Can lower electricity prices improve energy efficiency? Evidence from half a million Indian plants

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Abstract

India experienced a secular increase in aggregate industrial energy efficiency and aggregate electricity productivity from around 2000. During the same period, industrial electricity prices almost halved. Using a large panel of Indian manufacturing plants over 16 years with information on electricity quantity and prices at the plant level, I estimate the impact of electricity prices on electricity productivity. Based on two different instruments, I recover causal estimates at the micro level that can explain these aggregate trends. While lower electricity prices increase electricity consumption, they disproportionally increase output, and therefore improve electricity productivity. The causal estimates have the opposite sign of the OLS estimates. I explore mechanisms and find that lower electricity prices increase firm size, investment, productivity and markups. This is consistent with a complementarity between electricity and modern high performance production techniques. I estimate pass-through rates and calculate that the incidence share on consumers of this large industrial electricity prices reduction was two thirds. The causal effects of industrial coal prices are of opposite sign, which has important implications for climate policy and industrial development.

JEL: Q41, D24, D22, O14

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1 Introduction

High energy prices are often regarded as a barrier to industrial development. Upgrading capital vintages to take advantage of electric power and automation are key elements to improving performance in manufacturing industries. High energy, and in particular, high electricity prices can slow this process by reducing the incentives to switch production from more traditional manufacturing processes.[1] In developed countries, energy-intensive industries are often granted exemptions and subsidies for electricity costs to withstand international competition and avoid layoffs. At the same time, countries aim to improve their energy efficiency as part of their climate goals. At least for manufacturing, improving energy efficiency is one of the principal pillars to reduce the energy and carbon intensity of GDP. Low energy prices may in turn fail to provide sufficient incentives to improve energy efficiency.

A priori, electricity prices can have ambiguous effects on electricity productivity (output divided by electricity consumed). The more obvious channel is that higher prices improve electricity productivity by inducing substitution away from electricity and optimisation of production processes which improve electricity consumption per output. Lower prices, on the other hand, can also improve electricity productivity by incentivising upgrades of production processes to those that require more electricity but also increase output. The ratio between output and consumption can fall or rise when considering choices between different production techniques. While the pricing of electricity is important from an environmental and developmental perspective, we have little causal evidence on the net effect.

This paper examines the effect of electricity prices on electricity productivity. I use annual plant level panel data from Indian manufacturing from 1998 to 2013 which includes information on the quantity and the average price of electricity consumed. Addressing endogeneity concerns, I find that higher electricity prices *decrease* electricity productivity. While electricity consumption falls with higher prices, output decreases relatively more. This implies that lower electricity prices can not only increase output, but also *improve* energy efficiency. Policy makers often navigate trade-offs between developmental and environmental goals when it comes to energy prices. These results suggest that lowering electricity prices does not necessarily decrease energy efficiency. To my knowledge, these are the first causal estimates to show this for an entire manufacturing sector in a developing country.

I emphasise that this result is likely to be especially relevant in contexts of industrial development and where industrial electricity prices are comparatively high, which is both the

[1] Ryan (2018) provides evidence from a field experiment in Gujarat (India) on the complementarity of electricity and modern capital and skilled labour. Abeberese (2017) provides evidence on changes in production due to electricity prices in India.

case for India.[2] I find that the effect was stronger during high price periods. Furthermore, I show that this effect is unique to electricity: the effect of coal prices on coal productivity are the opposite – higher coal prices increase coal productivity and have no significant effect on different measures of firm performance.[3] Depending on the fuel mix of electricity generation, these results suggests that taxing dirtier fuels yields better economic and environmental outcomes than taxing electricity, most likely due to the special role of electricity in modern production. This finding is particularly relevant for climate policy in developing countries. Relatively lower industrial electricity prices than coal prices could deliver both, substitution from fossil fuels to electricity, and despite increasing electricity use, improving electricity productivity and output.

I begin the analysis by documenting that energy productivity in Indian manufacturing has been fairly flat since the 60s but increased sharply from around 2000. Electricity productivity increased from 2000 to 2013 by around 35%. Simultaneously, real average industrial electricity prices fell by around 45%, a robust finding across various data sources from plant level data to price indices and manually collected tariffs. Indian industries are characterised by significant cross-sectional dispersion of both electricity productivity and electricity prices across plants, even within states within industries. With the decrease in electricity prices, there has been a convergence of electricity prices across plants. The concurrent fall in prices and secular increase in efficiency provides motivating evidence for a careful econometric analysis.

Plant level electricity prices are subject to endogeneity concerns in a regression of electricity productivity on prices. For example, most Indian states have increasing block tariffs for industry such that plants with higher consumption pay higher prices, or plants may negotiate discounts or enjoy favourable relationships with state electricity providers, which could be correlated with their economic position. I use two different instruments to address these endogeneity concerns, based on the institutional context of Indian electricity pricing. The first is based on the electricity price paid by other plants in the same state but in a different industry. I kernel weight them by the distance to the other plants in terms of the electricity quantity purchased. The second is a Bartik (1991) shift-share instrument similar to the instrument constructed in Abeberese (2017). The shares are the state level shares of coal power plants in the total installed generation capacity fixed at a pre-sample period. These shares are interacted with a representative coal price that is set by coal companies for power utilities and shifts generation costs.

[2] Compared to average industrial electricity prices in G7 countries, India's prices have been around 80% higher in 1998. They only dropped below the G7 average after 2004 and were around half the G7 prices in 2013 (but still above US prices). In PPP terms, India's industrial electricity prices have been more than double the G7 average throughout (see Figure 20 and Table 10).

[3] The instruments used for coal prices are different to those used for electricity prices.

The bias in the OLS estimates is sizeable. While the OLS based elasticity of electricity productivity with respect to electricity prices is 0.37, the elasticities are -0.24 and -0.78 for the two IVs, all statistically significant. This positive bias could, for example, arise from less efficient plants receiving more favourable tariffs or exemptions, perhaps through corruption. It is worth noting that from a back of the envelope calculation, the size of the causal estimates from the micro data can explain the entire secular increase in *aggregate* electricity productivity remarkably well. I provide a range of robustness checks and an analysis of heterogeneous effects by industry.

To shed more light on mechanisms, I examine further plant decisions and outcomes. The effect of prices on output outweighs the effect on electricity consumption. Since total variable costs decrease, the results suggest that plants scale down with higher electricity prices. I present evidence that higher electricity prices significantly decrease profits, plant productivity (TFP), investment, employment, machine to labour ratios and markups. This is consistent with a setting where electricity prices influence production and investment decision beyond electricity consumption. Lower prices can incentivise firms to invest in modern electricity intensive machinery, processes and products. These, in turn, improve productivity, output and performance.

While there are clear positive effects of the decrease in electricity prices on firm performance and electricity productivity, there may have also been effects on consumers. The decrease in markups suggest that there is imperfect pass-through of electricity costs to consumers. I estimate the incidence of electricity prices as share of consumer surplus in total surplus. The degree to which consumers and producers share the surplus is determined by how well producers can substitute to electricity, by their market power and demand elasticities, and how marginal costs are passed-through to prices. Ganapati et al. (2016) show how incidence can be expressed as a function of these parameters in a generalised oligopoly. I exploit the detailed information on output quantities and prices in the data to estimate the pass-through elasticities by industry, using the above instruments for marginal costs, and combine these with my estimates of plant level market power and demand elasticities to recover pass-through rates and incidence shares at the plant level. On average, two thirds of the incidence of lower electricity prices fell on consumers. The pricing of electricity for industry is therefore not only highly relevant for firms, but has substantial welfare implications for consumers.

There are a number of related papers. The closest paper is perhaps Abeberese (2017). She studies the effect of electricity prices on firms switching industries within narrow industries in India, using a similar shift-share instrument. Her analysis covers nine years beginning in 2000. She finds that higher electricity prices make firms switch to less electricity-intensive industries, which is consistent with the story of this paper. She also finds negative effects on output, TFP, and the machine-labour ratio. The last section of this paper can confirm these latter findings using new data over 16 years, with three times the observations and two different instruments. Similarly, Elliott et al. (2019) find that higher electricity prices induce firms to switch to less energy-intensive products in China as well.

In the literature on energy prices and industrial energy efficiency, Davis et al. (2008) is one of the first studies to use micro data on prices and electricity productivity on a national scale. They find that the correlation of electricity productivity and electricity prices in US manufacturing industries is generally positive. An IV based on fuel shares in state power generation turns the elasticities for a small number of industries negative. Nevertheless, in contrast to India, this suggests that in a developed country like the US, the effects of higher electricity prices are dominated by the first channel through cost minimisation and substitution, rather than the second channel through TFP, investment and size reduction. This is not to say that the second channel is absent. Deschenes (2011) estimates a -0.12 elasticity of employment to electricity prices using state-industry level data in the US.[4] Aldy and Pizer (2015) find a negative impact of energy prices on output using a long industry level panel in the US. Linn (2008) also finds a positive elasticity of electricity productivity to energy prices in the US (0.22).[5] Popp (2002) also uses US state level prices for a bundle of energy to show a positive effect of energy prices on innovation. However, these elasticities are with respect to an index of all energy sources, not just electricity, and rely on state level prices. State level prices ignore the substantial heterogeneity in electricity prices across plants that Davis et al. (2013) report. Kahn and Mansur (2013) show that energy-intensive industries in the US tend to cluster in low electricity price counties. Bundling energy prices mix the (potentially opposite) effects of electricity and coal prices. The Porter and Van der Linde (1995) hypothesis, which postulates firm benefits from environmental regulation, may apply to fossil fuels, but not necessarily to electricity.

In the developing context, Fisher-Vanden et al. (2004) report a positive elasticity of electricity productivity to electricity prices (0.23) for a subsample of Chinese firms in 1997-1999. This is, however, based on OLS regressions and in line with my OLS estimates.[6] Rentschler and Kornejew (2017) examine Indonesian small and micro firms in 2013. They find that firm level electricity prices reduce profitability, but increase (total) energy efficiency,

[4]In France, Marin and Vona (2017) find an employment elasticity with respect to electricity price of -0.26 and an electricity consumption elasticity of -0.6. See Cox et al. (2014) for broadly comparable elasticities for Germany. Marin and Vona (2017) also find a negative -0.11 TFP elasticity.

[5]His findings suggest that entrants' energy efficiency respond more to energy prices than that of incumbents. See also Pizer et al. (2002) who study technology adoption, energy prices and aggregate energy efficiency.

[6]See also their later paper (Fisher-Vanden et al., 2016). Using aggregate data, Hang and Tu (2007) find a negative elasticity of electricity productivity to electricity prices in China after 1995.

based on OLS estimates. For India, Golder (2011) found that foreign firms have a higher energy productivity in 2008, and Sadath and Acharya (2015) report a negative elasticity of investment to energy prices. In the literature on decomposition analysis of energy efficiency, Mukherjee (2010, 2012) finds that energy productivity varies across Indian states, and that firms are not at their efficiency frontier. Ghani et al. (2014) report an increase in electricity productivity in the 2000s which was mainly through improvements in existing state-industry clusters.[7]

This paper is also related to the literature studying the firm level relationships between environmental and economic performance. In the developed country context, environmental policies such as the European Emission Trading scheme or carbon taxes are often found to improve environmental performance with little to no impact on economic performance (Martin et al., 2014, 2015; Dechezleprêtre and Sato, 2017).[8] This is not at odds with my findings. Carbon pricing increases fossil fuels prices more than electricity prices and I find a null effect of coal prices on productivity. As in Acemoglu et al. (2012), it is the relative price between clean and dirty energy that matters. The role of electricity is special, because it is a complementary input to modern machinery and production processes (Ryan, 2018). Reducing relative electricity prices can incentivise to improve production techniques and products, especially in the case of developing countries with already high electricity prices, as in India.

The paper also contributes to the literature on energy cost pass-through and incidence. The recent theoretical literature emphasises the importance of imperfect competition in accounting for incidence (Weyl and Fabinger, 2013). De Loecker et al. (2016) estimate imperfect marginal cost pass-through from input tariff reductions in large companies in India. I estimate marginal cost pass-through allowing for imperfect competition and input substitution following Ganapati et al. (2016). They study five specific products in US manufacturing and show that incidence on consumers is lower than under perfect competition models.[9] Miller et al. (2017) study pass-through and incidence in the US cement industry based on Weyl and Fabinger (2013). They estimate that pass-through of energy costs is above unity, and the share of incidence of carbon pricing for producers only 11%. I recover the distribution of pass-through rates where some plants and industries also fully pass on costs. A small literature focuses on energy and emission cost pass-through of utilities rather than firms (Fabra and Reguant, 2014; Hausman,

[7]For other decomposition studies of energy productivity, see e.g. Cornillie and Fankhauser (2004) for Eastern Europe and Liu and Ang (2007) for a review article on decompositions into within-energy productivity and product mix.

[8]The European Emission Trading scheme might have even spurred innovation (Calel and Dechezlepretre, 2016).

[9]In my analysis the incidence on consumers is also around 50% lower compared to an alternative perfect competition assumption.

2018).

While this paper focuses on the effects of electricity prices, a related literature focuses on the *reliability* of electricity and its implications. This is important in a developing country context where shortages are frequent. Allcott 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.[10] Due to the institutional context in India, shortages are not related to electricity prices, and I show that they are not significantly correlated. Nevertheless, I provide robustness analyses for my estimates controlling for power shortages.

The findings in this paper have important policy conclusions. While it is more obvious that low electricity prices can spur industrial development, it is rather novel evidence that low electricity prices can also *improve* energy efficiency (i.e. electricity productivity). In this context of industrial development and high electricity prices, and in contrast to taxing fossil fuels for industry, there appears to be little trade-off in electricity pricing between economic and electricity efficiency goals. Lower prices, however, still increase the quantity of electricity used. The size of the associated negative environmental externalities depends on the source of energy in generation, but taxing fossil fuels instead of taxing electricity use in industry is likely to have net economic and environmental benefits. I contribute to the literature by exploiting a large nationally representative panel of plants with plant level information on electricity quantity and expenditure. I develop an instrument for causal interpretations that is not reliant on additional information and can thus be readily calculated in similar contexts for other studies.

The rest of the paper sets the stage with a brief analysis of the Indian electricity market in Section 2. While the Indian electricity sector is interesting in its own right, the insights provide context for the identification strategy. I describe the data used in Section 2.2 and present aggregate trends and the dispersion of electricity productivity and prices in Section 2.3. Section 3 develops the empirical strategy. Section 4 discusses the results, potential mechanisms and incidence before I offer a brief conclusion in Section 5.

2 India's electricity sector and descriptive statistics

2.1 India's electricity sector

I briefly discuss the issues that are relevant for identification, interpretation or robustness checks. These include ownership, type of electricity generation, effects of deregulation, level

[10] See also Alam (2013) for evidence on India using satellite data, and Reinikka and Svensson (2002) and Foster and Steinbuks (2009) using data of African countries. Ryan (2017) simulates the impact of transmission capacity improvements on the Indian electricity wholesale market.

of electricity prices and cross-subsidisation, tariff setting, coal prices for utilities, and outages and self-generation.

India's electricity generation is dominated by state and central governments. In 1998, government owned 65% and 30% of installed capacity respectively, with the remaining 5% owned privately (Ministry of Power, 1998*a*; Planning Commission, 2001). The Electricity Act of 2003 aimed to open this heavily regulated sector to more competition.[11] This led to more privately owned power plants entering the electricity generation sector. By 2013, the share of privately owned capacity rose to 31%, cutting mostly into the share of state-owned capacity (40%), while the centrally owned share remained at 29% (Planning Commission, 2014). In February 2019, the share of the private sector (46%) was almost equal to the share of the combined government owned capacity (Central Electricity Authority, 2019). From 1998 to 2013, total installed capacity rose by 143%.

Most of India's electricity is generated from thermal plants (74% in 1998, 68% in 2013), with the remainder produced by hydro (25% in 1998, 18% in 2013) and renewables (1% in 1998, 12% in 2013) (Ministry of Power, 1998*a*; Planning Commission, 2014). Of the thermal generation, the lion's share falls on coal-based generation (around 85% throughout). The share of thermal generation in a state is mainly determined by the presence of coalfields, as coal accounts for up to two-thirds of production costs in these plants (IEA, 2015; Abeberese, 2017). I collect geo-referenced data on Indian coalfields and power plants by installed capacity, ownership and year of commission.[12] Figure 6 in Appendix A shows maps visualising the capacity increase and the clustering of coal-fired plants close to 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.[13]

The opening up of the power market after the Electricity Act of 2003 appears to have contributed to lower electricity prices. I examine the relationship between the median of the district level industrial electricity price and the share of installed coal fired capacity that is privately owned within a district. Table 8 in Appendix B shows that the share of privately owned plants is significantly negatively associated with median electricity prices – but only after 2003.[14] A one percentage point increase in the share of privately owned plants decreases

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

[12]See 2.2.2 for sources.

[13]This is from a regression of installed coal capacity on logged distance to the nearest coalfield, all at the district level in 2013. This is based on 594 Indian districts. The coefficient is -191.4 with a robust t-statistic of 3.8 and R^2 of 0.066.

[14]This holds conditional on district and year fixed effects, and conditional on district and region by year fixed effects. I also control for time-varying total district level installed capacity. As the last column shows, the share of private thermal capacity is also predicted by the distance to coalfields, which I will use to construct an instrument for robustness checks.

median electricity prices by 3%. I use the information on the distance to coalfields, the timing of the Electricity Act, and the share of privately owned plants for robustness checks in the empirical analysis below.

Industrial electricity prices are high in India, also due to heavy cross-subsidisation. Part of the reason why the share of privately owned plants may decrease industrial electricity prices is that they are not cross-subsidising as heavily between end-users as state and central governments.[15] Average electricity tariffs in 1998 were the equivalent of 15.7 US cents (2004 USD) for industrial users, but only 2.6 and 6.8 cents for agricultural and residential users respectively, despite cost of supply usually being lower for industry (Ministry of Power, 1998*b*).[16] While agricultural consumers made up 32% of electricity consumption in 1998, they only accounted for 3.6% of revenues from electricity sales (Planning Commission, 2002). The main reason for the heavy cross-subsidisation is political – farmers form important voting blocs that the governments try to cater to (Abeberese, 2017).

Despite efforts to reduce cross-subsidisation and depoliticize tariffs based on the Electricity Act (2003), industrial tariffs were still 7.6 US cents (2004 USD) compared to 2.2 cents for agricultural tariffs in 2013 (Ministry of Power, 2014*b*). Until 2004, India's industrial tariffs were higher than the average G7 tariff (Figure 20 and Table 10 in Appendix H) despite being a low-income country. In contrast, residential tariffs have been less than half of the G7 average.[17] While industrial tariffs have typically been above the average cost of supply, high subsidies are required for the agricultural sector. In part driven by the heavy cross-subsidisation, state electricity utilities have been loss-making almost across the board, recovering only between 73% and 89% of annual costs between 1998 and 2013 (Central Electricity Authority, 2008, 2009, 2011, 2013, 2015, 2018). The comparatively high industrial tariffs in India are important contextual information for the interpretation of the results of this paper.

Individual states can set tariffs and cross-subsidies for different end-users and locations within their jurisdiction.[18] Industrial tariffs mostly follow increasing block tariffs, as manually collected data from government reports shows.[19] The increase of tariffs in purchase quantity

[15] I am somewhat abstracting from generation, transmission and distribution, because utilities and generation are often integrated in India (Planning Commission, 2001; IEA, 2015).

[16] For the agricultural and residential tariffs, I calculated a simple average of state-wise average electricity tariffs, pooling consumption bands. The industrial tariffs are taken from the micro data and are comparable with reported simple averages. Values are deflated with the fuel and electricity deflator into base year 2004 and the 2004 exchange rate is applied.

[17] Based on the same data source, residential tariffs in G7 countries increased from 15.3 to 19.7 US cents (2004 USD).

[18] There is very limited regional trading of electricity. The networks across regions are in the process of getting better integrated (IEA, 2015).

[19] On average, a higher band (of five bands) is associated with a 2.5 percent increase in the tariff. This is from a regression of manually collected log deflated electricity tariffs at the state-year-band level on consumption bands, accounting for state-year fixed effects. Figure 17 in Appendix G shows the average tariffs

in India is in contrast to block tariffs that are typically decreasing for industry. In European countries, the tariff band for the largest consumers is on average less than half of the tariff band for the smallest consumers (Eurostat, 2016). In any case, increasing or decreasing block tariffs are one of the challenges to identify the effect of electricity prices on firm performance that I deal with below.

Electricity prices are to be adjusted in line with cost pressures according to the 2003 Electricity Act (see also Abeberese, 2017). Coal is the dominant cost factor in coal-based electricity production. In terms of coal production, the largest public company Coal India Limited acts almost as monopoly. It supplied 81% (in 1998) and 63% (in 2013) of total domestic and imported coal (Minsitry of Coal, 2006, 2015).[20] Other public companies (mainly Singareni Collieries Company Limited) accounted for around 10% while private companies accounted for only 5% throughout this period. The production, marketing and price setting of coal is effectively controlled by the government. The prices of coal for power utilities and industry differ and are set independently.[21] Coal price adjustments for power utilities are mainly due to changes in international coal prices and the cost of production (Minsitry of Coal, 2006, 2015; Abeberese, 2017). This, in turn, affects the costs of coal-fired power plants and electricity prices, and provides a rationale for a cost shifting instrument below.

Since 2010, the coal price also contains an additional tax of 50 ₹ /tonne (4% of the price) to incentivise cleaner and more energy efficient production and electricity generation. The Bureau of Energy Efficiency was created in 2002 under the Ministry of Power to coordinate policies aimed at energy efficiency. The main programmes are small credits for energy conservation, and subsidies for capital investment and energy audits (Bureau of Energy Efficiency, 2014). Ryan (2018) provides more details on these and internationally funded energy efficiency programmes in India.

Total generated electricity fell short of total required electricity by 4%-11% between 1998 and 2013 (Ministry of Power, 2018). Power shortages persist despite falling average plant load capacity factors from 79% in 2007 to 66% in 2013. In addition, India's electricity transmission losses are one of the highest in the world (IEA, 2015). Under peak times, the power shortages are higher by a few percentage points, partly driven by frequently occurring outages. Outages led to adoption of electricity generators by larger industrial plants. Importantly for the analysis below, the adoption of electricity generators is driven by smoothing over outages, not

across Indian states for industrial consumers of five different sizes in 2007, using data from one of the annual government reports (Central Electricity Authority, 2008).

[20] Coal imports grew from 5% to 23% during this period mainly eating into the market share of Coal India Limited. The share of imported coal specifically for electricity generation was even lower (Ministry of Power, 2014*a*).

[21] This is relevant for the exclusion restriction, which I will discuss further below. See also Figure 27 in Appendix J.

by electricity prices, since self-generation is typically more expensive than buying electricity.[22] Distribution companies are not allowed to adjust electricity pricing to clear markets as a response to shortages (Allcott et al., 2016). Therefore, the correlation between annual state level electricity shortages and electricity prices is insignificant and small (see Table 9 in Appendix C).[23] The main reason for shortages are problems with technical equipment or networks. Coal supply issues are only responsible for 0.2% to 3.3% of outages in thermal plants[24], and while coal supply affects electricity prices, it is thus unlikely to affect outages. These institutional features are important for the empirical analysis to identify the effect of electricity prices and not shortages. I control for shortages in robustness checks.

2.2 Data

2.2.1 Plant level data

The main data source is the Annual Survey of Industries (ASI), India's mandatory annual establishment level manufacturing survey since 1953. Its long history makes it a relatively reliable data source in the development country context. The survey divides plants into a census sector (all plants are sampled) and a sampling sector (20% within each state 4-digit-industry strata are sampled).[25] The formal firms in the ASI are representative of two-thirds of manufacturing output (Allcott et al., 2016). By combining the panel and the cross-sectional editions of the ASI, I retrieved panel identifiers as well as district codes, which are only available in the respective editions. I use an annual panel from 1998 to 2013 for the main analysis.[26]

I use the quantity and value of electricity purchased, electricity generated, and the quantity and value of coal purchased. By dividing electricity purchase value by quantity, I can calculate the average price paid for electricity at the plant level. I use further plant level data on output (sales), employees, wages, capital, investment in machineries, intermediate inputs, and other fuel expenditures (gas and oil). I construct total variable costs as the sum of wages, input costs and other expenses, and total revenues as the sum of sales and other receipts. The difference is total profits. For the analysis of cost pass-through and incidence, I exploit the

[22] Bhattacharya and Patel (2008) estimate self-generation to be around 25% more expensive than buying electricity.

[23] This is in line with Allcott et al. (2016) who provide further evidence and show that a rainfall based instrument for hydro generation is also not correlated with electricity prices in India.

[24] Calculated as share of total planned and unplanned outages, annually from 1998 to 2009 using data from Allcott et al. (2016).

[25] The cutoff for the census classifier is $\geq$ 100 employees (until 2004 $\geq$ 200). The sampling frame consists of all plants $\geq$ 10 employees with electricity and all plants with $\geq$ 20 employees without electricity.

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

information of output sales and output quantity at the plant-product level to construct a measure of output prices and quantity.[27]

I winsorize the lowest and highest percentile of each variable within each year to reduce the sensitivity to outliers.[28] All monetary values from all sources are deflated into a common base year 2004 throughout this paper.[29] I drop observations in non-manufacturing industries and those with a missing electricity price, electricity productivity or output. All regressions are weighted by the included sampling multiplier.

Table 1 shows that after the cleaning steps, there are 485948 plant year observations from 160955 plants. There is considerable self-generation as the average amount of electricity self-generated is a quarter of the amount of electricity bought. This is driven by the 35% of the plants that engage in self-generation, primarily to cope with outages as discussed in the previous section. Electricity productivity is based on electricity consumed which is the sum of self-generated and purchased electricity minus electricity sold. The average electricity productivity is lower when weighting by consumed electricity, which suggests that larger electricity consumers are less electricity productive.[30] On average, electricity has the largest share in fuel expenditure (0.63).[31] Electricity expenditure constitutes on average about 6% of total average costs. The average electricity price is around seven times higher than the coal price in kWh equivalent, as coal is a rawer form of energy. Machinery is the main type of capital and investment (as opposed to e.g. buildings). The average variable cost markup (total revenues divided by total variable costs) is 20%, slightly lower than the marginal cost markup of 30%. Marginal cost markups are calculated following De Loecker and Warzynski (2012). Plant total factor productivity (TFP) are similar for different methods, following Olley and Pakes (1996), Levinsohn and Petrin (2003) or Wooldridge (2009).[32]

For robustness checks and trends in aggregate statistics, I add the 1993 and 1996 cross sectional editions of ASI micro data. I also collected aggregate ASI data at the industry by

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

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

[29]I deflate outputs and inputs using 3-digit industry deflators, investment and installed capital and machinery using a machinery deflator, wages, total revenues, total costs and total profits using a state deflator, and fuels and manually collected tariffs and prices (electricity, coal, gas, oil) using a fuel and electricity deflator.

[30]Weighting by consumption maps plant level electricity productivity into aggregate electricity productivity, comparable with Figure 2.

[31]This is similar to the 60% that Marin and Vona (2017) report for France. Note that the share in raw energy is lower, because electricity prices are much higher per unit of energy than coal, gas or oil prices. As Figure 16 in Appendix F shows, the share of electricity in the energy mix in terms of energy units has been between 16 and 20% since 1998.

[32]See Singer (2018) for the details of an example of the TFP methodology and implementation of Wooldridge (2009) in the Indian context. Markups are calculated following De Loecker and Warzynski (2012) after estimating production functions following Wooldridge (2009).

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
Output (in mil. ₹)	119
Electricity share in total var cost	0.06
Electricity productivity (₹ per kWh)	449
Electricity productivity (₹ per ₹)	107
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	485948
Firms	160955
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.
Employees	72	485344
Total capital (in mil. ₹)	36	482756
Mach. capital (in mil. ₹)	21	474922
Capital investment (in mil. ₹)	8.1	483211
Mach. investment (in mil. ₹)	4.1	476043
Total revenue (in mil. ₹)	119	485867
Total variable costs (in mil. ₹)	101	485867
Total profit (in mil. ₹)	17	485867
AC-Markup (Price/AC)	1.2	485867
MC-Markup (Price/MC)	1.3	477712
TFP (Wooldridge)	7.3	477712
TFP (Levinsohn-Petrin)	9.8	477712
TFP (Olley-Pakes)	7	379040
Coal consumed (tonne)	383	485948
Coal price (₹ per tonne)	4153	49650
Coal price (₹ per kWh equivalent)	.64	49650
Coal productivity (₹ per th. tonne)	1076	49650
Coal productivity (₹ per ₹)	296	49650
Weighted by coal consumed:		
Coal productivity (₹ per th. tonne)	56	49650
Coal productivity (₹ per ₹)	23	49650

Notes: The table shows the sample means based on the pooled plant level data from 1998-2013. The means are calculated using the sampling multiplier as weights. Were indicated, the means are additionally weighted by the consumed electricity, fuel or coal to make the means more representative of aggregate productivities.

state by year level from 1967 to 1997 for long run trends.

2.2.2 Additional data

Coal prices for thermal power plants (as opposed to manufacturing plants) are from the Minsitry of Coal (2012, 2015). I use the published annual pit-head prices specifically for power utilities customers and inclusive of royalties and taxes, based on a representative Coal India Limited (CIL) mine and grade selected by the Minsitry of Coal (2012).[33] Shares of coal fired power plants in state installed capacity in 1998 are from the Ministry of Power (1998*a*, 2003).[34]

For the instrument for plant level coal prices (see Section 3.4), I use the pit-head prices specifically for industry with the appropriate coal grades (Minsitry of Coal, 2012, 2015). Geo-located data on Indian coalfields is from Trippi and Tewalt (2011) which I combine with geo-located data of the 541 districts to calculate distances.

State-level average tariffs by consumer type and size are collected from annual reports

[33] These are the ones of Eastern Coalfields Limited of Coal India Limited, Rajmahal field, Grade E. These are also in line with those used by Abeberese (2017). After 2011, India switched the coal grading from Useful Heat Value (UHV) to Gross Calorific Value (GCV). I used the prices of the new grades G9 based on the correspondence given in Minsitry of Coal (2013). Prices are deflated with the electricity and fuel deflator from Office of the Economic Adviser (2019). Figure 27 in Appendix J plots these prices in real terms.

[34] Thermal shares as on 31st of March 1998, one day before the beginning of the sample I use. Chhattisgarh, Jharkhand and Uttarakhand were created in 2000, and thermal shares correspond to 31st of Jan 2003, the first available data. I follow Abeberese (2017) using these shares.

of the Indian Central Electricity Authority (2008, 2009, 2010, 2011, 2012, 2013, 2015) and from Indiastat (2019) through Lok Sabha and Rajya Sabha questions. Data on international industrial energy prices comes from IEA (2018), and international GDP deflators, exchange rates and PPP conversion factors from World Bank (2017). Deflators for India (industry-wise, electricity and fuel, machinery) are from the Office of the Economic Adviser (2019) and the state-wise deflator is from the Reserve Bank of India (2019).

Data on state level power shortages comes from the Central Electricity Authority (2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014), and from Allcott et al. (2016) for before 2005.[35] Geo-located data on the location, capacity 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).

2.3 Trends in electricity productivity and prices

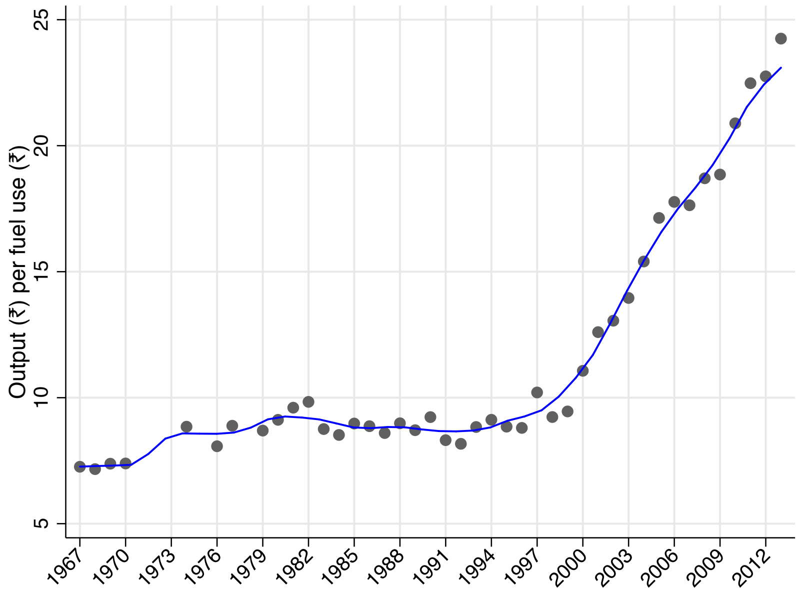
To motivate the empirical analysis, I next present relevant patterns and trends in the data.

2.3.1 Industrial energy efficiency from 1967-2013

Combining the plant level data with sector-state level data from 1967, Figure 1 plots the energy productivity in Indian manufacturing over 47 years. I calculate this ratio by dividing total deflated manufacturing output by total deflated fuel use (electricity, coal, oil, gas). Between 1967 and 1999, energy productivity was rather constant between 7 and 10 ₹ per ₹. From 2000, there was a remarkable increase in energy productivity, which more than doubled until 2013. This was not driven by a particular industry alone. Figure 10 in Appendix E shows that a similar trend appears from 2000 for different industry groups. Furthermore, Figure 7 in Appendix D shows that similar trends occurred across all states. This secular increase in India is entirely different than the evolution in OECD countries, as Figure 15 in Appendix F shows. The increase in energy productivity is consistent with the drop in emission intensity from 1990-2010 for a subsample of large firms reported in Barrows and Ollivier (2018). The fuel with the highest share in energy costs is electricity. I next examine electricity productivity.

[35] Data on the type of forced outages are also from Allcott et al. (2016).

Figure 1: Indian long run energy productivity in manufacturing



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

2.3.2 Industrial electricity productivity and prices 1993-2013

Figure 2 mirrors a similar trend in aggregated electricity productivity in output per kWh from 1993 using solely micro data. From 2000 electricity productivity increased by 35%.[36] This trend did not occur because of substitution away from electricity. The share of electricity in fuel expenditure was 65% in 2000 and 63% in 2013.[37] Interestingly, electricity prices fell from 1999/2000 during this secular increase in electricity productivity, and almost halved by 2013 (right panel of Figure 2). The purpose of this paper is to analyse whether there is a causal mechanism relating those two trends. In fact, the two figures of aggregate data visualise the causal results surprisingly well. A regression of the aggregate logged electricity productivity on aggregate logged electricity prices yields an elasticity of -0.4. This is the opposite sign of the OLS plant level estimate, but remarkably close to the IV estimates in the main analysis.

The increase in electricity productivity occurred in all sectors, except for perhaps metals and minerals (see Figure 11 in Appendix E), and in most states (see Figure 8 in Appendix D). Alternative data sources (IEA, 2016; UNIDO, 2016) match the pattern of electricity

[36] Also the "other" fuel productivity increased considerably since 2000, as Figure 14 in Appendix F shows.
[37] It was around 16 to 20% in energy unit terms, as Figure 16 in Appendix F shows.

productivity in Figure 15 in appendix F. The secular electricity price decline is similar within states (Figure 9) and within industries (Figure 12). Two alternative sources of electricity prices confirm the price trends. Figure 18 plots the electricity price index in real terms from the Office of the Economic Adviser (2019) (Appendix G), and Figure 19 plots the average of industrial electricity tariffs collected from the reports of the Central Electricity Authority. The price trend in the 2000s is in contrast to many other countries, where electricity prices rather increased. Figure 20 (Appendix H) plots industrial electricity prices for a range of OECD and non-OECD countries. While electricity prices in India almost halved during the sample period, prices in OECD countries grew by 40% (see Table 10).[38]

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

2.4 Heterogeneity in electricity productivity and prices

Is there much variation to explain across plants? The aggregate graphs in Figure 2 mask substantial heterogeneity, both in terms of productivity and prices. Figure 3 plots the histogram of electricity productivity and prices in 2003.[39] Even when partialling out state-industry (4-digit) effects, there remains substantial variation. The 90th to 10th percentile range drops from 3.5 to 2.7 for logged electricity productivity, and from 2.1 to 1.4 ₹ for electricity prices. The electricity productivity dispersion is even larger than the TFP dispersions found in the literature (Bartelsman and Doms, 2000; Syverson, 2004, 2011). Plants at the 90th percentile pay around 50% higher electricity prices than those at the 10th percentile.

I decompose the variance following Davis et al. (2013) (see Figure 4 for details). The state-industry effects can only account for around 60% of the cross-sectional variance in electricity prices, and 50% of electricity productivity (see Figure 23 in Appendix I).[40] For electricity productivity, there is more variation across industries, while for electricity prices there is more variation across states. This is intuitive, as production techniques tend to vary more across industries, while electricity price setting varies more by states as explained in Section 2.1. The main analysis accounts for industry by year by region fixed effects to account for differences in electricity productivity across industries. Importantly, we learn from these descriptives that there is enough interesting variation left after accounting for these fixed effects.

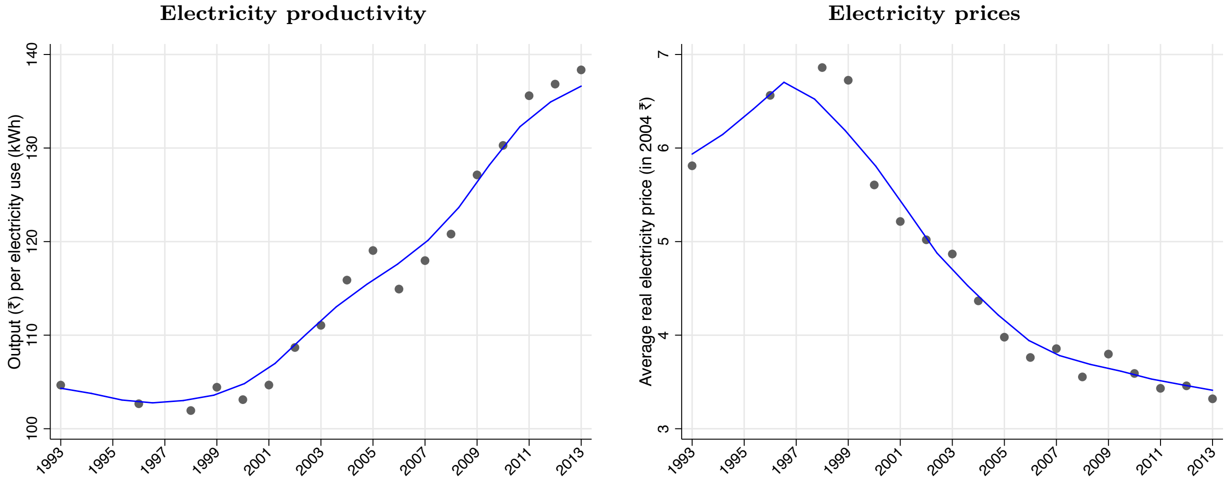
The deciles of electricity consumption in India cannot explain much of the variance. This

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

[39]Similar plots are shown in Figure 21 and Figure 22 in Appendix I for all years.

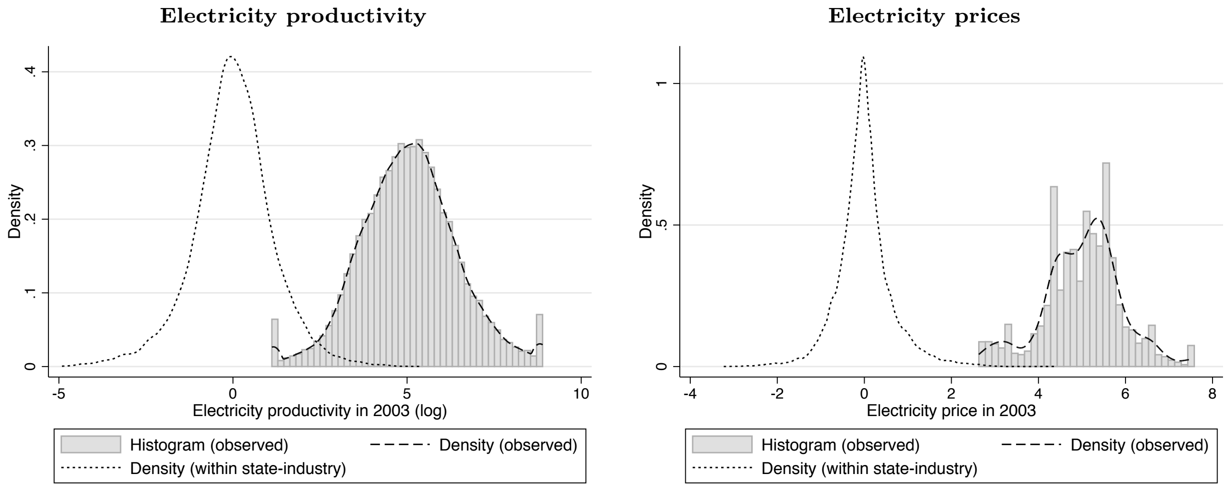
[40]Variation across districts (not plotted) can explain around 22% and 45% of electricity productivity and electricity prices respectively. Districts for the later years are not available for all observations.

Figure 2: Electricity productivity and electricity prices in manufacturing



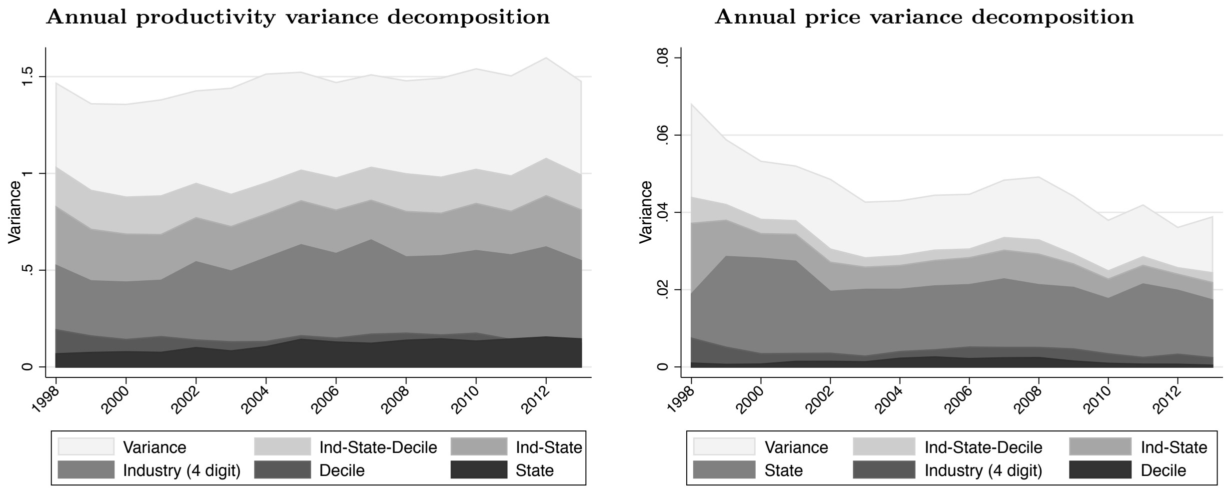
Notes: The left panel plots annual electricity productivity ratios (value of output divided by the quantity of electricity used in kWh). They are calculated by first aggregating the value of output and the quantity of electricity bought by plants, and then taking the ratio of the aggregates. The right panel plots real average electricity prices. They are calculated by first aggregating the value of electricity bought by plants and the quantity bought, and then taking the ratio of the aggregates. Plant output is deflated using 3-digit industry deflators before aggregating over industries. Electricity values are deflated using a general fuel and electricity wholesale price deflator. The base year for deflation is 2004 throughout this paper. Wholesale price deflators are from the Office of the Economic Adviser from the Government of India. All data points come from the raw plant level ASI data (from 711166 observations including years before 1998) and aggregated with sampling multipliers.

Figure 3: Heterogeneity in electricity productivity and in electricity prices



Notes: The left panel plots the histogram of plant level logged electricity productivity in 2003. Electricity productivity ratios are the value of output divided by the quantity of electricity used in kWh. The kernel density plot to the left shows the distribution of the residuals of logged electricity productivity after partialling out state by 4-digit industry by year fixed effects. The right panel plots the histogram of plant level electricity prices in 2003. The kernel density plot to the left shows the distribution of the residuals of electricity price after partialling out state by 4-digit industry by year fixed effects. Both panels are similar for all years as shown in Figure 21 and Figure 22 in Appendix I. Plant output is deflated using 3-digit industry deflators. Electricity prices are deflated using a general fuel and electricity wholesale price deflator. The base year for deflation is 2004 throughout this paper. Wholesale price deflators are from the Office of the Economic Adviser from the Government of India.

Figure 4: Electricity productivity and price variance decomposition

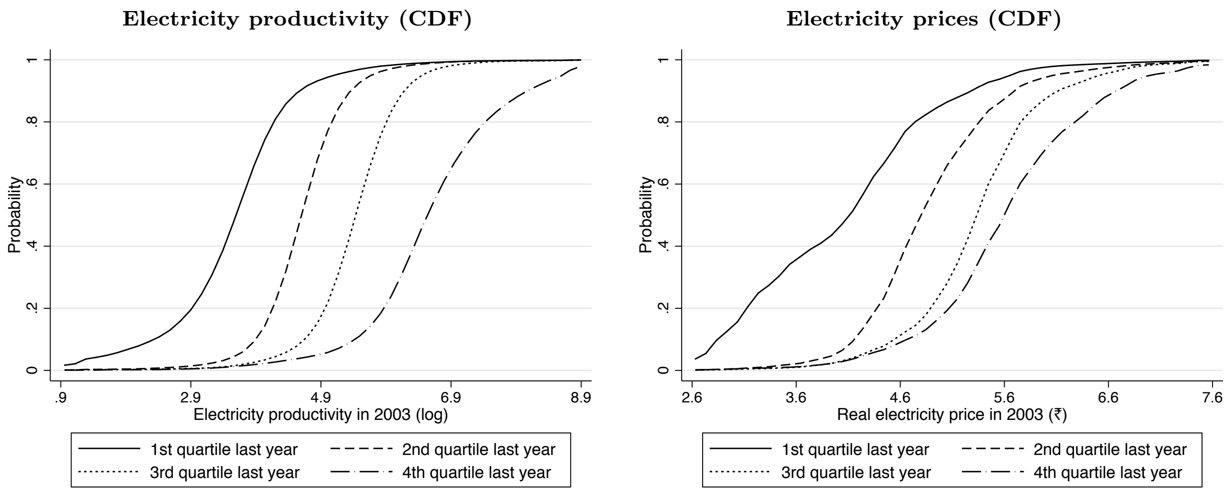


Notes: The left panel plots the annual total variance of logged electricity productivity and the variance explained by specified groups. The right panel plots the same for logged electricity prices. The annual variance is calculated as $V = \sum_e s_e \left(p_e - \overline{p}\right)^2$, where s_e are purchase weights multiplied by the sample multiplier, p_e are logged electricity productivity or prices, $\overline{p}$ the weighted average log productivity or price. I use the decomposition of Davis et al. (2013) to decompose total variance into a within "group" component V^W, and a component across "groups" V^G:

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

where $s_g = \sum_{e \in g} s_e$ and $\overline{p}_g$ the weighted average of log productivity or price within group g. I calculate the decomposition separately five times for the five groups shown in the graph. The regions plot V^G and correspond to the across-group variance in the total variance V, where higher shares explain more of the variation (see also Figure 23). Groups are deciles of electricity purchase quantity, 4-digit industries, states, and combinations. Plant output and electricity prices are deflated.

Figure 5: CDFs of plant electricity productivity and prices in 2003 conditional on 2002 quartiles



Notes: Plotted are the CDFs in 2003, separately for each quartile of the respective values in 2002. The left panel shows the distribution of the logged electricity productivity (i.e. the value of output divided by the electricity use in kWh). The right panel shows the distribution of the electricity price. The CDFs are empirical CDFs obtained through a Gaussian kernel smoother with bandwidth 0.1. The graphs show that each higher quartile first order stochastically dominates the lower quartiles. The conditional CDF of the plants that belong to the higher *previous* year quartile lies to the right of the CDF of the plants belonging to the lower *previous* year quartile. While individual plants move up and down the ranking of electricity productivity and energy prices from one year to the next, the probability of higher productivity and prices increases in last periods productivity and prices. The conditional CDFs for other years look similar, see Figure 25. Plant output and electricity prices are deflated.

is in contrast to the findings for the US (Davis et al., 2013) and France (Marin and Vona, 2017) and consistent with the observation in Section 2.1 that tariff schedules are increasing or decreasing in India. The variance in electricity prices has been decreasing from 1998 to 2013. Figure 24 in Appendix I plots quantiles of the distribution over time and shows a convergence in electricity prices that accompanied the secular decline. Interestingly, when we compare the decrease in the total variance of electricity prices in Figure 4 with the constant shares in Figure 23, we can conclude that the convergence has not been driven by reductions across industries or states alone, but by overall convergence.

Finally, I study the persistence of electricity productivity and prices within plants. Following Farinas and Ruano (2005), I plot the conditional (on previous period values) CDF of logged electricity productivity and electricity prices in Figure 5. I divide the sample into four quartiles based on previous period values and plot the four CDFs separately. As the CDF of the higher quartiles are to the right for every value, they first order stochastically dominate the distributions of plants ranked in lower previous period quartiles to the left. Plants from a higher previous quartile are more likely to belong to the higher quartile in the current period.[41] Both electricity productivity and electricity prices are persistent. The implication of this persistence for the analysis is that I use variation within *and* across plants, which I will discuss in the next section.

3 Empirical strategy

There are substantial endogeneity concerns when estimating the relationship between electricity productivity and electricity prices. The baseline specification is:

$$y_{jisrt} = \beta \log(P^E)_{jisrt} + \alpha_{irt} + \epsilon_{jisrt} \tag{1}$$

where y_{jisrt} is the logged outcome (electricity productivity as output divided by electricity consumed in kWh) for plant j in industry i in state s in region r in year t, and P^E is the electricity price. The analysis is conditional on 4-digit industry by region by year fixed effects α_{irt}. This accounts for aggregate technology and price trends that can differ by industry.[42] India is divided into six regions, and there is poor integration of electricity markets across regions (IEA, 2015; Ryan, 2017; Ministry of Power, 2018), and therefore α_{irt} allows for differential fixed effects across regions.

[41] See Figure 23 in Appendix I for the same conclusion for a different year.

[42] There are 133 4-digit industries in the final sample. There are six regions, 32 states and 541 districts in the final sample.

3.1 Endogeneity concerns

Within these clusters, there are still endogeneity concerns. The exogenous component of prices $\log(P^E)_{jisrt}$ are mostly at the state-year or district-year level as discussed in Section 2.1. These are price adjustment due to electricity generation cost pressures for example. However, $\log(P^E)_{jisrt}$ also contain endogenous variation. Suppose the endogenous elements contained in the price can be expressed as ξ_{jisrt} at the plant level and λ_{isrt} at the industry level within states. Both these elements are also contained in the composite error term $\epsilon_{jisrt} = \xi_{jisrt} + \lambda_{isrt} + \mu_{jisrt}$, where μ_{jisrt} is the true random component. Using plant fixed effects would not address any endogeneity that is time varying at the plant level. I return to additional problems associated with plant fixed effects in Section 3.6. Industry by state by year effects would eliminate most exogenous variation as well. My strategy is to rely on instruments which are not correlated with λ_{isrt} and ξ_{jisrt} and therefore isolate the exogenous price variation. Before explaining my identification strategy I describe the main endogeneity concerns.

First, shocks to output and electricity demand (in ξ_{jisrt}) also affect electricity prices due to different tariffs for different consumption bands (see e.g. Figure 17 in Appendix G). Second, plants or groups of firms within an industry may negotiate or exert pressure for lower electricity prices (in ξ_{jisrt} and λ_{isrt}). Their bargaining power in turn is likely related to their economic performance as well. This can lead to reverse causality problems at the plant level. Third, shocks to industries and regions may jointly affect economic performance, electricity productivity and electricity pricing (in λ_{isrt}). The third concern is at least partially taken care of by the industry by region by year effects. Prices may also be adjusted across the board as a response to changes in electricity productivity and electricity demand. I use lagged electricity prices to address reverse causality issues at the more aggregate level and find similar results. 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}). Sixth, average electricity prices at the plant level may suffer from measurement error (in ξ_{jisrt}). The two instruments discussed next aim to isolate the exogenous variation in prices from ξ_{jisrt} and λ_{isrt}.

3.2 An instrument based on other plants (IV^A)

The main idea of the first instrument is to extract the exogenous signal of the prices by relying on prices of other plants, which must also have been affected by exogenous electricity price changes. The exogenous part is mainly at the state-year level. Some weighted average of other plants could therefore extract the common exogenous signal. In order to avoid capturing the endogenous component λ_{isrt} in the instrument as well, I rely on information of plants in the same state, but in different industries. Specifically, I use prices of plants with similar purchase quantities in the same year, in the same state, but in different 2-digit industries i^{2d}. The underlying assumption is that the endogenous components λ_{isrt} are not correlated across 2-digit industries within a state. They are allowed to be correlated across 4-digit industries within 2-digit industries.[43] Recall that industry by region by year effects are taken out, so the element in λ_{isrt} common within regions are allowed to be correlated across 2-digit industries as well. The second assumption is that the (weighted) average of ξ_{jisrt} of plants in other industries is not correlated to the plant specific ξ_{jisrt}.

I use plants with similar purchase quantities to address the structure of tariffs which are based on purchase quantities. The instrument is a weighted average of prices of other plants, weighted by the distance in their purchase quantities, which smooths out individual shocks. I use a triangular kernel function to determine weights:

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

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

$$IV_{j^*isrt}^A = P_{jisrt}^E \frac{w_{q^*}(q_j)}{\sum_{q_j} w_{q^*}(q_j)} \tag{3}$$

This instrument alleviates the concerns laid out above. It takes care of bargaining power and price distortions through corruption of a particular plant, as well as groups of plants

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

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

within an industry, as only plants from all other 2-digit industries are considered. The kernel smooths over the discontinuities of different consumption and price bands. The instrument also takes care of plant location sorting within states and measurement error of prices at the plant level. What the instrument captures are price movements at the state level for similar consumption quantities, which are primarily driven by generation cost factors (see Section 2.1) after filtering out the endogenous components described above.

The instrument is similar to the Hausman instruments in demand estimation, which instrument 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). My (and the Hausman) instruments assume that there are no endogenous factors that are common across plants from *different* (2-digit) industries that affect their electricity productivity and the pricing of electricity simultaneously. In a robustness check, I also exclude plants from the instrument which are based in the same district (IV^C). This allows for endogenous components in prices that are spatially correlated within districts, and the results are quantitatively very similar.

The advantage of this instrument is that it can be readily calculated in other settings. This facilitates comparable analyses and further explorations of the relationship between electricity prices and electricity productivities in developing vs. developed, as well as in high price vs. low price, countries. Future work will follow up on this.

3.3 A shift-share instrument based on electricity generation (IV^B)

The main idea for the second instrument is to use a cost shifter for electricity generation directly, following Abeberese (2017).[45] Since coal is the largest cost factor in electricity generation (see Section 2.1), the price of coal shifts electricity generation costs, and therefore electricity prices. The instrument is based on a shift-share structure as in Bartik (1991). The shifters are nationally representative coal prices specifically for power utilities (see Section 2.2.2). It is weighted by the shares of thermal coal fired installed capacity in total installed capacity at the state level:

$$IV^B_{srt} = \log(P_t^{CoalPower}) \frac{\text{coal based installed capacity}_{sr_{1998}}}{\text{total installed capacity}_{sr_{1998}}} \tag{4}$$

I use the pre-sample shares of installed capacity in March 1998. I provide a map of the thermal shares in Figure 26 in Appendix J. As discussed in Section 2.2.2, the coal price for power

[45] A similar shift-share instrument for energy prices relying on thermal shares in generation has been used in Abeberese (2017), Ganapati et al. (2016) and Elliott et al. (2019). Linn (2008) and Marin and Vona (2017) use national energy prices directly interacted with fixed fuel shares at the plant level.

utilities is set independently to the coal price for industry, and is thus unlikely to directly affect manufacturing plants. Figure 27 in Appendix J plots both coal prices in real terms, and shows that often one decreases while the other increases at the same time.[46]

This isolates the exogenous movements in electricity prices, driven by cost pressures from coal prices. It addresses the endogeneity concerns raised in the beginning of the section, including common endogenous movements in electricity productivity and electricity prices at the state-year level, as the coal price used in the instrument does not vary across states. While the coal prices for power utilities and industries are set independently, I also exclude industries that use coal in the sectoral analysis and find similar results.

An advantage of instrument IV^B is that it might be less susceptible to the above described specific types of common shocks that threaten the validity of instrument IV^A, if they exist. The two disadvantages of IV^B are that it tends to be much weaker than IV^A and that it relies on external data.

3.4 Two similar instruments for coal prices (IV^E and IV^F)

In Section 4.4.4 I compare the effect of electricity prices to the effect of coal prices. This provides additional support for the hypothesis that electricity prices can have distinct effects. Specifically, I ask whether higher electricity prices have more adverse effects than higher coal prices. Coal prices suffer from a similar endogeneity concern as electricity prices. I construct two instruments that are similar to the ones above. The first instrument, IV^E is the analogue to IV^A, using coal prices of plants in the same state, but from different 2-digit industries, without the kernel weights. The second instrument, IV^F, is a shift-share instrument like IV^B. The shares are the logged distances of district centroids to the nearest coalfields. The distance increases sourcing costs. The shifter is the nationally representative coal price (at pit heads) for industry (as opposed to power utilities), taken from the Minsitry of Coal (2012, 2015). The location of coalfields is illustrated in Figure 6 in Appendix A.

3.5 Recovering pass-through rates and consumer incidence

While plants have to pay the electricity costs, the incidence of higher electricity prices may be shared between producers and consumers. The degree to which incidence falls on consumers depends on one hand on the degree to which electricity prices affect marginal costs ($\gamma \equiv dMC/dP^E$), which depends on the ability to substitute. On the other hand, it depends on the pass-through rate of marginal costs to output prices ($\rho_{MC} \equiv dP/dMC$), which depends on market structure and market power. I employ a partial equilibrium analysis

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

following Ganapati et al. (2016) that allows for factor substitution, incomplete pass-through and imperfect competition. As they show, under the assumption that average variable costs are equal to marginal costs ($AVC = MC$) incidence on consumers in a generalised oligopoly, where CS and PS are consumer and producer surplus, is:

$$I \equiv \frac{dCS/dP^E}{dPS/dP^E} = \frac{\rho_{MC}}{1 - (1 - L\epsilon_D)\,\rho_{MC}} \tag{5}$$

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

There is an established literature recovering markups μ from the production side from firm revenue and input data (Hall, 1988, 1990; Hall and Jones, 1999; De Loecker and Warzynski, 2012). The basic intuition is that if plants are cost minimising, we can use the first order condition of a variable input, which describes a relationship between markups, the output elasticity of that input, and the revenue share of that input. I follow this literature to estimate plant level markups (μ) and the plant level Lerner index L, using materials as variable input. I estimate the output elasticity along with TFP using Wooldridge (2009) building on Levinsohn and Petrin (2003).

It is well know that for standard oligopolistic environments, the first order conditions of firm profit maximisation imply a mapping between markups and demand elasticities. For the market level demand elasticities ϵ_D, I take the median of the plant level demand elasticities within a 4-digit industry by year by state cluster.[47] Market demand conditions are thus allowed to vary across industries, time and space. The alternative is to estimate demand functions as e.g. in Ganapati et al. (2016). The two approaches require different assumptions. Since we need to estimate markups and production functions in any case and assume oligopolistic competition and cost minimisation already, the additional profit maximisation assumption to recover demand elasticities appears innocuous. Independently of how demand elasticities are recovered, the main challenge is to get estimates for the pass-through.

Estimating the pass-through parameter ρ_{MC} requires data on revenues and output quantity. The most direct way is to regress prices on marginal cost. Revenues and quantities are separately reported for most plants in the data, which allows me to calculate average sales prices at the plant-product level. I calculate the plant level average price across products, weighted by the quantity of each product. From the estimated plant level price marginal cost

[47] Plant level markups (and demand elasticities) can diverge from the market demand elasticities due to distortions for example. Singer (2018) 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). The median is more robust to outliers.

markups μ, I can back out plant level marginal costs with these prices. I recover prices and marginal costs for 87% of the 485948 observations, covering 121 of the 133 4-digit industries. Since I also construct total variable cost, I can recover AVC by dividing total variable costs by quantity. This allows me to examine the validity of the underlying assumption ($AVC = MC$) for Equation (5). A regression of logged AVC on logged MC yields a coefficient of 0.98 and an R^2 of 0.95, which suggests that the assumption is not unreasonable.

The pass-through parameter ρ_{MC} is likely to differ by industry and firms, depending for example on the market structure, concentration or market power. I estimate a pass-through *elasticity* for each 4-digit industry separately, regressing prices ($\log(P)$) on marginal costs ($\log(MC)$). I instrument for the endogenous marginal costs using the two instruments for the electricity price IV^A and IV^B described above.[48] The pass-through elasticity is converted into the pass-through rate ρ_{MC} by multiplying it with the plant level markup μ. To summarise, the empirical components are:

$$\widehat{L}_{jisrt} = 1 - \frac{1}{\widehat{\mu_{jisrt}}} \tag{6}$$

$$\widehat{\epsilon}_{D,isrt} = \text{MEDIAN}_{isrt}\left(\frac{1}{1 - 1/\widehat{\mu_{jisrt}}}\right) \tag{7}$$

$$\widehat{\rho}_{MC,jisrt} = \widehat{\mu}_{jisrt}\frac{d\,\widehat{\log(P_{jisrt})}}{d\log(MC_{jisrt})} \tag{8}$$

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

$$I^{share} = I/(1 + I) \tag{9}$$

3.6 Specification choice and estimation

I conclude this section by making a few remarks about model specifications and estimation. First, I do not include state by year effects for the baseline specification. This is because IV^B only varies at the state by year level and most of the exogenous variation is also at the state by year level.

Second, I do not include plant fixed effects for the baseline specification. This is primarily because the IVs address time varying plant unobservables, while plant fixed effects cannot address those. On the contrary, plant fixed effects could introduce bias because of violations of the strict exogeneity assumption that comes with it. Past shocks to output and electricity

[48] Endogeneity concerns arise for example because marginal costs are estimated leading to measurement error. I use the instruments separately. For each industry, I take the weighted average of the two IV coefficients, where the weights are the t-statistics.

productivity are likely correlated with current electricity prices, as block tariffs increase or decrease with consumption, violating the strict exogeneity condition for fixed effects. Moreover, much of the interesting variation is between plants. I showed in Section 2.4 that electricity productivity and prices are persistent within plants. A regression of logged electricity productivity on plant fixed effects can explain 80% of the variation (R^2). Additionally, including plant fixed effects can be thought of as exploiting shorter-run variation, as in Ganapati et al. (2016) for example. The mechanisms in this paper, e.g. scaling and upgrading production processes, are likely to be more relevant in the medium to longer run. In robustness checks, I included state trends or plant fixed effects, which leaves us with broadly similar conclusions.

Third, I exploit the panel structure for calculation of standard errors in all specifications. I two-way cluster standard errors at the plant level, and at the state by year level, since one of the instruments varies at that level. I provide robustness checks clustering at the district, and the region by year level with similar results. Since I am running the same model with multiple outcomes, I apply the Holm (1979) Bonferroni correction for multiple hypothesis testing in Table 21 in Appendix M. Finally, I use the two instruments separately to enable comparisons, but provide an over-identified IV-regression with two instruments as robustness check.

4 Results

I first present the main results, along with robustness checks. Then I explore mechanisms and calculate incidence towards the end of this section.

4.1 Electricity prices and electricity productivity, use and output

4.1.1 First stages

The first stage coefficients, standard errors and Kleibergen Paap F-statistic are reported in each table for each regression separately. For the main specifications, Table 2 shows that both instruments are strong and shift the endogenous electricity price in the expected direction.

4.1.2 Lower electricity prices improve electricity productivity

The correlation between electricity prices and electricity productivity is positive. An OLS regression of logged electricity productivity on logged electricity prices suggests an elasticity of 0.37 (Column (1) in Table 2). The endogeneity bias in these estimates is large, however. The causal IV estimates in Column (2) and (3) are of opposite sign and statistically highly

Table 2: Electricity prices and electricity productivity

	Electricity productivity (log)		
	(1)	(2)	(3)
$\log(P^E)$	0.366***	-0.239***	-0.776***
	(0.044)	(0.070)	(0.105)
OLS/IV	OLS	IV^A	IV^B
Observations	485948	485948	485948
Ind-region-year FE	Yes	Yes	Yes
First stage coef.	-	0.97***	0.06***
First stage SE	-	0.005	0.003
F-stat (Kleib.-Paap)	-	43147.813	296.255
SE clustered by	Plant	Plant	Plant
No. of first clusters	160955	160955	160955
SE clustered by	State-year	State-year	State-year
No. of second clusters	501	501	501

Notes: The dependent variable is logged electricity productivity (value of output divided by the quantity of electricity used in kWh). Each column represents a separate regression at the plant level. The first column reports the results from an OLS regression on logged electricity prices. The second column uses the IV^A based on the electricity prices of similar plants. The third column uses the shift-share IV^B. The first stage statistics are reported. All regressions contain industry by year by region fixed effects. Regressions are weighted by the recorded sampling multiplier. Standard errors in parentheses are two-way clustered at the plant and the state by year level. Plant output is deflated using 3-digit industry deflators and electricity prices are deflated using a general fuel and electricity wholesale price deflator.

significant. A one percent increase in electricity prices is associated with a 0.24 or 0.78 percent decrease in electricity productivity for the IV^A based on other plants and the shift-share IV^B respectively. The positive bias in the OLS estimates suggests that less efficient plants also manage to obtain lower electricity prices through deliberate exemptions, negotiations, corruption or location choices, for example. The effect is more strongly negative for IV^B, which could be due to heterogeneous local average treatment effects, but it is reassuring that both instruments significantly correct the OLS bias in the same direction.

As documented in Section 2.3.2, there was a secular increase in aggregate electricity productivity (35%) with a concurrent reduction in electricity prices of 45% during the sample period . How well can the causal estimates from micro data explain this aggregate phenomenon? In a back of the envelope calculation taking the average of the IV^A and IV^B estimates as -0.51, the documented reduction of electricity prices predicts a $(1-0.45)^{-0.51} = 36\%$ increase in electricity productivity. Considering that the simple OLS correlation is of opposite sign, these estimates can explain the aggregate secular trends remarkably well.

4.1.3 Electricity prices affect electricity consumption and output

Why have lower electricity prices improved electricity productivity in India? Higher electricity prices still do reduce electricity consumption. Table 3a presents the regressions split up into the components of electricity productivity, with logged electricity consumption (in kWh) or logged output as dependent variables. In both the OLS and IV regressions, electricity prices reduce electricity consumption, with the causal effect being slightly larger. A one percent

Table 3: Electricity prices, output, electricity use, and lagged electricity prices

(a) Electricity prices, output and electricity use

	Output (log))			Electricity consumption (log)		
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(P^E)$	-0.0265	-0.743***	-1.597***	-0.385***	-0.479***	-0.797***
	(0.073)	(0.143)	(0.153)	(0.064)	(0.155)	(0.148)
OLS/IV	OLS	IV^A	IV^B	OLS	IV^A	IV^B
Observations	485948	485948	485948	485948	485948	485948
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)	-	43147.813	296.255	-	43147.813	296.255
Two-way cluster plant state-year	Yes	Yes	Yes	Yes	Yes	Yes

(b) Lagged electricity prices and electricity productivity

	Electricity productivity (log)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(P^E)$	0.296***	-0.272***	-0.735***			
	(0.049)	(0.062)	(0.087)			
Lagged $\log(P^E)$				0.0177	-0.274***	-0.727***
				(0.042)	(0.060)	(0.086)
OLS/IV	OLS	IV^A	IV^B	OLS	IV^A(lag)	IV^B(lag)
Observations	225833	225833	225833	225833	225833	225833
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes
First stage coef.	-	0.98***	0.06***	-	0.98***	0.07***
First stage SE	-	0.005	0.003	-	0.005	0.003
F-stat (Kleib.-Paap)	-	46140.249	421.264	-	39687.361	405.830
SE clustered by	Plant	Plant	Plant	Plant	Plant	Plant
No. of first clusters	67834	67834	67834	67834	67834	67834
SE clustered by	State-year	State-year	State-year	State-year	State-year	State-year
No. of second clusters	469	469	469	469	469	469

Notes: The dependent variable in panel (a) is logged output or logged electricity consumption (in kWh) as indicated. The dependent variable in panel (b) is logged electricity productivity (value of output divided by the quantity of electricity used in kWh). Each column represents a separate regression at the plant level. The first three columns in panel (b) restrict the sample to the same observations as in the last three columns, where lagged logged electricity prices (and lagged instruments) are used. Regressions are weighted by the recorded sampling multiplier. Standard errors in parentheses are two-way clustered at the plant and the state by year level. The rest of the table layout follows the same structure as the main Table 2.

increase in electricity prices reduces physical electricity consumption by 0.49 to 0.81 percent.

The OLS effect of electricity prices on output is close to zero. In contrast, the IV estimates of the output elasticity are large and negative (between -0.74 and -1.59). The endogeneity bias operates through both electricity consumption and output, but mainly through the latter. Tariff schedules that increases in size biases OLS output estimates upwards. The effects on electricity consumption and output are close to the ones in Abeberese (2017). While she does not examine electricity productivity at the plant level, she finds that firms with high electricity prices produce products that are typically less electricity intensive on average, suggesting product switching as a channel. I will explore further mechanisms in Section 4.4.

4.2 Stronger effect during high price periods

Next, I examine whether the effect was stronger for high price periods. It is likely that decreasing electricity prices have particularly strong effects on output when electricity prices are at high levels already. This particularly discourages plants from using electricity associated

Table 4: Electricity prices and electricity productivity in high price periods

	Electricity productivity (log)		
	(1)	(2)	(3)
$\log(P^E)$	0.471***	0.00847	-0.732***
	(0.061)	(0.094)	(0.168)
$\log(P^E) \cdot \mathbf{1}(year < 2006)$	-0.217**	-0.531***	-0.0926
	(0.084)	(0.128)	(0.193)
OLS/IV	OLS	IV^A	IV^B
Observations	485948	485948	485948
Ind by region by year FE	Yes	Yes	Yes
First stage coef. 1/1	-	0.96***	0.06***
First stage SE 1/1	-	0.006	0.005
First stage coef. 1/2	-	0.03***	0.01
First stage SE 1/2	-	0.009	0.007
First stage coef. 2/1	-	-0.00***	-0.00***
First stage SE 2/1	-	0.000	0.000
First stage coef. 2/2	-	0.99***	0.06***
First stage SE 2/2	-	0.007	0.005
F-stat (Kleibergen-Paap)	-	11055.255	68.011
Two-way cluster plant state-year	Yes	Yes	Yes

Notes: The dependent variable is logged electricity productivity (value of output divided by the quantity of electricity used in kWh). Each column represents a separate regression at the plant level. The independent variables are the logged electricity price, and an interaction with a dummy that is one for all years before 2006. Instruments are interacted in the same way. The first stage statistics refer to variable 1 and corresponding instrument 1 etc. Note that mainly the corresponding instruments shift the variables (i.e. 1/1 and 2/2). Regressions are weighted by the recorded sampling multiplier. Standard errors in parentheses are two-way clustered at the plant and the state by year level. The rest of the table layout follows the same structure as the main Table 2.

with modern productive production processes. The nature of the comparatively high Indian electricity prices (see Section 2.1 and Appendix H) and the subsequent halving of prices during the sample period (Figure 2) lend itself to test this hypothesis. I interact the electricity price with an indicator for the first eight years of the sample periods in Table 4. The average real price in the first eight years was 5.5 ₹ per kWh compared to 3.8 ₹ per kWh in the second eight years. The interaction term is negative for both IV and the OLS specifications. For the IV^A, the entire effect is driven by the period where electricity prices were high. For IV^B, the interaction effect is negative as well, but insignificant.[49] This suggests that the negative implications of high electricity prices on output and electricity productivity are particularly relevant in contexts with high electricity prices.

4.3 Robustness and further analysis

I conduct a range of robustness checks, with most of the results in Appendix K. First, I use lagged prices and lagged instruments to allow for some time to adjust to prices. This also addresses potential remaining reverse causality concerns. Using lags cuts the sample in around a half as spells of firm observations are required. Table 3b first shows the contemporaneous effects for the smaller sample and then the lagged effects. The IV estimates reassuringly hardly change. The positive bias in the OLS estimates is substantially reduced when using lags.

[49] The conclusions are similar when looking at three periods as in Table 17 in Appendix K.

Second, I use two alternative instruments. The first, IV^C, is similar to IV^A except that I exclude plants in the same districts for the construction of the instrument. The second one, IV^D, is similar to IV^B and is also a shift-share instrument. The shift uses the timing of the 2003 Electricity Act and the shares are the calculated distance of district centroids to coalfields. The rationale for the second instruments builds on the finding in Section 2.1 and Table 8 in Appendix B that the share of private power capacity can explain lower electricity prices, but only after 2003. Since local changes in private power share are likely to be endogenous, I use the distance to coalfields. Table 8 also shows that the distance of districts to coalfields predicts shares in the private power capacity. Therefore, I use the distance to coalfields interacted with the post 2003 dummy as an instrument, controlling for the distance to coalfields. Table 11 in Appendix K shows that the estimate using IV^C are very close to IV^A. The estimate for IV^D is -0.48, in magnitude similar to the other three instruments, but is insignificant, and also rather weak (F=7.2).

Third, I restrict the sample to electricity intensive sectors, loosely defined as the 2-digit sectors with an above average electricity intensity. The effects are marginally smaller as Table 12 in Appendix K shows. Fourth, I run the analysis by six broad industry groups in Table 16a and Table 16b. Only for metals and minerals, the estimates are non-negative, but insignificant, and there is still significant upward bias in the OLS estimates. The null effect for this sector might be explained with the basic metals industry predominately relying on coal across many production techniques, such that there is less scope to move to electricity based production. Figures 10 and 11 in Appendix E support this. While energy productivity rose in this sector, electricity productivity remained fairly stable.

Fifth, I run an over-identified model using both IV^A and IV^B simultaneously in Table 13. The effects are again similar, mainly driven by the stronger IV^A. The Sargan-Hansen J-test rejects that both instruments have the same effect. This is not too surprising given the difference in the estimates, which can, however, also be due to heterogeneous local average treatment effects.

Sixth, I control for the distance from districts to coalfields, for state-year level power shortages, and for both in Table 18. The estimates remain negative and are similar in magnitude. I already showed in Table 9 in Appendix C that shortages can not explain electricity prices. Both, the distance to coalfields and shortages are significant when explaining electricity productivity, however. Seventh, I control for state fixed effects, state trends, and then for plant fixed effects in Table 14. One of the estimates turns insignificant, but as discussed in Section 3.6, plant fixed effects can introduce bias. Eighth, I two-way cluster at the district and the region year level, allowing more generously for arbitrary correlation in errors, with slightly larger standard errors but still significant results (Table 15). Finally, I adjust all p-values upwards to account for multiple hypothesis testing in Table 21 in Appendix M. Almost all estimates remain statistically significant at conventional levels.

Overall, these checks reinforce the conclusion that the OLS estimates are significantly upward biased and higher electricity prices reduce electricity productivity.

4.4 Mechanisms and incidence

How do high electricity prices affect plants? In this section I explore the impacts of electricity prices on a range of outcomes to shed more light on mechanisms, as well as calculate incidence and contrast the effects with the impact of coal prices.

4.4.1 Plants scale up with lower electricity prices and substitute from coal

We have seen that higher electricity prices reduce output. Table 5a shows the effect on total revenues, total variable costs and profits (in levels).[50] Electricity prices reduce total revenues, but they also reduce total variable costs. A one percent increase in electricity prices reduces revenues by 1.3-1.4 million ₹, but also reduce total costs by 1.1 million ₹, and profits go down by 0.2 million ₹. This strongly suggest that plants scale down with rising electricity prices. It is difficult to think of an alternative mechanism that brings total costs down when electricity prices rise. Substitution to other fuels should generally increase costs. Table 5c shows that there is some substitution. The IV estimate of the effect of prices on the share of electricity expenditure in total fuel expenditure is near zero and insignificant. With these constant shares, electricity consumed must decrease with increasing prices (as shown in Table 3a). Using plants that report physical electricity and coal units, the ratio between electricity to coal energy inputs decreases with rising electricity prices in Columns (8-9), as plants substitute to coal. Finally, employment also decreases with higher electricity prices as Table 19 in Appendix K shows. These results are consistent with plant size increasing with lower electricity prices.

4.4.2 Electricity prices affect investment, productivity and markups

If electricity is complementary to modern production techniques, then lower electricity prices (compared to other fuels) can incentivise switching to these production techniques and scaling up. Table 5c reports the impact of higher electricity prices on investment in machinery and plant total factor productivity (TFP). Both investment and TFP decline. The effects on

[50]See Section 2.2.1 for their description.

Table 5: Electricity prices and firm performance: scale, substitution, productivity and markups

(a) Electricity prices, profits, revenues and costs (levels)

	Profits (mil. ₹)			Total revenues (mil. ₹)			Avg. variable costs (AVC) (mil. ₹)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(P^E)$	-4.952***	-20.63***	-22.43***	-30.18***	-132.6***	-139.9***	-24.12***	-109.1***	-114.3***
	(1.518)	(3.258)	(4.043)	(8.858)	(19.749)	(21.231)	(7.398)	(16.539)	(17.469)
OLS/IV	OLS	IV^A	IV^B	OLS	IV^A	IV^B	OLS	IV^A	IV^B
Observations	485867	485867	485867	485867	485867	485867	485867	485867	485867
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First stage coef.	-	0.97***	0.06***	-	0.97***	0.06***	-	0.97***	0.06***
First stage SE	-	0.005	0.003	-	0.005	0.003	-	0.005	0.003
F-stat (Kleib.-Paap)	-	43124.701	296.290	-	43124.701	296.290	-	43124.701	296.290
Two-way cluster plant state-year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

(b) Electricity prices and substitution: shares in fuel expenditure and ratio of electricity to coal consumption

	Electricity share in fuel expenditure			Other fuels' share in output			Ratio electricity to coal quantity		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(P^E)$	0.0251***	0.0144	-0.0233	0.00442***	0.0135***	0.0234***	-10.20***	-17.54***	-21.84*
	(0.006)	(0.013)	(0.020)	(0.001)	(0.002)	(0.003)	(3.099)	(5.790)	(12.354)
OLS/IV	OLS	IV^A	IV^B	OLS	IV^A	IV^B	OLS	IV^A	IV^B
Observations	485948	485948	485948	485948	485948	485948	48015	48015	48015
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First stage coef.	-	0.97***	0.06***	-	0.97***	0.06***	-	0.96***	0.05***
First stage SE	-	0.005	0.003	-	0.005	0.003	-	0.016	0.004
F-stat (Kleib.-Paap)	-	43147.813	296.255	-	43147.813	296.255	-	3705.137	157.253
Two-way cluster plant state-year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

(c) Electricity prices, TFP, investment and markups

	TFP (log) (Wooldridge, 2009)			Investment in machinery (IHS)			Price marginal cost markups $\log(\mu)$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(P^E)$	-0.00699***	-0.0156***	-0.0330***	0.162	-0.846**	-2.877***	-0.0184***	-0.0404***	-0.106***
	(0.002)	(0.003)	(0.006)	(0.204)	(0.390)	(0.442)	(0.006)	(0.011)	(0.019)
OLS/IV	OLS	IV^A	IV^B	OLS	IV^A	IV^B	OLS	IV^A	IV^B
Observations	477697	477697	477697	476042	476042	476042	485548	485548	485548
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First stage coef.	-	0.97***	0.06***	-	0.97***	0.06***	-	0.97***	0.06***
First stage SE	-	0.005	0.003	-	0.004	0.003	-	0.005	0.003
F-stat (Kleib.-Paap)	-	44391.045	297.573	-	46975.370	309.613	-	43180.457	296.198
Two-way cluster plant state-year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each column represents a separate regression at the plant level. The dependent variables are indicated and described in Section 2.2.1. In panel (a), the regressions are reported in levels because profits can be negative. In panel (b), other fuels refer to gas, coal and oil. The ratio of electricity to coal is in quantity terms in MWh per tonne. In panel (c), the inverse hyperbolic sine (IHS) of investment is taken to deal with zeros in investment. Regressions are weighted by the recorded sampling multiplier. Standard errors in parentheses are two-way clustered at the plant and the state by year level. The rest of the table layout follows the same structure as the main Table 2.

investment are sizeable.[51] The effects on TFP are small, but highly significant and robust to different methodologies to estimate TFP.[52] This is in line with Abeberese (2017), who found reductions in employment, investment and TFP to support her main analysis of product switching. My results are consistent with the finding of firms switching to products that require less electricity but also reduce performance. Vice versa, lower electricity prices incentivise to a switch to production techniques that rely on electricity, but improve performance. Ryan (2018) uses experimental variation through consulting services to show a positive effect of higher electricity productivity on the modernisation of plants' input mix in India.[53] Since higher efficiency reduces the de-facto price of electricity per unit produced, these results are both consistent with the effects of lower electricity prices on production technique. Table 19 in Appendix K provides support for this and shows that the machine to labour ratio falls with higher electricity prices, even though employment falls. The effect is large with an elasticity between -0.6 and -1.5.[54] There is also some evidence that lower electricity prices increase product scope measured as the number of products (Table 19).

There is no prior evidence on how electricity prices affect price over marginal cost markups $\mu \equiv P/MC$ in the Indian context. Table 5c shows that markups decrease 0.04 percent with a one percent increase in electricity prices. The reduction in profitability comes with a loss in market power. The adjustment of markups also suggests that there is imperfect pass-through of costs to consumers. This raises the important question of the incidence of electricity price changes which I examine next.

4.4.3 The incidence of electricity price changes

The degree to which firms can pass on increases or reductions in electricity prices to consumers determines the incidence of the electricity price changes. As described in Section 3.5 I estimate pass-through elasticities by industry. The cumulative distribution function of these pass-through elasticities, as well as two example regressions are presented in Figure 28 in Appendix L. The vast majority of pass-through elasticities is between 0.8 and 1.1. A pass-through elasticity of greater than one means that costs are disproportionately passed through to

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

[52] The baseline effects are on TFP measured via Wooldridge (2009) using deflated revenue data, so should be interpreted as revenue TFP. Since markups shrink, we would expect the impact on physical TFP to be larger. Table 20 in Appendix K provide the effects on TFP measured via Olley and Pakes (1996), Levinsohn and Petrin (2003) or Ackerberg et al. (2015).

[53] He runs a field experiment of energy audits in the state of Gujarat. He also finds that plants use more energy as a response to energy efficiency improvements, due to a rebound effect, consistent with a de-facto reduction in prices.

[54] The machine intensity of output also falls.

consumers.[55] This can be the case if producers fail to collude in an oligopoly. An increase in costs can help to solve the coordination problem of raising prices, which can explain pass-through rates greater than one.

The pass-through elasticities are combined with the plant level markups ($\widehat{\mu}$) into the pass-through rates $\widehat{\rho}_{MC}$. The three components to calculate incidence I^{share}, the Lerner index $\widehat{L}$, the market demand elasticity $\widehat{\eta}_D$ and the marginal cost to price pass-through rate $\widehat{\rho}_{MC}$ are reported in Table 6. The estimates shown are the median, the 25th and 75th percentile of the distribution across plants, sectors and years.[56] The estimates for the Lerner index are in line with the descriptive statistics of markups reported in the beginning.

Table 6 reports the median of I^{share} over all sectors and the whole sample period. The incidence on consumer surplus is 63%. The decline of electricity prices not only improved profits and electricity productivity, but also disproportionately affected consumer surplus. This implies that electricity pricing for industry is important for industrial development and consumer welfare alike. The reduction in the severe cross-subsidisation from industry to agriculture (see Section 2.1) may thus have also benefited non-industrial consumers.

There is some heterogeneity across industries and years. The 25th and 75th percentile in Table 6 are 53% and 79% respectively. Even at the 5th percentile, the share of consumer incidence was a quarter of the total. Figure 29 in Appendix L plots the incidence share over time for six aggregate industries. There has been a few percentage points decline of incidence over time. I also calculate the incidence under the extreme conduct assumptions of monopolies and perfect competition, where $L = 1/\epsilon_D$ and $L = 0$ respectively. As in Ganapati et al. (2016), the monopoly estimate is below the oligopolistic estimate, and the perfect competition higher than the oligopoly counterpart.[57]

How large was the gain in producer surplus (profits) and consumer surplus in terms of Rupees or USD? In a back of the envelope calculation, I start with the semi-elasticity of profits to electricity prices of -21.53. This is the average of the causal estimates (-20.63 and -22.43) in Table 5a. A 45% reduction of electricity prices over the sample period corresponds to an increase of $\log((1 - 0.45)^{-21.53}) = 12.87$ mil. ₹ for the average plant. In 1998, there were 113065 plants in the manufacturing sector sampling frame.[58] The gains in profits for the

[55]While the pass-through elasticity is smaller than one for the five industries studied in Ganapati et al. (2016), the pass-through *rate* ρ_{MC} is also greater than one for three of the five industries and in some of the studies cited therein.

[56]$\widehat{L}$ and $\widehat{\rho}_{MC}$ vary at the plant-year level, and $\widehat{\eta}_D$ varies at the industry-state-year level.

[57]For the perfect competition case, the incidence share is equivalent to the pass-through rate as $L = 0$ (see Equation (5)).

[58]Since not all plants are sampled every year, I recover the number of plants by summing over the sampling multiplier within a year. The regression estimates are weighted by the sampling multiplier and account for this. The number of plants in the analysis spanning 16 years is larger due to entry and exit.

Table 6: Electricity prices and the share of incidence on consumers

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

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

entire manufacturing sector from the electricity price reduction were thus 1.46 trillion ₹ (in constant 2004 terms). The halving of industrial electricity prices from its comparatively high level had substantial effects on the Indian economy. According to this simple calculation, it has contributed the equivalent of 32 billion USD to producer surplus, equivalent to 2% of Indian real GDP in 2013. The gains in consumer surplus has accordingly been 55 billion USD.

4.4.4 The contrary effects of coal prices and implications for climate policy

So far the analysis has been about electricity prices. The most plausible mechanism is that electricity prices affect output in particular because higher electricity prices deter from upgrading to more modern electricity using production processes. If this is the case, then the effect of higher coal prices should be different, as coal (or oil and gas) fuel is not generally associated with more modern productive production processes. To further test this hypothesis, I run regressions where the main independent variable is plant level coal prices for the roughly 45000 observations of plant-years that use coal. As these suffer from similar endogeneity problems as electricity prices, I construct two instruments as described in Section 3.4.

In contrast to electricity, higher coal prices significantly *improve* coal productivity. In the first three columns in Table 7a, both the OLS and the IV estimates are significantly positive, with the IV estimates being roughly double in magnitude.[59] While coal prices significantly reduce coal consumption, they only have a small and insignificant effect on output in the IV specifications, also shown in Table 7a. The impact on electricity use is either insignificant or positive. There is a small insignificant effect on profits and revenues and an ambiguous effect on costs (Table 7b). There is no similar scaling down effect with higher coal prices as there is with higher electricity prices. Contrary to electricity prices, higher coal prices also have no effect on TFP (Table 7b).

This is somewhat good news for climate policy in developing countries. In contrast

[59]The first stage is reported and the F-stats sufficiently high.

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

(a) Coal prices and coal productivity, output, coal use and electricity use

	Coal productivity (log)			Output (log)			Coal consumption (log)			Electricity consumption (log)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\log(P^C)$	0.846***	1.487***	1.612***	0.0899***	-0.300	-0.135	-0.756***	-1.843***	-1.796***	-0.0413	-0.426	0.734*
	(0.025)	(0.179)	(0.213)	(0.031)	(0.248)	(0.344)	(0.036)	(0.272)	(0.384)	(0.036)	(0.269)	(0.428)
OLS/IV	OLS	IV^E	IV^F	OLS	IV^E	IV^F	OLS	IV^E	IV^F	OLS	IV^E	IV^F
Observations	45009	45009	45009	45009	45009	45009	45009	45009	45009	45009	45009	45009
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First stage coef.	-	0.57***	0.01***	-	0.57***	0.01***	-	0.57***	0.01***	-	0.57***	0.01***
First stage SE	-	0.046	0.001	-	0.046	0.001	-	0.046	0.001	-	0.046	0.001
F-stat (Kleib.-Paap)	-	155.090	86.217	-	155.090	86.217	-	155.090	86.217	-	155.090	86.217
SE clustered by	Plant	Plant	Plant	Plant	Plant	Plant	Plant	Plant	Plant	Plant	Plant	Plant
No. of first clusters	16277	16277	16277	16277	16277	16277	16277	16277	16277	16277	16277	16277
SE clustered by	State-year	State-year	State-year	State-year	State-year	State-year	State-year	State-year	State-year	State-year	State-year	State-year
No. of second clusters	426	426	426	426	426	426	426	426	426	426	426	426

(b) Coal prices and profits, revenues, costs and TFP

	Profits (mil. ₹)			Total revenues (mil. ₹)			Avg. variable costs (AVC) (mil. ₹)			TFP (log) (Wooldridge, 2009)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\log(P^C)$	-5.917***	-5.745	-7.108	-19.99**	-18.74	-0.843	-14.36**	-27.76	4.644	-0.000544	-0.0198	-0.0306
	(1.624)	(15.031)	(25.898)	(7.990)	(85.440)	(128.629)	(6.583)	(70.784)	(103.547)	(0.002)	(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	45006	45006	45006	45006	45006	45006	45006	45006	45006	44582	44582	44582
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First stage coef.	-	0.57***	0.01***	-	0.57***	0.01***	-	0.57***	0.01***	-	0.57***	0.01***
First stage SE	-	0.046	0.001	-	0.046	0.001	-	0.046	0.001	-	0.046	0.001
F-stat (Kleib.-Paap)	-	155.060	86.214	-	155.060	86.214	-	155.060	86.214	-	153.047	88.672
Two-way cluster plant state-year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each column represents a separate regression at the plant level. Reported are results from OLS regression on logged coal prices, and IV regressions. The IV^E is based on the coal prices of similar plants. In the shift-share IV^F, the share is the logged distance of a district to the nearest coal mine and the shift is the logged raw coal price for industry at a representative mine. The dependent variables are indicated and described in Section 2.2.1. In panel (a), coal productivity is the value of output divided by the quantity of coal used in tonnes. In panel (b), the regressions are reported in levels except for TFP because profits can be negative. The first stage statistics are reported. All regressions contain industry by year by region fixed effects. Regressions are weighted by the recorded sampling multiplier. Standard errors in parentheses are two-way clustered at the plant and the state by year level. Plant output is deflated using 3-digit industry deflators and coal prices are deflated using a general fuel and electricity wholesale price deflator.

to electricity prices, the results suggest that taxing dirtier fuels has little effect on firm performance. Of course, this also depends on the fuel mix in electricity generation. With an increasing share of low carbon electricity generation from hydro, nuclear and renewables, carbon pricing may have limited effect on firms when taking these results at face value. On the other hand taxing electricity use may have perverse consequences in some circumstances, as it may lower industrial electricity productivity through its adverse impact on output. This is likely to be especially relevant in the context of developing industries in the process of adopting modern electricity intensive production techniques, and in contexts with already high electricity prices as in India in the late 90s and early 2000s.

5 Conclusion

In this paper, I estimate the causal effect of industrial electricity prices on electricity productivity using two alternative instruments and a large panel of Indian manufacturing firms. The effects are negative, especially during the high price period in the late 1990s and early 2000s. While higher electricity prices reduce electricity consumption, they also decrease electricity productivity. This is driven by the significant negative effects on output. The mechanisms that I explore support the hypothesis that electricity is a complementary production input to modern high performance production techniques. Investment and productivity are deterred by higher electricity prices, which may hold back industrial development.

I document a secular increase in aggregate manufacturing electricity productivity. My causal estimates of electricity prices can quantitatively explain this secular rise in electricity productivity remarkably well. Decreasing electricity prices may thus have significantly helped to improve efficiency through technology upgrading and performance improvements. The main message of this paper is that lower industrial electricity prices can actually *improve* the electricity intensity of output. I argue and provide some evidence that negative impacts of high electricity prices on firm performance are especially relevant in the context of industrial development and when electricity prices are already high.

Markups decrease as a result of higher electricity prices. I estimate marginal cost to price pass-through rates under imperfect competition and calculate the welfare incidence on producers and consumers. The share of incidence of consumers is around two thirds on average. The reduction in the severe cross-subsidisation from industry to agriculture and residential electricity users may thus have also benefited non-industrial consumers.

I end the paper by comparing the impacts of electricity prices to the impacts of coal prices. Higher coal prices improve coal productivity and hardly affect output, profits and productivity. This is consistent with the hypothesis that electricity is distinctive as a complement to modern production techniques. This has important implications for climate policy. Taxing electricity for industry harms firms and consumers, and may increase the electricity intensity of output. Taxing carbon and coal, on the other hand, improves energy efficiency and has limited impact on firm performance. Naturally, the fuel mix in electricity generation, as well as the pass-through rates of power utilities, determines how much electricity prices are affected by taxing carbon. Nevertheless, the relative price of coal to electricity would increase in any case. In the described contexts, relatively lower electricity prices for industry could deliver both: substitution from fossil fuels to electricity, and despite increasing electricity use, improving electricity productivity of output. Both are essential components of reducing industrial carbon emissions.

One of the instruments that I develop can readily be calculated in other settings, which I hope can foster more research on this important link. Future research aims to estimate the relationship between electricity pricing and production in a structural model and to explore the nuanced relationships in the context of other developing and developed countries.

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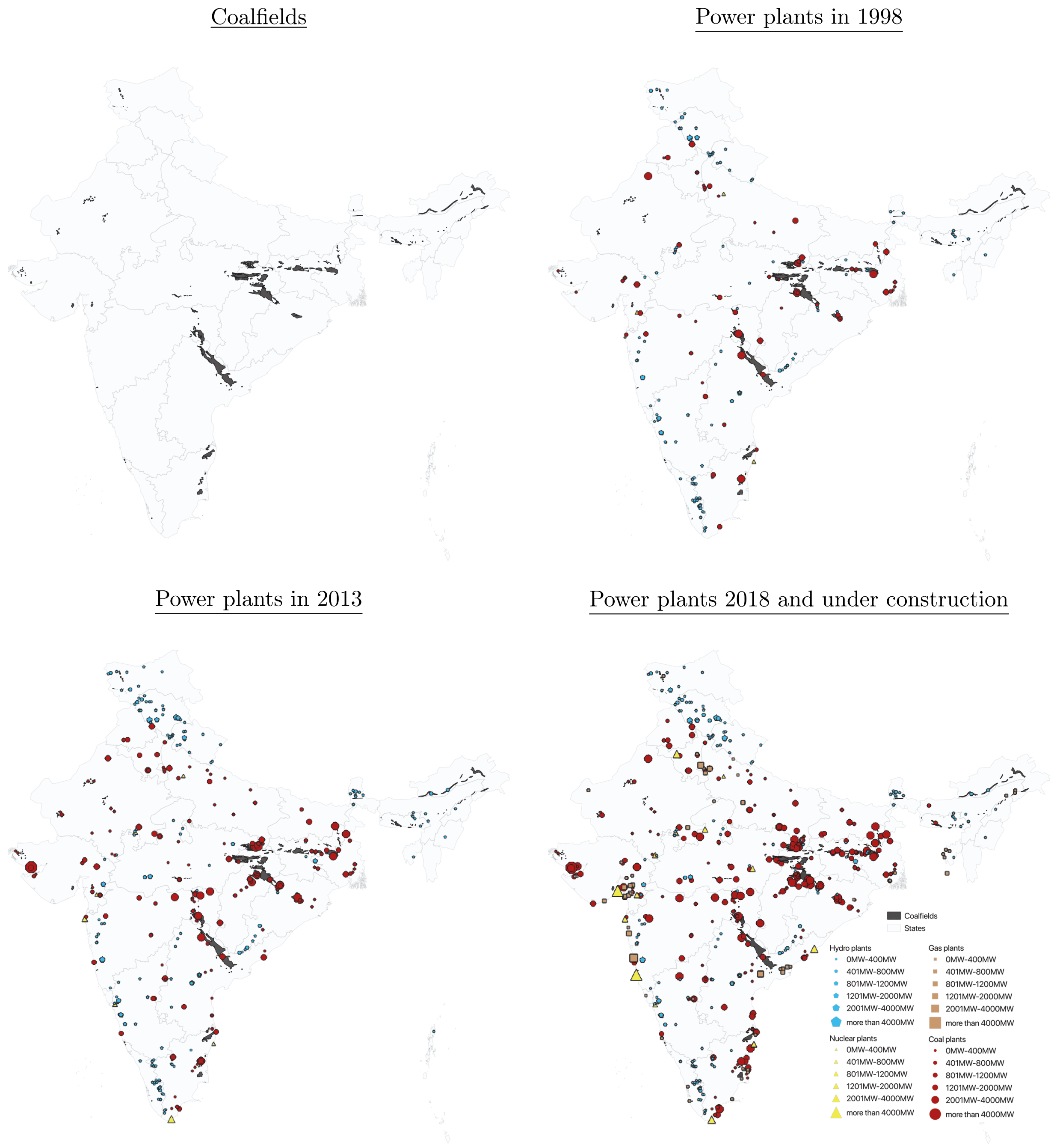
Appendix

A Maps of coal reservoirs and power plants

Figure 6: Maps of coalfields and powerplants by year



Notes: The maps plot the coalfields (time invariant) and the stock of power plants in the corresponding years. The size of the markers corresponds to installed capacity. Coal plants are built near coalfields. Hydro plants near rivers especially in the mountainous region. Nuclear plants are typically built near the sea or rivers. Gas plants are built near ports and the major gas pipelines (e.g. in the north east). Data sources are described in Section 2.2.2.

B Electricity prices and privately owned share in installed capacity

Table 8: Electricity prices and privately owned share in district installed capacity

	Electricity price				Priv. share
	(1)	(2)	(3)	(4)	(5)
Share private capacity	0.09	0.11	0.06	0.00	
	(0.96)	(1.17)	(0.63)	(0.03)	
Share private capacity x After 2003	-0.24***	-0.24***	-0.19**	-0.19**	
	(-2.93)	(-2.93)	(-2.34)	(-1.98)	
Distance to coalfield ('00 km) x After 2003				-0.09***	-0.03***
				(-3.15)	(-2.85)
N	7994	7994	7994	7994	7994
Total capacity	No	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Region-year FE	No	No	Yes	Yes	Yes

Notes: The table shows estimates from OLS regressions at the district year level with the median electricity price within a district as dependent variable in the first 4 columns. The Indian Electricity Act was introduced in 2003. The share of privately owned capacity in district level installed capacity includes private/state and private/central ownership categories. The total capacity covariate controls for total installed capacity at the district year level. The distance to coalfields at the district level is in hundreds of km. Column 5 has the share of privately owned capacity as dependent variable. Regressions are weighted by the sampling multipliers and by the number of plants within a district year cluster. Standard errors in parentheses are clustered at the district level. The coefficients on the interaction in column (1) and (2) correspond to a semi-elasticity of 0.03. Stars indicate p-values: * < 0.1, **< 0.05, ***< 0.01.

C No significant correlation between shortages and electricity prices

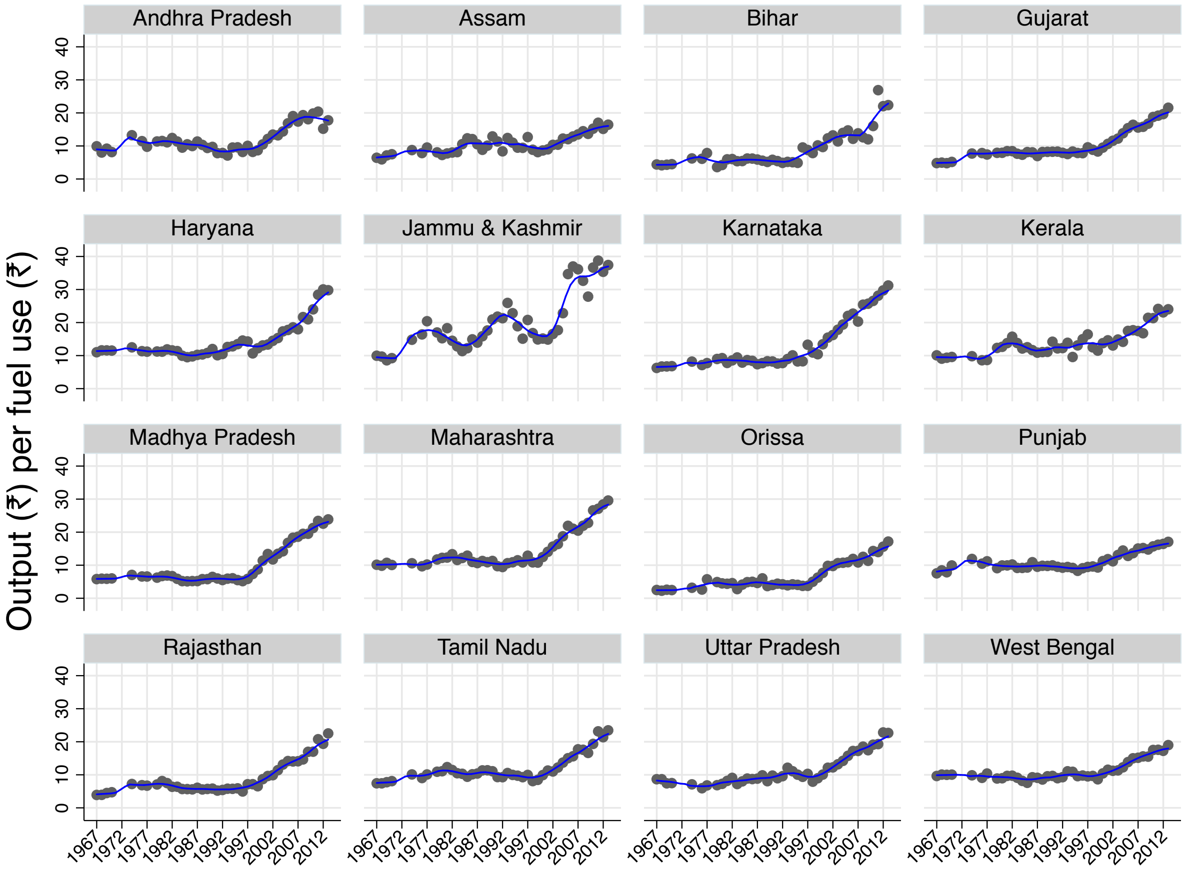
Table 9: Electricity prices and shortages

	Plant level			State level		
	(1)	(2)	(3)	(4)	(5)	(6)
Shortages	0.34	-0.02	0.12	1.08	-0.01	0.11
	(1.58)	(-0.20)	(0.94)	(1.02)	(-0.01)	(0.64)
N	475809	475809	475809	458	458	458
Year FE	No	Yes	Yes	No	Yes	Yes
State FE	No	Yes	Yes	No	Yes	Yes
Region-year FE	No	No	Yes	No	No	Yes

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

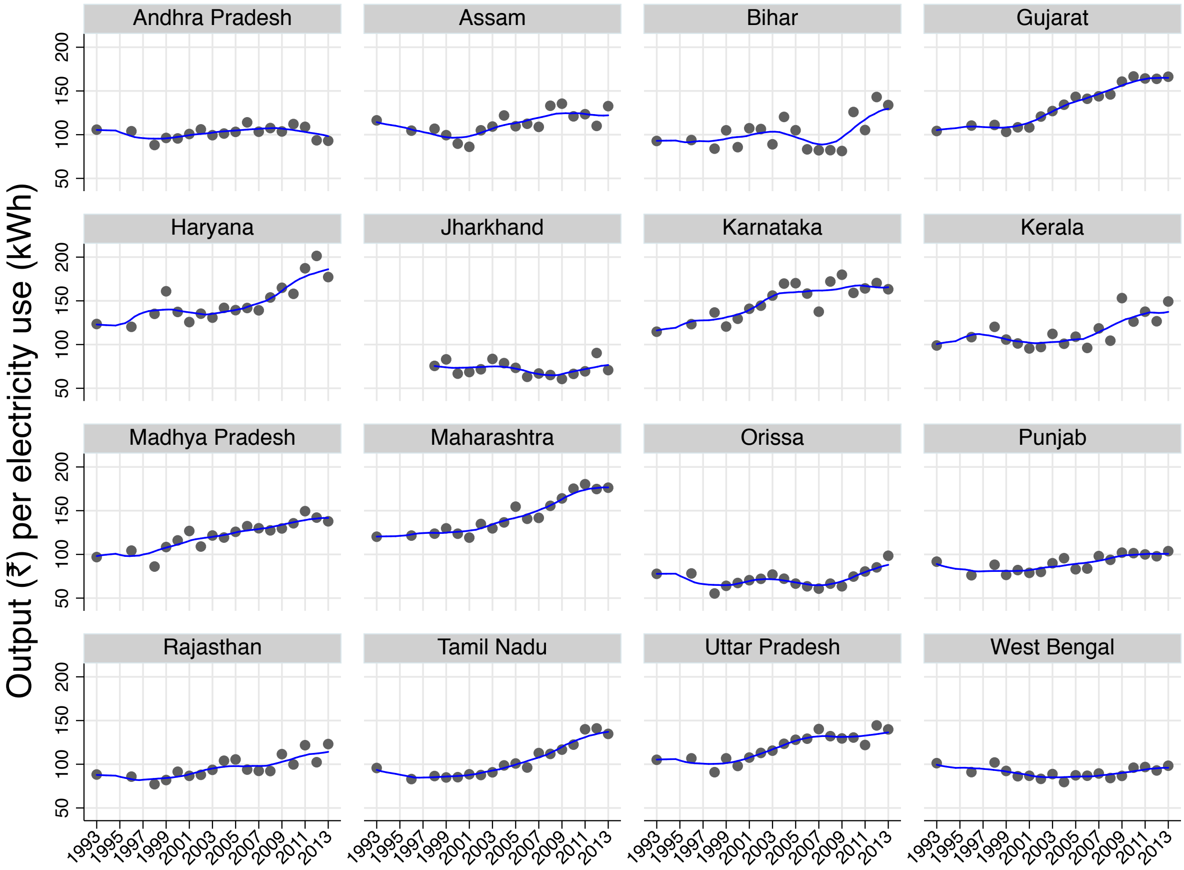
D State level trends

Figure 7: Energy productivity (per ₹) by state



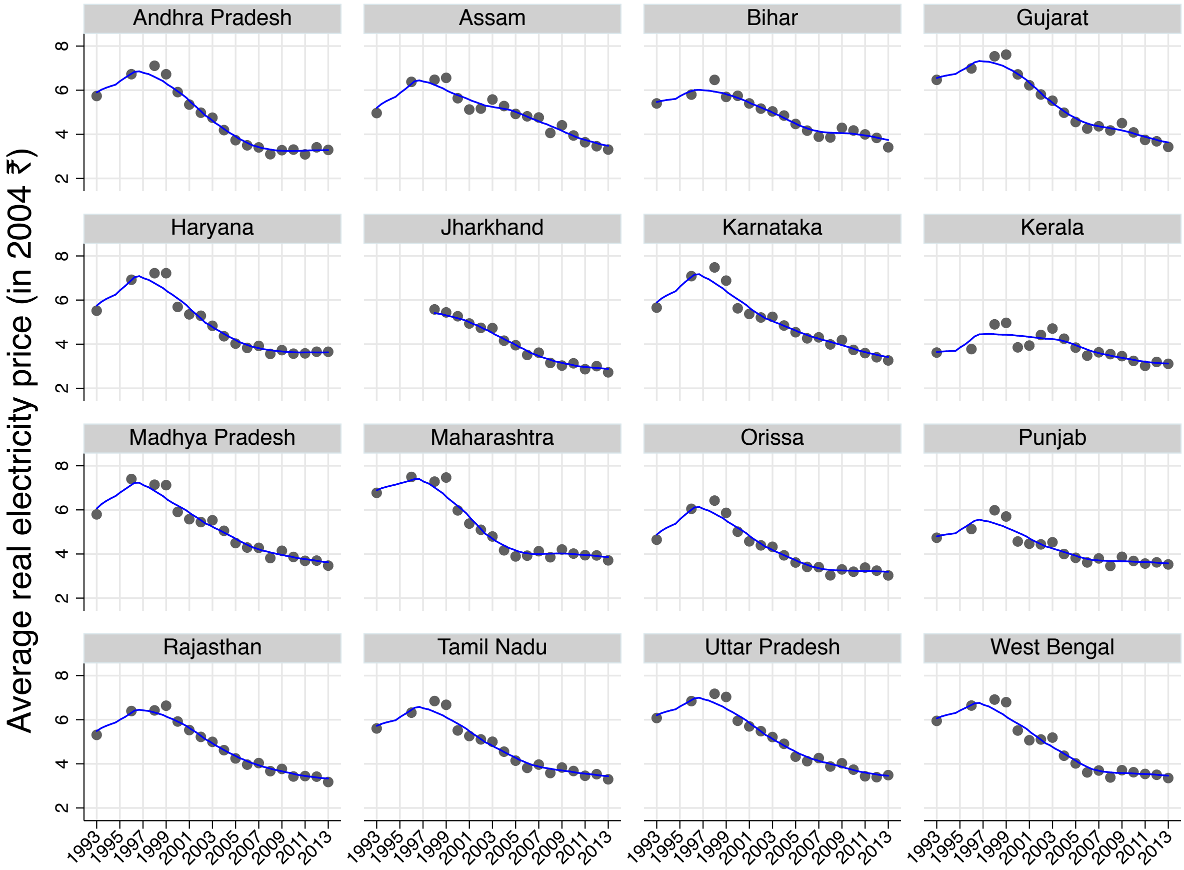
Notes: The figure plots the annual energy productivity ratios (value of output divided by the value of fuel and electricity used). Sixteen of the largest states are displayed in this figure. Output is deflated at the 2-digit industry level using 2-digit industry deflators before aggregating over industries.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

Figure 8: Electricity productivity (per kWh) by state



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

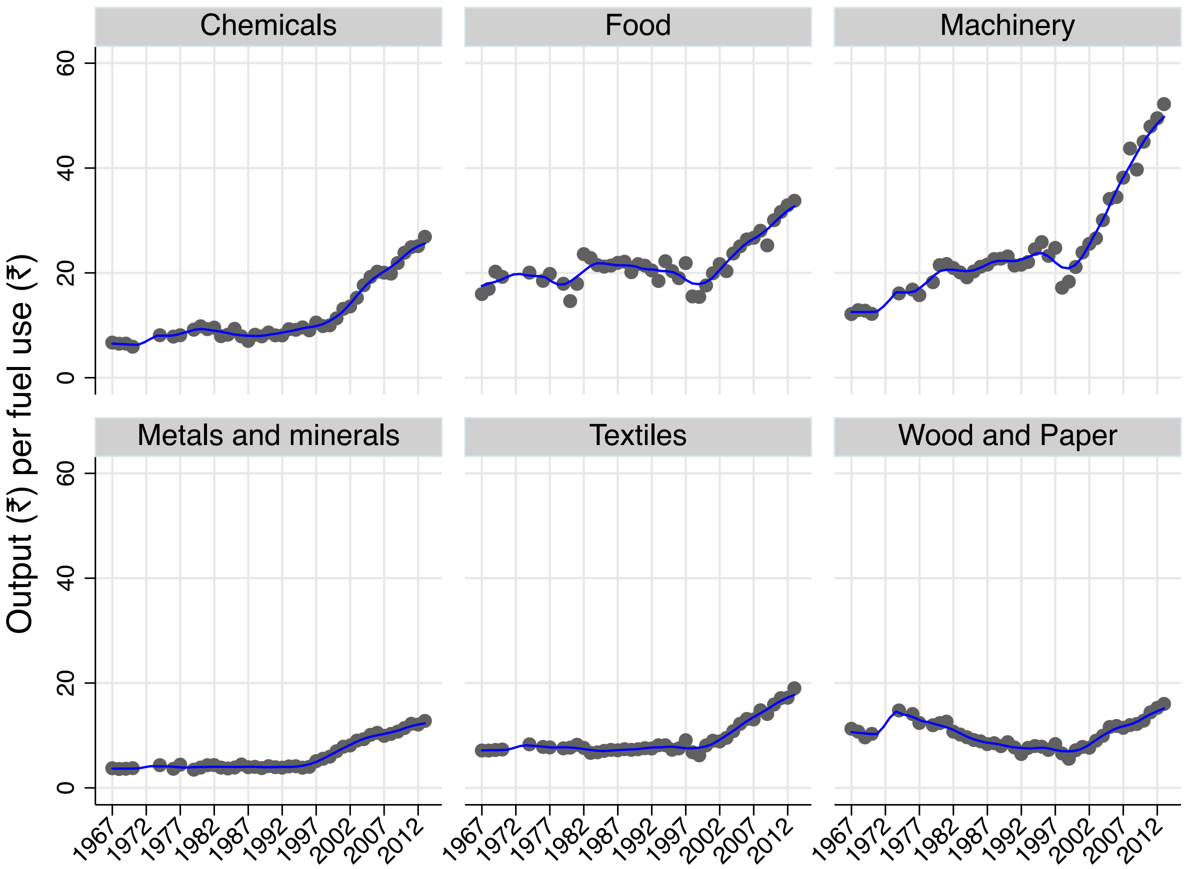
Figure 9: Electricity prices by state



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

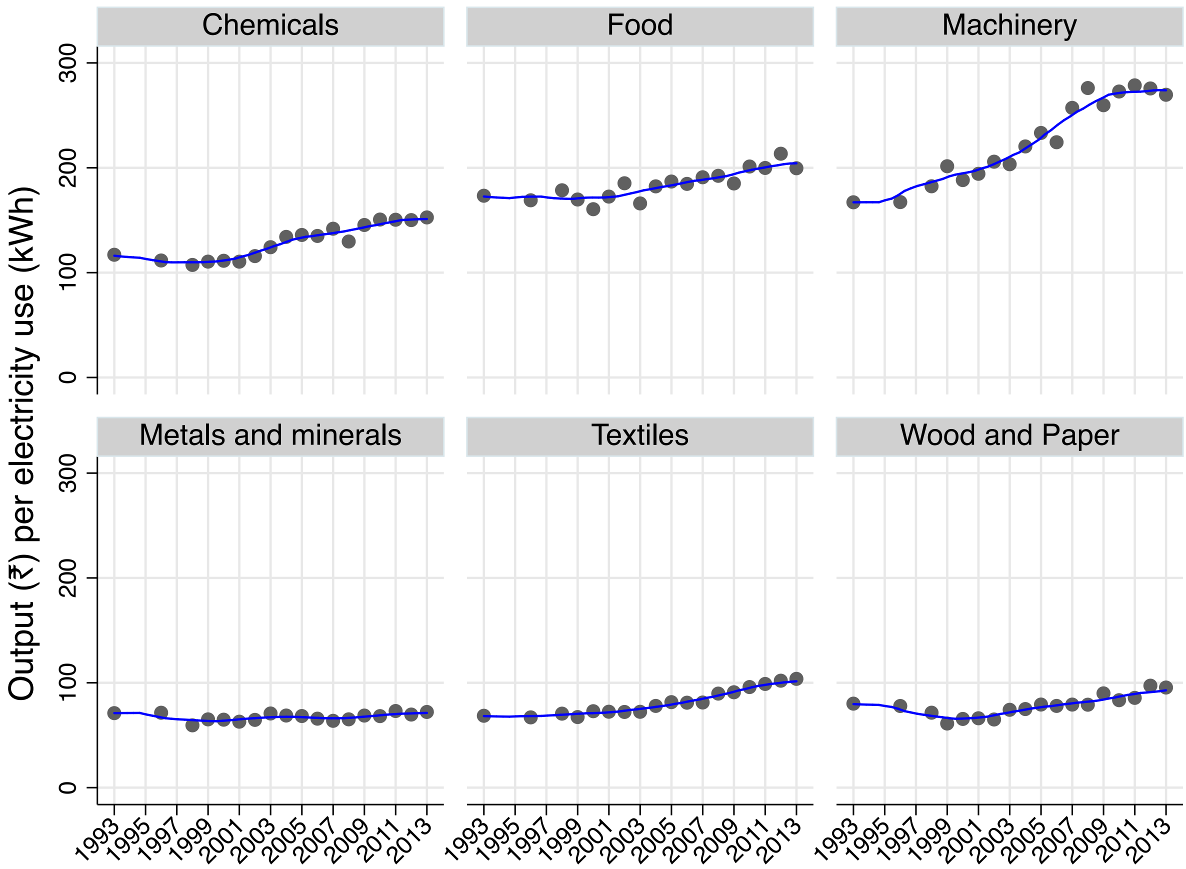
E Industry level trends

Figure 10: Energy productivity (per ₹) by industry



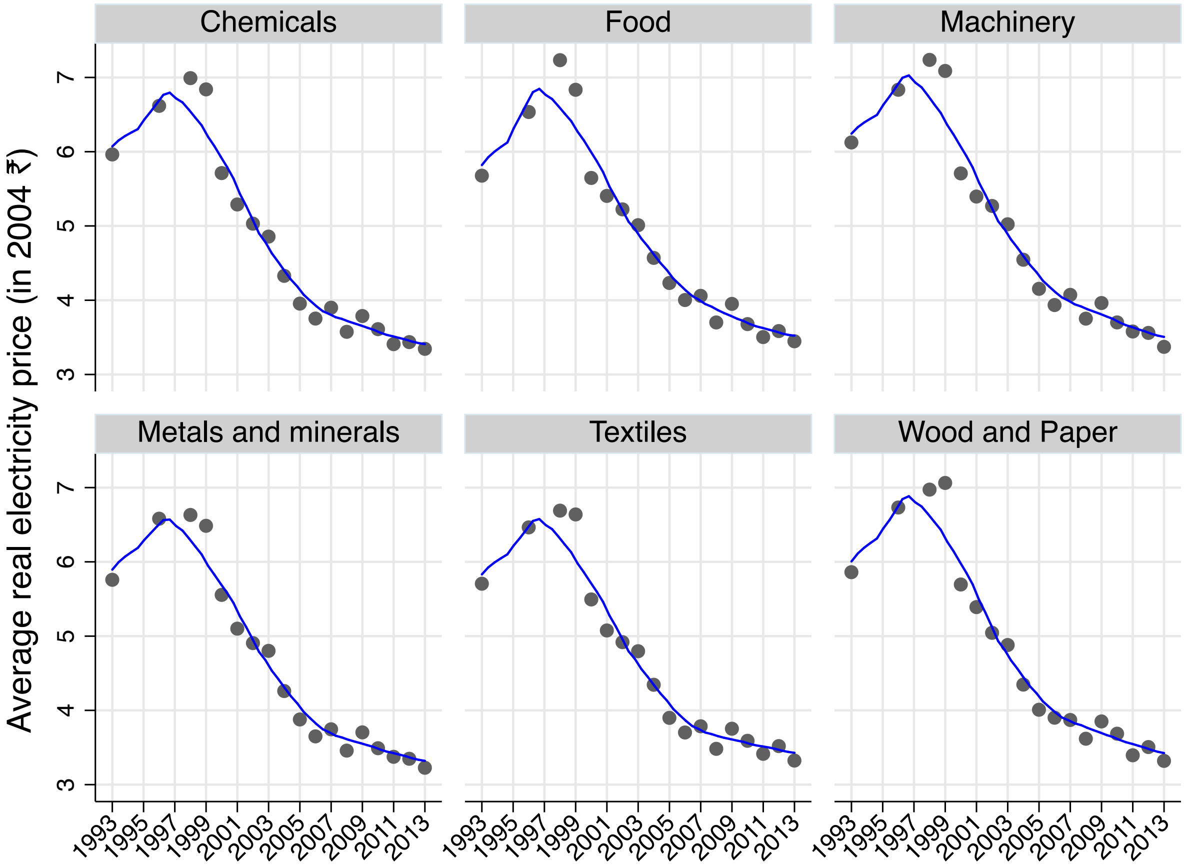
Notes: The figure plots the annual energy productivity ratios by industry (value of output divided by the value of fuel and electricity used). The industries are broad: chemicals includes rubber and plastics, machinery includes metal products, and textiles includes leather. Output is deflated at the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

Figure 11: Electricity productivity (per kWh) by industry



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

Figure 12: Electricity prices by industry



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

F Additional figures for energy and electricity productivity trends

Figure 13: Electricity productivity (per ₹)

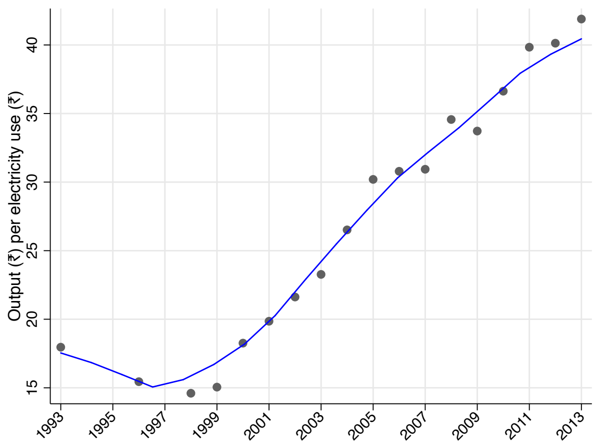
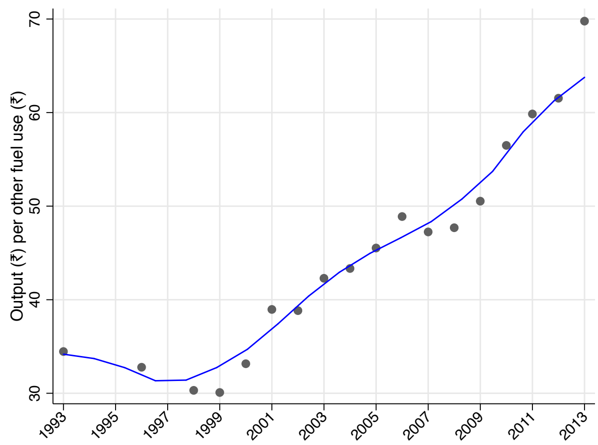


Figure 14: Other fuel productivity (per ₹)



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

Figure 15: Electricity productivity (per kWh)

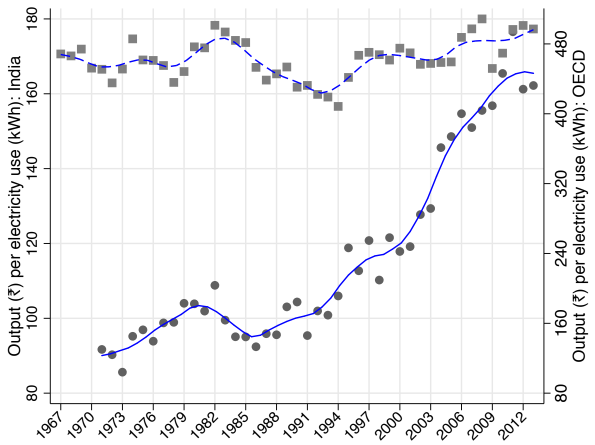
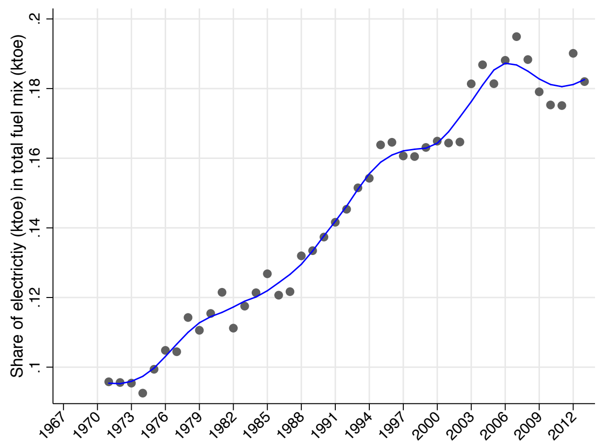


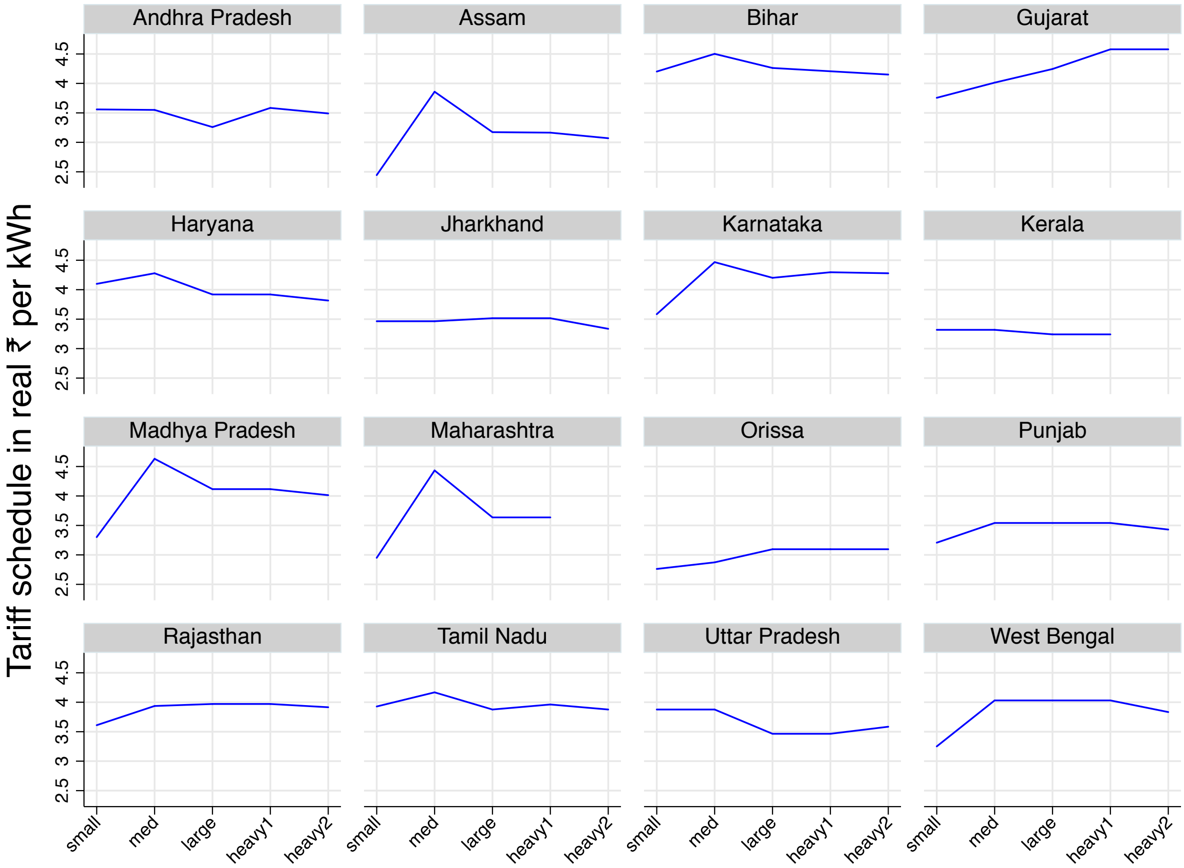
Figure 16: Share of electricity in fuel mix



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

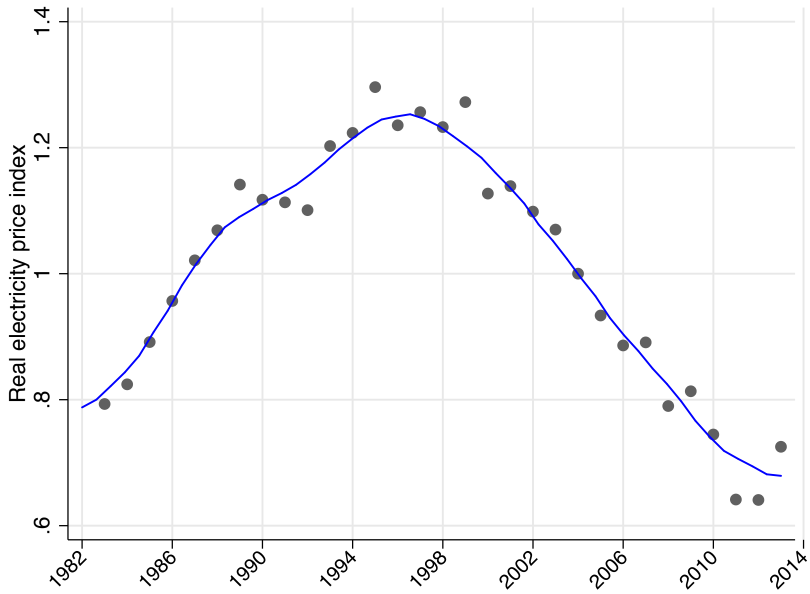
G Additional figures for electricity tariffs and price trends

Figure 17: Reported industrial average tariff schedules in large states in 2007



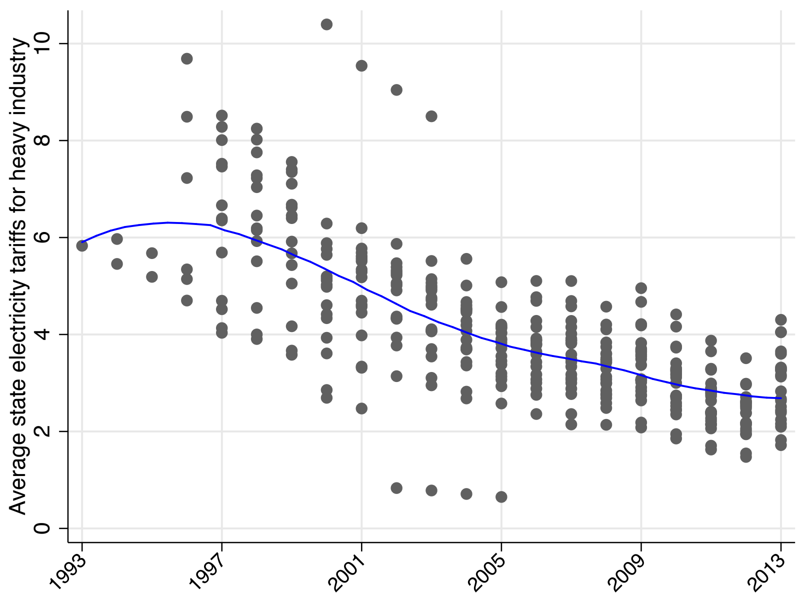
Notes: Plotted are the estimated average tariffs by state by size of industrial consumer. There are five categories increasing in electricity consumption from *small* to *heavy2*. The reported average tariffs are taken from the Indian Central Electricity Authority (2008). The tariffs are deflated with the general fuel and electricity wholesale price deflator. The base year for deflation is 2004 throughout this paper. Wholesale price deflators are from the Office of the Economic Adviser from the Government of India.

Figure 18: Real electricity price index



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

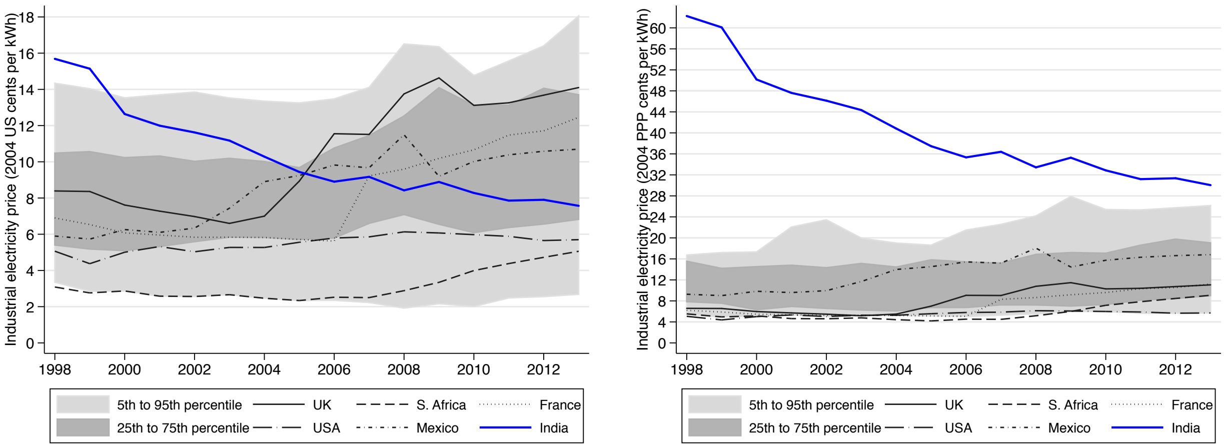
Figure 19: Average real state tariffs for heavy industry



Notes: Plotted is the real electricity tariff for heavy industry. The tariffs are manually collected from publications of the Indian Central Electricity Authority (2008, 2009, 2010, 2011, 2012, 2013, 2015) and from Indiastat (2019) through Lok Sabha and Rajya Sabha questions. Individual data points correspond to state level average tariffs for heavy industry. Tariffs are deflated using a general fuel and electricity wholesale price deflator. The base year for deflation is 2004 throughout this paper. Wholesale price deflators are from the Office of the Economic Adviser from the Government of India.

H International electricity price comparison

Figure 20: Industrial electricity prices in an international context (USD and PPP)



Notes: The figures plot real industrial electricity prices for six individual countries. The left figure is based on market exchange rates, the right figure 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), except for India, where the prices are based on the micro data in the main text. For India, IEA (2018) data is only available from 2006, which is similar to the plotted data. Prices are deflated with national GDP deflators and turned into USD or PPP-USD with exchange rates and PPP conversion factors from World Bank (2017). For India, prices are deflated using a general fuel and electricity wholesale price deflator as in the main text. The base year for deflation is 2004 throughout this paper. Wholesale price deflators are from the Office of the Economic Adviser from the Government of India. The 26 countries used for the percentiles are: Algeria, Canada, Czech Republic, Denmark, France, Germany, Hungary, India, Ireland, Israel, Italy, Japan, Kazakhstan, Mauritius, Mexico, New Zealand, Paraguay, Poland, Portugal, Slovak Republic, South Africa, Spain, Switzerland, Turkey, United Kingdom, United States.

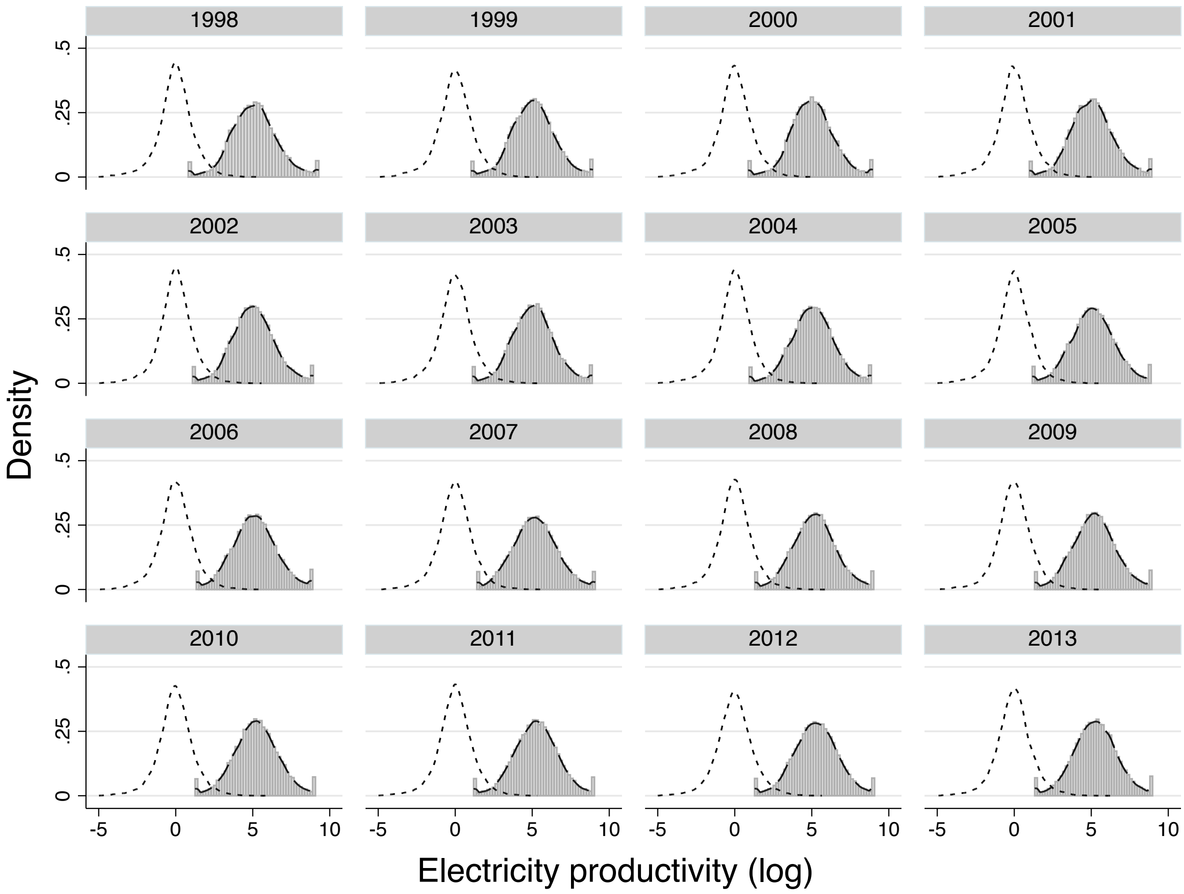
Table 10: Industrial electricity prices in US-cents: India and G7 average (USD and PPP)

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

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

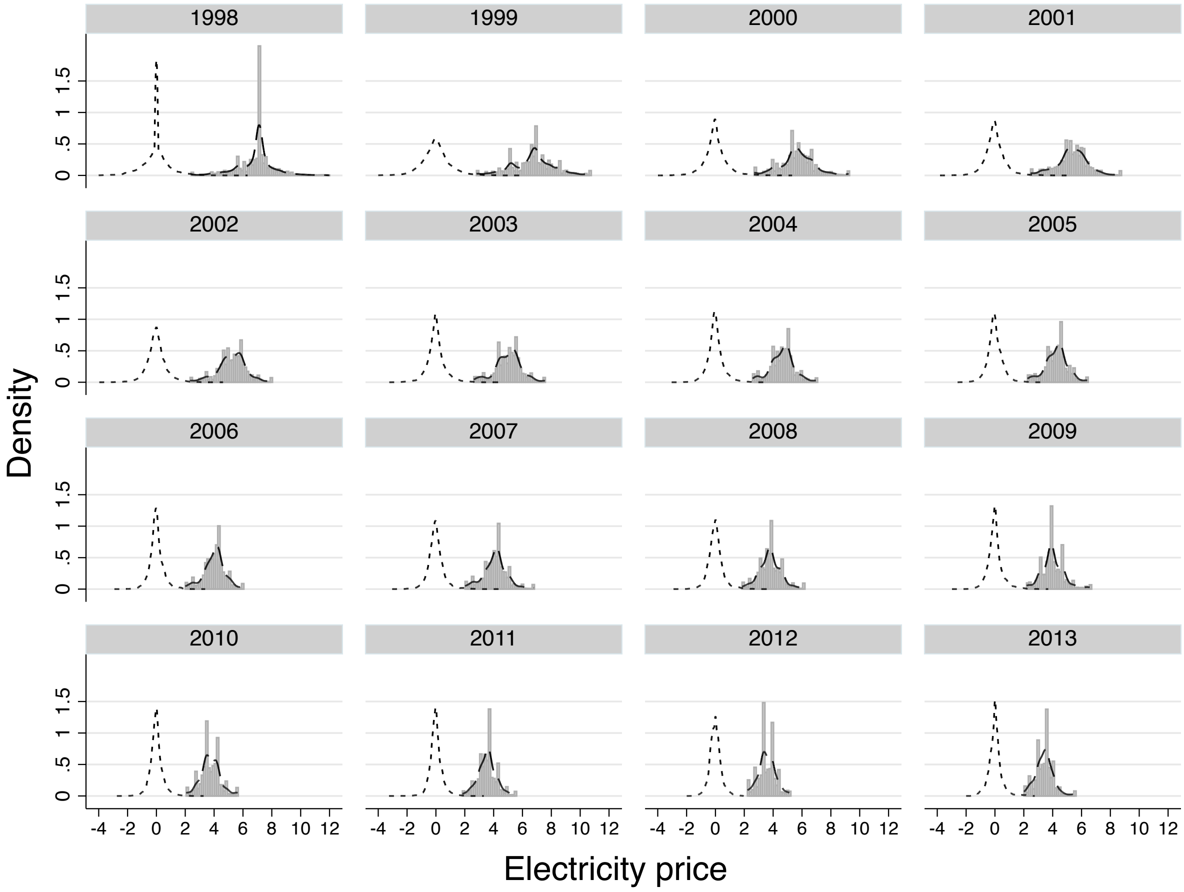
I Dispersion in electricity productivity and prices throughout the years

Figure 21: Heterogeneity in electricity productivity



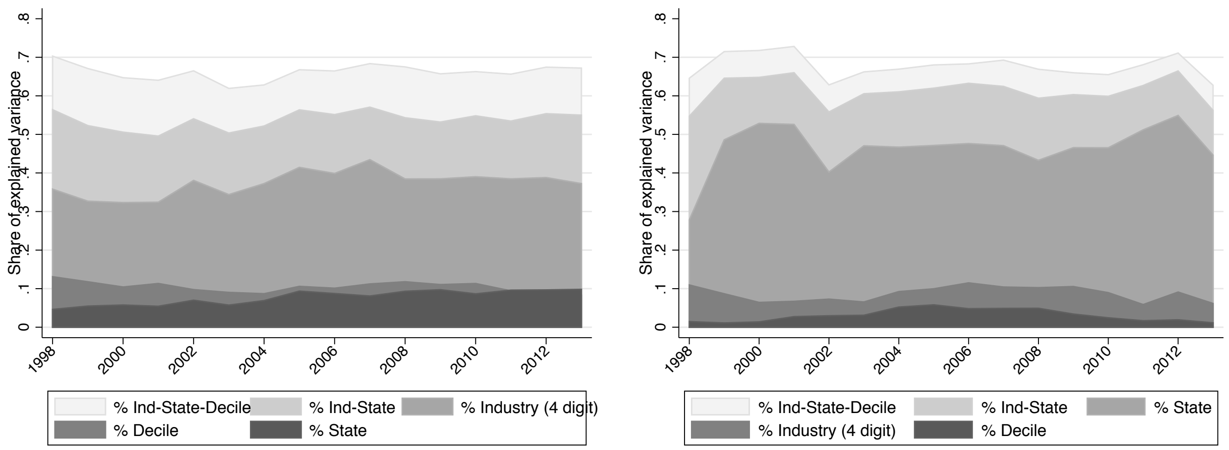
Notes: The figure plots the histograms of plant level logged electricity productivity by year. The left kernel density plot shows the distribution of the residuals of logged electricity productivity after partialling out state by 4-digit industry by year fixed effects. Electricity productivity ratios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

Figure 22: Heterogeneity in electricity prices



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

Figure 23: Electricity productivity and price variance decomposition: percentage shares

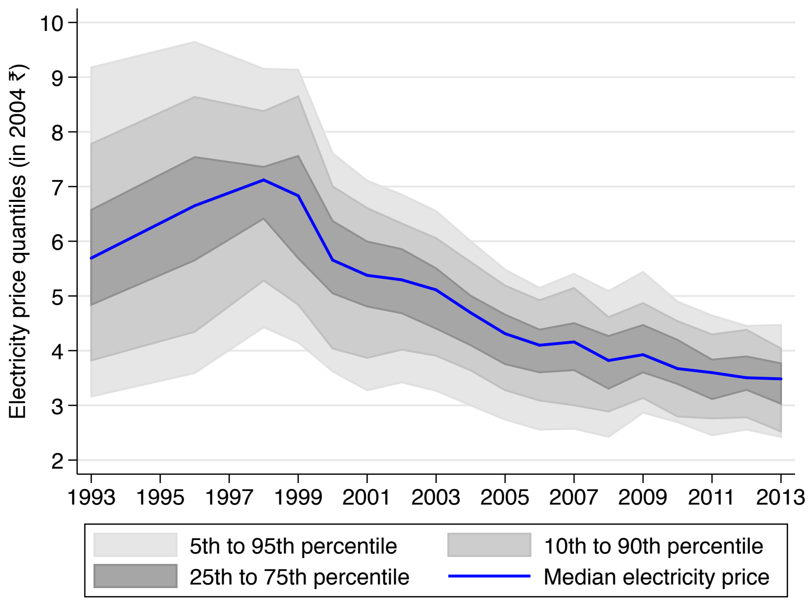


Notes: The left panel plots the share of the annual total variance of logged electricity productivity explained by specified groups. The right panel plots the same for logged electricity prices. The annual variance is calculated as $V = \sum_e s_e \left(p_e - \overline{p}\right)^2$, where s_e are purchase weights multiplied by the sample multiplier, p_e are logged electricity productivity or prices, $\overline{p}$ the weighted average log productivity or price. I use the decomposition of Davis et al. (2013) to decompose total variance into a within "group" component V^W, and a component across "groups" V^G:

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

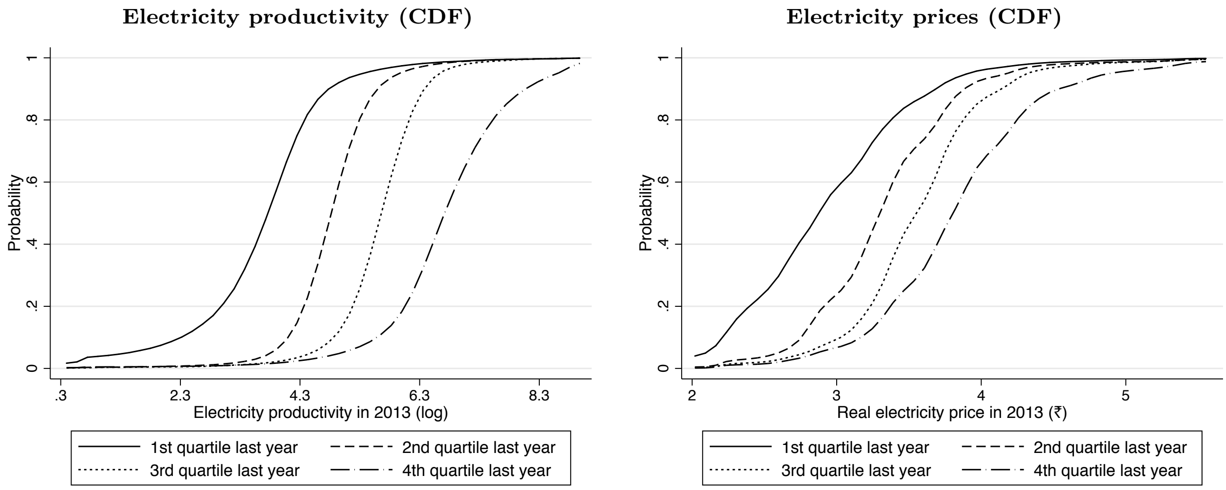
where $s_g = \sum_{e \in g} s_e$ and $\overline{p}_g$ the weighted average of log productivity or price within group g. I calculate the decomposition separately five times for the five groups shown in the graph. The regions plot the share of V^G in V (V^G/V), where higher shares explain more of the variation. Groups are deciles of electricity purchase quantity, 4-digit industries, states, and combinations. Plant output and electricity prices are deflated.

Figure 24: Convergence in electricity prices



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

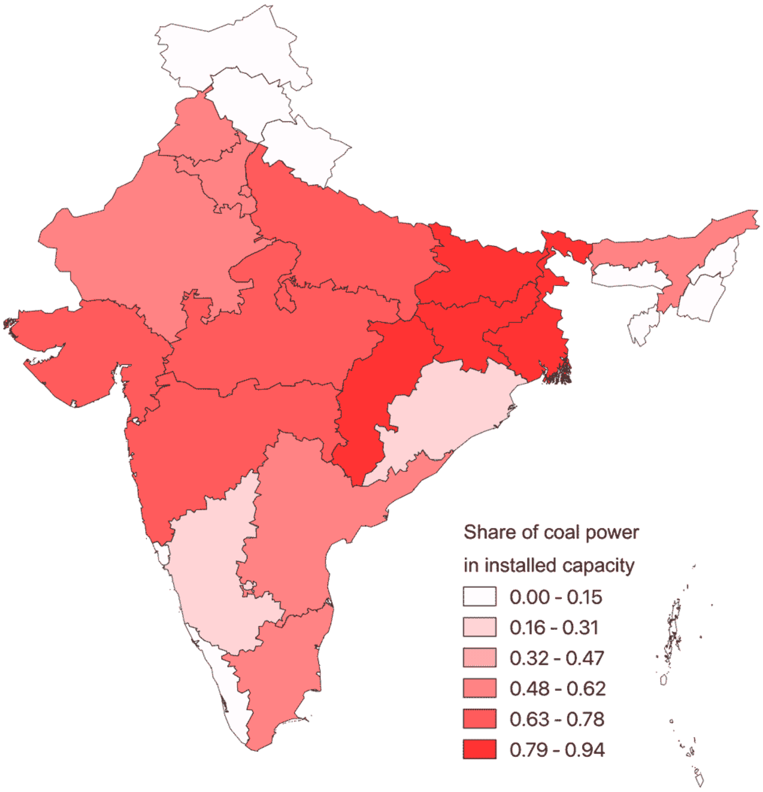
Figure 25: CDFs of plant electricity productivity and prices in 2013 conditional on 2012 quartiles



Notes: Plotted are the CDFs in 2013, separately for each quartile of the respective values in 2012. The left panel shows the distribution of the logged electricity productivity (i.e. the value of output divided by the electricity use in kWh). The right panel shows the distribution of the electricity price. The CDFs are empirical CDFs obtained through a Gaussian kernel smoother with bandwidth 0.1. The graphs show that each higher quartile first order stochastically dominates the lower quartiles. The conditional CDF of the plants that belong to the higher *previous* year quartile lies to the right of the CDF of the plants belonging to the lower *previous* year quartile. While individual plants move up and down the ranking of electricity productivity and energy prices from one year to the next, the probability of higher productivity and prices increases in last periods productivity and prices. Plant output is deflated using 3-digit industry deflators. Electricity prices are deflated using a general fuel and electricity wholesale price deflator. The base year for deflation is 2004 throughout this paper. Wholesale price deflators are from the Office of the Economic Adviser from the Government of India.

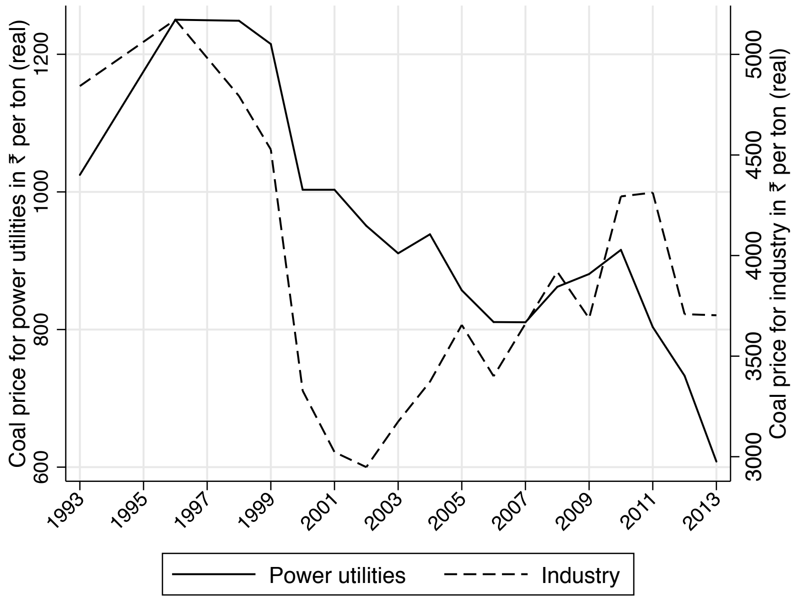
J Coal share in installed capacity and coal price for power utilities and industry

Figure 26: Share of coal power in total installed capacity



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

Figure 27: Coal price for power utilities and industry



Notes: The solid line plots the coal prices for thermal power plants and are from Minsitry of Coal (2012, 2015) as described in Section 2.2.2. Prices for coal used in manufacturing industries are plotted with the dashed line. These are averages of the coal prices at the plant level in the ASI micro data (see Section 2.2.1). All coal prices are in real terms and deflated using a general fuel and electricity wholesale price deflator. In nominal terms, coal prices have been mostly increasing. The base year for deflation is 2004 throughout this paper. Wholesale price deflators are from the Office of the Economic Adviser from the Government of India.

K Robustness checks and additional regressions

Table 11: Electricity prices and electricity productivity with two alternative instruments IV^C and IV^D

	OLS (1)	IV^C (2)	IV^D (3)
$\log(P^E)$	0.366***	-0.267***	-0.475
	(0.044)	(0.071)	(0.679)
Distance to coalfield			-0.0126
(in '00 km)			(0.009)
OLS/IV	OLS	IV^C	IV^D
Observations	485948	444952	444952
Ind-region-year FE	Yes	Yes	Yes
First stage coef.	-	0.97***	0.02***
First stage SE	-	0.005	0.008
F-stat (Kleib.-Paap)	-	37708.429	7.194
Two-way cluster plant state-year	Yes	Yes	Yes

Notes: See Table 2 for notes. The main difference in this table is the use of two alternative instruments, IV^C and IV^D.

Table 12: Electricity prices and electricity productivity in electricity intensive sectors

	OLS	IV^A	IV^B
	(1)	(2)	(3)
$\log(P^E)$	0.323***	-0.208***	-0.582***
	(0.047)	(0.074)	(0.102)
OLS/IV	OLS	IV^A	IV^B
Observations	260900	260900	260900
Ind-region-year FE	Yes	Yes	Yes
First stage coef.	-	0.97***	0.06***
First stage SE	-	0.005	0.004
F-stat (Kleib.-Paap)	-	32789.655	324.114
Two-way cluster plant state-year	Yes	Yes	Yes

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

Table 13: Electricity prices and electricity productivity: using both IVs

	OLS	IV^A & IV^B	IV^C & IV^B
	(1)	(2)	(3)
$\log(P^E)$	0.366***	-0.256***	-0.288***
	(0.044)	(0.068)	(0.069)
IV 1	-	IV^A	IV^C
IV 2	-	IV^B	IV^B
Observations	485948	485948	444952
Ind by region by year FE	Yes	Yes	Yes
State FE	No	No	No
Plant FE	No	No	No
State trends	No	No	No
State by year FE	No	No	No
First stage coef. 1/1	-	0.94***	0.94***
First stage SE 1/1	-	0.007	0.008
First stage coef. 1/2	-	0.00***	0.00***
First stage SE 1/2	-	0.001	0.001
F-stat (Kleibergen-Paap)	-	23320.712	20389.385
Anderson-Rubin F	-	0.000	0.000
J-statistic	-	26.12	28.81
Two-way cluster plant state-year	Yes	Yes	Yes

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

Table 14: Electricity prices and electricity productivity: additional fixed effects and trends

	OLS		IV^A		IV^B
	(1)	(2)	(3)	(4)	(5)
$\log(P^E)$	0.708***	0.684***	-0.545*	0.0229	-1.809*
	(0.030)	(0.018)	(0.291)	(0.056)	(0.982)
OLS/IV	OLS	OLS	IV^A	IV^A	IV^B
Observations	485948	425794	485948	425794	425794
Ind-year FE	Yes	Yes	Yes	Yes	Yes
Ind-region-year FE	Yes	No	Yes	No	No
State FE	Yes	Yes	Yes	Yes	Yes
Plant FE	No	Yes	No	Yes	Yes
State trends	Yes	No	Yes	No	No
First stage coef.	-	-	0.89***	0.92***	0.16**
First stage SE	-	-	0.015	0.009	0.069
F-stat (Kleib.-Paap)	-	-	3499.772	9379.183	5.204
SE clustered by	Plant	Plant	Plant	Plant	Plant
No. of first clusters	160955	100418	160955	100418	100418
SE clustered by	State-year	State-year	State-year	State-year	State-year
No. of second clusters	501	501	501	501	501

Notes: See Table 2 for notes. The main difference is the inclusion of different fixed effects as indicated.

Table 16: Electricity prices and electricity productivity by industry groups

(a) Electricity prices and electricity productivity (Chemicals, food, machinery))

	Chemicals			Food			Machinery		
	OLS	IV^A	IV^B	OLS	IV^A	IV^B	OLS	IV^A	IV^B
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(P^E)$	0.178***	-0.389***	-0.765***	0.572***	0.0436	-1.546***	0.217***	-0.629***	-1.250***
	(0.064)	(0.085)	(0.106)	(0.073)	(0.162)	(0.404)	(0.066)	(0.093)	(0.133)
OLS/IV	OLS	IV^A	IV^B	OLS	IV^A	IV^B	OLS	IV^A	IV^B
Observations	73838	73838	73838	96601	96601	96601	89944	89944	89944
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First stage coef.	-	0.98***	0.08***	-	0.91***	0.04***	-	1.01***	0.07***
First stage SE	-	0.007	0.003	-	0.014	0.003	-	0.007	0.004
F-stat (Kleib.-Paap)	-	17799.309	533.240	-	4339.858	115.564	-	23887.783	337.618
SE clustered by	Plant	Plant	Plant	Plant	Plant	Plant	Plant	Plant	Plant
No. of first clusters	26826	26826	26826	33492	33492	33492	29046	29046	29046
SE clustered by	State-year	State-year	State-year	State-year	State-year	State-year	State-year	State-year	State-year
No. of second clusters	472	472	472	500	500	500	440	440	440

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

	Metals and minerals			Textiles			Wood and Paper		
	OLS	IV^A	IV^B	OLS	IV^A	IV^B	OLS	IV^A	IV^B
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(P^E)$	0.476***	0.0885	0.210	0.410***	-0.177	-0.949***	0.342***	-0.227**	-0.733***
	(0.053)	(0.102)	(0.191)	(0.078)	(0.156)	(0.257)	(0.067)	(0.096)	(0.138)
OLS/IV	OLS	IV^A	IV^B	OLS	IV^A	IV^B	OLS	IV^A	IV^B
Observations	104738	104738	104738	71166	71166	71166	36352	36352	36352
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First stage coef.	-	0.96***	0.05***	-	0.99***	0.07***	-	0.99***	0.06***
First stage SE	-	0.009	0.003	-	0.012	0.005	-	0.009	0.004
F-stat (Kleib.-Paap)	-	11445.114	181.778	-	6266.604	196.845	-	11169.861	273.140
SE clustered by	Plant	Plant	Plant	Plant	Plant	Plant	Plant	Plant	Plant
No. of first clusters	40261	40261	40261	23117	23117	23117	13346	13346	13346
SE clustered by	State-year	State-year	State-year	State-year	State-year	State-year	State-year	State-year	State-year
No. of second clusters	486	486	486	443	443	443	499	499	499

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

Table 15: Electricity prices and electricity productivity: clustering at district and region year

	OLS (1)	IV^A (2)	IV^B (3)
log(P^E)	0.340*** (0.117)	-0.264* (0.154)	-0.818*** (0.218)
OLS/IV	OLS	IV^A	IV^B
Observations	444952	444952	444952
Ind-region-year FE	Yes	Yes	Yes
First stage coef.	-	0.98***	0.06***
First stage SE	-	0.018	0.010
F-stat (Kleib.-Paap)	-	3057.138	38.818
SE clustered by	District	District	District
No. of first clusters	541	541	541
SE clustered by	Region-year	Region-year	Region-year
No. of second clusters	96	96	96

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

Table 17: Electricity prices and electricity productivity interacted with three periods

	OLS (1)	IV^A (2)	IV^B (3)
log(P^E)	0.506*** (0.067)	0.0573 (0.111)	-0.719*** (0.200)
$\log(P^E) \cdot \mathbf{1}(year < 2003)$	-0.275*** (0.098)	-0.729*** (0.163)	-0.124 (0.234)
$\log(P^E) \cdot \mathbf{1}(year \geq 2003 \text{ or } year \leq 2007)$	-0.177* (0.104)	-0.272* (0.147)	-0.0682 (0.247)
OLS/IV	OLS	IV^A	IV^B
Observations	485948	485948	485948
Ind by region by year FE	Yes	Yes	Yes
First stage coef. 1/1	-	0.95***	0.05***
First stage SE 1/1	-	0.007	0.005
First stage coef. 1/2	-	0.04***	0.01
First stage SE 1/2	-	0.012	0.008
First stage coef. 1/3	-	0.03***	0.01
First stage SE 1/3	-	0.010	0.008
First stage coef. 2/1	-	0.00	0.00
First stage SE 2/1	-	0.000	0.000
First stage coef. 2/2	-	0.99***	0.06***
First stage SE 2/2	-	0.009	0.006
First stage coef. 2/3	-	0.00	-0.00
First stage SE 2/3	-	0.000	0.000
First stage coef. 3/1	-	-0.00***	0.00
First stage SE 3/1	-	.	0.000
First stage coef. 3/2	-	0.00***	-0.00
First stage SE 3/2	-	.	0.000
First stage coef. 3/3	-	0.98***	0.06***
First stage SE 3/3	-	0.007	0.007
F-stat (Kleibergen-Paap)	-	3875.232	35.761
Two-way cluster plant state-year	Yes	Yes	Yes

Notes: See Table 4 for notes. The main difference is that prices are interacted with three different periods (one baseline omitted).

Table 18: Electricity prices and electricity productivity: controlling for distance to coalfields and shortages

	OLS			IV^A			IV^B		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(P^E)$	0.343***	0.472***	0.459***	-0.255***	-0.130	-0.121	-0.827***	-0.938***	-0.980***
	(0.045)	(0.043)	(0.044)	(0.070)	(0.085)	(0.088)	(0.101)	(0.149)	(0.148)
Distance to coalfield	-0.0181***		-0.0192***	-0.0141**		-0.0178**	-0.0102		-0.0157*
(in '00 km)	(0.007)		(0.007)	(0.007)		(0.007)	(0.008)		(0.008)
Shortage		0.397*	0.282		0.644***	0.515***		0.976***	0.860***
		(0.226)	(0.239)		(0.187)	(0.192)		(0.198)	(0.201)
OLS/IV	OLS	OLS	OLS	IV^A	IV^A	IV^A	IV^B	IV^B	IV^B
Observations	444952	474029	433262	444952	474029	433262	444952	474029	433262
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First stage coef.	-	-	-	0.98***	0.97***	0.98***	0.06***	0.05***	0.05***
First stage SE	-	-	-	0.005	0.006	0.006	0.003	0.004	0.004
F-stat (Kleib.-Paap)	-	-	-	41022.067	25440.719	26150.603	307.715	173.552	176.792
Two-way cluster plant state-year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

Table 19: Electricity prices, employment, machine labour ratio and product scope

	Employees (log)			Ratio machinery to employees (log)			Number of products (log)		
	OLS	IV^A	IV^B	OLS	IV^A	IV^B	OLS	IV^A	IV^B
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(P^E)$	0.0119	-0.339***	-0.518***	-0.160**	-0.627***	-1.517***	0.0456***	-0.00288	-0.0960***
	(0.041)	(0.076)	(0.079)	(0.065)	(0.114)	(0.151)	(0.012)	(0.023)	(0.036)
OLS/IV	OLS	IV^A	IV^B	OLS	IV^A	IV^B	OLS	IV^A	IV^B
Observations	485342	485342	485342	467686	467686	467686	485067	485067	485067
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First stage coef.	-	0.97***	0.06***	-	0.97***	0.06***	-	0.97***	0.06***
First stage SE	-	0.005	0.003	-	0.005	0.003	-	0.005	0.003
F-stat (Kleib.-Paap)	-	43194.635	296.507	-	46754.073	308.855	-	43038.018	296.577
Two-way cluster plant state-year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

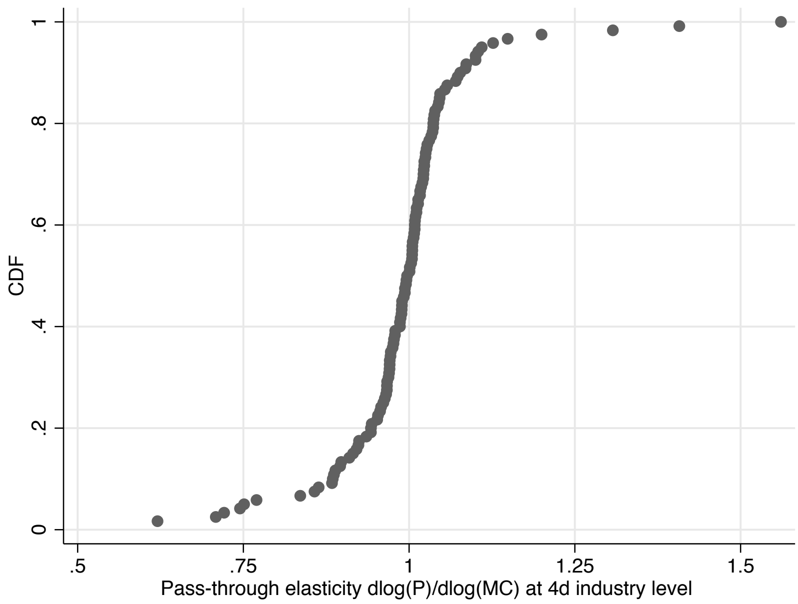
Table 20: Electricity prices and productivity (TFP): alternative methodologies

	log(TFP) (Olley and Pakes, 1996)			log(TFP) (Levinsohn and Petrin, 2003)			log(TFP) (Ackerberg et al., 2015)		
	OLS	IV^A	IV^B	OLS	IV^A	IV^B	OLS	IV^A	IV^B
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(P^E)$	-0.00735***	-0.0273***	-0.0387***	-0.000566	-0.0168***	-0.0321***	-0.00414**	-0.00761***	-0.0233***
	(0.002)	(0.004)	(0.005)	(0.002)	(0.004)	(0.007)	(0.002)	(0.003)	(0.006)
OLS/IV	OLS	IV^A	IV^B	OLS	IV^A	IV^B	OLS	IV^A	IV^B
Observations	378824	378824	378824	477697	477697	477697	477697	477697	477697
Ind-region-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First stage coef.	-	0.98***	0.06***	-	0.97***	0.06***	-	0.97***	0.06***
First stage SE	-	0.004	0.003	-	0.005	0.003	-	0.005	0.003
F-stat (Kleib.-Paap)	-	51023.623	390.549	-	44391.045	297.573	-	44391.045	297.573
Two-way cluster plant state-year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: See Table 2 for notes. The main difference is that different methods to recover TFP are used, and TFP used as dependent variable.

L Pass-through elasticities and incidence on consumers over time for aggregated industries

Figure 28: The distribution of pass-through elasticities

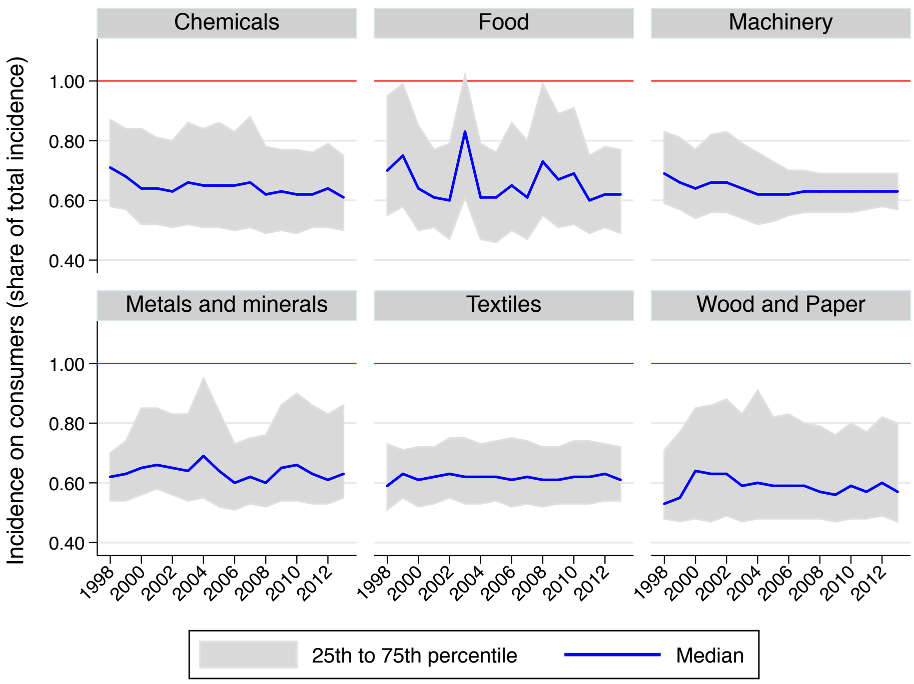


Notes: The figure plots the cumulative distribution function of the pass-through elasticities ($d\log(P)/d\log(MC)$). The pass-through elasticities vary at the 4-digit industry level: there are 121 different pass-through elasticities. The pass-through elasticities are the coefficient on a regression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

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

Notes above table.

Figure 29: Share of incidence on consumers from electricity price changes



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

M Holm-Bonferroni q-values for multiple hypothesis testing

Table 21 applies the Holm (1979) Bonferroni correction to the p-values to adjust for multiple hypothesis testing.

Table 21: 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)	0.366	8.5e-16***	1.8e-14***	-0.239	6.9e-04***	0.0041***	-0.776	5.3e-13***	6.4e-12***
Output (log)	-0.027	0.718	1	-0.743	2.7e-07***	2.7e-06***	-1.597	3.7e-23***	5.6e-22***
Electricity consumption (log)	-0.385	3.1e-09***	6.2e-08***	-0.479	0.0021***	0.0103**	-0.797	1.2e-07***	6.1e-07***
Profits	-4.952	0.0012***	0.0153**	-20.634	5.3e-10***	6.4e-09***	-22.429	4.7e-08***	2.8e-07***
Total revenues	-30.182	7.1e-04***	0.0113**	-132.586	5.2e-11***	7.2e-10***	-139.858	1.1e-10***	1.3e-09***
Avg. variable costs (AVC)	-24.118	0.0012***	0.0153**	-109.134	1.1e-10***	1.4e-09***	-114.291	1.5e-10***	1.4e-09***
Electricity share in fuel expenditure	0.025	7.0e-05***	0.0013***	0.014	0.265	0.53	-0.023	0.241	0.241
Other fuels' share in output	0.004	8.6e-04***	0.013**	0.014	1.2e-11***	1.7e-10***	0.023	6.3e-16***	8.2e-15***
Ratio electricity to coal quantity	-10.203	0.0011***	0.015**	-17.542	0.0026***	0.0103**	-21.836	0.0778*	0.156
TFP (log)	-0.007	0.0031***	0.0339**	-0.016	5.0e-06***	4.5e-05***	-0.033	2.9e-07***	1.1e-06***
Investment in machinery (IHS)	0.162	0.428	1	-0.846	0.0305**	0.0916*	-2.877	1.8e-10***	1.4e-09***
Price marginal cost markup log(μ)	-0.018	0.0035***	0.035**	-0.040	3.9e-04***	0.0028***	-0.106	3.4e-08***	2.4e-07***
Employees (log)	0.012	0.771	1	-0.339	1.1e-05***	8.7e-05***	-0.518	1.3e-10***	1.3e-09***
Ratio machinery to employees (log)	-0.160	0.0138**	0.102	-0.627	5.3e-08***	5.9e-07***	-1.517	8.3e-22***	1.2e-20***
Number of products (log)	0.046	1.8e-04***	0.0032***	-0.003	0.9	0.9	-0.096	0.0078***	0.0234**
Independent variable: log(coal price)									
Coal productivity (log)	0.846	0***	0***	1.487	1.5e-15***	1.2e-14***	1.612	2.1e-13***	1.7e-12***
Output (log)	0.090	0.0036***	0.035**	-0.300	0.226	0.903	-0.135	0.694	1
Coal consumption (log)	-0.756	0***	0***	-1.843	4.2e-11***	3.0e-10***	-1.796	3.9e-06***	2.7e-05***
Electricity consumption (log)	-0.041	0.246	1	-0.426	0.114	0.685	0.734	0.0873*	0.524
Profits	-5.917	3.0e-04***	0.0051***	-5.745	0.703	1	-7.108	0.784	1
Total revenues	-19.988	0.0127**	0.102	-18.739	0.827	1	-0.843	0.995	1
Avg. variable costs (AVC)	-14.357	0.0297**	0.178	-27.758	0.695	1	4.644	0.964	1
TFP (log)	-0.001	0.764	1	-0.020	0.124	0.685	-0.031	0.128	0.642

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