the shift-share IV^F, as indicated. Coal productivity is the value of output divided by the quantity of coal used in tonnes, and profits and costs are in levels. The first stage coefficients are 0.57 for IV^E with a KP F-stat of 154 and 0.01 for IV^F with an F-stat of 86. Regressions are weighted by the recorded sampling multiplier. Standard errors in parentheses are two-way clustered at the plant and the state by year level. Stars indicate p-values: * < 0.1, **< 0.05, ***< 0.01.

Table A.17: Product FE, or average product electricity intensity using nation-wide product averages

	Electricity productivity (log)			Simple avg. product elec. int. (log)			Weigh. avg. prod. elec. int. (log)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(P^E)$	0.31***	-0.40***	-0.67***	-0.011	-0.0026	0.088	-0.014	-0.017	0.078
	(0.043)	(0.066)	(0.092)	(0.024)	(0.039)	(0.062)	(0.024)	(0.040)	(0.064)
OLS/IV	OLS	IV^A	IV^B	OLS	IV^A	IV^B	OLS	IV^A	IV^B
Observations	342659	342659	342659	215151	215151	215151	215124	215124	215124
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	No	No	No	No	No	No
F-stat (Kleib.-Paap)	-	32763.849	260.232	-	36896.654	194.976	-	36896.575	194.962
Two-way clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: See Table 2 for notes. Columns 1-3 include product fixed effects. Columns 4-9 apply the constant nation-wide intensities to evolving product mix as dependent variables. I only use observations until 2009, as the product identification system changed in 2010.

Table A.18: Comparison to Table 3 of Abeberese (2017): Including partially omitted fixed effects

	Dummy for switching to less electricity-intensive				Simple avg. product elec. int. (log)				Weighted avg. product elec. int. (log)			
	Partial omission		No omission		Partial omission		No omission					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\log(P^E)$ [Reported]	1.462**	1.510*	-	-	-0.859***	-0.975***	-	-	-0.788***	-0.906***	-	-
	(0.673)	(0.767)			(0.279)	(0.324)			(0.301)	(0.327)		
$\log(P^E)$	1.561**	1.616**	-0.119	-0.405	-0.873***	-0.985***	0.210	-0.126	-0.810**	-0.925***	-0.398	-0.575
	(0.675)	(0.781)	(0.650)	(0.719)	(0.300)	(0.342)	(0.605)	(0.536)	(0.322)	(0.346)	(0.595)	(0.586)
Region1_Time2			0.0472**	0.0563**			-0.0236	-0.0131			0.00593	0.0121
			(0.021)	(0.024)			(0.024)	(0.023)			(0.025)	(0.025)
Region1_Time3			0.0900**	0.103**			-0.0372	-0.0219			0.00136	0.00842
			(0.041)	(0.044)			(0.038)	(0.032)			(0.038)	(0.034)
Region1_Time4			0.0827**	0.0958**			-0.0497	-0.0306			0.0190	0.0264
			(0.041)	(0.044)			(0.047)	(0.041)			(0.048)	(0.045)
Region1_Time5			0.123***	0.136***			-0.0706*	-0.0493			-0.0160	-0.00666
			(0.034)	(0.035)			(0.043)	(0.036)			(0.043)	(0.040)
Region1_Time6			-0.0107	-0.000343			-0.0784***	-0.0626**			-0.0411	-0.0339
			(0.025)	(0.027)			(0.029)	(0.026)			(0.031)	(0.030)
Region1_Time7			0.00972	0.00631			-0.0676***	-0.0690***			-0.0644***	-0.0659***
			(0.007)	(0.008)			(0.017)	(0.019)			(0.018)	(0.019)
Region2_Time2	-0.0632	-0.0637	0.00826	0.0220	0.0341	0.0384*	0.00362	0.0150	0.0351	0.0378*	0.0235	0.0293
	(0.047)	(0.050)	(0.033)	(0.036)	(0.021)	(0.021)	(0.026)	(0.024)	(0.022)	(0.023)	(0.026)	(0.026)
Region2_Time3	-0.0253	-0.0258	0.0712*	0.0931**	0.0687***	0.0830***	0.0204	0.0438	0.0716***	0.0815***	0.0533*	0.0661**
	(0.051)	(0.056)	(0.040)	(0.045)	(0.020)	(0.022)	(0.032)	(0.030)	(0.021)	(0.023)	(0.031)	(0.032)
Region2_Time4	-0.0615	-0.0612	0.0724	0.102*	0.0648**	0.0836***	-0.0147	0.0205	0.0626**	0.0753**	0.0324	0.0512
	(0.061)	(0.068)	(0.054)	(0.061)	(0.027)	(0.030)	(0.048)	(0.044)	(0.030)	(0.033)	(0.048)	(0.049)
Region2_Time5	-0.0575	-0.0570	0.101	0.139*	0.104***	0.134***	0.000208	0.0496	0.107***	0.128***	0.0682	0.0951
	(0.070)	(0.080)	(0.067)	(0.077)	(0.033)	(0.039)	(0.059)	(0.055)	(0.037)	(0.041)	(0.059)	(0.062)
Region2_Time6	-0.158***	-0.153***	-0.0559	-0.0268	0.0452**	0.0722**	-0.0214	0.0184	0.0385	0.0545*	0.0132	0.0347
	(0.046)	(0.051)	(0.043)	(0.050)	(0.023)	(0.030)	(0.039)	(0.040)	(0.025)	(0.030)	(0.038)	(0.042)
Region2_Time7	-0.0599**	-0.0525	-0.0251	-0.00879	-0.00322	0.0168	-0.0195	0.00382	-0.00745	0.00136	-0.0137	-0.00109
	(0.030)	(0.034)	(0.016)	(0.019)	(0.020)	(0.023)	(0.017)	(0.021)	(0.026)	(0.030)	(0.025)	(0.028)
Region3_Time2	-0.0835**	-0.0841*	-0.00971	0.00674	0.0372	0.0491*	-0.00942	0.0109	0.0245	0.0334	0.00679	0.0178
	(0.040)	(0.044)	(0.031)	(0.035)	(0.025)	(0.027)	(0.031)	(0.029)	(0.031)	(0.032)	(0.037)	(0.038)
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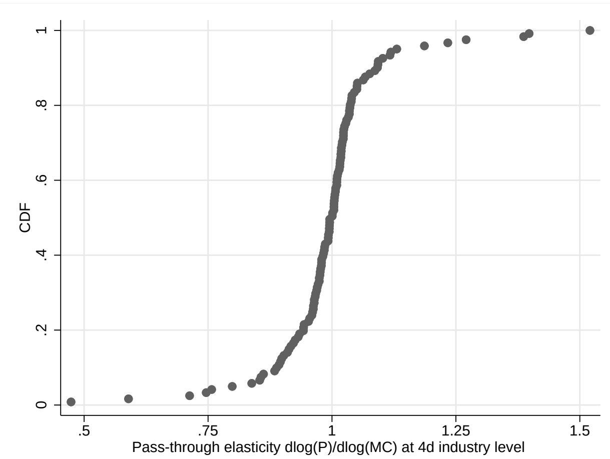
Region5_Time7	-0.0453**	-0.0473**	-0.00386	-0.000347	-0.0000711	-0.00412	-0.0256	-0.0229	0.00799	0.00644	-0.00171	-0.000839
	(0.019)	(0.021)	(0.017)	(0.017)	(0.017)	(0.017)	(0.022)	(0.019)	(0.020)	(0.021)	(0.023)	(0.022)
Region6_Time2	-0.0725**	-0.0721**	-0.00559	0.00963	-0.0597***	-0.0529**	-0.0654***	-0.0578***	0.00865	0.0121	0.00648	0.0106
	(0.031)	(0.034)	(0.028)	(0.032)	(0.022)	(0.024)	(0.018)	(0.019)	(0.020)	(0.021)	(0.017)	(0.018)
Region6_Time3	-0.0825	-0.0993	0.0426	0.0446	0.0458*	0.0204	-0.00628	-0.0190	0.0402*	0.0315	0.0204	0.0127
	(0.053)	(0.065)	(0.050)	(0.052)	(0.026)	(0.037)	(0.034)	(0.036)	(0.022)	(0.032)	(0.032)	(0.034)
Region6_Time4	-0.177*	-0.194*	0.0538	0.0776	0.0599	0.0483	-0.0660	-0.0500	0.0874**	0.0895*	0.0396	0.0472
	(0.093)	(0.111)	(0.090)	(0.096)	(0.041)	(0.051)	(0.073)	(0.066)	(0.041)	(0.047)	(0.070)	(0.068)
Region6_Time5	-0.212*	-0.228*	0.0592	0.0937	0.0200	0.0167	-0.126	-0.0982	0.0689	0.0760	0.0133	0.0275
	(0.110)	(0.129)	(0.105)	(0.114)	(0.042)	(0.051)	(0.082)	(0.073)	(0.045)	(0.051)	(0.081)	(0.079)
Region6_Time6	-0.235**	-0.248**	0.00184	0.0345	0.0484	0.0499	-0.0852	-0.0553	0.0640	0.0725	0.0132	0.0286
	(0.096)	(0.112)	(0.092)	(0.100)	(0.042)	(0.049)	(0.078)	(0.069)	(0.045)	(0.049)	(0.077)	(0.075)
Region6_Time7	-0.139**	-0.147**	0.00255	0.0228	0.0426	0.0450	-0.0406	-0.0206	0.0578*	0.0638*	0.0261	0.0365
	(0.057)	(0.067)	(0.055)	(0.060)	(0.030)	(0.033)	(0.049)	(0.044)	(0.030)	(0.033)	(0.048)	(0.047)
Observations	72987	72987	72987	72987	107891	107891	107891	107891	107891	107891	107891	107891
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Notes: These regressions follow the methodology and replication package of Abeberese (2017) using the same specification as well as the corresponding shorter sample from 2000/01 to 2007/08. I thank Ama Baafra Abeberese for correspondence and sharing the industry crosswalk used for this exercise. There are three different dependent variables indicated at the top corresponding to Panel B, C and D of Table 3 in Abeberese (2017) respectively. The first four columns use the dummy for switching to a less electricity-intensive five-digit industry, the second four columns are the log of the simple average productivity intensity of the product mix, and the last four columns are the log of the weighted average productivity intensity of the product mix, all constructed using the replication code. The specification in the paper includes firm fixed effects and uneven columns include additional controls, corresponding to Columns 5 and 6 of Table 3 of Abeberese (2017) respectively. Standard errors are clustered at the state by year level. The number of observations (72,987 and 107,891) are close to her reported number of observations (73,387 and 108,402). The small difference likely arises from updates to the ASI data versions, where I am using a more recent version. With the exception of the ASI raw data, I use all other data and deflators from her replication package. I can almost exactly replicate all summary statistics. The reported coefficients and standard errors in Abeberese (2017) are repeated in the first row, and almost identical replicated coefficients and standard errors in the second row. All of these are, however, only significant due to a coding issue. The region by year fixed effects are only partially included, due to being pre-generated in the replication code and how Stata generates fixed effects. This error is generated by the Stata command *xi i.region*i.t* (line 796) to generate the fixed effects, which should instead be *xi i.region*i.t, noomit*, as otherwise Stata also expects the uninteracted region and time fixed effects to be separately included in the regression, which they are not. As Columns 3-4, 7-8, and 11-12 show, all the relationships turn insignificant, and sometimes the coefficients change sign, once the fixed effects are included as intended in Abeberese (2017). Importantly, this is entirely consistent with my findings in Table A.17 that there is no decrease in electricity productivity coming from the product mix i.e. from what firms produce. My estimated effects on electricity consumption, employment and output are more comparable to the ones in Abeberese (2017). Stars indicate p-values: * < 0.1, **< 0.05, ***< 0.01.

Table A.19: 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	9.1e-16***	1.4e-14***	-0.251	5.3e-04***	0.0016***	-0.777	5.3e-13***	6.3e-12***
Labor productivity (log)	-0.028	0.514	1	-0.400	4.6e-06***	2.8e-05***	-1.063	1.0e-22***	1.6e-21***
Output (log)	-0.027	0.715	1	-0.828	3.4e-08***	3.4e-07***	-1.600	3.1e-23***	5.2e-22***
Electricity consumption (log)	-0.385	3.1e-09***	4.6e-08***	-0.550	9.9e-04***	0.00199***	-0.797	1.2e-07***	5.8e-07***
Employees (log)	0.012	0.771	1	-0.412	4.3e-07***	3.0e-06***	-0.518	1.3e-10***	1.3e-09***
Profits	-5.037	9.5e-04***	0.0109**	-27.863	1.4e-13***	2.0e-12***	-22.034	5.7e-08***	4.0e-07***
Total revenues	-30.407	6.5e-04***	0.00848***	-183.965	6.5e-15***	1.1e-13***	-139.505	1.1e-10***	1.3e-09***
Total variable costs	-24.247	0.00113***	0.011**	-152.584	1.2e-14***	2.0e-13***	-114.396	1.4e-10***	1.3e-09***
Ratio machinery to employees (log)	-0.160	0.0138**	0.069*	-0.668	1.9e-08***	2.1e-07***	-1.517	8.4e-22***	1.3e-20***
Machinery to electricity ratio (log)	0.259	1.3e-06***	1.8e-05***	-0.499	4.9e-11***	6.3e-10***	-1.178	1.2e-19***	1.7e-18***
Employment to electricity ratio (log)	0.380	1.2e-18***	2.0e-17***	0.117	0.236	0.236	0.283	0.00621***	0.0124**
Investment in machinery (PPML)	-0.276	0.00199***	0.0159**	-1.251	6.7e-14***	1.0e-12***	-0.713	7.1e-05***	2.1e-04***
Ratio electricity to coal quantity	-10.188	0.0011***	0.011**	-23.554	5.2e-05***	2.6e-04***	-22.088	0.0751*	0.0751*
Other fuels' share in output	0.004	9.1e-04***	0.0109**	0.013	1.6e-10***	1.9e-09***	0.023	5.0e-16***	6.5e-15***
Average wage per worker (log)	0.030	0.0333**	0.133	-0.158	1.4e-07***	1.1e-06***	-0.182	8.4e-08***	5.1e-07***
TFP (log)	-0.007	0.00308***	0.0216**	-0.019	4.1e-08***	3.7e-07***	-0.033	2.9e-07***	1.1e-06***
Price marginal cost markup $\log(\mu)$	-0.018	0.00364***	0.0218**	-0.045	7.7e-05***	3.1e-04***	-0.106	3.2e-08***	2.6e-07***
Independent variable: log(coal price)									
Coal productivity (log)	0.849	0***	0***	1.453	5.2e-15***	4.1e-14***	1.614	1.8e-13***	1.4e-12***
Labor productivity (log)	0.055	0.00716***	0.0286**	-0.021	0.876	1	0.311	0.106	0.532
Profits	-5.297	0.00282***	0.0169**	-4.151	0.794	1	-6.814	0.792	1
Output (log)	0.091	0.00309***	0.0169**	-0.310	0.211	0.845	-0.131	0.702	1
Coal consumption (log)	-0.759	0***	0***	-1.819	6.6e-11***	4.7e-10***	-1.793	3.7e-06***	2.6e-05***
Employees (log)	0.035	0.0928*	0.186	-0.323	0.0938*	0.563	-0.498	0.048**	0.288
Total variable costs	-14.557	0.0262**	0.0787*	-38.055	0.594	1	-2.466	0.981	1
TFP (log)	-0.001	0.701	0.701	-0.021	0.108	0.563	-0.031	0.119	0.532

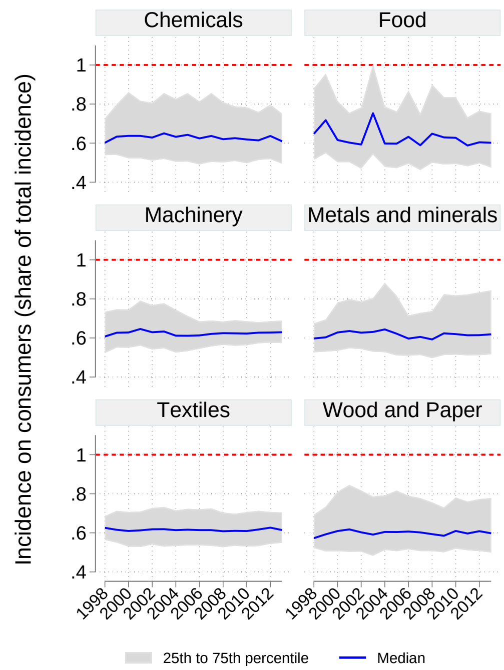
Notes: The table contains the coefficients and p-values from the original regressions in the main text. The q-values are the adjusted p-values for multiple hypothesis testing using the procedure outlined in Holm (1979). The correction procedures are separately applied by model (OLS, IV^A, IV^B) and by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



(a) Distribution of pass-through elasticities

	Manufacture of: Grain mill products	Structural non-refractory clay and ceramic products
$\log(MC)$	1.004***	0.730***
	(0.0151)	(0.0555)
OLS/IV	IV^A	IV^B
Observations	21812	6208
Region-year FE	Yes	Yes
F-stat (Kleib.-Paap)	35.74	28.98

(b) Two example pass through elasticities



(c) Consumer incidence over time

Figure A.16: Pass-through elasticities and consumer incidence share over time

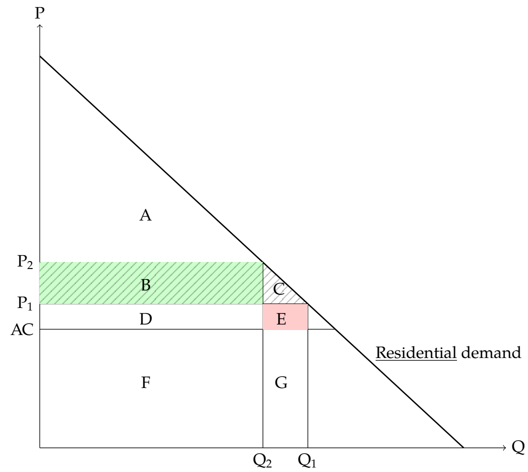
Notes: Panel (a) plots the cumulative distribution function of the pass-through elasticities ($d\log(P)/d\log(MC)$). There are 121 pass-through elasticities that vary at the 4-digit industry level. The pass-through elasticities are the coefficient on a regression of log prices on log marginal costs at 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. Panel (b) shows two example regressions for two different 4-digit industries of log prices on log marginal costs with different IVs. Panel (c) plots the median share of incidence on consumers I^{share} from electricity price changes for each year within each broad industry. The 25th and 75th percentiles are plotted as well. Chemicals includes rubber and plastics, machinery includes metal products, and textiles includes leather.

A.3 Welfare with non-final demand and residential tariff financing

Consumer surplus changes accounting for non-final demand: Industries differ in how much they sell to consumers (final demand). Using the 2007-08 input-output (IO) tables from the Central Statistics Office (2012), which report each industry's final-demand share, I manually match the more granular 133 4-digit industries in the sample along with their estimated incidence shares to the 58 IO industries. For each industry, I combine the final demand share s_{IOind} with the median of the estimated within-industry incidence share $I^{share}_{IOind}(\rho_{MC}, L, \epsilon_D)$. I then combine this with the industry-specific change in producer surplus dPS_{IOind}.[76] Change in total consumer surplus dCS is the sum over IO industries:

[76]The change in producer surplus equals the change in profits, irrespective of whether output is going to final demand. It is based on a common average profit semi-elasticity from Table 4a, but becomes industry-specific due to the varying size of sectors. As a robustness check, I additionally estimate separate profit semi-elasticities by IO industry for dPS_{IOind}. This could in principle increase or decrease dCS, depending on whether producers with a higher share going to final demand have higher or lower profit semi-elasticities. The results are similar with a total adjusted consumer surplus of US$ 32.1 billion.

Figure A.17: Changes in consumer surplus from residential electricity tariff changes



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

$dCS = \sum_{IOind} dPS_{IOind} \cdot s_{IOind} \cdot I_{IOind}(\rho_{MC}, L, \epsilon_D)$. The change in consumer surplus is US$ 36.2 billion. The final-demand adjustment is important, as the unadjusted figure would amount to US$ 71 billion.[77]

Financing through residential tariff increases: If the electricity price reduction for industry is financed entirely through higher rates for residential users, consumers have direct losses from paying higher rates. I next calculate this consumer welfare loss from financing the US$ 3.52 billion utility deficit (Section V.E). Figure A.17 depicts a simple demand curve for residential electricity with prevailing price P_1 and purchased electricity Q_1. To finance the deficit, utilities increase residential rates to P_2, generating additional revenue B, forgone sales $E + G$, and cost savings G, assuming constant average cost of supply AC. Overall, the utility makes additional profits $B - E$ from this residential rate increase. The corresponding loss in consumer surplus is $B + C$.

To quantify these changes, I use residential $P_1 = 4.9$ US cents per kWh and $AC = 6.9$ US cents per kWh from the Planning Commission (2001-2002); Ministry of Power (2002-2015), and $Q_1 = 125.447$ TWh of residential electricity consumption from the Central Statistics Office (2016), all averaged across the sample period.[78] I use an elasticity of residential demand of -0.41 (average between urban and rural India) from Table A.8 in Mahadevan (2023). This allows me to solve a system of equations for new prices and quantities as the two unknowns:

$$\text{Elasticity of residential demand} = \frac{(Q_2 - Q_1) * P_1}{(P_2 - P_1) * Q_1} = -0.41 \tag{A.6}$$

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

The solution is $P_2 = 8.0$ cents per kWh, implying a 63% increase in residential utility tariffs to

[77] To calculate change in unadjusted consumer surplus dCS, I set s_{IOind} to 1 and use median incidence I across all plants.
[78] Using residential prices and cost of supply values from different fixed years rather than averages does not change the resulting consumer surplus loss much.

finance the reduction in industrial tariffs. The resulting loss in consumer surplus in the residential sector is US$ 3.4 billion, which amounts to overall net gains for consumers of US$ 33 billion.

A.4 Details for calculating effects on CO_2 emissions

I combine regression estimates with fuel use data and emission factors to calculate the effect on CO_2 emissions. The first step is to calculate annual baseline CO_2 emissions in the manufacturing ASI micro data from electricity, coal and oil averaged across 1998-2000:

Electricity: For electricity, I use reported net consumption (adjusted for self generation and sale) in kWh and convert it to CO_2 emissions using the average emissions per kWh produced in the Indian electricity generating sector (0.84 tCO_2/MWh according to Central Electricity Authority (2006)).
Coal: For coal, I use reported quantity in tons and convert it to CO_2 emissions by taking (i) the net calorific value per ton for Indian manufacturing (6350 kcal/kg per Ministry 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 quantities and types of oil used. I convert quantities to energy units using IEA (2013) for different oil types, and then convert those to CO_2 emissions using IPCC (2006) tables for manufacturing industries. I then calculate the ratio of CO_2 emissions per ₹ spent on oil (with real prices) and apply this ratio to 1998-2000.

I multiply all observations by the sampling multipliers to estimate 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 as it represents only a fraction of CO_2 emissions (0.03Mt in 1996). I assume that emission intensities of a unit of electricity, coal or oil remains constant through 2013.

In the second step, I use my estimates to calculate the impact of the electricity price decreases. I use the average elasticity (from IV^A and IV^B in Columns 5-6 of Table 3) to calculate 48% price decrease impact on electricity consumption and embodied emissions. I combine these elasticities with those from a regression[79] of the log electricity to coal use ratio on electricity prices to calculate the effect on coal use and emissions, and analogously for emissions from oil use.[80] With these steps I obtain the estimates of Column 1 in Table 7.

The third step calculates the emission increases when switching off substitution between fuels or the electricity productivity effect. To make scenarios comparable I condition on reaching the same output gains. Switching off fuel substitution requires that the price decline has no effect on fuel use ratios. That is, coal and oil need to change by the same rate as electricity use as if Leontief. Switching off the electricity productivity effect requires that electricity use increases by the rate as output in the baseline scenario, while maintaining fuel substitution through changes in fuel ratios. Finally, I switch off both substitution and electricity productivity effects in the last column of Table 7.

[79] The average elasticity is -0.430.
[80] I rely on oil expenditure rather than quantities as for coal. The average elasticity of the electricity to oil ratio is -0.684.