Building Virtual Power Plants: Incentives and Automation for Demand-Side Flexibility *

Shefali Khanna† Ralf Martin‡ Mirabelle Muûls§

March 5, 2025

Abstract

Addressing renewable energy intermittency while meeting net zero emissions targets requires achieving flexibility in electricity demand. In a randomized control trial, we offer urban Indian households simple Wi-Fi-enabled smart switches that control an appliance. We trigger automated switch-off events rewarding participants per unit of energy they avoid consuming during the event that is the power they implicitly generated by not consuming. Using data from over 1,000 users, we find that switch-off events lead to a 60% reduction in appliance-level electricity usage and an 8.5% reduction in household-level electricity use during the event, with the load reduction effect being higher in hours that experience peak electricity demand. A comparison of household and device-level electricity consumption measurements indicates no evidence of leakage, where users might shift their electricity usage to other appliances not linked to the smart device. We find no evidence of load shifting effects on average implying that switch-off events reduce total consumption. Using new estimates of marginal emission factors as well as high-resolution generation cost data, we find that optimally timed and automated switch-offs could lead to meaningful emission reductions at low or even negative cost.

Keywords: electricity demand, demand-side management, automation, climate-change, renewable energy

JEL Codes: Q41, Q48

*We acknowledge technical support from Steve Todd and the Information and Communication Technology (ICT) team at Imperial College London for developing and maintaining the POWBAL web platform that we used to implement the study. We thank members of the electricity distribution company in Delhi and Mumbai for cooperating with us throughout the design and implementation of the randomised control trial. We are grateful to Ojasvi Bhardwaj, Sandra Jose, Shruti Kakade and Aditya Tomar from the Institute for Financial Management and Research (IFMR) for excellent research assistance and to seminar participants at ETH Zürich, KULeuven and Université libre de Bruxelles and participants of the 2023 CEPR Paris Symposium and the 2024 ASSA Annual Meeting for helpful feedback. We acknowledge grant funding from the International Growth Centre (IGC), Private Enterprise Development in Low-Income Countries (PEDL) and the Grantham Institute for Climate Change and the Environment at Imperial College London. This study has been registered in the AEA RCT Registry under ID AEARCTR-0009118 and has been approved by the Research Governance and Integrity Team at Imperial College London (SETREC Reference number: 6327551). All errors are our own.

†London School of Economics s.khanna13@lse.ac.uk

‡International Finance Corporation (IFC), Imperial College London, Centre for Economic Performance and CEPR; r.martin@imperial.ac.uk

§Imperial College London and CEPR m.muuls@imperial.ac.uk

1 Introduction

Decarbonizing the energy system to achieve global net-zero targets while meeting rising electricity demand requires widespread integration of renewable energy into power grids. A major challenge is the intermittent nature of renewables like solar and wind, which are variable and less predictable. Addressing intermittency often involves costly energy storage or standby conventional generation. Demand-side management offers a potentially cheaper alternative by encouraging consumers to align energy use with low-carbon or low-cost generation periods. Large industrial consumers have long participated in such programs, and schemes have been existing for lower power prices during nighttime for a long time. Scaling these efforts to include domestic and smaller commercial users could significantly aid the transition to renewables. Many household energy tasks, such as heating, cooling, laundry, and battery charging, allow flexibility in timing. As renewable intermittency leads to less predictable supply-demand imbalances, fully variable retail electricity pricing has been proposed, supported by smart meters that record real-time usage. However, effective demand management likely requires automation to avoid continued cognitive burden on consumers. Automated devices can adjust energy use based on price signals, but widespread adoption faces barriers like technical expertise and infrastructure availability. Delegated automation, where grid operators, energy retailers, or third parties manage demand via IoT devices, could simplify adoption. Such systems can work even without smart meters or flexible pricing but raise concerns about consumer privacy, control, and reliability. However, they might arise concerns by consumers about intrusion, reliability or malicious attacks.

This study explores household engagement with automated and delegated demand management through a field experiment. We partner with a large private electricity distribution company in India that operates the distribution network in parts of Delhi and Mumbai to conduct a randomized control trial. Residential customers of Tata Power are invited 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. We use a set of Application Programming Interfaces (APIs) and the POWBAL web platform we designed to monitor power consumption readings of connected appliances in real-time and to automatically trigger random 30-minute switch-off events at different times to each device. An SMS notification is given prior to each event alerting the user of the timing of the event and the potential reward per kWh. Indeed, 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. In other words, we reward consumers for the power they implicitly "generated" by not consuming in a

particular 30-minute period. We randomize within users the timing of the switch-off event, the reward rate we offer for the event and the amount of notice time we offer users prior to the event. We have sent three rounds of invites to 258,039 residential smart meter users of the company.[1] As of 31 July 2024, 512 of these had signed up for the trial, had a smart switch installed at their residence and participated. Among these customers, we see on average a 60% reduction in electricity use during the switch-off event. Using data from the households' smart meters, we find that household energy demand reduces by about 8.5% on average during switch-off events.[2] The size of the effect increases to 15% during the late afternoon and evening hours which coincide with with peaks of aggregate power demand. The observed reductions in electricity consumption at the device level closely align with those measured at the meter, 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, we find no compensating or rebound effects i.e., households consume reduced levels of electricity in periods shortly after a switch off. This finding can be interpreted as evidence of energy wastage. 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. Finally, characterizing our demand response trial as a virtual power plant where power generation corresponds to the energy consumption avoided due to switch off events, our virtual power plant generated nearly 7.35 MWh of electricity over the course of the trial. The average capacity factor of the virtual power plant is 72% in the first five minutes of the switch-off event, and drops to 40% towards the event of the event, reflecting that some consumers override the event.

This paper makes several contributions to the existing literature on demand-side management. To our knowledge, this is the first experimental trial to examine the role of incentives and automation in facilitating load shifting in a low- and middle-income country context. While only a few experimental trials have been conducted in high-income countries, their higher per-capita electricity consumption suggests greater load-shifting potential. In contrast, our study evaluates demand-side management as a tool for climate and co-pollution mitigation and energy system reliability improvements in low- and middle-income countries, where the current and projected energy and environmental outlook remains challenging across multiple dimensions. First, as has been widely documented, electric utilities in poorer countries experience high

[1] In a second phase extension, we have also invited 728,547 residential consumers without smart meters to join the trial. By the end of 2024 this led to a total of 1,051 households with installed smart switches. We will be using the full sample in a future version of this paper.

[2] Note that while having the smart meter data allows us to observe effects of the automated switch-off events on electricity consumption at the household level, they are not a prerequisite for automated load control, which can be implemented solely using Internet-of-Things (IoT) technologies such as smart thermostats, smart plugs and smart switches.

network losses and generally have a weak record of providing a reliable service (Burgess et al., 2020; Strbac and Wolak, 2017; Jha et al., 2022). Second, their energy demand, particularly for air conditioning, is growing rapidly as incomes and temperatures rise (Gertler et al., 2016; Davis et al., 2021). Third, fossil fuels, led by coal, are continuing to meet much of this growth (IEA, 2022). Finally, energy consumption supplied by fossil fuels continues to generate large global and local environmental externalities, with the effects being most pronounced in low- and middle-income countries, where the poorest populations are already experiencing higher rates of premature death (Burgess et al., 2017) and are expected to face lower agricultural output and manufacturing productivity (Burke et al., 2015; Lobell and Tebaldi, 2014). These trends suggest that that developing energy infrastructure in poorer countries with a focus on emissions reductions -such as deploying renewable energy and improving energy efficiency - could help avoid a more costly and chaotic transition in the future.

Demand-side management offers a cost-effective approach to accelerating the transition to a decarbonized energy system. Whether incentivized through dynamic electricity pricing or rewards for reducing low-value consumption, shifting electricity use away from periods with low renewable electricity production can deliver significant benefits. First, emissions are reduced by avoiding the need to bring expensive and polluting backup generators online. Second, the reduction in the cost of balancing and network reinforcement could lower energy bills. In India, utilities forward contract a large amount of generation capacity to meet the anticipated demand of only a few hours of the year. To the extent that load shifting lowers peak demand, the average cost of power procurement can be significantly reduced. Finally, load shifting can help avoid emergency response at times of system stress when margins are tight, reducing the likelihood of power cuts. Power outages are a common phenomenon in India, in part because regulated retail prices are set below cost for residential and agricultural consumers, forcing suppliers to choose between rationing or supplying electricity at a loss. Demand-side management could alleviate the pricing distortions that give rise to a less reliable electricity service, while also providing climate and local environmental benefits. 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; **?**; Fabra et al., 2021). In such cases, incentives alone may not be enough to harness any latent flexibility potential in household electricity demand. 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. This study builds on this literature by investigating the potential for demand flexibility in a fast-growing lower middle-income country, where the climate and co-benefits of a rapid transition to clean energy are large. This study develops experimental estimates of demand flexibility and the costs of power supply interruptions that could inform the design of policies on retail pricing and automated load control.

The remainder of the paper proceeds as follows. In Section 2, we detail the trial's implementation, experimental design, and the electricity consumption characteristics of the resulting sample. We discuss our empirical strategy in Section 3 and present our results in Section 4. Section 5 examines the short-run potential of our automated demand-side management approach to reduce CO_2 emissions. Section 6 discusses our conclusions and implications for policy.

2 Implementation and Experimental Design

Between March 2023 and July 2024, we invited 258,030 residential customers of Tata Power[3] via SMS, email and WhatsApp to participate in a study where they could earn rewards by using a Wi-Fi-enabled smart switch. This switch, installed by a representative from Tata Power, replaces a conventional one and allows users to remotely turn off the electricity supply to connected appliances and monitor their power consumption via the Tata Power EZ Home smartphone app.[4] Households can choose which appliance to connect to the smart switch. Approximately 74% 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

[3]Tata Power is one of India's largest private retail electricity suppliers and operates parts of the electricity distribution network in Delhi, Mumbai and Orissa. The company also has a presence across generation, transmission, and trading, as well as new energy businesses such as electric vehicle (EV) charging, home automation, solar rooftop and microgrids.

[4]A more detailed description of the implementation can be found in Appendix A

light bulbs, microwave ovens, washing machines, water pump motors and electric car chargers. Once the smart switch is installed and online, we begin monitoring power usage data through the device at a five-minute frequency using the POWBAL web platform [5], which was designed at Imperial College London. Once a customer is fully enrolled in the trial, Tata Power provides us with the household's real-time electricity consumption data from their smart meter. Starting a week after the device installation, we use the POWBAL web platform to automatically trigger random 30-minute switch-off events at varying times for each device. For each 30-minute interval between 8 AM and midnight, our algorithm determines whether a given switch turns off automatically, adhering to the following constraints: (a) no more than 2 events per day per user and (b) no more than 8 events per week per user.[6]

Participants are notified of upcoming switch-off events and can opt out through the smartphone app. They may also manually turn the device back on during the switch-off. However, if they allow the switch-off to occur, they are rewarded based on the amount of power avoided, calculated relative to the appliance's likely consumption had there been no switch-off event.[7] To assess whether power usage during switch-off events is influenced by the reward rate, we randomly assign each event a reward rate equal to either the average wholesale electricity price of INR 6 per kWh or a multiple of 2X, 3X, 4X, or 5X that amount. The text message before each event that alerts the customer of the timing also includes information about the reward associated with the event. However, we vary with equal probability the length of the notice period, so that customers receive the text message either two hours or eight hours before the start of the event.

Table 1 reports statistics on customer registrations and the type of appliances connected to the smart switch separately for Delhi and Mumbai. The share of invited customers who signed up after being invited was 1.13% in Mumbai and 0.97% in Delhi. A portion of these could not be contacted or changed their decision after signing up, and as a result the share of invited customers with devices installed and participating in the trial is lower – 0.26% in Mumbai and 0.32% in Delhi. While this paper does not focus on the adoption decision, we explain these low sign-up and conversion rates by a potential reluctance to have appliances remotely controlled by an external entity or the absence of marketing campaigns on social and traditional media. It could also be due to participation fatigue as Tata Power has invited some customers to participate in similar trials on demand-side management in recent years.

Figure 1 reports the number of connected devices and total power flow across all smart switches in-

[5]For further information, visit powbalenergy.net

[6]The power company did not permit us to conduct switch-off events during nighttime hours due to concerns about potential inconvenience to users.

[7]Rewards are earned in proportion 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.

stalled in Delhi and Mumbai since the trial commenced.[8] 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.[9]

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.

As shown in Table 1, we conducted 28,600 switch-off events, 13,982 of which were administered in Mumbai and 14,618 in Delhi. 39.5% of events in Mumbai and 36% of events in Delhi occurred at times when the power being consumed through the smart switch was greater than 0W. Of these events, 23% were overridden in Mumbai and 16% were overridden in Delhi. We define overrides as cases where the device was consuming power immediately before the event began, but the customer had either opted-out of the event on their smartphone app beforehand or immediately turned the device back on, and so there were no energy savings and therefore no reward was earned.

We aggregate the five-minute readings from all devices to the half-hour, so the dataset consists of 1,699,799 user x half hour observations. After merging these data with the smart meter readings, restricting the sample to households with at least 100 observations, and excluding values above the 95th percentile of meter-level electricity consumption, we are left with 1,379,976 observations for 512 households. We report summary statistics in Table 2. On average, 71% of devices are online at any given time. The average household in the sample consumes 332.55 Wh every half-hour, or 485.5 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). At the upper end of the distribution of meter-level electricity consumption, the maximum half-hourly household electricity use is nearly 16 times greater than at the 75th percentile implying the presence of some very large electricity consumers in the sample. The power flowing through the

[8]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.

[9]Devices could go offline if they were improperly installed (for example, the device was installed too far away from the home Wi-Fi router), or if the user performed a factory reset or permanently deleted their account on their smartphone app. Unless the user informed us of their intent to withdraw from the trial, we sent text alerts to users on a daily basis warning them that their device had gone offline with instructions on how they could bring it back online.

smart switch accounts for 13% of meter-level consumption on average. Figure 3 compares the distribution of half-hourly household-level electricity use of invited residential smart meter users that enrolled in the trial to those that did not enroll. We find that the means of these two groups are not statistically different from one another.

3 Empirical Strategy

In this section, we discuss our empirical strategy to study the effect of the switch-off events on electricity consumption both at the smart switch or device-level and at the household or meter-level as well as on overriding behavior.

3.1 Electricity consumption

We estimate the following model to study how switch-off events impact electricity consumption during the event and in the periods surrounding the event:

$$e_{i,t} = \sum_{\tau \in [-2,2]} \beta_\tau s_{i,t} + \gamma_i + \delta_{c,a,t} + \epsilon_{i,t} \tag{1}$$

where $e_{i,t}$ is the electricity consumption of user i in half-hour period t and $s_{i,t}$ is an indicator of whether a switch-off event occurs in period t. $\sum_{\tau \in [-2,2]} \beta_\tau$ is the cumulative effect of the switch-off event on electricity use beginning two periods prior to the start of the event and ending two periods after the end of the event. γ_i are user fixed effects. $\delta_{c,a,t}$ represents fixed-effect interactions between the user's city, appliance type, and specific half-hour interval. These capture systematic differences, such as how weather in each city may affect the usage patterns of various appliance types. Standard errors are clustered at the user level. With data from the smart meters, we estimate the same model using household-level electricity use for user i in period t on the left hand side. Since the power reading from the device is 0W for 55% of observations in our final data, we also estimate a Poisson version of this model and translate the effects in percentages.

We also examine heterogeneous effects by interacting $s_{i,t}$ with event characteristics, such as the time of day and the number of weeks the customer has participated in the trial, as well as customer characteristics, including the type of appliance connected to the switch and the quartile of baseline household electricity consumption to which the customer belongs. On the electronic sign-up form, users were asked to indicate whether they preferred the smart switch to remain off or automatically turn back on after each event. We interact their post switch-off preference with $s_{i,t-1}$ to test the effect on electricity use in the period following the event.

3.2 Overriding behaviour

We define overriding as a situation where a device was consuming power just before a scheduled switch-off event, but the user did not earn a reward. This could occur if they opted out of the event beforehand or immediately turned the device back on when the event began, resulting in no energy savings. To study how different event characteristics, such as the reward rate or notice period impact event overrides, we estimate the following model on a dataset where each observation is a scheduled switch-off event:

$$o_{i,t} = \beta_1 r_{i,t} + \beta_2 n_{i,t} + \beta_3 (r_{i,t} \times n_{i,t}) + \gamma_i + \delta_{c,a,t} + \epsilon_{i,t} \tag{2}$$

In equation 2, $o_{i,t}$ is an indicator for whether user i overrode the event that was scheduled to occur at time t. $r_{i,t}$ indicates the offered reward rate (i.e. 6, 12, 18, 24 or 30 INR per kWh of electricity use avoided during the switch-off event), and $n_{i,t}$ indicates the notice period (2 hours or 8 hours in advance of the event). We also explore the joint effect of the offered reward rate and notice period by including an interaction term. As in equation 1, we control for user fixed effects and fixed effect interactions of city, appliance type and the specific half-hour period. We cluster standard errors at the customer level.

4 Results

4.1 Impact of switch-off events on electricity use

Table 3 reports the results of estimating equation 1. In columns 1 and 2, we estimate Poisson regressions and the estimated coefficients are presented in log points. The dependant variable is device-level electricity consumption (in Wh). The coefficient estimate in column 1 implies a 62% reduction in device-level electricity use during the switch-off event (i.e. in period t) and is statistically significant at the 1% level. The model estimated in column 2 includes dummies for the two half-hour periods preceding the event and the two half-hour periods following the event. We observe that there is no rebound effect with device-level consumption decreasing by a further 14.62% in the half-hour following a switch-off, and 6.48% in next half-hour, both significant at 1%. The cumulative reduction in column 2 is of 83.1%. Columns 3 and 4 report the results of the equivalent OLS regressions showing in column 4 a 42.49 Wh cumulative effect of a switch-off.

Table 4 reports findings from estimating the same models as in Table 3, but includes device-level electricity consumption (in Wh) as the dependent variable in columns 1 and 2 and meter-level electricity consumption (in Wh) as the dependent variable in columns 3 to 6. The coefficient estimates in columns 1 and 2 are those of Table 3. The effect of a switch-off at the meter-level reveal an 8.13% reduction in household

electricity consumption during the event interval accompanied by a further 2.5% and 2% reductions in the following two half hours. Considering the device accounts for just over 10% of a household's average demand, these effects are substantial. When comparing columns 2 and 6, one can observe a slight substitution effect: the reduction is smaller at the meter level, implying that households might increase to a small extent consumption in other parts of their dwellings during the switch-offs, for example by increasing AC use in other rooms that those treated in the trial.

We now turn to exploring heterogeneous effects by characteristics of the switch-off events and characteristics of the users. Figure 4 illustrates the effect of switch-off events on device-level electricity consumption separately by the length of the notice period (left) and the level of the offered reward rate (right). Whether the notice period is two hours or eight hours, switch-off events consistently leads to the same reductions in device-level consumption, both at the time of switch-off and the half-hour following. Additionally, we find no significant heterogeneity in load reductions from switch-off events based on the reward rate offered. This suggests that incentives may have limited impact beyond the role of automation in facilitating the switch-offs.

Figure 5 shows the effects of switch-off events on electricity use (in Wh) at the device-level (orange -circle) and at the household-level (green-triangle) by the hour of day when the switch-off event occurs. The largest absolute reductions in electricity use during switch-off events are observed in the evening. As reflected in Table 4, the reductions at the device level do not always exactly align with those at the meter level, suggesting that households, at certain times of the day, compensate for the smart switch turning off by using other electricity loads during the event.

Figure 6 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. By comparing 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 programs could reduce peak demand and the likelihood that outages occur in the first place.

Figure 7 illustrates the effect of switch-off events on electricity use, both at t and the half-hour after, for each week that the customer spent in the trial both at the device level (left) and the meter level (right). The effects are more pronounced during the initial months but gradually diminish over time, particularly at the device level. This trend may reflect trial fatigue or changing seasonal patterns.

Figure 8 report the results separately for users whose smart switch is connected to an AC, electric geyser

and refrigerator. Using both device-level and meter-level consumption as the outcomes, we find that load reductions are largest for refrigerators. The effects are slightly smaller but more precisely estimated for air conditioners (ACs), while no significant effects are observed for electric geysers. These findings reflect the distinct usage patterns of these appliances. Refrigerators are typically connected to power continuously throughout the day, whereas AC usage depends heavily on temperature and the presence of household members. In contrast, geysers are used on-demand for short periods, particularly in the mornings, and are likely less time-flexible compared to the other appliances.

We also study the effect of switch-off events on energy use based on the user's preference as to whether their device should automatically turn back on or remain off after each event (Figure 9). At the time of device installation, we ask users for their preference and integrate it into the POWBAL algorithm when scheduling switch-off events. The top of the figure reports percentage changes while the bottom graphs show absolute effects in Wh. The effect after the event is unsurprisingly closer to zero for those that turn back on, both at the device- and meter-level.

Finally, we study the effect of switch-off events on energy use based on quartiles of household-level consumption (Figure 10). To divide households into quartiles of overall household electricity use, we regress meter-level consumption on household and month-by-half-hour fixed effects. The predicted values are used to bin users into quartiles. We then report the effects on device- and meter-level usage separately for each bin. We find that users in the upper quartiles of household electricity consumption reduce their usage more than do households in the lower quartiles. Since households in the upper quartiles are more likely to have their switches turned on for longer periods of the day, it could be more likely that they participate in switch-off events.

4.2 Impact of switch-off events on overriding behavior

Table 5 reports the results we obtain from estimating Equation 2. Columns 1 and 2 regress an indicator for an event override on the reward rate and notice period for the scheduled event, while columns 3 and 4 also include interactions between the reward rate and notice period. Columns 2 and 4 focus on switch-off events where the power reading just before the event begins is greater than zero. The estimates in column 1 suggest that offering a reward rate that is twice as high as the lowest reward rate of INR 6 per kWh is associated with a 4.9 percentage point reduction in the probability of an override and is statistically significant at the 1% level. The magnitude of the effect increases monotonically with the level of the reward rate. On the other hand, a longer notice period does not have a statistically significant effect on the probability of an override. The estimates on the interaction terms in column 3 suggest that offering a reward rate four or

five times higher than the lowest reward rate increases the marginal effect of a longer notice period on the probability of an override, although the effect is only statistically significant at the 10% level. The effects become more pronounced and significant when we consider only those switch-off events where the device was actively consuming power at the time of the event: compared to columns 1 and 3, the size of the estimated coefficients on the reward rate in columns 3 and 4 are approximately 2 times larger.

4.3 Virtual Power Plant

Demand response can be characterized as a virtual power plant where power generation corresponds to the energy consumption avoided due to switch off events. Figure 11 plots the capacity factor of our implicit virtual power plant, i.e. the fraction of potential implied power generation that has been realized across all switch-off events. The data is discretized at the level of five-minute intervals. The dotted lines indicate the beginning and start of switch off periods. On average, the power delivered to the grid is highest in the first five minutes of a switch-off event, where the capacity factor is 72%, and then drops to 40% towards the end of the event, reflecting consumers overriding the switch-off event. 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. This finding suggests that electricity may be used inefficiently by urban Indian households and highlights the potential of automated demand response to not only deliver benefits to the energy system, but to also make household power usage more efficient.

5 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.

Using detailed five-minute data on electricity system output and CO_2 emissions from electricity generation from www.carbontracker.in and hourly weather data from the ERA-5 Land product of the European Centre for Medium-Range Weather Forecasts (ECMWF), we estimate marginal emission effects for every

30-minute period in 2023 as follows:

$$CO_{2_t} = \sum_s \beta_s Q_t + \alpha_s + \epsilon_t \tag{3}$$

Equation 3 fits a model of CO_2 emissions from electricity production in India in 30-minute period t as a function of the country's aggregate electricity system output, Q, separately for four states, s: (i) above median solar radiation and low wind speed, (ii) above median solar radiation and above median wind speed, (iii) below median solar radiation and above median wind speed, and (iv) below median solar radiation and below median wind speed. α_s are state fixed effects and ϵ_t is the error term.

Figure 12 plots the distribution of the estimated 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 high ME period to a low ME period could result in a carbon saving of 0.6 tons of CO_2 .

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 analyze 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. We apply this switch-off schedule for a period of five years. [10] We summarize 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 net of any cost savings.

We find that electricity could have been delivered with 2.3% less emissions and 2.5% less cost for the 504 households in our sample for whom we have a full year of half-hourly electricity consumption data. There is however considerable variation across households as shown in Figure **??**. Figure 13 reports the resulting net marginal abatement cost schedule. [11] For almost 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

[10] 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 the power company.

[11] 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 calculation 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 the power company or indeed to all Indian households. We calculate the potential cost savings from having consumers participate in POWBAL by assuming that the power company's marginal cost of supply in each half-hour is the price of electricity in the Indian Energy Exchange (IEX). The company purchases electricity from the IEX in more than 95% of the half-hours in the year. The net marginal abatement cost for a given household is simply the difference between installation costs and cost savings divided by the reduction in the carbon emissions from their electricity use.

plugs at times when ME factors are high. Given that, as shown in Figure 3, the electricity usage patterns of households that did not participate in POWBAL closely mirror those of households that did participate, we can do the following exercise: if the 250,000 residential smart meter users of the power company had participated in POWBAL, 84,177 tons of CO_2 mitigation could be achieved at negative cost.

6 Conclusion

Simple and innovative IoT-based technologies for automated electricity demand management have the potential to make the energy sector cleaner and more efficient by shifting electricity consumption to periods when power generation is least carbon-intensive, resulting in both environmental and economic benefits. Our study, conducted in partnership with a large electricity distribution company in India, implemented a randomized experiment to assess the potential for demand flexibility among residential electricity consumers. The findings reveal that combining automation technologies with incentives can reduce household power demand by an average of 8%, a significantly larger reduction than incentives alone have been shown to achieve in similar contexts (Sudarshan, 2017). Furthermore, the results indicate minimal compensatory effects, where households offset load reductions by turning on other end uses of electricity. This suggests that smart devices can be effectively used to implement automated demand response programs even in households without smart meters, without compromising benefits to the grid.

In a large developing economy like India, which remains heavily reliant on fossil fuels but possesses significant potential for renewable energy adoption, demand-side management could play a crucial role in managing growing intermittency and reducing dependence on coal. By facilitating more efficient electricity use, such programs could also reduce the likelihood of outages and enhance energy system resilience. However, India's current structure of highly subsidized residential electricity prices, while keeping power affordable for households, forces distribution utilities to operate at a loss or resort to rationing. This creates a misalignment between energy supply and demand, disproportionately impacting low-income households through targeted outages and impeding long-term economic growth.

The growing share of variable renewable energy in the energy mix presents an opportunity to integrate automated demand-side management programs that address these inefficiencies. Future efforts should explore reforming retail electricity pricing to align with both the social marginal cost of electricity delivery and the varying demand across different times of the day. Such reforms, combined with automation and flexibility, could not only enhance the reliability and efficiency of the electricity grid but also provide a mechanism for allocating electricity to those who value it most.

Further research should investigate the long-term sustainability of these programs, including the per-

sistence of behavioral changes, the role of cultural and socioeconomic factors, and the integration of such systems with real-time grid management and renewable energy forecasting. Moreover, exploring the interaction between automated demand response and dynamic pricing models could yield valuable insights for designing scalable, cost-effective solutions to support global decarbonization goals and energy equity.

References

Alaa, M., Zaidan, A. A., Zaidan, B. B., Talal, M., and Kiah, M. L. M. (2017). A review of smart home applications based on internet of things. Journal of network and computer applications, 97:48–65.

Bailey, M., Brown, D. P., Shaffer, B., and Wolak, F. A. (2023). Centralized vs decentralized demand response: Evidence from a field experiment.

Blonz, J., Palmer, K., Wichman, C. J., Wietelman, D. C., et al. (2021). Smart thermostats, automation, and time-varying prices. Resources for the Future (RFF) Working Paper, pages 21–20.

Burgess, R., Deschenes, O., Donaldson, D., and Greenstone, M. (2017). Weather, climate change and death in india. University of Chicago.

Burgess, R., Greenstone, M., Ryan, N., and Sudarshan, A. (2020). The Consequences of Treating Electricity as a Right. Journal of Economic Perspectives, 34(1):145–169.

Burke, M., Hsiang, S. M., and Miguel, E. (2015). Global non-linear effect of temperature on economic production. Nature, 527(7577):235–239.

Coutellier, Q., Gosnell, G., Gürgüç, Z., Martin, R., and Muûls, M. (2020). Consumer-driven virtual power plants: A field experiment on the adoption and use of a prosocial technology. Grantham Research Institute on Climate Change and the Environment.

Davis, L., Gertler, P., Jarvis, S., and Wolfram, C. (2021). Air conditioning and global inequality. Global Environmental Change, 69:102299.

Fabra, N., Rapson, D., Reguant, M., and Wang, J. (2021). Estimating the elasticity to real-time pricing: evidence from the spanish electricity market. In AEA Papers and Proceedings, volume 111, pages 425–429. American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.

Gertler, P. J., Shelef, O., Wolfram, C. D., and Fuchs, A. (2016). The demand for energy-using assets among the world's rising middle classes. American Economic Review, 106(6):1366–1401.

Gilbert, B. and Zivin, J. G. (2014). Dynamic salience with intermittent billing: Evidence from smart electricity meters. Journal of Economic Behavior & Organization, 107:176–190.

IEA (2022). World energy outlook 2022. IEA Paris, France.

Jacobsen, G. D. and Stewart, J. I. (2022). How do consumers respond to price complexity? experimental evidence from the power sector. Journal of Environmental Economics and Management, 116:102716.

Jessoe, K., Rapson, D., and Smith, J. B. (2014). Towards understanding the role of price in residential electricity choices: Evidence from a natural experiment. Journal of Economic Behavior & Organization, 107:191–208.

Jha, A., Preonas, L., and Burlig, F. (2022). Blackouts in the developing world: The role of wholesale electricity markets. Technical report, National Bureau of Economic Research.

Khanna, S. and Rowe, K. (2024). The long-run value of electricity reliability in india. Resource and Energy Economics, page 101425.

Lobell, D. B. and Tebaldi, C. (2014). Getting caught with our plants down: the risks of a global crop yield slowdown from climate trends in the next two decades. Environmental Research Letters, 9(7):074003.

Nicholls, L., Strengers, Y., and Sadowski, J. (2020). Social impacts and control in the smart home. Nature Energy, 5(3):180–182.

Parrish, B., Gross, R., and Heptonstall, P. (2019). On demand: Can demand response live up to expectations in managing electricity systems? Energy Research & Social Science, 51:107–118.

Parrish, B., Heptonstall, P., Gross, R., and Sovacool, B. K. (2020). A systematic review of motivations, enablers and barriers for consumer engagement with residential demand response. Energy Policy, 138:111221.

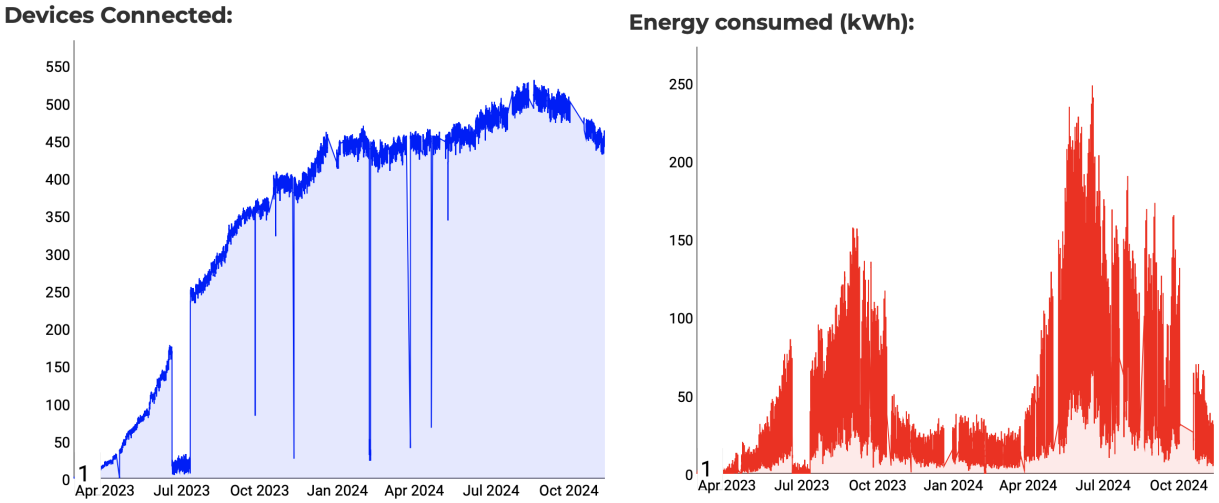
Sexton, S. (2015). Automatic bill payment and salience effects: Evidence from electricity consumption. Review of Economics and Statistics, 97(2):229–241.

Strbac, G. and Wolak, F. A. (2017). Electricity market design and renewables integration in developing countries.

Sudarshan, A. (2017). Nudges in the marketplace: The response of household electricity consumption to information and monetary incentives. Journal of Economic Behavior & Organization, 134:320–335.

Figures

Figure 1: Timeline of connected devices and energy consumption



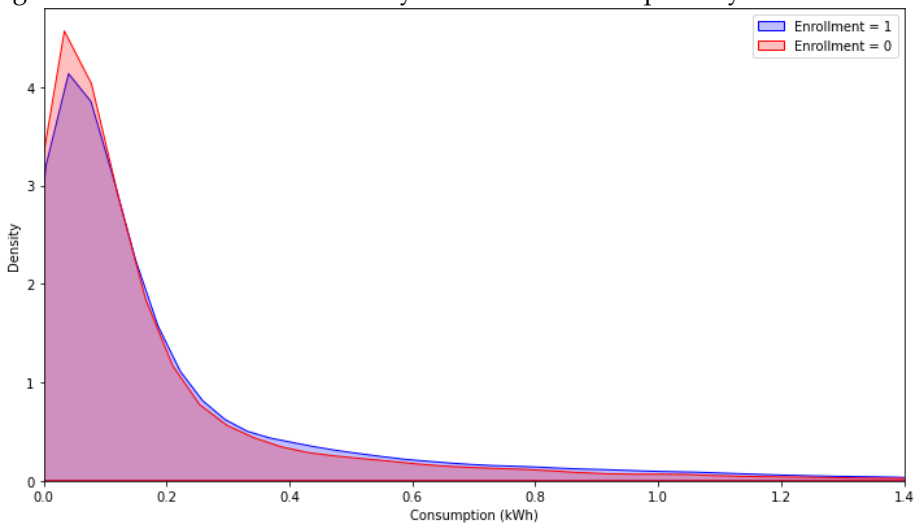
The figure reports the number of installations (dashed lines) and the total power usage (solid lines) for customers in Delhi and Mumbai over the course of the trial.

Figure 2: Mean device-level electricity use by city, month and hour-of-day



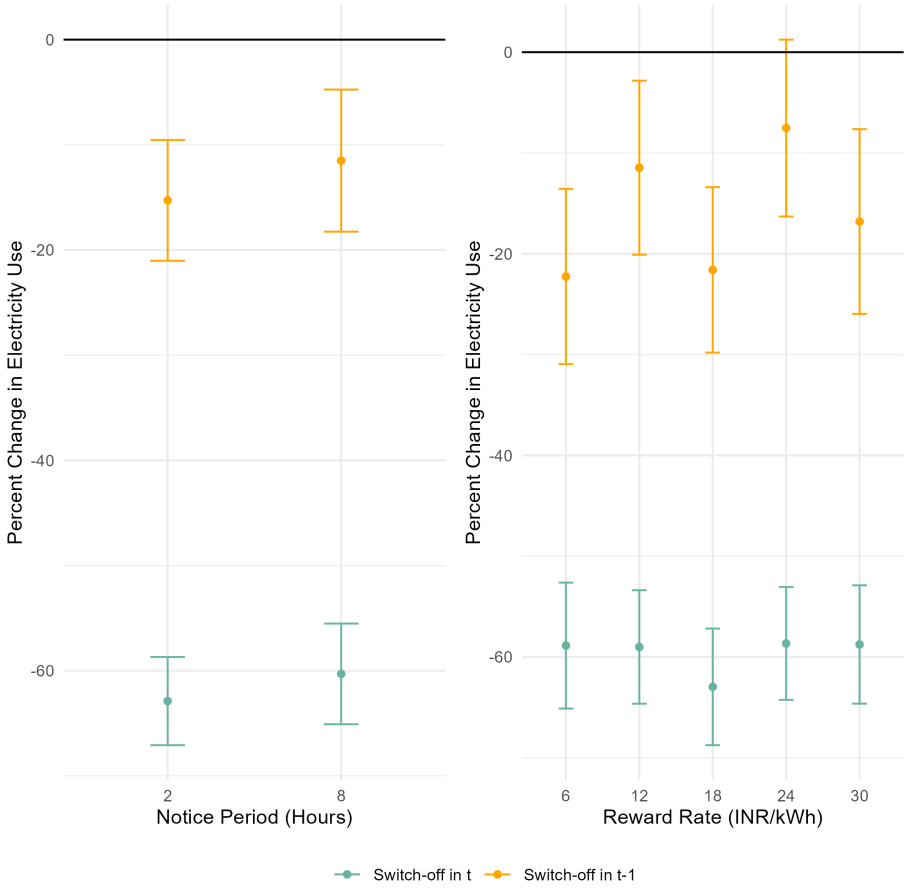
The figure presents locally estimated scatterplot smoothing (LOESS) regressions of device-level electricity use in kWh on the hour of day separately by city and month of the year.

Figure 3: Distribution of half-hourly household consumption by enrollment status



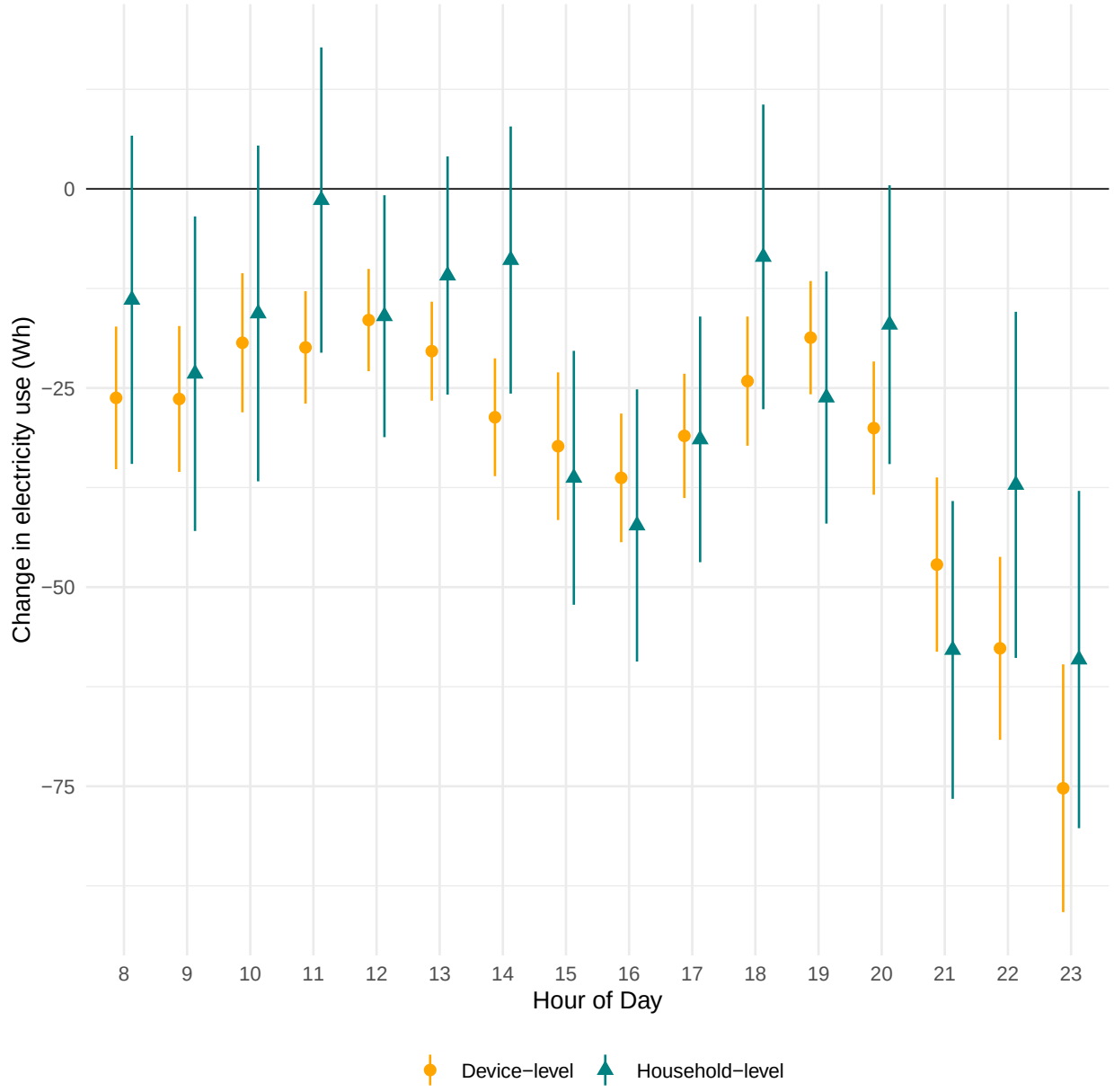
The figure presents the distribution of half-hourly household-level electricity use of invited residential smart meter users that enrolled in the trial (blue) and those that did not (red).

Figure 4: Effect of switch-off event on device-level energy use by notice time and reward rate



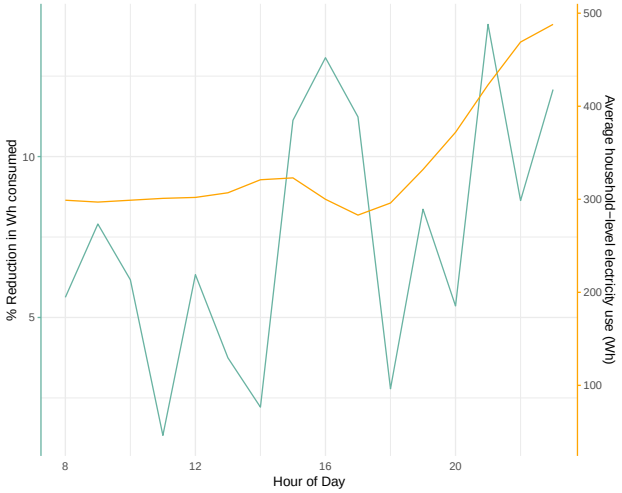
The figure plots the coefficient estimates and 95% confidence intervals of Poisson regressions of device-level electricity use on a set of dummy variables indicating switch-off events in periods t, $t+1$ and $t+2$ interacted with the length of the notice period (left) and the offered reward rate (right) 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.

Figure 5: Absolute effect of switch-off events on electricity use in Wh by hour



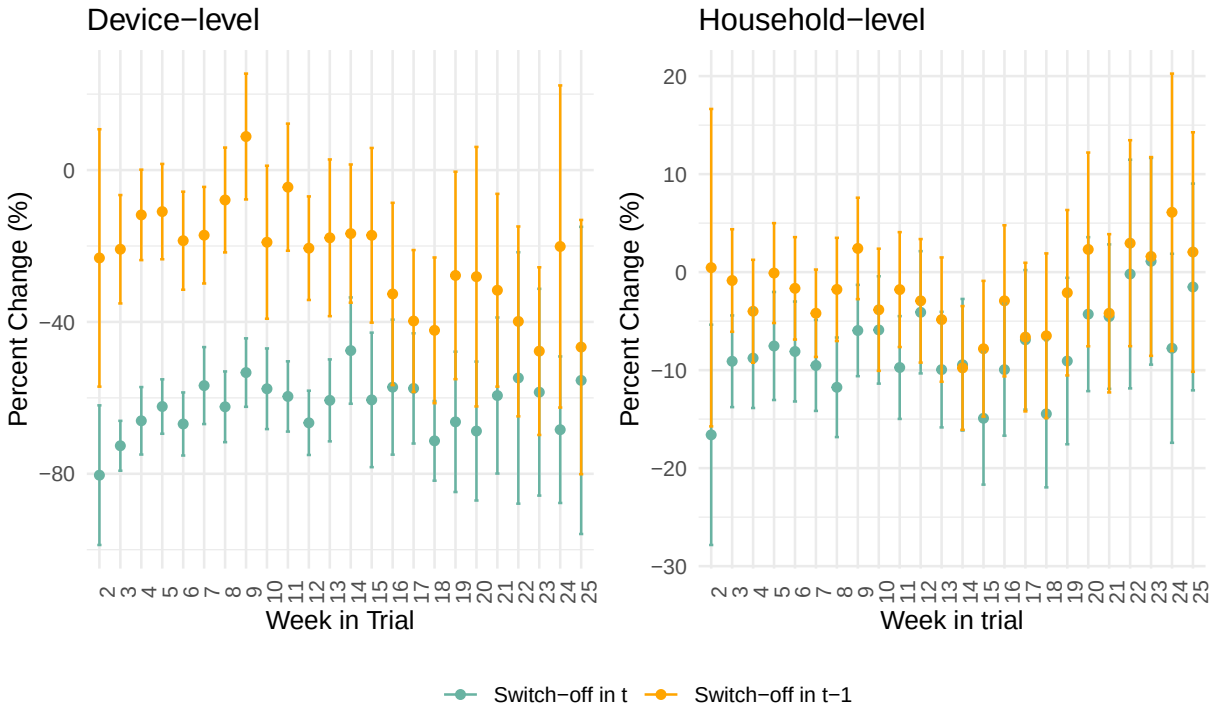
The figure plots the coefficient estimates and 95% confidence intervals of OLS regressions of device-level electricity use in Wh (left) and meter-level electricity use in Wh (right) on a set of dummy variables indicating switch-off events in periods t and $t+1$ interacted with the hour of day. The regressions control for user and city x appliance x t fixed effects and standard errors are clustered at the user level.

Figure 6: Demand flexibility potential and average residential electricity use by hour of day



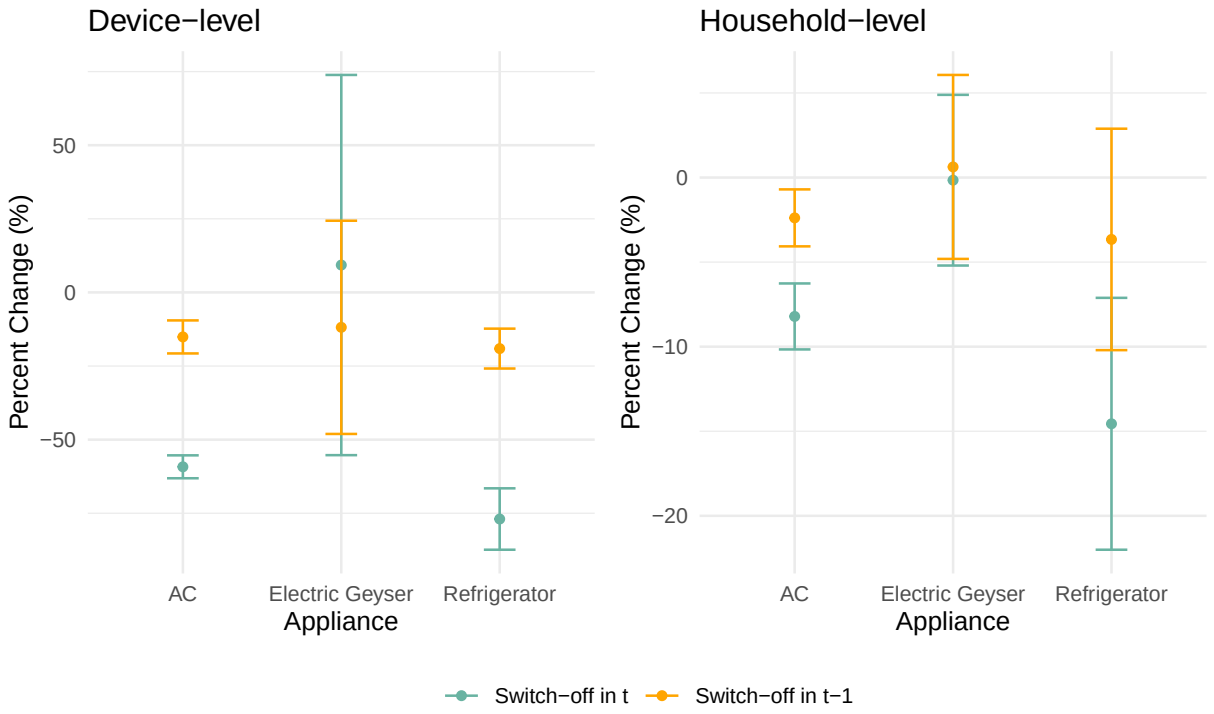
The figure plots the coefficient estimates (in percentages) of Poisson regressions of meter-level electricity use on a set of dummy variables indicating switch-off events in period t interacted with the hour of day (left) and average household-level electricity use (Wh) by hour of day (right).

Figure 7: Effect of switch-off events on electricity use by week in trial



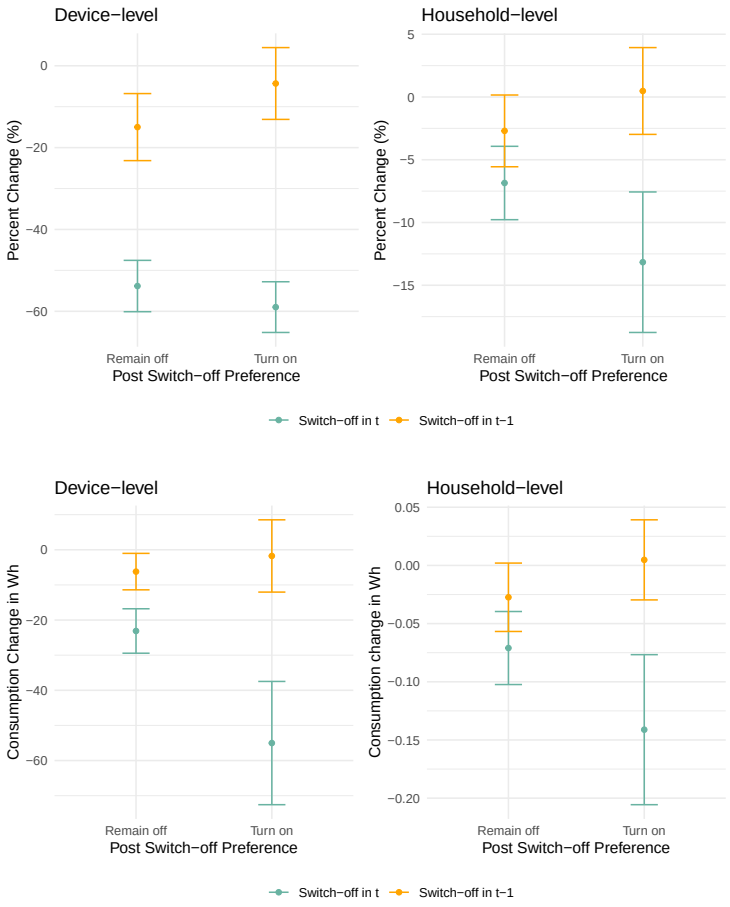
The figure plots the coefficient estimates and 95% confidence intervals of Poisson regressions of device-level electricity use (left) and meter-level electricity use (right) on a set of dummy variables indicating switch-off events in periods t and $t + 1$ interacted with the duration the customer has spent in the trial in weeks. The regressions control for user and city x appliance x t fixed effects and standard errors are clustered at the user level.

Figure 8: Effect of switch-off events on electricity use by appliance type



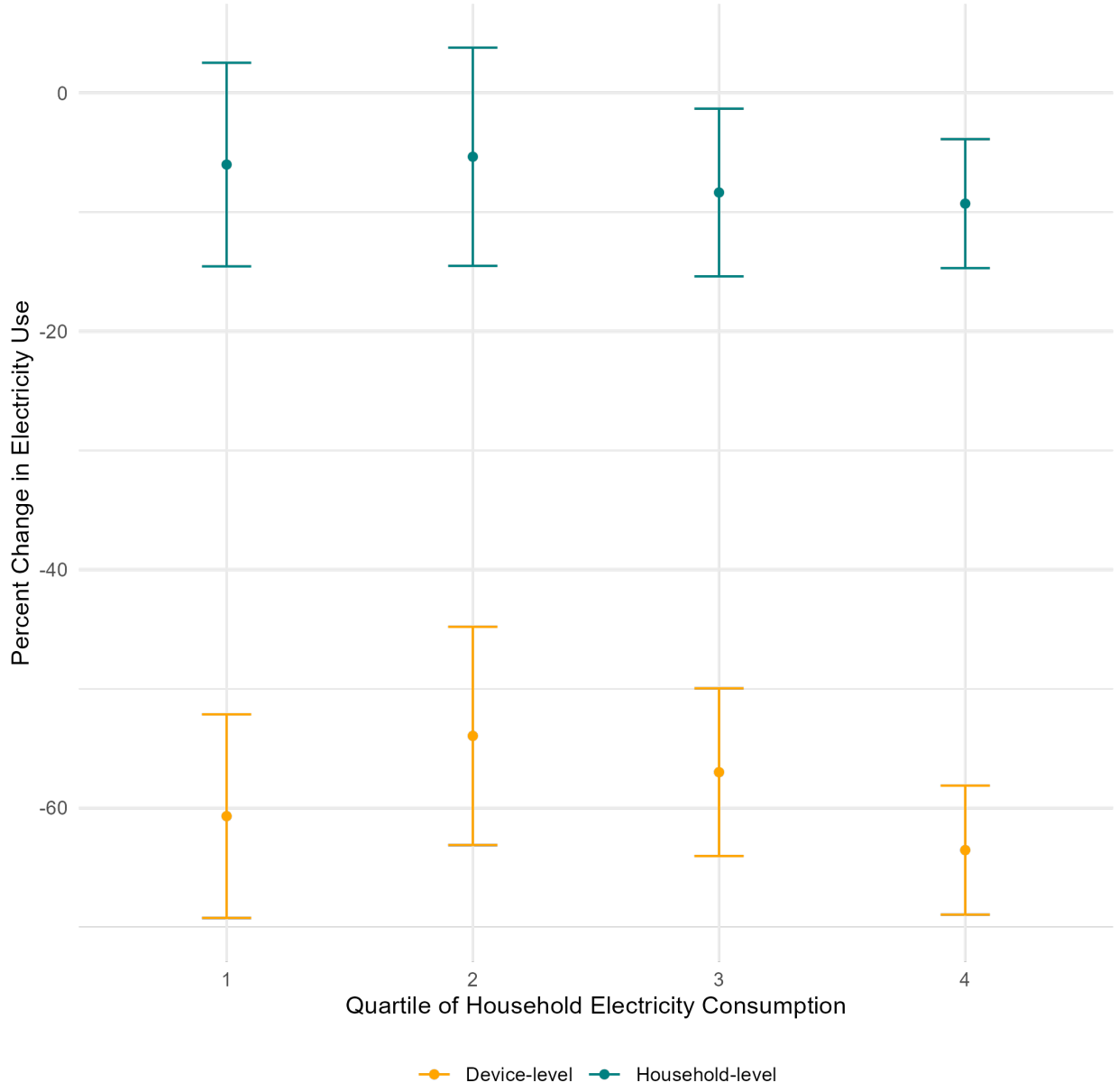
The figure plots the coefficient estimates and 95% confidence intervals of Poisson regressions of of device-level electricity use (left) and meter-level electricity use (right) on a set of dummy variables indicating switch-off events in periods t and $t+1$ interacted with whether the user's switch is connected to an air conditioner, an electric geyser or a refrigerator. The regressions control for user and city x appliance x t fixed effects and standard errors are clustered at the user level.

Figure 9: Effect of switch-off events on electricity use by post switch-off preference



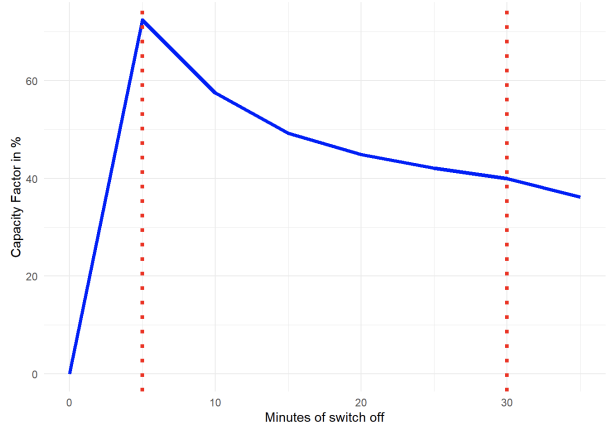
The figure plots the coefficient estimates and 95% confidence intervals of Poisson regressions of of device-level electricity use (left) and meter-level electricity use (right) on a set of dummy variables indicating switch-off events in periods t, $t-1$ and $t-2$ interacted with whether the user's opted to have their smart switch remain off or turn on automatically after each switch-off event. The regressions control for user and city x appliance x t fixed effects and standard errors are clustered at the user level.

Figure 10: Effect of switch-off events on electricity use by quartiles of meter-level electricity use



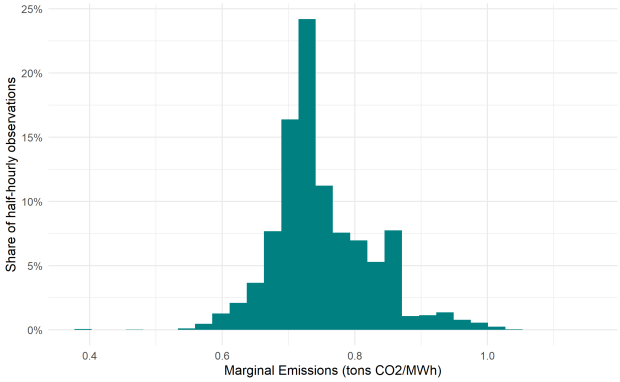
The figure plots the coefficient estimates and 95% confidence intervals of Poisson regressions of of device-level electricity use (left) and meter-level electricity use (right) on a set of dummy variables indicating switch-off events in periods t and $t + 1$ interacted with the quartiles of demeaned 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.

Figure 11: Capacity factor of virtual power plant around switch-off events



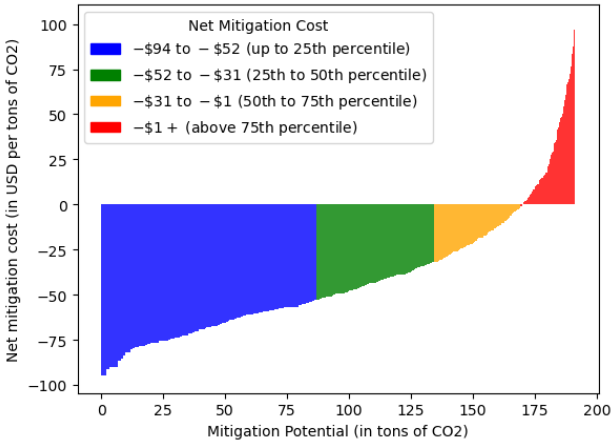
The figure depicts the capacity factor of the virtual power plant we developed via the demand response trial. The capacity factor measures the fraction of potential implied power generation that has been realised across all switch-off events. The capacity factor is calculated at five-minute intervals before and during the switch-off events. The dotted lines indicate the beginning and end of switch-off events.

Figure 12: Estimated marginal CO_2 emissions factors of the Indian power grid in 2023



The figure plots marginal emission factors (tons CO_2 per MWh) 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 electricity production and electricity system output from www.carbontracker.in and collected hourly weather data from the ERA5-Land product of ECMWF.

Figure 13: Counterfactual Analysis: Net CO_2 Mitigation Cost



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.

Tables

Table 1: City-level summary statistics

	Mumbai	Delhi
Share of invited customers who signed up	1.13%	0.97%
Share of invited customers with devices installed	0.26%	0.32%
Number of installed devices	210	375
Number of deactivated devices	23	21
Share of devices connected to air conditioners	83%	77%
Share of devices connected to refrigerators	9%	4%
Share of devices connected to geysers/water heaters	6%	12%
Number of switch-off events administered	13,982	14,618
Number of switch-off events occurring when power is consumed	5,528	5,322
Number of switch-off overrides	1,265	875
Percent of switch-off events overridden	23%	16%

The table reports summary statistics on sign-ups, installations, the types of devices connected to the smart switch and the number of switch-off events administered and overridden in Delhi and Mumbai.

Table 2: Summary statistics of half-hourly data from 512 smart switch users

	Mean	SD	Min	P25	P50	P75	Max	N
Share of devices online (%)	70.85	13.23	1.03	69.08	72.99	77.96	100.00	1,379,976
Power (W)	129.56	398.78	0.00	0.00	0.00	5.09	5,152.21	1,379,976
Non-zero power (W)	333.59	584.30	1.00	2.35	19.35	353.45	5,152.21	543,332
Device-level electricity use (Wh)	67.28	191.25	0.00	0.00	0.00	6.65	3,440.40	1,379,976
Meter-level electricity use (Wh)	349.50	389.85	0.02	110.00	200.00	459.00	7,242.00	1,379,976
Device share of meter-level electricity use (%)	13	28	0.00	0.00	0.00	4	135	1,379,976
Pre-switch-off power (W)	92.66	321.16	0.00	0.00	0.00	2.20	3,310.15	24,289
Reward earned per event (INR)	0.65	2.76	0.00	0.00	0.00	0.01	44.90	24,379
Non-zero reward earned per event (INR)	2.22	4.74	0.01	0.02	0.14	1.79	44.90	7,183
Number of events per day	0.74	0.81	0.00	0.00	1.00	1.00	2.00	1,379,976
Number of events per week	4.68	3.13	0.00	2.00	5.00	7.00	10.00	1,379,976

The table reports summary statistics on power readings, device and meter-level electricity consumption, the number of switch-off events and the earned rewards at the user x half-hour level.

Table 3: Effect of switch-off events on device electricity use

	Device level energy in Wh			
	(1)	(2)	(3)	(4)
	Poisson	Poisson	OLS	OLS
Switch Off in t	-0.9745***	-0.9754***	-32.02***	-32.03***
	(0.0524)	(0.0525)	(2.557)	(2.560)
Switch Off in t-1		-0.1580***		-7.554***
		(0.0309)		(1.652)
Switch Off in t-2		-0.0670***		-2.902**
		(0.0248)		(1.441)
Switch Off in t+1		-0.0543*		-2.176
		(0.0280)		(1.328)
Switch Off in t+2		-0.0654**		-2.643**
		(0.0299)		(1.296)
R^2	0.43722	0.43736	0.29415	0.29434
Observations	1,277,343	1,275,134	1,379,976	1,377,933
Household FE	✓	✓	✓	✓
City x Appliance x Time FE	✓	✓	✓	✓

The table reports the coefficient estimates and standard errors of Poisson regressions of device-level electricity use on a set of dummy variables indicating switch-off events starting two half-hour periods preceding the switch-off event and ending two half-hour periods following the switch-off event.

Table 4: Effect of switch-off events on device and meter electricity use in relative terms

	Device level energy in Wh			Meter level energy in Wh		
	(1)	(2)	(3)	(4)	(5)	(6)
	Poisson	OLS	Poisson	Poisson	OLS	OLS
Switch Off in t	-0.9754***	-32.03***	-0.0848***	-0.0856***	-27.24***	-27.46***
	(0.0525)	(2.559)	(0.0111)	(0.0111)	(3.827)	(3.823)
Switch Off in t-1	-0.1580***	-7.556***		-0.0253***		-8.235***
	(0.0309)	(1.652)		(0.0085)		(3.144)
Switch Off in t-2	-0.0670***	-2.904**		-0.0204**		-6.830**
	(0.0248)	(1.441)		(0.0083)		(2.980)
Switch Off in t+2	-0.0655**	-2.645**		-0.0043		-0.9910
	(0.0299)	(1.296)		(0.0087)		(2.772)
Switch Off in t+1	-0.0544*	-2.177		-0.0149*		-4.452
	(0.0280)	(1.328)		(0.0090)		(2.944)
R^2	0.43736	0.29433	0.49615	0.49624	0.44489	0.44503
Observations	1,274,826	1,377,522	1,379,506	1,377,522	1,379,506	1,377,522
Household FE	✓	✓	✓	✓	✓	✓
City x Appliance x Time FE	✓	✓	✓	✓	✓	✓

The table reports the coefficient estimates and standard errors of Poisson regressions of device and meter-level electricity use on a set of dummy variables indicating the switch-off event and the periods surrounding the event. column 1 includes the dummy for a switch-off event. Column 2 includes dummies starting a half-hour period before the switch-off event and ending a half-hour period after the switch-off event. Column 3 includes dummies starting two half-hour periods preceding the switch-off event and ending two half-hour periods following the switch-off event. The meter-level electricity consumption data is trimmed at the 95th percentiles to remove outliers.

Table 5: Effect of reward rate and notice period on override (i.e. pre-event power > 0 & reward = 0)

Dependent Variable:	Override			
Model:	(1)	(2)	(3)	(4)
Variables				
Reward rate = 12 INR/kWh	-0.0489***	-0.1174***	-0.0566***	-0.1377***
	(0.0101)	(0.0245)	(0.0110)	(0.0280)
Reward rate = 18 INR/kWh	-0.0651***	-0.1344***	-0.0678***	-0.1408***
	(0.0101)	(0.0225)	(0.0111)	(0.0255)
Reward rate = 24 INR/kWh	-0.0676***	-0.1632***	-0.0757***	-0.1784***
	(0.0097)	(0.0229)	(0.0109)	(0.0271)
Reward rate = 30 INR/kWh	-0.0693***	-0.1696***	-0.0776***	-0.1933***
	(0.0106)	(0.0253)	(0.0119)	(0.0284)
Notice time = 8 hours	0.0026	-0.0033	-0.0152	-0.0469*
	(0.0051)	(0.0113)	(0.0118)	(0.0266)
Reward rate = 12 INR/kW × Notice time = 8 hours			0.0260*	0.0664**
			(0.0138)	(0.0337)
Reward rate = 18 INR/kW × Notice time = 8 hours			0.0091	0.0233
			(0.0138)	(0.0342)
Reward rate = 24 INR/kW × Notice time = 8 hours			0.0269*	0.0502
			(0.0144)	(0.0354)
Reward rate = 30 INR/kW × Notice time = 8 hours			0.0279*	0.0794**
			(0.0144)	(0.0338)
Fixed-effects				
User	Yes	Yes	Yes	Yes
City × appliance × t	Yes	Yes	Yes	Yes
Fit statistics				
Sample	All events	Pre-switch-off power > 0	All events	Pre-switch-off power > 0
Observations	28,593	10,889	28,593	10,889
R^2	0.41379	0.69234	0.41406	0.69290
Within R^2	0.01160	0.03767	0.01205	0.03941

Clustered (user) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

The table reports the coefficient estimates and standard errors from OLS regressions of an indicator for an event override on characteristics of the event. The models in column 1 and 2 regress the override indicator on the level of the offered reward rate and the length of the notice period associated with the event. The models in column 3 and 4 also include interactions between the values of the reward rate and notice period. Columns 2 and 4 restrict the sample to switch-off events where the power reading immediately before the event started is greater than 0W.

A Implementation details

The implementation of the trial proceeded in five steps as illustrated in Figure 14. First, the power company we partnered with shared with us customer account numbers of their nearly 250,000 residential customers with smart meters, which accounted for a tenth of their residential customer base, as well as those of 650,000 residential customers without smart meters. The company did not share any contact information of these customers with us. We created sign-up links linked to the customer account number, which these customers could use to enroll in the trial. The power company sent messages with the respective sign-up links to these customers via SMS, email, and WhatsApp. The sign-up links directed the customer to an online form hosted on the POWBAL platform that described the objectives, procedures, and benefits of participating in the trial. The form included a brief consent form and asked the customer to confirm whether they have a Wi-Fi router at their residence. The customer was also asked to select time windows (i.e. 6AM-12PM, 12PM-6PM, 6PM-12AM and 12AM-6AM) for each day of the week when they would prefer not to have any switch-off event, and their stated preferences were then incorporated into the algorithm that would later create the switch-off event schedule for their device. After filling in these details, the customer could submit the form and complete the registration process.

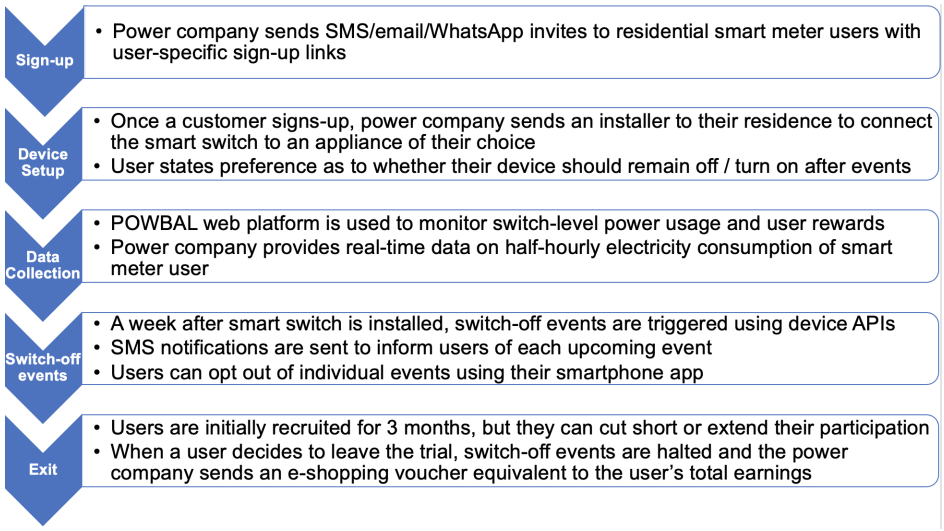


Figure 14: Implementation

The figure illustrates an individual participant's journey through the study.

Templates of the SMS, WhatsApp and email messages we sent customers inviting them to participate in the trial as well as all the other messages that were sent throughout the trial are shown in Appendix B, C and D respectively. In the recruitment message, we mention that if the customer chooses to participate in

the study, the smart switch, which the company sells for INR 4,749 (GBP 45), will be provided and installed in the customer's home at no cost to them. The smart switch we used for the trial is a product of the power company's home automation business.[12] The manufacturing cost of the device is GBP 14. The research team covered the manufacturing cost of the device as well as the installation service charges, which amounted to GBP 20 per participant. We staggered sending the invitation messages as the company only had a limited number of technicians who could install the devices, and we tried to ensure that customers did not have to wait longer than a week for their device to be installed after signing up.

Once a customer signed-up, we provided their customer account number to the power company, and the company's calling centre team called the customer to schedule a time when a technician could install their smart switch. To ensure that the SMS notifications are sent to the customer residing at the property linked to their customer account number (i.e. where the smart switch would be installed), the calling centre team also verified on the call that (a) the customer uses the mobile number linked to their customer account number, and (b) the customer is a resident of the address in which the meter linked to their customer account is installed. Once this information was verified, the technician visited the home of the customer at the scheduled time to install and configure the smart switch, which involved connecting it to an appliance of the customer's choice and to the customer's home WiFi router. The technician also provided the customer with verbal instructions on how they can remotely operate the device using the company's smartphone app.[13] Finally, the technician asked the customer whether they would prefer that their smart switch turn off or remain on after each switch-off event. In the case of a refrigerator, all users that gave us a preference opted for the device to turn back on automatically after the event, whereas in the case of electric geysers, which are generally used as an on-demand service in India, all customers opted for the device to remain off after the switch-off event. Room air conditioners may be operated continuously or intermittently depending on the temperature and whether a member of the household is present at home. Of the 267 users with ACs connected to the smart switch, 80% opted for the device to remain off after the event, while the rest opted for the device to turn back on after the event.

In order to collect baseline data on power usage through the smart switch, we triggered the first switch-off event a week after the customer's device was installed. SMS notifications were sent to inform users of each upcoming event. The messages also informed users that they could opt out of the event simply by deleting the event from their smartphone app. We posted the events to the smart switch API at the same time as when the text message was sent to the user so that they could easily delete the event from their

[12] Technical specifications of the smart switch (product code: SW07) can be found here: https://www.tatapower.com/ezhome/products/wifi-smart-30a-power-switch-convertor.aspx#tabDiv2.

[13] These instructions are also present on the participant information sheet and FAQ page, which the technician handed to the customer during the visit.

smartphone app if they wished as soon as they received the text alert. However, the power company's smart switch API only allowed us to post the switch-off events on the day of the event, which meant that we could send the text message no earlier than the day of the event as well.

Once a fortnight, we sent the user a text message with the total rewards they had earned up until that point in the trial. The message also contained a link to the POWBAL platform where they could monitor their rewards in real time. Users were initially asked to participate in the study for three months, although they were free to withdraw at any time. At the end of their first three months, the company's calling centre team called the customer to ask whether they would like to exit the trial and receive their earned rewards or extend their participation for another three months, in which case they would receive their rewards at the end of six months in the trial. Whenever a customer decided to leave the trial, we stopped administering switch-off events to the device, and a text message was sent to them with instructions on how they can redeem an e-shopping voucher equivalent to their total reward earnings.[14]

[14]Participants were provided an email address on which they could contact the research team to ask questions, express complaints or withdraw from the trial. This email address was monitored on a daily basis throughout the trial.

B SMS notifications

Sign-up:

Dear Customer, join us in taking a step towards sustainability and earn attractive rewards! Register for the POWBAL study and receive a free smart switch worth Rs 4,749 that can monitor and control power hungry devices like an AC, geyser, etc., via the internet. To learn more and register for our study, please click: {#Var#}.

Acknowledgement:

Dear Customer, thank you for signing up. We will contact you shortly to arrange a time when a technician can install your smart switch.

Upcoming switch-off event:

Dear Customer, you will earn a reward of Rs {#Var#} per kWh of energy you save via your smart switch during a {#Var#}-min switch-off event that will occur at {#Var#} on {#Var#}. To opt-out, delete the scheduled switch-off and switch-on events from the Schedule Timing page on your EZ Home App.

Earned rewards:

Dear Customer, as of {#Var#}, you have earned a total of Rs {#Var#} for the energy you saved during the switch-off events! View your current rewards on this link: {#Var#}.

Offline device warning:

Dear Customer, we noticed that your smart switch is currently offline. To reconnect, kindly follow the steps mentioned on our FAQ page: https://tata.powbal.net/faq.

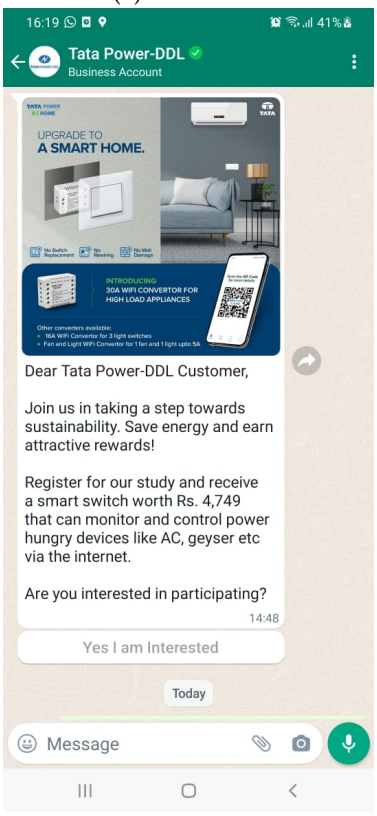
Reward voucher:

Dear Customer, Congratulations! You've earned a reward voucher worth {#Var#} for participating in the POWBAL project against CA No. {#Var#}. To claim your voucher please follow the steps here {#Var#} and enter the 16-digit alpha-numeric voucher no. {#Var#} and PIN {#Var#}. Please note that the validity of this voucher is till #Var#}.

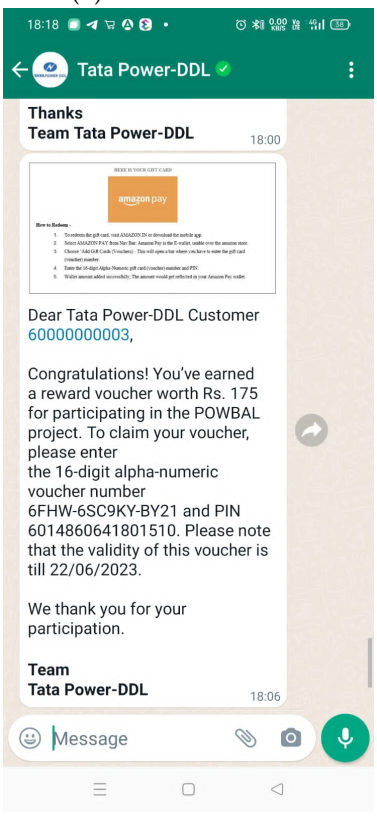
C WhatsApp notifications

Figure 15: Recruitment and reward voucher messages on WhatsApp

(a) Invitation



(b) Reward Voucher



The image on the left illustrates an example of a WhatsApp message we sent to invite users to participate in the trial. The image on the right illustrates an example of a WhatsApp message we sent to provide users with instructions on how they can redeem their shopping vouchers.

D Email notifications

Sign-up:

Subject: Save energy & earn rewards! Join the Tata Power & POWBAL study today

Dear Tata Power Customer,

We invite you to take part in the POWBAL research project as part of which you can earn rewards. POWBAL is a web platform developed by a team at Imperial College London that focuses on making the energy sector cleaner by moving power consumption to the time periods when power generation is the least carbon-intensive, leading also to cost savings. You were randomly selected from a sample of nearly 3,000 residential smart-meter users of Tata Power to be invited to participate in the study. We will be enrolling 300 participants every three months in the study. Participants will take part in the study for three months unless they choose to withdraw earlier.

How does POWBAL work?

We will install a Wi-Fi enabled smart switch in your house for free. The smart switch will be connected to a home appliance such as an AC, geyser, fans, washing machines, etc. and you can continue to use your appliance normally. Once configured to your home Wi-Fi via our Tata Power EZ Home app, you will be able to use the app to remotely control your appliance through the app, monitor your historical and real-time energy consumption via the smart switch and schedule times when you want your switch to turn on/off.

To see how flexible your energy consumption is, we will initiate short switch-off events during the day, which will automatically switch off the appliance connected to this smart switch for #Var#} minutes no more than twice a day. You will receive advance notification before every switch-off and you can opt out by deleting both the switch-off and switch-on event via the app or by turning the switch back on during the event. You will be offered cash rewards in proportion to the amount of energy saved during each event, which you can monitor on your POWBAL account.

To register please follow these simple steps:
1. Please click on the registration link here: {#Var#}.
2. Please read the participant information sheet provided.
3. Please complete the brief consent form and sign-up survey.
4. And that's it! We will install a free Wi-Fi-enabled smart switch at no cost to you.

For general queries, please see our FAQ page here: https://tata.powbal.net/faq

If you have any questions about the study, please contact us at powbal.tata@imperial.ac.uk.

We look forward to your participation in the study.

Thank you,

Tata Power and the POWBAL team

Acknowledgement:

Subject: Thank you for registering for the Tata Power POWBAL study!

Dear Tata Power Customer,

Thank you for signing up to participate in the POWBAL research project.

As a next step, Tata Power will be contacting you shortly to arrange a time when a technician can visit and install your smart switch and connect an appliance you select (e.g., ACs, geysers, etc.) at no cost to you.

The technician will also help you download the Tata Power EZ Home smartphone app and configure your smart switch to your home Wi-Fi router using the app. You can use the app to remotely control your appliance, monitor your historical and real-time energy consumption via the smart switch and schedule times when you want your switch to turn on/off.

Please note that once the switch is installed and configured, the technician will take a photo of the device ID from the Device Information page on your smartphone app for maintaining records.

How can you earn rewards?

Once your smart switch is installed, we will conduct brief automated switch-off events with the appliance connected to your smart switch to better understand your energy demand patterns and help you save energy at specified times. The switch will turn-off automatically for brief intervals, and you will be notified of each switch-off event in advance via an SMS. If you wish to opt-out of any event, you may do so by simply deleting the event from the Schedule Timing page on your Tata Power EZ Home app.

You will earn rewards in proportion to the reduction in the amount of energy your device consumed during each switch-off event relative to how much energy the device was consuming just before the event started. You will be able to monitor the rewards you earn in real time on the POWBAL web platform.

Unlike schemes where you are asked to manually turn off devices at specific times of the day, which requires attention and some effort, we are testing an automated demand response programme with Tata Power where the appliance connected to your smart switch turns off on its own at the scheduled time (provided it was on before). Therefore, you do not need to take any manual action to ensure that the device is turned off around the time of the event. We encourage you to continue using your appliance as you normally would.

As a token of our appreciation for your participation in the study, you can keep the smart switch for free after the study.

If you have any questions or concerns, please contact the research team at powbal.tata@imperial.ac.uk.

Thank you,

Tata Power and the POWBAL team

Earned rewards:

Subject: View your earned rewards!

Dear Tata Power Customer,

Thank you for participating in the POWBAL research project.

We are pleased to inform you that as of {#Var#}, you have earned a total of Rs {#Var#} for the energy you saved during the switch-off events!

As a reminder, rewards are calculated in proportion to the amount of energy you save during a switch-off event. You can monitor the rewards you earn in real time on the POWBAL web platform. To view your current rewards, click on the link here: {#Var#}

We look forward to your cooperation and participation in the study.

If you have any questions or concerns, please contact us at powbal.tata@imperial.ac.uk.

Thank you,

Tata Power and the POWBAL team

Offline device warning:

Subject: Attention required! Your smart device is currently offline

Dear Tata Power Customer,

We noticed that your smart switch is currently offline. To reconnect, kindly follow these steps mentioned on our FAQ page https://tata.powbal.net/faq:

- If your smart switch is "offline", please ensure that the Wi-Fi signal is strong enough near your smart switch (e.g., by connecting your phone or laptop to the Wi-Fi network and checking the strength near your switch).
- If your smart switch remains offline, please contact the Tata Power EZ Home customer support number at 1800-2-12345. If your switch remains offline for two days, you will be contacted by Tata Power, who will assist you in reconnecting your smart switch. If your problem is not resolved over the phone, they will arrange a time when a technician can visit your house to reconnect the switch for you.

We hope you are available to reconnect your smart switch.

We look forward to your cooperation and participation in the study.

If you have any questions or concerns, please contact us at powbal.tata@imperial.ac.uk.

Thank you,

Tata Power and the POWBAL team

Reward voucher:

Subject: Congratulations! You've Earned Rewards!

Dear Tata Power Customer,

We are pleased to inform you that you have earned a reward voucher worth Rs. {#Var#} for your participation in the POWBAL project. Your valuable contributions have played a significant role in shaping the success of this project.

To redeem your reward voucher, kindly follow the instructions provided in the link here: {#Var#}. Please enter the details below

1. 16-digit alpha-numeric voucher number: {#Var#}.
2. PIN: {#Var#}.

It's important to note that this voucher is valid until {#Var#}, so please make sure to redeem it before the expiration date.

Once again, we extend our sincere gratitude for your participation and contribution in the POWBAL project.

Best regards,

Tata Power and the POWBAL team