Blackouts: The role of India's wholesale electricity market

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Abstract

Electricity blackouts impose substantial costs in developing countries. We advance a new explanation for their prevalence in India: utilities' wholesale electricity demand is downward-sloping. We construct a novel dataset on India's wholesale electricity sector. Instrumenting for average variable cost with plausibly exogenous power plant equipment outages, we estimate a wholesale demand elasticity of -0.49. Voltage monitoring data confirm that equipment outages drive blackouts. Increases in procurement costs therefore reduce the quantity of electricity delivered to end-use consumers. Our counterfactual simulations suggest that lowering wholesale electricity 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 blackouts in the developing world: utilities are price-sensitive and purchase less electricity when wholesale procurement costs are high, leading to retail power shortages. In contrast, higher wholesale electricity prices do not lead to blackouts in high-income countries, where strictly enforced regulatory mandates require utilities to satisfy all retail electricity demand regardless of cost. Blackouts in high-income countries are consequently rare, occurring almost exclusively due to extreme weather events and distribution infrastructure failures (Harris (2023)). In developing countries without such regulatory mandates, when wholesale electricity procurement costs rise, the amount of power that utilities purchase for distribution to retail customers may fall—translating directly to blackouts.

We empirically demonstrate the importance of this new mechanism for blackouts 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)).[1]

1. In addition to the capital costs of purchasing generators, households and firms incur ongoing expenses to operate them. Generator fuel costs for households are approximately Rs 18/kWh (Sargsyan et al. (2011)), substantially larger than retail electricity tariffs, which ranged from Rs 0.75–6.37/kWh in 2021 (Central

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.[2] We show that equipment outages are uncorrelated with electricity demand shifters, suggesting that this instrument satisfies the exclusion restriction. We estimate an average variable cost elasticity of demand of -0.49. 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.

Because electricity storage is cost-prohibitive, reductions in wholesale electricity purchases must correspond either to voluntary decreases in end-user demand or to blackouts. Since exceedingly few Indian electricity consumers face time-varying prices, blackouts are the far more likely explanation. To confirm this intuition, we leverage high-frequency data from power grid monitors installed around the country by an Indian non-profit organization. Using these data, we estimate that increases in power plant equipment outage rates cause meaningful increases in blackouts—thereby empirically linking wholesale market cost shocks to blackouts experienced by retail consumers.

Next, 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 62.4 GWh, 41.7 GWh, and 32.8 GWh, which would be sufficient to eliminate blackouts for

Electricity Authority (2021b)).

2. We use "blackouts" to refer to both scheduled and unscheduled power supply interruptions experienced by retail consumers. We use "outages" to refer to unavailable generating capacity at power plants.

134.1, 89.8, and 70.6 million Indian households, respectively. 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 illustrate that wholesale procurement costs are linked to blackouts in India, and thus policies that reduce electricity production costs can have the added benefit of improving electricity reliability for households and firms.

Finally, we discuss how a U.S.-style quantity mandate would impact India's wholesale electricity market. Such a mandate would force utilities to purchase electricity at a price higher than their marginal willingness to pay, creating deadweight loss in the wholesale market. Our simulation model suggests that mandating that utilities supply enough electricity to eliminate blackouts for Indian households would reduce welfare by a relatively modest 2.1% in the wholesale power market. However, whether a mandate lowers welfare overall is not obvious. While some Indian consumers have invested in back-up power technologies, signaling a high willingness to pay to avoid blackouts, most have not. Moreover, as Indian households face retail tariffs below the marginal cost of electricity supply, a quantity mandate could exacerbate existing distortions. A quantity mandate would also likely be politically infeasible in India, as it would worsen utilities' already significant financial losses.

This paper makes 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, arguing that bill non-payment and regulated retail prices set below marginal cost lead utilities to ration power supply (Dzansi et al. (2021); Jack and Smith (2020); Burgess et al. (2020); Mahadevan (2024)). 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)).[3] To our knowledge, this is the first paper to demonstrate that blackouts arise in the developing world because utilities purchase less power when their wholesale procurement costs increase.

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., Mercadal (2022); Jha and Wolak (2023)), 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 is downward-sloping, providing the first empirical link between wholesale procurement costs and power quality— thereby uncovering a new reason blackouts occur in low-income countries.

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. (2024)) can all limit the effectiveness of environmental regulations and energy-related technologies when implemented in developing countries.[4] We demonstrate that absent a regulatory mandate that all retail demand is satisfied—a ubiquitous feature of wholesale elec-

3. 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.

4. Outside 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.

tricity 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 supply-side 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 main econometric results, demonstrating that wholesale electricity demand in India is downward-sloping. Section 4 uses voltage monitoring data to establish an empirical link between wholesale cost shocks and blackouts experienced by consumers. Section 5 simulates hypothetical approaches to reducing blackouts, underscoring the economic importance of our estimated demand elasticity. Section 6 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.

2.1 Distribution utilities

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 (Burgess et al. (2020)). Low bill payment rates compound this cost-recovery problem (Gaur and Gupta (2016)).

Utilities respond to these financial difficulties by choosing not to satisfy electricity demand in all hours and locations.[5] Rolling blackouts (often called "load shedding") are common across the country. Since regulated retail rates are fixed and electricity storage is extremely costly, 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 wholesale procurement costs increase (i.e., that wholesale electricity demand in India is downward-sloping).

Policymakers recognize that there is a "vicious cycle" of financial woes and blackouts (McRae (2015); Burgess et al. (2020)). Utilities across India regularly earn negative profits, even net of state-level tariff subsidies (Pargal and Banerjee (2014); Power Finance Corporation Ltd. (2009–2021)).[6] In order to keep these utilities financially solvent, the Government of India launched the Ujwal Discom Assurance Yojana (UDAY) program in 2015 to provide financial relief to state-owned utilities through more frequent adjustments to regulated retail prices, lower borrowing costs, and operational improvements (Ministry of Power, Government of India (2015)). While the program has fallen short of achieving 24×7 power for all, its existence demonstrates that regulators understand the link between utilities' financial incentives and the quantity of electricity received by retail customers.[7]

5. We confirmed our understanding of these and other institutional details in conversations with engineers and power traders at the Indian Energy Exchange and Tata Power Trading Co. Ltd.

6. States often deliver subsidies well after losses are incurred, and may not cover the full losses associated with selling electricity at retail prices significantly below costs (Burgess et al. (2020)). By law, utilities should be insulated from shocks to wholesale procurement costs: all "reasonable" costs are supposed to be passed through to consumers via increases in regulated retail prices (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)).

7. For example, in 2025, the Ministry of Power considered "injecting cash into heavily-indebted government-owned distribution utilities." An internal regulatory document pertaining to this proposal notes: "The financial health of distribution companies (discoms) is crucial for sustaining a reliable and uninterrupted electricity supply to consumers," and "discoms face challenges such as inadequate tariff structures, rising power procurement costs . . . which can lead to revenue shortfalls and operational inefficiencies" (Reuters (2025)). In 2019, Power Minister R. K. Singh even went so far as to claim that discom losses are the "only difficulty" in providing 24×7 electricity (Press Trust of India (2019)).

2.2 Wholesale electricity demand and supply

Grid Controller of India Limited (GRID-INDIA) operates the national electricity transmission grid.[8] GRID-INDIA must balance the levels of supply and demand across locations on the grid, while respecting numerous plant operating and transmission capacity constraints. We use GRID-INDIA data on the quantity of wholesale electricity purchased at the state-day level as the main outcome variable in our empirical analysis (GRID-INDIA (2013–2019)).

We also use 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 at current retail prices given their existing contract portfolios.

2.3 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 making their capacity 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.[9] This means that owners of

8. At the time of data collection, GRID-INDIA was known by its former name: the Power System Operation Corporation Limited (POSOCO).

9. 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: traded volumes were 1% of total generation as of April 2021 (Garg (2021)).

contracted plants cannot pay lower-cost plants to generate in their stead, preventing any short-run reallocation of production that would lower procurement costs. Though utilities cannot purchase electricity from plants that are under contract with other parties, the typical utility has contracts with multiple plants and can freely call on any plant in its portfolio to generate.

While we lack contract-level data, the structure of long-term contracts directly informs our empirical strategy. To estimate the cost elasticity of wholesale demand, we require an instrument that shifts supply. However, since most power is sold via bilateral fixed-price contracts, and as domestic fuel prices are strictly regulated, plant-level power prices and operating costs are unlikely to meaningfully shift supply in the short run. Instead, we exploit the fact that utilities purchase from multiple contracted power plants—utilizing exogenous short-run shocks to the *set* of plants that are available to generate. This strategy leverages power plant equipment failures, which we discuss in detail below.

Short-term transactions make up approximately 7% of Indian electricity sales, with around 5% of electricity being traded on short-term bilateral contracts with a duration of less than 1 year, and 2% being traded on the Indian Electricity Exchange (IEX), a day-ahead power market that clears 24 hours before power delivery.[10] Utilities can purchase from the IEX when one of their contracted plants is unavailable to generate. To complement our main analysis on the full wholesale sector, we conduct auxiliary analyses using aggregated IEX bid-based demand curves.

The remaining 3% of power generation is unscheduled, with real-time imbalances between supply and demand resolved through the "deviation settlement mechanism." This mechanism provides small financial incentives to make minor generation adjustments to stabilize the frequency of grid.

10. A second day-ahead market, Power Exchange India (PXIL), contributes under 0.25% of electricity sales (Central Electricity Regulatory Commission (2019)). IEX and PXIL prices are nearly perfectly correlated (Ryan (2021)).

2.4 Electricity generation

We collect data on daily generation and production capacity at power plants, using the CEA's *Daily Generation Reports* from 2013–2019 (Central Electricity Authority (2013–2019)). These reports cover all utility-scale fossil, hydroelectric, and nuclear plants in India.[11] Our plant-day panel includes 506 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. India's power plants are far from being operated at capacity: the overall plant load factor (i.e., generation as a share of capacity) in our data is just 56 percent.[12]

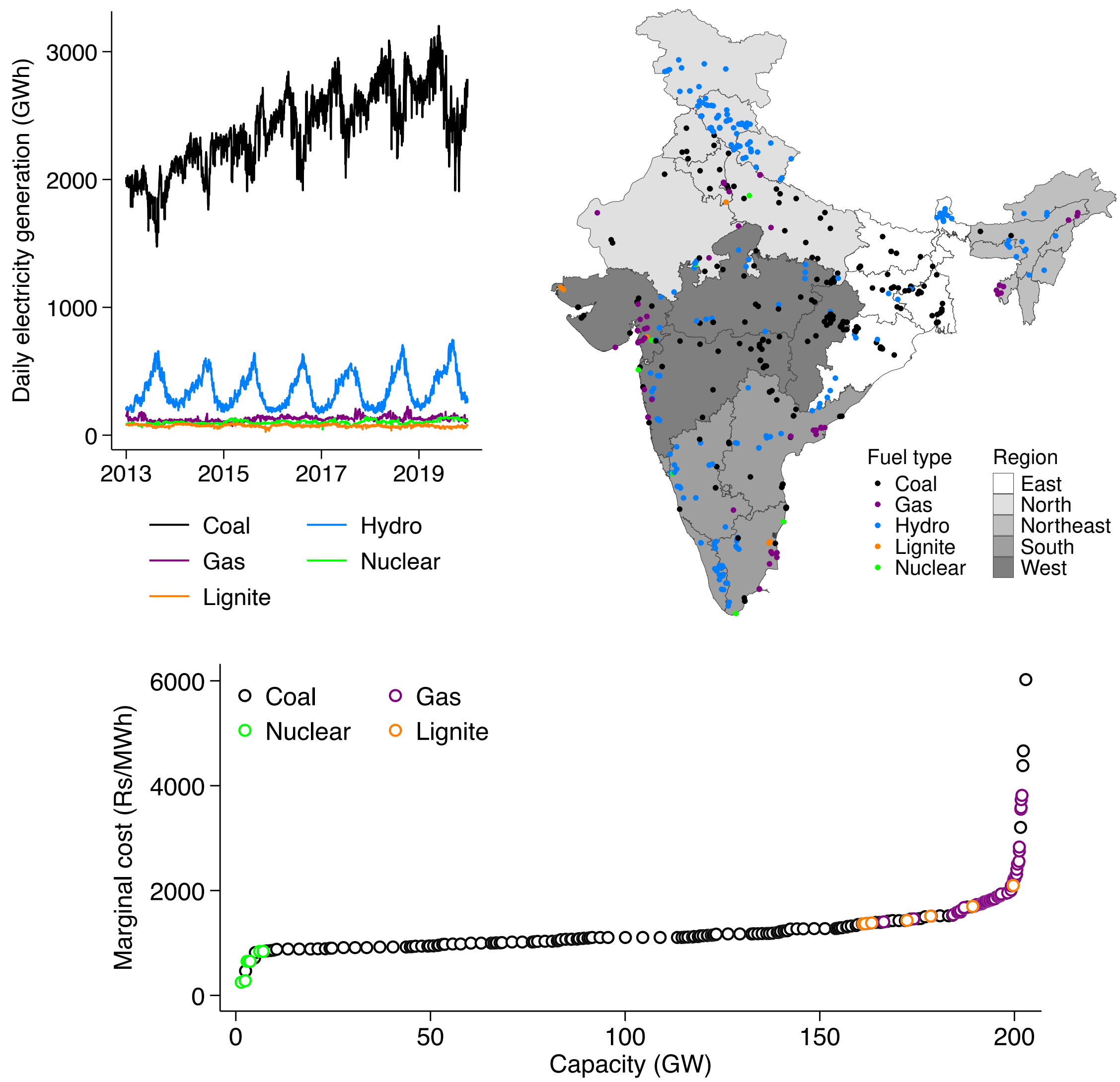
We construct marginal costs over time for each plant in our sample. Following the economics literature on electricity production, we assume that a plant's marginal cost does not vary with its level of output (e.g., Borenstein, Bushnell, and Wolak (2002); Mansur (2008); Clay et al. (2022)). For coal plants, we start with minemouth coal prices, reported aperiodically by coal suppliers. We add rail freight costs based on the shortest path along India's rail network (following Preonas (2024) and using the ML Infomap (2008) railroad map), as well as royalties and other taxes. We convert the resulting fuel 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).[13]

11. 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% of India's total generation in 2018–19 (Central Electricity Authority (2019a)). Our sample period largely predates India's rapid expansion of wind and solar generating capacity.

12. Even accounting for the power plant outages we discuss below, 22% of available generating capacity remains idle on the average day. Appendix Figure C.3 shows that the share of idle generating capacity is stable and high over time.

13. We thank 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* (Central Electricity Authority (2011–2014)). We combine these data with coal consumption data from the CEA's *Monthly Coal Reports* (Central Electricity Authority (2013–2019)) to infer each plant's coal grade. Where missing, we assign plants the grade of the closest coal field using rail distances from ML Infomap, spatial data on coal

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 506 plants in these data produce 3.05 TWh of electricity per day on average. Averages of daily aggregate output by fuel type are: 2.39 TWh for 205 coal plants, 355 GWh for 203 hydroelectric plants, 127 GWh for 65 gas plants, 102 GWh for 7 nuclear plants, 73 GWh for 9 lignite plants, and 3 GWh for the 17 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 17 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.

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fields from Trippi and Tewalt (2011), and field-specific coal grade data from U.S. Geological Survey (2010) and the *Coal Directory of India* (Coal Controller's Organization (2013–2018)). Appendix C.1 details how we construct plant-specific marginal costs, and compares our constructed costs to plant-specific variable costs reported by the Ministry of Power. We inflation-adjust to constant 2016 rupees.

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. 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)).[14]

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.[15] We use these plant-specific marginal costs to construct state-wide average variable costs for our demand regressions in Section 3.2, and also as an input to our counterfactual simulations in Section 5.

2.5 Power plant outages

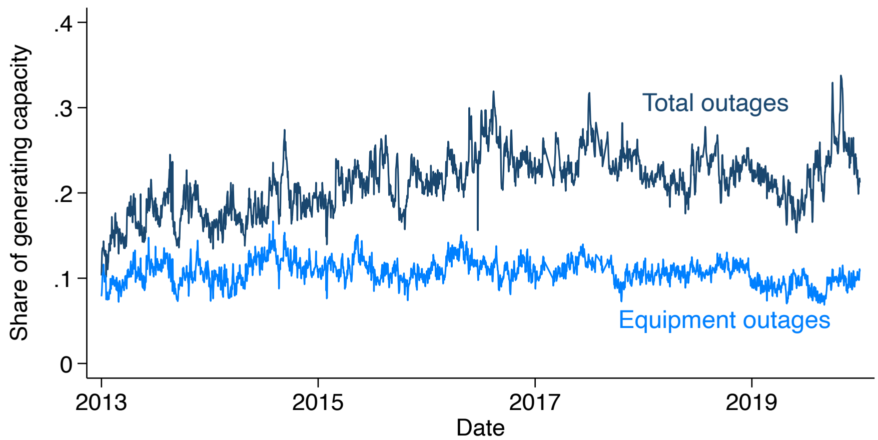
The CEA's *Daily Outage Reports* publish the amount of capacity under outage for each plant-day. On the average day between 2013–2019, 21% of thermal generating capacity was under outage and therefore unavailable to generate.[16] As a point of comparison, the

14. 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.

15. 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 (2024)). Non-dispatchable run-of-river hydro (along with wind and solar) enters the supply curve at (virtually) zero marginal cost.

16. This does not include outages due to scheduled plant maintenance, which impacts up to 8% of thermal capacity each day. Misreporting or nonreporting of outages comes with fines and threat of imprisonment under the Electricity Act of 2003 (Parliament of India (2003); Central Electricity Authority (2007)).

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



Notes: This figure plots the share of 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.

capacity-weighted outage factor across coal-fired power plants in the United States and Canada was roughly 5% during this time period.[17]

Regulators require plant managers to state a reason for going on outage. The CEA's *Daily Outage Reports* list these reasons, which we string parse to isolate the subset of outages caused by equipment failures.[18] Equipment outages are the most common type of outage, affecting roughly 10% of India's thermal generating capacity on the average day.[19] Figure 2 plots the time series of total outages and equipment outages, each as a share of total thermal capacity.[20] We use equipment outages as a cost shifter to estimate the elasticity of

17. 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" counts hours in the year after the unit first came online. As with our treatment of outages for India, "forced outage hours" do not include scheduled plant maintenance.

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

19. Appendix Figure C.1 plots the distribution of outages by category. The prevalence of "discretionary" outages—arising from the utility's decision not to purchase from the contracted plant for economic reasons—directly supports the claim that our wholesale demand elasticity estimates reflect utilities' *choosing* not to purchase power.

20. Hydroelectric plants have extremely few equipment outages. We lack daily plant-level outage data for non-hydro renewable generators.

wholesale electricity demand, which we discuss immediately below.

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 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 C.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:[21]

$$\begin{aligned} [\text{Equip. outage rate}]_{ist} \;&=\; \beta_1 [\text{Temp. } (^\circ\text{C})]_{st} \;+\; \beta_2 \log\big([\text{Energy req}]_{st}\big) \\ &\quad +\; \alpha_i \;+\; \psi_t \;+\; \theta_{ry} \;+\; \delta_{rm} \;+\; \varepsilon_{ist} \end{aligned} \tag{1}$$

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

21. Our weather data come from NOAA National Centers for Environmental Information (2012), which we map to state boundaries using a shapefile of Indian states from Development Data Lab (2025).

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)	(5)
Mean temperature in state (°C)	−0.0005	−0.0012	−0.0012	0.0003	0.0011
	(0.0003)	(0.0010)	(0.0011)	(0.0017)	(0.0015)
log (State's forecasted energy req.)			−0.0011	−0.0092	−0.0127
			(0.0113)	(0.0191)	(0.0148)
Split on plants' marginal cost				Low MC	High MC
Plant + month-of-sample FEs	Yes	Yes	Yes	Yes	Yes
Region-year, region-month FEs	Yes	Yes	Yes	Yes	Yes
Mean of dep. var.	0.1110	0.1135	0.1135	0.1307	0.0735
Plant-day observations	510,466				
Plant-month observations		19,420	19,420	7,935	7,430

Notes: The dependent variable is plant i's equipment outage rate (i.e. the daily share of its total capacity on equipment outage). Column (1) estimates Equation (1) at the plant-day level (we only observe forecasted energy requirements at the monthly level). Columns (2)–(5) estimate Equation (1) at the plant-month level, averaging equipment outage rate and temperature over all days in sample month m. All regressions control for the total number of dispatchable plants in each state, to account for differential market expansions across states. Columns (4)–(5) split the sample on plants with below- versus above-median marginal costs, dropping the 32% of plants where we cannot populate marginal costs per kWh. Standard errors are clustered by sample month. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

region-by-calendar-month fixed effects (ψ_t, θ_{ry}, and δ_{rm} respectively); we cluster standard errors by sample month.[22]

Table 1 demonstrates that equipment outages do not systematically respond to either temperature or forecasted demand. We can reject even moderate changes in equipment outage rates in response to these demand shifters.[23]

22. Clustering by sample month accounts both for within-month, within-state serial correlation and for within-month, between-state correlations arising from a shared electricity grid.

23. Columns (1)–(3) use the full sample of plants. Column (1) uses a plant-day panel (i.e., daily outage rates and daily temperature), noting that we utilize monthly forecasted energy requirement. In Columns (4)–(5), we split the sample to include only plants with below- versus 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 called by suppliers. Finally, Appendix Tables A.7 and A.8 show that equipment outage rates do not respond to lags of either temperature or realized quantity demanded, suggesting that previous periods of high demand do not make technical failures more likely.

3.2 The elasticity of demand

Next, we present empirical evidence that wholesale electricity demand falls when procurement costs rise. We first show that the 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 outage rates and quantity demanded:

$$\log\big([\text{Quantity}]_{st}\big) \;=\; \beta[\text{Equip. outage rate}]_{st} \;+\; \alpha_s \;+\; \psi_t \;+\; \theta_{ry} \;+\; \delta_{rm} \;+\; \varepsilon_{st} \tag{2}$$

The outcome variable is the natural logarithm of electricity purchased in the wholesale sector in state s, in transmission region r, on day-of-sample t. This corresponds 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 the causal effect of short-run changes in the equipment outage rate, aggregated across all thermal generating capacity in state s, on quantity demanded. 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 (θ_{ry} and δ_{rm} respectively) to control for region-specific trends and seasonality in demand. We cluster standard errors by month-of-sample.[24]

The first three 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

24. Our estimated standard errors are virtually identical if we instead cluster by region-by-month-of-sample or by state-by-month-of-sample.

Table 2: Wholesale demand is downward-sloping

	Outcome: log (Quantity)					
	(1) OLS	(2) OLS	(3) OLS	(4) IV	(5) IV	(6) IV
Equipment outage rate	-0.09^{***}	-0.12^{**}	-0.10^{***}			
	(0.03)	(0.05)	(0.04)			
log (Average variable cost)				-0.49^{**}	-0.42^{**}	-0.49^{**}
				(0.21)	(0.20)	(0.21)
Idle capacity available		Yes			Yes	
Equip. outages already 5+ days			Yes			Yes
State + date FEs	Yes	Yes	Yes	Yes	Yes	Yes
Region-year, region-month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Mean demand met (in GWh)	90.25	150.29	90.25	90.25	150.29	90.25
State-day observations	42,212	13,722	42,212	42,212	13,722	42,212
First-stage estimate				0.18^{***}	0.29^{***}	0.20^{***}
				(0.03)	(0.05)	(0.04)
Kleibergen-Paap F-statistic				30.28	37.01	26.75
Mean of equipment outage rate	0.10	0.09	0.08	0.10	0.09	0.08
SD of equipment outage rate	0.09	0.07	0.08	0.09	0.07	0.08
Mean potential GWh (idle cap.)	8.92	27.43	8.92	8.92	27.43	8.92

Notes: This table presents results from estimating Equation (2). The dependent variable is the natural logarithm of total GWh of energy purchased by in the wholesale sector in state s on date t. Columns (1)–(2) are reduced-form regressions, where the independent variable is the equipment outage rate at the state-day level. 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). Column (3) is identical to Column (1), except that the numerator of the equipment outage rate includes only continuous equipment outages that started at least four days earlier. Columns (4)–(6) use 2SLS to estimate the elasticity of demand with respect to the average variable cost of generation, instrumenting for costs using the equipment outage rate. Column (4) is our preferred specification, and is analogous to Column (1). Columns (5) and (6) are analogous to Columns (2) and (3), respectively. 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.

available generating capacity could be driving this reduction, if equipment outages render utilities unable to purchase the quantity of electricity they desire.[25] To rule this mechanism out, Column (2) restricts the sample to only state-days with idle capacity—that is, days

25. 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.

in which some plants located in state s did not produce despite having been available.[26] This yields an even larger point estimate (also significant at the 1% level). To rule out the possibility that these results are driven by short-run adjustment frictions (e.g., start-up or ramping costs), Column (3) reconstructs the equipment outage rate using only equipment outages that have already lasted for at least five consecutive days (i.e., starting at least four days prior to the day-of-sample). This yields a nearly identical point estimate (still significant at the 1% level).

These results provide strong evidence that utilities—by far the largest buyers in the wholesale electricity market—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 27.43 GWh on the average state-day.

Next, we estimate the short-run cost elasticity of wholesale demand, using two-stage least squares (2SLS) and instrumenting for the average variable cost of electricity generation with the equipment outage rate.[27] The exclusion restriction requires that variation in equipment outage rates only affects quantity demanded through its effect on procurement costs. This is plausible given that equipment 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.[28] The endogenous variable in these regressions is the log of average variable

26. 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. Our results are similar under alternate definitions of available idle capacity (see Appendix Table A.3).

27. In addition to being straightforward to interpret as an elasticity, the log-log functional form is particularly useful in our setting where there is substantial dispersion across states in the scale of electricity demand (e.g., utilities in Maharashtra purchase 20 times more wholesale electricity than utilities in Jharkhand). The log-log functional form predicts that utilities ration power proportionate to the size of their customer base. Appendix Table A.6 shows that the results are broadly similar using a linear functional form.

28. In most market settings, the equilibrium price for all units is determined by the marginal cost of the marginal unit supplied. However, in India, plants on long-term contracts receive regulated prices pegged

cost in state s on date t: $\text{AVC}_{st} \equiv \frac{\sum_{i \in s} MC_{it} q_{it}}{\sum_{i \in s} q_{it}}$, where MC_{it} and q_{it} represent plant i's constructed marginal cost and quantity generated on date t respectively.[29]

Column (4) of Table 2 estimates 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 (significant at the 5% level). Columns (5)–(6) find nearly identical elasticity estimates when restricting the sample to state-days with idle capacity (as in Column (2)), and modifying the instrument to include only equipment outages on at least their fifth consecutive day (as in Column (3)).

These estimates demonstrate that India's wholesale electricity demand is downward-sloping. Reductions in the quantity of wholesale demand do not appear to reflect generating capacity constraints (see Column (5)) or plants' inability to adjust production in the short term (see Column (6)). Appendix Table A.2 shows that these reductions in wholesale demand are also unlikely to be driven by within-state transmission constraints: we estimate an elasticity of -0.55 (significant at the 1% level) when instrumenting only with equipment outages outside of high-demand areas where local transmission constraints are most likely to bind.[30] Taken together, our results reinforce that higher procurement costs lead Indian

to their variable costs, while utilities receive regulated retail tariffs that reflect their average variable cost of wholesale procurement. For this reason, our primary specifications focus on average variable cost. As a robustness check, Appendix Table A.5 estimates wholesale demand elasticities with respect to state-wide marginal costs. We find elasticity estimates of -0.25 and -0.39 using the 95th and 98th percentiles of marginal costs across operating plants in each state-day (both significant at the 5% level). The first stage is underpowered when using the maximum marginal cost among operating units, likely because the maximum is particularly prone to outliers induced by measurement error in our constructed marginal costs.

29. Following the electricity literature (e.g., Cicala (2022)), we assume MC_{it} is constant with respect to the plant's output q_{it} (making marginal cost equal to average variable cost within each plant). In addition, q_{it} must lie between zero and the plant's strict capacity constraint.

30. We classify plants as being in a "load pocket" (i.e., a high-demand area) if they are located in one of India's 20 most populous districts, per the 2011 Census of India (Office of the Registrar General & Census Commissioner (2011)). Then, we instrument with only non-load-pocket equipment outages, while also restricting the sample to state-days with idle capacity available outside of load pockets. We find similar results when restricting to days with no intra-regional transmission congestion in the IEX (Appendix Table A.4). Appendix Table A.2 shows that our results are similarly robust to: using all days of 5-day equipment outages (i.e., not excluding days 1-4), lagging our preferred instrument by 4 days (to capture anticipation effects), and expanding our sample to include the 2% of state-days where our cost and outage data cover less than 50% of total (thermal + hydro) generating capacity.

utilities to purchase less power to supply to end-users.

Why is wholesale quantity demanded sensitive to cost? Appendix Table A.1 splits the sample into states with above- versus below-median average variable costs.[31] We do this to test the hypothesis that utilities that may be losing more money on the margin are more cost-sensitive. We find suggestive evidence that this is the case: for states with above-median average variable costs, we estimate a cost elasticity of demand of -0.54 ($p < 0.01$). However, for states with below-median average variable costs, we find an elasticity of -0.09 (not statistically different from zero).

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 (Indian Energy Exchange (2014–2019)). The mean IEX demand elasticity is -0.75, while the median is -0.31. This aligns with our estimates from Table 2, providing further evidence that wholesale demand is downward-sloping.[32]

Could our demand elasticity estimates in Table 2 be fully explained by changes in the equilibrium quantity sold in the IEX? According to Column (4), a one standard deviation increase in the equipment outage rate leads to a roughly 2% increase in average variable cost, and a corresponding 1% decrease in *aggregate* wholesale quantity sold. Given that the IEX contributes only 2% of aggregate quantity sold, the mean IEX demand elasticity of -0.75 is two orders of magnitude too small to account fully for our estimated aggregate wholesale demand elasticity. Hence, there must be meaningful wholesale demand elasticity outside of the IEX.

31. To do this, we construct a capacity-weighted mean average variable cost for each state, over our full sample period.

32. Appendix C.3 discusses the IEX market in further detail, and outlines how we digitized IEX data to extract IEX demand elasticities.

4 Linking wholesale electricity demand to blackouts

We argue that reductions in wholesale quantity demanded directly lead to blackouts. Because grid-scale storage is cost-prohibitive, a reduction in wholesale electricity demand *must* lead to a reduction in end-user electricity consumption.[33] This can take one of two forms: voluntary demand response, or involuntary blackouts. Given that the vast majority of electricity consumers in India face retail tariffs that do not reflect short-run changes in wholesale market costs (i.e., there is no "dynamic pricing"), these end-users lack the incentive to alter their consumption in real-time when their utilities' wholesale procurement costs unexpectedly rise.[34] Moreover, as discussed by Ryan (2021), elastic demand in the day-ahead Indian electricity market tends to come from utilities rather than large industrial customers. It follows that when utilities purchase less electricity, retail consumers almost certainly face involuntary blackouts rather than choose to reduce their electricity use.

We provide direct empirical support for this claim using rich data from Prayas Energy Group, an Indian non-profit. As part of its Electricity Supply Monitoring Initiative (ESMI), Prayas installed voltage monitors on electricity distribution feeders around the country, which report minute-by-minute data on retail power supply (Prayas, Energy Group (2019)). The ESMI data comprise an unbalanced panel of monitor readings from 60 districts across 23 states, beginning in 2014. The raw data report voltage at the monitor-by-minute level, with readings of zero voltage corresponding to blackouts.[35]

We aggregate the count of zero-voltage readings from the monitor-minute level to the state-day level, to align with the unit of analysis in Equation (2). Table 2 shows that

33. India only installed its first utility-scale battery system in 2019, with a capacity of just 10 MW (Colthorpe (2019)).

34. According to an industry report, only 2.4 million smart meters had been installed in India by 2021 (PowerLine India (2021)), less than 1% of the 334.5 million total electricity consumers at the time (Central Electricity Authority (2021a)). As a result, utilities lacked the technical capacity to send a time-varying price signal to 99% of retail consumers.

35. Prayas's stated goal in installing these monitors was to "...provide evidence based feedback about the quality of supply to all stakeholders in the electricity sector." While these data are likely not from a fully random sample of feeders, they provide objective information on power outages, which is virtually impossible to obtain elsewhere.

increases in equipment outage rates lead to reductions in electricity purchases by utilities (see Columns (1)–(3) of Table 2). We now estimate the same specification with the voltage monitoring data as the outcome of interest to test whether these exogenous equipment outages also lead to detectable increases in retail blackouts:

$$\mathbf{1}[\text{ESMI blackout rate} > 50\%]_{st} \; = \; \beta[\text{Equip outage rate}]_{srt} + \alpha_s + \psi_t + \theta_{ry} + \delta_{rm} + \varepsilon_{st} \quad (3)$$

The dependent variable is equal to 1 if there were zero-voltage readings in over 50% of the minutes reported by ESMI monitors located in state s on day t.[36] The independent variable is the average rate of equipment outages for plants in state s on day t. As in Equation (2), we include fixed effects at the state (α_s), day-of-sample (ψ_t), region-by-year (θ_{ry}) and region-by-month (δ_{rm}) levels, and cluster standard errors by month-of-sample.

Table 3 presents our results. Column (1) shows that an 8 pp (1 SD) increase in the share of generating capacity on equipment outage leads to a 0.4 pp ($p < 0.01$) increase in retail blackouts—a 20% increase on the baseline blackout rate of 1.8 pp. In Columns (2)–(4), we construct the dependent variable using only ESMI monitors on residential, commercial/industrial, or agricultural feeders. This reveals that our pooled estimate is almost entirely driven by residential blackouts: Column (2) shows that a 1 SD increase in equipment outage rates causes a 23% increase in blackouts among residential distribution feeders. We find no impacts on commercial or industrial feeders (Column (3)). Though imprecisely estimated, the large point estimate and high average rate of blackouts for agricultural feeders (Column (4)) aligns with prior evidence that these customers, who pay a flat monthly fee for electricity if they are charged at all, face a disproportionate share of India's blackouts (Burgess et al. (2020); Ryan and Sudarshan (2022)).

Due to the sparseness of ESMI monitor locations, we lack the statistical power to esti-

36. The 50% cutoff is arbitrary. We recover similar estimates for cutoffs ranging from 40% to 90%, but not for cutoffs below 40%, which suggests that power plant equipment outages disproportionately cause blackouts of 9 hours or longer.

Table 3: Equipment outages cause a measurable increase in retail blackouts

	Outcome: $\mathbf{1}\big[\text{Blackout in} > 50\% \text{ of minutes monitored}\big]_{st}$			
	(1)	(2)	(3)	(4)
	OLS	OLS	OLS	OLS
Equipment outage rate	0.045***	0.043***	−0.005	0.416
	(0.014)	(0.014)	(0.020)	(0.769)
Subset of monitors	All sectors	Residential	Comm./Industrial	Agricultural
State + date FEs	Yes	Yes	Yes	Yes
Region-year, region-month FEs	Yes	Yes	Yes	Yes
Mean of dep var	0.018	0.015	0.012	0.378
State-day observations	21,925	21,108	12,073	1,336
Mean monitors per state-day	10.96	9.09	3.47	2.97

Notes: This table presents results from estimating Equation (3). The dependent variable is the share of minutes in each state-day cell that reports a voltage of zero, taking an unweighted average across reporting ESMI monitors with usable data. Column (1) averages across all ESMI monitors. Columns (2)–(4) construct the dependent variable using only monitors on residential, commercial/industrial, and agricultural feeders, respectively. Subsetting by sector reduces both the number of state-day observations and the average number of monitors per state-day. All regressions control for average daily temperature (for precision), and the total number of dispatchable power plants in state s (to account for differential market expansions across states over time). Consistent with Table 2, 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: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

mate the 2SLS version of Equation (3) using the equipment outage rate as an instrument for average variable cost. The results in Table 3 nevertheless provide a direct empirical link between our wholesale demand regressions in Table 2 and blackouts experienced by Indian retail consumers. They demonstrate that equipment outages—shown in Section 3.2 to increase utilities' wholesale procurement costs and lower the quantity of wholesale electricity demanded—lead to retail blackouts.

5 Approaches to reducing blackouts

In this section, we study the impacts of reducing blackouts through (i) supply side policies which reduce wholesale procurement costs or (ii) a quantity mandate in the wholesale market. We begin by outlining the economic intuition behind these two approaches using a stylized model. Next, we specify a simple structural model of India's wholesale electricity market. Then, we use the model to measure the quantity impacts of supply-side interventions. We close with a discussion of the welfare impacts of simply mandating that utilities purchase more electricity from the wholesale market.

5.1 Illustrative model

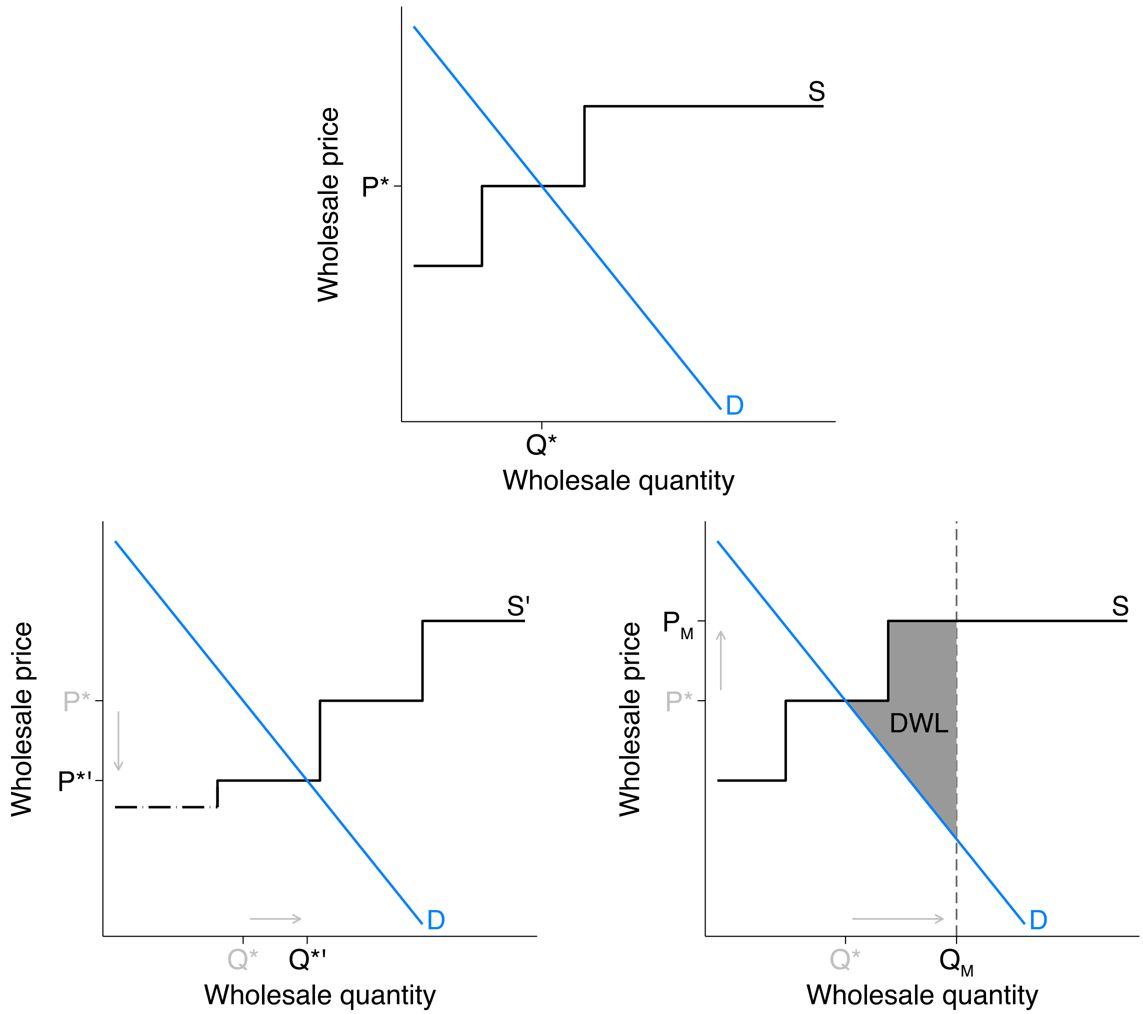
Figure 3 presents an illustrative model of the Indian wholesale electricity market, where power plants supply electricity according to the supply curve S and utilities have a downward-sloping demand curve D. In the top panel (our base case), the market clears where supply and demand intersect, resulting in equilibrium price P^* and quantity Q^*.

In the bottom-left panel, we add a new low-cost power plant into the market, shifting out the supply curve from S to S'. Equilibrium quantity increases from Q^* to $Q^{*'}$, and equilibrium price falls from P^* to $P^{*'}$. Because demand is downward-sloping, supply-side reforms that reduce wholesale procurement costs (such as reducing power plant outages or building new, low-cost power plants) increase the equilibrium quantity of electricity supplied, thereby reducing blackouts.

In the bottom-right panel, we start with the base case and instead add a mandate that utilities purchase at least $Q_M > Q^*$. The resulting price increases to $P_M > P^*$. The mandate lowers surplus in the wholesale market by forcing utilities to purchase electricity beyond their marginal willingness-to-pay, resulting in deadweight loss (DWL, shaded gray).

Figure 3 focuses on the wholesale electricity market alone. It does not capture the costs of adding low-cost generating capacity to the supply curve or the benefits of fewer retail blackouts. However, this framework is useful in illustrating the importance of accounting for downward-sloping demand when considering potential approaches to reducing blackouts.

Figure 3: Illustrative model of India's wholesale electricity market



Notes: This figure presents a stylized model of the Indian wholesale electricity market. In the top panel (our base case), the market has three power plants, each with constant marginal costs and a strict capacity constraint. The market clears at equilibrium price (P^*) and quantity (Q^*). In the bottom row, we present two counterfactual scenarios. In the left panel, we add a fourth low-cost plant, denoted with the dot-dashed region of the supply curve, to the market. Equilibrium outcomes move to $P^{*'}$ and $Q^{*'}$. In the right panel, we introduce a quantity mandate at $Q_M > Q^*$, which raises the price to P_M. With a mandate, deadweight loss in the wholesale market is indicated by DWL and is shaded in gray.

5.2 Simple structural model

We specify a simple structural model in order to quantitatively assess the wholesale market impacts of cost-reducing supply-side policies and a quantity mandate. We provide a sketch of the model here; Appendix B.1 presents the full model in detail.

Demand side We specify constant-elasticity wholesale demand, setting a price elasticity of demand of -0.49 based on Column (4) of Table 2. 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. Our demand curve therefore passes through the point defined by the observed quantity supplied and observed average variable cost.[37] We assume that retail electricity prices do not respond to counterfactual changes in wholesale procurement costs (i.e., we hold the wholesale demand curve fixed).

Supply side We clear the wholesale electricity market for each state-day by simulating power plant dispatch.[38] We stack all generating capacity that is available (i.e., not on outage) within each state from lowest to highest marginal cost. Then, we dispatch power plants following this marginal cost curve, allowing us to simulate dispatch under alternate supply scenarios.

This least-cost dispatch assumption is likely overly optimistic, as our simulations may dispatch plants that could not have generated in reality due to technical constraints—such as within-state transmission constraints (Davis and Hausman (2016)) or ramping constraints (Reguant (2014); Jha and Leslie (2025)). However, many low- and middle-income countries have systems where generating units are dispatched from lowest to highest marginal cost (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 supply-side reform compares quantity supplied under least-cost dispatch versus observed dispatch.

37. We conduct sensitivity analyses assuming linear demand (as opposed to constant-elasticity demand), and assuming utilities respond to marginal cost (as opposed to average variable cost). In the latter sensitivity analyses, the demand curve passes through observed quantity and the 98th percentile of marginal cost, to align with the elasticity estimate in Column (2) of Appendix Table A.5.

38. 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 decreases in wholesale cost.

5.3 Supply-side interventions to reduce procurement costs

Using this simple structural model, we assess the quantity impacts 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 India's coal 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 thermal efficiency between India and the U.S.).

Second, we ask: what if the outage rate of Indian coal-fired power plants fell to the U.S. rate of approximately 5%?[39] 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 Ultra-Mega Power Plants ("UMPPs") awarded to successful bidders between 2007–2009 (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 25th percentile of its respective state-day distribution.[40]

Table 4 presents the findings of this counterfactual exercise.[41] Column (1) of this table 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 marginal cost, the corresponding decrease in average

39. 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).

40. We take plant locations and capacities from Ministry of Power (2021). We choose the 25th percentile of the state-month distribution of marginal costs 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.

41. In Appendix Table B.1, we assume linear demand rather than constant-elasticity demand. In Appendix Table B.2, we assume that utilities respond to marginal costs instead of average variable costs. Though the magnitudes vary based on the assumptions, the qualitative conclusions are the same: the hypothetical supply-side interventions all lead to meaningfully fewer blackouts.

Table 4: 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)	44.9	44.9	44.9	44.9
Incremental quantity increase relative to LC (GWh/day)		62.4	41.7	32.8
Incremental HHs shifted to 24×7 power		134.1M	89.8M	70.6M

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.

variable cost would cause price-responsive utilities to purchase an additional 44.9 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 62.4 GWh/day; reducing forced outages to U.S. levels would translate to an incremental 41.7 GWh/day; and building four low-cost UMPPs would translate to an incremental increase of 32.8 GWh/day.

To what extent would an increase of 32.8–62.4 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, 32.8–62.4 additional GWh/day could provide 3.4 hours/day worth of electricity to 70.6–134.1 million households. In other words, the quantities reported in Table 4 would be sufficient to eliminate blackouts and achieve 24×7 power for 27–51% of all households in India.[42]

42. During this period, there were roughly 266 million households in India. In reality, households likely

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).

Of course, each of these supply-side interventions would require expensive investments towards 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, and we note that given that India's retail electricity consumers pay prices below the private cost of supply, costly interventions to increase quantity supplied may further exacerbate retail distortions. Nevertheless, our findings highlight the importance of considering downward-sloping demand when evaluating policies to reduce production costs in India's wholesale power sector.

5.4 Welfare consequences of a quantity mandate

Table 4 shows that supply-side interventions that decrease wholesale procurement costs can also meaningfully increase quantity supplied. What if India's electricity regulators instead simply imposed a quantity mandate requiring utilities to purchase more than the equilibrium wholesale quantity? In principle, such a mandate would provide enough electricity to satisfy all retail demand at the prices faced by end-use consumers. Using the aforementioned statistics on energy use among Indian households implies that in order to eliminate blackouts for all 266 million Indian households, utilities would have to procure an additional 105

would not receive all of the increased power supply. However, Table 3 suggests that blackouts induced by wholesale cost shocks primarily impact residential consumers.

GWh/day (a 5% increase above equilibrium quantity supplied).[43] We proportionally allocate this aggregate increase across states: on each day, each state must increase quantity supplied by the same percentage relative to its equilibrium quantity supplied. Appendix Figure B.1 considers a range of potential mandates from 0% to 10% increases in quantity supplied.

Using our simple structural model, we find that mandating a 105 GWh/day increase in electricity purchases would decrease welfare in the wholesale market by 2.1% relative to our no-mandate baseline.[44] These wholesale welfare losses come entirely from utilities' decreased consumer surplus.[45] Importantly, 2.1% is likely a lower bound—because utilities pay power plants regulated prices above their marginal operating costs, and because our model assumes least-cost dispatch, which removes meaningful distortions from the Indian power market.

How do utility losses compare to the benefits to retail consumers from avoided blackouts? Our simulations imply that a mandate would lower utilities' wholesale market surplus by Rs 0.8/kWh, or approximately 20% of India's average residential retail tariff (Central Electricity Authority (2019b)). Some Indian households install and operate costly back-up power sources—spending approximately Rs 7/kWh to operate a battery and inverter system, or Rs 18/kWh to operate a diesel generator—and would thus benefit from a quantity mandate.[46] However, even in relatively wealthy Delhi, only 8% of households report having

43. 2.8 kWh/HH-day $\div$ 24 hours/day $\times$ 3.4 hours/day $\div$ 1 million kWh/GWh $\times$ 266 million HH = 105 GWh/day. Note that these figures hold retail tariffs fixed, and tariffs are set below private marginal cost. If a mandate was accompanied with an increase in retail electricity tariffs, quantity demanded would fall (Mahadevan (2024) estimates a price elasticity of retail demand of -0.60 in India), and thus utilities would need to purchase less than 105 GWh per day of electricity to satisfy all demand.

44. Appendix Table B.3 reports welfare changes for our preferred model, as well as two sensitivities: linear (as opposed to constant elasticity) wholesale demand, and setting prices equal to marginal cost (as opposed to average variable cost). The mandate decreases wholesale market welfare in both sensitivities. As Appendix Figure B.1 demonstrates, the differences in wholesale market welfare losses between constant-elasticity versus linear demand are relatively small over the range of quantity increases relevant for eliminating blackouts for households.

45. Utilities are consumers in the wholesale market. Our model has zero producer surplus, since we set the wholesale price equal to the average marginal cost of operating power plants.

46. Battery/inverter systems let households charge during periods with power supply and discharge during blackouts. The primary operating cost of these systems comes from charging. We calculate Rs 7/kWh by scaling the national average residential electricity price in 2019 (Rs 3.97/kWh averaged across Indian states) by the 42% energy loss inherent to charging and discharging lead-acid batteries (Seetharam et al. (2013)).

made such investments (Khanna and Rowe (2024)), implying that the average Indian household is willing to pay much less than Rs 7–18/kWh to avoid blackouts. In addition, since Indian electricity consumers face retail tariffs that are regulated at prices below marginal cost, reducing blackouts may lower total welfare by encouraging further over-consumption. Therefore, it remains unclear whether such a mandate would be welfare-improving overall.

Moreover, as we discuss in Section 2.1, Indian utilities already require subsidies and federal government interventions to remain financially solvent. Mandating that they purchase even more power from the wholesale sector—thereby exacerbating their financial challenges—would be extremely politically challenging. Any regulatory reform to increase quantity supplied would therefore likely need to be accompanied with an increase in retail tariffs, which is perhaps even less plausible given India's norm of treating electricity access as a right (Burgess et al. (2020)). In light of these political and regulatory constraints, supply-side policies that lower wholesale procurement costs may serve as a more realistic strategy to mitigate blackouts in India.

6 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 that utility buyers purchase substantially less electricity when wholesale procurement costs increase. We next establish a direct empirical link between wholesale cost shocks and blackouts experienced by end-use electricity consumers. Lowering wholesale procurement costs can therefore meaningfully increase the quantity of energy supplied to retail consumers, in turn 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 of electricity 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.

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)). In this paper, we emphasize one key institutional difference between India and high-income countries: India lacks a mandate that utilities must satisfy all retail electricity demand. Though we show that such a mandate reduces welfare in the wholesale electricity market, its overall welfare impacts are unclear, owing to substantial distortions in the retail electricity sector. Quantifying the full welfare effects of improving power supply via a mandate will require future research on consumers' willingness to pay to avoid blackouts and the deadweight loss generated by setting retail prices below marginal cost.

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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 related to our demand estimation.

Appendix B provides details on our simple structural model, as well as robustness and supplementary results.

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

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A Demand estimation appendix

A.1 States with high versus low generation costs

As discussed in the main text, we re-estimate our demand regressions splitting the sample by high versus low average-variable-cost states. To do this, we take the sample-wide average of average variable costs across power plants in each state s, weighting plants by their average capacity. Then, we split the sample to states above versus below the median of this capacity-weighted average variable cost. We present these split sample results in Appendix Table A.1: states facing higher average variable costs of production exhibit a higher cost elasticity of demand on average. This suggests that utilities that may be losing more money on the margin are more sensitive to wholesale cost increases—supporting our central hypothesis that utilities *choose* to purchase less electricity when procurement costs are higher.

Table A.1: Demand regressions splitting states by high versus low average variable costs

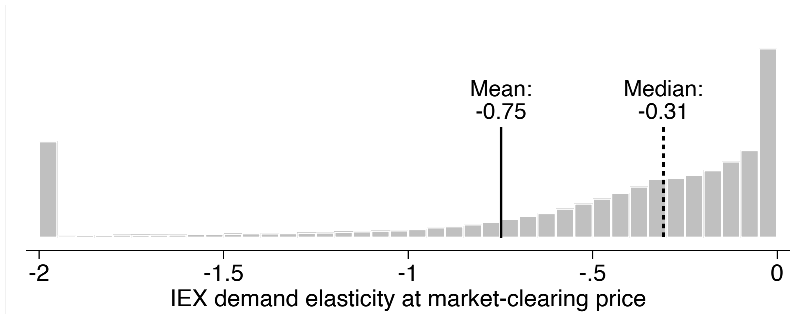
	Outcome: log (Quantity)			
	(1)	(2)	(3)	(4)
	OLS	IV	OLS	IV
Equipment outage rate	-0.14^{***}		-0.02	
	(0.04)		(0.05)	
log (Average variable cost)		-0.54^{***}		-0.09
		(0.18)		(0.27)
Split on states' average variable cost	High AVC	High AVC	Low AVC	Low AVC
State + date FEs	Yes	Yes	Yes	Yes
Region × year, region × month FEs	Yes	Yes	Yes	Yes
Mean demand met (in GWh)	68.76	68.76	118.12	118.12
State-day observations	20,993	20,993	21,219	21,219
First-stage estimate		0.26^{***}		0.19^{***}
		(0.06)		(0.02)
Kleibergen-Paap F-statistic		22.44		94.87

Notes: This table presents additional results from estimating Equation (2). The dependent variable is the natural logarithm of total GWh of energy purchased in the wholesale sector in state s on date t. We split the sample on states' average variable cost of generation (i.e., above/below-median of the capacity-weighted state-level average variable costs over our sample period). Columns (1) and (3) are otherwise identical to Column (1) of Table 2. Columns (2) and (4) are otherwise identical to Column (4) of Table 2. Standard errors are clustered by sample month. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

A.2 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 -0.75, with a median of -0.31, 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 price 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.3 Robustness: Demand estimation

Appendix Table A.2 provides sensitivity analysis for our demand elasticity estimates in Table 2. Column (1) accounts for local (within-state) transmission constraints. We assign plants to "load pockets" (i.e, high-demand areas)—proxied by being located within one of India's 20 most populous districts. Then, we construct the instrument using only equipment outages outside of these load pockets. Column (1) also restricts the sample to state-days with idle capacity outside of load pockets, which are unlikely to have faced a local transmission constraint.

Next, Appendix Table A.2 provides two alternate versions of Column (6) in Table 2, which jointly removes potential short-outage effects and anticipation effects by instrumenting using only equipment outages already on at least their fifth day. Column (2) instruments using all days of 5-day-or-longer equipment outages (i.e., not omitting days 1–4), which isolates potential differences in outage type (i.e., long versus short equipment outages). Column (3) lags our preferred instrument based on all equipment outages by 4 days, which removes any potential anticipation effects. Both sensitivities yield similar elasticity estimates.

Table A.2: Sensitivities for demand regressions – sample restrictions

	Outcome: log (Quantity)			
	(1) IV	(2) IV	(3) IV	(4) IV
log (Average variable cost)	-0.55^{***}	-0.54^{**}	-0.39^{*}	-0.50^{**}
	(0.20)	(0.22)	(0.21)	(0.21)
Equip. outages outside load pockets	Yes			
Idle capacity available outside load pockets	Yes			
Equip. outages that span 5+ days		Yes		
Equip. outages lagged 4 days			Yes	
Include state-days with < 50% coverage				Yes
State + date FEs	Yes	Yes	Yes	Yes
Region × year, region × month FEs	Yes	Yes	Yes	Yes
Mean demand met (in GWh)	150.12	90.25	90.26	88.70
State-day observations	12,093	42,212	38,842	43,044
First-stage estimate	0.31^{***}	0.19^{***}	0.17^{***}	0.18^{***}
	(0.05)	(0.04)	(0.03)	(0.03)
Kleibergen-Paap F-statistic	37.49	27.79	24.13	30.24

Notes: Column (1) shows that our demand elasticity estimates are robust to transmission constraints around load pockets: the instrument only includes equipment outages at plants not located in one of India's 20 most populous districts, and restricts the sample to state-days where a "non-load-pocket" plant reported idle capacity. Column (2) is similar to Column (6) of Table 2, except that the instrument also includes days 1–4 of equipment outages that (eventually) persist for at least 5 consecutive days. Column (3) is identical to Column (4) of Table 2, except that the instrument is lagged by 4 days. Column (4) is identical to Column (4) of Table 2, except that it includes 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. Regressions are otherwise identical to Table 2. Standard errors are clustered by sample month. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Finally, Column (4) of Appendix Table A.2 relaxes our preferred sample restriction, where we omit observations for which our state-day equipment outage rate and average variable cost are calculated using less than 50% of total (thermal + hydro) capacity. In the main text, we impose this restriction to account for the incompleteness of our plant-day 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-day level demand. However, we estimate an even larger demand elasticity when we include these state-days in the regression.

Appendix Table A.3 conducts sensitivity analysis on our definition of "idle capacity available." Columns (2) and (5) of Table 2 report results based on our preferred definition of idle capacity: if any capacity (> 0 MW) in state s on day t was available to generate (i.e., was not on outage) but did not. For this specification, we estimate a reduced-form effect of -0.12 and an IV estimate of -0.42. Columns (1)–(2) of Appendix Table A.3 strengthen

Table A.3: Sensitivities for demand regressions – idle capacity available

	Outcome: log (Quantity)			
	(1) OLS	(2) IV	(3) OLS	(4) IV
Equipment outage rate	-0.16^{***}		-0.16^{*}	
	(0.06)		(0.09)	
log (Average variable cost)		-0.62^{**}		-0.39
		(0.28)		(0.29)
Idle capacity available	Yes	Yes	Yes	Yes
Definition of idle capacity	$>$ 250 MW idle in state		$\geq$ 2 plants idle in state	
State + date FEs	Yes	Yes	Yes	Yes
Region $\times$ year, region $\times$ month FEs	Yes	Yes	Yes	Yes
Mean demand met (in GWh)	184.59	184.59	218.43	218.43
State-day observations	10,625	10,625	5,564	5,564
First-stage estimate		0.26^{***}		0.41^{***}
		(0.06)		(0.11)
Kleibergen-Paap F-statistic		21.63		14.10
Mean of equipment outage rate	0.08	0.25	0.08	0.25
SD of equipment outage rate	0.06	0.06	0.26	0.26
Mean potential GWh (idle cap.)	35.00	35.00	55.77	55.77

Notes: This table presents sensitivity analysis on our preferred definition of "idle capacity avaiable". (i.e. any plant in the state with any positive capacity that was avaiable to generate but did not). Columns (1)–(2) strengthen this definition from ≥ 0 MW to ≥ 250 MW of idle capacity in the state.Columns (3)–(4) apply an alternate definition: at least 2 plants in the state must have capacity that was avaiable to generate but did not.Columns (1) and (3) are otherwise identical to Column (2) of Table 2. Columns (2) and (4) are otherwise identical to Column (5) of Table 2. Standard errors are clustered by sample month. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

this definition to at least ($>$ 250 MW) of idle capacity in state s on day t. This yields similar cost-elasticity of demand estimates. In Columns (3)–(4), we apply the stronger sample restriction that at least 2 plants in state s had idle capacity on day t. This shrinks the sample considerably, causing us to lose statistical power. Nevertheless, we still recover similar point estimates.

Appendix Table A.4 conducts sensitivity analysis to assuage concerns that our demand elasticities are driven by transmission constraints, as opposed to utilities choosing to purchase less power. Using data on IEX market-clearing prices at the subregion/15-minute-interval level (Indian Energy Exchange (2014–2019)), we identify region-days where there were zero price wedges between constituent subregions.[1] Columns (1)–(2) reveal that our

1. Each of the India's 5 market regions comprises 2–3 subregions. IEX price wedges between subregions

Table A.4: Sensitivities for demand regressions – no intra-regional IEX price wedges

	Outcome: log (Quantity)			
	(1) OLS	(2) IV	(3) OLS	(4) IV
Equipment outage rate	-0.08^{**}		-0.07^{*}	
	(0.03)		(0.04)	
log (Average variable cost)		-0.46^{**}		-0.33^{*}
		(0.23)		(0.17)
No IEX price wedges within region	Yes	Yes	Yes	Yes
Idle capacity available in region			Yes	Yes
State + date FEs	Yes	Yes	Yes	Yes
Region × year, region × month FEs	Yes	Yes	Yes	Yes
Mean demand met (in GWh)	87.09	87.09	104.24	104.24
State-day observations	38,792	38,792	32,424	32,424
First-stage estimate		0.16^{***}		0.22^{***}
		(0.04)		(0.03)
Kleibergen-Paap F-statistic		21.36		49.96
Mean of equipment outage rate	0.10	0.30	0.10	0.30
SD of equipment outage rate	0.09	0.09	0.34	0.34
Mean potential GWh (idle cap.)	8.64	8.64	10.34	10.34

Notes: This table tests whether our demand estimates are driven by trading frictions by including only the subset of state-days with zero intra-regional wedges in the market-clearing IEX price. We construct this subsample using IEX prices IEX at the subregion by 15-minute interval level, classifying a region-day as having "no wedges" if within-interval prices were identical for all subregions, for all 96-minute intervals of the the day. Columns (1)–(2) apply this sample restriction, and are otherwise identical to Columns (1) and (4) of Table 2. Columns (3)–(4) are analogous, but impose an additional restriction of there being idle capacity available in the region. Standard errors are clustered by sample month. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

demand elasticity estimates are robust to dropping state-days with intra-regional IEX price wedges. Columns (3)–(4) find similar results when we impose the additional restriction of idle generating capacity being available within the region. These results support the interpretation that our estimates in Table 2 indeed reflect downward-sloping utility demand.

In Appendix Table A.5, we estimate the wholesale demand elasticity with respect to marginal cost, rather than average variable cost. Columns (1)–(2) use the 95th and 98th percentiles (respectively) of the realized marginal cost distribution for operating plants in each state-day. This yields similar demand elasticity estimates, despite the fact that using marginal cost does not align with the incentives implied by cost-of-service regulation in this setting (i.e., prices are set by regulators based on average costs rather than market-based

indicate that transmission constraints prevented unconstrained power trade between subregions.

Table A.5: Demand regressions using marginal cost instead of average variable cost

	Outcome: log (Quantity)		
	(1) IV	(2) IV	(3) IV
log (95th percentile of marginal cost)	-0.25^{**}		
	(0.10)		
log (98th percentile of marginal cost)		-0.39^{**}	
		(0.19)	
log (Maximum marginal cost)			-0.61
			(0.40)
State + date FEs	Yes	Yes	Yes
Region × year, region × month FEs	Yes	Yes	Yes
Mean demand met (in GWh)	90.25	90.25	90.25
State-day observations	42,212	42,212	42,212
First-stage estimate	0.35^{***}	0.22^{***}	0.14^{*}
	(0.06)	(0.06)	(0.07)
Kleibergen-Paap F-statistic	40.86	14.37	3.61

Notes: These regressions estimate the wholesale demand elasticity with respect to alternate constructions of marginal cost (as opposed to our preferred average variable costs). Columns (1) and (2) use the 95th and 98th percentiles of marginal costs among operating plants within each state-day; and Column (3) uses the maximum marginal cost for each state-day. Regressions are otherwise identical to Column (4) of Table 2. Standard errors are clustered by sample month. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

dispatch). Column (3) uses the maximum marginal cost among operating plants in each state-day, which is most analogous to a conventional competitive market equilibrium where the aggregate marginal cost curve intersects demand. This yields an underpowered first stage, which makes sense given that the maximum is particularly prone to outliers induced by measurement error in our constructed marginal costs.

We next conduct sensitivity analysis on our preferred log-log functional form of demand. Appendix Table A.6 presents a version of Table 2 under the assumption of linear demand. This yields reduced-form estimates in Columns (1)–(3) that are larger in magnitude than in our main specification: the 25.32 GWh/day reduction in quantity supplied implied by the point estimate in Column (1) corresponds to a 17% change in quantity supplied. Columns (4)–(6) likewise imply larger demand elasticities than our preferred log-log model. For Column (4), a 10% increase in average variable cost (i.e., a 0.14 Rs/kWh increase) causes wholesale quantity to fall by 21 GWh/day (i.e., a 14% decrease)—implying a cost elasticity of demand of -1.4. However, we interpret this estimate with caution due to the low first-stage F-statistic. For Column (5) where the F-statistic is larger, a 10% increase in AVC (i.e.,

Table A.6: Demand regressions assuming linear demand instead of log-log demand

	Outcome: Quantity (GWh)					
	(1) OLS	(2) OLS	(3) OLS	(4) IV	(5) IV	(6) IV
Equipment outage rate	-25.32^{***}	-37.61^{***}	-28.42^{***}			
	(4.60)	(9.84)	(4.83)			
Average variable cost (Rs/kWh)				-149.48^{**}	-104.92^{***}	-141.49^{***}
				(59.45)	(36.67)	(53.52)
Idle capacity available		Yes			Yes	
Equip. outages already 5+ days			Yes			Yes
State + date FEs	Yes	Yes	Yes	Yes	Yes	Yes
Region-year, region-month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Mean demand met (in GWh)	145.71	202.72	145.71	145.71	202.72	145.71
State-day observations	42,215	13,722	42,215	42,215	13,722	42,215
First-stage estimate				0.17^{***}	0.36^{***}	0.20^{***}
				(0.06)	(0.07)	(0.07)
Kleibergen-Paap F-statistic				7.37	30.16	7.66
Mean of avg variable cost (Rs/kWh)				1.41	1.33	1.41
SD of avg variable cost (Rs/kWh)				0.59	0.49	0.59
Mean of equipment outage rate	0.10	0.09	0.08	0.10	0.09	0.08
SD of equipment outage rate	0.09	0.07	0.08	0.09	0.07	0.08
Mean potential GWh (idle cap.)	8.92	27.43	8.92	8.92	27.43	8.92

Notes: This table is identical to Table 2, except that rather than estimating a log-log model, we estimate a linear model. The outcome variable is GWh of energy purchased by in the wholesale sector in state s on date t (in levels). The endogenous right-hand-side variable is the average variable cost of generation in Rs/kWh in state s on date t (in levels). Standard errors are clustered by sample month. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. See notes under Table 2 for further details.

0.13 Rs/kWh) causes wholesale quantity to fall by 14 GWh/day (i.e., a 6.7% decrease)—implying an elasticity of -0.67. This is within the 95% confidence interval of the elasticity estimate implied by our log-log specification (see Column 5 of Table 2).

A.4 Robustness: Equipment outages and lagged demand

Dynamics in power plant maintenance present a potential concern for our estimates in Table 1. It is possible that technical failures are more likely after periods of high demand (e.g., if plants have run "too hot" for many consecutive days, or if high demand causes them to forgo their planned maintenance). We address these concerns by adding lags to our regressions of equipment outage rates on demand shocks.

Appendix Table A.7 conducts robustness on Column (1) of Table 1, adding daily lags of temperature and the realized quantity of wholesale electricity demanded. We cannot control for contemporaneous quantity demanded because of simultaneity—the equilibrium quantity demanded is directly impacted by equipment-outage-induced cost shocks. Appendix Table A.7 reveals no meaningful dynamics related to temperature. While the coefficient on contemporaneous daily temperature is statistically significant at the 10% level, its magnitude is extremely small: we can reject that a 1°C change is associated with a 0.1 pp change in equipment outage rates.

We find a statistically significant correlation between equipment outage rates and the 3-day lag of state-level demand, but statistically insignificant estimates on the corresponding 1-, 2-, 4-, and 5-day lags. The magnitude of the coefficient on the 3-day lag is extremely small: we can reject that a 10% increase in 3-day-lagged quantity demanded is associated with a 0.1 pp increase in equipment outage rates. Given the lack of impacts for the other lags, this correlation likely stems from sampling variability.

Appendix Table A.8 conducts robustness on Column (3) of Table 1, adding 2 monthly lags of temperature, forecasted demand (only observed at the monthly level), and realized quantity demanded. We find no evidence that equipment outage rates are correlated with lagged temperature or lagged forecasted demand. While we recover a statistically significant correlation between equipment outage rates and the 1-month lag of realized quantity demanded, this magnitude is not economically meaningful: we can reject that a 10% increase in 1-month-lagged equilibrium quantity demanded is associated with a 1 pp increase in equipment outage rates. Again, this correlation with the 1-month lag likely stems from sampling variability given the small magnitude and lack of impacts from other lags.

Table A.7: Equipment outage rates do not respond to elec. demand shocks (daily lags)

	Outcome: Share of plant's capacity on equip. outage	
	(1)	(2)
Mean temperature in state (°C)	-0.0005^{*}	-0.0004^{*}
	(0.0003)	(0.0003)
Mean temperature in state (°C), 1-day lag	0.0001	0.0003
	(0.0002)	(0.0002)
Mean temperature in state (°C), 2-day lag	-0.0002	-0.0002
	(0.0002)	(0.0002)
Mean temperature in state (°C), 3-day lag	-0.0000	-0.0002
	(0.0002)	(0.0002)
Mean temperature in state (°C), 4-day lag	0.0000	-0.0000
	(0.0002)	(0.0002)
Mean temperature in state (°C), 5-day lag	-0.0003	-0.0003
	(0.0002)	(0.0003)
log (Quantity demanded in state), 1-day lag		-0.0064
		(0.0043)
log (Quantity demanded in state), 2-day lag		0.0042^{*}
		(0.0025)
log (Quantity demanded in state), 3-day lag		0.0064^{***}
		(0.0022)
log (Quantity demanded in state), 4-day lag		0.0008
		(0.0035)
log (Quantity demanded in state), 5-day lag		0.0006
		(0.0050)
Plant + month-of-sample FEs	Yes	Yes
Region-year, region-month FEs	Yes	Yes
Mean of dep. var.	0.1110	0.1110
Plant-day observations	400,711	400,676

Notes: Regressions are identical to Column (1) of Table 1, except that we add 5 daily lags of temperature and 5 daily lags of the realized quantity of wholesale electricity demanded in state s. We omit the contemporaneous realized quantity demanded because equipment-outage-related cost shocks directly affect the market equilibrium. The dependent variable is plant i's equipment outage rate (i.e. the daily share of its total capacity on equipment outage). Both regressions control for the total number of dispatchable plants in each state. Standard errors are clustered by sample month. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.8: Equipment outage rates do not respond to elec. demand shocks (monthly lags)

	Outcome: Share of plant's capacity on equip. outage	
	(1)	(2)
Mean temperature in state (°C)	−0.0007	0.0001
	(0.0014)	(0.0014)
Mean temperature in state (°C), 1-month lag	−0.0007	−0.0019
	(0.0014)	(0.0015)
Mean temperature in state (°C), 2-month lag	−0.0015	−0.0019
	(0.0012)	(0.0012)
log (State's forecasted energy req.)	−0.0028	−0.0229
	(0.0145)	(0.0139)
log (State's forecasted energy req.), 1-month lag	0.0063	
	(0.0158)	
log (State's forecasted energy req.), 2-month lag	−0.0080	
	(0.0119)	
log (Quantity demanded in state), 1-month lag		0.0401**
		(0.0191)
log (Quantity demanded in state), 2-month lag		−0.0180
		(0.0163)
Plant + month-of-sample FEs	Yes	Yes
Region-year, region-month FEs	Yes	Yes
Mean of dep. var.	0.1137	0.1140
Plant-month observations	19,023	18,440

Notes: Regressions are identical to Column (3) of Table 1, except that we add 2 monthly lags of temperature, forecasted energy requirement, and realized quantity of wholesale electricity demanded in state s. We omit contemporaneous realized quantity demanded because equipment-outage-related cost shocks directly affect the market equilibrium. The dependent variable is plant i's equipment outage rate (i.e. the daily share of its total capacity on equipment outage). All regressions control for the total number of dispatchable plants in each state. Standard errors are clustered by sample month. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

B Structural model appendix

B.1 Further details on our simple structural model

This section provides details on the simple structural model sketched out in Section 5. We discuss the demand side and the supply side of the model in turn.

Demand side For our preferred specification, we assume constant-elasticity wholesale demand, setting a cost elasticity of demand of -0.49 (based on Column (4) of Table 2). For state s on day t, quantity demanded is:

$$Q_{st} \;=\; \alpha_{st}\, AVC_{st}^{-0.49}$$

where average variable cost is defined as:

$$AVC_{st} \;\equiv\; \frac{\sum_{i \in s} MC_{st}\, Q_{st}}{\sum_{i \in s} Q_{it}}$$

We calibrate α_{st} to the observed quantity supplied Q^*_{st} and average variable cost AVC^*_{st}:

$$\alpha_{st} \;\equiv\; \frac{Q^*_{st}}{(AVC^*_{st})^{-0.49}}$$

We conduct sensitivity analyses assuming linear demand:

$$Q_{st} \;=\; a_{st} \;+\; b_{st}\, AVC_{st}$$

To set the slopes b_{st}, we assume that the cost elasticity of demand is -0.49 at the observed quantity supplied Q^*_{st} and average variable cost AVC^*_{st} (i.e., $b_{st} = -0.49\dfrac{Q^*_{st}}{AVC^*_{st}}$). Then, we calibrate the intercepts $a_{st} = Q^*_{st} - b_{st}AVC^*_{st}$.

These intercepts play an important role across specifications: for both constant-elasticity and linear demand, we set the choke price (where $Q_{st} = 0$) equal to a_{st}. This means that, even under constant-elasticity demand, we assume that $Q_{st} = 0$ for all $AVC_{st} \geq a_{st}$, in order to avoid consumer surplus being overly-sensitive to the curvature of demand close to $Q_{st} = 0$.

We also conduct sensitivity analyses assuming utilities respond to marginal cost (MC) as opposed to AVC. In this case, the demand curve passes through observed quantity Q^*_{st} and the 98th percentile of marginal cost MC^{98*}_{st}, and we assume an elasticity of -0.39 (based on Column (2) of Appendix Table A.5):

$$\begin{aligned} Q_{st} &= \alpha_{st}\,(MC^{98}_{st})^{-0.39} \\ \alpha_{st} &\equiv \frac{Q^*_{st}}{(MC^{98*}_{st})^{-0.39}} \end{aligned}$$

As above, we set the choke point based on the intercept implied by linear demand with the same elasticity: $b_{st} = -0.39 \times \dfrac{Q^*_{st}}{MC^{98,*}_{st}}$, $a_{st} = Q^*_{st} - b_{st}MC^{98,*}_{st}$. Then, we set $Q_{st} = 0$ for all $MC^{98}_{st} \geq a_{st}$.

For the supply-side interventions considered in Section 5.3, we assume that retail electricity prices do not respond to counterfactual changes in wholesale procurement costs. In other words, we hold the wholesale demand curve fixed when applying these supply-side interventions.

Supply side For each date t, we clear the market for each state s separately, conservatively assuming no interstate trade.[2] We stack all generating capacity that is available (i.e., not on outage) within each state from lowest to highest marginal cost, and then dispatch power plants in this order. Inframarginal plants produce at capacity, where we calculate capacity based on the 98th percentile of generation over the past year. The marginal plant produces output between zero and its capacity, such that quantity demanded implied by the relevant cost (either AVC or MC, depending on specification) is equal to the implied total quantity supplied.

B.2 Sensitivity analysis: Supply-side interventions

Appendix Tables B.1 and B.2 present robustness for our counterfactual simulations. In Appendix Table B.1, we model utilities as responding to average variable cost, but assuming linear demand rather than constant elasticity demand. In Appendix Table B.2, we model

2. By ignoring the potential benefits from reallocating output across states, we likely understate the increases in power supply that would result from decreases in wholesale procurement costs.

utilities as responding to marginal cost rather than average variable cost (using an elasticity of −0.39 from Column 2 of Table A.5), and assuming constant elasticity demand.

Table B.1: Quantity impacts of different supply-side interventions: Linear 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)	43.3	43.3	43.3	43.3
Incremental quantity increase relative to LC (GWh/day)		57.5	36.5	26.1
Incremental HHs shifted to 24×7 power		123.7M	78.6M	56.2M

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 4 in the main text, we assume linear demand rather than constant-elasticity 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.

As in Table 4, Column (1) presents the difference in quantity supplied between observed dispatch and least-cost dispatch. In our main specification, this difference is 44.9 GWh/day. This difference is very close to our main estimate under linear demand (43.3 GWh/day), and larger when utilities respond to marginal cost (94.1 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 57.5 GWh/day, 36.5 GWh/day, and 26.1 GWh/day under linear demand, and increases of 27.3 GWh/day, 163.1 GWh/day, and 103.5 GWh/day when utilities respond to marginal cost. These increases are broadly similar to the main results in Table 4.

Table B.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)	94.1	94.1	94.1	94.1
Incremental quantity increase relative to LC (GWh/day)		27.3	163.1	103.5
Incremental HHs shifted to 24×7 power		58.8M	350.9M	222.7M

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 4 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.

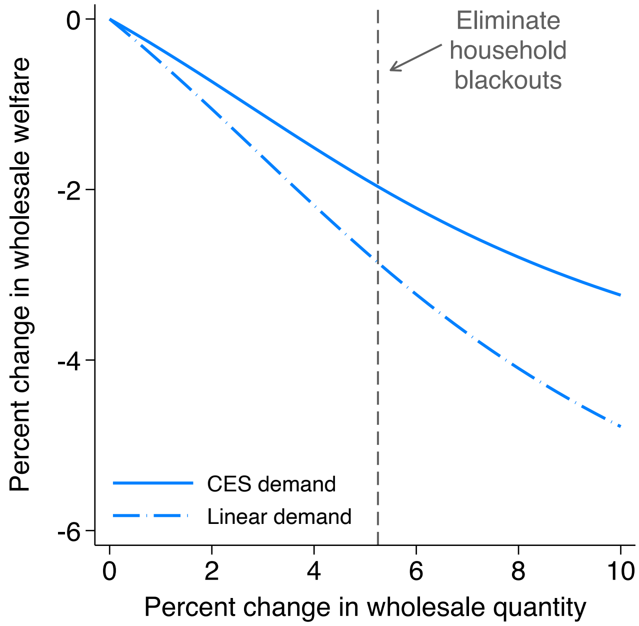
B.3 Additional results: Quantity mandate

Here we present additional results pertaining to the simulated impacts of a quantity mandate (as presented in Section 5.4). Appendix Figure B.1 plots the percentage decrease in wholesale welfare associated with moving from our baseline least-cost scenario to a mandate that $X\%$ more quantity must be supplied (varying X between 0–10%). The vertical line denotes the percentage increase in quantity supplied that would bring all households to 24×7 power (i.e., 105 GWh/day $=$ 266 million households $\times \frac{2.8 \text{ kWh}}{24 \text{ hours}} \times 3.4 \frac{\text{hours}}{\text{day}}$).[3]

This figure shows that even a roughly 5% increase in quantity supplied would be sufficient to bring households to 24×7 power. In addition, we see that wholesale welfare falls at a slower rate at greater increases in quantity supplied. This stems primarily from capacity constraints limiting the amount of quantity that can be produced in a given state-day. For this reason, we focus our discussion on the relatively smaller quantity increases implied by bringing households to 24×7 power.

3. Our model distributes this daily national increase in quantity supplied proportionately across states.

Figure B.1: Changes in wholesale welfare from increases in wholesale quantity



Notes: This figure plots the percentage decrease in wholesale welfare associated with shifting from equilibrium to a quantity mandate that $X\%$ more quantity must be supplied, varying X between 0–10%. We do so under the assumption that wholesale demand is constant-elasticity (solid line) versus under the assumption that wholesale demand is linear (dashed line). The vertical line denotes the percentage increase in quantity supplied that would bring all households to 24×7 power under the constant-elasticity assumption (i.e., 105 GWh/day = 266 million households $\times \frac{2.8 \text{ kWh}}{24 \text{ hours}} \times 3.4 \frac{\text{hours}}{\text{day}}$); this daily national increase in quantity is distributed proportionately across the states. See Sections 5.2 and 5.4 for more details on the model and discussion of the findings, respectively.

Appendix Table B.3 presents the percentage changes in wholesale welfare, consumer surplus, and producer surplus from moving from our least-cost baseline scenario to a quantity mandate that requires 24×7 power for households. Column (1) presents our preferred specification, assuming that demand is constant elasticity (CE), markets clear and power plants are dispatched at the state/day level, and wholesale prices are set based on average variable cost (AVC) of supply. Producer surplus (i.e., generator profits) is zero by construction under AVC pricing (hence the label "NA"); consequently, wholesale welfare is equal to consumer (i.e., utility) surplus.

Column (2) conducts sensitivity analysis assuming linear demand, which has minimal effects on the wholesale welfare losses from a quantity mandate (1.7% versus 2.1% in our preferred specification with CE demand). If utilities were to respond to marginal cost (MC) rather than AVC, as in Column (3)'s sensitivity analysis, wholesale welfare would fall by

Table B.3: Wholesale market impacts of a quantity mandate to eliminate HH blackouts

	(1)	(2)	(3)
Consumer surplus (% change)	−2.1	−1.7	−11.7
Producer surplus (% change)	NA	NA	108.9
Wholesale welfare (% change)	−2.1	−1.7	−0.2
Functional form of demand	CE	Linear	CE
Prices = AVC or MC?	AVC	AVC	MC

Notes: This table reports the changes in consumer surplus, producer surplus, and wholesale welfare from moving from our baseline least-cost scenario to a quantity mandate sufficient to eliminate blackouts among households. We calculate the increase in national daily total quantity required to bring all households to 24×7 power as follows: 105 GWh/day = 266 million households $\times \frac{2.8 \text{ kWh}}{24 \text{ hours}} \times 3.4 \frac{\text{hours}}{\text{day}}$); the daily national increase in quantity supplied is distributed proportionately across the states. Our preferred specification in Column (1) assumes that demand is constant elasticity (CE), markets clear and power plants are dispatched at the state/day level, and wholesale prices are set based on average variable cost (AVC) of supply. Column (2) assumes linear demand (as opposed to CE demand), while Column (3) models wholesale prices set equal to marginal cost (MC, as opposed to AVC). When setting prices based on AVC, producer surplus (i.e, generator profits) is zero by construction (hence "NA" in Columns (1)–(2)). See Sections 5.2 and 5.4 for more details on the model and discussion of the findings, respectively.

much less from a quantity mandate (0.2% versus 2.1% in our preferred specification with AVC pricing). This is because a much larger 11.7% reduction in utility surplus would be almost fully offset by a 109% increase in profits earned by inframarginal power plants.

C Further details on the data

C.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).[4] 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.

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

4. We thank the authors for sharing these data.

Coalfields Limited (prices reported in rupees per kg).[5] "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.[6]

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 (Trippi and Tewalt (2011)). Data on the rail network in India is from ML ML Infomap (2008)).

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/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/kg for non-lignite coal plants.[7]

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 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.[8] 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.

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

6. 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)).

7. 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's daily generation data.

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

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.[9] 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.[10] Finally, the Ministry of Coal charges a Rs 10/1,000 kg "stowing excise duty" related to the "assessment and collection of excise duty levied on all raw coal..."[11]

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).

Lignite plants: We obtain the lignite coal price per kg from the Central Electricity Regulatory Commission.[12] 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

9. 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

10. 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

11. 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

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

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.[13]

Nuclear plants: We assign each of the 7 nuclear plants in our sample a marginal cost based on tariff documents.[14]

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 (2024)). Thus, we exclude hydro, wind, and solar resources from the analysis, implicitly assuming that they are inframarginal.

C.2 Power plant outages

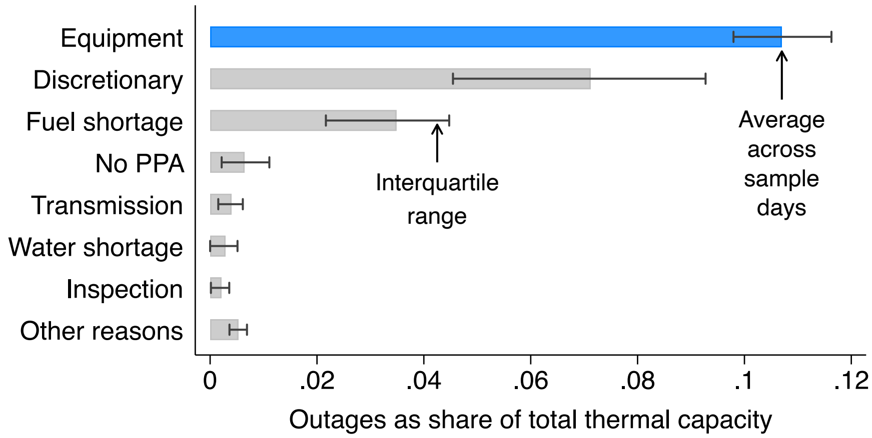
We string parse the CEA's *Daily Outage Reports* to classify eight mutually exclusive outage categories: equipment, discretionary, fuel shortage, no power purchase agreement (PPA), transmission problem, water shortage, inspection, and other. Figure C.1 shows the frequencies of these categories, plotting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

Appendix Figure C.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.

13. 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.

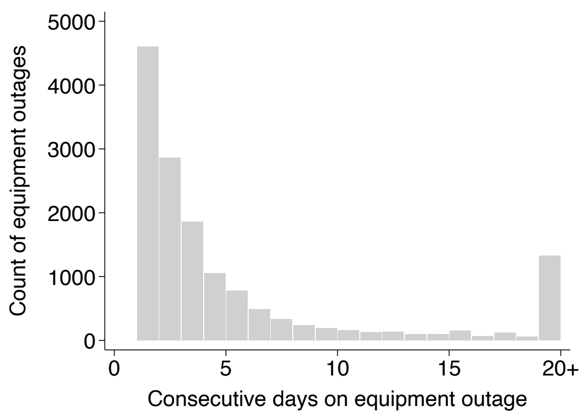
14. These data are reported in the following article by the chairman of an expert committee for the Department of Atomic Energy: http://www.thehindu.com/todays-paper/tp-opinion/Why-India-should-opt-for-nuclear-power/article14850892.ece

Figure C.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*.

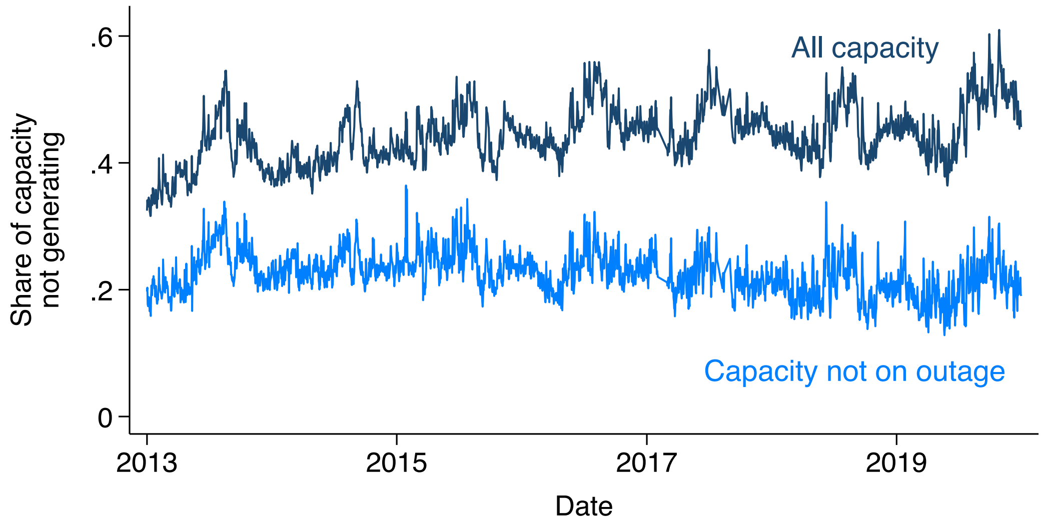
Figure C.2: Distribution of outage durations



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.

Appendix Figure C.3 plots unused power plant generating capacity over our sample period. The navy line reports 1 − (generation / nameplate capacity), while the blue line reports 1 − (generation / nameplate capacity less outages). On average, 44% of all generating capacity is not being used, with 22% of capacity not on outage sitting idle. This illustrates that India has substantial excess generating capacity.

Figure C.3: Time series of unused generating capacity



Notes: This figure plots unused generating capacity in the Indian electricity sector. The navy line plots $1 - $ (generation / nameplate capacity), and the light blue line plots $1 - $ (generation / nameplate capacity less declared outages). On average, 44% of all capacity, or 22% of capacity not on outage, is unused on the average day.

C.3 Indian Energy Exchange (IEX) data

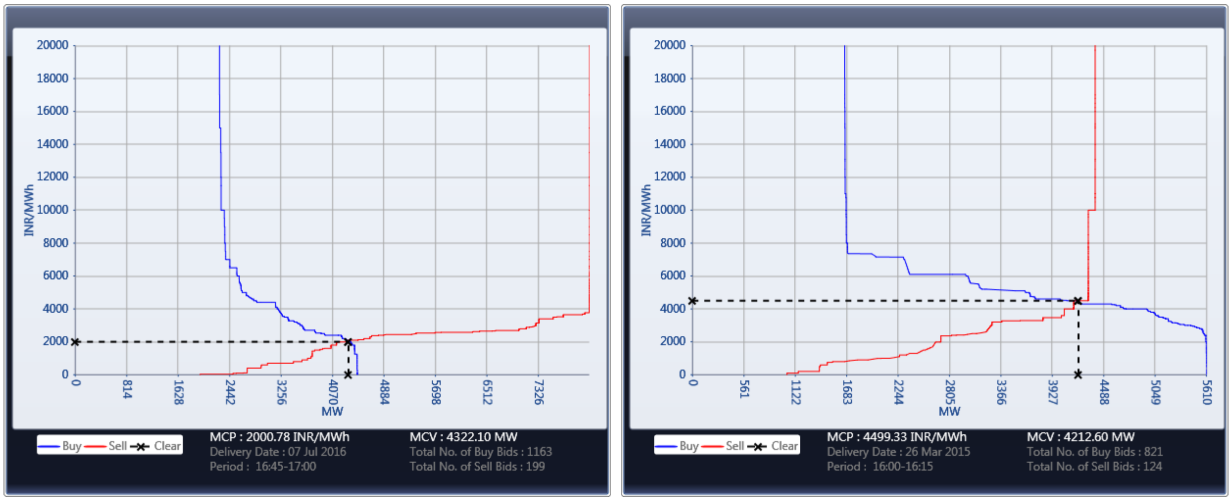
The Indian Energy Exchange (IEX) runs uniform-price auctions, where electricity suppliers submit offer curves, buyers (e.g., utilities) submit demand bid curves, and the market clears by aggregating supply and demand. Prices and quantities from the unconstrained market clearing process are adjusted to 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 1st, 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.[15] Appendix Figure C.4 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 in-

15. These images are available from the following link: https://www.iexindia.com/marketdata/demandsupply.aspx.

Figure C.4: 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.

terval for each of India's five transmission regions.[16] Across our sample, the average IEX market clearing price was Rs 3,121/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.[17]

C.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.[18]

16. The price data are available from https://www.iexindia.com/marketdata/areaprice.aspx. The quantity data are available from https://www.iexindia.com/marketdata/areavolume.aspx.

17. 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/MWh up versus moving Rs 5/MWh down the demand curve.

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

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