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BLACKOUTS IN THE DEVELOPING WORLD:  
THE ROLE OF WHOLESALE ELECTRICITY MARKETS

Akshaya Jha (r)

Louis Preonas (r)

Fiona Burlig (r)

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Blackouts in the Developing World: The Role of Wholesale Electricity Markets  
Akshaya Jha, Louis Preonas, and Fiona Burlig  
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**ABSTRACT**

Blackouts impose substantial economic costs in developing countries. This paper advances a new explanation for their continued prevalence: unlike in high-income countries, where regulatory mandates require utilities to satisfy all electricity demand, utilities in developing countries respond to wholesale electricity prices. As a result, misallocation of output across power plants can decrease the quantity of electricity supplied to end-users. We provide empirical support for this explanation using novel data from India, home to the world's third-largest electricity sector. In contrast to the developed world, we find that Indian wholesale demand is downward-sloping. Reducing supply-side misallocation would increase electricity supply for the average household by 1.7 percent (enough to power 4.6 million additional households). Justifying a mandate that utilities must satisfy all end-use demand would require consumers to value electricity far above the cost of diesel backup generation. However, such a mandate would likely be cost-effective if paired with supply-side reforms.

Akshaya Jha  
Carnegie Mellon University  
Hamburg Hall Office 2218  
4800 Forbes Avenue  
Pittsburgh, PA 15232  
Website: <http://www.akshayajha.com>  
[akshayaj@andrew.cmu.edu](mailto:akshayaj@andrew.cmu.edu)

Fiona Burlig  
Harris School of Public Policy  
University of Chicago  
1307 East 60th Street  
Chicago, IL 60637  
and NBER  
[burlig@uchicago.edu](mailto:burlig@uchicago.edu)

Louis Preonas  
Department of Agricultural and  
Resource Economics  
University of Maryland  
2200 Symons Hall  
7998 Regents Drive  
College Park, MD 20742  
[lpreonas@umd.edu](mailto:lpreonas@umd.edu)

# 1 Introduction

All wealthy countries consume large amounts of electricity (Gertler et al. (2016)). Electricity demand in the developing world is projected to rise dramatically over the coming decades, as households become richer and purchase electric appliances (Wolfram, Shelef, and Gertler (2012)). However, electricity blackouts remain ubiquitous in the developing world (Gertler, Lee, and Mobarak (2017)). Blackouts are costly, reducing firm productivity (Allcott, Collard-Wexler, and O’Connell (2016); Cole et al. (2018)), increasing production costs (Steinbuks and Foster (2010); Fisher-Vanden, Mansur, and Wang (2015)), and lowering household income (Burlando (2014)).

Why do blackouts persist in the developing world? Economists have previously attributed blackouts to limited electricity generating capacity (Dzansi et al. (2018)) and failing distribution infrastructure (McRae (2015); Carranza and Meeks (2021)). This paper proposes an alternative mechanism: utilities in developing countries are price-sensitive, purchasing less electricity when wholesale procurement costs are high. It follows that if supply-side distortions raise wholesale procurement costs, the equilibrium quantity purchased from the wholesale market falls. Since storage is cost-prohibitive, this leads to blackouts for end-use consumers.<sup>1</sup> This contrasts with the developed world, where strictly enforced regulatory mandates require utilities to satisfy all end-use electricity demand regardless of cost—and where blackouts are consequently rare.

We empirically demonstrate the importance of this mechanism in the context of India, which is home to the world’s third largest electricity market (Zhang (2019)) and whose citizens experience frequent blackouts despite a surplus of generating capacity (Bhattacharya and Patel (2008); Ryan (2021)). Using data on the aggregate demand curve in the Indian Energy Exchange (IEX), the country’s largest day-ahead electricity market, we find that

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1. This extends and is consistent with previous work arguing that bill nonpayment (Jack and Smith (2020)) and electricity theft (Burgess et al. (2020b); Gaur and Gupta (2016)) contribute to blackouts in developing countries, since both nonpayment and theft reduce the profits earned by utilities from providing electricity.

utilities are price-sensitive, with an average price elasticity of demand of  $-0.7$  around the market clearing price. While only 3–5 percent of electricity is traded on the IEX, we also show that the total quantity of electricity demanded falls as the share of capacity on plausibly exogenous equipment-related outages rises, even when idle power plant capacity is available to produce.<sup>2</sup> Together, these findings demonstrate that utilities have downward-sloping demand, responding to higher procurement costs by buying less electricity—causing blackouts for downstream retail consumers.

India’s wholesale electricity market institutions give rise to misallocation of output across plants, driving up utilities’ procurement costs. Unlike in electricity markets in high-income countries, the vast majority of Indian power plants sign long-term contracts for *physical* delivery of electricity. Contract positions cannot be sold to other buyers, and financial trades are not permitted between suppliers or utility buyers. This means that if a plant’s own contracted counterparty chooses not to purchase its power, the plant will not produce—even if a different utility would be willing to purchase from the plant. Moreover, these contracts specify fixed regulated prices, meaning that plants do not face stronger incentives to produce on days when demand is high and electricity is particularly valuable. As a result, even in the absence of technical issues, low-cost plants frequently go on “discretionary outage,” forcing higher-cost plants to produce in their stead. This gives rise to supply-side misallocation in India’s power market.

We empirically demonstrate that discretionary outages create substantial misallocation across Indian power plants. We compare the total variable costs of observed generation vs. a “least-cost” counterfactual scenario where plants are re-dispatched each day in order of lowest to highest marginal cost (as in Borenstein, Bushnell, and Wolak (2002); Cicala (forthcoming)). While this least-cost scenario is unlikely to be feasible due to technical constraints, it serves as a benchmark for assessing sources of supply-side misallocation. This

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2. Throughout this paper, we use “blackouts” to refer to electricity shutoffs experienced by end-use consumers, and “outages” to refer to offline generating capacity at power plants.

comparison reveals that discretionary outages are responsible for a significant share of the cost difference between observed and least-cost dispatch. In a counterfactual exercise that eliminates discretionary outages at low-cost plants and returns these plants to service, the equilibrium quantity of electricity in the IEX increases by 12.8 percent. We estimate that this single change would increase electricity consumption for the average Indian household by 1.7 percent, sufficient to power an additional 4.59 million households.

Finally, we consider the economics of a “full-demand mandate” where utilities can no longer choose to purchase less electricity when costs rise. We estimate counterfactual outcomes under such a mandate by forcing the IEX market to clear at the observed endpoint of the demand curve. This reveals that a full-demand mandate would be very costly: while quantity supplied in the IEX would rise by 9.6 percent, consumer surplus in the wholesale market would fall by 169.3 percent. Utilities would require transfers of 943 million rupees per day to prefer a full-demand mandate over the status quo of downward-sloping demand. In order to justify such transfers, the average end-user would need to value electricity at 90,052 rupees per MWh—which is 3–7 times larger than the average cost of diesel backup generation, and far above the highest retail electricity price paid by Indian households. However, reducing supply-side distortions would substantially improve the economics of a full-demand mandate. In a world without discretionary outages at low-cost plants, utilities would require compensatory transfers of just 25,397 rupees per MWh—which is comparable to the average cost of diesel backup generation. This suggests that Indian regulators could justify a full-demand mandate under reasonable assumptions about consumers’ willingness to pay to avoid blackouts, if such a mandate were coupled with supply-side reforms.

This paper contributes to three separate strands of literature. First, by providing evidence that supply-side misallocation reduces the quantity of electricity supplied to end users in India, home to the world’s third-largest power sector, we build on a rich body of work studying wholesale electricity markets in developed countries. This literature has highlighted supply-side distortions induced by cost-of-service regulation (e.g., Fabrizio, Rose,

and Wolfram (2007); Davis and Wolfram (2012); Cicala (forthcoming)) and limited financial trading (e.g., Jha and Wolak (2020); Mercadal (forthcoming))—two factors that increase the costs of wholesale electricity supply in India as well. We extend this work by identifying a key feature of electricity markets in developing countries that directly links supply-side distortions to blackouts faced by end-users: downward-sloping wholesale power demand. Unlike in developed countries where regulatory mandates ensure that wholesale demand is inelastic (Borenstein, Bushnell, and Wolak (2002); Mansur (2008)), supply-side distortions can reduce the quantity of electricity that reaches end-users in developing countries lacking such a mandate. Beyond its relevance in the developing world, this finding is increasingly relevant in high-income countries due to the advent of real-time pricing and the adoption of automated demand response (e.g., Wolak (2011); Bollinger and Hartmann (2019); Blonz et al. (2021)).<sup>3</sup>

Second, by demonstrating that Indian wholesale electricity demand is downward-sloping, we suggest a novel explanation for blackouts in developing countries. Prior work at the intersection of energy and development economics has found substantial negative impacts of blackouts on end-use consumers (e.g., Allcott, Collard-Wexler, and O’Connell (2016); Fisher-Vanden, Mansur, and Wang (2015)), while attributing blackouts to limited generating capacity (Dzansi et al. (2018)) or infrastructure failures (McRae (2015); Carranza and Meeks (2021)). However, there is relatively little existing research on wholesale electricity markets in developing countries. Ryan (2021) is the main exception for India; Rudnick and Velasquez (2018) surveys existing work in this space, none of which (to our knowledge) focuses on the role of the wholesale sector in downstream blackouts. Our analysis expands on the prior literature on electricity in developing countries, which has largely focused on energy access, payment, and end-use consumption (e.g. Dinkelman (2011); Lee, Miguel, and

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3. For example, the literature estimating market power in wholesale electricity markets in developed countries assumes perfectly inelastic wholesale demand (e.g., Wolfram (1999); Borenstein, Bushnell, and Stoft (2000); Reguant (2014)). However, wholesale market power could distort downward the quantity of energy consumed by households in high-income countries with (for example) automated smart thermostats.

Wolfram (2020); Jack and Smith (2015); Jack and Smith (2020); Burgess et al. (2020a); Burlig and Preonas (2021)). Our results imply that in a setting where political and economic factors contribute to an equilibrium with frequent blackouts (Burgess et al. (2020b)), correcting supply-side distortions both (i) substantially reduces blackouts, and (ii) greatly improves the economics of a regulatory mandate to satisfy all demand.

Third, we show that it can be extremely costly for a developing country to adopt a policy used in wealthy countries (e.g. a full-demand mandate) without correcting other interacting market distortions. This builds on a literature in development economics highlighting the importance of local market failures. Credit constraints (Berkouwer and Dean (2021)), corruption (Duflo et al. (2013)), poor program implementation (Davis, Fuchs, and Gertler (2014)), intra-household bargaining challenges (Jack, Jayachandran, and Rao (2017)), and inappropriate intervention design (Davis, Martinez, and Taboada (2020)) can all inhibit the effectiveness of environmental regulations and energy-related technologies when implemented in a developing-country context. This is not unique to the energy/environmental domain: for example, technologies and institutions which 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. This paper also follows a prominent tradition in development economics showing that institutions and market structure are important determinants of economic prosperity (e.g., Acemoglu, Johnson, and Robinson (2001); Banerjee and Iyer (2005); Field (2007)).

This paper proceeds as follows. Section 2 presents key institutional features of India's electricity sector and describes our data. Section 3 outlines an illustrative model of a wholesale electricity market in a developing country with vs. without a full-demand mandate. Section 4 demonstrates that wholesale electricity demand in India is downward-sloping. Section 5 documents substantial supply-side misallocation among Indian power plants, which meaningfully reduces the quantity of electricity supplied. Section 6 quantifies the costs of

implementing a full-demand mandate in the IEX day-ahead market. Section 7 discusses the policy implications of our findings.

## 2 Background and data

This section discusses India’s wholesale and retail electricity sectors, and the data used in our analysis. We focus on the wholesale sector, where suppliers own power plants and sell electricity to distribution utilities. These sales occur on bilateral contracts subject to regulatory constraints (roughly 95% of volume) and via short-term markets (roughly 5% of volume). In the retail sector, distribution utilities sell electricity to end-use consumers.

### 2.1 Wholesale electricity demand

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

Utilities respond to these financial difficulties by choosing not to satisfy electricity demand in all hours and locations. Rolling blackouts are common across the country. Since regulated retail rates are fixed and electricity storage is not yet cost-effective, short-run changes in retail electricity provision primarily reflect variation in the amount of wholesale electricity utilities choose to purchase (Central Electricity Authority (2018)).



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

## 2.2 Long-term contracts and the short-term market

Nearly 90 percent 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 and the share of each unit’s capacity to be dedicated exclusively to the buyer. It also lists each unit’s “plant load factor”: the expected annual output from the unit’s contracted capacity as a share of total potential output. This obliges the seller to allocate a proscribed share of its expected production exclusively to its contracted buyer.<sup>4</sup> However, the buyer is *not* obliged to purchase all electricity to which it is entitled.

The contract price (in rupees per kWh) is set by a regulator based on their assessment of the plant’s fixed and variable costs. This price has two components. The first component is an availability charge (or “capacity charge”) meant to cover fixed operating costs and long-term financing. When a contracted plant stands ready to sell, but the utility exercises its right not to buy, the utility must still pay the availability charge based on the expected output from the contracted capacity. The second component is an energy charge per kWh actually sold. This energy charge is typically constant across all hours of the year, providing plants no dynamic incentive to operate at times when the value of power is high, or to shift outages to times when the value of power is low.<sup>5</sup>

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4. For example, if a unit with 100 MW of capacity is contracted for 100 percent of its capacity with a plant load factor of 85 percent, then it is obliged to deliver 744.6 GWh per year (i.e.,  $100 \text{ MW} \times 8,760 \text{ hours} \times 0.85$ ).

5. Some contracts list higher prices for output sold in excess of the plant’s load factor, but these higher prices per kWh are not tied to short-run demand variability. Planned outages must be scheduled one year in advance. Plants cannot use planned outages to avoid operating in unexpectedly high-cost periods, and

Unlike most developed-country electricity markets, financial trading has (until recently) been prohibited in India’s power sector.<sup>6</sup> This means that owners of contracted plants cannot pay lower-cost plants to generate in their stead. In addition, transmission rights are explicitly tied to long-term contracts—even if financial trading were permitted, suppliers would need to arrange for transmission from an alternative lower-cost plant to the contracted demand location. Finally, a utility may exercise its right not to buy power until 90 minutes before plants actually produce, leaving plants effectively no opportunity to sell output from unused contracted capacity in the short-term or day-ahead markets (Central Electricity Regulatory Commission (2018b)).

Short-term transactions make up the remaining 10 percent of Indian electricity sales. Approximately 5 percent is traded on short-term bilateral contracts with a duration of less than 1 year. 3–4 percent of power is traded on the Indian Electricity Exchange (IEX), a day-ahead power market that clears 24 hours before power delivery.<sup>7</sup> Utilities can therefore adjust their scheduled long-term contract purchases after observing the realized IEX equilibrium price and quantity.

The IEX market 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: North, Northeast, East, West, and South (see Figure 1). Due to the one-sided restrictions of bi-

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utilities cannot ask the plant to shift their planned maintenance to low-value periods once the maintenance schedule has been set.

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

7. A second day-ahead market, Power Exchange India (PXIL), contributes less than 0.25 percent of electricity sales (Central Electricity Regulatory Commission (2019)). The market clearing prices in the IEX and PXIL have near perfect correlation (Ryan (2021)). The remaining transactions occur through the “deviation settlement mechanism”, which balances deviations from scheduled generation to ensure that supply meets demand instantaneously across the grid.

lateral contracts, a lack of financial trading, and rules governing transmission, plants may only offer uncontracted capacity into the IEX (Central Electricity Regulatory Commission (2018a)). This prevents most plants from participating in day-ahead trading, limiting the IEX’s size.

We have compiled IEX data from April 1, 2014 to December 31, 2019. For each 15-minute interval in the dataset, we observe the full aggregate supply and demand curve, as well as the region-specific market clearing prices and quantities. Across our sample, the average IEX market clearing price was 3,121 Rs/MWh, while the average volume cleared was 1,128 MWh per 15-minute interval.<sup>8</sup>

### 2.3 Electricity generation

The Central Electricity Authority (CEA) publishes Daily Generation Reports, which include daily operational capacity and observed production for all utility-scale fossil, hydroelectric, and nuclear plants in India.<sup>9</sup> We digitized daily reports from January 1, 2013 to December 31, 2019.

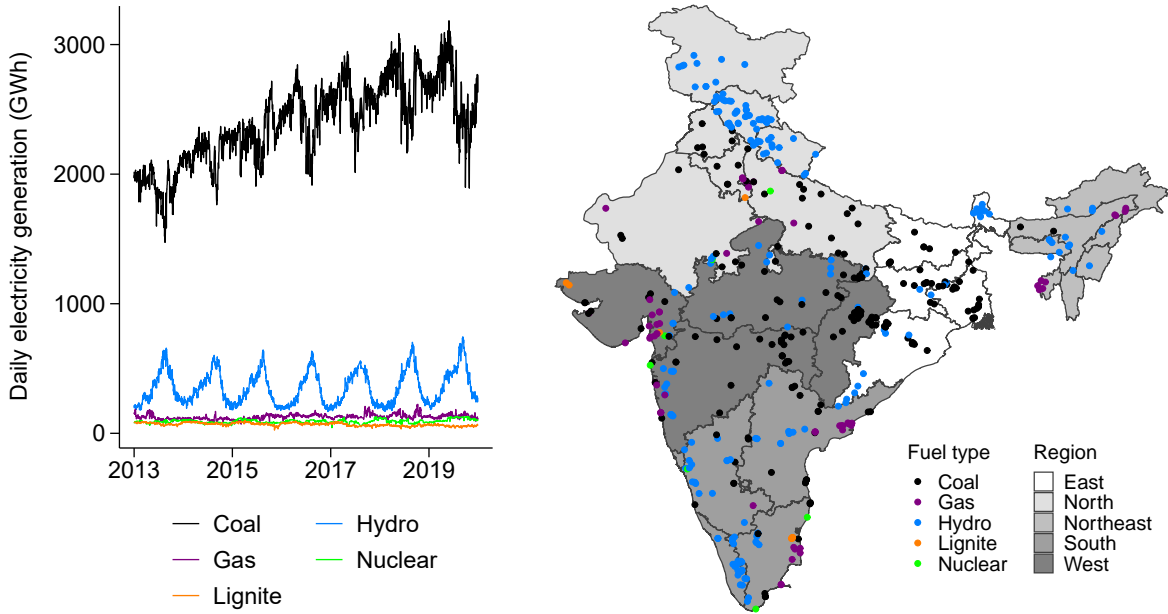
This yields a panel dataset with 508 plants that represents 301 GW of India’s 383 GW of electric generating capacity, with an average total production of approximately 3.05 TWh per day. The left panel of Figure 1 plots daily total output across plants by source type; the vast majority of output comes from the 205 coal-fired power plants, with the remainder coming primarily from hydro sources. The right panel maps the locations of power plants across India and the five transmission regions.

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8. The IEX publishes supply and demand curves in `.jpeg` format. Appendix Figure A.1 presents raw data for two 15-minute intervals in our dataset. Appendix A.1 describes how we digitized these images and validated our digitized data using publicly posted market clearing prices and quantities.

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

Figure 1: Electricity generation in India



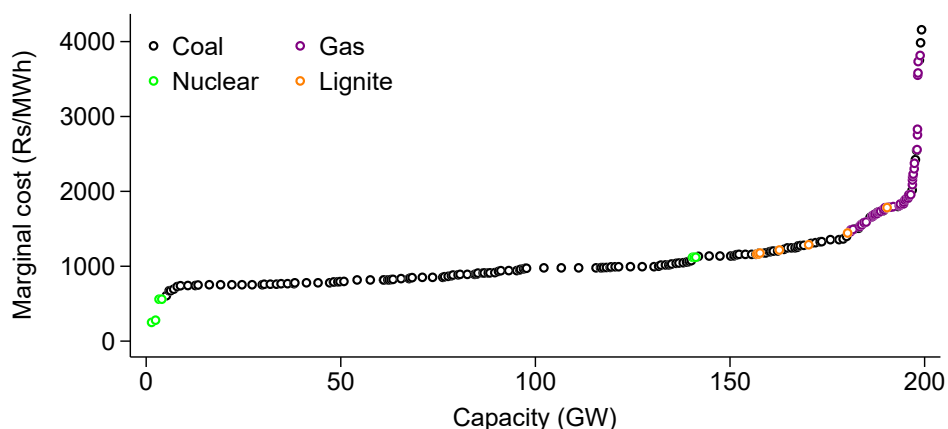
**Notes:** The left panel of this figure presents daily total electricity production across plants of each fuel type, using daily unit-level data from January 1, 2013 through December 31, 2019 from the Central Electricity Authority’s Daily Generation Reports. In aggregate, the 508 plants in these data produce 3.05 TWh of electricity per day on average. Averages of daily aggregate output by fuel type are: 2.40 TWh for 205 coal plants, 354 GWh for 204 hydroelectric plants, 127 GWh for 65 gas plants, 94 GWh for 7 nuclear plants, 69 GWh for 9 lignite plants, and 6 GWh for the 18 diesel plants (omitted here). The right panel maps the location of these plants in India, as well as the five major transmission regions.

**Marginal costs** We compute marginal costs over time for each plant in our sample, assuming that a plant’s marginal cost does not vary with its level of output.<sup>10</sup> To construct marginal costs for coal plants, we start with minemouth coal prices (in Rs/kg), reported aperiodically by coal suppliers. Using plant-level data on heat rates (i.e., heat input divided by electricity output) and coal consumption (in kg), we infer each plant’s coal grade and convert minemouth prices to costs per unit of electricity output (Rs/kWh).<sup>11</sup> We also add

10. This follows the standard approach in the electricity economics literature, which assumes that each unit’s production function is Leontief in fuel input (Fabrizio, Rose, and Wolfram (2007); Clay et al. (2021)). Fuel costs make up roughly 80% of the overall operating costs incurred by U.S. fossil-fuel power plants (Fabrizio, Rose, and Wolfram (2007)). We inflation-adjust to constant 2016 rupees using the monthly consumer price index for all items for India reported by the Organization for Economic Co-operation and Development.

11. We thank the authors of Chan, Cropper, and Malik (2014) for sharing data on plant-level heat rates, which we use to supplement the CEA’s *Annual Performance Reviews of Thermal Power Stations*. Coal consumption data come from the CEA’s Daily Coal Reports.

Figure 2: Marginal cost curve of thermal power plants



**Notes:** This figure 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. We omit 18 diesel plants and 65 plants lacking data to estimate marginal costs (51 coal, 12 gas, and 2 lignite). The exchange rate is roughly 60 Indian rupees to 1 US dollar.

rail freight costs based on the shortest path along India’s rail network (following Preonas (2017)), as well as royalties and other taxes.

For the few natural gas plants in our sample, we collect data on gas prices from the Ministry of Petroleum and Natural Gas and convert these prices to marginal costs per kWh using data on heat rates. For nuclear plants, we simply use the marginal costs reported by tariff documents, described in Srinivasan (2007). Figure 2 ranks thermal power plants from lowest to highest marginal cost, plotting marginal costs as a function of cumulative capacity.<sup>12</sup> This figure shows that nuclear plants tend to have the lowest marginal costs, followed by coal, lignite, and gas plants.

12. We omit hydroelectric resources since dispatchable hydro units face a complex dynamic optimization problem: today’s output may come at the expense of future output due to a finite supply of water (Archsmith (2019)). Non-dispatchable run-of-river hydro (along with wind and solar resources) enters the supply curve at (virtually) zero marginal cost. Appendix A.3 provides further detail on how we construct plant-specific marginal costs, and compares our constructed costs to plant-specific variable costs as reported by the Ministry of Power.

## 2.4 Power plant outages

The CEA’s Daily Outage Reports provide us with the amount of capacity under outage for each plant on each day. Figure 3 plots daily outage rates for thermal plants in our sample. On the average day between 2013–2019, 29 percent of generating capacity was under outage and therefore unavailable to generate. As a point of comparison, the total outage rate for coal-fired power plants in the United States and Canada ranged from 18 to 22 percent during this time period.<sup>13</sup> This discrepancy aligns with Chan, Cropper, and Malik (2014), who document relatively low technical efficiency of Indian power plants.

Regulators require plant managers to state a reason for going on outage. We use these reported reasons to classify two key groups of outages: “equipment” outages, related to technical failures on site that are likely outside of the plant’s immediate control; and “discretionary” outages, where plants specifically cite poor market conditions or insufficient private incentive to stand ready to generate.<sup>14</sup> Most equipment outages last less than 3 days; discretionary outages are similarly short-run, with a median duration of 5 days. While 84 percent of plants reported at least one equipment outage during our sample period, 16 percent of plants contributed the majority of discretionary outages (see Appendix Figures A.2–A.3).

We treat equipment outages as exogenous, since they are caused by technical failures rather than market conditions. These short-run disruptions to plants’ availability likely increase utilities’ costs of procuring electricity in the wholesale sector.

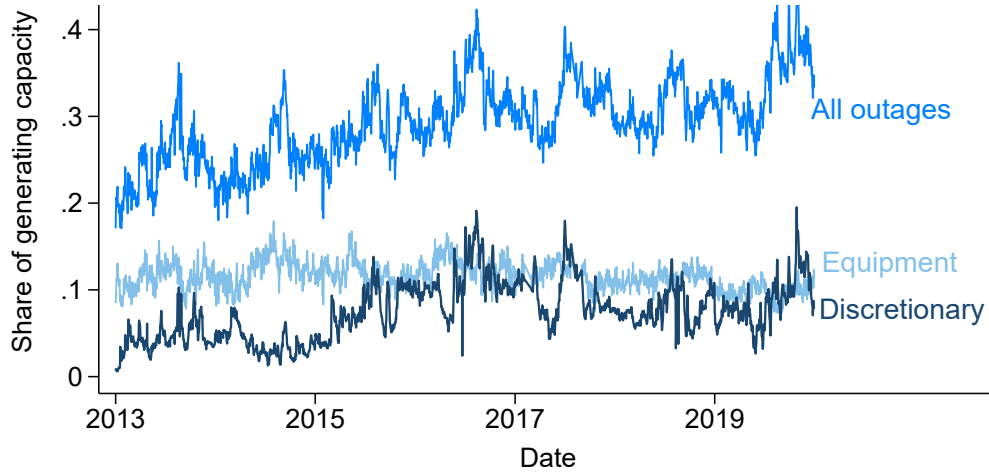
In contrast, we argue that discretionary outages declared by low-cost plants likely reflect

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13. This statistic comes from data on annual aggregate equivalent availability factor from the North American Electric Reliability Corporation. A plant’s annual “availability factor” is its total hours on outage divided by its total hours online (i.e., 8,760 hours if it began operate prior to the current year).

14. Common examples of equipment outages are: “water wall tube leakage”, “super heater tube leakage”, “ash handling system problems”, “furnace fire out/flame abnormal”. Common examples of discretionary outages are: “reserve shutdown”, “uneconomical operation”, “low system demand/costly fuel”, “other commercial reason”. These two categories are far from exhaustive, and plants report a variety of other outage reasons relating to planned maintenance, fuel shortages, transmission failures, etc.

Figure 3: Time series of daily outage rates



**Notes:** This figure reports the share of total thermal power plant capacity that was on outage (i.e. unavailable to generate), on each each day in our sample. The top line divides capacity under outage for *any* reason by total capacity. In the bottom two lines, we divide capacity under equipment outage and capacity under discretionary outage, respectively, by total capacity. We manually classify outages into these categories using the reasons listed in the CEA’s Daily Outage Reports.

supply-side misallocation. Due to the trading frictions in the Indian electricity market (e.g. fixed transmission rights and prohibition on financial trading), a contracted plant that is unlikely to be called on to produce *by its utility counterparty* may choose to go on outage rather than incur the costs required to be available to generate.<sup>15</sup> As a result, even though another utility’s willingness to pay for power may exceed the plant’s marginal cost, the plant goes on discretionary outage and is unavailable to produce. Moreover, since contract prices are not time-varying, contracted plants face limited incentives to avoid outages during high-demand periods when production from low-cost plants would be especially valuable.

These patterns motivate two empirical questions central to our analysis. First, to what extent do discretionary outages explain the wedge between observed dispatch and a competitive benchmark where plants are dispatched from lowest to highest marginal cost? Second, given that utilities’ wholesale demand is downward-sloping, to what extent do discretionary

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15. These costs include start-up, material, labor, and hassle costs. While long-term contracts typically provide “fixed cost” payments to incentivize plants to make their capacity available, this incentive may be too weak when the probability of selling energy is low.

outages reduce the quantity of energy supplied to end-use consumers?

### 3 Conceptual framework

**Model setup and notation** Here, we outline an illustrative model of a wholesale electricity market in the developing world, which is characterized by downward-sloping demand  $D(p)$ . This contrasts with most developed countries, where regulators require utilities to satisfy all end-use electricity demand regardless of cost. We model this alternative, a “full-demand mandate” resulting in perfectly inelastic wholesale electricity demand, as  $\bar{D} \equiv D(0)$ .

The supply side of this model comprises three power plants  $i \in \{1, 2, 3\}$ , each with constant marginal cost  $MC_i$  and a strict capacity constraint  $K_i$ . We order plants such that  $MC_1 < MC_2 < MC_3$ .<sup>16</sup>

**Equilibrium quantities and prices** Figure 4a presents the wholesale market with all three power plants available to produce. In the elastic demand scenario (subscripted  $E$ ), only plant 1 operates; in the inelastic demand scenario (subscripted  $I$ ), plants 1 and 2 operate. The quantity  $(Q_I^* - Q_E^*)$  is left unsatisfied in the elastic case, but wholesale prices are lower ( $P_E^* < P_I^*$ ).

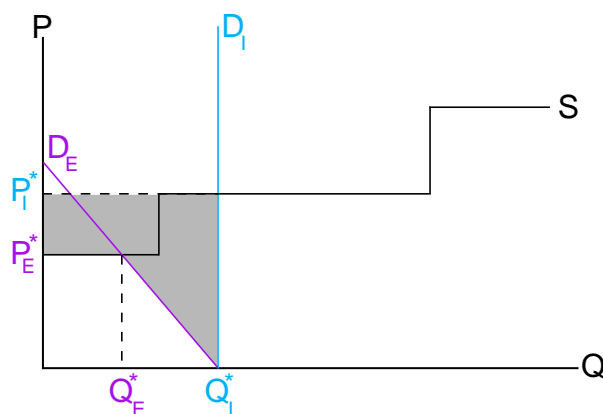
Figure 4b considers the scenario where the lowest cost plant (plant 1) is removed from the market. Removing plant 1 decreases the quantity of electricity supplied in the elastic demand scenario from  $Q_E^*$  to  $Q_E^{*}$ ; higher wholesale prices ( $P_E^{*} > P_E^*$ ) cause utilities to purchase less electricity, increasing the incidence of blackouts faced by end-use consumers. In the inelastic demand scenario, removing plant 1 does not change the equilibrium quantity (or, in this case, the equilibrium price).<sup>17</sup>

16. We formalize this illustrative model in Appendix B.

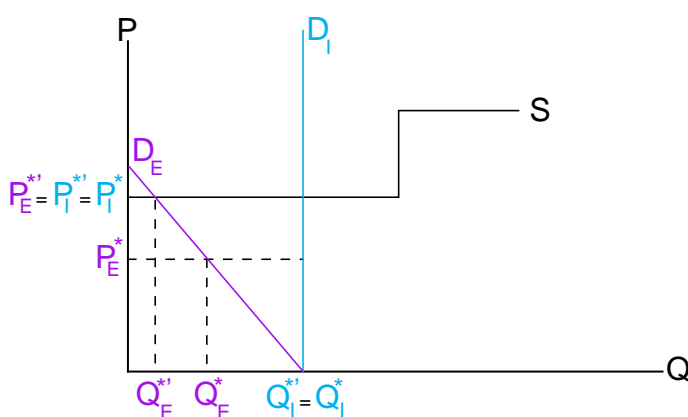
17. Depending on the shape of the supply curve, removing a low-cost plant may increase the equilibrium price in the inelastic case as well. The salient point is that inelastic wholesale electricity demand ensures that supply-side distortions do not alter the equilibrium quantity of energy supplied.



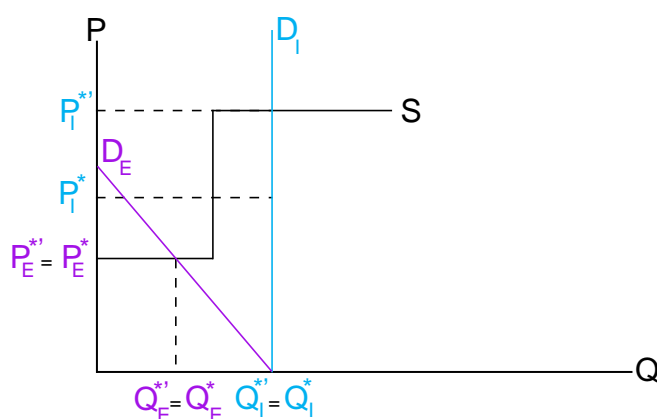
Figure 4: Illustrative model of the wholesale electricity market



(a) Baseline, with all three plants



(b) Removing plant 1



(c) Removing plant 2

**Notes:** This figure presents our illustrative model of the wholesale electricity market. The market has three power plants, each with constant marginal costs and a strict capacity constraint. We depict market clearing prices ( $P^*$ ) and quantities ( $Q^*$ ) for both an elastic demand case (subscripted  $E$ , in purple) and a full-demand mandate where regulators require demand to be perfectly inelastic (subscripted  $I$ , in cyan). Panel (a) presents the baseline scenario in which all three plants are available to produce. In Panel (b), we remove plant 1 from the supply curve; in Panel (c), we instead remove plant 2. In Panel (a), we shade the loss in utilities' consumer surplus from a full-demand mandate (i.e., moving from the elastic to the inelastic equilibrium).

In Figure 4c, we instead remove a higher cost plant (plant 2) from the market. Since plant 2 is above the equilibrium price in the elastic demand scenario, removing it does not alter the equilibrium price or quantity. By contrast, removing plant 2 increases the equilibrium price (to  $P_I^{*'} > P_I^*$ ) in the inelastic demand scenario, while quantity again remains unchanged. This illustrates the trade-off inherent to mandating that all demand be satisfied: satisfying all demand may require dispatching plants with very high marginal costs, resulting in high equilibrium prices, and thus making any supply-side distortions more costly to end-use consumers.

**Key implications** This model illustrates two stylized facts. First, absent a full-demand mandate forcing demand to be perfectly inelastic, removing a low-cost plant from the market decreases the quantity of electricity purchased by utilities. However, if demand is elastic, removing higher-cost plants from the market should be less likely to decrease the quantity of energy supplied by utilities to end-users in the absence of a full-demand mandate (see Figure 4c). Hence, the extent to which mitigating supply-side misallocation would reduce blackouts in developing countries like India—where wholesale demand is elastic—is an empirical question. Section 5 quantifies these impacts in the Indian wholesale electricity sector.

Second, a full-demand mandate can result in utilities losing substantial wholesale market consumer surplus, as illustrated by the shaded area in Figure 4a. Whether this lost surplus is larger or smaller than end-use consumers’ value from facing fewer blackouts is an empirical question, as neither the elastic nor inelastic wholesale demand curve is likely to reflect the preferences of retail consumers.<sup>18</sup> To this end, in Section 6, we quantify how high

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18. The vast majority of electricity consumers around the world pay fixed retail prices that do not vary with the wholesale price (Dutta and Mitra (2017), International Energy Agency (2020)). In developed countries, mandating that all electricity demand from end-users must be met implicitly assumes that the marginal willingness to pay to avoid blackouts is weakly greater than the marginal cost of the highest-cost plant. However, some consumers would almost surely reduce their electricity consumption if retail prices rose to reflect wholesale market scarcity (Borenstein and Holland (2005)). In developing countries such as India, utilities may impose blackouts on end-user consumers if their marginal revenue from selling energy is less than the corresponding cost of procuring energy from the wholesale market, regardless of consumers’ willingness to pay to avoid blackouts.

consumers’ value from avoiding blackouts (i.e. the value of lost load) would need to be to offset the utilities’ lost consumer surplus under such a mandate.

## 4 Price elasticity of wholesale electricity demand

This section provides empirical evidence that Indian wholesale electricity demand is downward-sloping. First, we demonstrate that demand for electricity traded on the IEX, the largest day-ahead market for power in India, is quite elastic. Next, we show that the quantity of demand satisfied outside of the IEX does not respond to the IEX price, implying that wholesale buyers do not substitute on the margin between the IEX and their long-term contracts. Finally, we show that equipment outages cause utilities to purchase less electricity even when generating capacity remains available to produce. This suggests that utilities choose to purchase less electricity when procurement costs rise. Taken together, these findings provide strong evidence that India’s distribution utilities are price-elastic: wholesale electricity demand is downward-sloping.

### 4.1 Electricity demand in the IEX

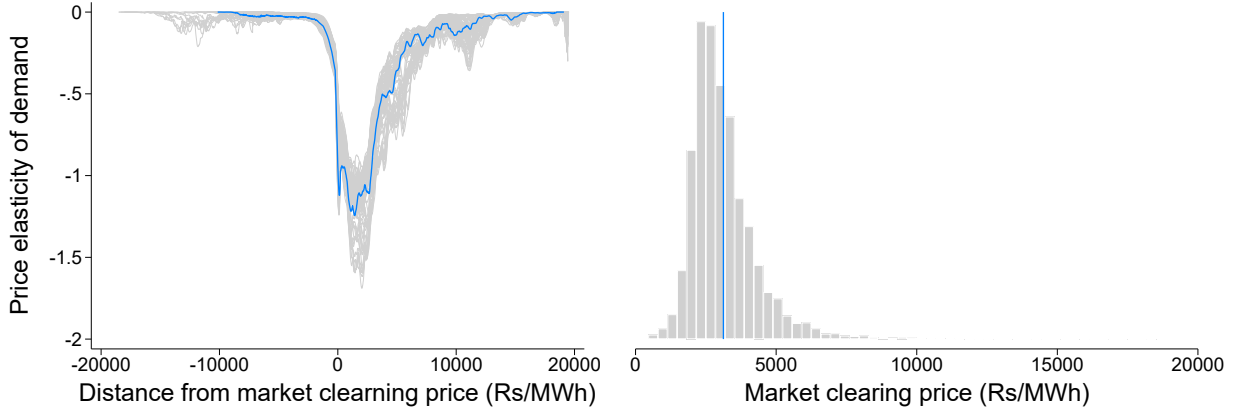
The IEX reports the aggregate supply and demand curves constructed using the bids submitted by market participants for each 15 minute interval. This allows us to calculate the price elasticity of demand in the IEX. The left panel of Figure 5 plots demand elasticity as a function of the distance from the market clearing price, averaged within each 15-minute interval across days-of-sample (in grey) and across all observations (in blue).<sup>19</sup> The right panel presents the distribution of market clearing prices in our sample.

Figure 5 demonstrates that demand for electricity in the IEX is highly elastic, in stark

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19. 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 5 rupees per MWh up versus moving 5 rupees per MWh down the demand curve.

Figure 5: Elasticity of IEX demand



**Notes:** This figure displays data from the Indian Energy Exchange (IEX). The left panel shows the price elasticity of demand in the IEX as a function of distance from the market clearing price, averaged within each 15-minute interval. We construct these elasticities by smoothing each date-interval demand curve using a 100 Rs/MWh kernel, and then computing elasticities for 5 Rs/MWh price changes; we average within each interval (in grey) and pooling all intervals (in blue). The average elasticity is close to  $-0.73$  in the neighborhood of the market clearing price, which stands in contrast to the perfectly inelastic wholesale demand characteristic of power markets in developed countries. The right panel plots a histogram of market clearing prices; the mean is approximately 3,125 Rs/MWh.

contrast with the perfectly inelastic wholesale electricity demand characteristic of high-income countries. The average elasticity at the IEX market clearing price is  $-0.73$ , averaged across all 15-minute intervals.<sup>20</sup>

## 4.2 The IEX market is marginal

While the IEX market clears 24 hours before physical electricity delivery, utilities are able to revise their scheduled contract purchase quantities up until 90 minutes before delivery. This means that utilities could strategically react to high (low) IEX prices by purchasing more (less) electricity from their long-term contracts. This type of arbitrage could result in a

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20. For elastic IEX demand to impact end-use consumers of electricity, the elastic portion of the IEX demand curve must include bids from distribution utilities rather than other IEX participants (e.g. manufacturing plants). We have three pieces of evidence that this is the case. First, using confidential data on the identity of IEX bidders (albeit from an earlier time period), Ryan (2021) notes that “the large, flat steps in the demand curve are bids of electricity distribution companies.” Second, analogous demand curves from PXIL, the smaller of India’s two power exchanges, are also highly elastic; nearly all PXIL buyers are distribution utilities. Third, we communicated directly with IEX officials, who confirmed that elastic bids near the market clearing price are typically from utilities.

downward-sloping IEX demand curve even if utilities’ total wholesale demand was inelastic. We empirically test for this by estimating how non-IEX generation responds to the IEX market clearing price using an instrumental variables approach:

$$\log(Q_t^{\text{non-IEX}}) = \eta_m + \delta_y + \beta \log(\widehat{P}_t^{\text{IEX}}) + \gamma \mathbf{X}_t + \varepsilon_t \quad (1)$$

$$\log(P_t^{\text{IEX}}) = \alpha_m + \omega_y + \theta[\text{IEX equip. outage rate}]_t + \psi \mathbf{X}_t + v_t \quad (2)$$

where  $Q_t^{\text{non-IEX}}$  is the total quantity of energy supplied across the Indian grid less the total supplied from the IEX on day-of-sample  $t$ .  $P_t^{\text{IEX}}$  is the IEX market clearing price averaged across all 96 intervals on each day  $t$ . Both equations include month-of-year fixed effects and year-of-sample fixed effects. Standard errors account both for heteroskedasticity and 7 days of autocorrelation in the error term (Newey and West (1987)).

To isolate movements along the demand curve, we instrument for the IEX price using the share of capacity at privately owned IEX-participant plants under equipment outages.<sup>21</sup> The timing of these equipment failures is unlikely to be correlated with market conditions.<sup>22</sup>

The key exclusion challenge is that both suppliers and utility buyers could potentially respond to equipment outages.<sup>23</sup> However, we are in the unusual and advantageous position of observing the IEX supply and demand curves for each interval, which allows us to estimate impacts controlling for the level of demand at different price points. The vector  $\mathbf{X}_t$  controls for the endpoints of the IEX demand curve for each day  $t$ , isolating movements *along* the IEX demand curve due to changes in supply offers.<sup>24</sup> We interact these demand curve

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21. IEX officials provided us with a list of all privately owned plants that sell electricity into the IEX, but did not provide this list for publicly owned plants.

22. A potential concern is that plants falsely report equipment outages to avoid generating. We see this as extremely unlikely. Ryan (2021) demonstrates that plants operating in the IEX exercise market power by simply withholding capacity, without needing to report fake equipment outages.

23. For example, utility buyers might be less likely to participate in the IEX market if they observe an IEX plant going on equipment outage.

24. We find similar results if we control for points along the demand curve (e.g., daily total demand bid in on day  $t$  at 2000, 3000, and 4000 rupees per MW). Our results are also similar if we estimate Equations (1)–(2) in levels rather than logs (see Appendix Table C.1.)

Table 1: Aggregate demand does not respond to IEX price

	$\log(P^{\text{IEX}})$	$\log(Q \text{ wholesale elec demand})$	
	1st stage (1)	Non-IEX only (2)	IEX only (3)
$\log(P^{\text{IEX}})$		-0.078 (0.059)	-0.705*** (0.159)
Share of privately owned IEX capacity on equipment outage	0.565*** (0.085)		
IEX demand curve controls	Yes	Yes	Yes
Region-day temperature controls	Yes	Yes	Yes
Month-of-year FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
Number of sample days	2,409	2,287	2,409
First-stage $F$ -stat (IV)		37.63	43.77

**Notes:** This table presents instrumental variables (IV) estimates of the impact of the log of IEX market clearing price on log quantity demanded outside of the IEX (Column (2)) and in the IEX (Column (3)). We instrument for the IEX market clearing price with the equipment outage rate for privately owned capacity selling into the IEX, following Equations (1)–(2). Column (1) presents the corresponding first-stage estimates. Each time-series regression uses day-of-sample as the unit of observation. Each regression controls for the daily minimum and maximum of the total quantity of electricity demand bid into the IEX interacted with both month-of-year and year fixed effects, to remove anticipated changes in demand and account for changes in IEX market size. We also control for mean daily temperature across each electricity transmission region, month-of-year fixed effects, and year fixed effects. Standard errors account for both heteroskedasticity and 7 days of autocorrelation in the error term. Significance: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.10$ . We report Kleibergen-Paap first-stage  $F$ -statistics, where the Stock-Yogo critical value is 16.38.

controls with year and month-of-year fixed effects to allow for seasonality and trends in the size of the IEX market.  $\mathbf{X}_t$  also includes average daily maximum temperatures for each transmission region, which increases precision due to the strong relationship between temperature and electricity demand.

Table 1 reports the results. Column (1) presents the first stage: a 10 percentage point increase in the share of privately owned IEX capacity under equipment outage causes a 5.65 percent increase in the average IEX market clearing price. As expected, when equipment outages shift the IEX supply curve left, the market clearing price rises. Column (2) reports the IV estimate from Equation (1). We fail to reject the null hypothesis that higher IEX prices do not increase non-IEX generation; in fact, we find the opposite sign. This confirms that utilities do not systematically arbitrage high IEX prices by buying more from their portfolio of contracts, or vice versa. Absent such arbitrage, elastic IEX demand, as evidenced

by the calculations in Figure 5 and the estimate in Column (3) of Table 1, implies downward-sloping *aggregate* wholesale electricity demand.

### 4.3 Plant outages decrease demand met

Finally, we estimate whether the total quantity of wholesale demand falls when plants go on outage while other idle plants stand ready to generate. While some developing countries lack the generating capacity to replace the output lost from plant outages (e.g. Ghana’s “Dumsor” power crisis described in Dzansi et al. (2018)), Indian utilities often have idle dispatchable generating capacity available to buffer against unanticipated plant outages. If the total quantity of demand (inclusive of both contract and IEX purchases) falls with plant outages while neighboring plants remain idle, then absent transmission constraints and trading frictions, utilities must be choosing not to use this available generating capacity. This would imply that utilities’ wholesale electricity demand falls as procurement costs rise.

We estimate the following panel regression using data from the full wholesale sector:

$$[\text{Demand met}]_{srt} = \alpha_s + \delta_t + \theta_{ry} + \psi_{rm} + \beta[\text{Equip. outage rate}]_{srt} + \gamma\mathbf{X}_{srt} + \varepsilon_{srt} \quad (3)$$

where  $[\text{Demand met}]_{srt}$  is the total amount of electricity purchased by utilities in state  $s$ , which belongs to electricity transmission region  $r$ , on date-of-sample  $t$  in month  $m$  and year  $y$ . This corresponds directly to the quantity of electricity received by retail consumers, net of any transmission and distribution losses. Our coefficient of interest  $\beta$  measures the effect of the share of each state’s total generating capacity on equipment-related outage. All else equal, plants’ equipment failures should weakly increase the variable costs of meeting wholesale electricity demand; we focus on equipment-related outages, as they are plausibly unrelated to market conditions.

$\mathbf{X}_{srt}$  controls for the total quantity of demand met for each region-day, which accounts for

interstate, intraregional spillovers.  $\mathbf{X}_{srt}$  also includes state-level average daily temperature (which improves precision), and the number of dispatchable plants in each state (which controls for differential changes in market size). Day-of-sample fixed effects  $\delta_t$  account for common shocks and interregional spillovers, state fixed effects  $\alpha_s$  account for persistent differences across states, region-by-year fixed effects  $\theta_{ry}$  account for region-specific trends in demand, and region-by-month fixed effects  $\psi_{rm}$  account for region-specific seasonality in demand. We cluster standard errors by month-of-sample to accommodate serial correlation within each month and contemporaneous dependencies across states.

Table 2 reports results from estimating Equation (3). In Column (1), we find that a 1 percentage point increase in a state’s equipment outage rate causes its demand met to decrease by 12.23 GWh on average (statistically significant at the 1 percent level). However, a lack of available generating capacity could be driving these reductions, if equipment outages render utilities unable to purchase the quantity of electricity they desire. Columns (2)–(3) restrict the sample to only state-days with idle capacity—that is, days in which some plants located in the state did not produce despite being available. Columns (4)–(5) impose a further sample restriction by removing states with multiple utilities, to ensure that our estimates capture utility demand rather than trading frictions across utilities.<sup>25</sup> Both sample restrictions increase the magnitude of our results.

Taken together, the results in Table 2 provide strong evidence that utilities are choosing to provide less power when more of their state’s generating capacity goes on equipment outage. Our point estimate in Column (3) implies that an 8 percentage point (1 standard deviation) increase in the equipment outage rate causes a 2.8 GWh (1.6 percent) average reduction in demand met—despite the fact that roughly 707 MW of idle but available capacity could have produced 16.8 GWh on the average state-day. This result persists

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25. Suppose utility A experiences an equipment outage at one of its contracted plants. If idle generating capacity exists in the state, but that capacity is contracted to a different utility B, utility A cannot replace its own lost generation with generation from this idle plant due to the prohibition of financial trading. Restricting the sample to single-utility states prevents us from erroneously attributing reductions in demand to contracting frictions.



Table 2: Total demand met responds to power plant outages

	Outcome: [Demand met] <sub>srt</sub> (GWh)				
	(1)	(2)	(3)	(4)	(5)
[Equipment outage rate] <sub>srt</sub>	-12.23*** (4.32)	-71.01*** (9.32)	-36.09*** (7.34)	-94.61*** (15.45)	-27.17* (14.39)
Idle capacity available		Yes	Yes	Yes	Yes
Single-utility states				Yes	Yes
Region-day demand met control	Yes	Yes	Yes	Yes	Yes
State-day temperature controls	Yes	Yes	Yes	Yes	Yes
State + date FEs	Yes	Yes	Yes	Yes	Yes
Region × year, region × month FEs	Yes	Yes	Yes	Yes	Yes
State-specific linear trends	Yes		Yes		Yes
State-day observations	47,334	18,605	18,605	9,046	9,046
Mean of dep var	136.01	169.05	169.05	134.90	134.90
Mean of equipment outage rate	0.096	0.072	0.072	0.051	0.051
SD of equipment outage rate	0.091	0.078	0.078	0.070	0.070
Mean potential GWh from idle capacity	6.622	16.841	16.841	8.122	8.122

**Notes:** This table presents results from estimating Equation (3). The dependent variable is total GWh energy met in state  $s$  on date  $t$  (equivalent to the quantity of wholesale electricity demand). The independent variable is the share of each state’s generating capacity reported to be on outage due to equipment failure. Column (1) presents results without conditioning on idle capacity being available. Columns (2)–(3) restrict 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). Columns (4)–(5) further restricts the sample to the subset of states with a single utility, which removes unobserved inter-utility intrastate trading frictions. All regressions control for contemporaneous demand met with each state’s transmission region, daily average temperatures, and the total number of dispatchable plants in state  $s$  (to account for differential market expansions across states). All regressions include for state, date-of-sample, region-by-year, and region-by-month fixed effects. 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 potential GWh from available capacity that presumably stood ready to generate, but was not called.

when focusing on single-utility states, meaning that trading frictions do not explain these effects.<sup>26</sup> Instead, our estimates indicate that Indian utilities simply decrease the amount they purchase from the wholesale sector when procurement costs rise.

<sup>26</sup>. Any within-state transmission constraints are unlikely to explain a six-fold gap between decreased demand met and potential generation that sat idle.

## 5 Supply-side misallocation

### 5.1 Deviations from least-cost dispatch

Given that wholesale electricity demand in India is downward sloping, decreases in wholesale procurement costs will increase the quantity of electricity that reaches retail consumers. This raises the question: how much opportunity exists for efficiency improvements on the supply side? To answer this question, we compare the total variable costs of producing the observed level of demand across two scenarios: the factual scenario based on each plant’s observed output vs. a competitive benchmark where we dispatch plants from lowest to highest marginal cost.<sup>27</sup>

We first compute the total variable costs of the observed level of output for each plant  $i$  on each day  $t$  in our sample. We do so by multiplying observed output  $Q_{it}^{OBS}$  by the plant’s marginal cost  $MC_{it}$ .<sup>28</sup> Summing across plants yields total observed costs:

$$TC_t^{OBS} \equiv \sum_i MC_{it} Q_{it}^{OBS} \quad (4)$$

Next, we calculate the total variable cost under “least-cost” dispatch,  $TC_t^{LC}$ . To do this, we redispatch plants in order from lowest to highest marginal cost, respecting each plant’s capacity constraint.<sup>29</sup> Formally, the total variable cost implied by least-cost dispatch on day  $t$  is the solution to following optimization problem:

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27. This is a common approach for quantifying the consequences of supply-side distortions in wholesale electricity markets in the developed world (e.g. Wolfram (1999); Borenstein, Bushnell, and Wolak (2002); Cicala (forthcoming)).

28. Our results are similar if we use the variable costs reported by the Ministry of Power rather than our constructed costs (see panel D of Appendix Table C.2).

29. Each inframarginal plant produces at its capacity; the marginal plant produces the remaining quantity required to achieve total observed generation on day  $t$ . We calculate each plant’s capacity as the 98th percentile of its observed output over the 365-day window centered around day  $t$ . Our results are similar if we instead calculate capacity using the 80th percentile (see Panel C of Appendix Table C.2).

$$TC_t^{LC} = \min_{\{Q_{it}^{LC}\}} \sum_i MC_{it} Q_{it}^{LC} \quad \text{s.t.} \quad \underbrace{\sum_i Q_{it}^{LC} = \sum_i Q_{it}^{OBS}}_{\text{Supply = Demand}}, \quad \underbrace{Q_{it}^{LC} \in [0, \bar{Q}_{it}] \quad \forall \{it\}}_{\text{Capacity constraints}} \quad (5)$$

This least-cost benchmark is unlikely to be feasible, since it abstracts away from the technical constraints associated with electricity generation and transmission.<sup>30</sup> Consequently, comparing  $TC_t^{OBS}$  to  $TC_t^{LC}$  likely overstates the true level of supply-side distortions. However, this approach is useful for quantifying the relative contributions of different factors that cause supply-side misallocation.

We consider four dispatch scenarios. First, our “national” dispatch scenario assumes that any plant can be redispatched to meet demand anywhere in India. We relax this assumption in our “regional” dispatch scenario by imposing interregional autarky—only plants within each transmission region can be redispatched to satisfy demand in that region.<sup>31</sup> These first two scenarios ignore all plant outages, assuming that all generating capacity is available to be (re)dispatched. In reality, nearly 30 percent of capacity is unavailable on any given day; our “respecting all outages” dispatch scenario thus takes all outages as given, only redispatching capacity that was not on outage. Finally, our “ignoring discretionary outages” scenario redispatches plants under discretionary outages (which likely reflect misallocation), but respects all other non-discretionary outages (which are likely due to physical factors).

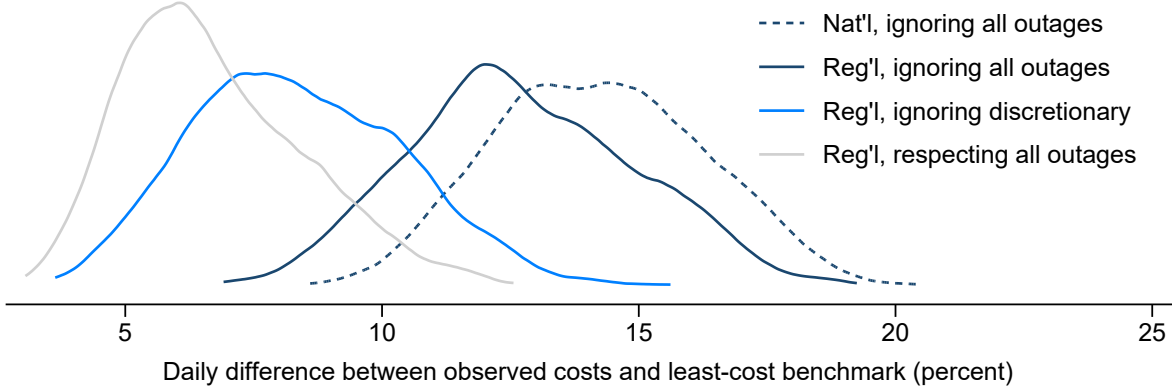
Figure 6 plots the percentage difference between observed costs and the least-cost benchmark under each scenario, over all days in our sample. Table 3 presents these results numerically. In the national dispatch scenario, the mean cost difference is 337 million rupees, or

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30. For example, Equation (5) ignores transmission constraints and plants’ dynamic operating constraints (e.g., minimum ramp times), though our results are similar when we clear the market separately under peak and off-peak periods (see Panel B of Appendix Table C.2).

31. To do this, we solve Equation (5) separately for each region. This conservatively assumes that there is no transmission capacity across regions. We find similar results under the even more conservative assumption of autarky within each of India’s 13 sub-regions (see Panel A of Appendix Table C.2).

Figure 6: Kernel densities of variable cost gap



**Notes:** This figure plots kernel densities of the percentage difference between the total observed variable costs vs. total variable costs under least-cost dispatch (i.e. the rightmost column of Table 3). Each density includes 2,506 sample days, for one of the four scenarios in Table 3. See notes under Table 3 for details.

Table 3: Variable costs of electricity supply

Redispatching scenario	Observed (M Rs / day)	Least-cost (M Rs / day)	Cost Difference (M Rs / day)	$100 \times \frac{\text{Difference}}{\text{Observed}}$
National, ignoring all outages	2,444 [1,846, 3,133]	2,106 [1,513, 2,808]	337 [295, 386]	14.21 [10.11, 18.70]
Regional, ignoring all outages	2,444 [1,846, 3,133]	2,140 [1,551, 2,832]	304 [255, 348]	12.73 [9.25, 16.48]
Regional, ignoring discretionary outages	2,444 [1,846, 3,133]	2,246 [1,648, 2,949]	198 [150, 246]	8.35 [5.18, 11.88]
Regional, respecting all outages	2,444 [1,846, 3,133]	2,285 [1,681, 2,977]	159 [118, 207]	6.72 [4.27, 9.98]

**Notes:** This table compares the total observed variable costs of electricity generation to total counterfactual variable costs under least-cost dispatch. The first column reports the total observed variable costs (per Equation (4)), while the second column reports total variable costs under least-cost dispatch (per Equation (5)). We report costs in millions of 2016 rupees per day; during our 2013–2019 sample period, the exchange rate was 53–77 Indian rupees per US dollar. The third column reports the difference between columns 1 and 2. The fourth column divides column 3 by column 1. All columns report averages across 2,506 sample days, with the 5th and 95th percentiles in brackets. The “National” scenario constructs least-cost dispatch for each date  $t$ , ignoring interregional transmission constraints. “Regional” scenarios restrict least-cost redispatching to within each of India’s five transmission regions, which conservatively assumes zero interregional transmission capacity. “Ignoring all outages” scenarios redispatch plants based on their capacity, regardless of whether they have declared outages on date  $t$ . The “ignoring discretionary outages” scenario avoids redispatching any capacity under outage on date  $t$ , unless the outage is classified as “discretionary”. Finally, the “respecting all outages” scenario takes all declared outages as given (including discretionary outages), and only redispatches capacity that was available to generate on date  $t$ . See text for further detail. Figure 6 plots kernel densities of the distributions in column 4.

approximately 14.2 percent. Interregional transmission constraints matter relatively little: in the regional dispatch scenario, which ignores all outages, the average daily cost difference is still 12.7 percent (304 million rupees).

When we avoid redispatching capacity on outage (“respecting all outages”), the average daily cost difference shrinks from 12.7 to 6.7 percent. This means that 47 percent of the potential cost savings from least-cost dispatch arise from utilizing capacity that was declared unavailable. However, much of this wedge is explained by discretionary outages at low-cost plants: ignoring discretionary outages increases the cost gap to 8.4 percent. Discretionary outages are therefore responsible for 13 percent of the cost difference between observed vs. least-cost dispatch. This implies that improving low-cost plants’ incentives to remain available could substantially reduce misallocation in Indian wholesale electricity supply.

## 5.2 Reducing supply-side misallocation

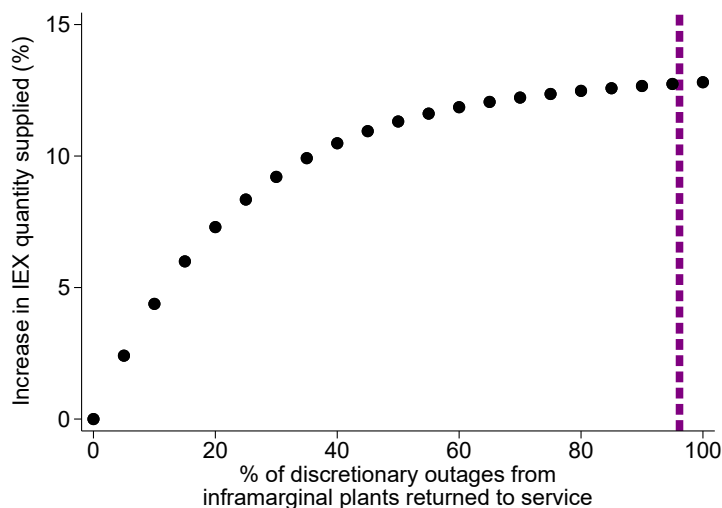
Having established that wholesale electricity demand is elastic and that substantial supply-side misallocation exists, we now conduct a counterfactual exercise to estimate how reducing supply-side distortions would impact quantity supplied. To do this, we eliminate inframarginal discretionary outages, returning this capacity to service by offering their production into the IEX at marginal cost. To ensure that measurement error in marginal costs does not lead us to overstate the potential benefits of reducing misallocation, we only eliminate discretionary outages at plants with marginal costs lower than half of the observed IEX market clearing price in the relevant interval. This restriction is conservative, ensuring that the plants would surely have been dispatched if they had offered their output into the IEX.<sup>32</sup>

Figure 7 illustrates the quantity impacts of eliminating inframarginal discretionary out-

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32. We “bid” capacity that was on discretionary outage into the IEX as a way of returning these plants to production, while accounting for their variable production costs. This does not require assuming that plants on long-term contracts are counterfactually exposed to day-ahead market incentives.

Figure 7: Returning discretionary outages to service increases IEX quantity supplied



**Notes:** This figure plots the percent change in quantity supplied in the IEX from counterfactually returning varying shares of inframarginal capacity on discretionary outage to service. By eliminating 96 percent of discretionary outages, this counterfactual exercise brings India’s *overall* (discretionary + non-discretionary) inframarginal outage rate in line with the total outage rate for North American coal plants (the purple dashed line indicates this benchmark of comparison).

ages. Returning half of this capacity to service increases quantity supplied in the IEX by 11.3 percent. Returning *all* capacity on discretionary outage increases quantity supplied by only an additional 1.5 percent, signalling diminishing returns as prices fall. As a benchmark, lowering India’s overall inframarginal outage rate to the total outage rate of North American coal plants—which requires eliminating 96 percent of inframarginal discretionary outages—increases quantity supplied in the IEX by 12.7 percent.<sup>33</sup>

This exercise implies that eliminating discretionary outages would yield potentially large gains in the amount of power that reaches end users. As one point of reference, residential electricity consumption per household in India was 1,028 kWh in 2017.<sup>34</sup> During our sample period, eliminating discretionary outages at low-cost plants would increase the quantity demand satisfied by 4,719 GWh per year. Addressing this single source of supply-side

33. We compute the North American coal-fired outage rate using 2019 data from the Generating Availability Data System administered by the North American Electric Reliability Corporation. This is a reasonable point of comparison, as 87 percent of India’s inframarginal capacity was coal-fired in 2019.

34. Ministry of Power (2020) reports total residential consumption of 273,545 GWh in 2017. There are approximately 266 million Indian households.

misallocation would increase electricity consumption for the average Indian household by approximately 1.7 percent per year. Equivalently, 4,719 GWh could power 4.59 million additional households for one year at the average consumption level.

## 6 The economics of a full-demand mandate

Finally, we consider the impacts of a regulatory mandate requiring that all of the demand bid into the IEX be satisfied—which would reduce blackouts caused by elastic wholesale electricity demand.<sup>35</sup> There is a meaningful amount of demand bid into the IEX at prices below the observed market clearing price: in the average 15-minute interval, 565 MW (10 percent) of demand bids remained unsatisfied. Our “full-demand mandate” counterfactuals impose perfectly inelastic IEX demand at the quantity implied by the endpoint of each observed IEX demand curve (as in Figure 4).

Panel A of Table 4 presents the average daily changes in IEX consumer surplus and quantity supplied from moving from observed market outcomes to a full-demand mandate.<sup>36</sup> A full-demand mandate would increase average IEX quantity supplied by 10.5 GWh per day—9.6 percent above observed average quantities—but would reduce IEX consumer surplus by Rs. 943 million per day (169 percent). Consumer surplus would be negative under the full-demand mandate, since a large share of utilities’ demand bids would fall below the higher market clearing price (as illustrated by the shading in Figure 4a). Consequently, utilities would have to be paid at least Rs. 943 million per day in order to prefer a full-demand mandate over the status quo of downward-sloping demand.

To justify such a transfer to utilities, the average retail consumer would need to value the

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35. Note that satisfying all IEX demand need not correspond to all end-users across India receiving  $24 \times 7$  power. Utilities should bid demand into the IEX only up to the point where they would receive weakly negative revenue per kWh sold. Even at an energy price of 0 Rs/kWh, Indian utilities might still earn negative profits per kWh due to a combination of low regulated retail tariffs and bill non-payment.

36. In 27 percent of 15-minute intervals, the total amount of supply bid into the IEX was smaller than the total quantity of demand bids. For these intervals, we dispatch all supply, and some demand remains unsatisfied. Appendix Table C.5 shows that our results are similar when we exclude these intervals.

Table 4: Market impacts of a full-demand mandate

IEX market outcome	Full-demand mandate	Observed demand (elastic)	Mandate – Observed	% Difference
<b>A: Observed IEX supply curve</b>				
Consumer surplus (M Rs / day)	–308.1	634.8	–942.9	–169.3
Quantity supplied (GWh / day)	120.7	110.3	10.5	9.6
<b>B: Adjusted IEX supply curve, eliminating inframarginal discretionary outages</b>				
Consumer surplus (M Rs / day)	688.5	873.9	–185.4	–26.4
Quantity supplied (GWh / day)	131.7	124.4	7.3	6.3

**Notes:** This table presents changes in market outcomes in the IEX day-ahead market from mandating that all demand bid into the IEX must be satisfied. Panel A holds the observed IEX supply curve fixed. In Panel B, we eliminate all discretionary outages at inframarginal plants, shifting the IEX supply curve right by the resulting increases in available capacity (see Section 5.2 for details). Each cell reports the daily mean over the sample period. The first column presents counterfactual market outcomes implied by imposing the full-demand mandate, while the second column presents the market outcomes implied by the observed (elastic) IEX demand curve. The third column subtracts observed from counterfactual outcomes, and the fourth column presents this difference as a percent of the outcomes based on observed IEX demand. We report IEX consumer surplus in constant 2016 rupees.

increase in electricity consumed due to the full-demand mandate at Rs. 90,052 per MWh.<sup>37</sup>

As a point of comparison, retail electricity prices in India ranged from Rs. 0 to Rs. 13,534 per MWh in 2019 (Central Electricity Authority (2019b)). In addition, the average net present cost of installing and operating a diesel generator, a common form of adaptation to blackouts (Allcott, Collard-Wexler, and O’Connell (2016)), ranges from roughly Rs. 13,456 to Rs. 35,883 per MWh.<sup>38</sup> These two benchmarks suggest that the decrease in utilities’ consumer surplus under a full-demand mandate would likely far exceed the benefits to end-users of additional electricity supplied.<sup>39</sup>

In Panel B of Table 4, we consider a counterfactual world without discretionary out-

37. Rs. 942.9M per day  $\div$  10.5 GWh per day = Rs. 90,052 per MWh.

38. Electricity from a diesel generator ranges costs 15–40 Rs. per kWh, while the capital costs of installation constitute roughly 6–7 percent of the lifetime cost of a diesel generator (Gupta (2019)).

39. Here, we only consider the buy-side of the market. In Appendix Table C.3, we compute changes in welfare under the assumption that the IEX market is perfectly competitive. Even accounting for producer surplus in this manner, the welfare costs of the full-demand mandate are substantially larger than reasonable estimates of the average end-user’s benefit from increased electricity consumption. In support of the assumption of perfect competition, Ryan (2021) suggests that suppliers had limited opportunities to exercise market power during our sample period due to transmission expansions. Appendix Table C.4 shows similar results using only the subset of intervals without binding transmission constraints—in which the market was likely (close to) competitive.



ages at inframarginal power plants, shifting out the IEX supply curve as in Section 5.2. Eliminating these outages increases average IEX quantity supplied by 14.1 GWh per day (see Figure 7) and lowers market clearing prices, in turn increasing average IEX consumer surplus to Rs. 873.9 million per day. From this new baseline, a full-demand mandate would increase average IEX quantity supplied by an additional 7.3 GWh per day (6.3 percent), while decreasing average IEX consumer surplus by just 26.4 percent. Having shifted out the IEX supply curve by returning discretionary outages to service, a full-demand mandate becomes both less severe (since less IEX demand remains unsatisfied) and less costly (since more low-cost plants are available to satisfy the mandate). In fact, in a world without inframarginal discretionary outages, utilities would only require transfers of Rs. 185.4M per day, or Rs. 25,397 per MWh of additional electricity supplied, to prefer a full-demand mandate over downward-sloping demand. This per-MWh transfer is comparable to the average cost of a diesel backup generator—a cost which many end-users already incur to buffer against blackouts.

In summary, we find that that imposing a full-demand mandate alone would prove extremely costly to utilities. Making utilities whole would require transfers far larger than typical end-users' value of blackouts avoided. However, these large costs appear to be driven by supply-side misallocation. Reducing discretionary outages would substantially improve the economics of a full-demand mandate, to the point where policymakers could justify such a regulation using reasonable assumptions regarding end-users' disutility of blackouts.

## 7 Conclusion

Economic growth is dependent on energy consumption, but frequent blackouts hamper productivity in developing countries (Allcott, Collard-Wexler, and O'Connell (2016)). This paper shows that wholesale electricity market institutions play a key role in determining the extent to which end-use consumers face blackouts. Using novel data on the Indian wholesale

electricity sector, we demonstrate that: (i) Indian electric utilities purchase less electricity when procurement costs are higher, leading to downstream blackouts; (ii) discretionary outages create substantial supply-side misallocation of output across Indian power plants, which increases utilities' procurement costs and lowers the quantity of electricity supplied to end-users; and (iii) implementing market reforms to reduce supply-side distortions could greatly improve the economics of a regulatory mandate that requires utilities to satisfy all electricity demand regardless of cost.

Our findings further indicate that reducing trading frictions in developing country power markets has the potential to deliver significant benefits. Though financial trading was prohibited in India during our sample period, several recent policy changes have introduced limited financial instruments to India's wholesale electricity sector (Garg (2021)). Our results suggest that such reforms are likely to substantially lower the aggregate costs of electricity production, resulting in more power reaching end-use consumers.

Our findings also have implications for electricity markets outside of the developing world. With the growth of intermittent wind and solar capacity, utilities around the world are facing greater fluctuations in wholesale procurement costs. In response, these utilities are beginning to implement "real-time" pricing and automated demand response programs designed to better communicate wholesale market price signals to retail electricity consumers (e.g., Wolak (2011); Bollinger and Hartmann (2019); Blonz et al. (2021)). Such programs make wholesale electricity demand more elastic. Consequently, the lessons from this paper—that supply-side distortions can substantially reduce the quantity supplied to (or purchased by) end-use electricity consumers—may become increasingly relevant in high-income countries.

## References

- Acemoglu, Daron, Simon Johnson, and James A. Robinson. 2001. “The colonial origins of comparative development: An empirical investigation.” *American Economic Review* 91 (5): 1369–1401.
- Allcott, Hunt, Allan Collard-Wexler, and Stephen D O’Connell. 2016. “How do electricity shortages affect industry? Evidence from India.” *American Economic Review* 106 (3): 587–624.
- Archsmith, James. 2019. “Dam Spillovers: The direct and indirect costs from environmental constraints on hydroelectric generation.” Working paper.
- Banerjee, Abhijit, and Lakshmi Iyer. 2005. “History, institutions, and economic performance: The legacy of colonial land tenure systems in India.” *American Economic Review* 95 (4): 1190–1213.
- Berkouwer, Susana B., and Joshua T. Dean. 2021. “Credit, attention, and externalities in the adoption of energy efficient technologies by low-income households.” Working paper.
- Bhattacharya, Saugata, and Urjit R Patel. 2008. “The power sector in India: An inquiry into the efficacy of the reform process.” In *India Policy Forum*, 4:211–283. 1. National Council of Applied Economic Research.
- Blonz, Joshua, Karen Palmer, Casey J. Wichman, and Derek C. Wietelman. 2021. “Smart thermostats, automation, and time-varying prices.” Resources for the Future working paper no. 21-20.
- Bollinger, Bryan K., and Wesley R. Hartmann. 2019. “Information vs. automation and implications for dynamic pricing.” *Management Science* 66 (1): 290–314.
- Borenstein, Severin, James Bushnell, and Steven Stoft. 2000. “The competitiveness effects of transmission capacity in a deregulated electricity industry.” *RAND Journal of Economics* 31 (2): 294–325.
- Borenstein, Severin, James B Bushnell, and Frank A Wolak. 2002. “Measuring market inefficiencies in California’s restructured wholesale electricity market.” *American Economic Review*, 1376–1405.
- Borenstein, Severin, and Stephen Holland. 2005. “On the efficiency of competitive electricity markets with time-invariant retail prices.” *The Rand Journal of Economics* 36 (3): 469.
- Burgess, Robin, Michael Greenstone, Nicholas Ryan, and Anant Sudarshan. 2020a. “Demand for electricity on the global electrification frontier.” Working paper.
- . 2020b. “The consequences of treating electricity as a right.” *Journal of Economic Perspectives* 34 (1): 145–169.
- Burlando, Alfredo. 2014. “Transitory shocks and birth weights: Evidence from a blackout in Zanzibar.” *Journal of Development Economics* 108:154–168.

- Burlig, Fiona, and Louis Preonas. 2021. “Out of the darkness and into the light? Development effects of rural electrification.” Energy Institute at Haas working paper no. 268R.
- Carranza, Eliana, and Robyn Meeks. 2021. “Energy efficiency and electricity reliability.” *Review of Economics and Statistics* 103 (3): 461–475.
- Central Electricity Authority. 2018. *Load Generation Balance Report, 2018–19*.
- . 2019a. *CEA Annual Report 2018-19*. [https://cea.nic.in/wp-content/uploads/2020/03/annual\\_report-2019.pdf](https://cea.nic.in/wp-content/uploads/2020/03/annual_report-2019.pdf).
- . 2019b. *Electricity Tariff and Duty and Average rates of electricity supply in India*. [https://cea.nic.in/wp-content/uploads/2021/03/tariff\\_2019.pdf](https://cea.nic.in/wp-content/uploads/2021/03/tariff_2019.pdf).
- Central Electricity Regulatory Commission. 2018a. *Discussion Paper on Market Based Economic Dispatch of Electricity: Re-designing of Day-ahead Market (DAM) in India*. [http://www.cercind.gov.in/2018/draft\\_reg/DP31.pdf](http://www.cercind.gov.in/2018/draft_reg/DP31.pdf).
- . 2018b. *Discussion paper on re-designing real time electricity markets in India*. [https://cercind.gov.in/2018/draft\\_reg/RTM.pdf](https://cercind.gov.in/2018/draft_reg/RTM.pdf).
- . 2018c. *Report on Short-term Power Market in India: 2017–2018*. <http://www.cercind.gov.in/2018/MMC/AR18.pdf>.
- . 2019. *Report on Short-term Power Market in India: 2019–2020*. <http://www.cercind.gov.in/2018/MMC/AR18.pdf>.
- Chan, Hei Sing Ron, Maureen L. Cropper, and Kabir Malik. 2014. “Why are power plants in India less efficient than power plants in the United States?” *American Economic Review* 104 (5): 586–590.
- Cicala, Steve. Forthcoming. “Imperfect markets versus imperfect regulation in U.S. electricity generation.” *American Economic Review*.
- Clay, Karen, Akshaya Jha, Joshua A Lewis, and Edson R Severnini. 2021. “Impacts of the Clean Air Act on the power sector from 1938-1994: Anticipation and adaptation.” National Bureau of Economic Research working paper no. 28962.
- Cole, Matthew A., Robert J. R. Elliott, Giovanni Occhiali, and Eric Strobl. 2018. “Power outages and firm performance in Sub-Saharan Africa.” *Journal of Development Economics* 134:150–159.
- Cole, Shawn, Xavier Giné, Jeremy Tobacman, Petia Topalova, Robert Townsend, and James Vickery. 2013. “Barriers to household risk management: Evidence from India.” *American Economic Journal: Applied Economics* 5 (1): 104–135.
- Davis, Lucas W, Alan Fuchs, and Paul Gertler. 2014. “Cash for coolers: evaluating a large-scale appliance replacement program in Mexico.” *American Economic Journal: Economic Policy* 6 (4): 207–38.

- Davis, Lucas W, Sebastian Martinez, and Bibiana Taboada. 2020. “How effective is energy-efficient housing? Evidence from a field trial in Mexico.” *Journal of Development Economics* 143:102390.
- Davis, Lucas W, and Catherine Wolfram. 2012. “Deregulation, consolidation, and efficiency: Evidence from US nuclear power.” *American Economic Journal: Applied Economics*, 194–225.
- Dinkelman, Taryn. 2011. “The effects of rural electrification on employment: New evidence from South Africa.” *The American Economic Review* 101 (7): 3078–3108.
- Duflo, Esther, and Abhijit Banerjee. 2006. “Addressing absence.” *Journal of Economic Perspectives* 20 (1): 117–132.
- Duflo, Esther, Michael Greenstone, Rohini Pande, and Nicholas Ryan. 2013. “Truth-telling by third-party Auditors and the response of polluting firms: Experimental evidence from India.” *The Quarterly Journal of Economics* 128 (4): 1499–1545.
- Duflo, Esther, Michael Kremer, and Jonathan Robinson. 2011. “Nudging farmers to use fertilizer: Theory and experimental evidence from Kenya.” *American Economic Review* 101 (6): 2350–2390.
- Dutta, Goutam, and Krishnendranath Mitra. 2017. “A literature review on dynamic pricing of electricity.” *Journal of the Operational Research Society* 68 (10): 1131–1145.
- Dzansi, James, Steven L. Puller, Brittany Street, and Belinda Yebuah-Dwamena. 2018. “The vicious circle of blackouts and revenue collection in developing economies: Evidence from Ghana.” Working paper.
- Fabrizio, K.R., N.L. Rose, and C.D. Wolfram. 2007. “Do markets reduce costs? Assessing the impact of regulatory restructuring on US electric generation efficiency.” *The American Economic Review* 97 (4): 1250–1277.
- Field, Erica. 2007. “Entitled to work: Urban property rights and labor supply in Peru.” *Quarterly Journal of Economics* 122 (4): 1561–1602.
- Fisher-Vanden, Karen, Erin T. Mansur, and Qiong (Juliana) Wang. 2015. “Electricity shortages and firm productivity: Evidence from China’s industrial firms.” *Journal of Development Economics* 114:172–188.
- Garg, Vibhuti. 2021. *Deepening India’s Short-Term Power Market with Derivatives*. [http://ieefa.org/wp-content/uploads/2021/06/Deepening-Indias-Short-Term-Power-Market-With-Derivatives\\_June-2021.pdf](http://ieefa.org/wp-content/uploads/2021/06/Deepening-Indias-Short-Term-Power-Market-With-Derivatives_June-2021.pdf).
- Gaur, Vasundhara, and Eshita Gupta. 2016. “The determinants of electricity theft: An empirical analysis of Indian states.” *Energy Policy* 93:127–136.
- Gertler, Paul J, Kenneth Lee, and A Mushfiq Mobarak. 2017. “Electricity reliability and economic development in cities: A microeconomic perspective.” Energy and Economic Growth state-of-knowledge paper no. 3.2.

- Gertler, Paul J., Ori Shelef, Catherine D. Wolfram, and Alan Fuchs. 2016. “The demand for energy-using assets among the world’s rising middle classes.” *American Economic Review* 106 (6): 1366–1401.
- Gupta, Ankita. 2019. *Changing Cost Dynamics*. <https://powerline.net.in/2019/01/19/changing-cost-dynamics/>.
- International Energy Agency. 2020. *Electricity Market Report*. [https://iea.blob.core.windows.net/assets/a695ae98-cec1-43ce-9cab-c37bb0143a05/Electricity\\_Market\\_Report\\_December\\_2020.pdf](https://iea.blob.core.windows.net/assets/a695ae98-cec1-43ce-9cab-c37bb0143a05/Electricity_Market_Report_December_2020.pdf).
- Jack, Kelsey, Seema Jayachandran, and Sarojini Rao. 2017. “Environmental externalities and intrahousehold inefficiency.” NBER working paper no. 24192.
- Jack, Kelsey, and Grant Smith. 2015. “Pay as you go: Prepaid metering and electricity expenditures in South Africa.” *American Economic Review* 105 (5): 237–241.
- . 2020. “Charging ahead: Prepaid metering, electricity use, and utility revenue.” *American Economic Journal: Applied Economics* 12 (2): 134–68.
- Jha, Akshaya, and Frank Wolak. 2020. “Can forward commodity markets improve spot market performance? Evidence from wholesale electricity.” Working paper.
- Lee, Kenneth, Edward Miguel, and Catherine Wolfram. 2020. “Experimental evidence on the economics of rural electrification.” *Journal of Political Economy* 128 (4).
- Mansur, Erin T. 2008. “Measuring welfare in restructured electricity markets.” *The Review of Economics and Statistics* 90 (2): 369–386.
- McRae, Shaun. 2015. “Infrastructure quality and the subsidy trap.” *American Economic Review* 105 (1): 35–66.
- Mercadal, Ignacia. Forthcoming. “Dynamic competition and arbitrage in electricity markets: The role of financial traders.” *American Economic Journal: Microeconomics*.
- Ministry of Power. 2020. “Growth of electricity sector in India from 1947-2020.”
- Newey, Whitney K, and Kenneth D West. 1987. “A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix.” *Econometrica: Journal of the Econometric Society*, 703–708.
- Pargal, Sheoli, and Sudeshna Ghosh Banerjee. 2014. *India Power Sector Review: More Power to India: The Challenge of Distribution*. The World Bank Group.
- Preonas, Louis. 2017. “Market power in coal shipping and implications for U.S. climate policy.” Energy Institute at Haas Working Paper No 285.
- Reguant, Mar. 2014. “Complementary bidding mechanisms and startup costs in electricity markets.” *Review of Economic Studies* 81 (4): 1708–1742.
- Rudnick, Hugh, and Constantin Velasquez. 2018. “Taking stock of wholesale power markets in developing countries: A literature review.” World Bank Policy Research working paper no. 8519.

- Ryan, Nicholas. 2021. “The competitive effects of transmission infrastructure in the Indian electricity market.” *American Economic Journal: Microeconomics* 13 (2): 202–42.
- Srinivasan, M.R. 2007. *Why India should opt for nuclear power*. <https://www.thehindu.com/todays-paper/tp-opinion/Why-India-should-opt-for-nuclear-power/article14850892>. ece, October.
- Steinbuks, Jevgenijs, and Vivien Foster. 2010. “When do firms generate? Evidence on in-house electricity supply in Africa.” *Energy Economics* 32:505–514.
- Wolak, Frank A. 2011. “Do residential customers respond to hourly prices? Evidence from a dynamic pricing experiment.” *American Economic Review* 101 (3): 83–87.
- Wolfram, Catherine, Ori Shelef, and Paul Gertler. 2012. “How will energy demand develop in the developing world?” *Journal of Economic Perspectives* 26 (1): 119–138.
- Wolfram, Catherine D. 1999. “Measuring duopoly power in the British electricity spot market.” *American Economic Review* 89 (4): 805–826.
- Zhang, Fan. 2019. “In the Dark: How much do power sector distortions cost South Asia?” World Bank South Asia Development Forum report.

BLACKOUTS IN THE DEVELOPING WORLD:  
THE ROLE OF WHOLESALE ELECTRICITY MARKETS

**Supplementary Appendix: For online publication**

Akshaya Jha      ©      Louis Preonas      ©      Fiona Burlig\*

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

Appendix B expands the conceptual framework discussed in Section 3.

Appendix C presents robustness checks and additional empirical results.

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\*. Jha: H. John Heinz III College, Carnegie Mellon University. Email: akshayaj@andrew.cmu.edu.  
Preonas: Department of Agricultural and Resource Economics, University of Maryland. Email: lpreonas@umd.edu.  
Burlig: Harris School of Public Policy and Energy Policy Institute (EPIC), University of Chicago, and NBER. Email: burlig@uchicago.edu.

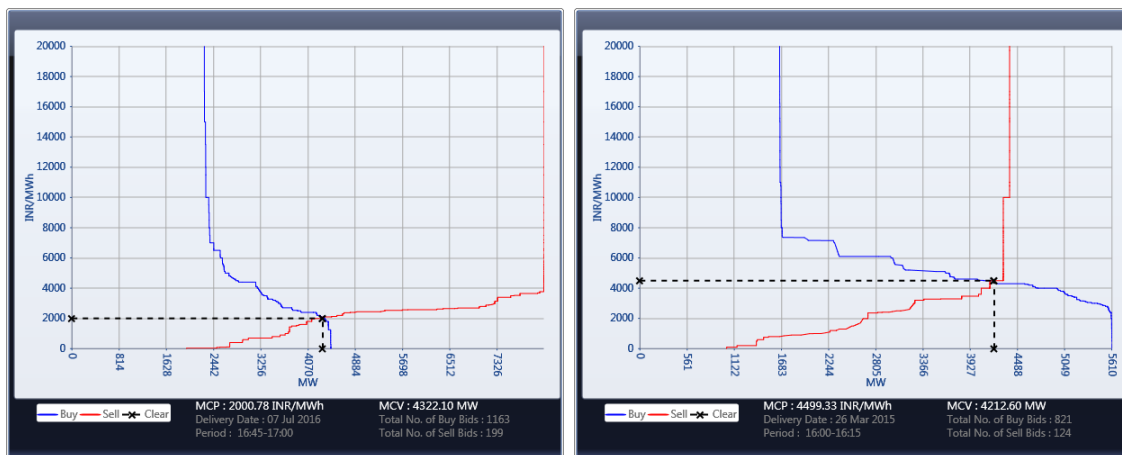


# A Data appendix

## A.1 Indian Energy Exchange data

The Indian Energy Exchange (IEX) provides .jpeg images of the aggregate supply and demand curves for each 15-minute interval-of-sample. We downloaded these data from January 1st, 2013 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.<sup>1</sup> Figure A.1 presents two of the 201,024 15-minute intervals in our dataset.

Figure A.1: 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.

The IEX also provides market clearing price and quantity data for each 15-minute interval for each of India’s five transmission regions.<sup>2</sup> Across our sample, the average IEX market clearing price was 3,121 Rs/MWh, while the average volume cleared was 1,128 MWh per 15-minute interval. We compare the equilibrium outcomes implied by our converted

1. These images are available from the following link: <https://www.iexindia.com/marketdata/demandsupply.aspx>.  
2. 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>.

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.<sup>3</sup>

## A.2 Power plant operations data

**Power plant generation:** The Central Electricity Authority (CEA) publishes *Daily Generation Reports*, which include daily operational capacity, scheduled production, and observed production for all utility-scale fossil, hydroelectric, and nuclear plants in India.<sup>4</sup> We digitized daily reports from January 1, 2013 to December 31, 2019. This yields a panel dataset of 508 unique plants that represent 301 GW of India’s 383 GW of electric generating capacity, with an average total production of approximately 3.05 TWh per day. Wind and solar resources fall instead under the Ministry of Renewable Energy. To our knowledge, there is no publicly available dataset on daily generation from non-hydro renewables, which comprised 9.2 (5.5) percent of India’s total generation in 2018/19 (2014/15) (Central Electricity Authority (2019)).

**Power plant outages:** The CEA’s Daily Outage Reports provides us with the amount of capacity under outage for each plant in each day. Regulators require plant managers to state a reason for going on outage. This allows us to classify two subsets of outages: “equipment” outages, related to technical failures on site that are likely outside of plants’ immediate control; and “discretionary” outages, where plants specifically cite poor market conditions or insufficient private incentive to stand ready to generate.<sup>5</sup> These two categories are far from exhaustive, and plants report a variety of other outage reasons relating to planned

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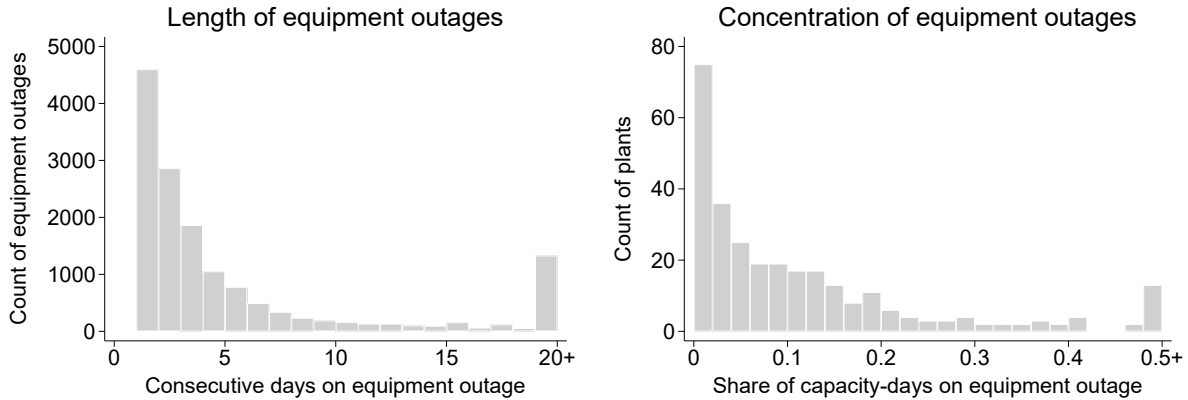
3. The average market clearing price during our sample period reported by the IEX versus calculated using the converted images is 3,124 Rs/MWh and 3,147 Rs/MWh respectively.

4. As an example, the link to this report for August 24 2021: <https://npp.gov.in/public-reports/cea/daily/dgr/24-08-2021/dgr2-2021-08-24.pdf>.

5. Common examples of equipment outages are: “water wall tube leakage”, “super heater tube leakage”, “ash handling system problems”, “furnace fire out/flame abnormal”. Common examples of discretionary outages are: “reserve shutdown”, “uneconomical operation”, “low system demand/costly fuel”, “other commercial reason”.

maintenance, fuel shortages, transmission failures, etc. Our full mapping from the detailed reasons listed to the broad categories of outage utilized in the analysis is available upon request.

Figure A.2: Distribution of equipment outages

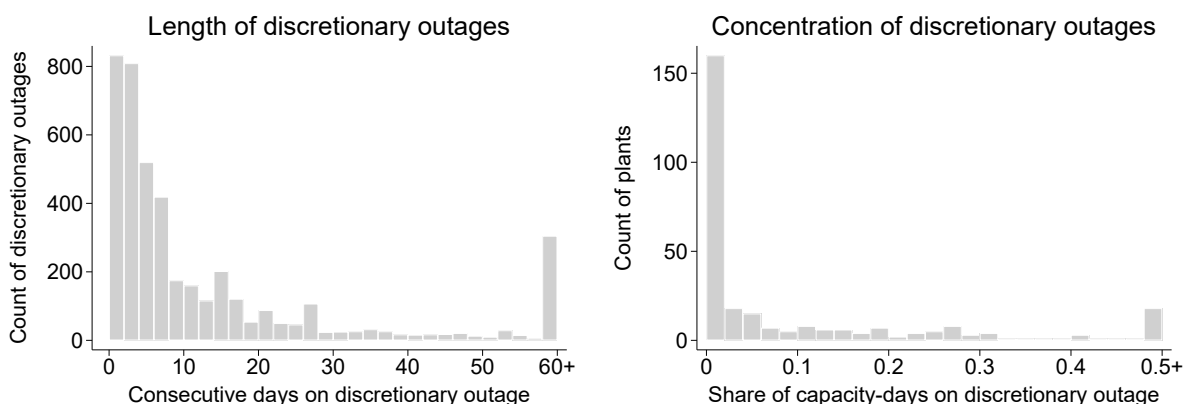


**Notes:** The left histogram summarizes the length of equipment outages; each observation is a set of consecutive days where a plant reports some capacity on equipment outage. During our sample period, the median equipment outage lasted 2 days. The right histogram summarizes the share of total capacity-days on equipment outage; each observation is a plant. During our sample period, the median plant had an equipment outage rate of 6.7 percent.

Figure A.2 characterizes the distribution of equipment outages during our sample period. The left panel shows that the median equipment outage lasts just 2 days, while 95 percent of equipment outages are shorter than 33 days long. This supports our assumption that equipment outages represent short-lived exogenous shocks to utilities’ wholesale procurement costs. The right panel illustrates how the majority of plants (84 percent) reported an equipment outage during our sample period, with the median plant being on equipment outage for 6.7 percent of capacity-days.

Figure A.3 characterizes the distribution of discretionary outages during our sample period. This reveals two important patterns in the data. First, the left panel shows that most discretionary outages last between 1 and 5 days—likely reflecting short-run negative shocks to plants’ potential revenues from making their capacity available to generate. This supports the plausibility of our counterfactual analysis that returns capacity on discretionary outage to service, since the representative discretionary outage occurs at a plant that stood

Figure A.3: Distribution of discretionary outages



**Notes:** The left histogram summarizes the length of discretionary outages; each observation is a set of consecutive days where a plant reports some capacity on discretionary outage. During our sample period, the median discretionary outage lasted 5 days. The right histogram summarizes the share of total capacity-days on discretionary outage; each observation is a plant. During our sample period, the median plant had a discretionary outage rate of 1.2 percent.

ready to generate at some point within the same week. Second, the right panel shows that the majority of plants have discretionary outage rates less than 1.2 percent. Reassuringly, 50 percent of capacity-days on discretionary outage come from just 16 percent of plants—the subset of plants for whom short-run shocks to the cost or probability of being called on to generate by their contracted buyer are pivotal for whether production is profitable.

**Heat rates:** A plant’s heat rate, a measure of efficiency, is defined to be the amount of heat input (in kcal) required to produce one MWh of electricity. For coal and lignite plants, we obtain 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). We thank the authors for sharing these data. Since our analysis spans 2013–2019, we assign each plant its most recent heat rate observed in our data. For only 16 plants appearing in the *Reviews*, this most recent heat rate was reported prior to 2012. For these plants, 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 available for the years 2012, 2016, and 2017 only; 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.

**Fuel prices:** 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.<sup>6</sup>

**Coal consumption:** We use CEA’s Monthly Coal Reports on monthly coal consumption in kilograms to calculate the grade of coal burned by each plant as well as convert coal prices from rupees per kilogram to rupees per kWh.

### A.3 Constructing marginal costs

**Coal plants:** We construct marginal costs for each coal-fired power plant as follows. We begin by collecting grade-specific coal prices reported aperiodically by Coal India Limited and Western Coalfields Limited (prices reported in rupees per kg).<sup>7</sup> “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.

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

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6. These are regulated “pithead” prices, and they do not include the cost of transporting the 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. The coal prices for Coal India Limited are available at <https://www.coalindia.in/Manage/ViewDocumentModule.aspx>.

on India’s coalfields from the U.S. Geological Survey. Data on the rail network in India is created by ML InfoMap.<sup>8</sup>

We approximate the grade of coal burned by the plant as follows. First, we divide annual total quantity of electricity produced by each plant (in kWh) by the annual total quantity of coal consumed by each plant (in kg). This annual ratio is multiplied by each plant’s heat rate in each year (in kcal per kWh). The resulting quantity is the annual aggregate amount of kcal of input heat energy obtained by the plant from one kg of coal. Taking the mean of this quantity gives us the approximate grade of coal burned by the plant, which ranges from 1,118 to 8,254 kcal per kg for non-lignite coal plants.<sup>9</sup>

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.<sup>10</sup> The value-added tax is 2% if the coal comes from out of state but 5% if the coal comes from the same state as the plant. The excise tax is 6% across the nation. West Bengal also charges a 25% tax on coal mined in its state.

We next add transportation charges, additional taxes, stowing duty, and the West Bengal specific royalty adder to the minemouth price. Transportation charges, assessed in rupees per kg, vary both over time and by distance between mine and plant. We collect rail rates from the Indian Railway website, calculating the relevant distance between plant and coalfield as discussed above.<sup>11</sup> The majority of power plants receive coal from trains. The

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8. More information on these data can be found here: <https://searchworks.stanford.edu/view/ww857qy4996>.

9. We have heat rate and coal grade data for 84 coal-fired plants and 7 lignite-fired plants, representing approximately 50 and 80 percent of each fuel’s respective generating capacity from the CEA’s daily generation data.

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

11. 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](http://www.indianrailways.gov.in/railwayboard/uploads/directorate/traffic.comm/downloads/Freight_Rate_2018/RC_19_2018.PDF)

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.<sup>12</sup> Finally, the Ministry of Coal charges a 10 rupees per 1,000 kg “stowing excise duty” related to the “assessment and collection of excise duty levied on all raw coal...”<sup>13</sup>

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.<sup>14</sup> 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 as discussed above for coal plants, we multiply by an estimate of the heat content of lignite coal (in kcal per kg) from the same source as the price. Finally, we multiply the lignite coal price (now in rupees per kcal) by the plant’s heat rate to obtain the marginal cost (in rupees per kWh) for each lignite plant.

**Gas plants:** For natural gas plants, we use gas prices originally reported in rupees per 1,000 cubic meters. We assume that 1 cubic meter of natural gas contains 10,000 kcal of heat energy, using this conversion factor to obtain gas prices in rupees per kcal. Finally,

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12. 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>

13. 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](https://www.eria.org/uploads/media/07_RPR_FY2018_15_Chapter_6.pdf)

14. The data are here: <http://cercind.gov.in/2017/orders/255.pdf>

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.<sup>15</sup>

**Nuclear plants:** We assign each of the 7 nuclear plants in our sample a marginal cost based on tariff documents.<sup>16</sup>

**Hydro, wind, and solar:** 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 (2019)). Consequently, we exclude hydro, wind, and solar resources from the analysis, implicitly assuming that they are infra-marginal; they would be dispatched as observed even in the least-cost benchmark discussed in Section 5.1. To the extent that dispatchable hydro resources are dispatched suboptimally due to a lack of incentives to operate when costs are low and/or the value of electricity is high, our estimates in Section 5.1 represent a lower bound on the costs of misallocation in wholesale electricity supply.

## A.4 Marginal costs reported by the Ministry of Power

As a robustness check, we also perform the analyses in Section 5 using marginal costs reported by the Ministry of Power rather than our own constructed marginal costs.<sup>17</sup> Table A.1 lists summary statistics by resource type for each data source.

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15. 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.

16. 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>

17. The marginal costs reported by the Ministry of Power can be found here: <http://meritindia.in/>



Table A.1: Marginal costs: constructed vs. Ministry of Power

	<b>Data Source</b>	<b>Mean</b>	<b>Std. Dev.</b>	<b>5th %</b>	<b>95th %</b>
Coal	Constructed	1.2	0.5	0.7	2.0
	Reported	2.4	0.9	1.2	3.8
Lignite	Constructed	1.6	0.3	1.2	2.3
	Reported	2.3	0.8	1.4	3.8
Gas	Constructed	2.1	0.8	1.3	3.9
	Reported	2.4	1.0	1.3	4.7
Nuclear	Constructed	0.7	0.4	0.3	1.1
	Reported	2.6	0.8	1.1	4.1

**Notes:** This table presents summary statistics on average marginal costs for coal, lignite, gas, and nuclear generating units. “Constructed” refers to marginal costs constructed by the authors while “Reported” refers to the measure of variable costs reported by the Ministry of Power.

The mean marginal cost reported by the Ministry of Power is higher than our constructed marginal costs for every source type. This is likely because the Ministry of Power’s estimates include nonfuel expenses such as labor costs and expenditures on shorter-run maintenance.

## A.5 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.<sup>18</sup>

## B Additional details on the conceptual framework

Here, we formalize the intuition discussed in Section 3. Appendix B.1 presents the setup and notation, while Appendix B.2 assesses the impacts of the full-demand mandate (analogous to our calculations in Table 4). Appendices B.3 and B.4 examine how removing plant 1 and plant 2 from the market impacts outcomes, analogous to the empirical exercise in Section

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

5.2. Appendix B.5 shows that the impacts of jointly eliminating a supply-side distortion and imposing a full-demand mandate are ambiguous: utilities' consumer surplus will decrease, but wholesale market welfare may either increase or decrease.

## B.1 Setup and notation

Demand  $D(p)$  is a function of price. We assume that  $D(p)$  is strictly decreasing and therefore invertible. We argue that wholesale electricity demand is downward-sloping in many developing countries. This contrasts with most developed countries, where regulation requires utilities to satisfy all end-use electricity demand regardless of cost. This full-demand mandate imposes that utilities' wholesale demand for electricity is inelastic, with quantity supplied equal to  $\bar{D} \equiv D(0)$ .

The supply side of this model comprises three power plants, indexed by  $i$ , each with constant marginal cost  $MC_i$  and a strict capacity constraint  $K_i$ . We order plants such that  $MC_1 < MC_2 < MC_3$ , and make the following restrictions on plant capacities:  $D(MC_1) < K_1 < \bar{D} < K_1 + K_2$ ,  $D(MC_2) < \bar{D} < K_2$ , and  $\bar{D} < K_1 + K_3$ . For simplicity, we assume throughout the following derivations that the market is perfectly competitive. This assumption is not required for interpreting how removing low-cost and high-cost plants impact market clearing prices and quantities, under elastic versus inelastic demand (as we discuss in Section 3 and illustrate in Figure 4). The assumption made here that the supply curve is equal to the aggregate marginal cost curve is not necessary for interpreting the findings in the main text.

## B.2 Market outcomes in equilibrium vs. full-demand mandate

Figure 4a presents the equilibrium outcomes with all three plants in the market, along with the market outcomes implied by a full-demand mandate. Throughout the section, we

will denote the market with all three plants with the superscript  $(1, 2, 3)$ , the equilibrium outcomes implied by elastic demand with the subscript  $E$ , and the outcomes implied by the full-demand mandate with the subscript  $I$  (for inelastic). The top panel of Table 4 is the empirical analogue to the comparison considered in this subsection.

**Prices and quantities:** It is obvious that market clearing quantities and prices are higher under the full-demand mandate relative to elastic demand:

$$P_E^{(1,2,3)} = MC_1 < P_I^{(1,2,3)} = MC_2 \quad \text{and} \quad Q_E^{(1,2,3)} = D(MC_2) < D(0) \equiv \bar{D} = Q_I^{(1,2,3)}$$

**Consumer surplus:** We can express consumer surplus as:

$$CS_E^{(1,2,3)} = \int_{MC_1}^{\infty} D(p) dp$$

$$CS_I^{(1,2,3)} = \int_0^{\infty} D(p) dp - MC_2 \bar{D}$$

Proving that consumer surplus is higher under elastic demand than under the full-demand scenario:

$$\begin{aligned} CS_E^{(1,2,3)} - CS_I^{(1,2,3)} &= \int_{MC_1}^{\infty} D(p) dp - \int_0^{\infty} D(p) dp + MC_2 \bar{D} \\ &= - \int_0^{MC_1} D(p) dp + MC_2 \bar{D} \\ &> - \int_0^{MC_1} D(0) dp + MC_2 \bar{D} \\ &> -MC_1 \bar{D} + MC_2 \bar{D} \\ &= [MC_2 - MC_1] \bar{D} > 0 \end{aligned}$$

**Producer surplus:** Suppliers' profits increase under the FDM relative to elastic demand:

$$\begin{aligned}
\Pi_E^{(1,2,3)} - \Pi_I^{(1,2,3)} &= MC_1 D(MC_1) - MC_1 D(MC_1) - [MC_2 \bar{D} - MC_1 K_1 - MC_2(\bar{D} - K_1)] \\
&= -MC_2 \bar{D} + MC_1 K_1 + MC_2(\bar{D} - K_1) \\
&= MC_1 K_1 - MC_2 K_1 = [MC_1 - MC_2] K_1 < 0
\end{aligned}$$

**Welfare:** Using the above derivations, we can show that wholesale market welfare goes down under the FDM:

$$\begin{aligned}
W_E^{(1,2,3)} - W_I^{(1,2,3)} &= \Pi_E^{(1,2,3)} + CS_E^{(1,2,3)} - \Pi_I^{(1,2,3)} - CS_I^{(1,2,3)} \\
&= - \int_0^{MC_1} D(p) dp + MC_2 \bar{D} + [MC_1 - MC_2] K_1 \\
&> - \int_0^{MC_1} D(0) dp + MC_2 \bar{D} + [MC_1 - MC_2] K_1 \\
&= -MC_1 \bar{D} + MC_2 \bar{D} + [MC_1 - MC_2] K_1 \\
&= -\bar{D} [MC_1 - MC_2] + [MC_1 - MC_2] K_1 \\
&= [MC_1 - MC_2] (K_1 - \bar{D}) < 0
\end{aligned}$$

### B.3 Changes in market outcomes with vs. without plant 1

Figure 4b depicts market outcomes with plant 1 removed from the supply curve. The equilibrium under elastic demand becomes  $P_E^{(2,3)} = MC_2$  and  $Q_E^{(2,3)} = D(MC_2)$ . The market clearing price and quantity under the FDM is the same with vs. without plant 1:  $P_I^{(2,3)} = P_I^{(1,2,3)} = MC_2$  and  $Q_I^{(2,3)} = Q_I^{(1,2,3)} = \bar{D}$ . Consequently, there are no changes in consumer surplus, producer profits, and welfare from removing plant 1 from the market under the FDM. Hence, we only provide derivations for the elastic demand scenario.

**Prices and quantities:** It is obvious that market clearing prices are higher without plant 1, relative to with plant 1. This means that market clearing quantities are lower without plant 1:

$$P_E^{(1,2,3)} = MC_1 < P_E^{(2,3)} = MC_2$$

$$Q_E^{(1,2,3)} = D(MC_1) > Q_E^{(2,3)} = D(MC_2)$$

**Consumer Surplus:** Without plant 1, consumer surplus falls in the elastic demand scenario:

$$CS_E^{(1,2,3)} = \int_{MC_1}^{\infty} D(p)dp > CS_E^{(2,3)} = \int_{MC_2}^{\infty} D(p)dp$$

**Producer surplus:** Suppliers' profits remain zero in the elastic case:

$$\Pi_E^{(2,3)} = MC_2 D(MC_2) - MC_2 D(MC_2) = 0 = \Pi_E^{(1,2,3)}$$

**Welfare:** Since consumer surplus falls while producer surplus remains unchanged, welfare falls in the elastic demand scenario when plant 1 is removed from the market.

## B.4 Changes in market outcomes with vs. without plant 2

Figure 4c depicts market outcomes with plant 2 removed from the supply curve. The equilibrium under elastic demand remains the same with vs. without plant 2:  $P_E^{(1,3)} = P_E^{(1,2,3)} = MC_1$  and  $Q_E^{(1,3)} = Q_E^{(1,2,3)} = D(MC_1)$ . Consequently, we only provide derivations for the FDM scenario.

**Prices and quantities:** It is obvious that market clearing prices are higher without plant 2, relative to with plant 2. Of course, market clearing quantities remains the same under the full-demand mandate:

$$P_I^{(1,3)} = MC_3 > MC_2 = P_I^{(1,2,3)}$$

$$Q_I^{(1,3)} = Q_I^{(1,2,3)} = \bar{D}$$

**Consumer surplus:** Consumer surplus falls when plant 2 is removed from the market:

$$CS_I^{(1,3)} - CS_I^{(1,2,3)} = \int_0^\infty D(p)dp - MC_3\bar{D} - \int_0^\infty D(p)dp + MC_2\bar{D}$$

$$CS_I^{(1,3)} - CS_I^{(1,2,3)} = (MC_2 - MC_3)\bar{D} < 0$$

**Producer surplus:** Suppliers' profits increase when plant 2 is removed from the market:

$$\Pi_I^{(1,3)} - \Pi_I^{(1,2,3)} = MC_3\bar{D} - MC_3(\bar{D} - K_1) - MC_1K_1 - MC_2\bar{D} + MC_2(\bar{D} - K_1) + MC_1K_1$$

$$\Pi_I^{(1,3)} - \Pi_I^{(1,2,3)} = \bar{D}(MC_3 - MC_2) + (MC_2 - MC_3)(\bar{D} - K_1)$$

$$\Pi_I^{(1,3)} - \Pi_I^{(1,2,3)} = -K_1(MC_2 - MC_3) > 0$$

**Welfare:** Wholesale welfare under the FDM decreases without plant 2:

$$W_I^{(1,3)} - W_I^{(1,2,3)} = [CS_I^{(1,3)} - CS_I^{(1,2,3)}] + [\Pi_I^{(1,3)} - \Pi_I^{(1,2,3)}]$$

$$W_I^{(1,3)} - W_I^{(1,2,3)} = (MC_2 - MC_3)\bar{D} - K_1(MC_2 - MC_3)$$

$$W_I^{(1,3)} - W_I^{(1,2,3)} = (MC_2 - MC_3)(\bar{D} - K_1) < 0$$

## B.5 FDM + all plants vs. elastic demand + removing a plant

Here, we consider a derivation analogous to the empirical exercise in Panel B of Table 4. We compare market outcomes under the FDM with all three plants versus under elastic demand but removing a plant from the market. The key takeaway is that jointly eliminating supply-side distortions and imposing an FDM has an ambiguous impact on wholesale market welfare. If plant 1 is returned to the market along with the FDM, wholesale welfare may either increase or decrease. However, if plant 2 is returned to the market along with the FDM, wholesale welfare unambiguously decreases.

**Market clearing prices and quantities:** If the removal of plant 1 corresponds to the pre-existing supply-side distortion:

$$P_I^{(1,2,3)} = P_E^{(2,3)} = MC_2$$

$$Q_I^{(1,2,3)} = \bar{D} > D(MC_2) = Q_E^{(2,3)}$$

If the removal of plant 2 corresponds to the pre-existing supply-side distortion:

$$P_I^{(1,2,3)} = MC_2 > MC_1 = P_E^{(1,3)}$$

$$Q_I^{(1,2,3)} = \bar{D} > D(MC_1) = Q_E^{(1,3)}$$

**Consumer surplus:** If the removal of plant 1 corresponds to the pre-existing supply-side distortion:

$$CS_I^{(1,2,3)} - CS_E^{(2,3)} = \int_0^\infty D(p)dp - MC_2\bar{D} - \int_{MC_2}^\infty D(p)dp$$

$$CS_I^{(1,2,3)} - CS_E^{(2,3)} = \int_0^{MC_2} D(p)dp - MC_2\bar{D}$$

$$CS_I^{(1,2,3)} - CS_E^{(2,3)} < MC_2\bar{D} - MC_2\bar{D} = 0$$

If the removal of plant 2 corresponds to the pre-existing supply-side distortion:

$$CS_I^{(1,2,3)} - CS_E^{(1,3)} = CS_I^{(1,2,3)} - CS_E^{(1,2,3)} < 0$$

**Producer surplus:** If the removal of plant 1 corresponds to the pre-existing supply-side distortion:

$$\Pi_I^{(1,2,3)} - \Pi_E^{(2,3)} = MC_2 \bar{D} - MC_2(\bar{D} - K_1) - MC_1 K_1 - 0 > 0$$

If the removal of plant 2 corresponds to the pre-existing supply-side distortion:

$$\Pi_I^{(1,2,3)} - \Pi_E^{(1,3)} = MC_2 \bar{D} - MC_2(\bar{D} - K_1) - MC_1 K_1 - 0 > 0$$

**Welfare:** If the removal of plant 1 corresponds to the pre-existing supply-side distortion:

$$\begin{aligned} W_I^{(1,2,3)} - W_E^{(2,3)} &= CS_I^{(1,2,3)} - CS_E^{(2,3)} + \Pi_I^{(1,2,3)} - \Pi_E^{(2,3)} \\ W_I^{(1,2,3)} - W_E^{(2,3)} &= \underbrace{\int_0^{MC_2} D(p) dp - MC_2 \bar{D}}_{CS_I^{(1,2,3)} - CS_E^{(2,3)}} + \underbrace{MC_2 \bar{D} - MC_2(\bar{D} - K_1) - MC_1 K_1}_{\Pi_I^{(1,2,3)} - \Pi_E^{(2,3)}} \\ W_I^{(1,2,3)} - W_E^{(2,3)} &= \int_0^{MC_2} D(p) dp - MC_2 \bar{D} + MC_2 K_1 - MC_1 K_1 \\ \underbrace{-MC_1 K_1 - MC_2(\bar{D} - K_1)}_{<0} &< W_I^{(1,2,3)} - W_E^{(2,3)} < \underbrace{K_1(MC_2 - MC_1)}_{>0} \end{aligned}$$

Hence, there is an ambiguous welfare effect of jointly returning plant 1 to service and imposing an FDM. However, wholesale market welfare unambiguously falls when returning plant 2 to service instead:

$$W_I^{(1,2,3)} - W_E^{(1,3)} = W_I^{(1,2,3)} - W_E^{(1,2,3)} < 0$$



## C Robustness checks and sensitivity analyses

### C.1 Price elasticity of demand

Table C.1 replicates Table 1 in levels rather than logs. The results are quite similar. Column (1) shows a strong first stage, where a 10 percentage point increase in the share of privately owned IEX capacity under equipment outage causes a roughly Rs. 192 per MWh increase in the average IEX market clearing price. The IV estimate in Column (2) confirms that non-IEX demand does not systematically increase when the IEX price rises. Column (3) confirms that IEX demand is downward-sloping.

Table C.1: Aggregate demand does not respond to IEX price (in levels)

	$P^{\text{IEX}}$ (Rs/MWh)	$Q$ wholesale elec demand (GWh)	
	1st stage (1)	Non-IEX only (2)	IEX only (3)
$P^{\text{IEX}}$ (Rs/MWh)		-0.075 (0.053)	-0.020*** (0.004)
Share of privately owned IEX capacity on equipment outage	1915.955*** (289.537)		
IEX demand curve controls	Yes	Yes	Yes
Region-day temperature controls	Yes	Yes	Yes
Month-of-year FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
Number of sample days	2,409	2,287	2,409
First-stage $F$ -stat (IV)		39.76	43.79
Mean $Q$ (GWh)		3048.89	105.02
Mean $P$ (Rs/MWh)	3194.63	3188.92	3194.63

**Notes:** This table is identical to Table 1 from the main text, except that we estimate Equations (1) and (2) in levels instead of logs. Column (1) presents the corresponding first-stage estimates. The unit of observation for each time-series regression is day-of-sample. Each regression controls for the daily minimum and maximum of the total quantity of electricity demand bid into the IEX interacted with both month-of-year and year fixed effects, to remove anticipated changes in demand and account for changes in IEX market size. We also control for mean daily temperature across each electricity transmission region, month-of-year fixed effects, and year fixed effects. Standard errors account for both heteroskedasticity and 7 days of autocorrelation in the error term. Significance: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.10$ . We report Kleiberben-Paap first-stage  $F$ -statistics, where the Stock-Yogo critical value is 16.38.

## C.2 Supply-side misallocation

### C.2.1 Deviations from least-cost dispatch

Table C.2 presents four sensitivity analyses pertaining to Table 3. First, while our “regional dispatch” scenarios conservatively assume that no electricity can flow across regions, intraregional transmission constraints may also matter. In Panel A of Table C.2, instead of imposing autarky for each region, we impose autarky for each of India’s 13 transmission subregions. Second, our least-cost dispatch model ignores within-day variation in demand. Panel B redispatches plants separately for peak hours (when demand is high) and off-peak hours (when demand is low). Third, if capacity is mismeasured, our least-cost counterfactuals might overstate the amount of power an idle plant could have realistically provided. Panel C more conservatively redispatches plants up to the 80th percentile of their observed output, rather than the 98th percentile.

Finally, measurement error in our constructed marginal costs could potentially exaggerate the importance of discretionary outages. Panel D addresses this concern by using plant-specific variable costs reported by the Ministry of Power rather than our constructed marginal costs (see Appendix A.4). Across all four sensitivity analyses, discretionary outages continue to explain a substantial share of the cost difference between observed versus least-cost dispatch.

### C.2.2 Reducing supply-side misallocation

Figure C.1 plots the share of 15-minute intervals-of-sample for which returning discretionary outages to service, as described in Section 5.2, results in all of the demand in the IEX being satisfied. Though the share of intervals where demand is fully satisfied increases at higher percentages of inframarginal capacity returned, demand is fully satisfied in only roughly 40% of intervals even when all of the inframarginal capacity on discretionary outage is returned

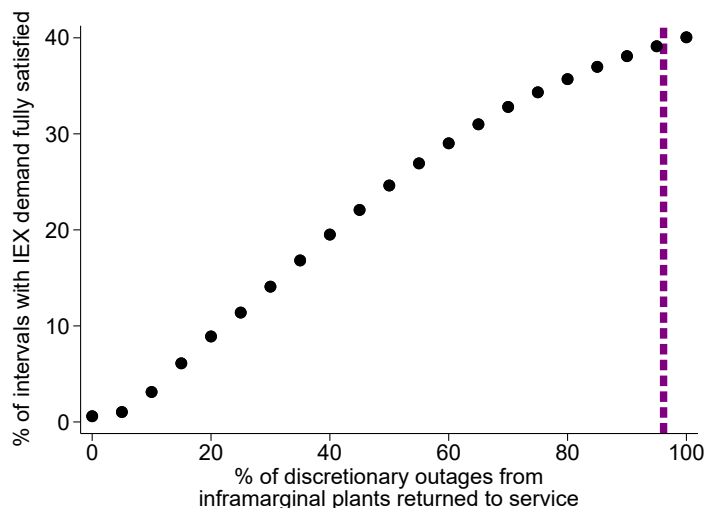
to service.

Table C.2: Variable costs of electricity supply – sensitivity analysis

Redispatching scenario	Observed (M Rs / day)	Least-cost (M Rs / day)	Cost Difference (M Rs / day)	$100 \times \frac{\text{Difference}}{\text{Observed}}$
<b>A. Subregional dispatch</b>				
Subregional, ignoring all outages	2,444 [1,846, 3,133]	2,160 [1,586, 2,852]	284 [229, 342]	11.84 [8.69, 15.16]
Subregional, ignoring discretionary outages	2,444 [1,846, 3,133]	2,266 [1,676, 2,980]	178 [128, 233]	7.49 [4.43, 10.72]
Subregional, respecting all outages	2,444 [1,846, 3,133]	2,301 [1,707, 2,995]	142 [101, 196]	6.00 [3.72, 8.94]
<b>B. Peak vs. off-peak generation</b>				
Regional, ignoring all outages	2,444 [1,846, 3,133]	2,091 [1,510, 2,775]	353 [294, 403]	14.77 [11.14, 19.16]
Regional, ignoring discretionary outages	2,444 [1,846, 3,133]	2,210 [1,615, 2,908]	234 [170, 296]	9.85 [6.30, 13.93]
Regional, respecting all outages	2,444 [1,846, 3,133]	2,257 [1,660, 2,941]	187 [119, 248]	7.84 [4.75, 11.72]
<b>C. 80th percentile of capacity</b>				
Regional, ignoring all outages	2,444 [1,846, 3,133]	2,143 [1,548, 2,842]	301 [242, 354]	12.65 [8.82, 17.23]
Regional, ignoring discretionary outages	2,444 [1,846, 3,133]	2,252 [1,650, 2,958]	192 [136, 250]	8.13 [4.80, 12.02]
Regional, respecting all outages	2,444 [1,846, 3,133]	2,286 [1,692, 2,975]	158 [113, 210]	6.69 [4.17, 10.16]
<b>D. MERIT variable costs</b>				
Regional, ignoring all outages	4,981 [4,142, 5,601]	4,354 [3,505, 4,944]	627 [494, 777]	12.69 [9.52, 16.03]
Regional, ignoring discretionary outages	4,981 [4,142, 5,601]	4,616 [3,716, 5,271]	365 [254, 485]	7.45 [4.81, 10.99]
Regional, respecting all outages	4,981 [4,142, 5,601]	4,658 [3,767, 5,297]	323 [220, 437]	6.59 [4.20, 9.73]

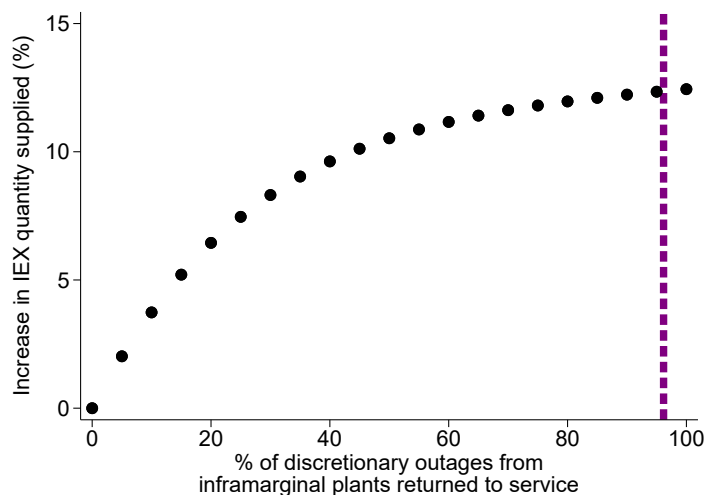
**Notes:** This table conducts four sensitivity analyses on the bottom three rows of Table 3. Panel A restricts redispatching to be within each subregion, rather than within each region. Panel B accounts for within-day variation in demand by redispatching separately for peak and off-peak periods. Panel C redispatches plant capacity up to the 80th percentile of each plant’s observed daily generation, rather than the 98th percentile. Panel D uses the variable costs reported by the Ministry of Power rather than our constructed marginal costs (see the discussion in Appendix A.4).

Figure C.1: Impact of reducing discretionary outages on the share of intervals with fully satisfied demand



**Notes:** This figure plots the relationship between the share of intervals in which all of the demand bid into the IEX is satisfied and the share of discretionary outages from inframarginal plants returned to service. The purple dashed line presents a benchmark based on reducing the total outage rate of inframarginal capacity in India to the total outage rate across all coal plants in the United States and Canada.

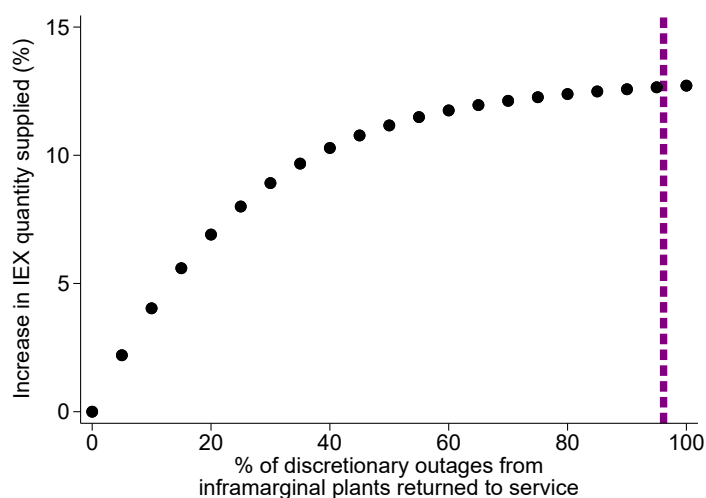
Figure C.2: Changes in quantity supplied from returning inframarginal capacity on discretionary outages to service, excluding intervals with fully satisfied demand



**Notes:** This figure plots the aggregate increase in quantity supplied from counterfactually decreasing the percentage of inframarginal capacity on discretionary outage, bidding the resulting output into the IEX at marginal cost. In contrast with Figure 7, we exclude intervals in which demand in the IEX would be fully satisfied when eliminating discretionary outages when calculating the aggregates for all of the scenarios considered. The purple dashed line presents a benchmark based on reducing the total outage rate of inframarginal capacity in India to the total outage rate across all coal plants in the United States and Canada.

**Intervals with unsatisfied demand:** Figure C.2 plots the aggregate increase in quantity of energy sold from adding different percentages of inframarginal discretionary outages back into the IEX. In contrast with Figure 7, intervals-of-sample where demand is fully satisfied when eliminating discretionary outages are excluded in the aggregates plotted in Figure C.2. The figure looks similar whether intervals with fully satisfied demand are included or excluded; the conclusion remains unchanged: returning inframarginal discretionary outages to service results in substantial increases in quantity supplied.

Figure C.3: Changes in quantity supplied from returning inframarginal capacity on discretionary outages to service, excluding intervals with transmission congestion



**Notes:** This figure plots the aggregate increases in quantity supplied from counterfactually decreasing the percentage of inframarginal capacity on discretionary outage, bidding the resulting output into the IEX at marginal cost. In contrast with Figure 7, we exclude intervals in which the IEX price differs across regions, indicative of interregional transmission congestion. The purple dashed line presents a benchmark based on reducing the total outage rate of inframarginal capacity in India to the total outage rate across all coal plants in the United States and Canada.

**Uncongested intervals only:** Figure C.3 plots the percentage change in quantity supplied from returning inframarginal capacity on discretionary outages back to service. In this figure, we exclude intervals-of-sample in which the IEX prices across regions differ; in doing so, we focus on intervals where the IEX market clearing outcomes are not determined by binding interregional transmission capacity constraints. The increases in quantity supplied from returning inframarginal discretionary outages to service are quite similar whether

intervals influenced by transmission congestion are included or excluded. This assuages concerns that the conclusions drawn from the analysis are driven by binding interregional transmission capacity constraints.

### **C.3 Full-demand mandate**

#### **C.3.1 IEX market welfare**

Table C.3 presents the daily averages of market outcomes implied by the observed market equilibrium versus the equilibrium implied by mandating that all of the demand bid into the IEX must be satisfied. Under the assumption that the IEX supply curve is equal to the aggregate marginal cost curve, we can calculate suppliers' operating costs, operating profits, and therefore wholesale welfare in the IEX market.<sup>19</sup>

Under the assumption of perfect competition, IEX market welfare necessarily decreases when deviating from the observed market equilibrium by imposing the full-demand mandate. The bulk of this reduction is due to a massive decrease in utilities' consumer surplus: utilities are forced to purchase electricity at prices far higher than their willingness to purchase. On the other hand, supplier profits are higher under the full-demand mandate relative to the observed equilibrium: though operating costs are higher due to the full-demand mandate, market prices and consequently operating revenues increase by a larger amount.

To justify the welfare reductions from satisfying all demand in the IEX, the average end-user would need to value electricity at Rs. 53,752 per MWh. However, in a world without inframarginal discretionary outages (Panel B), the average end-user would need to value electricity at only Rs. 22,013 per MWh to offset the wholesale welfare reductions from a full-demand mandate. This is quite close to the per-MWh transfer implied by Panel B of Table 4, and is comparable to the average cost per MWh of a diesel backup generator.

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19. In support of the assumption of perfect competition, Ryan (2021) suggests that suppliers had limited opportunities to exercise market power during our sample period due to transmission expansions.

Table C.3: Market impacts of a full-demand mandate

IEX market outcome	Full-demand mandate	Observed demand (elastic)	Mandate – Observed	% Difference
<b>A: Observed IEX supply curve</b>				
Wholesale welfare (M Rs / day)	302.4	865.2	–562.8	–65.4
Consumer surplus (M Rs / day)	–308.1	634.8	–942.9	–169.3
Firm profits (M Rs / day)	610.5	230.4	380.1	151.9
Production costs (M Rs / day)	151.3	123.9	27.4	23.0
Quantity supplied (GWh / day)	120.7	110.3	10.5	9.6
<b>B: Adjusted IEX supply curve, eliminating inframarginal discretionary outages</b>				
Wholesale welfare (M Rs / day)	788.4	949.1	–160.7	–17.5
Consumer surplus (M Rs / day)	688.5	873.9	–185.4	–26.4
Firm profits (M Rs / day)	99.9	75.1	24.7	20.3
Production costs (M Rs / day)	87.4	85.6	1.8	1.8
Quantity supplied (GWh / day)	131.7	124.4	7.3	6.3

**Notes:** This table presents changes in market outcomes in the IEX day-ahead market from mandating that all demand bid into the IEX must be satisfied. In contrast with Table 4, we assume that the IEX supply curve is equal to the aggregate marginal cost curve, allowing us to calculate operating costs, operating profits, and wholesale welfare. Panel A holds the observed IEX supply curve fixed. In Panel B, we eliminate all discretionary outages at inframarginal plants, shifting the IEX supply curve right by the resulting increases in available capacity (see Section 5.2 for details). Each cell reports the daily mean over the sample period. The first column presents counterfactual market outcomes implied by imposing the full-demand mandate, while the second column presents the market outcomes implied by the observed, elastic IEX demand curve. The third column subtracts observed from counterfactual outcomes, and the fourth column presents this difference as a percent of the outcomes implied by observed IEX demand. We report wholesale welfare, consumer surplus, firm profits, and production costs in constant 2016 rupees.

Our conclusion therefore remains similar when we consider full IEX market welfare rather than just utilities' consumer surplus: the loss in wholesale market welfare under a full-demand mandate likely far exceeds end-users' value of reduced blackouts, unless supply-side misallocation has been mitigated (or eliminated).

### C.3.2 Uncongested intervals only

In Section 6, we calculate IEX consumer surplus under the assumption that utilities bid their true willingness to pay. This assumption seems innocuous given that many buyers across India participate in the IEX market. Ryan (2021) makes this assumption when assessing the welfare impacts of supply-side market power, providing evidence that suppliers exercise market power in the IEX when interregional transmission capacity constraints bind. While IEX buy-side market power seems unlikely in any interval, it seems especially unlikely in intervals without interregional transmission congestion.

Table C.4 includes only the subset of intervals where IEX prices are identical across all five regions, implying unconstrained interregional transmission. After applying this sample restriction, we scale up intervals within days to reflect daily totals (e.g., each interval in a day with 36 intervals after applying the sample restriction would receive a weight of  $96/36$ ). The magnitudes in Table C.4 are similar to the magnitudes based on the full sample in Table 4. This suggests that buy-side market power (to the extent that it exists) is not causing us to mischaracterize the economics of a full-demand mandate.

### C.3.3 Periods where supply offers exceed demand bids

Table 4 includes all IEX intervals in our data, including the 27 percent of intervals where total IEX demand bids exceed total IEX supply offers. In such intervals, the observed supply bids are insufficient to satisfy a full-demand mandate. Table C.5 excludes these intervals from both Panels A and B. To make Table C.5 comparable to Table 4, we scale up 15-minute intervals to reflect daily totals. For example, if 87 of the 96 intervals in a day-of-sample have total supply offers greater than total demand bids, then each of these intervals would be scaled up by a factor of  $1.1 = \frac{96}{87}$ .

This slightly alters our results from Panel A of Table 4: by removing intervals where the counterfactual market clearing price is at the highest point on the IEX supply curve (i.e.



Table C.4: Market impacts of a full-demand mandate, only uncongested intervals

IEX market outcome	Full-demand mandate	Observed demand (elastic)	Mandate – Observed	% Difference
<b>A: Observed IEX supply curve</b>				
Consumer surplus (M Rs / day)	–421.6	737.9	–1,159.5	–179.1
Quantity supplied (GWh / day)	141.6	128.7	12.9	10.3
<b>B: Adjusted IEX supply curve, eliminating inframarginal discretionary outages</b>				
Consumer surplus (M Rs / day)	794.2	1,024.5	–230.3	–30.7
Quantity supplied (GWh / day)	154.8	146.4	8.4	6.2

**Notes:** This table presents changes in market outcomes in the IEX day-ahead market from mandating that all demand bid into the IEX must be satisfied. In contrast with Table 4, we keep only 15 minute intervals in which the IEX market clearing price is the same across transmission regions (i.e., the equilibrium prices and quantities do not need to be adjusted for transmission congestion). Intervals are summed to the daily level, multiplying by the relevant factor to represent daily totals (e.g., if there are 3 intervals in a day-of-sample after applying the sample restriction, the market outcomes for each of these intervals would be multiplied by  $32 = \frac{96}{3}$ ). Panel A holds the observed IEX supply curve fixed. In Panel B, we eliminate all discretionary outages at inframarginal plants, shifting the IEX supply curve right by the resulting increases in available capacity (see Section 5.2 for details). Each cell reports the daily mean over the sample period. The first column presents counterfactual market outcomes implied by imposing the full-demand mandate, while the second column presents the market outcomes implied by the observed, elastic IEX demand curve. The third column subtracts observed from counterfactual outcomes, and the fourth column presents this difference as a percent of the outcomes based on observed IEX demand. We report IEX consumer surplus in constant 2016 rupees.

intervals where IEX supply is exhausted before satisfying all demand bids), a full-demand mandate no longer leaves utilities with negative consumer surplus on the average day *of this subsample*. However, the implied transfers required to make utilities whole under a full-demand mandate would still be quite large: Rs. 38,142 per MWh (i.e., dividing Rs. –457.7M by 12.0 GWh). This still exceeds Rs. 35,883 per MWh, the upper bound estimate of the average net present cost of purchasing and operating diesel backup generation. Panel B of Tables C.5 and 4 are quite similar.

Table C.5: Market impacts of a full-demand mandate, excluding intervals where total demand bids exceed total supply bids

IEX market outcome	Full-demand mandate	Observed demand (elastic)	Mandate – Observed	% Difference
<b>A: Observed IEX supply curve</b>				
Consumer surplus (M Rs / day)	233.0	690.7	–457.7	–70.8
Quantity supplied (GWh / day)	127.9	115.9	12.0	10.5
<b>B: Adjusted IEX supply curve, eliminating inframarginal discretionary outages</b>				
Consumer surplus (M Rs / day)	725.1	880.3	–155.2	–18.3
Quantity supplied (GWh / day)	132.3	124.5	7.8	6.5

**Notes:** This table presents changes in market outcomes in the IEX day-ahead market from mandating that all demand bid into the IEX must be satisfied. In contrast with Table 4, the summary statistics in this table are based only on 15 minute intervals-of-sample in which total demand bid into the market is smaller than total supply offered into the market. Intervals are summed to the daily level, multiplying by the relevant factor to represent daily totals (e.g., if there are 3 intervals in a day-of-sample after applying the sample restriction, the market outcomes for each of these intervals would be multiplied by  $32 = \frac{96}{3}$ ). Panel A holds the observed IEX supply curve fixed. In Panel B, we eliminate all discretionary outages at inframarginal plants, shifting the IEX supply curve right by the resulting increases in available capacity (see Section 5.2 for details). Each cell reports the daily mean over the sample period. The first column presents counterfactual market outcomes implied by imposing the full-demand mandate, while the second column presents the market outcomes implied by the observed, elastic IEX demand curve. The third column subtracts observed from counterfactual outcomes, and the fourth column presents this difference as a percent of the outcomes based on observed IEX demand. We report IEX consumer surplus in constant 2016 rupees.