BLACKOUTS:
THE ROLE OF INDIA'S WHOLESALE ELECTRICITY MARKET

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ABSTRACT

Electricity blackouts impose substantial costs on developing countries. We advance a new explanation for their continued prevalence in India, the world's third-largest power sector. Constructing a novel dataset spanning the sector, we demonstrate that whole- sale power demand is downward-sloping: demand falls when wholesale procurement costs rise. Supply-side misallocation increases costs, thereby decreasing the quantity of electricity supplied to retail customers. We highlight a key source of misallocation: discretionary power plant outages resulting from weak incentives rather than technical issues. Eliminating these outages significantly lowers procurement costs, increasing the quantity supplied by enough to eliminate blackouts for 23 million Indian households.

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1 Introduction

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

This paper demonstrates a new mechanism for the prevalence of these blackouts, which arises from the upstream wholesale electricity sector. Utilities in developing countries may be price-sensitive, purchasing less electricity when wholesale procurement costs are high. This contrasts with the developed world, where strictly enforced regulatory mandates require utilities to satisfy all retail electricity demand regardless of cost, and where blackouts are rare. In high-income countries, supply-side distortions that raise wholesale electricity prices lead to higher retail prices but not blackouts. In contrast, when supply-side distortions raise electricity procurement costs in developing countries, the equilibrium quantity purchased from the wholesale sector may fall.[1] Since electricity storage is cost-prohibitive, this leads to blackouts for retail consumers. We empirically demonstrate the importance of this mechanism in India, which is home to the world's third-largest power sector (Zhang (2019)), and has frequent blackouts despite a surplus of generating capacity (Bhattacharya and Patel (2008); Ryan (2021)).

We digitize novel data on power plant operations and demand, which cover the vast majority of India's wholesale electricity sector. We use these data to estimate the short-run elasticity of wholesale demand by instrumenting with a plausibly exogenous cost-shifter: the

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1. Retail prices are typically set via cost-of-service regulation. In theory, regulators raise prices to allow "reasonable" costs to be passed through to consumers (Parliament of India (2003)). In practice, they are less likely to allow pass-through of high *ex post* cost realizations (Borenstein, Busse, and Kellogg (2012); Jha (2022)).

rate of equipment-related outages at power plants.[2] We show that equipment outages, which stem from technical failures, are uncorrelated with electricity demand shifters. We find a cost elasticity of demand of -0.43. By contrast, regulatory mandates force this short-run elasticity to be virtually zero in the developed world. Our results show that Indian utilities purchase substantially less electricity when wholesale procurement costs increase—causing blackouts for downstream retail consumers.

The institutions governing Indian wholesale electricity supply give rise to misallocation of output across plants, driving up utilities' procurement costs. Unlike 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 which precludes financial trading between suppliers or utility buyers. If a plant's contracted utility counterparty chooses not to purchase its power, the plant will likely be unable to sell—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, plants frequently declare discretionary outages, where they make themselves unable to produce. Unlike equipment outages, discretionary outages are endogenous, stemming from trading frictions and weak incentives rather than technical issues.

Discretionary outages at low-cost plants force high-cost plants to produce instead, giving rise to supply-side misallocation. We provide suggestive evidence that such misallocation is more prevalent in states with multiple utilities, which likely stems from within-state trading frictions. To assess the share of total misallocation that is attributable to discretionary outages, we compare the total variable costs of observed production to two "least-cost" scenarios—one that respects discretionary outages and one that eliminates discretionary outages. In both scenarios, we re-dispatch available plants from lowest to highest marginal

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

cost (as in Borenstein, Bushnell, and Wolak (2002); Cicala (2022)). The scenario that eliminates discretionary outages has substantially lower production costs, which increases the wedge between least-cost and observed costs by 34%. This demonstrates that discretionary outages are an economically important source of misallocation in Indian electricity supply.

Finally, we combine our demand- and supply-side analyses to assess the extent to which eliminating discretionary outages would increase the quantity of power that reaches end-use consumers. We simulate the wholesale market under a counterfactual where we eliminate all discretionary outages. Since this lowers procurement costs, and because utilities' demand is downward-sloping, the aggregate quantity of electricity supplied increases by 10.8 GWh per day on average. To benchmark this magnitude, 10.8 GWh per day would be sufficient to completely eliminate blackouts for roughly 23 million households (8% of households). Monetizing these gains using retail electricity prices and the costs of backup generation technologies (i.e., battery/inverter systems or diesel generators), we calculate an aggregate benefit to Indian households of Rs. 47–680 million per day (roughly US $1–10 million per day).[3]

This paper make three main contributions. First, we build on a rich literature studying wholesale electricity markets, which has largely focused on developed countries (Ryan (2012) is a notable exception). Previous work has highlighted supply-side distortions induced by cost-of-service regulation (e.g., Borenstein and Bushnell (2015); Cicala (2015)), market power (Kellogg and Reguant (2021)), and limited financial trading (e.g., Jha and Wolak (2023); Mercadal (2022)). We provide suggestive evidence that financial trading restrictions are especially important in India. We also demonstrate that Indian wholesale electricity demand is downward-sloping, unlike in developed countries where regulatory mandates ensure that short-run wholesale demand is perfectly inelastic (Mansur (2008)).[4]

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3. As one point of comparison, Ryan (2021) estimates that a 1,200 MW expansion in transmission capacity would increase surplus in India's wholesale electricity sector by US $276,000 per day.

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

Second, our paper adds to the literature on electricity reliability in developing countries. Prior research has documented that blackouts impose significant economic costs (Gertler, Lee, and Mobarak (2017)). A small literature documents the role of retail electricity distribution in blackouts: Dzansi et al. (2018), Jack and Smith (2020), and Burgess et al. (2020) argue that bill non-payment and regulated retail prices set below marginal cost lead utilities to ration power supply. This is the first paper (to our knowledge) to highlight the role of the wholesale electricity sector in blackouts.

Third, we build on a literature in development economics on the importance of market features that are specific to low-income countries. Credit constraints (Berkouwer and Dean (2022)), corruption (Duflo et al. (2013)), and intra-household bargaining challenges (Jack, Jayachandran, and Rao (2018)) can all limit the effectiveness of environmental regulations and energy-related technologies when implemented in a developing-country context.[5] We demonstrate that absent a regulatory mandate that all retail demand is satisfied—a ubiquitous feature of developed-country power markets—wholesale demand in India is downward-sloping. As a result, we show that supply-side reforms in the Indian power market would reduce blackouts rather than acting as a simple transfer between producers and consumers. Though we focus on one potential supply-side reform—reducing financial trading barriers—our findings highlight that mitigating any supply-side distortion (e.g., underinvestment in transmission capacity, market power, fuel market inefficiencies) can meaningfully improve the reliability of electricity in low- and middle-income countries.

The 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 with downward-sloping versus perfectly inelastic demand. Section 4 demonstrates that wholesale electricity demand in India is downward-sloping. Section 5 documents that discretionary outages at low-cost plants are a key form of supply-

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

side misallocation. Section 6 quantifies the increases in quantity supplied from eliminating discretionary outages. Section 7 discusses the policy implications of our findings.

2 Background and data

This section discusses electricity supply in India, and the data used in our analysis. We focus on the wholesale sector, where suppliers own power plants and sell electricity to distribution utilities. 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 (Gaur and Gupta (2016)). As a result, most utilities need government subsidies to remain financially solvent (Burgess et al. (2020)). Even with these subsidies, utilities in many states do not earn positive profits (Pargal and Banerjee (2014); Central Electricity Regulatory Commission (2018b)).

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

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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.

We also collect data from the Central Electricity Authority (CEA)'s monthly power supply position reports on each state's *ex ante* forecasted energy requirement (following Allcott, Collard-Wexler, and O'Connell (2016)). The CEA estimates counterfactual wholesale electricity demand at current prices in the absence of supply shortages, based on historical utility demand and seasonal factors (e.g., predicted weather, holidays). These state-month demand forecasts therefore reflect what utilities would choose to purchase given their existing contract portfolios.[6]

2.2 Long-term contracts and the short-term exchange

Nearly 90% of India's electricity is sold via long-term contracts between electricity producers and utilities. The typical contract specifies a set of electricity generating units 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.[7] However, the buyer is *not* obliged to purchase all electricity to which it is entitled.

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6. The CEA's forecasts take input from Regional Power Committees and states. While there is likely measurement error in these forecasts, Allcott, Collard-Wexler, and O'Connell (2016) show that the difference between forecasted energy requirement and realized demand met is strongly related to self-generation and total factor productivity in manufacturing plants, and is also correlated with coal plant capacity and World Bank Enterprise Survey reports of power quality.

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

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.[8]

Unlike electricity markets in most developed countries, financial trading has—until recently—been prohibited in India's power sector.[9] 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 of electricity were permitted, absent additional financial instruments governing transmission capacity, the transmission flows needed to execute a trade would not be guaranteed.

Short-term transactions make up the remaining 10% of Indian electricity sales. Approximately 5% of all electricity is traded on short-term bilateral contracts with a duration of less than 1 year. 3–4% of power is traded on the Indian Electricity Exchange (IEX), a day-ahead power market that clears 24 hours before power delivery.[10] A utility may exercise its right not to purchase from its long-term contracts until 90 minutes before its plant coun-

8. 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 utilities cannot ask the plant to shift their pre-scheduled maintenance to low-value periods.

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

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

terparty actually would produce. This leaves plants effectively no opportunity to sell output from unused contracted capacity in the day-ahead market (Central Electricity Regulatory Commission (2018a)).
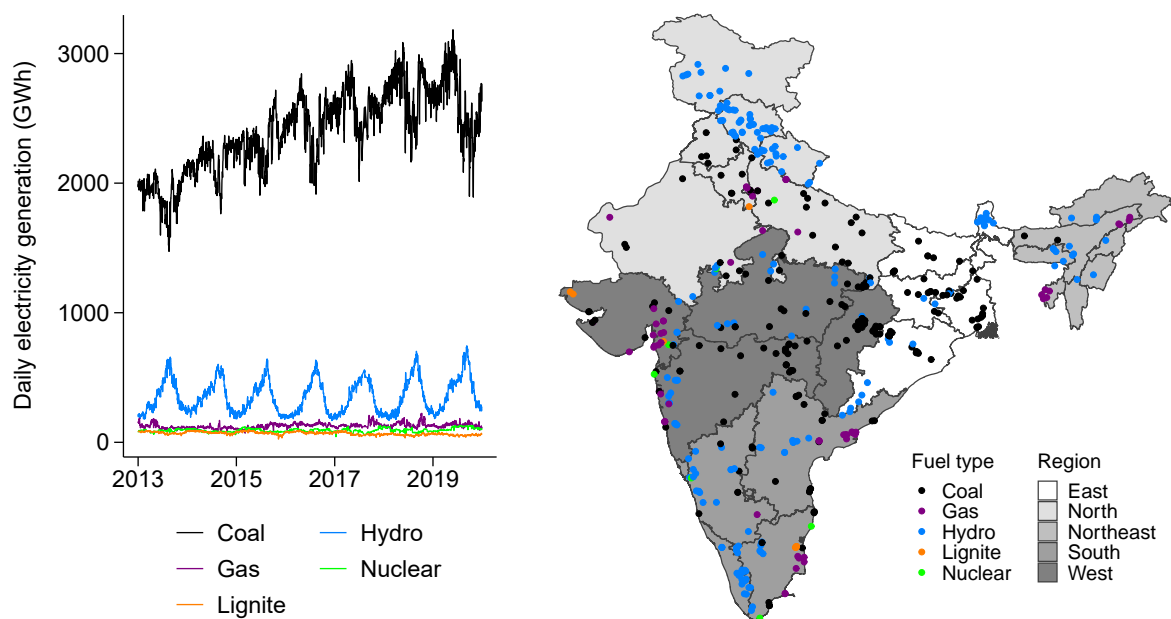
2.3   Electricity generation

We collect data on daily generation and operational capacity at power plants, using the CEA's *Daily Generation Reports* from 2013 to 2019. These reports cover all utility-scale fossil, hydroelectric, and nuclear plants in India.[11] Our plant-day panel includes 508 plants, representing 301 GW of India's 383 GW of generating capacity, with aggregate production of 3.05 TWh per day. The left panel of Figure 1 plots daily total generation by source type; 205 coal-fired plants contribute the vast majority of output, with the remainder coming primarily from hydro sources. The right panel maps the locations of power plants across India's five transmission regions: North, Northeast, East, West, and South.

Marginal costs   We construct 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. For coal plants, we start with minemouth coal prices (in rupees per 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 (rupees per kWh).[12] We also add rail freight costs based on the shortest path along India's rail network (following Preonas (2022)), as well

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

12. We follow the standard approach in the electricity economics literature by assuming that each unit's production function is Leontief in fuel input (Fabrizio, Rose, and Wolfram (2007); Clay et al. (2021); Cicala (2022)). 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. Appendix A.1 details on how we construct plant-specific marginal costs, and compares our constructed costs to the plant-specific variable costs reported by the Ministry of Power. We inflation-adjust to constant 2016 rupees using the monthly consumer price index for all items for India reported by the Organization for Economic Co-operation and Development.

Figure 1: Electricity generation in India

Notes: 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.

as royalties and other taxes. For natural gas plants, we perform an analogous calculation using gas price data from the Ministry of Petroleum and Natural Gas. For nuclear plants, we simply use the marginal costs reported in regulatory tariff documents (described in Srinivasan (2007)).

Figure 2 ranks thermal power plants from lowest to highest marginal cost, plotting marginal costs as a function of cumulative capacity.[13] This figure shows that nuclear plants tend to have the lowest marginal costs, followed by coal, lignite, and gas plants.

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13. We omit hydroelectric plants since dams face complex dynamic optimization problems: today's output may constrain future output due to a finite supply of water (Archsmith (2022)). Non-dispatchable run-of-river hydro (along with wind and solar) enters the supply curve at (virtually) zero marginal cost.

Figure 2: Marginal cost curve of thermal power plants
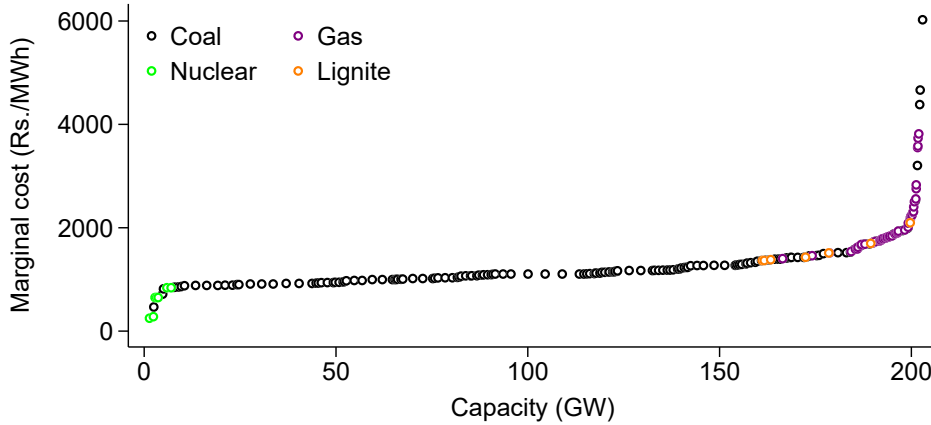
Notes: This figure presents the merit order of Indian thermal electricity generating capacity, ranking plants from lowest to highest marginal cost. Each dot represents a single plant for which we can construct marginal cost estimates. While our main constructed cost measures are time-varying (e.g., due to changing fuel prices), this figure plots the sample-average marginal cost for each plant. We omit the 18 diesel plants and 56 plants for which we lack data to estimate marginal costs (47 coal, 7 gas, and 2 lignite). The exchange rate is roughly 60 Indian rupees to 1 US dollar.

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% of power plant 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 18–22% during this time period.[14] 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 incen-

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14. 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 in operation.

Figure 3: Daily aggregate outage rates across Indian thermal power plants
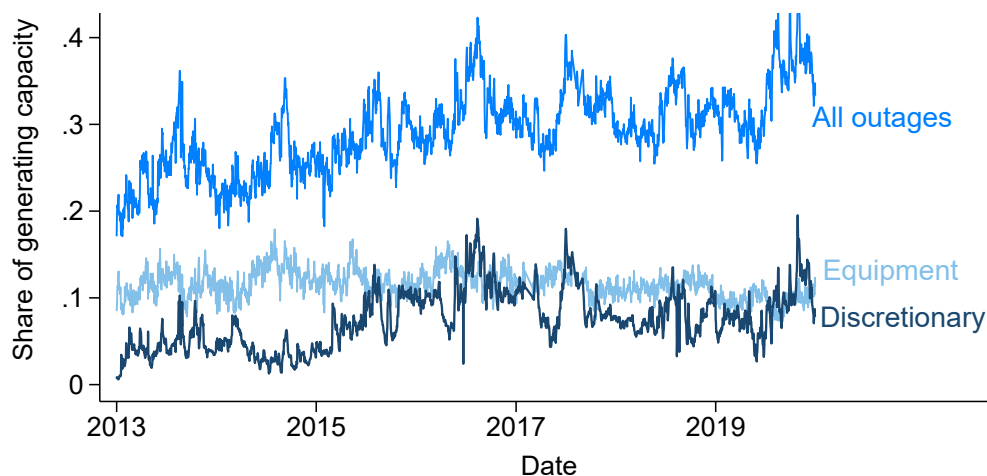
Notes: This figure reports the share of total thermal power plant capacity that was on outage (i.e. unavailable to generate) on each each day in our sample. The top line divides capacity under outage for *any* reason by total capacity. In the bottom two lines, we divide capacity under equipment outage 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.

tives to stand ready to generate. Most equipment outages last less than 3 days; discretionary outages are similarly short-run, with a median duration of 5 days. While 84% of plants reported at least one equipment outage during our sample period, 16% of plants contributed the majority of discretionary outages (see Appendix Figures A.1–A.2). These two categories represent only a subset of plant outages.[15]

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 wholesale electricity. As a test of exogeneity, we show that equipment outages are not correlated with two key demand-side factors—temperature and forecasted demand—by estimating the following regression at the plant-month level:

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15. Plants report a variety of other outage reasons relating to planned maintenance, fuel shortages, transmission failures, etc.—all of which we exclude from our definitions of equipment outages and discretionary outages. 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". Appendix A.3 provides further discussion on both types of outage.

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

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

In contrast, we argue that discretionary outages declared by low-cost plants likely reflect supply-side misallocation.[17] Due to trading frictions in the Indian electricity sector (e.g., no financial trading and fixed transmission rights), 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.[18] 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. Since contract prices are not time-varying, contracted plants face limited incentives to avoid discretionary outages during high-demand periods when production from low-cost plants would be especially valuable.

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

17. Unlike equipment outages, discretionary outages vary with demand shifters (see Appendix Table B.1).

18. 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.

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

	Outcome: Share of plant's capacity on equipment outage			
	(1)	(2)	(3)	(4)
Mean monthly temperature in state (°C)	−0.0011	−0.0011	0.0004	0.0010
	(0.0009)	(0.0009)	(0.0017)	(0.0014)
log (State's forcasted energy requirement)		−0.0007	−0.0097	−0.0110
		(0.0100)	(0.0191)	(0.0140)
Split sample for high/low marginal cost plants			Low MC	High MC
Plant + month-of-sample FEs	Yes	Yes	Yes	Yes
Region × year, region × month FEs	Yes	Yes	Yes	Yes
Mean of dep. var.	0.1040	0.1040	0.1307	0.0698
Plant-month observations	21,268	21,268	7,935	7,821

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

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 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 India, 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. This results in perfectly inelastic wholesale electricity demand: $\overline{D} \equiv D(0)$.

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 $MC_1 < MC_2 < MC_3$.

Equilibrium quantities and prices Figure 4a presents the wholesale market with all three power plants available to produce. In the downward-sloping demand scenario (subscripted A), only plant 1 operates; in the perfectly inelastic demand scenario (subscripted B), plants 1 and 2 operate. The quantity $(Q_B^* - Q_A^*)$ is left unsatisfied in the downward-sloping demand case, but wholesale prices are lower $(P_A^* < P_B^*)$.

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 downward-sloping demand scenario from Q_A^* to $Q_A^{*'}$; higher wholesale prices $(P_A^{*'} > P_A^*)$ cause utilities to purchase less electricity, increasing the incidence of blackouts faced by end-use consumers. In the perfectly inelastic demand scenario, removing plant 1 does not change the equilibrium quantity (or, in this case, the equilibrium price).[19]

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 downward-sloping demand scenario, removing it does not alter the equilibrium price or quantity. By contrast, removing plant 2 increases the equilibrium price (to $P_B^{*'} > P_B^*$) in the perfectly inelastic demand scenario, while quantity again remains unchanged. This illustrates the trade-off inherent to requiring that all demand be satisfied: doing so may necessitate dispatching plants with very high marginal costs, resulting in high equilibrium prices, and ultimately making any supply-side distortions more costly to end-use consumers.

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19. Depending on the shape of the supply curve, removing a low-cost plant may increase the equilibrium price in the perfectly inelastic case as well. The salient point is that perfectly 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
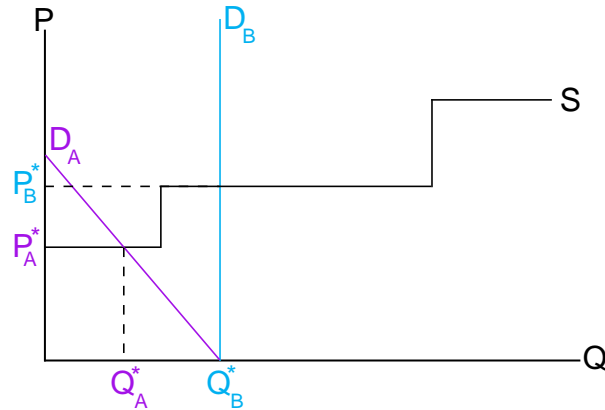
(a) Baseline, with all three plants
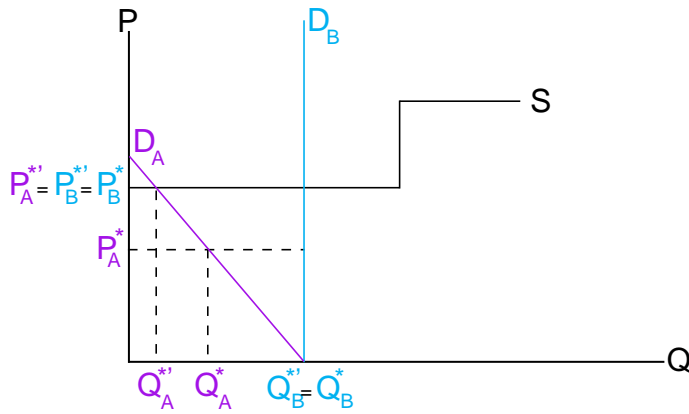
(b) Removing plant 1
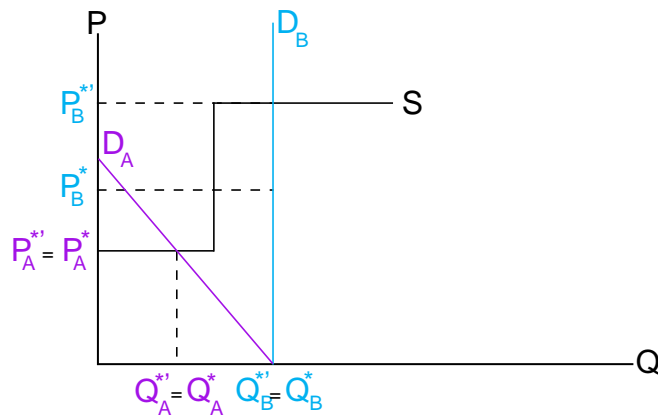
(c) Removing plant 2

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 a downward-sloping demand case (subscripted A, in purple) and a case where regulators require demand to be perfectly inelastic (subscripted B, 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.

Implications: This model illustrates a key stylized fact. When demand is downward-sloping, removing a low-cost plant from the market will decrease the quantity of electricity purchased by utilities, unlike in the perfectly inelastic demand case. In contrast, removing a high-cost plant from the market is unlikely to reduce equilibrium quantity in either scenario (see Figure 4c). Therefore, the extent to which supply-side misallocation (e.g., the removal of low-cost plants) reduces the quantity of power supplied to end users is an empirical question. Section 6 quantifies these impacts in the Indian wholesale electricity sector.

4 Downward-sloping wholesale electricity demand

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

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

$$\log\left([\text{Demand met}]_{srt}\right) = \beta[\text{Equip. outage rate}]_{srt} + \alpha_s + \psi_t + \delta_{rt} + \varepsilon_{srt} \quad (2)$$

Because equipment outages are caused by technical failures, they are plausibly exogenous; see Table 1 for evidence that, in the short run, equipment outages are uncorrelated with demand shifters. The outcome variable is the natural logarithm of electricity purchased by utilities in state s, in transmission region r, on date-of-sample t. This equilibrium quantity of wholesale demand corresponds directly to the quantity of electricity received by retail consumers, net of transmission and distribution losses. Our coefficient of interest β captures the causal effect of short-run changes in the daily equipment outage rate, aggregated across

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

Table 2: Total demand met responds to power plant outages

	Outcome: $\log\left(\text{Demand met}\right)$				
	(1) OLS	(2) OLS	(3) IV	(4) IV	(5) IV
Equipment outage rate	−0.07** (0.03)	−0.18*** (0.04)			
$\log\left(\text{Avg. variable cost}\right)$			−0.43** (0.21)	−1.05*** (0.32)	
$\log\left(\text{95th pctile marginal cost}\right)$					−0.20** (0.10)
Idle capacity available		Yes		Yes	
State + date FEs	Yes	Yes	Yes	Yes	Yes
Region × year, region × month FEs	Yes	Yes	Yes	Yes	Yes
Mean demand met (in GWh)	88.70	143.61	88.70	143.61	88.70
State-day observations	43,044	18,817	43,044	18,817	43,044
First-stage estimate			0.17*** (0.03)	0.17*** (0.03)	0.36*** (0.06)
Kleibergen-Paap F-statistic			28.17	30.14	41.66
Mean of equipment outage rate	0.10	0.10	0.10	0.10	0.10
SD of equipment outage rate	0.09	0.08	0.09	0.08	0.09
Mean potential GWh from idle capacity	10.29	23.40	10.29	23.40	10.29

Notes: This table presents results from estimating Equation (2). The dependent variable is the natural logarithm of total GWh energy met in state s on date t (i.e. the quantity of wholesale electricity demand). Columns (1)–(2) are reduced-form regressions, where the independent variable is equipment outage rate at the state-day level. Columns (3)–(5) use two-stage least squares to estimate the elasticity of demand with respect to average variable cost of generation (Columns (3)–(4)) and marginal cost of generation (Column (5)), instrumenting for costs using the equipment outage rate. We use the 95th percentile of marginal cost because this yields a stronger first stage than using the maximum marginal cost. Columns (2) and (4) 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). All regressions control for daily average temperatures (for precision), and the total number of dispatchable plants in state s (to account for differential market expansions across states). 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.

The first two columns of Table 2 report these reduced-form results. In Column (1), we find that a 10 pp increase in a state's equipment outage rate causes energy demanded to decrease by 0.7% on average (statistically significant at the 5% level). However, a lack of available generating capacity could be driving this reduction, if equipment outages render utilities unable to purchase the quantity of electricity they desire.[20] Column (2) restricts the sample to only state-days with idle capacity—that is, days in which some plants located in state s did not produce despite having been available.[21] This yields a estimate over twice as large, and significant at the 1% level.

These results provide strong evidence that utilities purchase less power when more of their state's generating capacity goes on equipment outage. Our point estimate in Column (2) implies that an 8 pp (1 standard deviation) increase in the equipment outage rate causes a 2.07 GWh (1.4%) average reduction in demand met—despite the fact that roughly 975 MW of idle but available capacity could have produced 23.40 GWh on the average state-day.

Next, we estimate the short-run cost elasticity of wholesale demand, using two-stage least squares and instrumenting for the cost of electricity generation with the equipment outage rate. The exclusion restriction requires that variation in equipment outages only affects demand met through its effect on procurement costs. This is plausible given that equipment outages are uncorrelated with demand shocks (see Table 1). Since wholesale contract prices are regulated based on plant-specific variable costs, and retail prices are fixed in the short-run, we estimate demand elasticities with respect to the average variable cost of production. As a robustness check, we also use the 95th percentile of marginal cost.[22]

Columns (3)–(5) of Table 2 estimate a two-stage least squares version of Equation (2),

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20. While some developing countries lack the generating capacity to replace the output lost due to plant outages (e.g., Ghana's "Dumsor" power crisis described in Dzansi et al. (2018)), Indian utilities often have idle generating capacity available to buffer against unanticipated plant outages.

21. This restriction keeps state-days with idle *thermal* generating capacity. For some state-days, the only idle dispatchable capacity could be hydroelectric. However, due to the complex dynamic constraints inherent to hydro production, we cannot identify which idle hydro capacity is dispatchable.

22. We use the 95th percentile instead of the maximum due to potential measurement error in marginal costs.

Figure 5: Histogram of observed demand elasticities in the IEX day-ahead market
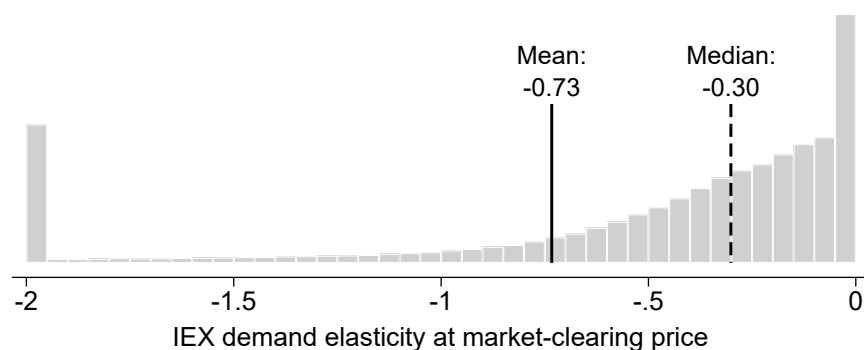
Notes: We extract the elasticity of IEX demand from observed aggregate bid curves for 201,012 separate 15-minute intervals. We bottom-code this distribution at -2 for ease of presentation. The solid (dashed) line reports the mean (median) elasticity.

which has a strong first stage: a 10 pp increase in the equipment outage rate causes average variable costs to rise by 1.7% (significant at the 1% level). We estimate a wholesale demand elasticity of -0.43 with respect to average variable cost (Column (3); significant at the 5% level). When we restrict the sample to the subset of state-days with idle capacity, we recover a much larger elasticity estimate of -1.05 (Column (4); significant at the 1% level). Finally, we estimate a demand elasticity of -0.20 with respect to marginal cost (Column (5); significant at the 5% level). These estimates reinforce that higher procurement costs lead Indian utilities to choose to supply less electricity to end-users. We use these short-run elasticity estimates in our counterfactual calculations in Section 6.

Finally, we note that our demand elasticity estimates come from the full wholesale power sector, rather than the 3% subset of wholesale electricity sold on the IEX day-ahead market studied in Ryan (2021). We can directly calculate the demand elasticity in this 3% segment of the sector. Figure 5 plots the distribution of IEX demand elasticities at the market-clearing price, extracted from aggregate bid curves across 201,012 15-minute intervals. The mean IEX demand elasticity is -0.73, while the median is -0.30. This aligns with our estimates from Table 2, providing further evidence that wholesale demand is downward-sloping.[23]

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23. Appendix A.4 discusses the IEX market in further detail, and outlines how we digitize the IEX data and extract IEX demand elasticities.

5 Supply-side misallocation

Having established that wholesale electricity demand slopes down, we now investigate misallocation in wholesale electricity supply. Because demand is downward-sloping, any distortions that raise the cost of supply will cause utilities to purchase less wholesale power, increasing blackouts. We focus on one specific supply-side distortion: "discretionary" outages where power plants are unavailable for reasons tied to economic incentives rather than technical conditions.

5.1 Discretionary outages and trading frictions

We expect that trading frictions between utilities in the same state are an important driver of discretionary outages, and therefore of misallocation. To test for this, we compare discretionary outage rates for states with a single utility vs. states with multiple utilities. Our hypothesis is that when demand is high, within-state trading frictions between multiple utilities will result in relatively more discretionary outages among low-cost plants.

For concreteness, consider a state with two distribution utilities, A and B. Utility A has long-term contracts with two low-cost plants, A_1 and A_2; utility B has a long-term contract with a high-cost plant, B_1. Suppose that utility A only purchases output from plant A_1. Utility B would ideally prefer to purchase from plant A_2 rather than plant B_1. However, financial trading between utilities is not possible due to legal barriers and non-fungible transmission rights. Consequently, utility B is likely to purchase from its own contracted plant, B_1. Plant A_2 is left with little economic incentive to avoid a discretionary outage. If utilities A and B were consolidated into a single utility AB, the low-cost plant A_2 would have greater incentive to avoid outages—especially when forecasted demand is high. This intuition explains how across-utility trading frictions likely drive differences in discretionary outage rates between single- vs. multi-utility states.

We estimate the following triple-difference specification at the plant-month level:

$$[\text{Disc. outage rate}]_{isrt} = \log\left([\text{Energy req}]_{srt}\right) \cdot [\text{Single}]_s \cdot \left(\beta_1 + \beta_2[\text{LowMC}]_i\right) \qquad (3)$$

$$+ \log\left([\text{Energy req}]_{srt}\right) \cdot [\text{Multi}]_s \cdot \left(\beta_3 + \beta_4[\text{LowMC}]_i\right) + \alpha_i + \delta_{rt} + \varepsilon_{isrt}$$

The outcome variable is the discretionary outage rate for plant i in state s in region r in sample month t. We interact the log of *ex ante* forecasted demand ($[\text{Energy req}]_{srt}$) with an indicator for plant i having below-median marginal costs ($[\text{LowMC}]_i$), and with indicators for states with a single utility ($[\text{Single}]_s$) vs. multiple utilities ($[\text{Multi}]_s$). As in Equation (1), we control for plant fixed effects (α_i); month-of-sample, region-by-year, and region-by-month fixed effects (δ_{rt}); and cluster our standard errors by sample month.[24]

Figure 6 presents our estimates of the coefficients of interest, $\hat{\beta}_2$ and $\hat{\beta}_4$. For single-utility states, we find that an increase in forecasted demand causes the discretionary outage rate to fall differentially more for low-cost plants than for high-cost plants ($\hat{\beta}_2 = -0.14$, significant at the 1% level). This is consistent with what one would expect in a well-functioning market: when forecasted demand increases, utilities purchase first from their low-cost contracted assets, providing a stronger incentive for these plants to avoid outages.

In contrast, in multi-utility states, we find no statistical difference in discretionary outage rates across low- vs. high-cost plants ($\hat{\beta}_4 = 0.07$, not statistically different from zero). This suggests that when demand is high in a multi-utility state, low-cost plants do not receive a stronger incentive than high-cost plants. If a low-cost plant under long-term contract with one utility cannot sell its energy to another utility, the plant may have no option but to go on discretionary outage if its contracted utility refuses to purchase its output.

These findings align with our hypothesis that contracting frictions are an important source of supply-side misallocation in India. However, there likely exist other forms of

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24. This model compares (i) higher vs. lower forecasted energy demand in (ii) single- vs. multi-utility states at (iii) high vs. low marginal cost plants. In this specification, we fully interact all time fixed effects with the $[\text{Multi}]_s$ indicator.

Figure 6: Response of discretionary outages to forecasted demand
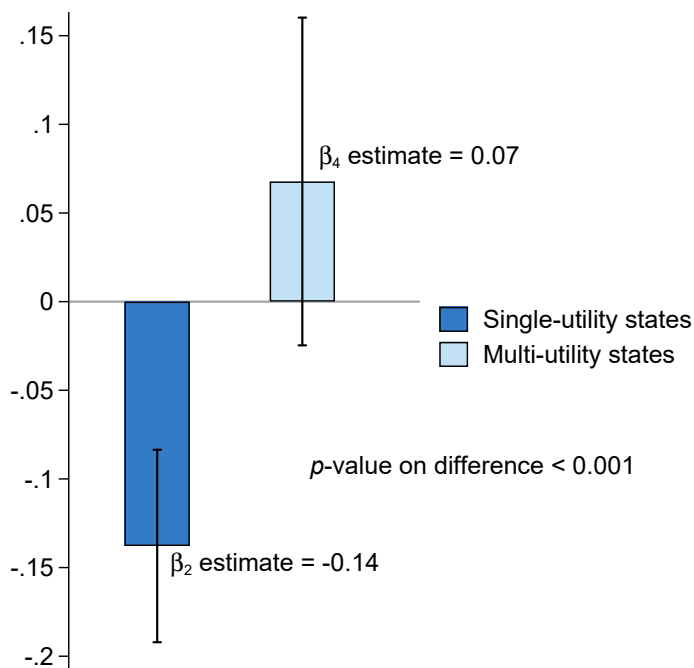
Notes: Bars report $\hat{\beta}_2$ and $\hat{\beta}_4$ from estimating Equation (3) on a sample of 133 coal plants with non-missing marginal costs. $\hat{\beta}_2$ is the differential increase in discretionary outage rates for low-cost plants (compared to high-cost plants) when forecast demand increases, for single-utility states. $\hat{\beta}_4$ is the same, but for multi-utility states. The dependent variable is plant i's monthly average discretionary outage rate. As in Table 1, we control for average temperature by state-month; the number of dispatchable plants in each state; and plant, month-of-sample, region × year, and region × month fixed effects, all fully interacted with a multi-utility dummy. We cluster standard errors by sample month. Whiskers denote 95% confidence intervals.

supply-side misallocation besides within-state contracting frictions—in both single- and multi-utility states.

5.2 Deviations from least-cost dispatch

Having provided evidence of one source of supply-side misallocation—contracting frictions—the question remains: how much opportunity exists to reduce such misallocation? To answer this question, we compare the total variable costs of producing the observed quantity demanded across two scenarios: the factual scenario based on each plant's observed output versus a competitive benchmark where we dispatch plants from lowest to highest marginal

cost.[25] Comparing counterfactuals with vs. without discretionary outages enables us to assess the economic importance of this form of misallocation.

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 multiply observed output Q_{it}^{OBS} by the plant's marginal cost MC_{it}.[26] Summing across plants yields total observed costs:

$$TC_t^{OBS} \equiv \sum_i MC_{it} Q_{it}^{OBS} \tag{4}$$

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.[27] Formally, the total variable cost implied by least-cost dispatch on day t is the solution to following optimization problem:

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

This least-cost benchmark is unlikely to be feasible, since it abstracts away from the technical constraints associated with electricity generation and transmission.[28] Consequently, comparing TC_t^{OBS} to TC_t^{LC} likely overstates the true level of supply-side distortion. However, this approach is useful for quantifying the relative contributions of different factors that cause supply-side misallocation.

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25. This is a common approach for quantifying the cost of distortions in wholesale electricity supply in the developed world (e.g., Wolfram (1999); Borenstein, Bushnell, and Wolak (2002); Cicala (2022)).

26. Our results are similar if we use the variable costs reported by the Ministry of Power rather than our constructed costs (see Appendix A.2 and Panel E of Appendix Table B.2).

27. Each inframarginal plant produces at its capacity; the marginal plant produces the remaining quantity required to meet 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 D of Appendix Table B.2).

28. 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 for peak and off-peak periods (see Panel C of Appendix Table B.2).

Figure 7: Kernel densities of variable cost gap
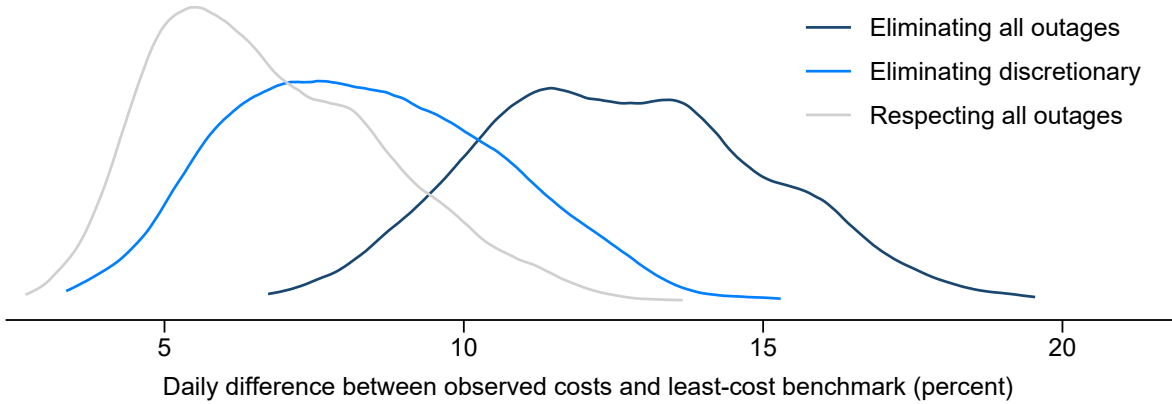
Notes: This figure plots kernel densities of the percentage difference between the total observed variable costs vs. total variable costs under least-cost dispatch (i.e., in the rightmost column of Table 3). Each density includes 2,506 sample days, and corresponds to one of the three scenarios in Table 3. See notes under Table 3 for details.

We consider three dispatch scenarios, each of which imposes interregional autarky.[29] In our "eliminating all outages" scenario, we allow any plant to be redispatched to satisfy demand within its transmission region—under the assumption that all generating capacity is available. In reality, nearly 30% 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 "eliminating discretionary outages" scenario redispatches plants on discretionary outages (which likely reflect misallocation), but respects all other non-discretionary outages (which are likely due to physical factors).

Figure 7 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. If we eliminate all outages, the mean cost difference is Rs. 317 million, or approximately 12.6% of observed costs. When we avoid redispatching capacity on outage ("respecting all outages"), the average daily cost difference shrinks to 6.8%. This means that 46% of the potential cost savings from least-cost dispatch arise from utilizing capacity

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29. 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 if we relax all trading restrictions or if we impose autarky within each of India's 13 sub-regions (see Panels A–B of Appendix Table B.2).

Table 3: Variable costs of electricity supply

Redispatching scenario	Observed (M Rs./day)	Least-cost (M Rs./day)	Cost Difference (M Rs./day)	$100 \times \dfrac{\text{Difference}}{\text{Observed}}$
Eliminating all outages	2,580 [1,934, 3,308]	2,263 [1,623, 3,007]	317 [264, 370]	12.61 [8.89, 16.63]
Eliminating discretionary outages	2,580 [1,934, 3,308]	2,372 [1,723, 3,138]	208 [157, 267]	8.34 [5.07, 12.13]
Respecting all outages	2,580 [1,934, 3,308]	2,411 [1,763, 3,161]	168 [124, 224]	6.77 [4.19, 10.22]

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. All three scenarios restrict least-cost redispatching to within each of India's five transmission regions, which conservatively assumes zero interregional transmission capacity. The "eliminating all outages" scenario redispatches plants based on their capacity, regardless of whether they have declared outages on date t. The "eliminating discretionary outages" scenario avoids redispatching any capacity under outage on date t, unless the outage is classified as "discretionary". 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 7 plots kernel densities of the distributions in column 4.

that was declared unavailable. Much of this wedge is explained by discretionary outages at low-cost plants: eliminating discretionary outages increases the cost gap to 8.3%. This shift from 6.8% to 8.3%—a 34% increase—occurs because eliminating discretionary outages substantially lowers the least-cost benchmark. This implies that eliminating discretionary outages could substantially reduce misallocation in Indian wholesale electricity supply.

6   Reducing misallocation increases quantity supplied

We combine our supply- and demand-side analyses to assess the extent to which reducing supply-side misallocation would increase the quantity of electricity provided to retail consumers. Our results in Section 5 suggest that eliminating discretionary outages would significantly lower utilities' wholesale procurement costs. Our demand-side estimates in Section 4 imply that this would cause utilities to purchase more from the wholesale sector

due to downward-sloping demand. This section quantitatively explores the implications of counterfactually eliminating discretionary outages at coal power plants.

Supply-side We clear the wholesale electricity market twice for each state-day, first factually respecting and then counterfactually ignoring discretionary outages. We assume that generation supply curves are equal to each state-day's aggregate marginal cost curve, stacking all available plants from lowest-to-highest marginal cost. As robustness checks, we also provide results based on clearing the market at the sub-region and region levels.

Demand-side We assume linear wholesale electricity demand, with an elasticity at the observed quantity supplied of -0.43 (see Table 2, Column (3)). This implicitly assumes that utilities respond to average variable cost, rather than to the marginal cost of the marginal unit. This aligns with the fact that both retail electricity tariffs and wholesale contract prices are set by regulators to reflect the costs incurred by utilities and power plants, respectively. For robustness, we separately consider constant-elasticity demand, and have utilities respond to the 95th percentile of marginal cost (using the elasticity -0.20 from Table 2, Column (6)).

Results Table 4 presents the findings of this counterfactual exercise. For each scenario, we report the daily average aggregate increase in quantity supplied that would result from eliminating discretionary outages. In our preferred scenario (Column (1)), eliminating discretionary outages decreases average variable costs such that utilities in aggregate purchase 10.8 additional GWh per day on average. As a benchmark, in 2017, the average Indian household consumed 2.82 kWh per day and faced 3.4 hours per day of blackouts (Agrawal et al. (2020)). This implies that a 10.8 GWh increase in the quantity of electricity supplied by utilities to households is sufficient to eliminate blackouts for 23.2 million households—

roughly 8% of Indian households.[30]

We also present a series of robustness checks. We recover similar increases in quantity supplied per day if we clear the wholesale electricity market at the subregion or region levels instead (Columns (2)–(3)), or if we assume constant-elasticity demand rather than linear demand (Column (4)). Assuming utilities respond to marginal cost rather than average variable cost yields similar quantity increases, as larger decreases in marginal cost outweigh the effect of a smaller demand elasticity (see Column (5)). Finally, Column (6) illustrates that using our larger demand elasticity of -1.05 (from Table 2, Column (4)) doubles the implied increase in quantity supplied.

Interpretations   To value the increase in electricity supplied to households, we first calculate the counterfactual increase in retail revenues using state-specific retail electricity prices from 2019.[31] Next, we quantify the corresponding reduction in spending on backup sources of electricity. Households faced with blackouts have two primary options to complement intermittent grid power: inverter/battery systems and backup generators ("gensets").

Inverter systems charge batteries when grid-based electricity is available, letting households store this electricity in order to power necessary appliances during blackouts (Seetharam et al. (2013)). The primary operating costs associated with these systems are the costs of purchasing grid power to charge batteries; we also account for the fact that some of this power is lost in the converting and discharging process, as well as periodic battery replacement costs. Gensets burn fuel—typically diesel—to generate electricity and power appliances when grid-based electricity is unavailable. Their primary operating costs are fuel purchases and maintenance.[32]

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30. In practice, some of this 10.8 GWh would go to firms in the commercial and industrial sectors. Since firms likely exhibit higher willingness to pay to eliminate blackouts than households, our ensuing monetizations which focus on households likely understate the true benefits of increased electricity quantity.

31. If we assume households would purchase electricity at the retail price if it were offered (i.e., there is no theft and/or non-payment), this represents a lower bound on the consumer surplus benefits of reduced blackouts—Rs. 47 million per day in our preferred scenario (Table 4, Column (1)).

32. Appendix C describes how we calculate each technology's assumed operating and investment costs.

Table 4: Quantity impacts of eliminating discretionary outages

	(1)	(2)	(3)	(4)	(5)	(6)
Scenario:						
Dispatch level	State	Subregion	Region	State	State	State
Utilities respond to	AVC	AVC	AVC	AVC	MC	AVC
Functional form	Linear	Linear	Linear	CE	Linear	Linear
Demand elasticity estimate utilized	-0.43	-0.43	-0.43	-0.43	-0.20	-1.05
Quantity response:						
Increase in quantity supplied (GWh)	10.8	11.6	13.5	11.3	12.6	22.2
# of hh shifted to 24 × 7 power (mill.)	23.2	24.9	29.0	24.3	27.1	47.8
Monetizing Q increases (million Rs./day)						
Increase in retail revenues (mill. Rs)	47	36	43	49	56	96
Using inverter systems						
Avoided operating cost (mill. Rs)	66	51	61	69	80	136
Avoided investment cost (mill. Rs)	105	112	131	110	122	216
Avoided total cost (mill. Rs)	125	127	149	130	146	256
Using gensets						
Avoided operating cost (mill. Rs)	278	298	347	291	324	572
Avoided investment cost (mill. Rs)	449	481	560	470	523	924
Avoided total cost (mill. Rs)	680	743	864	712	791	1,401

Notes: This table reports counterfactual effects of eliminating discretionary outages at coal-fired power plants. Each column reports a different scenario for the geographic scale at which markets are cleared ("Dispatch level"), the functional form of demand (linear vs. constant-elasticity ("CE")), the demand elasticity estimate used, and whether utilities respond to average variable cost ("AVC") or the 95th percentile of marginal cost ("MC"). We report the daily average aggregate increase in quantity purchased by utilities in the wholesale sector (in GWh/day), and the corresponding number of households that would be brought to zero blackouts (i.e., 24×7 power) by this increase in power supply. In this counterfactual, households would have less need for backup inverters or generators ("gensets"). We monetize the reliability gains implied by eliminating discretionary outages either using estimates of operating and investment costs for these two backup technologies. See text for details.

Assuming that the 10.8 GWh per day increase in grid power supply (Table 4, Column (1)) would displace power from existing backup inverter/battery systems, the corresponding gross operating cost savings would be roughly Rs. 61 million per day. Instead, if 10.8 GWh of production from existing gensets were displaced, the aggregate gross savings would be much larger—Rs. 278 million per day.[33] Our "gross" savings exclude the additional costs of purchasing grid power to replace these backup technologies.

We also consider the extensive margin of inverter systems and genset ownership. Suppose 23.2 million households are shifted to 24×7 power (i.e., no blackouts), as in our pre-

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33. All costs are converted to 2016 rupees.

ferred scenario in Table 4, Column (1). If all of these households own inverter systems in the factual world but not in the counterfactual world, then the aggregate avoided costs of inverter adoption would be approximately Rs. 105 million per day.[34] Taking the sum of operating and investment costs, but netting out the counterfactual increase in spending on grid electricity, the total avoided costs of inverters is Rs. 119 million per day. On the other hand, if all 23.2 million households own backup gensets in the factual world but not in the counterfactual world, then the aggregate avoided genset investment costs would be roughly Rs. 449 million per day, for a total avoided genset cost of Rs. 680 million per day.

This counterfactual exercise illustrates that reducing supply-side misallocation can yield meaningful increases in the quantity of electricity supplied to retail consumers—due to downward-sloping wholesale electricity demand. This increase in quantity supplied reduces the level of blackouts faced by households and firms, providing substantial economic benefits to end-users who currently rely on more expensive backup power technologies. This underscores the potential benefits of wholesale sector reforms aimed at reducing supply-side misallocation, such as the introduction of financial trading, which have the potential to substantially lower wholesale procurement costs and thereby improve the reliability of electricity provision.

7 Conclusion

Developing countries have made substantial gains in electricity access, but frequent blackouts limit the welfare gains from electrification (Lee, Miguel, and Wolfram (2020); Burlig and Preonas (2021)). This paper demonstrates that key features of India's wholesale electricity sector impact the level of blackouts faced by retail consumers. We construct a novel dataset on daily power plant operations spanning the Indian wholesale sector, and demonstrate that: (i) wholesale demand is downward-sloping, meaning buyers purchase less

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34. To compute daily costs, we amortize investment costs over the assumed lifetime of each technology.

electricity when wholesale procurement costs increase; (ii) discretionary outages at low-cost plants create substantial supply-side misallocation; and (iii) reducing supply-side distortions lowers wholesale procurement costs and thus meaningfully increases the quantity of energy supplied to retail consumers.

We provide suggestive evidence that trading frictions are a key driver of supply-side misallocation. Though financial trading was prohibited in India during our sample period, several recent policy changes have introduced financial instruments to India's wholesale electricity sector. However, financial trading in India remains extremely limited, with less than 1% of electricity traded via financial contracts (Garg (2021)). Our results suggest that expanding these reforms is likely to substantially lower the aggregate costs of electricity production, resulting in more power reaching retail consumers.

Our work highlights the need for more research on electricity markets in developing countries. These countries share many of the institutions of electricity markets in the developed world, such as cost-of-service regulation (e.g., Borenstein and Bushnell (2015); Cicala (2015)) and inefficient retail pricing (e.g., Holland and Mansur (2008)). However, we emphasize a key institutional difference between India and high-income countries: India lacks a mandate that utilities satisfy all retail electricity demand. We demonstrate that absent such a mandate, Indian wholesale electricity demand is downward-sloping. This means that supply-side distortions impact both generation costs *and* the quantity of electricity that reaches retail consumers.

Finally, with the rapid growth of intermittent wind and solar production capacity around the world, utilities in both developed and developing countries are facing greater fluctuations in wholesale procurement costs. At the same time, many utilities are beginning to install smart meters, implement "real-time" pricing, and automated demand response programs designed to better communicate wholesale market price signals to retail electricity consumers (e.g., Wolak (2011); Bollinger and Hartmann (2019); Blonz et al. (2021); Meeks

et al. (2023)). Such programs make wholesale electricity demand more elastic. The lessons from this paper are therefore becoming increasingly relevant as many countries shift away from dispatchable fossil generation and towards intermittent renewables.

References

Agrawal, Shalu, Sunil Mani, Abhishek Jain, and Karthik Ganesan. 2020. *State of Electricity Access in India: Insights from the India Residential Energy Survey (IRES) 2020.* Council on Energy, Environment / Water.

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. 2022. "Dam spillovers: The direct and indirect costs from environmental constraints on hydroelectric generation." Working paper.

Berkouwer, Susanna B., and Joshua T. Dean. 2022. "Credit, attention, and externalities in the adoption of energy efficient technologies by low-income households." *American Economic Review* 122 (10): 1–41.

Bhattacharya, Saugata, and Urjit R. Patel. 2008. "The power sector in India: An inquiry into the efficacy of the reform process." *India Policy Forum* 4 (1): 211–283.

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, and James Bushnell. 2015. "The US electricity industry after 20 years of restructuring." *Annual Review of Economics* 7 (1): 437–463.

Borenstein, Severin, James B. Bushnell, and Frank A. Wolak. 2002. "Measuring market inefficiencies in California's restructured wholesale electricity market." *American Economic Review* 92 (5): 1376–1405.

Borenstein, Severin, Meghan R. Busse, and Ryan Kellogg. 2012. "Career concerns, inaction and market inefficiency: Evidence from utility regulation." *The Journal of Industrial Economics* 60 (2): 220–248.

Burgess, Robin, Michael Greenstone, Nicholas Ryan, and Anant Sudarshan. 2020. "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.*

———. 2019. *CEA Annual Report 2018-19.* https://cea.nic.in/wp-content/uploads/2020/03/annual_report-2019.pdf.

Central Electricity Regulatory Commission. 2018a. *Discussion paper on re-designing real time electricity markets in India.* https://cercind.gov.in/2018/draft_reg/RTM.pdf.

———. 2018b. *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. 2015. "When does regulation distort costs? Lessons from fuel procurement in U.S. electricity generation." *American Economic Review* 105 (1): 411–44.

———. 2022. "Imperfect markets versus imperfect regulation in U.S. electricity generation." *American Economic Review* 112 (2): 409–441.

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.

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." *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.

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, Kira R., Nancy L. Rose, and Catherine D. Wolfram. 2007. "Do markets reduce costs? Assessing the impact of regulatory restructuring on US electric generation efficiency." *American Economic Review* 97 (4): 1250–1277.

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.

Fried, Stephie, and David Lagakos. 2023. "Electricity and firm productivity: A general-equilibrium approach." *American Economic Journal: Macroeconomics.*

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.

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.

Holland, Stephen, and Erin T. Mansur. 2008. "Is real-time pricing green? The environmental impacts of electricity demand variance." *Review of Economics and Statistics* 90 (3): 550–561.

Jack, Kelsey, Seema Jayachandran, and Sarojini Rao. 2018. "Environmental externalities and intrahousehold inefficiency." NBER working paper no. 24192.

Jack, Kelsey, and Grant Smith. 2020. "Charging ahead: Prepaid metering, electricity use, and utility revenue." *American Economic Journal: Applied Economics* 12 (2): 134–68.

Jha, Akshaya. 2022. "Regulatory induced risk aversion in coal contracting at U.S. power plants: Implications for environmental policy." *Journal of the Association of Environmental and Resource Economists* 9 (1): 51–78.

Jha, Akshaya, and Frank Wolak. 2023. "Can forward commodity markets improve spot market performance? Evidence from wholesale electricity." *American Economic Journal: Economic Policy.*

Kellogg, Ryan, and Mar Reguant. 2021. "Energy and environmental markets, industrial organization, and regulation." In *Handbook of Industrial Organization,* 5:615–742. 1. Elsevier.

Lee, Kenneth, Edward Miguel, and Catherine Wolfram. 2020. "Experimental evidence on the economics of rural electrification." *Journal of Political Economy* 128 (4): 1523–1565.

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.

Meeks, Robyn C., Arstan Omuraliev, Ruslan Isaev, and Zhenxuan Wang. 2023. "Impacts of Electricity Quality Improvements: Experimental Evidence on Infrastructure Investments." Working paper.

Mercadal, Ignacia. 2022. "Dynamic competition and arbitrage in electricity markets: The role of financial players." *American Economic Journal: Microeconomics* 14 (3): 665–99.

Pargal, Sheoli, and Sudeshna Ghosh Banerjee. 2014. *India Power Sector Review: More Power to India: The Challenge of Distribution.* The World Bank Group.

Parliament of India. 2003. *The Electricity Act, 2003.*

Preonas, Louis. 2022. "Market power in coal shipping and implications for U.S. climate policy." Energy Institute at Haas Working Paper no. 285R.

Ryan, Nicholas. 2021. "The competitive effects of transmission infrastructure in the indian electricity market." *American Economic Journal: Microeconomics* 13 (2): 202–42.

Ryan, Stephen P. 2012. "The costs of environmental regulation in a concentrated industry." *Econometrica* 80 (3): 1019–1061.

Seetharam, Deva P, Ankit Agrawal, Tanuja Ganu, Jagabondhu Hazra, Venkat Rajaraman, and Rajesh Kunnath. 2013. "Hidden costs of power cuts and battery backups." In *Proceedings of the fourth international conference on Future energy systems,* 39–50.

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 (3): 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 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: The role of India's wholesale electricity market

Supplementary appendix: For online publication

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

Appendix B presents robustness checks and additional empirical results.

Appendix C outlines our assumptions for monetizing increases in power supply.

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A Further details on the data

A.1 Constructing marginal costs

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

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

We first discuss where we obtain data on heat rates, and then proceed to describe how we construct the full marginal cost, including fuel prices, separately for each type of plant.

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.

Coal plants: We construct marginal costs for each coal-fired power plant as follows. We collect grade-specific coal prices reported aperiodically by Coal India Limited and Western Coalfields Limited (prices reported in rupees per kg).[1] "Grades" refer to the kilocalories (kcal) of heat energy per ton of coal. We assign "minemouth" coal prices to each power plant based on the grades of coal mined from the coalfield and the geographic proximity of the plant to the coalfield. Nearly all of India's coal-fired power plants buy their coal at grade-specific prices set by the Ministry of Coal through long-term Fuel Supply Agreements.[2]

For geographic proximity, we calculate the distance by rail between coal plants and coalfields. To do so, we combine hand-coded plant latitude/longitude with geospatial data on India's coalfields from the U.S. Geological Survey. Data on the rail network in India is created by ML InfoMap.[3]

We approximate the grade of coal burned by the plant as follows, using data from the CEA's Monthly Coal Reports. First, we divide annual total quantity of electricity produced by each plant (in kWh) by the annual total quantity of coal consumed by each plant (in kg). This annual ratio is multiplied by each plant's heat rate in each year (in kcal per kWh). The resulting quantity is the annual aggregate amount of kcal of input heat energy obtained by the plant from one kg of coal. Taking the mean of this quantity gives us the approximate grade of coal burned by the plant, which ranges from 1,118 to 8,254 kcal per kg for non-lignite coal plants.[4]

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

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

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

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

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

Bengal. The royalty rate is 14% for coal mined from all states other than West Bengal; in West Bengal, the royalty adder is applied in rupees per kg rather than percentage.[5] 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.[6] The majority of power plants receive coal from trains. The remaining two major categories are "pithead" plants colocated next to a mine (for whom transportation charges are zero) and plants who burn imported coal. In the absence of high quality data on the coal prices paid by plants burning imported coal, we assign these plants a domestic coal price based on the grade of coal closest to the one they actually burn.

India also charged a "clean energy" cess per kg of coal purchased, which we add to the minemouth price.[7] Finally, the Ministry of Coal charges a Rs. 10 per 1,000 kg "stowing excise duty" related to the "assessment and collection of excise duty levied on all raw coal..."[8]

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).

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

6. 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

7. 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

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

Lignite plants: We obtain the lignite coal price per kg from the Central Electricity Regulatory Commission.[9] 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, 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.[10]

Nuclear plants: We assign each of the 7 nuclear plants in our sample a marginal cost based on tariff documents.[11]

Hydro, wind, and solar plants: Non-dispatchable run-of-river hydroelectric, wind, and solar resources have near-zero marginal cost. Dispatchable hydro generators face a complex dynamic optimization problem, as generation today may come at the expense of generation tomorrow due to a finite supply of water (Archsmith (2022)). Consequently, we exclude hydro, wind, and solar resources from the analysis, implicitly assuming that they are infra-

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

10. 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.

11. 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

marginal; they would be dispatched as observed even in the least-cost benchmark discussed in Section 5.2. 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 5.2 represent a lower bound on the costs of misallocation in wholesale electricity supply.

A.2 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.[12] Table A.1 lists summary statistics by resource type for each data source. 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.

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

|	Data Source	Mean	Std. Dev.	5th %	95th %
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. Here, we report costs in rupees per kWh.

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

A.3 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. 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. Our full mapping from the detailed reasons listed to the broad categories of outage utilized in the analysis is available upon request.
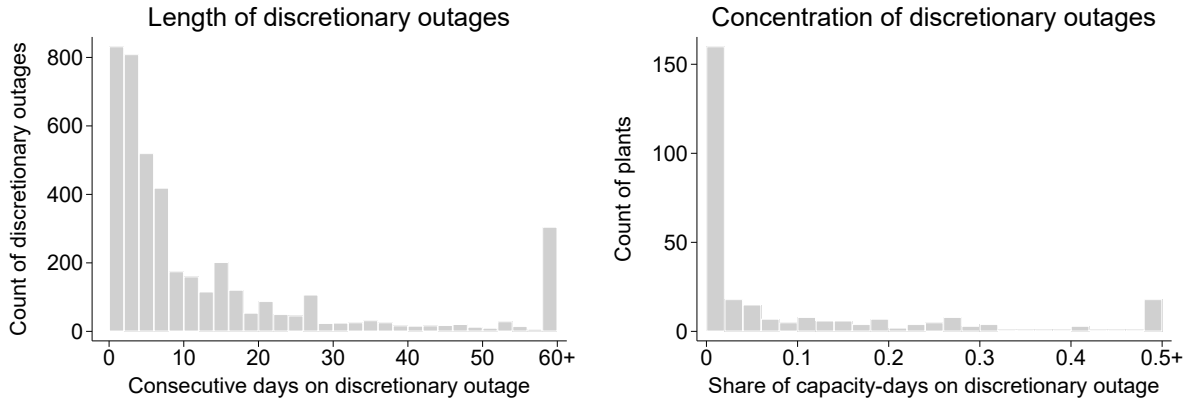
Figure A.1: Distribution of equipment outages
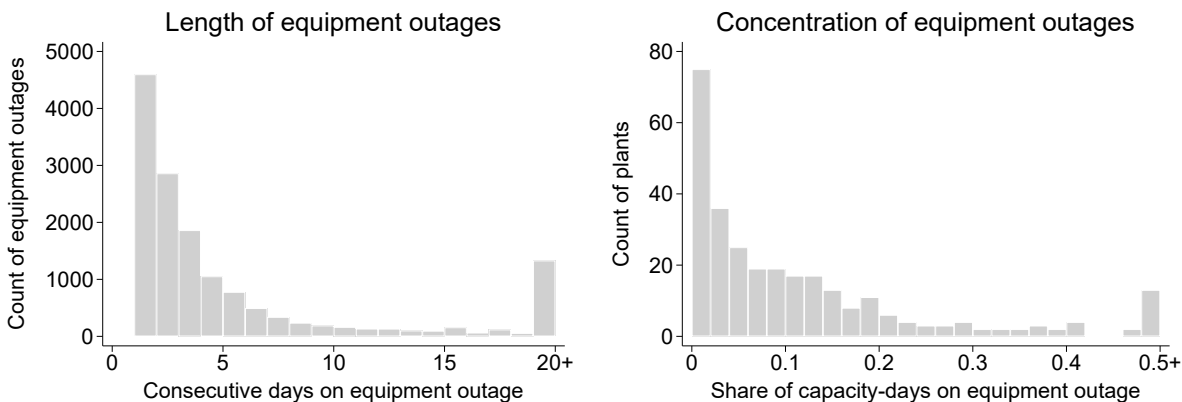
Notes: The left histogram summarizes the length of equipment outages; each observation is a set of consecutive days where a plant reports some capacity on equipment outage. During our sample period, the median equipment outage lasted 2 days. The right histogram summarizes the share of total capacity-days 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.1 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% 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%) reported an

equipment outage during our sample period, with the median plant being on equipment outage for 6.7% of capacity-days.

Figure A.2: 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.

Figure A.2 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 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%. Reassuringly, 50% of capacity-days on discretionary outage come from just 16% of plants—likely 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.

8

A.4 Indian Energy Exchange (IEX) data

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

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

The IEX also provides market clearing price and quantity data for each 15-minute interval for each of India's five transmission regions.[14] Across our sample, the average IEX market clearing price was Rs. 3,121 per MWh, while the average volume cleared was 1,128 MWh per 15-minute interval. We compare the equilibrium outcomes implied by our converted images to those provided by the IEX. The correlation between the two is extremely high—99.8%—which gives us confidence that the image conversion is working properly.

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

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

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

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

Figure A.3: Example IEX demand and supply curves
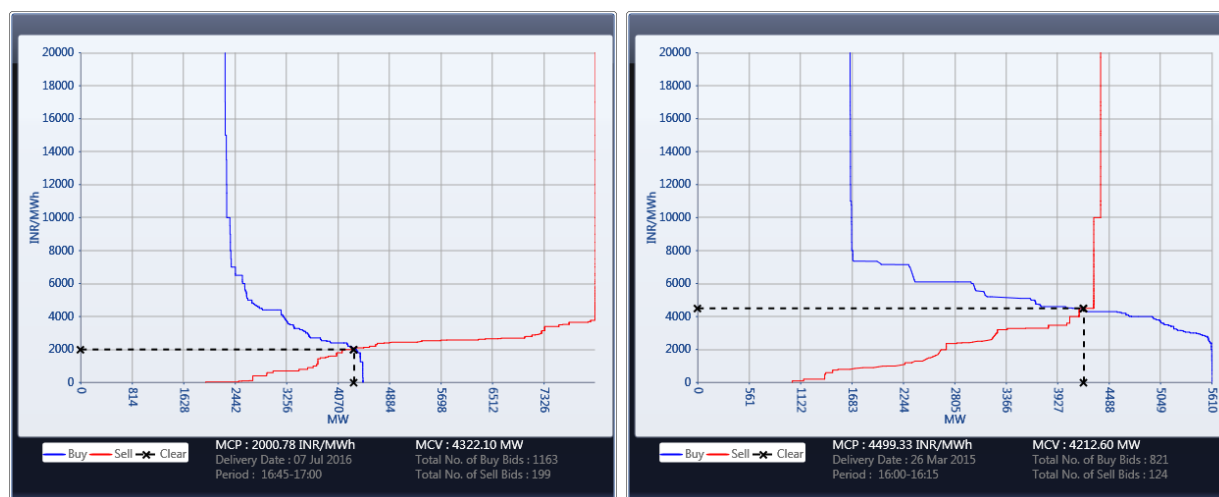
Notes: This figure displays two examples of the raw data we obtained from the Indian Energy Exchange. The left image shows the aggregate demand and supply curves for the 16:00–16:15 interval on March 26, 2015. The right image shows the same curves for the 16:45–17:00 interval on July 7, 2016. We digitized these images, originally in JPEG format, using OCR software.

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.[16]

B Robustness checks and sensitivity analyses

B.1 Endogeneity of discretionary outages

Table 1 shows that equipment outages are uncorrelated with demand-side factors, which supports our assumption that equipment outages are exogenous. Table B.1 replicates Table 1 by estimating Equation (1) using discretionary outages as the dependent variable. We see strong evidence that discretionary outages are endogeous: a 10% higher forecasted demand is correlated with a 1 pp decrease in the discretionary outage rate. Columns (3)–(4) suggest that this correlation is more pronounced for lower-cost plants than for high-cost plants.

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

Table B.1: Discretionary outage rates respond to electricity demand shocks

	Outcome: Share of plant's capacity on discretionary outage			
	(1)	(2)	(3)	(4)
Mean monthly temperature in state (°C)	0.0012	0.0025*	−0.0004	0.0023
	(0.0013)	(0.0013)	(0.0015)	(0.0026)
log (State's forcasted energy requirement)		−0.1015***	−0.1223***	−0.0739***
		(0.0137)	(0.0194)	(0.0174)
Split sample for high/low marg. cost plants			Low MC	High MC
Plant + month-of-sample FEs	Yes	Yes	Yes	Yes
Region × year, region × month FEs	Yes	Yes	Yes	Yes
Mean of dep. var.	0.0990	0.0990	0.0767	0.0914
Plant-month observations	21,268	21,268	8,153	7,603

Notes: This table is identical to Table 1, except that we estimate Equation (1) with a different dependent variable: plant i's monthly discretionary outage rate. See notes under Table 1 for details. Standard errors are clustered by sample month. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

B.2 Deviations from least-cost dispatch

Table B.2 presents five sensitivity analyses pertaining to Table 3. First, while our preferred scenarios conservatively assume interregional autarky, power does flow between regions. In Panel A, we relax this assumption to allow for redispatching to/from anywhere in India. Second, intraregional transmission constraints may also matter. In Panel B, we impose a stronger autarky for each of India's 13 transmission subregions. Third, our least-cost dispatch model ignores within-day variation in demand. Panel C redispatches plants separately for peak hours (when demand is high) and off-peak hours (when demand is low). Fourth, if capacity is mismeasured, our least-cost counterfactuals might overstate the amount of power an idle plant could have realistically provided. Panel D more conservatively redispatches plants up to the 80th percentile of their observed output, rather than the 98th percentile. Fifth, measurement error in our constructed marginal costs could potentially exaggerate the importance of discretionary outages. Panel E addresses this concern by using plant-specific variable costs reported by the Ministry of Power rather than our constructed marginal costs (see Appendix A.2). Across all five sensitivity analyses, discretionary outages continue to explain a substantial share of the cost difference between observed versus least-cost dispatch.

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

Redispatching scenario	Observed (M Rs./day)	Least-cost (M Rs./day)	Cost Difference (M Rs./day)	$100 \times \dfrac{\text{Difference}}{\text{Observed}}$
A. National dispatch				
Eliminating all outages	2,580 [1,934, 3,308]	2,224 [1,584, 2,972]	356 [306, 422]	14.21 [9.83, 19.03]
Eliminating discretionary outages	2,580 [1,934, 3,308]	2,338 [1,685, 3,118]	241 [179, 315]	9.75 [5.65, 14.28]
Respecting all outages	2,580 [1,934, 3,308]	2,383 [1,726, 3,144]	196 [145, 264]	7.93 [4.71, 12.22]
B. Subregional dispatch				
Eliminating all outages	2,580 [1,934, 3,308]	2,280 [1,652, 3,021]	300 [243, 363]	11.89 [8.42, 15.48]
Eliminating discretionary outages	2,580 [1,934, 3,308]	2,386 [1,753, 3,147]	193 [141, 257]	7.73 [4.52, 11.10]
Respecting all outages	2,580 [1,934, 3,308]	2,422 [1,787, 3,165]	158 [112, 215]	6.30 [3.80, 9.31]
C. Peak vs. off-peak generation				
Eliminating all outages	2,580 [1,934, 3,308]	2,213 [1,584, 2,942]	366 [308, 427]	14.56 [10.72, 19.16]
Eliminating discretionary outages	2,580 [1,934, 3,308]	2,336 [1,693, 3,087]	243 [182, 316]	9.73 [6.09, 14.07]
Respecting all outages	2,580 [1,934, 3,308]	2,385 [1,735, 3,120]	194 [132, 260]	7.77 [4.71, 11.73]
D. 80th percentile of capacity				
Eliminating all outages	2,580 [1,934, 3,308]	2,269 [1,621, 3,018]	311 [251, 379]	12.41 [8.43, 17.25]
Eliminating discretionary outages	2,580 [1,934, 3,308]	2,379 [1,734, 3,137]	201 [142, 272]	8.08 [4.75, 12.19]
Respecting all outages	2,580 [1,934, 3,308]	2,415 [1,773, 3,156]	164 [116, 222]	6.59 [4.04, 10.15]
E. MERIT variable costs				
Eliminating all outages	5,054 [4,214, 5,677]	4,419 [3,581, 5,014]	635 [508, 778]	12.66 [9.60, 15.87]
Eliminating discretionary outages	5,054 [4,214, 5,677]	4,674 [3,774, 5,339]	380 [277, 496]	7.64 [5.16, 11.03]
Respecting all outages	5,054 [4,214, 5,677]	4,714 [3,827, 5,371]	341 [245, 449]	6.84 [4.53, 9.85]

Notes: This table conducts five sensitivity analyses on the bottom three rows of Table 3. Panel A allows for national redispatching, rather than restricting dispatch within each region. Panel B restricts redispatching to be within each subregion, rather than within each region. Panel C accounts for within-day variation in demand by redispatching separately for peak and off-peak periods. Panel D redispatches plant capacity up to the 80th percentile of each plant's observed daily generation, rather than the 98th percentile. Panel E uses MERIT variable costs, rather than our constructed marginal costs (see Appendix A.2).

C Details on monetization of power supply increases

In Section 6, we monetize increases in quantity supplied in three separate ways, converting all costs to 2016 rupees. First, we calculate the retail revenues associated with the counterfactual increases in quantity supplied. We multiply the daily state-level increases in quantity by the state-level retail prices in 2019 faced by households at the price step relevant for the national average household consumption level (1,028 kWh per year, which implies 85 kWh per month). State-level retail prices in 2019 are from Central Electricity Authority (2019).

We also monetize the reliability benefits associated with counterfactual increases in quantity supplied based on two different backup technologies. Households faced with blackouts have two primary options to continue consuming electricity: inverter/battery systems and backup generators. We use estimates of operating and purchase costs from a variety of sources, discussed below.

Inverter systems: Households with inverter/battery systems charge their batteries when grid-based electricity is available, storing this electricity to power necessary appliances when grid-based electricity is unavailable (Seetharam et al. (2013)). The primary operating costs associated with these systems come from the power lost during the charging, converting, and discharging process, as well as replacing the battery. Following Seetharam et al. (2013), we assume that 42.4% of the power drawn from the grid when electricity is available is lost. In other words, 1 kWh drawn from the grid can power only 0.576 kWh worth of appliances during a blackout. We value electricity losses using the same 2019 state-level retail prices discussed above. Mitra and Miller (2004) note that batteries must be replaced every 1.5 years, at a approximate cost of Rs. 3,000 (2004 rupees). We divide this replacement cost by 547.5 ($= 365 \times 1.5$) to reflect a daily magnitude, and include it as part of our assumed operating costs for inverter system. Mitra and Miller (2004) also note that purchasing a new inverter/battery system costs roughly Rs. 7,000 (2004 rupees). This broadly aligns with the prices for household inverter/battery systems listed on Amazon and other online retailers.

Gensets: Backup generators ("gensets") burn fuel—typically diesel—in order to generate electricity and power appliances when grid-based electricity is unavailable. The primary operating costs associated with gensets come from the fuel burned to produce electricity and from servicing the genset. Following Bhatia and Banerjee (2011), we assume that genset fuel costs are Rs. 18 per kWh. Mitra and Miller (2004) also assume a servicing cost of Rs. 3,000 per year, which we divide by 365 to convert to a daily magnitude. Finally, Mitra and Miller (2004) report that purchasing a genset costs roughly Rs. 30,000 (2004 rupees). Again, this broadly aligns with the prices for household generator systems listed on Amazon and other online retailers.

Appendix references

Archsmith, James. 2022. "Dam spillovers: The direct and indirect costs from environmental constraints on hydroelectric generation." Working paper.

Bhatia, Mikul, and Sudeshna Ghosh Banerjee. 2011. *Unleashing the potential of renewable energy in India.* World Bank Publications.

Central Electricity Authority. 2019. *Electricity Tariff and Duty and Average rates of electricity supply in India.* https://cea.nic.in/wp-content/uploads/2021/03/tariff_2019.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.

Chirayil, Maria, and Ashok Sreenivas. 2010. *Coal auctions still far from transparent.* https://www.thehindubusinessline.com/opinion/coal-auctions-still-far-from-transparent/article29281446.ece, August.

Cicala, Steve. 2022. "Imperfect markets versus imperfect regulation in U.S. electricity generation." *American Economic Review* 112 (2): 409–441.

Fabrizio, Kira R., Nancy L. Rose, and Catherine D. Wolfram. 2007. "Do markets reduce costs? Assessing the impact of regulatory restructuring on US electric generation efficiency." *American Economic Review* 97 (4): 1250–1277.

Mitra, Shalini, and Mark Miller. 2004. "Power Cuts in Delhi: How Much Does it Cost You?" Working paper.

Seetharam, Deva P, Ankit Agrawal, Tanuja Ganu, Jagabondhu Hazra, Venkat Rajaraman, and Rajesh Kunnath. 2013. "Hidden costs of power cuts and battery backups." In *Proceedings of the fourth international conference on Future energy systems,* 39–50.