Blackouts: The role of India's wholesale electricity market

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Abstract

Blackouts impose substantial costs on electricity consumers in developing countries. We advance a new explanation for their continued prevalence in India, the world's third-largest power sector: unlike in the developed world, utilities' wholesale electricity demand is downward-sloping. We construct a novel dataset on power plant operations and demand. Instrumenting for cost with plausibly exogenous power plant equipment outages, we estimate a wholesale demand elasticity of -0.43. As a result, any increase in procurement costs will reduce the amount of electricity retail customers receive. Wholesale market simulations suggest that lowering procurement costs could eliminate blackouts for millions of Indian households.

Keywords: Wholesale electricity demand; Blackouts; Electricity supply; India
JEL Codes: L94, O13, Q41

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1 Introduction

Despite recent gains in electricity access, frequent blackouts remain ubiquitous in the developing world (Gertler, Lee, and Mobarak (2017)). Unreliable power supply reduces firm productivity (Allcott, Collard-Wexler, and O'Connell (2016); Cole et al. (2018); Fried and Lagakos (2023)), increases production costs (Steinbuks and Foster (2010); Fisher-Vanden, Mansur, and Wang (2015)), and lowers household income (Burlando (2014)). Previous research has attributed blackouts to limited electricity generating capacity (Dzansi et al. (2021)) or poor distribution infrastructure (McRae (2015); Carranza and Meeks (2021)).

This paper demonstrates a new mechanism for the prevalence of these blackouts, which arises from the upstream wholesale electricity sector. Utilities in developing countries may be price-sensitive, purchasing less electricity when wholesale procurement costs are high. This contrasts with the developed world, where strictly enforced regulatory mandates require utilities to satisfy all retail electricity demand regardless of cost, and where blackouts are rare. In high-income countries, higher wholesale electricity prices lead to higher retail prices but not blackouts. In contrast, when wholesale electricity procurement costs rise in developing countries, the amount of power that distribution utilities purchase may fall.[1] Since electricity storage is cost-prohibitive, this leads to blackouts for retail consumers.

We empirically demonstrate the importance of this mechanism in India, which is home to the world's third-largest power sector (Zhang (2019)). India has frequent blackouts despite a surplus of generating capacity (Bhattacharya and Patel (2008); Ryan (2021)). According to a recent industry report, the size of the Indian diesel backup generator market was approximately $1.5 billion in 2022, reflecting the high economic cost of power outages (Renub Research (2023)).[2]

1. Retail prices are typically set via cost-of-service regulation, and thus all "reasonable" costs are supposed to be passed through to consumers (Parliament of India (2003)). In practice, regulators are less likely to allow pass-through of high *ex post* cost realizations (Borenstein, Busse, and Kellogg (2012); Jha (2022)). As a result, regulated utilities are still likely to be sensitive to changes in wholesale procurement costs.

2. In addition to the costs of purchasing generators, households and firms also spend resources to op-

We digitize novel data on power plant operations and electricity demand, which cover the vast majority of India's wholesale electricity sector. We use these data to estimate the short-run elasticity of wholesale demand with respect to production costs, instrumenting with a plausibly exogenous cost shifter: the rate of equipment-related outages at power plants.[3] We show that equipment outages are uncorrelated with electricity demand shifters, suggesting that this instrument satisfies the exclusion restriction. We estimate a cost elasticity of demand of -0.43. By contrast, regulatory mandates force this short-run elasticity to be virtually zero in the developed world. Our results show that Indian utilities purchase substantially less electricity when wholesale procurement costs increase—causing blackouts for downstream retail consumers.

We simulate India's wholesale power sector to assess how three hypothetical approaches to reducing procurement costs might increase the equilibrium quantity of electricity supplied: (i) improving India's power plant thermal efficiency to U.S. levels (addressing the issues raised in Chan, Cropper, and Malik (2014)); (ii) reducing plant outage rates to U.S. levels; and (iii) accelerating the construction of new low-cost Ultra Mega Power Plants (following plans outlined in Ministry of Power (2021)). We find that these scenarios would increase the quantity of power that reaches retail consumers on the average day by 57.5 GWh, 36.4 GWh, and 25.7 GWh, respectively. As a point of reference, these increases in power supply would be sufficient to eliminate blackouts for 123.7, 78.3, and 55.4 million Indian households, respectively.[4] While these scenarios may not correspond to reforms that are fully feasible in practice, our simulations highlight the importance of downward-sloping demand in India's wholesale power sector. We show that wholesale procurement costs are directly linked to blackouts in India, and thus policies that reduce electricity production costs have the

erate them. Generator fuel costs are approximately Rs. 18/kWh for households (Sargsyan et al. (2011)), substantially larger than domestic retail tariffs, which ranged from Rs. 0.75–6.37 per kWh in 2021 (Central Electricity Authority (2021)).

3. Throughout this paper, we use "blackouts" to refer to electricity shutoffs experienced by retail consumers, and "outages" to refer to unavailable generating capacity at power plants.

4. To arrive at this calculation, we note that the average Indian household in 2017 consumed roughly 2.8 kWh/day and faced 3.4 hours/day of blackouts (Agrawal et al. (2020)).

substantial additional benefit of improving electricity reliability for households and firms.

This paper make three main contributions. First, we add to the literature on electricity reliability in developing countries. Prior research has documented that blackouts impose significant economic costs on households and firms (Gertler, Lee, and Mobarak (2017)). A small literature documents the role of the retail electricity sector in blackouts: Dzansi et al. (2021), Jack and Smith (2020), and Burgess et al. (2020) argue that bill non-payment and regulated retail prices set below marginal cost lead utilities to ration power supply. We contribute to this literature by demonstrating that Indian wholesale electricity demand is downward-sloping, unlike in developed countries where regulatory mandates ensure that short-run wholesale demand is perfectly inelastic (Mansur (2008)).[5] To our knowledge, this is the first paper to highlight the role of the wholesale electricity sector in blackouts.

Second, we contribute to a rich literature studying wholesale electricity markets, which has largely focused on developed countries. Previous work has highlighted mechanisms for reducing wholesale procurement costs, such as improved financial trading (e.g., Jha and Wolak (2023); Mercadal (2022)), market power mitigation (e.g., Bushnell, Mansur, and Saravia (2008); Kellogg and Reguant (2021)), and transmission capacity expansions (e.g., Borenstein and Bushnell (2000); Davis and Hausman (2016)). However, since wholesale demand in high-income countries is perfectly inelastic, this literature has overwhelmingly focused on the effects of these supply-side interventions on retail prices and productive efficiency. In the Indian context, Ryan (2021) shows that expanding transmission capacity increases the competitiveness of the Indian Energy Exchange, where roughly 2% of electricity is sold. We contribute to this literature by demonstrating that demand in the full wholesale electricity sector slopes down, providing the first link between wholesale procurement costs and power quality.

5. While forward electricity markets in high-income countries can exhibit downward-sloping demand, regulatory mandates, a lack of storage, and extremely limited demand response ensure that *real-time* electricity demand is (almost) perfectly inelastic. We show that real-time electricity demand is downward-sloping in India, which lacks any such regulatory mandate.

Third, we build on a literature in development economics on the importance of market features that are specific to low-income countries. Credit constraints (Berkouwer and Dean (2022)), corruption (Duflo et al. (2013)), and intra-household bargaining challenges (Jack et al. (2023)) can all limit the effectiveness of environmental regulations and energy-related technologies when implemented in developing countries.[6] We demonstrate that absent a regulatory mandate that all retail demand is satisfied—a ubiquitous feature of wholesale electricity sectors in high-income countries—wholesale demand in India is downward-sloping. Therefore, unlike in high-income countries, where blackouts are avoided through (costly) mandates, we show that reforms that result in reductions in wholesale procurement costs could meaningfully improve reliability in India.

The paper proceeds as follows. Section 2 presents key institutional features of India's electricity sector and discusses our data. Section 3 outlines our empirical strategy and presents our econometric results, demonstrating that wholesale electricity demand in India is downward-sloping. Section 4 simulates hypothetical electricity market reforms in order to assess the economic importance of our estimated demand elasticity. Section 5 concludes.

2 Background and data

This section discusses electricity supply in India, and the data used in our analysis. We focus on the wholesale sector, where suppliers own power plants and sell electricity to distribution utilities. In the retail sector, distribution utilities sell electricity to end-use consumers.

6. Outside of the energy/environmental domain, technologies and institutions that have proven effective in the developed world—such as fertilizer (Duflo, Kremer, and Robinson (2011)), schools (Duflo and Banerjee (2006)), and insurance (Cole et al. (2013))—can fail in developing countries absent complementary policies.

2.1 Wholesale electricity demand

Electricity distribution utilities ("discoms") purchase most of the electricity sold by Indian power plants. Utilities resell electricity to consumers at prices set by state or federal regulatory commissions. These retail prices are regulated to ensure affordable power for residential consumers, and they are typically too low for utilities to recover the costs of purchasing and distributing electricity. Low bill payment rates compound this cost-recovery problem (Gaur and Gupta (2016)). As a result, most utilities need government subsidies to remain financially solvent (Burgess et al. (2020)). Even with these subsidies, utilities in many states do not earn positive profits (Pargal and Banerjee (2014); Central Electricity Regulatory Commission (2018b)).

Utilities respond to these financial difficulties by choosing not to satisfy electricity demand in all hours and locations. Rolling blackouts (often called "load shedding") are common across the country. Since regulated retail rates are fixed and electricity storage is not yet cost-effective, short-run changes in retail electricity provision primarily reflect variation in the amount of wholesale electricity utilities choose to purchase (Central Electricity Authority (2018)). In Section 3.2, we demonstrate that utilities choose to purchase less power when procurement costs increase (i.e., that wholesale electricity demand in India is downward-sloping).

The Power System Operation Corporation (POSOCO) operates the national electricity transmission grid. Since electricity is largely nonstorable, POSOCO must balance the levels of supply and demand across locations on the grid, while respecting numerous plant operating and transmission capacity constraints. Our empirical analysis uses POSOCO data on the quantity of wholesale electricity purchased by utilities at the state-day level.

We also collect data from the Central Electricity Authority (CEA)'s *Monthly Power Supply Position Reports* on each state's *ex ante* forecasted energy requirement (following Allcott, Collard-Wexler, and O'Connell (2016)). These state-month demand forecasts reflect what utilities would choose to purchase given their existing contract portfolios.

2.2 Long-term contracts and the short-term exchange

Nearly 90% of India's electricity is sold via long-term contracts between electricity producers and utilities. The typical contract specifies a set of electricity generating units, the share of each unit's capacity to be dedicated exclusively to the buyer, each unit's "plant load factor": the expected annual output from the unit's contracted capacity as a share of total potential output, and a price. Contract prices are set by a regulator based on their assessment of the plant's fixed and variable costs. Utilities pay plants both for being available (regardless of whether they generate) and for producing (paid per kWh of generation). Unlike electricity markets in most developed countries, financial trading of contracted positions has—until recently—been prohibited.[7] This means that owners of contracted plants cannot pay lower-cost plants to generate in their stead, preventing any short-run reallocation of production that would lower procurement costs.

Short-term transactions make up the remaining 10% of Indian electricity sales. Approximately 5% of all electricity is traded on short-term bilateral contracts with a duration of less than 1 year. 2% of power is traded on the Indian Electricity Exchange (IEX), a day-ahead power market that clears 24 hours before power delivery.[8]

7. Following a regulatory change in July 2020 (after our 2013–19 sample period), nascent financial instruments have been created with the goal of introducing risk hedging and flexibility in long-term contracts. However, the market remains very thin, with traded volumes representing just 1% of total generation as of April 2021 (Garg (2021)).

8. A second day-ahead market, Power Exchange India (PXIL), contributes less than 0.25% of electricity sales (Central Electricity Regulatory Commission (2019)). IEX and PXIL prices are nearly perfectly correlated (Ryan (2021)). Remaining real-time imbalances between supply and demand are resolved through the "deviation settlement mechanism," which provides small financial incentives to make minor generation adjustments to stabilize the frequency of grid.

2.3 Electricity generation

We collect data on daily generation and production capacity at power plants, using the CEA's *Daily Generation Reports* from 2013 to 2019. These reports cover all utility-scale fossil, hydroelectric, and nuclear plants in India.[9] Our plant-day panel includes 508 plants, representing 301 GW of India's 383 GW of generating capacity, with aggregate production of 3.05 TWh per day. The top left panel of Figure 1 plots daily total generation by source type; 205 coal-fired plants contribute the vast majority of output, with the remainder coming primarily from hydro sources. The top right panel maps the locations of power plants across India's five transmission regions: North, Northeast, East, West, and South.

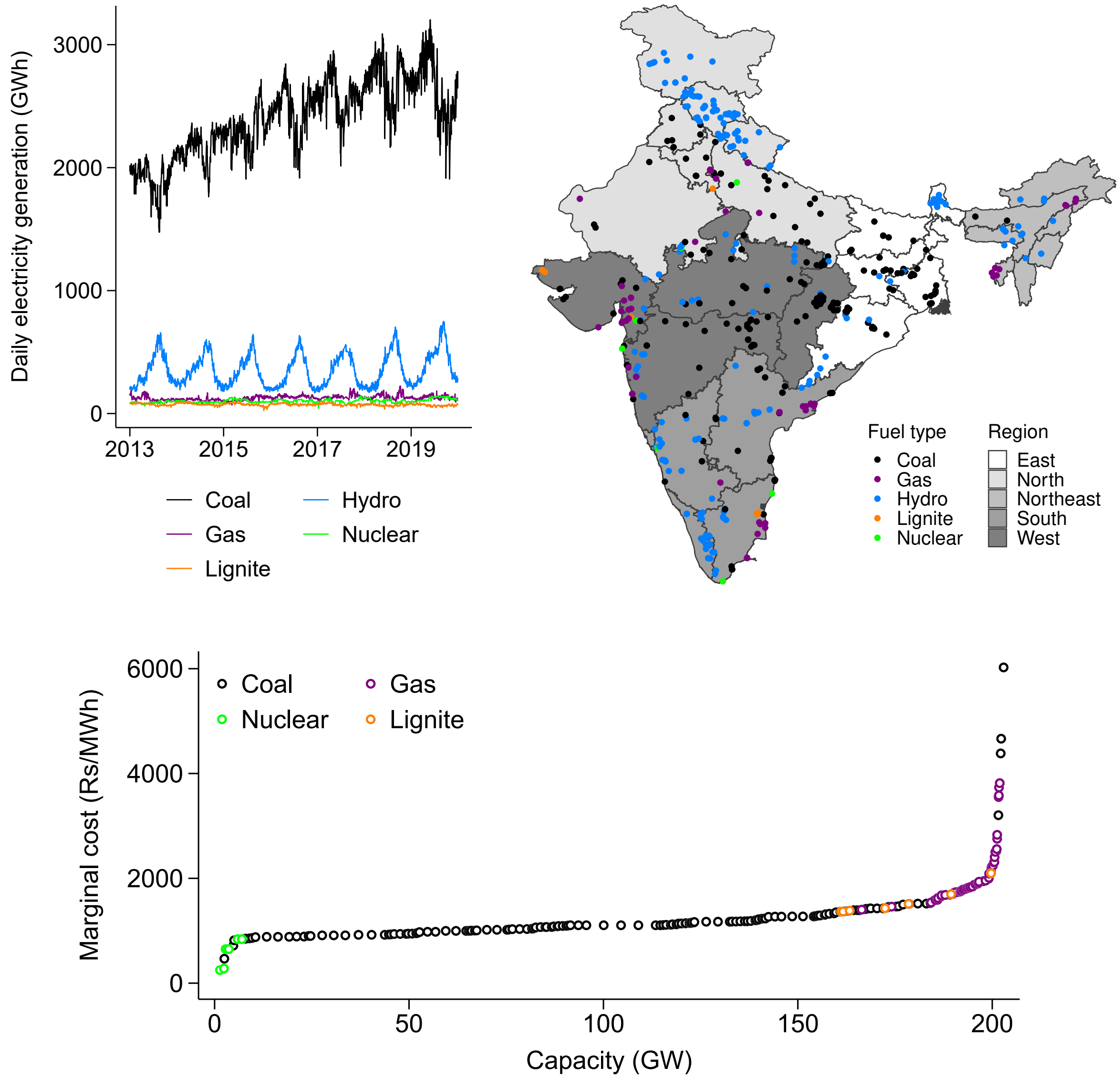
We construct marginal costs over time for each plant in our sample. Following the economics literature on electricity production, we assume that a plant's marginal cost does not vary with its level of output (e.g., Borenstein, Bushnell, and Wolak (2002); Mansur (2008); Clay et al. (2021)). For coal plants, we start with minemouth coal prices , reported aperiodically by coal suppliers, and add rail freight costs based on the shortest path along India's rail network (following Preonas (2023)), as well as royalties and other taxes. We convert these prices to costs per unit of electricity output using plant-level data on coal consumption and thermal efficiency (i.e., heat input divided by electricity output).[10]

Indian coal plants have systematically lower thermal efficiency—and therefore higher costs per kWh produced—than U.S. coal plants of similar vintage and capacity (Chan, Cropper, and Malik (2014)). As one strategy for lowering power generation costs, the Ministry of Power launched its Ultra Mega Power Projects (UMPPs) program in 2005.

9. Wind and solar resources fall instead under the Ministry of Renewable Energy. To our knowledge, there is no publicly available dataset on daily generation from non-hydro renewables, which comprised 9.2% (5.5%) of India's total generation in 2018–19 (2014–15) (Central Electricity Authority (2019)).

10. We thank the authors of Chan, Cropper, and Malik (2014) for sharing data on plant-level thermal efficiency, which we use to supplement the CEA's *Annual Performance Reviews of Thermal Power Stations*. Coal consumption data come from the CEA's *Daily Coal Reports*, and we infer each plant's coal grade. Appendix B.1 details on how we construct our panel of plant-specific marginal costs, and compares our constructed costs to the plant-specific variable costs reported by the Ministry of Power. We inflation-adjust to constant 2016 rupees using the monthly consumer price index for all items for India reported by the Organization for Economic Co-operation and Development.

Figure 1: Electricity generation in India



Notes: This figure presents key summary statistics of Indian electricity production. The top left panel plots daily total electricity production across plants of each fuel type, using daily unit-level data from January 1, 2013 through December 31, 2019 from the Central Electricity Authority's Daily Generation Reports. In aggregate, the 508 plants in these data produce 3.05 TWh of electricity per day on average. Averages of daily aggregate output by fuel type are: 2.40 TWh for 205 coal plants, 354 GWh for 204 hydroelectric plants, 127 GWh for 65 gas plants, 94 GWh for 7 nuclear plants, 69 GWh for 9 lignite plants, and 6 GWh for the 18 diesel plants (omitted here). The top right panel maps the location of these plants in India, as well as the five major transmission regions. The bottom panel presents the merit order of Indian thermal electricity generating capacity, ranking plants from lowest to highest marginal cost. Each dot represents a single plant for which we can construct marginal cost estimates. While our main constructed cost measures are time-varying (e.g., due to changing fuel prices), this figure plots the sample-average marginal cost for each plant. We omit the 18 diesel plants and 56 plants for which we lack data to estimate marginal costs (47 coal, 7 gas, and 2 lignite). The exchange rate is roughly 60 Indian rupees to 1 US dollar.

This initiative sought to bring about the construction of large (4,000 MW), highly-efficient coal power plants. However, construction of these UMPPs has largely stalled, due in part to contract re-negotiations that took place after contracts were awarded to developers, but before the plants were built (Ryan (2020)).[11]

For natural gas plants, we perform an analogous calculation using gas price data from the Ministry of Petroleum and Natural Gas. For nuclear plants, we simply use the marginal costs reported in regulatory tariff documents (described in Srinivasan (2007)). The bottom panel of Figure 1 ranks thermal power plants from lowest to highest marginal cost, plotting marginal costs as a function of cumulative capacity. Nuclear plants tend to have the lowest marginal costs, followed by coal, lignite, and gas plants.[12]

2.4 Power plant outages

The CEA's *Daily Outage Reports* publish the amount of capacity under outage for each plant-day. On the average day between 2013–2019, 21% of thermal generating capacity was under outage and therefore unavailable to generate.[13] As a point of comparison, the capacity-weighted outage factor across coal-fired power plants in the United States and Canada was roughly 5% during this time period.[14]

Regulators require plant managers to state a reason for going on outage. The CEA's

11. The government originally envisioned the construction of fifteen UMPPs (Ministry of Power (2021)). As of 2024, four contracts have been awarded and two–Sasan UMPP in Madhya Praesh and Mundra UMPP in Gujarat–have been built and are producing electricity.

12. We omit hydroelectric plants since dams face complex dynamic optimization problems: today's output may constrain future output due to a finite supply of water (Archsmith (2023)). Non-dispatchable run-of-river hydro (along with wind and solar) enters the supply curve at (virtually) zero marginal cost.

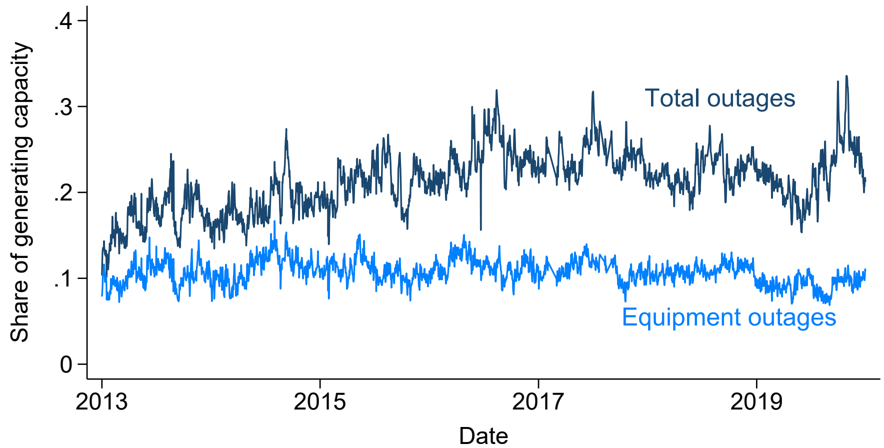
13. This does not include outages due to scheduled plant maintenance, which impacts up to 8% of thermal capacity each day.

14. Annual capacity-weighted forced outage factors (WFOFs) come from the North American Electric Reliability Corporation:

$$\text{WFOF} = \frac{\sum_{\text{gen. units}} \text{forced outage hours} \times \text{capacity}}{\sum_{\text{gen. units}} \text{potential hours} \times \text{capacity}}$$

where "potential hours" reflects the number of hours in the year after the unit first came online. As with our treatment of outages for India, "forced outage hours" does not include scheduled plant maintenance.

Figure 2: Daily aggregate outage rates across Indian thermal power plants



Notes: This figure reports the share of total thermal power plant capacity that was on outage (i.e., unavailable to generate) on each day in our sample. The top line reports all forced outages (i.e., removing outages due to scheduled maintenance). The bottom line reports all equipment-related outages, which we classify using the CEA's *Daily Outage Reports*. The denominator for both time series is total thermal capacity.

Daily Outage Reports list these reasons, which we string parse to isolate the subset of outages caused by equipment failures.[15] Equipment outages are the most common type of outage, affecting roughly 10% of India's thermal generating capacity on the average day. Figure 2 plots the time series of total outages and equipment outages, each as a share of total capacity.

3 Estimating the elasticity of wholesale demand

3.1 Using equipment outages as an instrument

To estimate the elasticity of Indian wholesale electricity demand, we require an exogenous supply shifter that affects procurement costs but is unrelated to demand. Equipment outages are one such supply shifter, since they are related to technical failures on site that are likely

15. Common equipment outage reasons include are "water wall tube leakage", "super heater tube leakage", "ash handling system problems", and "furnace fire out/flame abnormal." Note that these equipment outages are distinct from from equipment-related maintenance, which is typically planned.

Table 1: Equipment outage rates do not respond to electricity demand shocks

	Outcome: Share of plant's capacity on equipment outage			
	(1)	(2)	(3)	(4)
Mean monthly temperature in state (°C)	−0.0012	−0.0012	0.0004	0.0011
	(0.0010)	(0.0010)	(0.0017)	(0.0015)
log (State's forcasted energy requirement)		−0.0011	−0.0092	−0.0127
		(0.0113)	(0.0191)	(0.0148)
Split sample for high/low marginal cost plants			Low MC	High MC
Plant + month-of-sample FEs	Yes	Yes	Yes	Yes
Region × year, region × month FEs	Yes	Yes	Yes	Yes
Mean of dep. var.	0.1135	0.1135	0.1307	0.0735
Plant-month observations	19,420	19,420	7,935	7,430

Notes: This table presents results from estimating Equation (1). The dependent variable is plant i's monthly equipment outage rate (i.e. the daily share of its total capacity on equipment outage, averaged over all days in sample month m). We average daily mean temperature across space in state s and across days in month m. All regressions control for the total number of dispatchable plants in each state, to account for differential market expansions across states. Columns (3)–(4) split the sample on plants with below- vs. above-median marginal costs, which drops the 32% of plants where we cannot populate marginal costs per kWh. Standard errors are clustered by sample month. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

outside of plants' immediate control. Most equipment outages last less than 3 days, and 84% of plants reported at least one equipment outage during our sample period (see Appendix Figure B.2). These short-run disruptions to plants' availability likely increase utilities' costs of procuring wholesale electricity.

We argue that equipment outages are exogenous with respect to wholesale demand, since they are caused by technical failures rather than market conditions. As a test of exogeneity, we show that equipment outages are not correlated with two key demand-side factors—temperature and forecasted demand—by estimating the following regression at the plant-month level:

$$[\text{Equip. outage rate}]_{isrt} = \beta_1[\text{Temp. (°C)}]_{srt} + \beta_2 \log\big([\text{Energy req}]_{srt}\big) + \alpha_i + \delta_{rt} + \varepsilon_{isrt} \quad (1)$$

The outcome variable is the average share of plant i's capacity that is on equipment outage across all days in sample month t. The coefficient β_1 captures the effect of mean daily temperature in state s, which belongs to electricity transmission region r, in month t. The coefficient β_2 captures the effect of the forecasted energy requirement (in GWh) for state s in month t. We include plant fixed effects (α_i) as well as sample month, region-by-year, and region-by-calendar-month fixed effects (δ_{rt}); we cluster standard errors by sample month. Table 1 demonstrates that equipment outages do not systematically respond to either temperature or forecasted demand, and we can reject even moderate changes in equipment outage rates in response to these demand shifters.[16]

3.2 The elasticity of demand

Next, we present empirical evidence that wholesale electricity demand falls when procurement costs rise. We first show that equilibrium quantity demanded falls as the equipment outage rate rises. All else equal, we expect equipment failures to weakly increase the variable costs of meeting wholesale demand, leading to decreases in quantity demanded if utility demand is indeed downward-sloping.

We begin with the following reduced-form test of the relationship between equipment outages and quantity demanded:

$$\log\big([\text{Quantity}]_{srt}\big) \;=\; \beta[\text{Equip. outage rate}]_{srt} \;+\; \alpha_s \;+\; \psi_t \;+\; \delta_{rt} \;+\; \varepsilon_{srt} \qquad (2)$$

The outcome variable is the natural logarithm of electricity purchased by utilities in state s, in transmission region r, on date-of-sample t. This corresponds directly to the amount of electricity received by retail consumers, net of transmission and distribution losses. Our independent variable of interest is the daily equipment outage rate, which is uncorrelated with short-run demand shifters (see Table 1) and therefore plausibly exogenous. β captures

16. In Columns (1)–(2), we use the full sample of plants. In Columns (3)–(4), we split the sample to include only plants with below- vs. above-median marginal costs, which yields similar estimates that are not distinguishable from zero. The fact that low-marginal-cost plants are not more responsive than high-marginal-cost plants further suggests that equipment outages are not strategically arranged by suppliers.

the causal effect of short-run changes in the equipment outage rate, aggregated across all observed thermal generating capacity in state s, on quantity. Day-of-sample fixed effects ψ_t account for common shocks and interregional spillovers, while state fixed effects α_s account for persistent differences across states. We also include region-by-year and region-by-month fixed effects (in δ_{rt}) to control for region-specific trends and seasonality in demand. We cluster standard errors by month-of-sample.

The first two columns of Table 2 report these reduced-form results. In Column (1), we find that a 10 pp increase in a state's equipment outage rate causes energy demanded to decrease by 0.9% on average (statistically significant at the 1% level). However, a lack of available generating capacity could be driving this reduction, if equipment outages render utilities unable to purchase the quantity of electricity they desire.[17] Column (2) restricts the sample to only state-days with idle capacity—that is, days in which some plants located in state s did not produce despite having been available.[18] This yields an even larger point estimate that is also statistically significant at the 1% level.

These results provide strong evidence that utilities purchase less power when more of their state's generating capacity goes on equipment outage. Our point estimate in Column (2) implies that a 7 pp (1 standard deviation) increase in the equipment outage rate causes a 1.26 GWh (0.8%) average reduction in quantity—despite the fact that roughly 1.14 GW of idle-but-available capacity could have produced 27.44 GWh on the average state-day.

Next, we estimate the short-run cost elasticity of wholesale demand, using two-stage least squares and instrumenting for the cost of electricity generation with the equipment outage rate. The exclusion restriction requires that variation in equipment outages only affects quantity through its effect on procurement costs. This is plausible given that equip-

17. While some developing countries lack the generating capacity to replace the output lost due to plant outages (e.g., Ghana's "Dumsor" power crisis described in Dzansi et al. (2021)), there is often idle generating capacity available in India to buffer against unanticipated plant outages.

18. This restriction keeps state-days with idle *thermal* capacity. For some state-days, the only idle dispatchable capacity might be hydroelectric. Due to the complex dynamic constraints inherent to hydro production, we cannot identify whether idle hydro capacity could have been dispatched on a given day.

Table 2: Wholesale demand is downward-sloping

	Outcome: log (Quantity)			
	(1) OLS	(2) OLS	(3) IV	(4) IV
Equipment outage rate	−0.09***	−0.12**		
	(0.03)	(0.05)		
log (Average variable cost)			−0.49**	
			(0.21)	
log (95th percentile of marginal cost)				−0.25**
				(0.10)
Idle capacity available		Yes		
State + date FEs	Yes	Yes	Yes	Yes
Region × year, region × month FEs	Yes	Yes	Yes	Yes
Mean demand met (in GWh)	90.25	150.29	90.25	90.25
State-day observations	42,212	13,721	42,212	42,212
First-stage estimate			0.18***	0.35***
			(0.03)	(0.06)
Kleibergen-Paap F-statistic			30.66	40.58
Mean of equipment outage rate	0.10	0.09	0.10	0.10
SD of equipment outage rate	0.09	0.07	0.09	0.09
Mean potential GWh from idle capacity	8.97	27.44	8.97	8.97

Notes: This table presents results from estimating Equation (2). The dependent variable is the natural logarithm of total GWh of energy purchased by utilities in state s on date t (i.e. the quantity of wholesale electricity demand). Columns (1)–(2) are reduced-form regressions, where the independent variable is equipment outage rate at the state-day level. Columns (3)–(4) use two-stage least squares to estimate the elasticity of demand with respect to average variable cost of generation (Column (3)) and marginal cost of generation (Column (4)), instrumenting for costs using the equipment outage rate. We use the 95th percentile of marginal cost because this yields a stronger first stage than using the maximum marginal cost. Column (2) restricts the sample to observations where state s has excess generating capacity on day t (i.e. idle capacity not on outage, which could have generated). All regressions control for daily average temperatures (for precision), and the total number of dispatchable plants in state s (to account for differential market expansions across states). We drop the 2% of observations where our cost and outage data cover less than 50% of total generating capacity (thermal + hydro) in that state-day cell. Standard errors are clustered by sample month. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. The bottom row multiplies the average MW of idle capacity by 24/1000 to provide an upper bound on the maximum amount of energy (in GWh) that could have been produced by available capacity that presumably stood ready to generate, but was not called.

ment outages are uncorrelated with demand shocks (see Table 1). Since both wholesale contract prices and retail tariffs are set via cost-of-service regulation, we estimate demand elasticities with respect to the average variable cost of production. As a robustness check, we also use the 95^{th} percentile of marginal costs across operating plants in the state-day.[19]

19. We use the 95^{th} percentile instead of the maximum due to potential measurement error in marginal

Columns (3)–(4) of Table 2 estimate a two-stage least squares version of Equation (2), which has a strong first stage: a 10 pp increase in the equipment outage rate causes average variable costs to rise by 1.8% (significant at the 1% level). We estimate a wholesale demand elasticity of -0.49 with respect to average variable cost (Column (3); significant at the 5% level). We also estimate a demand elasticity of -0.25 with respect to marginal cost (Column (4); significant at the 5% level). These estimates reinforce that higher procurement costs lead Indian utilities to choose to supply less electricity to end-users.

Finally, we note that our demand elasticity estimates come from the full wholesale power sector, rather than the 2% subset of wholesale electricity sold on the IEX day-ahead market studied in Ryan (2021). We can directly calculate the demand elasticity in this 2% segment of the sector. Appendix Figure A.1 plots the distribution of IEX demand elasticities at the market-clearing price, extracted from aggregate bid curves across 201,012 15-minute intervals. The mean IEX demand elasticity is -0.73, while the median is -0.30. This aligns with our estimates from Table 2, providing further evidence that wholesale demand is downward-sloping.[20]

4 Quantity impacts of hypothetical cost reductions

Having established that India's wholesale electricity demand is downward-sloping, we now investigate the impacts of a series of hypothetical supply-side interventions on the equilibrium quantity supplied to retail electricity consumers. We build and simulate a simple structural model of the wholesale electricity market, which allows us to assess the economic importance of downward-sloping demand on blackouts.

costs. Appendix Table A.1 shows that using the 98^{th} percentile or the maximum marginal cost yields a weaker first stage, likely owing to measurement error in our marginal cost data.

20. Appendix B.3 discusses the IEX market in further detail, and outlines how we digitize the IEX data and extract IEX demand elasticities.

Demand side We specify linear wholesale demand, setting a price elasticity of demand of -0.49 (Column (3) of Table 2) at the observed quantity demanded.[21] In our preferred estimates, we assume that utilities respond to average variable cost (rather than marginal cost), to align with the fact that both wholesale contract prices and downstream retail prices are cost-of-service regulated.[22] In both our main specification and robustness checks, our demand curve intersects the point defined by the observed quantity supplied and the relevant observed cost (average variable cost of production in the main specification, the 95^{th} percentile of marginal cost in robustness).

Supply side We clear the wholesale electricity market for each state-day by simulating power plant dispatch.[23] We stack all generating capacity that is available (i.e. not on outage) within each state from lowest to highest marginal cost. Then, we assume these aggregate marginal cost curves are equal to supply curves (i.e., "least-cost dispatch")—allowing us to simulate dispatch under alternate supply scenarios.

This assumption of least-cost dispatch is likely overly optimistic, as our simulations may dispatch plants that could not have generated in reality due to technical constraints (e.g., within-state transmission constraints as in Davis and Hausman (2016), or between-day ramping constraints as in Reguant (2014)). However, many low- and middle-income countries have systems where generating units are dispatched from lowest to highest marginal cost (e.g., Rudnick and Velasquez (2018); Gonzales, Ito, and Reguant (2023)), and this setup aligns with policy reforms that are currently under discussion in India (Central Electricity Regulatory Commission (2018b)). Therefore, our first hypothetical scenario (Table 3,

21. As robustness, Appendix Table A.3 presents the same analysis with constant elasticity demand.

22. As robustness, Appendix Table A.2 presents the same analysis with utilities responding to the 95^{th} percentile of marginal cost (using the elasticity -0.25 from Column (4) of Table 2). As we discuss above, using the 95^{th} percentile of marginal costs rather than the maximum of this distribution accommodates measurement error in our marginal cost variable.

23. Since it is challenging to ascertain the daily quantity of available cross-state transmission capacity, we clear the market for each state separately, conservatively assuming no interstate trade. By ignoring the potential benefits from reallocating output across states, we likely understate the increases in power supply that would result from wholesale cost decreases.

Column (1)) compares quantity supplied under least-cost dispatch versus observed dispatch.

We then assess the quantity impacts under least-cost dispatch of three additional hypothetical supply-side interventions. Each intervention would reduce wholesale electricity procurement costs in India in a different way.

First, we ask: what if the Indian coal-fired fleet was as thermally efficient as its U.S. counterpart? Following Chan, Cropper, and Malik (2014), we lower each Indian coal-fired power plant's marginal cost by 8% (the gap in efficiency between India and the U.S.).

Second, we ask: what if we reduced the outage rate of Indian coal-fired power plants to the U.S. rate of approximately 5%?[24] We reduce each coal plant's outage rate (excluding scheduled maintenance) to the U.S. rate on each sample day.

Third, we ask: what if the four UMPPs awarded to successful bidders between 2007 and 2009 (Ministry of Power (2021)) had come online by January 1, 2013 (i.e., the start of our sample period)? We add four coal-fired power plants into the supply curve, each with a capacity of 4,000 MW and marginal costs at the 25^{th} percentile of its respective state-day distribution.[25]

Results Table 3 presents the findings of this counterfactual exercise.[26] Column (1) compares (counterfactual) quantity supplied under least-cost dispatch to the (factual) observed quantity supplied. Our simulations suggest that if plants were dispatched within each state in order of lowest to highest cost, the corresponding decrease in average variable cost would

24. This is the annual capacity-weighted forced outage factor for the North American coal-fired fleet from the North American Electric Reliability Corporation (NERC) from 2013–2019. NERC's area of responsibility spans the continental U.S. Canada, and northern Baja California, Mexico (https://www.nerc.com/AboutNERC/Pages/default.aspx).

25. We take plant locations and capacities from Ministry of Power (2021). We choose the 25^{th} percentile of the state-month distribution of marginal cost to simulate low-cost plants while remaining conservative. One of the four UMPPs is included in our sample; we drop factual observations for this plant to avoid double counting its capacity.

26. As discussed above, Table 3 assumes that utilities respond to average variable cost. In Appendix Table A.2, we instead assume that utilities respond to marginal costs, and in Appendix Table A.3, we assume a constant-elasticity of demand of -0.49. In both cases, the results are broadly similar to our main estimates.

Table 3: Quantity impacts under alternative supply scenarios

Supply curve scenario:	(1) Least-cost dispatch (LC)	(2) LC + US efficiency	(3) LC + US outage rate	(4) LC + 4 new UMPPs
Quantity increase relative to observed dispatch (GWh/day)	43.2	43.2	43.2	43.2
Incremental quantity increase relative to LC (GWh/day)		57.5	36.4	25.7
Incremental HHs shifted to 24×7 power		123.7M	78.3M	55.4M

Notes: This table reports the daily average national-level quantity impacts of different hypothetical interventions to the supply side of the Indian wholesale electricity market. Column (1) reports the change in quantity supplied implied by switching from observed dispatch to dispatching plants from lowest-to-highest marginal cost within state/day. The first row is the same across all three incremental hypothetical supply-side interventions, each of which builds upon this "least-cost" scenario. The second row reports the incremental increase in quantity supplied under least-cost dispatch from: improving the thermal efficiency of Indian coal-fired plants to the average levels observed in the United States (following Chan, Cropper, and Malik (2014); Column (2)); reducing the forced outage rate of Indian coal-fired power plants to U.S. levels (Column (3)); and adding four 4,000 MW Ultra Mega Power Plants (UMPPs) with relatively low marginal costs to the supply curve (Column (4)). The bottom row reports the number of households that could be shifted to 24×7 power from each incremental increase in quantity supplied, assuming that Indian households currently face 3.4 hours per day of blackouts on average (Agrawal et al. (2020)). See text for further details.

cause price-responsive utilities to purchase an additional 43.2 GWh of electricity on the average day.

Columns (2)–(4) present three additional counterfactuals, each of which reduces wholesale procurement costs in a different way. Under our least-cost simulation, improving the efficiency of Indian coal plants to U.S. levels would translate to an incremental increase in quantity supplied of 57.5 GWh/day; reducing forced outages to U.S. levels would translate to an incremental 36.4 GWh/day; and building four low-cost UMPPs would translate to an incremental increase of 25.7 GWh/day.

Importantly, each of these scenarios would require expensive investments to improving or expanding India's existing fleet of coal plants. Our results do not capture the full economic costs and benefits of these hypothetical interventions. Nevertheless, our findings highlight the importance of considering downward-sloping demand when evaluating policies to reduce costs in India's wholesale power sector.

Interpretations: To what extent would an increase of 25.7–57.5 GWh/day improve power quality for Indian consumers? As one point of comparison, the average Indian household in 2017 consumed roughly 2.8 kWh/day and faced 3.4 hours/day of blackouts (Agrawal et al. (2020)). At this rate of hourly consumption, 25.7–57.5 additional GWh/day could provide 3.4 hours/day worth of electricity to 55.4–123.7 million households. In other words, the quantities reported in Table 4 would be sufficient to eliminate blackouts and achieve 24×7 power for 18–47% of all households in India.[27]

This exercise illustrates the economic importance of downward-sloping wholesale electricity demand. There are many opportunities to reduce wholesale electricity procurement costs in the Indian power market. Our findings demonstrate that any such supply-side reform would yield meaningful increases in the quantity of electricity supplied to retail customers. This would reduce the level of blackouts faced by households and firms, providing substantial economic benefits to end-users who currently rely on more expensive backup power technologies (e.g., backup diesel generators). While the scenarios in Table 3 would necessitate substantial changes to India's existing capital stock, more modest reductions in electricity production costs would still likely provide meaningful increases in the quantity of electricity supplied to Indian electricity consumers.

5 Conclusion

Developing countries have made substantial gains in electricity access, but frequent blackouts limit the welfare gains from electrification (Lee, Miguel, and Wolfram (2020); Burlig and Preonas (2024)). This paper argues that downward-sloping wholesale demand is an important contributor to blackouts in India. We construct a novel dataset on daily power plant operations spanning the sector, and use an instrumental variables framework to demonstrate

27. During this period, there were roughly 266 million households in India. In reality, households would not receive all of the increased power supply, since firms would also benefit from improved electricity reliability.

that utility buyers purchase substantially less electricity when wholesale procurement costs increase. Lowering wholesale procurement costs can therefore meaningfully increase the quantity of energy supplied to retail consumers, reducing blackouts.

Our results suggest that supply-side reforms that reduce electricity production costs will also reduce blackouts faced by retail consumers in India. We present evidence that improving thermal efficiency, reducing outages at power plants, and building new, low-cost plants will increase the quantity supplied to India's retail consumers thanks to downward-sloping wholesale demand. In addition to these hypothetical interventions, reforms such as the introduction of market-based dispatch (Central Electricity Regulatory Commission (2018a)) or financial instruments (Garg (2021)) could also be particularly beneficial.[28]

More broadly, our work highlights the need for more research on electricity markets in developing countries. These countries share many of the institutions of electricity markets in the developed world, such as cost-of-service regulation (e.g., Borenstein and Bushnell (2015); Cicala (2015)) and inefficient retail pricing (e.g., Holland and Mansur (2008)). However, we emphasize a key institutional difference between India and high-income countries: India lacks a mandate that utilities must satisfy all retail electricity demand. We demonstrate that, absent such a mandate, wholesale electricity demand in India is downward-sloping. Consequently, any assessment of the costs and benefits of supply-side reforms in the Indian electricity sector must account for the potential benefits associated with increases in equilibrium quantity supplied.

Finally, with the rapid growth of intermittent wind and solar production capacity around the world, utilities in both developed and developing countries are facing greater fluctuations in wholesale procurement costs. In response, many utilities are beginning to install smart meters, implement "real-time" pricing, and automated demand response programs designed to better communicate wholesale market price signals to retail electricity consumers (e.g.,

28. Wholesale power contracts in India are for physical delivery of electricity. Consequently, unlike in high-income countries, owners of contracted plants cannot pay lower-cost plants to generate in their stead, and utilities cannot purchase power from capacity that is contracted to a different buyer.

Wolak (2011); Bollinger and Hartmann (2019); Blonz et al. (2023); Meeks et al. (2023)). Such programs make wholesale electricity demand more elastic. The lessons from this paper are therefore becoming increasingly relevant as many countries shift away from polluting fossil-fuel electricity production towards clean but intermittent renewables.

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Blackouts: The role of India's wholesale electricity market

Supplementary appendix: For online publication

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Appendix A provides additional results and sensitivity analysis.

Appendix B provides further details on data sources and data construction.

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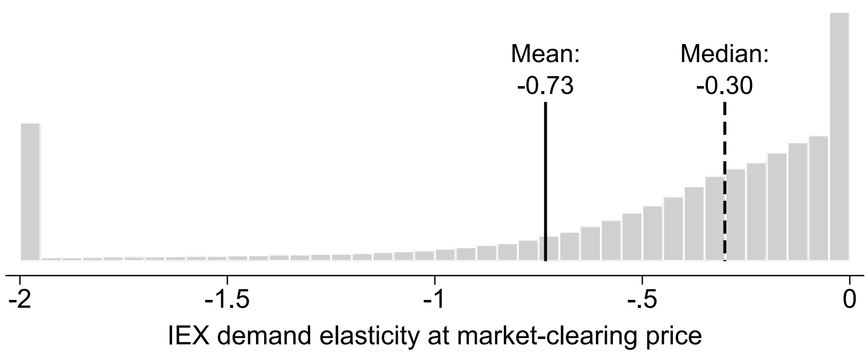
A Additional results and sensitivity analysis

A.1 Price elasticity of demand in the IEX

As discussed in the main text, Appendix Figure A.1 plots the elasticity of demand for electricity in the IEX at the market-clearing price over all 15-minute intervals in our sample. The mean elasticity in this market is -0.73, with a median of -0.30, reinforcing that demand for power in India's wholesale market is downward sloping.

Figure A.1: Histogram of observed demand elasticities in the IEX day-ahead market



Notes: We extract the elasticity of IEX demand from observed aggregate bid curves for 201,012 separate 15-minute intervals. We bottom-code this distribution at -2 for ease of presentation. The solid (dashed) line reports the mean (median) elasticity.

A.2 Robustness: Demand estimation

Table A.1 provides sensitivity analysis for our demand estimates in Table 2. Column (1) relaxes our preferred sample restriction, where we omit observations for which our state-day equipment ratio and average variable cost cover less than 50% of total thermal capacity. In the main text, we impose this restriction to account for the incompleteness of our plant-level outage and cost data: if less than 50% of capacity is represented in our right-hand-side variables, they might have a weaker relationship with state-level demand (which is an aggregate measure). However, we recover an even larger demand elasticity when we include these state-days in the regression.

Table A.1: Sensitivity for demand regressions

	Outcome: log (Quantity)			
	(1) IV	(2) IV	(3) IV	(4) IV
log (Average variable cost)	-0.50^{**}	-0.42^{**}		
	(0.21)	(0.19)		
log (98th percentile of marginal cost)			-0.41^{**}	
			(0.19)	
log (Maximum marginal cost)				-0.63
				(0.41)
Include state-days with < 50% coverage	Yes			
Idle capacity available		Yes		
State + date FEs	Yes	Yes	Yes	Yes
Region × year, region × month FEs	Yes	Yes	Yes	Yes
Mean demand met (in GWh)	88.70	150.29	88.70	88.70
State-day observations	43,044	13,721	43,044	43,044
First-stage estimate	0.18^{***}	0.29^{***}	0.22^{***}	0.14^{*}
	(0.03)	(0.05)	(0.06)	(0.07)
Kleibergen-Paap F-statistic	30.63	36.19	14.33	3.67
Mean of equipment outage rate	0.28	0.24	0.28	0.28
SD of equipment outage rate	0.33	0.29	0.33	0.33
Mean potential GWh from idle capacity	8.82	27.44	8.82	8.82

Notes: Column (1) is identical to Column (3) of Table 2, except that we include the 2% of observations where our cost and outage data cover less than 50% of total generating capacity (thermal + hydro) in that state-day cell. Column (2) is the 2SLS analog of Column (2) of Table 2. Columns (3)–(4) are analogous to Column (4) of Table 2, using alternative constructions of marginal cost. Column (3) uses the 98th percentile of realized marginal costs within each state-day, and Column (4) takes the state-day maximum, which is most analogous to a conventional market equilibrium. Regressions are otherwise identical to Table 2.Standard errors are clustered by sample month. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Column (2) presents the two-stage-least-squares analog to Column (2) of Table 2, yielding a similar demand estimate on days with idle capacity available. Columns (3)–(4) use alternative definitions of marginal cost: either the 98^{th} percentile or the maximum of the realized cost distribution within each state-day. Using the maximum is most analogous to a conventional market equilibrium where supply meets demand. Moving towards the maximum (from our preferred 95^{th} percentile) weakens the first stage: attenuating the point estimate, reducing precision, and lowering the first-stage F-statistic. This makes sense, given that India's wholesale sector is not cleared using market-based dispatch and given measurement error in our measure of marginal costs.

A.3 Robustness: Hypothetical supply-side interventions

Tables A.2 and A.3 present robustness for our counterfactual simulations. In Table 3 in the main text, we model utilities as responding to average variable cost, in keeping with cost-of-service regulation governing both bilateral contracts between utilities and power plants and retail tariffs. In Table A.2, we instead model utilities as responding to marginal cost, using an elasticity of -0.25 (Column (4) of Table 2). In Table A.3, we model utilities as responding to average variable cost, but assume constant elasticity rather than linear demand. As in Table 3, Column (1) presents the difference in quantity supplied between observed dispatch and least-cost dispatch. In our main specification, this difference is 43.2 GWh/day. This difference is larger when utilities respond to marginal cost (77.4 GWh/day), and very close to the main estimate under constant elasticity (44.8 GWh/day). Columns (2)–(4) present incremental impacts of improving the thermal efficiency of the Indian coal fleet to U.S. levels, applying the U.S. outage rate, and building four new UMPPs, respectively. These yield increases in quantity supplied of 17.1 GWh/day, 64.1 GWh/day, and 34.0 GWh/day when utilities respond to marginal cost, and increases of 62.4 GWh/day, 41.6 GWh/day, and 32.3 GWh/day when demand is constant elasticity. These estimates are broadly similar to the main results in Table 3.

Table A.2: Quantity impacts of different supply-side interventions: Utilities respond to MC

Supply curve scenario:	(1) Least-cost dispatch (LC)	(2) LC + US efficiency	(3) LC + US outage rate	(4) LC + 4 new UMPPs
Quantity increase relative to observed dispatch (GWh/day)	77.4	77.4	77.4	77.4
Incremental quantity increase relative to LC (GWh/day)		17.1	64.1	34.0
Incremental HHs shifted to 24×7 power		36.8M	137.9M	73.2M

Notes: This table reports the daily average national-level quantity impacts of different hypothetical interventions to the supply side of the Indian wholesale electricity market. In contrast with Table 3 in the main text, we assume that utilities respond to the marginal cost of the marginal unit rather than average variable cost. Column (1) reports the change in quantity supplied implied by switching from observed dispatch to dispatching plants from lowest-to-highest marginal cost within state/day. The first row is the same across all three incremental hypothetical supply-side interventions, each of which builds upon this "least-cost" scenario. The second row reports the incremental increase in quantity supplied under least-cost dispatch from: improving the thermal efficiency of Indian coal-fired plants to the average levels observed in the United States (following Chan, Cropper, and Malik (2014); Column (2)); reducing the forced outage rate of Indian coal-fired power plants to U.S. levels (Column (3)); and adding four 4,000 MW Ultra Mega Power Plants (UMPPs) with relatively low marginal costs to the supply curve (Column (4)). The bottom row reports the number of households that could be shifted to 24×7 power from each incremental increase in quantity supplied, assuming that Indian households currently face 3.4 hours per day of blackouts on average (Agrawal et al. (2020)). See text for further details.

Table A.3: Quantity impacts of different supply-side interventions: Constant-elasticity demand

Supply curve scenario:	(1) Least-cost dispatch (LC)	(2) LC + US efficiency	(3) LC + US outage rate	(4) LC + 4 new UMPPs
Quantity increase relative to observed dispatch (GWh/day)	44.8	44.8	44.8	44.8
Incremental quantity increase relative to LC (GWh/day)		62.4	41.6	32.3
Incremental HHs shifted to 24×7 power		134.2M	89.4M	69.5M

Notes: This table reports the daily average national-level quantity impacts of different hypothetical interventions to the supply side of the Indian wholesale electricity market. In contrast with Table 3 in the main text, we assume constant-elasticity demand rather than linear demand. Column (1) reports the change in quantity supplied implied by switching from observed dispatch to dispatching plants from lowest-to-highest marginal cost within state/day. The first row is the same across all three incremental hypothetical supply-side interventions, each of which builds upon this "least-cost" scenario. The second row reports the incremental increase in quantity supplied under least-cost dispatch from: improving the thermal efficiency of Indian coal-fired plants to the average levels observed in the United States (following Chan, Cropper, and Malik (2014); Column (2)); reducing the forced outage rate of Indian coal-fired power plants to U.S. levels (Column (3)); and adding four 4,000 MW Ultra Mega Power Plants (UMPPs) with relatively low marginal costs to the supply curve (Column (4)). The bottom row reports the number of households that could be shifted to 24×7 power from each incremental increase in quantity supplied, assuming that Indian households currently face 3.4 hours per day of blackouts on average (Agrawal et al. (2020)). See text for further details.

B Further details on the data

B.1 Constructing marginal costs

For fossil-fuel power plants, we follow the electricity economics literature (Fabrizio, Rose, and Wolfram (2007); Cicala (2022)) in approximating marginal costs as:

$$MC_{it} = \text{Fuel price}_{it} \cdot \text{Heat rate}_{it}$$

We first discuss where we obtain data on heat rates, and then proceed to describe how we construct fuel prices (inclusive of transportation costs and relevant taxes) separately for each type of plant.

Heat rates: A plant's heat rate is defined as the amount of heat input (in kcal) required to produce one MWh of electricity. For coal and lignite plants, we obtained heat rate data from the CEA's annual *Review of Performance of Thermal Power Stations*. We digitized the 2012–2014 *Reviews* (the most recent years available), and we obtained the 1997–2009 data from Chan, Cropper, and Malik (2014).[1] Since our analysis spans 2013–2019, we assign each plant its most recent heat rate observed in our data. For the 16 plants whose most recent heat rate was reported prior to 2012, we obtained more recent heat rate data from tariff petitions to the Central Electricity Regulatory Commission.

For natural gas-fired power plants, we assign heat rates based on the CEA's Monthly Gas Reports. These reports are only available for 2012, 2016, and 2017; we assign each plant its average observed heat rate. We follow the Ministry of Natural Gas and Petroleum in assuming that 10,000 kCal of heat energy is contained in one standard cubic meter of natural gas. These data enable us to assign heat rates for 58 of the 62 gas plants in our daily CEA sample.

1. We thank the authors for sharing these data.

Coal plants: We construct marginal costs for each coal-fired power plant as follows. We collect grade-specific coal prices reported aperiodically by Coal India Limited and Western Coalfields Limited (prices reported in rupees per kg).[2] "Grades" refer to the kilocalories (kcal) of heat energy per ton of coal. We assign "minemouth" coal prices to each power plant based on the grades of coal mined from the coalfield and the geographic proximity of the plant to the coalfield. Nearly all of India's coal-fired power plants buy their coal at grade-specific prices set by the Ministry of Coal through long-term Fuel Supply Agreements.[3]

For geographic proximity, we calculate the distance by rail between coal plants and coalfields. To do so, we combine hand-coded plant latitude/longitude with geospatial data on India's coalfields from the U.S. Geological Survey. Data on the rail network in India is created by ML InfoMap.[4]

We approximate the grade of coal burned by the plant as follows, using data from the CEA's Monthly Coal Reports. First, we divide annual total quantity of electricity produced by each plant (in kWh) by the annual total quantity of coal consumed by each plant (in kg). This annual ratio is multiplied by each plant's heat rate in each year (in kcal per kWh). The resulting quantity is the annual aggregate amount of kcal of input heat energy obtained by the plant from one kg of coal. Taking the mean of this quantity gives us the approximate grade of coal burned by the plant, which ranges from 1,118 to 8,254 kcal per kg for non-lignite coal plants.[5]

Having assigned minemouth coal prices to plants, we next multiply these prices by one plus the royalty rate, the value-added tax, the excise tax, and a cess specific to West

2. Coal prices for Coal India Limited are available at: https://www.coalindia.in/Manage/ViewDocumentModule.aspx.

3. These are regulated "pithead" prices, which do not include the cost of transporting coal from mines to plants. The government implemented the "Scheme to Harness and Allocate Kolya (Coal) Transparently in India" policy (a.k.a. Shakti) in September 2017, which allocates *new* coal contracts to privately owned generating units based on an auction mechanism. There were two auctions during our sample period; the winning coal plants made up a very small share of the overall coal-fired capacity in our sample (Chirayil and Sreenivas (2010)).

4. For more information on these data, see: https://searchworks.stanford.edu/view/ww857qy4996.

5. We have heat rate and coal grade data for 84 coal-fired plants and 7 lignite-fired plants, representing approximately 50% and 80% of each fuel's respective generating capacity in CEA daily generation data.

Bengal. The royalty rate is 14% for coal mined from all states other than West Bengal; in West Bengal, the royalty adder is applied in rupees per kg rather than percentage.[6] The value-added tax is 2% if the coal comes from out of state but 5% if the coal comes from the same state as the plant. The excise tax is 6% across the nation. West Bengal also charges a 25% tax on coal mined in its state.

We next add transportation charges, additional taxes, stowing duty, and the West Bengal specific royalty adder to the minemouth price. Transportation charges, assessed in rupees per kg, vary both over time and by distance between mine and plant. We collect rail rates from the Indian Railway website, calculating the relevant distance between plant and coalfield as discussed above.[7] The majority of power plants receive coal from trains. The remaining two major categories are "pithead" plants colocated next to a mine (for whom transportation charges are zero) and plants who burn imported coal. In the absence of high quality data on the coal prices paid by plants burning imported coal, we assign these plants a domestic coal price based on the grade of coal closest to the one they actually burn.

India also charged a "clean energy" cess per kg of coal purchased, which we add to the minemouth price.[8] Finally, the Ministry of Coal charges a Rs. 10 per 1,000 kg "stowing excise duty" related to the "assessment and collection of excise duty levied on all raw coal..."[9]

To convert coal prices from rupees per kg to rupees per kWh, we multiply the relevant price by the plant's aggregate quantity of electricity produced (in kWh) and divide by the plant's aggregate quantity of coal consumed (in kg).

6. The royalty adder in West Bengal differs based on the grade of coal, ranging from Rs. 4.5 per 1,000 kg to Rs. 8.5 per 1,000 kg; further details are available upon request.

7. For example, the freight rate relevant for dates after November 1, 2018 is available here: http://www.indianrailways.gov.in/railwayboard/uploads/directorate/traffic_comm/downloads/Freight_Rate_2018/RC_19_2018.PDF

8. The Clean Energy Cess was replaced by the GST Compensation Cess in July 2017. Information on the history of the Clean Energy Cess is available at: http://iisd.org/sites/default/files/publications/stories-g20-india-en.pdf

9. Many of the taxes and subsidies relevant to the coal sector in India are discussed here: https://www.eria.org/uploads/media/07_RPR_FY2018_15_Chapter_6.pdf

Lignite plants: We obtain the lignite coal price per kg from the Central Electricity Regulatory Commission.[10] All lignite plants in India are colocated next to their source mine, so transportation costs are zero. After multiplying or adding the relevant royalties, taxes, and clean energy cess discussed above for coal plants, we multiply by an estimate of the heat content of lignite coal (in kcal per kg) from the same source as the price. Finally, we multiply the lignite coal price (now in rupees per kcal) by the plant's heat rate to obtain the marginal cost (in rupees per kWh) for each lignite plant.

Gas plants: For natural gas plants, we use gas prices originally reported in rupees per 1,000 cubic meters. We assume that 1 cubic meter of natural gas contains 10,000 kcal of heat energy, using this conversion factor to obtain gas prices in rupees per kcal. Finally, we multiply this price by each plant's heat rate (in kcal per kWh) to get each gas plant's marginal cost. Though this marginal cost does not include the costs associated with transporting gas, they are in line with the estimates reported by the Ministry of Power, which do include these costs.[11]

Nuclear plants: We assign each of the 7 nuclear plants in our sample a marginal cost based on tariff documents.[12]

Hydro, wind, and solar plants: Non-dispatchable run-of-river hydroelectric, wind, and solar resources have near-zero marginal cost. Dispatchable hydro generators face a complex dynamic optimization problem, as generation today may come at the expense of generation tomorrow due to a finite supply of water (Archsmith (2023)). Consequently, we exclude hydro, wind, and solar resources from the analysis, implicitly assuming that they are in-

10. The data are here: http://cercind.gov.in/2017/orders/255.pdf

11. The average marginal cost per kWh we construct using data on gas prices is 2.09 while the corresponding average for the marginal costs reported by the Ministry of Power is 2.42.

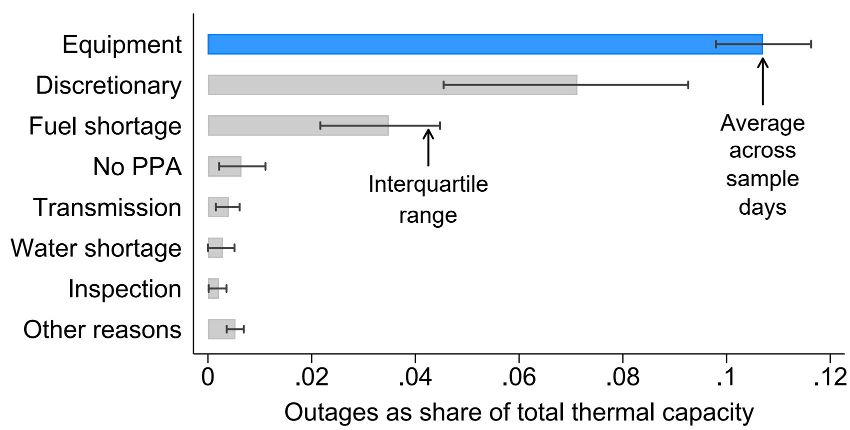
12. These data are reported in the following article by the chairman of an expert committee for the Department of Atomic Energy: http://www.thehindu.com/todays-paper/tp-opinion/Why-India-should-opt-for-nuclear-power/article14850892.ece

framarginal. To the extent that dispatchable hydro resources are dispatched suboptimally due to a lack of incentives to operate when costs are low and/or the value of electricity is high, our counterfactual calculations in Table 3 will weakly understate the extent to which eliminating discretionary outages would reduce blackouts.

B.2 Power plant outages

We string parse the CEA's *Daily Outage Reports* to classify eight mutually exclusive outage categories: equipment, discretionary, fuel shortage, no power purchase agreement (PPA), transmission problem, water shortage, inspection, and other. Figure B.1 shows the frequencies of these categories, plotting the share of total thermal plant capacity on each type of outage on the average day. Our empirical analysis only uses the equipment category.

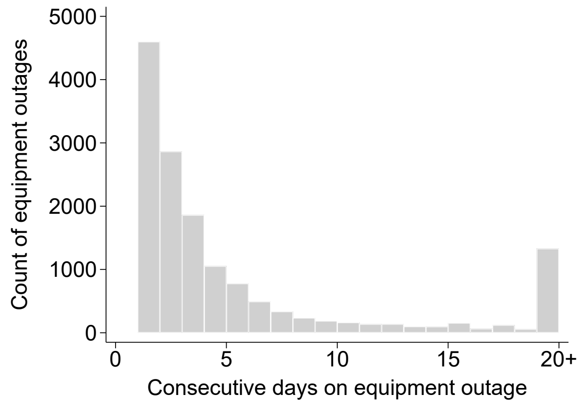
Figure B.1: Descriptive statistics on daily plant outages



Notes: Each bar shows the average share of total thermal capacity that reported an outage of a specific category. Bars report averages across 2,453 sample days, while whiskers report the interquartile range of daily outage shares. We manually classify outages into these categories using the reasons listed in the CEA's *Daily Outage Reports*.

Figure B.2 characterizes the duration of equipment outages during our sample period. The left panel shows that the median equipment outage lasts just 2 days, while 95% of equipment outages are shorter than 33 days long. This supports our assumption that equipment outages are short-lived exogenous shocks to utilities' wholesale procurement costs.

Figure B.2: Distribution of outage durations



Notes: This histogram summarizes the length of equipment outages; each observation is a set of consecutive days where a plant reports some capacity on equipment outage. During our sample period, the median equipment outage lasted 2 days.

B.3 Indian Energy Exchange (IEX) data

The Indian Energy Exchange (IEX) runs uniform-price auctions, where electricity suppliers submit offer curves, buyers (e.g., utilities) submit demand bid curves, and the market clears by aggregating supply and demand. Prices and quantities from the unconstrained market clearing process are adjusted to reflect transmission constraints. This results in separate prices and quantities for each 15-minute interval for each of India's five transmission regions.

The IEX publishes `.jpeg` images of the aggregate supply and demand curves for each 15-minute interval-of-sample. We downloaded these data from April 1, 2014 through December 31st, 2019. We converted these images into data using the online WebPlotDigitizer tool (https://automeris.io/WebPlotDigitizer/). To do this, we upload the image and then label four points, which allows the software to convert the image into data on the price-quantity steps displayed for the aggregate supply and demand curves.[13] Figure B.3 presents two of the 201,012 15-minute intervals in our dataset.

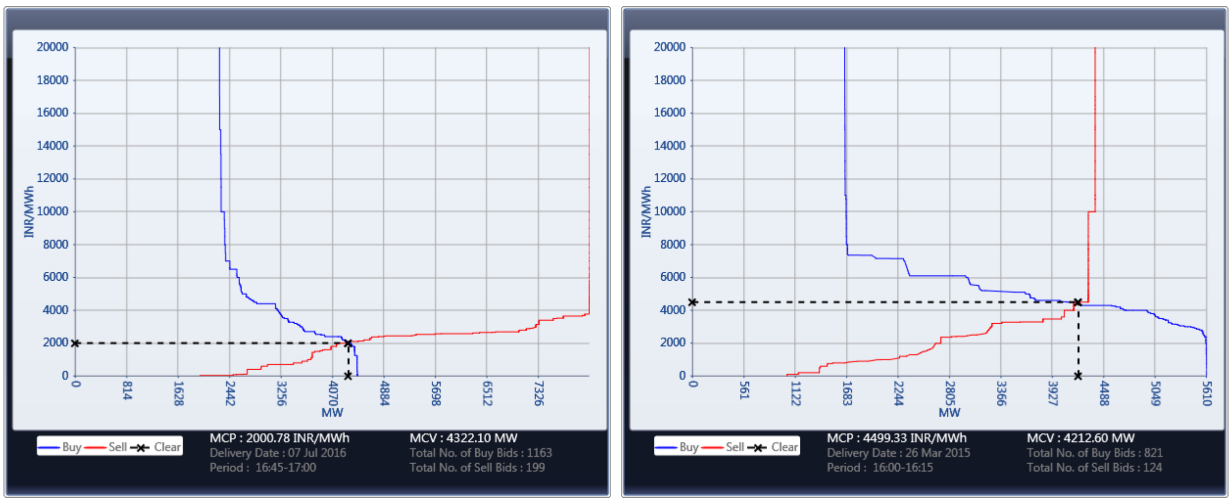
The IEX also provides market clearing price and quantity data for each 15-minute interval for each of India's five transmission regions.[14] Across our sample, the average

13. These images are available from the following link: https://www.iexindia.com/marketdata/demandsupply.aspx.
14. The price data are available from https://www.iexindia.com/marketdata/areaprice.aspx. The quantity

IEX market clearing price was Rs. 3,121 per MWh, while the average volume cleared was 1,128 MWh per 15-minute interval. We compare the equilibrium outcomes implied by our converted images to those provided by the IEX. The correlation between the two is extremely high—99.8%—which gives us confidence that the image conversion is working properly.

We use these digitized interval-specific demand curves to calculate the price elasticity of IEX demand.[15]

Figure B.3: Example IEX demand and supply curves



Notes: This figure displays two examples of the raw data we obtained from the Indian Energy Exchange. The left image shows the aggregate demand and supply curves for the 16:00–16:15 interval on March 26, 2015. The right image shows the same curves for the 16:45–17:00 interval on July 7, 2016. We digitized these images, originally in JPEG format, using OCR software.

B.4 Inflation adjustment

When relevant, all magnitudes are reported in 2016 constant rupees. We adjust for inflation using the monthly consumer price index for all items for India reported by the Organization for Economic Co-operation and Development.[16]

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data are available from https://www.iexindia.com/marketdata/areavolume.aspx.

15. To construct the elasticity at a given price-quantity point for each interval-specific demand curve, we smooth the demand curve and compute the "finite central difference" elasticity implied by moving Rs. 5 per MWh up versus moving Rs. 5 per MWh down the demand curve.

16. Data can be accessed here: https://fred.stlouisfed.org/series/INDCPIALLMINMEI

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