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Leveraging Automation and Incentives to Enhance Power Demand Flexibility

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We also note Dr Khanna and Dr Muûls' present affiliations in the *Hitachi-Imperial Centre for Decarbonisation and Natural Climate Solutions*, a five-year initiative collaborating with Hitachi Ltd and Hitachi Europe in fundamental and applied research to drive the transition to zero pollution. www.imperial.ac.uk/hitachi-centre/

Finally, we direct the interested reader to more information about POWBAL, an initiative and research project by Imperial and LSE researchers. POWBAL aims to make the energy sector cleaner by moving power consumption to time periods when power generation is cleanest. At POWBAL we develop simple technological solutions to facilitate load shifting and examine the adoption behaviour by users. https://powbalenergy.net/

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Executive Summary

- Active demand management is a crucial tool for balancing electricity markets and managing the increased volatility caused by intermittent renewable generation.

- While much of demand management is focused on large industrial users, the POWBAL Tata trial focused on the potential of household customers to contribute to such load balancing.

- The POWBAL Tata Project rolled out Wi-Fi connected power switches in over 1000 households in Delhi and Mumbai.

- Households could choose which appliances to connect to those switches with most opting (80%) for an air conditioning unit.

- Randomized and remotely triggered switch off events lead to an average reduction of household electricity demand of 8%.

- The reduction effect is much higher (up to 15%) during hours of the day that experience peak demand.

- Users had the option to override switch-off events either directly on their devices or by responding to an announcement message on their smartphones. Approximately 30% of users chose to opt out of these events.

- A comparison of household and device-level electricity consumption measurements indicates no evidence of demand leakage, where users might shift their electricity usage to other appliances not connected to the scheme.

- Surprisingly, there is also no rebound effect in periods following a switch-off event, which points to inefficiencies in electricity use (e.g. air conditioning units operating without thermostats or being set at too low temperatures).

- Households were offered varying reward rates for participating in switch-off events without overriding them; however, there is no evidence that higher rewards led to increased participation.

- There is also no evidence that users respond differently to varying announcement periods for the switch-off events.

- To assess the aggregate potential of a POWBAL-like demand management approach, we conduct a counterfactual exercise. With new estimates of the marginal emission factors of the Indian power grid and estimates of fine-grained household level responses, we analyse the potential reduction in household carbon emissions achievable with the existing generation assets.

- We find an average CO_2 emission reduction effect of around 2.3%, increasing to more than 3% in some households, and an average cost saving of 2.5%.

- Taking the device and installation costs of the smart switches into account, the average net mitigation cost is -\$23.1 per ton of CO_2. We compute a negative net carbon mitigation cost for nearly three-quarters of the households in our sample.

- We conclude that household-level demand management can play an effective and economically meaningful role in the Indian electricity system.

- In future work, we will examine how a POWBAL-like demand management approach could interact with potential future investment pathways for generation assets. We will consider how demand management could reduce the system cost of adding intermittent renewable generation assets.

1. Introduction

In recent years, India has made significant progress in increasing renewable energy generation, while expanding access to electricity across its population and closing its power deficit. With its rapidly growing economy, electricity demand will continue to surge in the coming years. Meeting this demand with fossil fuels rather than clean energy would have a dangerous impact on global carbon emissions and local pollution levels. In signing the Paris Agreement in 2015, India has committed to reduce the emissions intensity of its economy by 45% between 2005 and 2030 and to achieve net-zero emissions by 2070. Although renewable energy capacity (excluding hydro and nuclear) represents more than a quarter of total installed generation capacity, coal-fired electricity generation still accounts for three-quarters of annual electricity output. According to the International Energy Agency, electricity and heat producers are responsible for 51% of the country's total energy-related CO_2 emissions, with power plants being the largest source. To achieve its climate aspirations, India will need to decouple energy demand from carbon emissions by replacing coal-fired generation with non-fossil-based energy capacity, which the government is already aiming for with over 500 GW due to be integrated by 2030. Investments in supply-side infrastructure including energy storage and transmission will be essential to enable the deployment of this new capacity and maintain security of energy whilst the share of fossil-based generation decreases. However, increasing the amount of renewable generation in the electricity supply mix creates challenges for electricity grid operators due to their intermittency, which makes it difficult to ensure electricity supply matches demand throughout the day. Demand side interventions, such as shifting electricity demand from periods when renewable energy is scarce to periods when it is more available, can therefore play an important role in maintaining balance across the system and reducing costs. In addition, with high levels of variable renewable energy on the grid, peak demand might not coincide with moments of the day at which the marginal cost of generation, or the marginal grid carbon intensity, are at their lowest. As a result, spreading demand more evenly across the day can avoid the need to dispatch expensive and polluting power plants, thereby lowering the carbon intensity of grid-supplied electricity and the overall cost of electricity generation. Lastly, greater demand flexibility can help system operators avoid outages at times of system stress when financial profit margins are tight.

This briefing paper begins with a short overview of the latest literature on technological and behavioural tools for electricity demand flexibility. It then presents the results of a randomised control trial (RCT)[2] with residential customers of Tata Power that studies the role of incentives and automation technologies in making electricity demand more flexible. This research provides valuable insight for electricity regulators and retail electricity suppliers looking to design and implement automated demand response programmes to minimise the cost of electric power procurement and balancing, whilst maximising decarbonisation of our energy system.

[2] In randomised control trial subjects are randomly assigned to one of two groups: the experimental group receiving the intervention that is being tested, and a comparison group that does not receive the intervention. Randomisation ensures that these two groups are similar on average, implying that any observed differences in outcomes can be attributed to the intervention and not to any other confounding factors.

2. Existing evidence on demand management

Demand-side management consists of a broad class of schemes aimed at modifying patterns of electricity use. In the retail market, these might include various forms of dynamic pricing, such as real-time, time-of-use, variable peak and critical peak pricing, as well as schemes that reward consumers for shutting off low-value electricity consumption at specified times such as critical peak rebates (Badtke-Berkow et al, 2015). Such measures can be optimised to maximise avoided climate and local pollution damages whilst lowering balancing and network reinforcement cost, as well as decreasing the likelihood of forced outages. Nevertheless, attempting to make demand more flexible by pricing electricity dynamically or by offering dynamic rewards may be less effective if consumers are inattentive to electricity prices as has been shown in the case of the residential sector (Jacobsen and Stewart, 2022; Parrish et al., 2019; Sexton, 2015; Jessoe et al., 2014; Gilbert and Zivin, 2014; Houde et al., 2013, Fabra et al., 2021). In such cases, incentives alone may not always be enough to harness any latent demand flexibility.

As an alternative, with the installation of smart meters, retail electricity suppliers could control load at the meter level directly and in exchange offer discounted tariffs to consumers that sign up for interruptible or curtailable service contracts. However, the feasibility of this approach remains uncertain given the potential inconvenience to consumers from having the electricity to their entire house being shut off periodically. The development of Internet of Things (IoT) technologies has brought the possibility of automating demand-side management at the level of individual appliances, allowing consumers to tailor the parameters of automation to their preferences. Automation is increasingly being considered as a low-cost opportunity to make small changes in electricity demand that can result in large electricity supply cost reductions (Blonz et al., 2021; Bailey et al., 2023; Coutellier et al., 2020). In principle, dynamic pricing of electricity could encourage consumers to adopt these IoT technologies, however they can face technical barriers to adoption, such as difficulty in finding installers with the requisite skills. Adoption of automation may also be hampered if consumers are less concerned with the cost of their electricity consumption. Lastly, IoT technologies might generate concerns of safety and data security (Alaa et al., 2017; Nicholls et al., 2020; Parrish et al., 2020). These factors are likely to constrain the large-scale take-up of IoT technologies needed to induce greater responsiveness from the demand side to changing energy system conditions.

The study we present in the next section builds on these different parts of the literature by exploring in an experimental setting (RCT) how consumers adopt and interact with automation devices and how this intervention can contribute to demand flexibility and load balancing in the Indian context.

3. POWBAL-Tata Power Randomised Control Trial

Overview:

Starting in March 2023, we invited over 850,000 residential customers of Tata Power via SMS, email and WhatsApp to participate in a study in which they can earn rewards for using a Wi-Fi enabled "smart" switch, i.e. a Wi-Fi connected switch enabling to remotely turn off the electricity supply of connected appliances as well as to monitor their power consumption via a smartphone app. As of July 2024, 1,000 residential customers of Tata Power have registered for the trial and are using the smart switches. Approximately two-thirds of these customers have smart meters. Households can choose which appliance to connect to the smart switch and about 80% connected an air conditioning (AC) unit.

We use the POWBAL web platform,[3] which was designed at Imperial College London, to monitor power consumption readings in real-time and to automatically trigger random 30-minute switch-off events at different times to each device. These events occur between 8am and midnight no more than twice a day and no more than eight times a week for each device. Participants can choose to opt-out when given notice, or to turn the device back on manually if it switches off. However, by incurring the switch-off, they are rewarded in proportion to the power consumption that is avoided relative to how much the appliance would most likely have consumed if there was no switch-off event.[4]

Using data from the households' smart meters, we find that **household energy demand reduces by about 8.5% on average during switch-off events**. The size of the effect increases to 15% during the late afternoon and evening hours which coincide with peaks of aggregate power demand. The observed reductions in electricity consumption at the device level closely align with those measured at the meter level, suggesting that **data from smart switches alone may suffice for implementing automated demand response programs**, even for consumers without smart meters, without sacrificing grid benefits. Throughout the trial, we varied reward rates for each user event but found **no evidence that households reduced their electricity usage more in response to higher rewards**.

Interestingly, and contrary to expectations, we also do not find any evidence for compensating effects i.e., **households do not consume any more electricity in periods shortly after a switch off**, which **might imply** a certain degree of wastage in how energy is used. For example, if air conditioning units are operating without thermostatic control or are set too high, a temporary switch-off would not trigger any compensating response. We can also characterise this demand response trial as a virtual power plant where power generation corresponds to the energy consumption avoided due to the switch-off events. In this way, our virtual power plant has generated 5.4 MWh since the trial began in the spring of 2023.

Description of data collected during the trial:

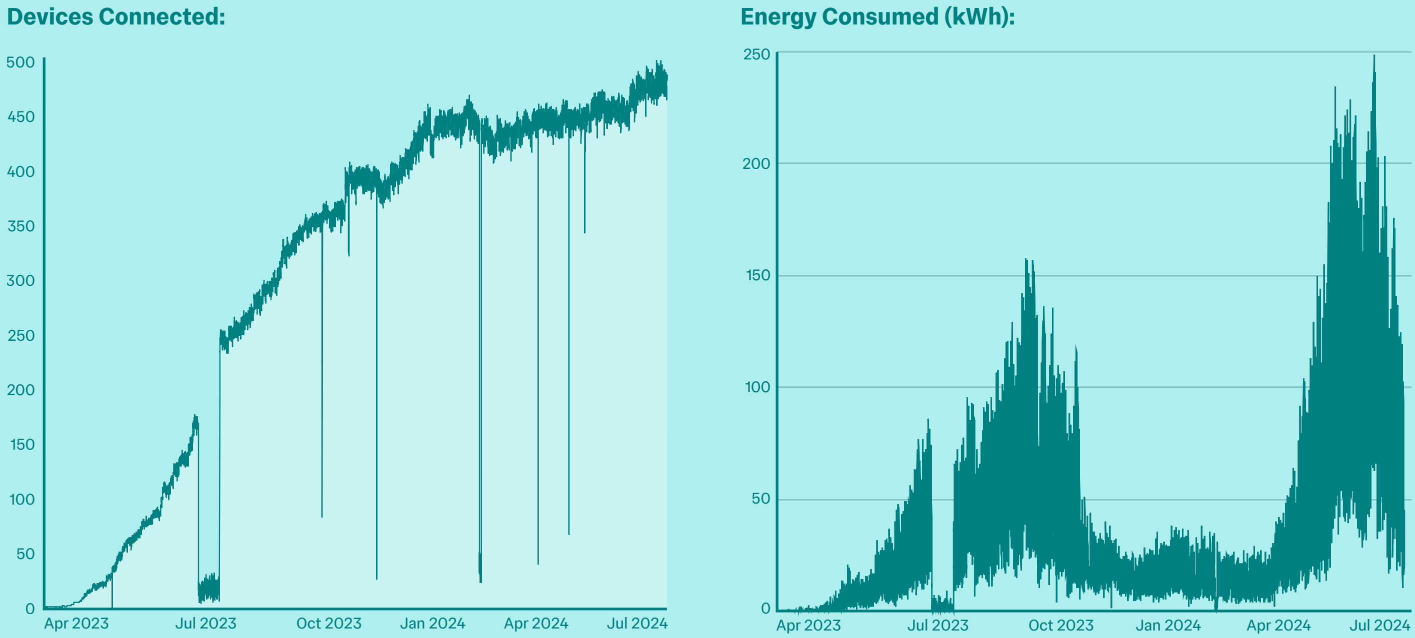
The share of customers that accepted the SMS, email or WhatsApp invitation to participate and followed through with devices installed is 0.1%. These low sign-up and conversion rates might be driven by a reluctance to have appliances remotely controlled by an external entity or the absence of marketing campaigns on social and traditional media. Approximately 80% of the smart switches are connected to AC units, while the rest are mostly connected to refrigerators and electric geysers (i.e. water heaters) and a handful are connected to light bulbs, microwave ovens, washing machines, water pump motors and electric car chargers.

[3] For further information, visit powbalenergy.net

[4] We set rewards to be proportional to the per-kWh reduction in the energy consumed during the event relative to the energy the device consumed in the five minutes before the event started; i.e. we assume that in absence of the switch-off, customers would have used the same amount of electricity throughout the 30 minutes of the switch-off event as they did in the five minutes prior to switch-off.

Figure 1 reports the number of connected devices and total power flow across all smart switches installed in Delhi and Mumbai since the trial commenced.[5] The high prevalence of ACs connected to smart switches in the trial explains the steep incline in power usage at the onset of summer and sharp reduction at the onset of winter – a trend particularly driven by smart switch users in Delhi that experience hotter summers and colder winters than do users in Mumbai. Reductions in power usage could also reflect some users withdrawing from the trial and/or their smart switches going offline permanently.

Figure 1: *Online smart switches and total power usage across all smart switches*



Note: The figure on the left indicates smart switches connected to Wi-Fi at five-minute intervals since the trial started until July 2024. The figure on the right indicates total power usage across connected smart switches at five-minute intervals over the same period.

Combining data from the devices with the smart meter readings and removing outlier observations,[6] we have 1,398,971 user-half-hours of meter-level and smart switch electricity consumption. On average, 71% of devices are online at any given time. The average household in the sample consumes 349.50 Wh every half-hour, or 510 kWh per month, which is 2.5 times larger than the median electricity consumption for residential customers using traditional power meters in Delhi (Khanna and Rowe, 2024). The power flowing through the smart switch accounts for 13% of meter-level consumption on average, with higher shares at night.[7]

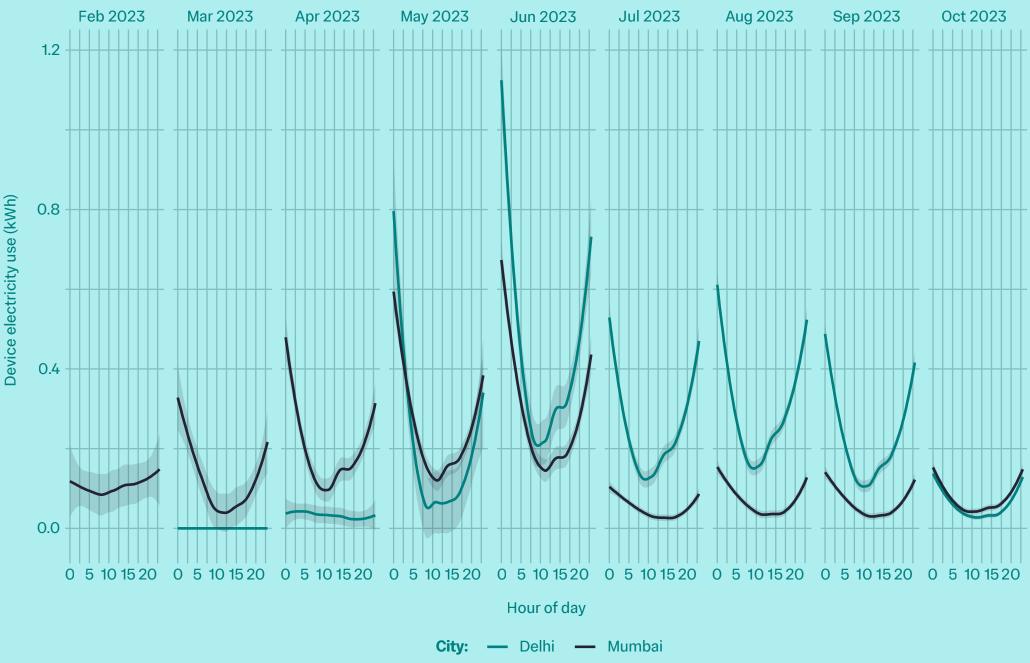
Different appliances naturally display variance in the distribution of their power consumption in time. For example, if the difference between the room temperature and that of the refrigerator or AC thermostat setting is small, the appliance may remain on while consuming near-zero power. However, operating at full power, a refrigerator consumes 100-200W and a room AC unit 1,500-2,500W depending on its size and efficiency. Figure 2 shows average device-level electricity usage by month-of-year, separately for both cities. The U-shaped pattern is driven by consumers running their ACs primarily at night. We see a stronger seasonal pattern, and greater night-time AC usage in Delhi due to temperatures peaking in June.

[5] The figures also depict a period in July 2023 when data could not be queried from the smart switches due to a malfunction with the device APIs.

[6] Observations above the 95th percentile of meter-level electricity use are removed from the final dataset.

[7] We report summary statistics in the appendix.

Figure 2: *Average device-level electricity usage by hour of day, month and cityswitches*



Note: The figure indicates the average device-level electricity use by hour of day, month, and city from February 2023 until October 2023. Participants were recruited starting in February 2023 in Mumbai and in March 2023 in Delhi.

With the described infrastructure of POWBAL switches in place, we conducted 117,227 switch-offs at the user-event level between 8am and midnight. 29% of these events occurred at times when the power consumed through the smart switch was greater than 0W. 23% of these events were overridden by the user. Overrides are cases where the device was consuming power immediately before the event, but the customer either opted-out of the event on their app beforehand or immediately turned the device back on, such that there were no energy savings and therefore no reward was earned. The following sections present the impact of POWBAL events on electricity consumption and overriding behaviour.

Impact of POWBAL switch-off events on electricity consumption and drivers of flexibility

We study the effects of the switch-off events on electricity use both at the smart switch or device-level and at the household or meter-level during the 30-minute events, as well as the half-hour periods around these. We use an econometric estimation approach called panel data fixed effects. This approach allows us to account for any time-invariant differences between users that affect their electricity use, for example property size. Factors that vary at the city-by-half-hour-by-appliance type level such as weather differences that may drive systematic trends in appliance use are also accounted for.

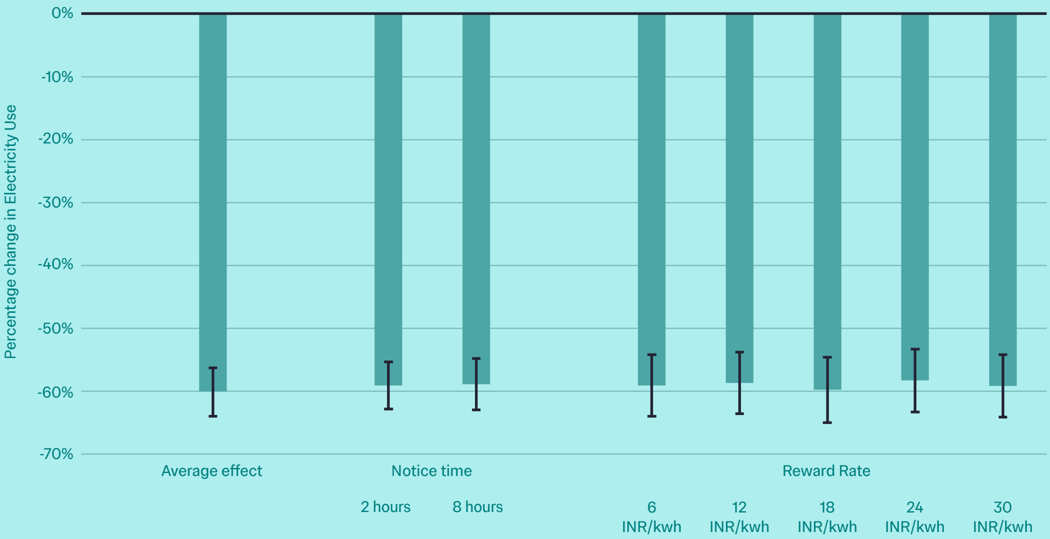
On average, switch-off events lead to a 60% reduction in device-level electricity consumption during the 30-minute event interval. This average reflects the fact that while some users may turn their devices back on either immediately or at various points during the interval, others may not turn them back on at all. Using data from the users' smart meters, we find that this effect corresponds to an 8.5% average reduction in household-level electricity during switch-offs.

This effect varies for different types of switch-off events and users. Figure 3 shows that neither the notice period duration (whether two or eight hours before the switch-off event) nor the reward rate (multiples of INR 6/kWh) significantly influences the extent of the reduction in electricity consumption at the device level. This suggests that larger financial incentives may not have much of an additional impact when demand response is facilitated using smart technologies.

In unreported results, we find that users do not increase their consumption in the aftermath of a switch-off, and that some users anticipate a switch-off by reducing their energy use before it starts. As a result, the reduction during the 2.5 hours that include the hours prior and after the 30-minute switch-off, amounts to 69%, corresponding to a 14% reduction in household-level electricity use.

It is important to note that a two-hour notice period leads to a statistically significant 9% reduction in electricity use during the period immediately before the switch-off event, whereas an eight-hour notice period does not have the same effect. This reduction likely occurs because users manually turn off their devices upon receiving the notification about the upcoming switch-off. This behaviour may indicate a misunderstanding of the reward scheme by some users, as turning off the device prematurely results in no reward being earned. These findings suggest that a longer notice period or no notice at all could prompt a more optimal behavioural response.

Figure 3: *Effect of switch-off events on device-level energy use by notice time and reward rate.*



Note: The figure plots the estimates of percent changes in electricity use and 95% confidence intervals from Poisson regressions of device-level electricity use on a set of dummy variables indicating switch-off events in period t interacted with the length of the notice period (left) and the offered reward rate (right) for the event. The regressions control for user and city x appliance x t fixed effects and standard errors are clustered at the user level.

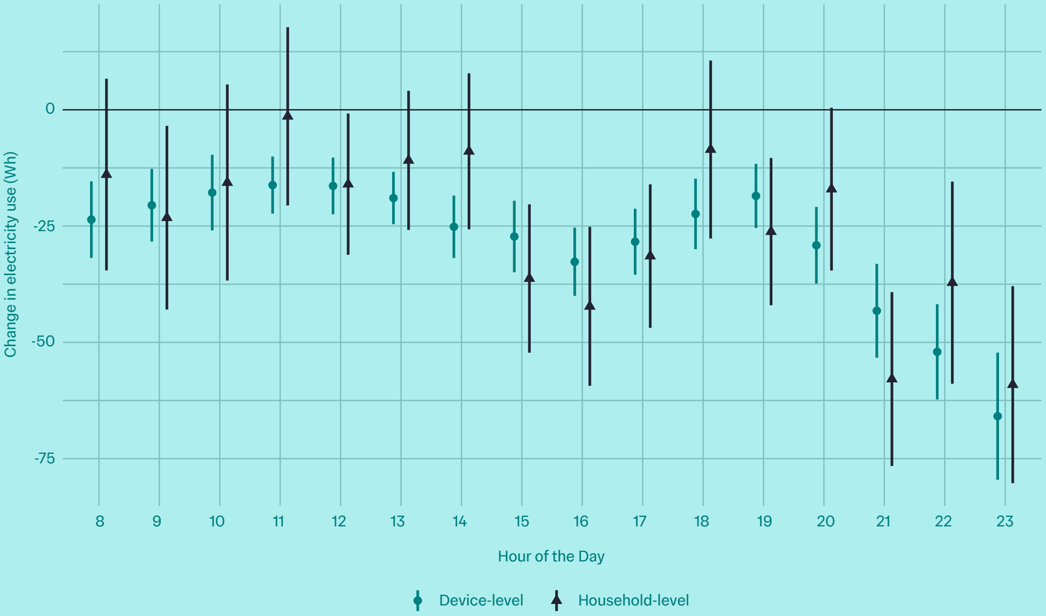
Does the time of the day at which the event is scheduled alter the effect of switch-off events? Figure 4 compares the percentage load reduction potential observed during events with the average hourly meter-level consumption. The data reveals that household energy demand is more flexible at specific times of the day, particularly during peak hours. These are also the times when the distribution network is most susceptible to overload and when outages are more common. This finding suggests that scaling up automated demand flexibility programmes could reduce peak demand and the likelihood that outages occur in the first place.

Figure 4: *Hourly Potential for Meter-Level Electricity Reduction vs. Average Consumption*

Note: The figure plots the estimated percent reduction in household electricity use during the automated switch-off events on the left y-axis and the average household-level electricity consumption on the right y-axis by hour of day.

This conclusion is further reinforced by the absolute impact of the 30-minute switch-off events on power consumption, as shown in Figure 5 for various times of the day. The most significant reductions in electricity use occur in the evenings, both at the device level and meter level. The similar magnitude of effects at both levels suggests that users do not offset these reductions by shifting their electricity usage to other devices during the 30-minute events. This also suggests that using readings from smart devices to implement demand-response programmes with consumers that do not have smart meters could be achieved without compromising on the benefits to the grid.

Figure 5: *Hourly Impact of Switch-Off Events on Electricity Consumption*

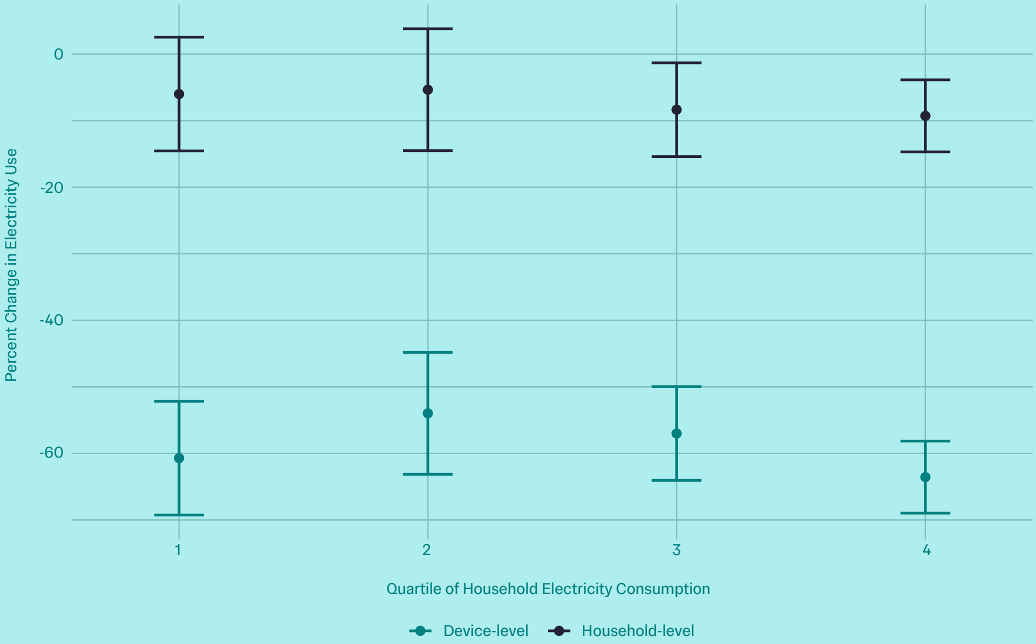


Note: The figure plots the coefficient estimates and 95% confidence intervals of ordinary least squares (OLS) regressions of device-level electricity use and meter-level electricity use in Wh on a set of dummy variables indicating a switch-off event in period t interacted with the hour of day. The regressions control for user and city x appliance x t fixed effects and standard errors are clustered at the user level.

Further analysis, detailed in the appendix, shows that the effects on device-level consumption are not influenced by the number of weeks a user has participated in the trial, nor by their preference for whether their device should turn off or remain on after each event. The most significant load reductions during the switch-off periods are observed for refrigerators, with slightly smaller but more precisely measured reductions for air conditioners (ACs). This difference reflects the distinct usage patterns of these appliances: refrigerators are typically powered continuously, while AC usage varies based on temperature and the presence of household members.

Finally, we divide households into quartiles of overall household electricity use. Figure 6 shows that the reductions in device- and meter-level electricity use is larger for users in the upper quartiles of household electricity consumption than among users in the lower quartiles.

Figure 6: *Electricity Use Changes by Consumption Quartiles During Switch-Off Events*



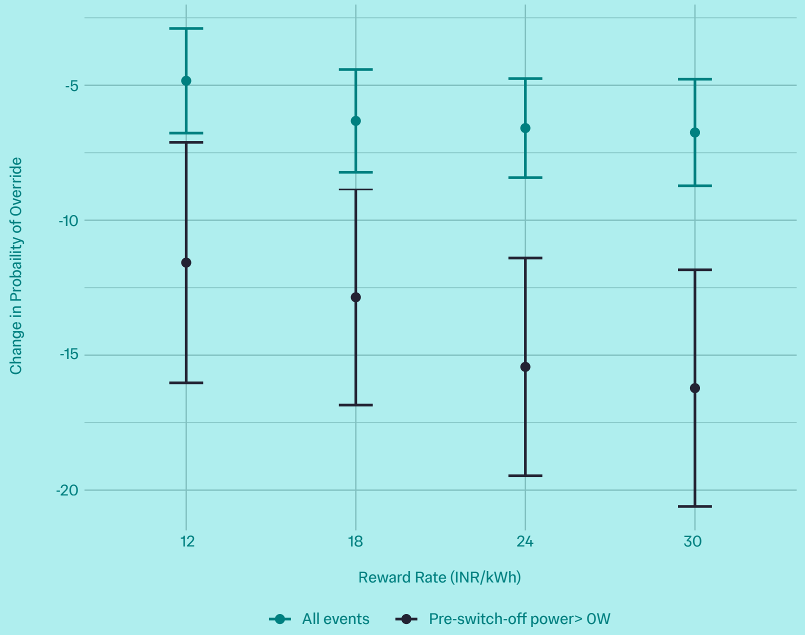
Note: The figure plots the coefficient estimates, and 95% confidence intervals of Poisson regressions of device-level electricity use and meter-level electricity use on a dummy variable indicating a switch-off event in period t interacted with the quartiles of demeaned and detrended half-hourly meter-level electricity consumption. The regressions control for user and city x appliance x t fixed effects and standard errors are clustered at the user level.

A Virtual Power Plant

How do features of events drive overriding behaviour?

Reward rates impact the probability of an override: doubling the reward rate from INR 6 per kWh to 12 is associated with a 4.9 percentage point reduction in the probability of an override, as shown in Figure 7. The effect becomes even more pronounced when we consider only those switch-off events where the device was actively consuming power at the time of the event. On the other hand, a longer notice period does not have a statistically significant effect on the probability of an override.

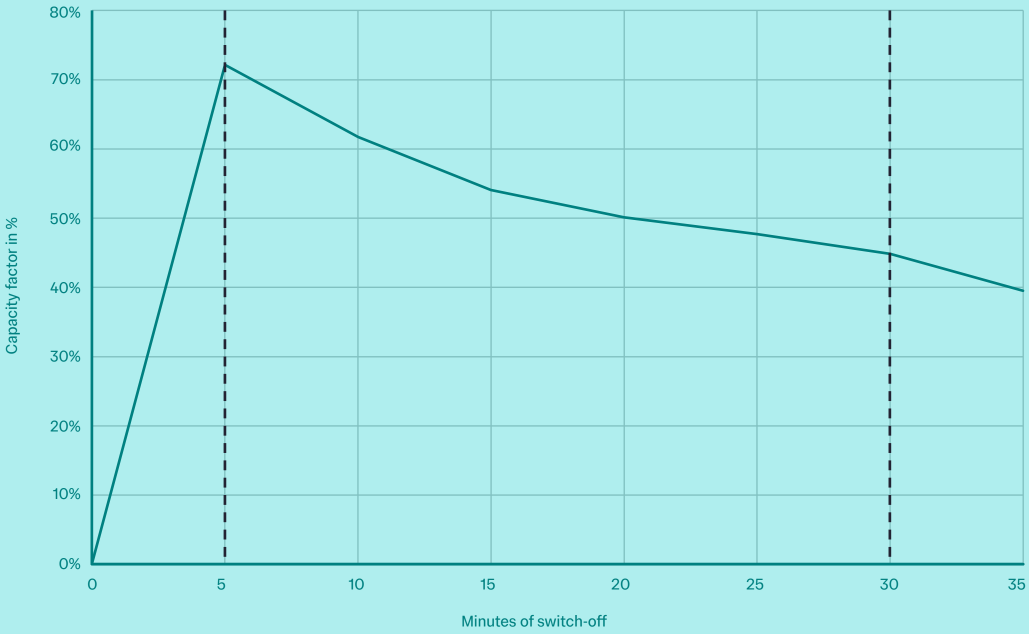
Figure 7: *Effect of the level of the reward rate on probability of overriding switch-off events*



Note: The figure plots the coefficient estimates and 95% confidence intervals of Ordinary Least Squares (OLS) regressions of the occurrence of a switch-off event overridden by the user on the reward rate (INR/kWh) that the user was offered for the event on a sample that consists of all events and a sample that includes only those events where the power consumed prior to the event was greater than 0W. The regressions control for user and city x appliance x t fixed effects and standard errors are clustered at the user level.

Given these findings, Figure 8 displays the computed capacity factor of our implicit virtual power plant, measuring the fraction of potential implied power generation that has been realised across all switch-off events. The capacity factor is calculated at five-minute intervals before and during the switch-off events and the dotted lines indicate the beginning and end of switch-off periods. On average, the power delivered to the grid is highest in the first five minutes of a switch-off event, with a capacity factor of 73%. This drops to 45% by the end of the event, indicating that some consumers override the switch-off. Even after the 30-minute event concludes, devices typically do not return to their pre-switch-off consumption levels, meaning our virtual power plant continues to supply power. This suggests that some devices remain off, and those that do turn back on do not fully compensate for the power saved during the switch-off period.

Figure 8: *Average capacity factor of virtual power plant around switch-off period*



Note: The figure plots the capacity factor of our implicit virtual power plant, i.e. the fraction of potential implied power generation that has been realised across all switch-off events. The data is discretised at the level of five-minute intervals. The dotted lines indicate the beginning and start of switch off periods.

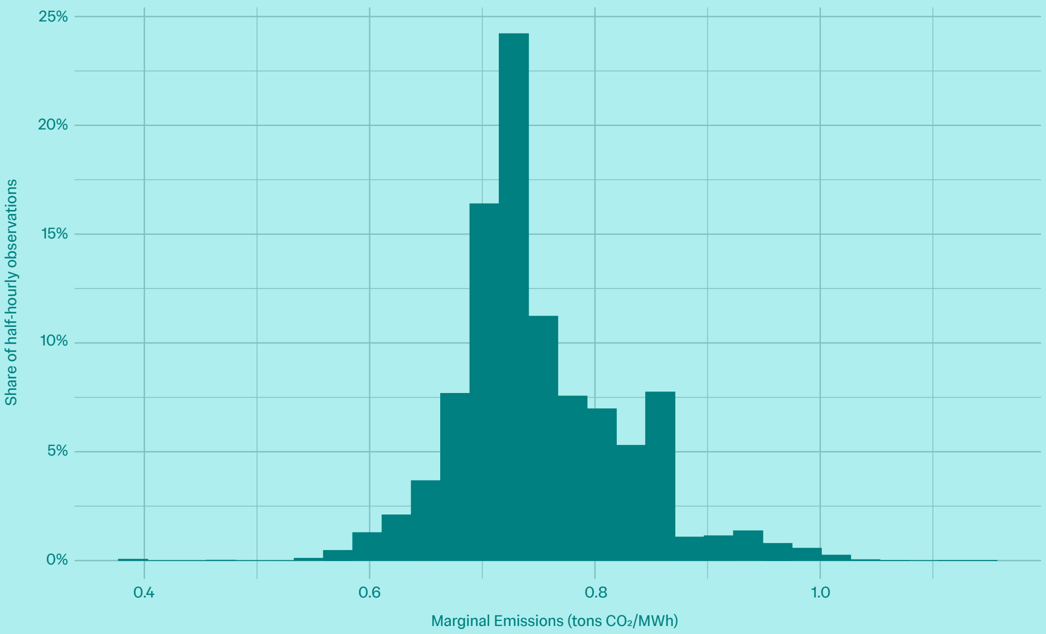
The short run potential to avoid CO_2 emissions

A key motivation for exploring demand management options is the potential to expand renewable energy generation while minimizing the reliance on expensive backup solutions like batteries or fossil fuels. In doing so, demand management reduces the emissions intensity, operating costs and the need for load shedding of any given electricity system.

To explore this in our context, we measure the potential of the current POWBAL setup to mitigate CO_2 emissions. Fundamental to this approach is the concept of marginal emissions (ME), i.e. the change in aggregate emissions resulting from a change in electricity production.[8] Figure 9 plots the distribution of ME factors for all 30-minute periods in India throughout 2023. These factors vary from 0.4 tons of CO_2 per MWh to over 1 ton of CO_2 per MWh. Consequently, shifting 1 MWh of electricity consumption from a low ME period to a high ME period could result in a carbon saving of 0.6 tons of CO_2.

[8] In Appendix C we describe how we estimate marginal emission factors for the Indian electricity grid.

Figure 9: *Estimated marginal emission factors, 2023*



Note: The figure plots marginal emission factors which are estimated for every 30-minute period in 2023 by fitting a model of CO_2 emissions from power production in India as a function of electricity system output and a set of weather bins: high solar radiation and low wind speed, high solar radiation and high wind speed, low solar radiation and high wind speed, and low solar radiation and low wind speed. We scraped five-minute data on CO_2 emissions from power production and electricity system output from www.carbontracker.in and used hourly weather data from the ERA5-Land product of ECMWF.

The carbon impact of load shifting depends on two key factors: (1) how marginal emissions factors (ME) fluctuate within short time frames, and (2) the degree to which consumer responsiveness to switch-off events aligns with these variations in ME factors. To analyse these impacts, we use real-world 30-minute response elasticity estimates from our trial to explore a counterfactual scenario. Imagine that in 2023, we had optimally switched off the devices of participating households no more than once every three hours, targeting the 30-minute period within each three-hour window when the ME factor was highest.[9] We summarise the effect of this counterfactual scenario using two statistics: (i) the implied household and aggregate level reduction in carbon emissions, and (ii) the implied CO_2 mitigation cost.

We find that electricity could have been delivered with 2.3% less emissions for the 504 households in our sample for which we have a full year of half-hourly electricity consumption data. There is however considerable variation across households.

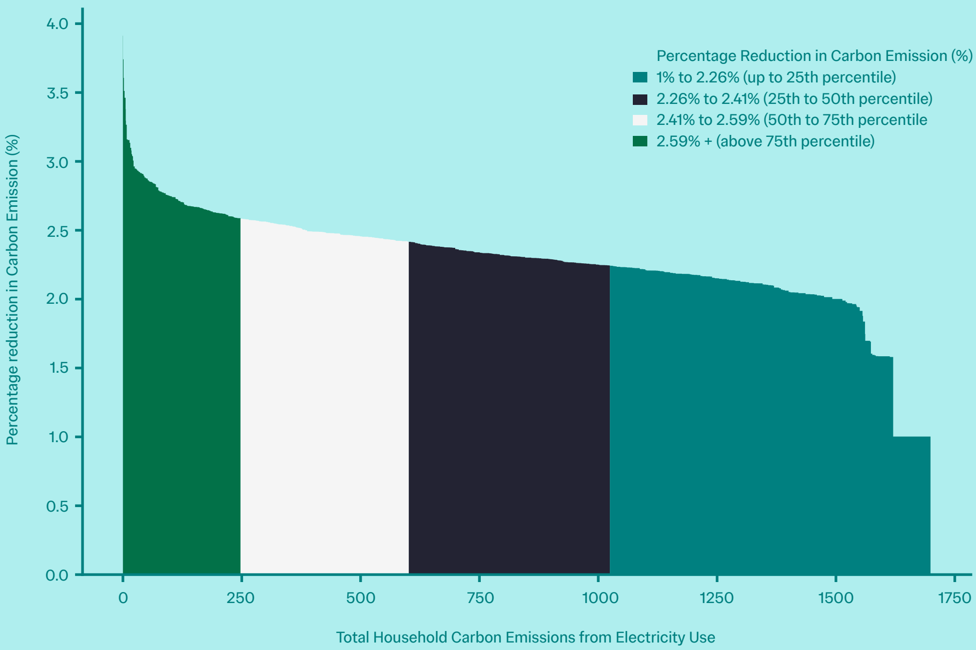
As shown in Figure 10, the percentage reduction in carbon emissions that can be achieved with the POWBAL switch-off events is larger for households with a larger emissions footprint.

[9] We conduct this exercise for the 360 participating smart meter users in Delhi and 144 participating smart meter users in Mumbai for whom we received one full year of half-hourly household-level electricity consumption data from Tata Power.

Figure 11 reports the resulting in the net marginal abatement cost schedule.[10] For more than 75% of the households the net mitigation costs are in fact negative. The mitigation costs will be higher for households that consume very little via the plugs at times when ME factors are high.[11]

Using data from the smart meters, we find that the electricity usage patterns of households that did not participate in POWBAL closely mirror those of households that did participate. If the nearly 250,000 residential smart meter users of Tata Power participated in POWBAL, 84,177 tons of CO_2 mitigation could be achieved at negative cost.

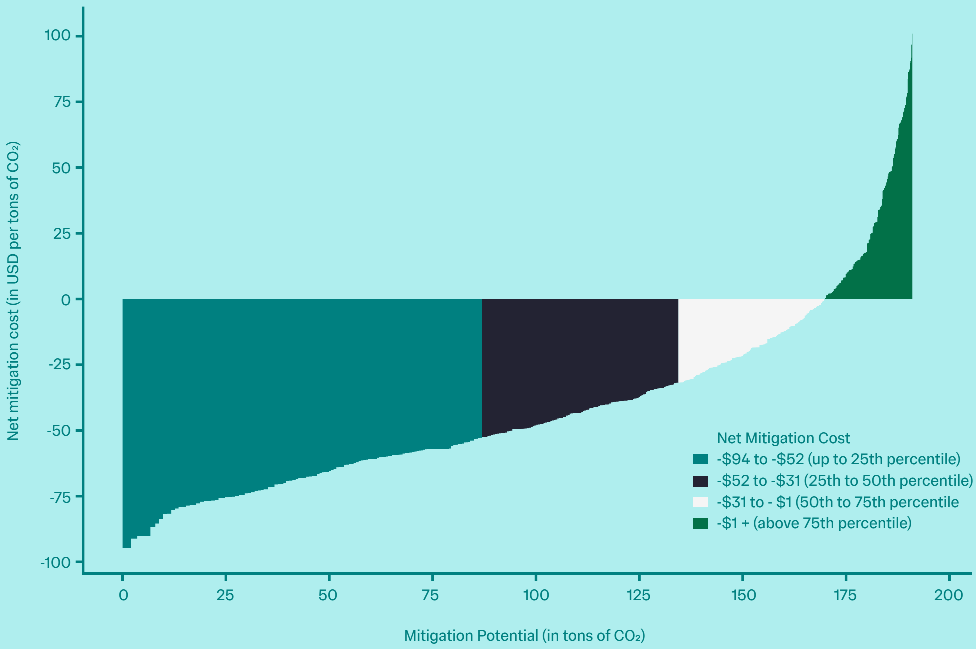
Figure 10: *Reductions in CO_2 emissions from household electricity use: Counterfactual Analysis*



Note: The figure plots the counterfactual percent reduction in carbon emissions because of the POWBAL setup for the distribution of 504 households in our sample against their total carbon emissions from electricity use (in tons of CO_2). In our counterfactual scenario, a switch-off event is conducted for the 30 minute-period in every three-hour window in 2023 when the estimated marginal emissions factor is the highest. We assume that households use the smart switch for five years and the same emission reductions can be achieved by repeating the schedule of switch-off events every year over that period.

[10] To obtain marginal abatement costs we consider the costs of procuring and installing smart switches in individual households, which currently amounts to $24 per household. Note that this abstracts from additional costs of operating the system. However, such costs would become negligible if a POWBAL-like approach were scaled to all residential customers of TATA Power or indeed to all Indian households. For further details on the mitigation cost calculation, see Appendix D.
[11] e.g. see [CO_2 emissions abatement costs and drivers for Indian thermal power industry - ScienceDirect]

Figure 11: *Net CO_2 mitigation cost: Counterfactual analysis*



Note: The figure plots the counterfactual net CO_2 mitigation cost ($ per ton of CO_2) of the POWBAL setup for the distribution of 504 households in our sample against their mitigation potential (in tons of CO_2). In our counterfactual scenario, a switch-off event is conducted for the 30 minute-period in every three-hour window in 2023 when the estimated marginal emissions factor is the highest. We assume that households use the smart switch for five years and the same emission reductions can be achieved by repeating the schedule of switch-off events every year over that period.

4. Conclusions

How representative of a broader population are these results? While our study focuses on an urban population, the analysis suggests that our findings could be applicable to residential consumers in general. The key factor is that when a smart device automatically turns off an appliance, underlying differences in sensitivity to price incentives become less significant—no manual action is required to reduce consumption, and overriding the switch-off via the app still demands some effort and attention. Additionally, even within our relatively affluent urban sample, there is no evidence of substitution to other electricity uses during switch-offs. Less affluent consumers, who may have fewer alternative appliances, are even less likely to engage in substitution. Lastly, we observe no significant differences across different quartiles of household electricity use in terms of the percentage reduction during switch-offs.

Considering existing literature, our findings indicate that combining automation with price incentives can lead to greater reductions in consumption than relying on price incentives alone. (Sudarshan, 2017). A key explanation for this result is that automation reduces the cognitive burden on consumers to provide flexibility to the system.

This project is the product of a long-standing research partnership between Imperial College London and Tata Power in India, demonstrates how energy suppliers and academics can collaborate effectively to design demand response programs that maximize grid benefits while minimizing costs to consumers through careful and thoughtful design. Evidence generated by the study could facilitate a dialogue on cost-effective strategies for scaling automated demand-side management and ultimately accelerate the transition to clean, reliable and affordable energy globally. Simple and innovative IoT-based technologies for automated electricity demand management have the potential to significantly reduce the carbon footprint of the energy sector by shifting consumption to times when power generation is less carbon-intensive, while also offering cost savings.

In a large developing economy like India, which is heavily reliant on fossil fuels yet has significant potential for renewable energy, demand-side management could be crucial in managing the growing intermittency of power supply and reducing the dependence on coal in the energy mix. Furthermore, it could help lower the likelihood of outages by making electricity supply more efficient. Highly subsidized residential electricity prices help keep power affordable for households but put electricity suppliers in a difficult position, forcing them to choose between supplying power at a loss or rationing it. When utilities opt to ration power, the heavily redistributive pricing structure creates strong incentives to impose outages on low-price residential customers, particularly those who struggle the most to pay their bills. Suboptimal energy supply can consequently adversely affect long-run economic growth. The increasing share of variable renewable energy in the energy mix offers a unique opportunity to reform retail electricity prices, aligning them with the social marginal cost of electricity delivery and the varying demand for uninterrupted power throughout the day. Automation and flexibility can serve as effective tools for optimally allocating electricity to those who value it most during specific times.

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