Shifting Household Power Demand across Time: Incentives and Automation*

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September 15, 2024

Abstract

Addressing renewable energy intermittency while meeting net zero emissions targets necessitates unlocking flexibility in electricity demand. As part of a randomised control trial, we offer urban Indian households simple Wi-Fi-enabled smart switches that control the operation of an appliance. We trigger 30-minute automated switch-offs through the smart switch, rewarding participants per unit of energy they avoid consuming during the event. 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. Furthermore, we find no evidence that higher rewards drive higher participation. Appliance-level power usage also does not return to pre-switch-off levels at the end of events, which suggests that automated demand response programmes can not only deliver benefits to the energy system, but could also make household electricity use more efficient. Taking into account new estimates of marginal emission factors and the cost of installing smart switches, we compute the average net mitigation cost of the scheme to be -\$23.1 per ton of CO_2, with negative net carbon mitigation costs calculated for nearly three-quarters of the households in our sample.

Keywords: electricity demand, demand-side management, automation

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 updating 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 also 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 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.

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1 Introduction

Decarbonising the energy system to achieve global net-zero targets requires a considerable deployment of variable renewable energy on the grid. Potential measures to address their intermittency include investment in storage as well as demand-side management. Demand-side management is a broad class of programmes designed to encourage consumers to modify their pattern of energy use. With dynamic electricity pricing, consumers can be incentivised to shift power consumption to time periods when renewable power generation is at its highest. These programmes are considered essential to accommodate (clean) energy demand growth while minimizing costs. Consumers, in particular households, use energy services that are often time flexible. Washing machines, clothes dryers, dishwashers, and immersion heaters are examples of power-intensive appliances that can potentially be shifted over time at minimal cost. In addition to using price incentives, we can now leverage a range of smart technologies such as smart thermostats that automate demand-side management and effectively lower the cognitive burden on users to participate in these programmes.

Electricity system operators are experimenting with different types of demand-side management programmes to harness demand flexibility for balancing grids with increasingly greater intermittency. For example, the UK's electricity system operator, NationalGridESO, launched the Demand Flexibility Service (DFS) in the winter of 2022/23. As part of the scheme, NationalGridESO issues a service requirement in the day-ahead or intraday market with specific time periods when demand flexibility is needed to address an anticipated imbalance between demand and supply. Electricity suppliers then ask their customers to voluntarily reduce demand during those times and receive payments for the energy savings. The consumers that participate in the scheme are providing a positive externality to the system by helping to make the grid more efficient, which justifies the reward they receive from the supplier. If the load reductions are large enough to reduce peak demand, and therefore lower the cost of power procurement, these programs can effectively pay for themselves. Over 1.6 million residential and business customers in the UK participated in the DFS, providing 350MW of flexibility to the ESO.[1]

In this paper, we study the role of incentives and automation technologies in making residential energy demand more flexible. 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 randomised control trial. Residential consumers of the company that choose to participate in the trial are provided access to simple WiFi enabled smart switches for remote control of their appliances. Using a set of APIs, we are able to monitor power flowing through the smart switch in real time and trigger automated 30-minute switch-off

[1]Further details on the NationalGridESO Demand Flexibility Service are available here: https://www.nationalgrideso.com/industry-information/balancing-services/demand-flexibility-service-dfs

events at different times for different users. We reward consumers for each kWh of electricity they avoid using during the events. We have developed a web application called POWBAL that communicates with the smart switches and provides users with a platform to monitor the rewards they earn throughout the trial. Through the power company, we send SMS notifications prior to each event alerting the user of the timing of the event and the reward they will earn per kWh of electricity they save during the event. We randomise 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 the roughly 250,000 residential smart meter users of the company. As of 30 January 2024, 734 participants have signed up for the trial and have a smart switch installed at their residence. Among consumers that signed up, we see an average of a 69% reduction in electricity use during the switch-off event and a 74% reduction in the period starting an hour before the event and ending an hour after the event. Using data on half-hourly electricity consumption from these users' smart meters, we find that switch-off events reduce household power demand by 8.5% during the event, suggesting that the overall effects are not offset by substitution to other electricity uses.[2] The size of the effect increases to 15% during the late afternoon and evening hours which coincide with higher power demand on aggregate. The absolute reductions in Watts consumed at the device level closely match those at the meter level, indicating that automated demand response trials could reliably be implemented across consumers that do not have smart meters without necessarily compromising on the benefits to the energy system. We do not find any evidence that households respond more strongly to higher reward rates. Interestingly, and contrary to expectations, we 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 implies a certain degree of wastage in how electricity is used. For example, if air conditioning units are operating without thermostatic control or are set at too high a level, a temporary switch-off event would not trigger any compensating response. Finally, interpreting 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 3MWh of electricity over the course of the trial. The average capacity factor of the virtual power plant is 73% in the first five minutes of the switch-off event, and drops to 45% 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, ours is the first experimental trial that investigates the role of incentives and automation in facilitating load shifting in a lower middle income country context. Thus far, only a handful of experimental trials have been conducted in high-income settings. While higher per-capita electricity consumption

[2]Note that while having the smart meter data allow 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 IoT technologies such as smart thermostats, smart plugs and smart switches.

in high-income countries suggests a larger potential for load shifting, we focus on evaluating the use of demand-side management as a tool for climate and co-pollution mitigation and improvements in energy system reliability in low- and middle-income countries, where the current and projected energy and environmental outlook is bleak on various dimensions. First, as has been widely documented, electric utilities in poorer countries experience high 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 generates 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 building energy infrastructure in poorer countries in a way that locks-in emissions reductions, for example, through renewable energy deployment and energy efficiency improvements, could prevent a more costly and disorderly transition in the future.

Demand-side management could provide one of many cost-effective approaches for accelerating the transition to a decarbonised energy system. Regardless of whether load shifting is incentivised by pricing electricity dynamically or by providing rewards to shut off low-value electricity consumption, shifting consumption away from periods when the share of electricity produced using renewable energy is relatively low could have many potential benefits. First, emissions are lowered by avoiding the need to bring online polluting backup generators. 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 shaves peak demand, the average cost of power procurement can be significantly reduced. Finally, load shifting can help to avoid emergency response at times of system stress when margins are tight, which would reduce 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 it at a loss. Demand-side management could potentially alleviate the pricing distortions that give rise to a less reliable electricity service, while also providing climate and local environmental benefits.

However, attempting to make demand more flexible by fixing pricing alone may be insufficient. The downside of dynamic pricing or dynamic reward schemes is that residential consumers' are often inattentive to electricity prices (Jacobsen and Stewart, 2022; Parrish et al., 2019; Sexton, 2015; Jessoe et al., 2014; Gilbert and Zivin, 2014; Houde et al., 2013). In such cases, incentives alone may not be enough to harness the latent demand flexibility that exists. Automation is increasingly being considered a low-cost opportunity to make small changes in electricity demand with potentially large electricity supply cost reductions (Blonz et al., 2021; Bailey et al., 2023; Coutellier et al., 2020). In principle, flexible prices could encourage users to adopt automation themselves, but there may be technical barriers, such as difficulty in finding installers with the requisite skills, or it may simply be a low priority for some consumers. The deployment of IoT technologies may also raise concerns of safety and data security (Alaa et al., 2017; Nicholls et al., 2020; Parrish et al., 2020). These factors may constrain the large-scale take-up needed to induce greater responsiveness to time-of-use pricing (Fabra et al., 2021). 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 describe the implementation of the trial and our experimental design. Section 3 presents summary statistics using the switch-level and meter-level electricity consumption data. We discuss our empirical strategy in Section 4 and present our results in Section 5. Section 7 discusses our conclusions and implications for policy.

2 Implementation and Design

The implementation of the trial proceeded in five steps as illustrated in Figure 1. 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. 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.

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 A, B and C 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.[3] The manufacturing cost of the device is GBP 14. We paid the company for 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.[4] 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.

Once the smart switch was installed and online, we begun monitoring power usage data through the device at a five-minute frequency via the POWBAL web platform. The power company provided us with real-time household consumption data from the smart meter after a customer signed-up for the trial. For

[3]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.

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

each half-hour interval between 8AM and midnight, our algorithm varies whether a given switch turns off automatically for 30 minutes, subject 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.[5] 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. To test whether power usage during the switch-off event is sensitive to the reward rate, we randomly assigned each event a reward rate, either equal to the average wholesale electricity price of INR 6/kWh or a rate that was 2X, 3X, 4X or 5X that level. As the power company did not permit us to turn off devices without giving any advance notice to customers, we sent a text message prior to each event alerting the customer of the timing and reward associated with the event. However, we varied with equal probability the length of the notice period, so that customers either received the text message either two hours or eight hours before the start of 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 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.[6]

In total, 720 smart switches were installed in 2023, approximately 80% of which were connected to AC units, while the rest were mostly connected to refrigerators and electric geysers. A handful of cus-

[5]The power company did not permit us to conduct switch-off events during nighttime hours as they were concerned it might inconvenience users.

[6]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.

tomers also connected the smart switch to other types of appliances, such as air coolers, light bulbs, microwave ovens, washing machines, water pump motors and electric car chargers. Table 1 reports statistics on customer registrations and the type of appliances connected to the smart switch separately for Delhi and Mumbai as of 30 November 2023. The share of invited customers who signed up was 1.13% in Mumbai and 0.97% in Delhi. As some customers could not be contacted or changed their decision after signing up, the share of invited customers with devices installed is lower – 0.26% in Mumbai and 0.32% in Delhi. These low sign-up and conversion rates could be driven by people's fears and reluctance towards having their appliances be remotely controlled by an external entity. Based on the marketing campaigns used by electricity suppliers in other countries to enroll consumers in demand flexibility programmes, advertising the trial in local newspapers or on social media could have boosted the sign-up rate. However, we instead chose to send consumer-specific sign-up links directly via SMS, email, and WhatsApp to avoid needing customers to create an account on our web platform to sign-up, which would have required them to share personally identifiable information with us. We are also reassured by the fact that the power company we partnered with has invited these customers to participate in similar trials on demand-side management in recent years, so these customers may have been more accustomed to receiving such messages.

Figure 2 reports the number of smart switch installations (dashed lines) and device-level power usage (solid lines) over time in Delhi and Mumbai since the trial commenced in February 2023. The power company has roughly 200,000 smart meter customers in Delhi, and 50,000 in Mumbai, which explains why more than 60% of participating users were based in Delhi. Given than Delhi experiences hotter summers and colder winters than does Mumbai and more than three-quarters of users had connected their smart switch to a window/wall air conditioning unit, we see a steeper incline in power usage at the onset of summer and a sharper reduction in power usage at the onset of winter in Delhi. The reduction in power usage we see in the second half of 2023 in both cities also reflects attrition as some users withdrew from the trial or their devices went offline, in which case we would not be able to receive power readings from the device or trigger switch-off events, and the user would not earn rewards. Devices could go offline if they were improperly installed (for example, the device was installed too far away from the home WiFi 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.

As shown in Table 1, as of 30 November 2023, 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.

3 Summary Statistics

We aggregate the five-minute readings from all devices to the half-hour, so the dataset consists of 1,699,075 user x half hour observations. After merging these data with the smart meter readings, we are left with 1,398,971 observations, as some data from the smart meters is missing and we exclude observations below the 5th percentile and above the 95th percentile of meter-level electricity consumption to remove outliers. We report summary statistics in Table 2. On average, 72% of devices are online at any given time. The average household in the sample consumes 332.55 Wh every half-hour, or 479 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 smart switch accounts for 11% of meter-level consumption on average.

Figure 3 plots the distribution of non-zero power consumption through the smart switch by appliance type. Power readings below 20W have been excluded to remove the large mass of observations where devices use negligible amounts of electricity, possibly indicating that they are on standby mode. 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, while a refrigerator operating at full power may consume 100-200W, a room AC operating at full power may consume 1,500-2,500W depending on its capacity and efficiency. On the other hand, electric geysers are typically used only during periods when household members need to take showers and are kept off at other times. When operating at maximum power, electric geysers consume between 1,000-2,000W, again depending on its capacity and efficiency.

Figure 4 illustrates device usage (left) and the percentage of devices that are online in each half-hour (right) by hour of day with a smooth curve fit through the data points. The u-shaped pattern in device-level electricity consumption is driven by consumers running their ACs primarily at night. The share of devices that are online increases very slightly from morning to nighttime hours. Figures 6 and 8 present device usage by day-of-week and month-of-year, while Figures 7 and 9 show the share of devices online by day-of-week and month-of-year, separately for both cities. We see a stronger seasonal pattern in device usage in Delhi, where AC usage typically peaks in June when temperatures are the highest, followed by a sharper reduction in the autumn months. The diurnal pattern in device usage is also flatter in Mumbai than in Delhi, which could be driven by differences in climate that give rise to greater nighttime AC use in Delhi. The share of devices online reduces in both cities from 90% in March to 60% in September, which is driven both by households withdrawing from the trial and by additional devices going offline due to faulty installation or being disconnected from Wi-Fi.

Figure 5 illustrates device usage (left) and the share of devices online (right) over the weeks the customer spends in the trial with a smooth curve fitted through the data points. Device usage begins to decline by the user's tenth week in the trial. While this downward trend could be explained by changing weather, fatigue may be another contributor as the share of devices online also begins to trend downward by the user's tenth week in the trial. Consumers are asked to remain in the trial for three months when they sign-up and the power company sends the e-shopping vouchers only when the customer finally leaves the trial as the power company preferred sending the users a larger reward voucher at the end of the trial rather than smaller reward vouchers throughout the trial. This decision may have led to more attrition if customers have a high discount rate and were impatient to receive their reward vouchers. However, given the relatively high socioeconomic levels of these consumers, we suspect the rewards may not have been large enough to trigger this perverse response. [7]

Figures 10 and 11 illustrate the smart switch's share of meter-level electricity consumption by hour of day and over the weeks the customer spent in the trial with a smooth curve fitted through the data points. We still observe a u-shaped pattern in this variable over the hours of the day, indicating the substantial share of household consumption accounted for by AC usage. The device's share of household consumption remains stable between 10 and 20% over the duration of the trial.

4 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 behaviour.

[7] All participants were informed at the time of sign-up that they would only receive their reward vouchers once they left the trial. This condition was also communicated on the customised page we developed for users to be able to view their current reward balance.

4.1 Electricity consumption

Since the power reading from the device is 0W for 55% of observations in our final data, we estimate a Poisson fixed effects model to study how switch-off events impact electricity consumption during the event and in the periods surrounding the event:

$$e_{i,t} = \exp(\beta_1 s_{i,t+1} + \beta_2 s_{i,t} + \beta_3 s_{i,t-1} + \gamma_i + \delta_{c,a,t} + \epsilon_{i,t}) \tag{1}$$

In equation 1, $e_{i,t}$ is the electricity consumed through the device belonging to user i in half-hour period t and $s_{i,t+1}$, $s_{i,t}$, and $s_{i,t-1}$ are indicators for whether a switch-off event will occur in the next period, is occurring in the current period, or occurred in the previous period, respectively. γ_i are user fixed effects and $\delta_{c,a,t}$ are fixed effect interactions of the user's city, their appliance type and the specific half-hour interval. 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.

We also explore heterogeneous effects by interacting $s_{i,t}$ with characteristics of the event such as the time-of-day and the number of weeks the customer spent in the trial, as well as by customer characteristics, such as the type of appliance connected to the switch and the quartile of household-level electricity consumption the customer falls into. Since we had asked users on the electronic sign-up form whether they would prefer the smart switch to remain on or turn off automatically 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.

4.2 Overriding behaviour

We define overriding as a case where a device was consuming power just prior to the scheduled switch-off event, but the user did not earn any reward as they may have opted out of the event beforehand or immediately turned the device back on at the time when the event was scheduled to begin, implying that there were 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.

5 Results

5.1 Impact of switch-off events on electricity use

Table 3 reports the results of estimating equation 1. Since we estimate Poisson regressions, the estimated coefficients are presented in log points. The coefficient estimate in Column 1 implies a 59% 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 half-hour period preceding the event and the half-hour period following the event, while the model estimated in Column 3 includes dummies for the two half-hour periods preceding the event and the two half-hour periods following the event. The estimates reported in column 2 imply a cumulative reduction of 67% in device-level electricity use, while the estimates reported in column 3 imply a 71% cumulative reduction in device-level electricity use during those time windows.

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 1-3 and meter-level electricity consumption (in Wh) as the dependent variable in columns 4-6. Note that there are 269,820 fewer observations than in Table 3 as some observations are missing in the smart meter data and we trim the sample below the 5th percentile and above the 95th percentile of meter-level consumption to remove outliers. The coefficient estimate in Column 1 implies a 60% reduction in device-level electricity use during the switch-off event. The estimates reported in column 2 imply a cumulative reduction of 60% in device-level electricity use, while the estimates reported in column 3 imply a 69% cumulative reduction in device-level electricity use during those wider time windows. Similarly, the estimates in columns 4-6 suggest that switch-off events lead to an 8.5% reduction in household electricity consumption during the event interval and a 14% reduction in household electricity consumption in the period beginning an hour before and ending an hour after the event. Since the device's share of household electricity consumption is 13% on average, we interpret the effects on meter-level electricity use as being large, which is ultimately what matters from the perspective of the energy system operator.

We now turn to exploring heterogeneous effects by characteristics of the switch-off events and characteristics of the users. Figure 12 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). Regardless of whether the length of the notice period is two hours or eight hours, we find that switch-off events reduce device-level usage by 65%. Interestingly, we find that a two-hour notice period leads to a 9% reduction in the two periods immediately preceding the event and the estimate is statistically significant at the 1% level. On the contrary, an eight-hour notice period does not have a statistically significant effect on device-level usage. The findings that users manually turn off their device when they receive a notification about an imminent switch-off event might reflect that they misunderstand the reward scheme. While this behaviour does lead to a larger load reduction than would be the case if the device turned off automatically at the scheduled time, users will not earn any reward as the electricity savings are calculated with reference to the amount of electricity the device was consuming in the five minutes before the event started. These findings suggest that a longer notice period or no notice at all would lead to a more optimal behavioural response. We do not find significant heterogeneity in load reductions caused by switch-off events depending on the reward rate that was offered for the event, which suggests that incentives may not have much of an impact beyond using automation to facilitate the switch-off events.

Figure 13 shows the effects of switch-off events on device-level (left) and meter-level (right) electricity use by the hour of day when the switch-off event is scheduled to occur. We see the largest effects on electricity use during switch-off events that occur in the morning. On average, we find a 76% reduction in device-level electricity use for switch-off events that occur at 9AM. The effect reduces to a 50% reduction by 1PM, then increases to a 65% reduction by 6PM, and then reduces again to a 50% reduction by 11PM. We do not find an effect in the half-hour interval preceding the switch-off event. The effects on meter-level consumption follow a similar pattern, although they are noisier. Figure 14 shows the absolute load reductions (in W) by hour of day as a result of the switch-off events at the device-level (left) and the meter-level (right). The reductions at the device-level closely match those at the meter-level, indicating that households do not compensate for the smart switch turning off by turning on other electricity loads during the event. The meter-level results can be interpreted as more reliable measurements of the actual impact of the switch-off events on the grid as there is less noise distorting the actual signal.

Figure 15 shows the percentage reduction in electricity consumption as a result of switch-off events by hour of day on the left axis and average hourly household-level electricity consumption (Wh) on the right axis. We see the greatest reduction in household electricity use in the late afternoon and evening hours, which coincides with higher aggregate residential power demand. If outages are more likely to occur at peak times when the distribution network is overloaded *and* household energy demand can be more flexible at times when outages are more prevalent, scaling up demand flexibility programmes could reduce peak demand and significantly reduce the likelihood that outages occur in the first place.

Figure 16 illustrates the effect of switch-off events on electricity use for each week that the customer spent in the trial both at the device level (left) and the meter level (right). The effects are large in the first couple of weeks, but then begin to reduce from the third until the ninth week, after which they increase again. In general, these estimates are fairly stable ranging from a 50% reduction in the ninth week to a 70% reduction in the third and the 18th week in the trial. Since we only began administering switch-off events after the customer's first week in the trial, we report the estimates for weeks 2. As of 30 November 2023, there were few users that had been in the trial for up to 36 weeks, but the estimates beginning in week 25 become increasingly noisy, so we report them until week 24 only. The effects on meter-level consumption are stable until week 18, after which they consistently reduce in magnitude and significance.

Figure 17 report the results separately for users whose smart switch is connected to an AC, electric geyser and refrigerator. With both device-level and meter-level consumption as the outcome, we observe that load reductions in the switch-off event period are largest for refrigerators. The effects are slightly smaller, but more precisely estimated, for ACs and we do not find any effect for electric geysers. These findings reflect the different usage patterns of these appliances. Refrigerators are typically connected to power throughout the day, while AC usage is highly dependent on temperature and the presence of household members at home. Geysers are used on-demand for short periods, particularly in the mornings, and may be more time-inflexible compared to the other appliances.

We also study the effect of the switch-off events on energy use based on the user's preference as to whether their device should turn off or remain on after each event (Figure 18). We ask users for their preference at the time when their device is installed and incorporate their preference into our POWBAL algorithm when scheduling the events. The effects on device-level usage are negative and statistically significant in the half-hour period following the switch-off event for users who decided to have their device remain off, while the effects are no longer significant for users who decided to have their device remain on. The effects follow a similar pattern with meter-level usage, but are noisier.

Finally, we study the effect of switch-off events on energy use based on quartiles of household-level consumption (Figure 19). We regress meter-level consumption on household and month-by-half-hour fixed effects and use the predicted values 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 device 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, they may be more likely to participate in switch-off events.

5.2 Impact of switch-off events on overriding behaviour

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. 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, with the effect being statistically significant at the 5% level. While columns 1 and 3 estimate the model on a dataset comprising all switch-off events, columns 2 and 4 estimate the model on a restricted sample of scheduled switch-off events where the device was consuming power greater than 0 W immediately before the event started. Compared to columns 1 and 3, the size of the estimated coefficients on the reward rate in columns 3 and 4 are approximately 2.5 times larger.

5.3 Virtual Power Plant

Demand response can be characterised as a virtual power plant where power generation corresponds to the energy consumption avoided due to switch off events. Figure 20 displays the computed capacity factor of our implicit virtual power plant. The capacity factor measures the fraction of potential implied power generation that has been realised across all switch-off events. We calculate this capacity factor at five-minute intervals before and during the switch-off events. 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, where the capacity factor is 73%, and then drops to 45% towards the end of the event, reflecting consumers overriding the switch-off event. Even after the switch-off event is over, we find that on average devices do not return to consumption levels before the switch-off event started. After minute 30, our virtual power plant provides power as shown by a positive capacity factor, which reflects that some devices remain off but even those that turn back on typically do not compensate for 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.

6 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 CO2 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.

Figure 21 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 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 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.[8] 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 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 22. Figure 23 reports the resulting in the net marginal abatement cost schedule. [9] 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 plugs at times when ME factors are high. 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

[8]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.

[9]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.

did participate. If the nearly 250,000 residential smart meter users of the power company participated in POWBAL, 84,177 tons of CO2 mitigation could be achieved at negative cost.

7 Conclusion

Simple and innovative IoT-based technologies for automated electricity demand management have the potential to make the energy sector cleaner by shifting electricity consumption to the hours when power generation is the least carbon-intensive, leading also to cost savings. A research partnership with a large private electricity distribution company in India enabled us to conduct a randomised experiment in which we will offered residential electricity consumers access to these technologies with the purpose of examining the scope for flexibility in their electricity demand. Our results suggest that automation technologies coupled with incentives could reduce household power demand by 8.5% on average, significantly larger effects than what incentives could potentially achieve on their own.[10] Moreover, the absence of compensatory effects, where households offset the load reduction at the device level by turning on other electricity end uses, suggests that smart devices can be used to implement automated demand response programmes with consumers that do not have smart meters without necessarily compromising on the benefits to the grid.

In a large developing economy like India that remains heavily reliant on fossil fuels but has significant potential to harness renewable energy to meet its power demand, demand-side management could play a pivotal role in accommodating increasing intermittency and displacing coal from the generation mix. Furthermore, it could help lower the likelihood of outages by making electricity prices more efficient. Highly subsidised residential retail prices keep electricity affordable for households, but force distribution utilities to choose between supplying power at a loss or rationing power. Moreover, when utilities choose to ration power, the deeply redistributive pricing structure creates strong incentives to allocate outages to low-price residential customers and to those who have the most trouble paying their bills. Suboptimal energy supply can consequently adversely affect long-run economic growth. The growing share of variable renewable energy in the energy mix presents an opportunity to reform retail electricity prices so that they reflect both the social marginal cost of delivering electricity and the demand for uninterrupted electricity at different times of the day, which would in turn provide a mechanism to allocate electricity to those that value it the most.

[10]For comparison, (Sudarshan, 2017) estimates a short-run price elasticity of electricity demand of -0.56 in India. The impact of peer comparison reports alone was equivalent to increasing tariffs by about 12.5 percent.

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.

Houde, S., Todd, A., Sudarshan, A., Flora, J. A., and Carrie Armel, K. (2013). Real-time feedback and electricity consumption: A field experiment assessing the potential for savings and persistence. The Energy Journal, 34(1):87–102.

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

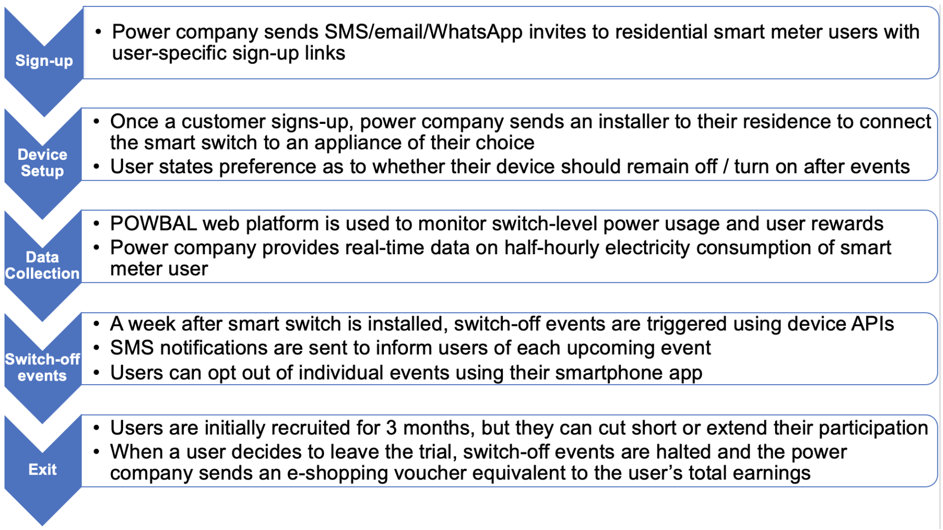


Figure 1: Implementation

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

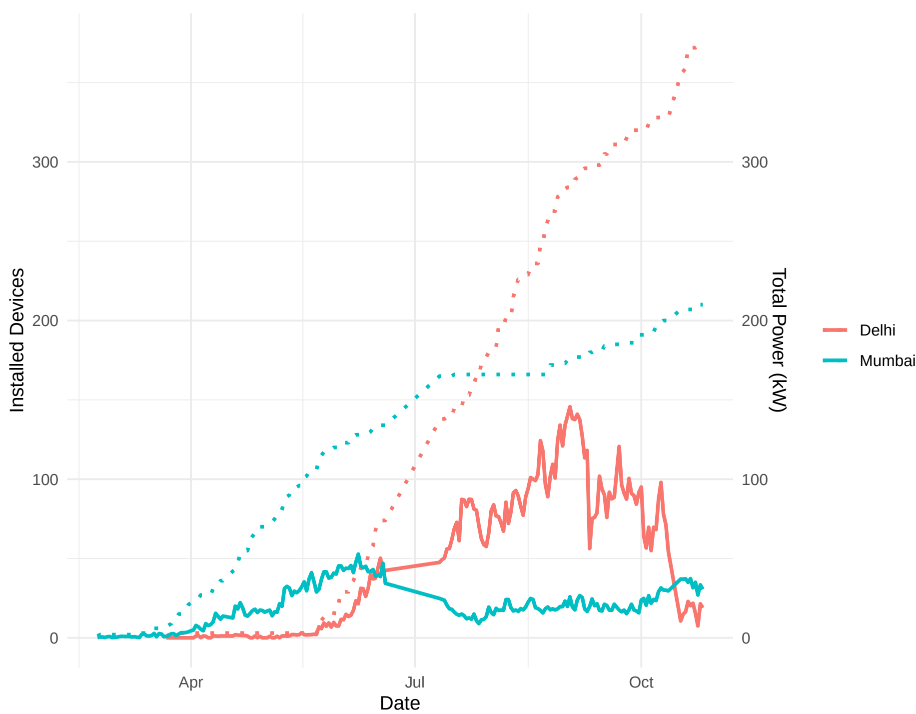


Figure 2: Timeline of installations and total device-level power

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 in 2023.

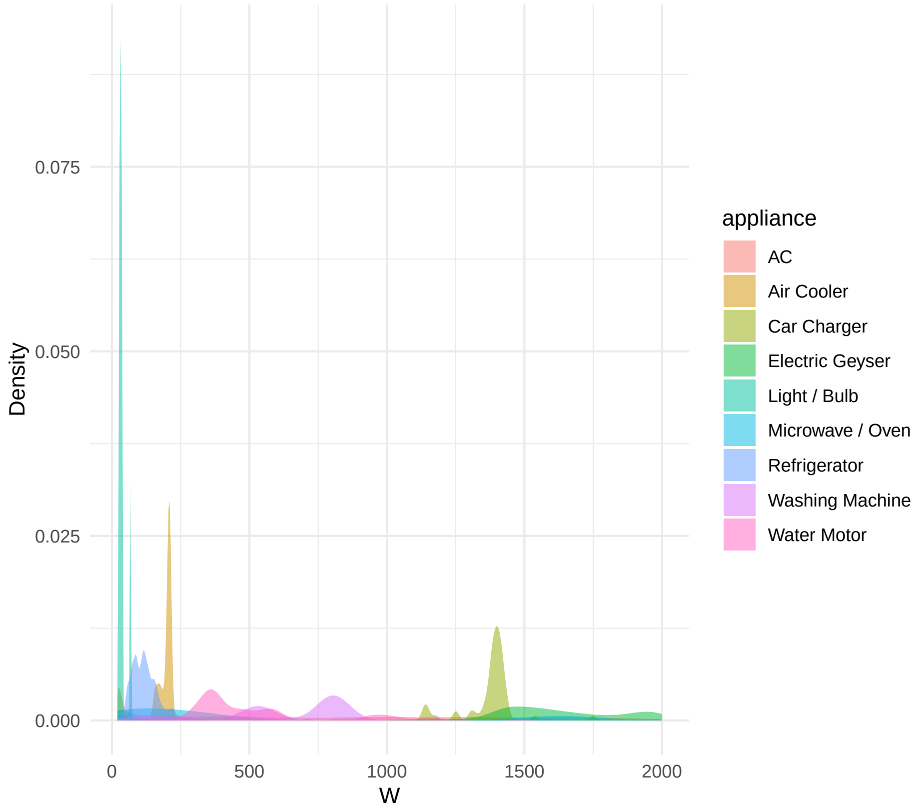


Figure 3: Distribution of non-zero device-level power by appliance type

The figure reports the distribution of non-zero power flowing through the smart switch by appliance type. Readings below 20 W and above 2,000 W have been excluded.

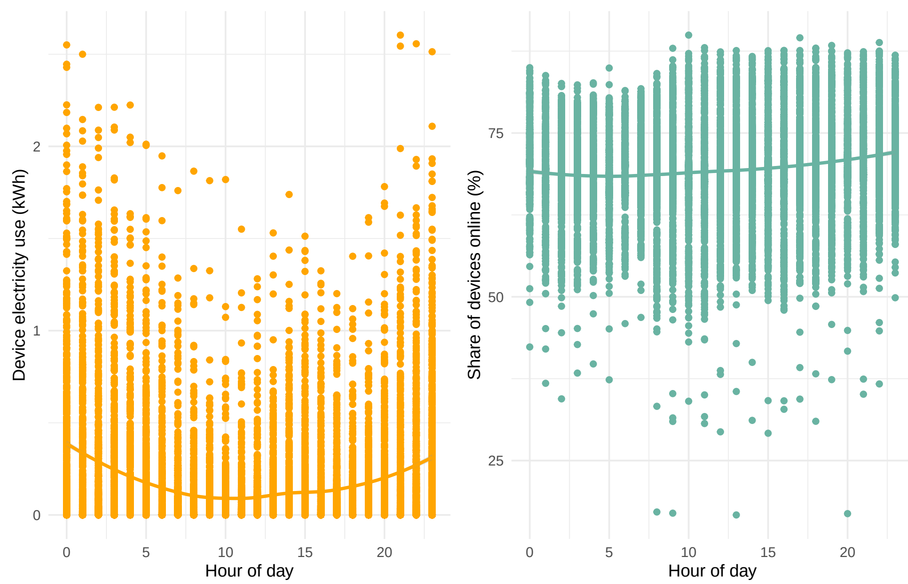


Figure 4: Device electricity use and share of devices online by hour of day

The figures present scatterplots and locally estimated scatterplot smoothing (LOESS) regressions of device-level electricity use in kWh (left) and the percentages of devices that are connected to Wi-Fi (right) on the hour of day.

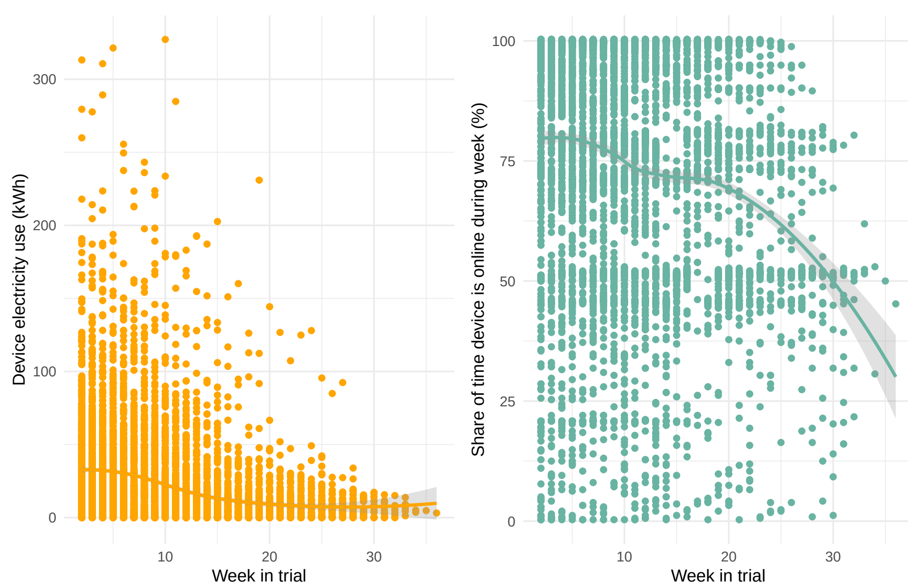


Figure 5: Device electricity use and share of devices online by week in trial

The figures present scatterplots and locally estimated scatterplot smoothing (LOESS) regressions of device-level electricity use in kWh (left) and the percentages of devices that are connected to Wi-Fi (right) on the duration the customer has spent in the trial in weeks.

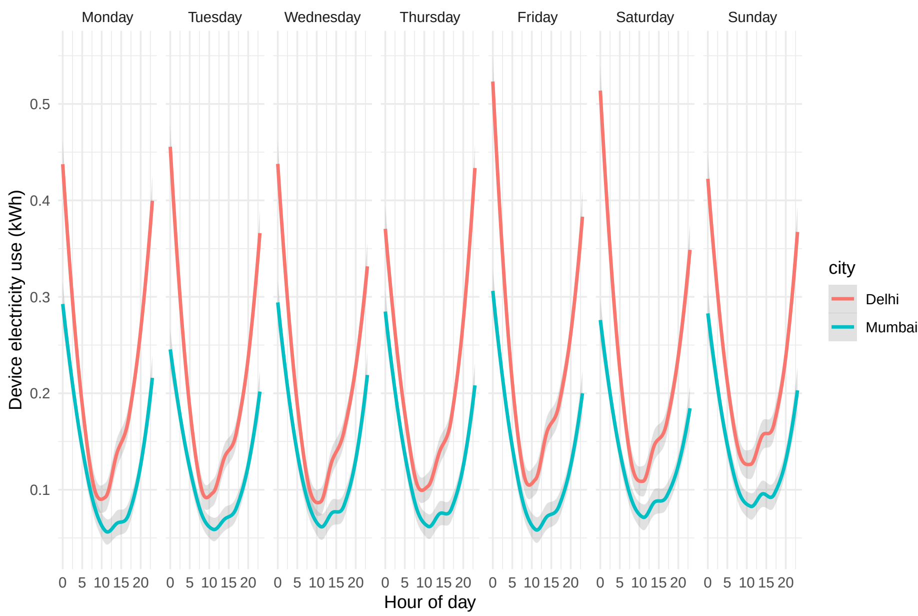


Figure 6: Device electricity use by city, day-of-week and hour-of-day

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 day of the week.

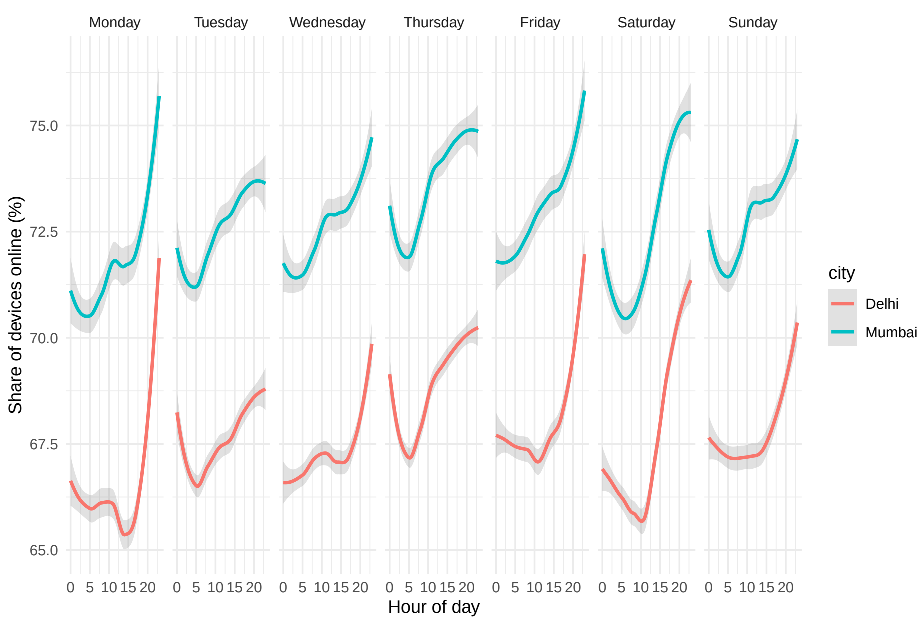


Figure 7: Share of devices online by city, day-of-week and hour-of-day

The figure presents locally estimated scatterplot smoothing (LOESS) regressions of the percentage of devices that are connected to Wi-Fi on the hour of day separately by city and day of the week.

Figure 8: Device 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.

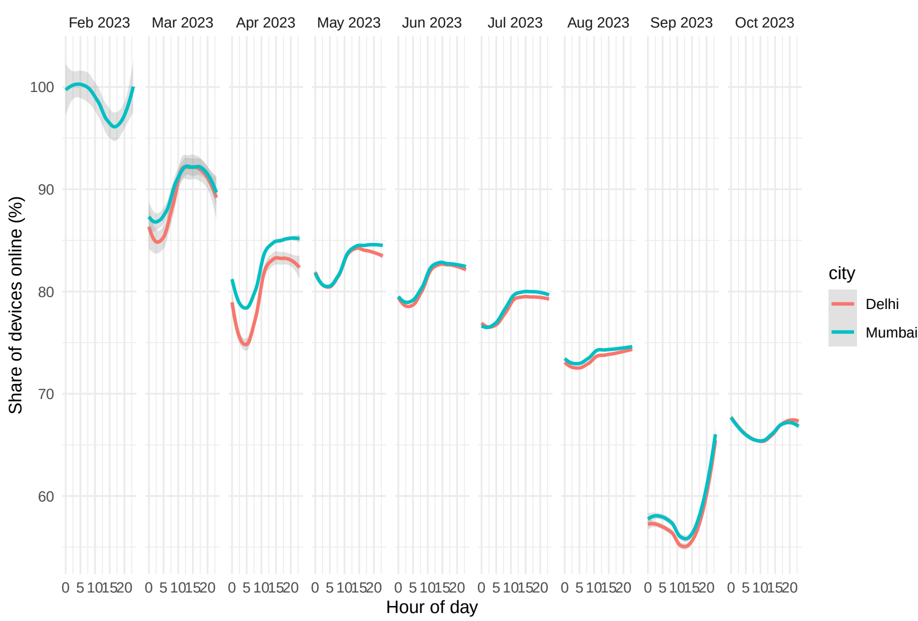


Figure 9: Share of devices online by city, month and hour-of-day

The figure presents locally estimated scatterplot smoothing (LOESS) regressions of the percentage of devices that are connected to Wi-Fi on the hour of day separately by city and month of the year.

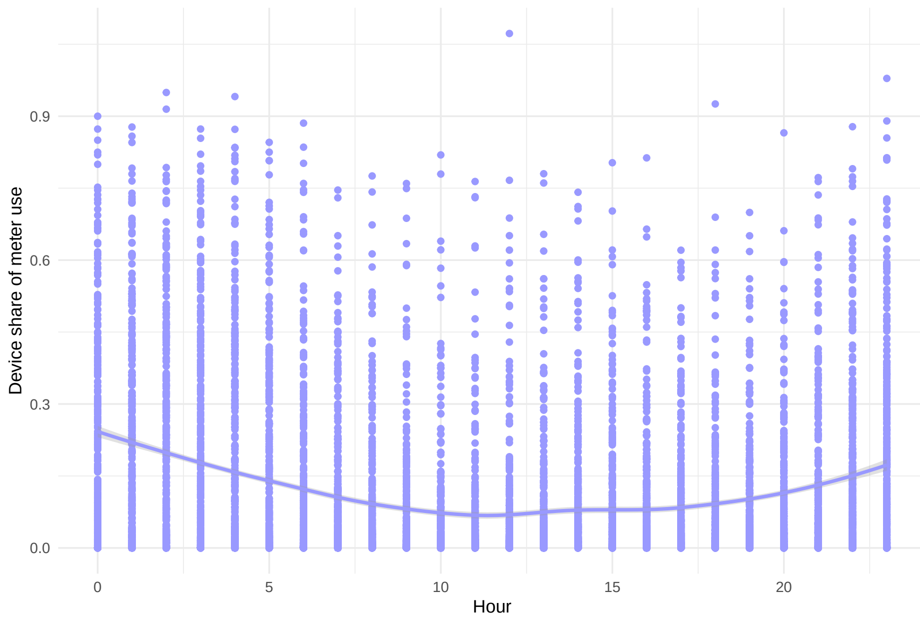


Figure 10: Device share of meter-level electricity use

The figure presents a scatterplot and locally estimated scatterplot smoothing (LOESS) regressions of the fraction of meter-level electricity use accounted for by the device on the hour of day.

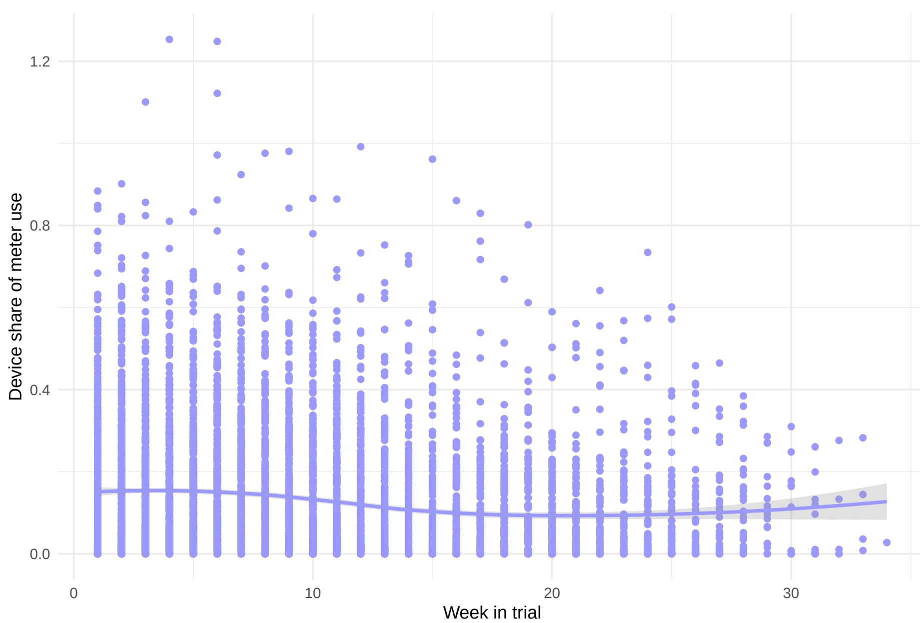


Figure 11: Device share of meter-level electricity use

The figure presents a scatterplot and locally estimated scatterplot smoothing (LOESS) regressions of the fraction of meter-level electricity use accounted for by device usage on the duration the customer has spent in the trial in weeks. The meter-level electricity consumption data is trimmed at the 5th and 95th percentiles to remove outliers.

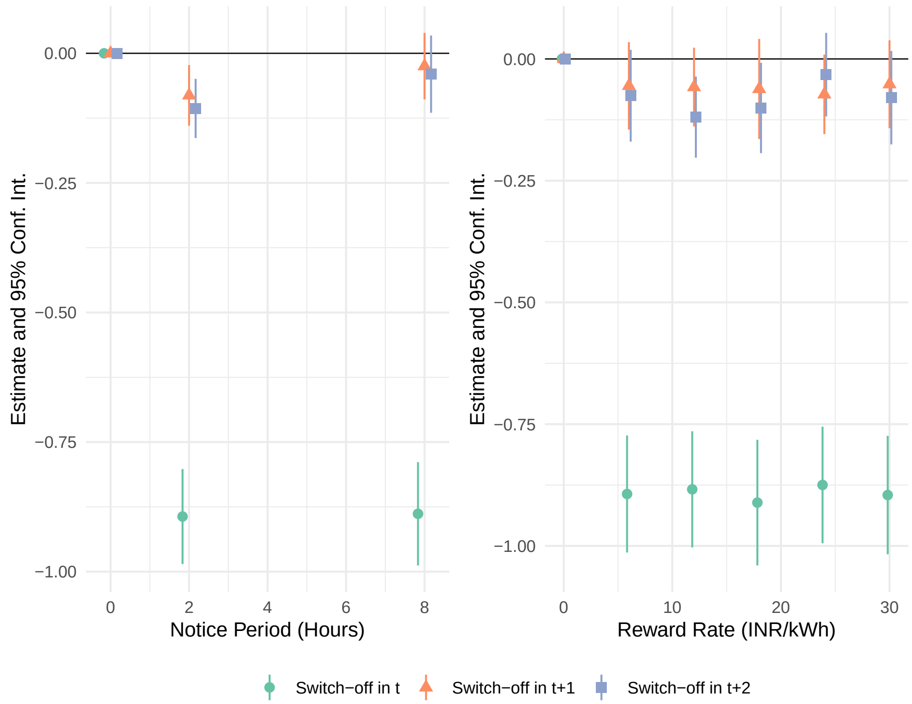
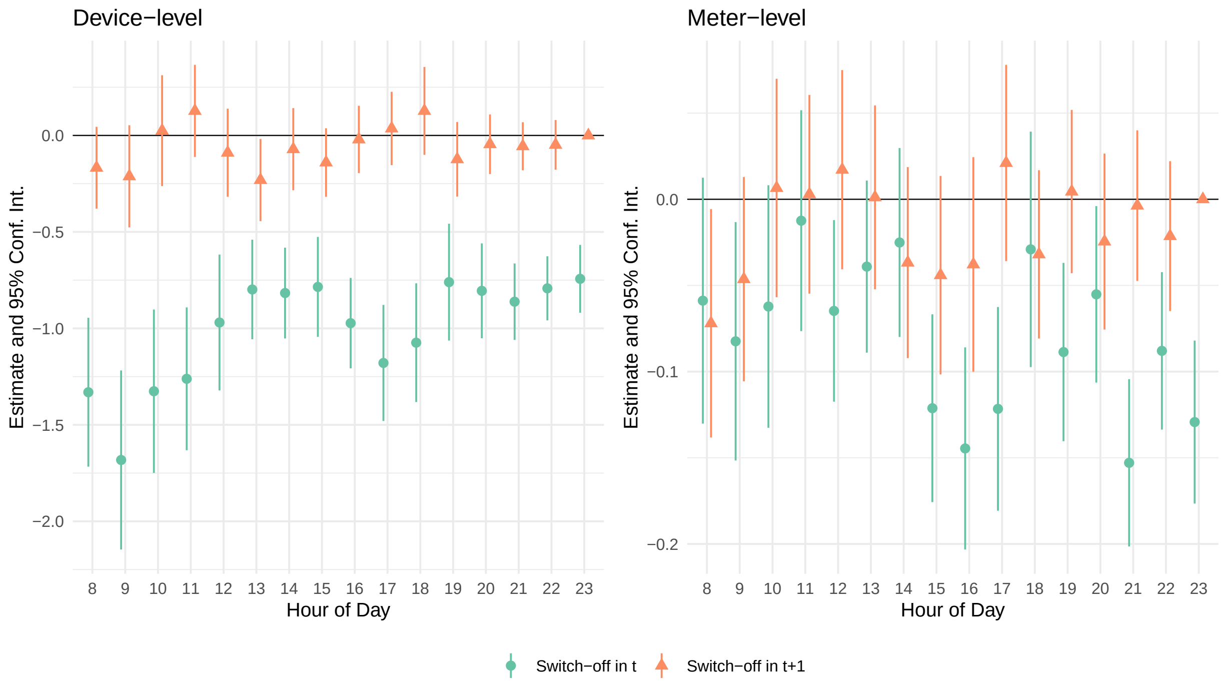


Figure 12: Effect of switch-off event on device-level energy use by notice time and reward rate

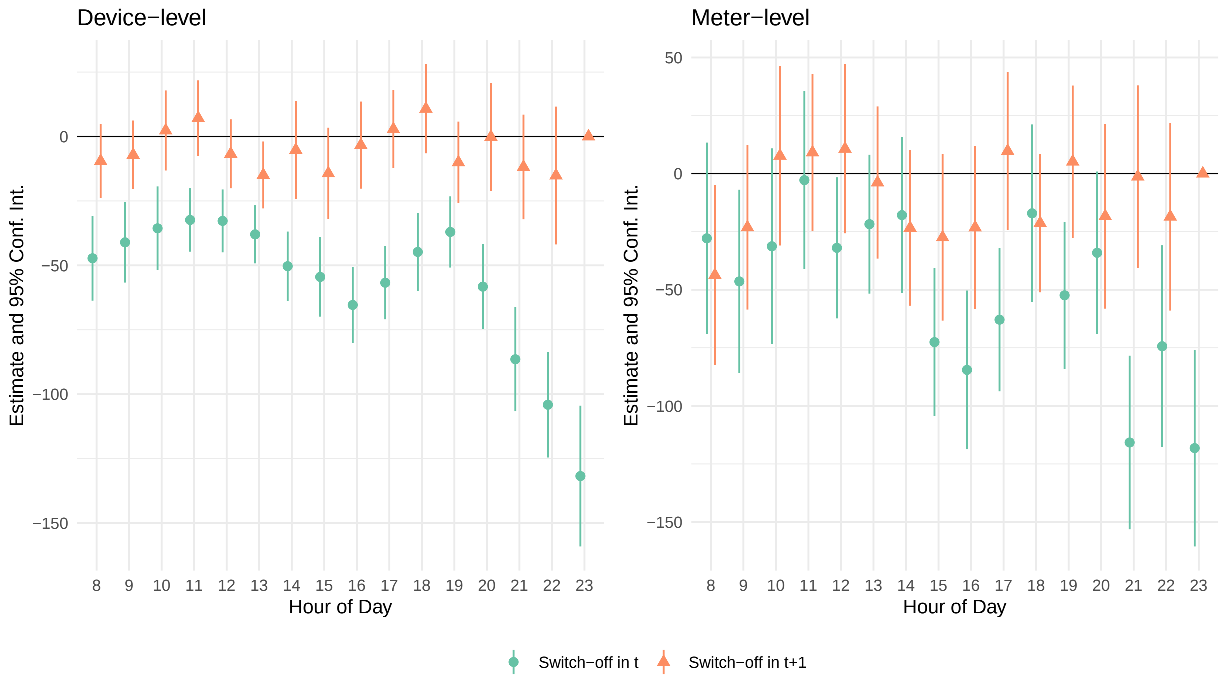
The figure plots the coefficient estimates and 95% confidence intervals of Poisson regressions of device-level electricity use on a set of dummy variables indicating switch-off events in periods t, $t+1$ and $t+2$ interacted with the length of the notice period (left) and the offered reward rate (right) 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 13: Effect of switch-off events on electricity use by hour



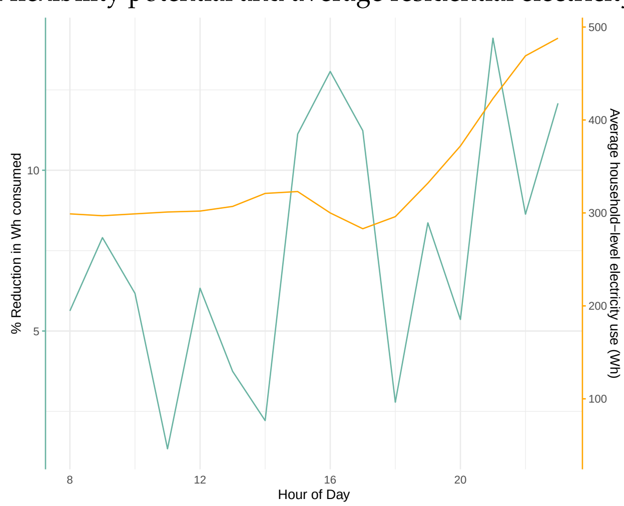
The figure plots the coefficient estimates and 95% confidence intervals of Poisson regressions of device-level electricity use (left) and meter-level electricity use (right) on a set of dummy variables indicating switch-off events in periods t and $t+1$ interacted with the hour of day. The regressions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

Figure 14: Absolute effect of switch-off events on electricity use in W by hour



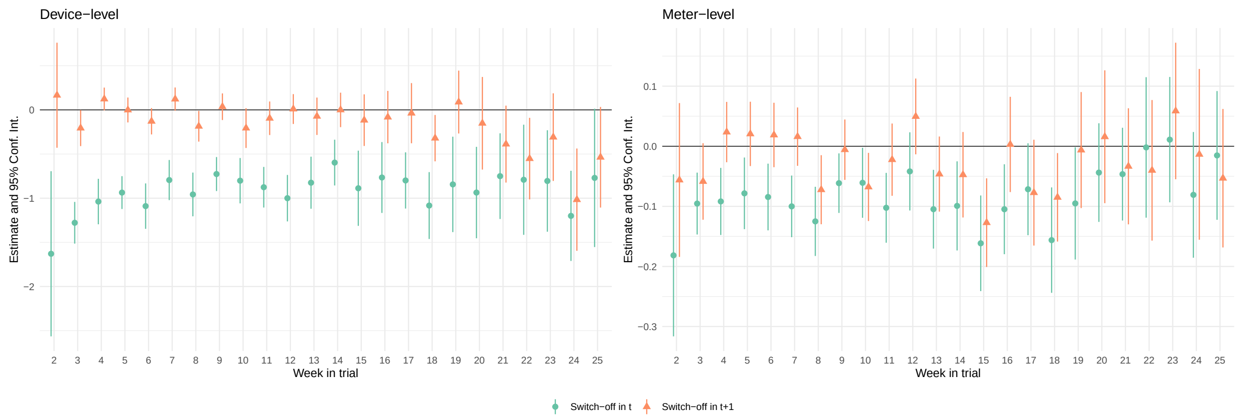
The figure plots the coefficient estimates and 95% confidence intervals of OLS regressions of device-level electricity use in W (left) and meter-level electricity use in W (right) on a set of dummy variables indicating switch-off events in periods t and $t+1$ interacted with the hour of day. The regressions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

Figure 15: Demand flexibility potential and average residential electricity use by hour of day



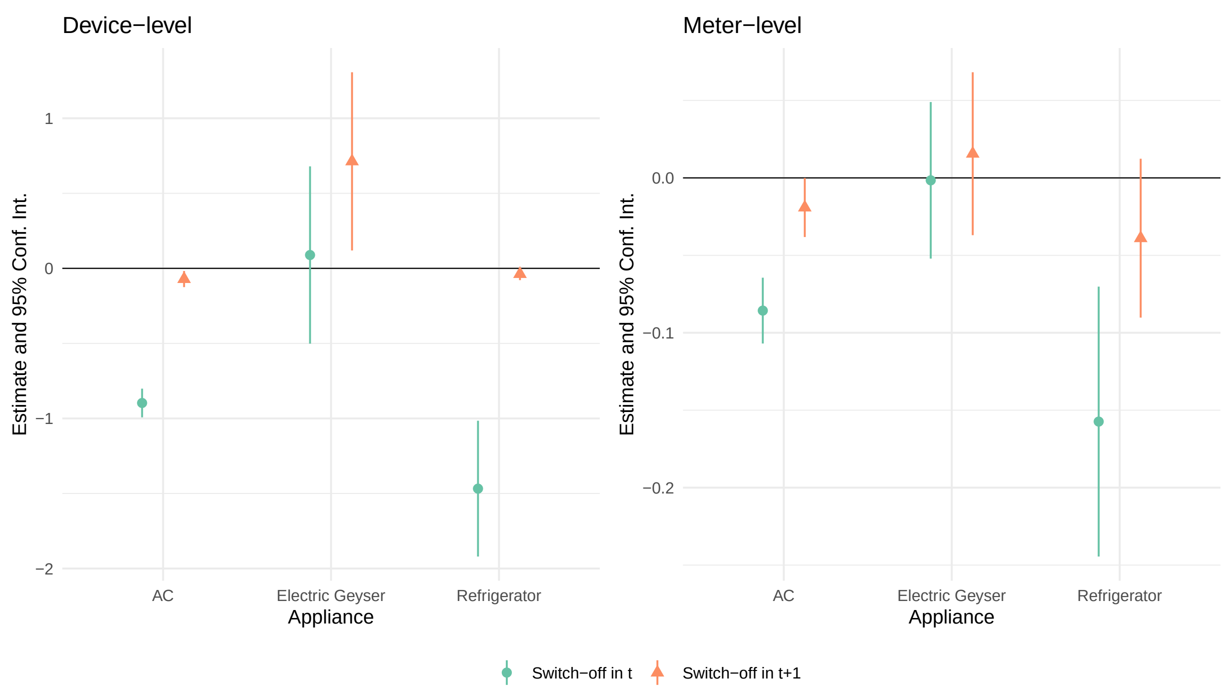
The figure plots the coefficient estimates (in percentages) of Poisson regressions of meter-level electricity use on a set of dummy variables indicating switch-off events in period t interacted with the hour of day (left) and average household-level electricity use (Wh) by hour of day (right).

Figure 16: Effect of switch-off events on electricity use by week in trial



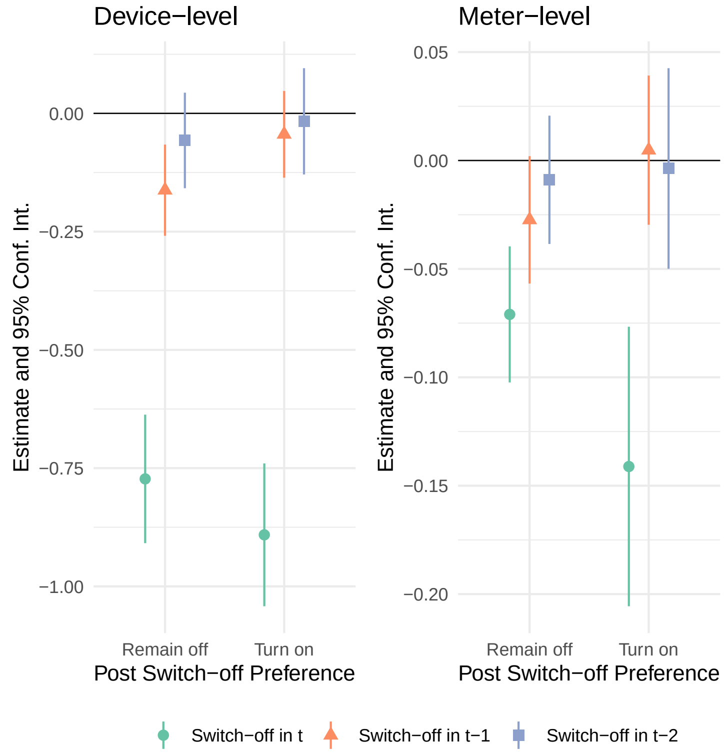
The figure plots the coefficient estimates and 95% confidence intervals of Poisson regressions of device-level electricity use (left) and meter-level electricity use (right) on a set of dummy variables indicating switch-off events in periods t and $t+1$ interacted with the duration the customer has spent 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 17: Effect of switch-off events on electricity use by appliance type



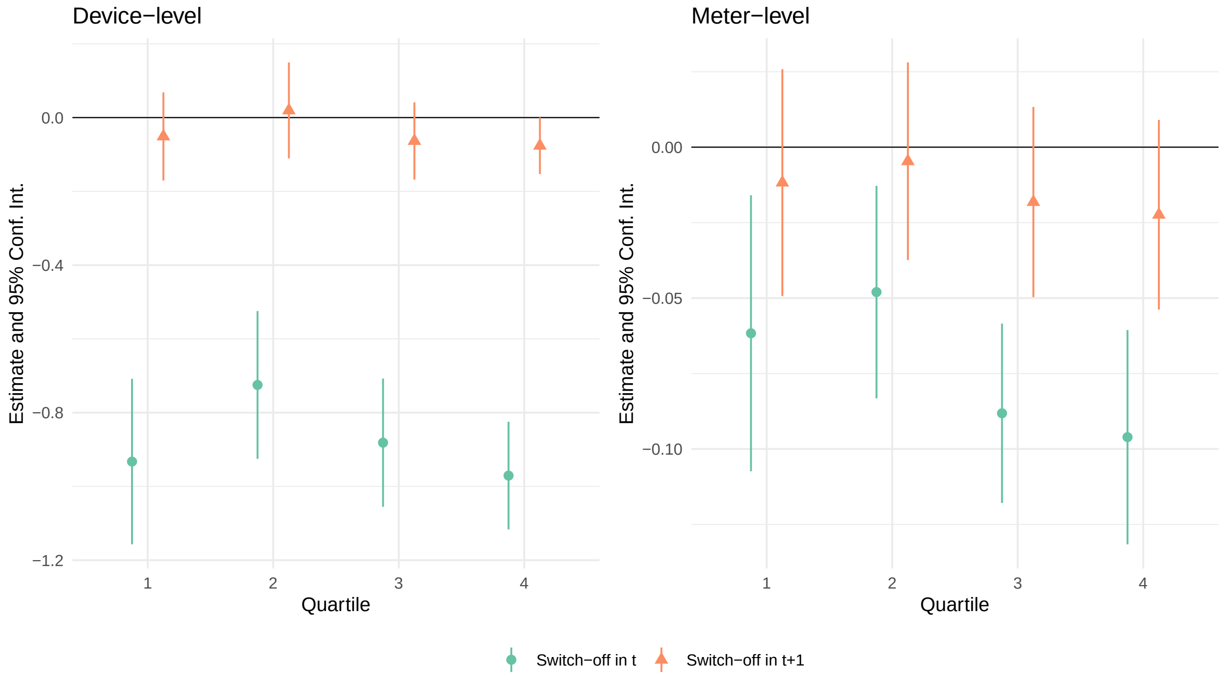
The figure plots the coefficient estimates and 95% confidence intervals of Poisson regressions of of device-level electricity use (left) and meter-level electricity use (right) on a set of dummy variables indicating switch-off events in periods t and $t+1$ interacted with whether the user's switch is 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 18: Effect of switch-off events on electricity use by post switch-off preference



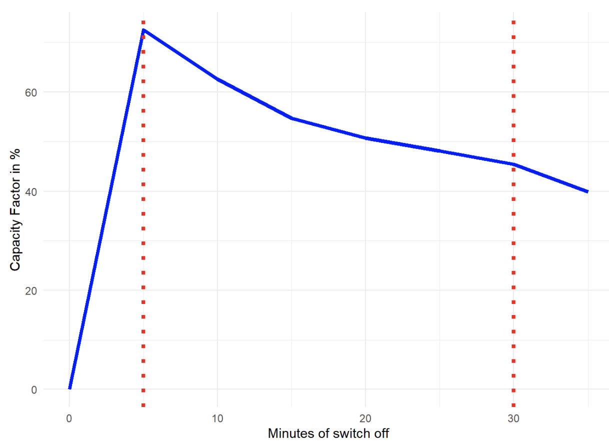
The figure plots the coefficient estimates and 95% confidence intervals of Poisson regressions of of device-level electricity use (left) and meter-level electricity use (right) on a set of dummy variables indicating switch-off events in periods t, $t-1$ and $t-2$ interacted with whether the user's opted 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 19: Effect of switch-off events on electricity use by quartiles of meter-level electricity use



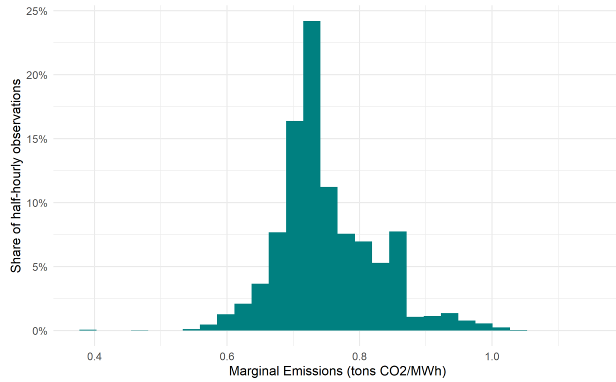
The figure plots the coefficient estimates and 95% confidence intervals of Poisson regressions of of device-level electricity use (left) and meter-level electricity use (right) on a set of dummy variables indicating switch-off events in periods t and $t + 1$ interacted with the quartiles of demeaned 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 20: Capacity factor of virtual power plant around switch-off events



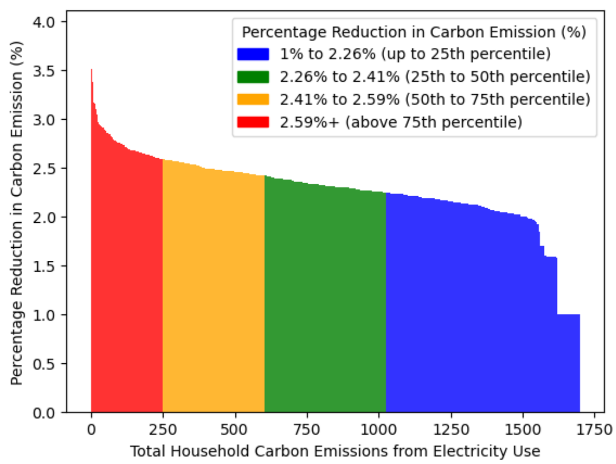
The figure depicts the capacity factor of the virtual power plant we developed via the demand response trial. The capacity factor measures the fraction of potential implied power generation that has been realised across all switch-off events. The capacity factor is calculated at five-minute intervals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

Figure 21: Estimated marginal CO_2 emissions factors of the Indian power grid in 2023



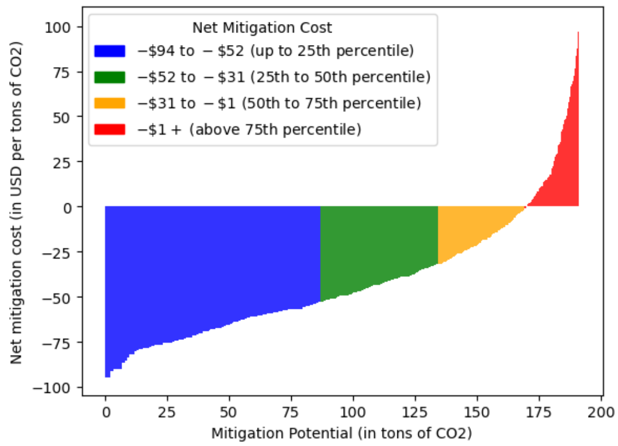
The figure plots marginal emission factors which are estimated for every 30-minute period in 2023 by fitting a model of CO_2 emissions from power production in India as a function of electricity system output and a set of weather bins: high solar radiation and low wind speed, high solar radiation and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

Figure 22: Counterfactual Analysis: Reduction in CO_2 Emissions



The figure plots the counterfactual percent reduction in carbon emissions resulting from 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.

Figure 23: 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 584 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	1,398,971
Power (W)	129.56	398.78	0.00	0.00	0.00	5.09	5,152.21	1,398,971
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	1,398,971
Meter-level electricity use (Wh)	349.50	389.85	0.02	110.00	200.00	459.00	7,242.00	1,398,971
Device share of meter-level electricity use (%)	13	28	0.00	0.00	0.00	4	135	1,398,971
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	1,398,971
Number of events per week	4.68	3.13	0.00	2.00	5.00	7.00	10.00	1,398,971

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

Dependent Variable:	Device-level consumption (Wh)		
Model:	(1)	(2)	(3)
Variables			
Switch-off in $t+2$			-0.0826***
			(0.0262)
Switch-off in $t+1$		-0.0618**	-0.0622**
		(0.0252)	(0.0253)
Switch-off in t	-0.8916***	-0.8923***	-0.8924***
	(0.0411)	(0.0412)	(0.0412)
Switch-off in $t-1$		-0.1715***	-0.1719***
		(0.0278)	(0.0279)
Switch-off in $t-2$			-0.0426*
			(0.0234)
Fixed-effects			
User	Yes	Yes	Yes
City x Appliance x t	Yes	Yes	Yes
Fit statistics			
Observations	1,549,085	1,549,085	1,549,085
Squared R^2	0.40831	0.40841	0.40843

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

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

Dependent Variables:	Device-level consumption (Wh)			Meter-level consumption (Wh)		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Switch-off in $t+2$			-0.0878***			-0.0125
			(0.0307)			(0.0093)
Switch-off in $t+1$		-0.0751**	-0.0756**		-0.0195**	-0.0196**
		(0.0302)	(0.0303)		(0.0098)	(0.0098)
Switch-off in t	-0.9193***	-0.9201***	-0.9202***	-0.0885***	-0.0886***	-0.0885***
	(0.0493)	(0.0493)	(0.0493)	(0.0109)	(0.0109)	(0.0109)
Switch-off in $t-1$		-0.1815***	-0.1820***		-0.0249***	-0.0250***
		(0.0336)	(0.0337)		(0.0088)	(0.0088)
Switch-off in $t-2$			-0.0742***			-0.0199**
			(0.0277)			(0.0092)
Fixed-effects						
User	Yes	Yes	Yes	Yes	Yes	Yes
City x Appliance x t	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	1,279,265	1,279,265	1,279,265	1,279,265	1,279,265	1,279,265
Pseudo R^2	0.43558	0.43569	0.43572	0.48329	0.48330	0.48331

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

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 5th and 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 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.

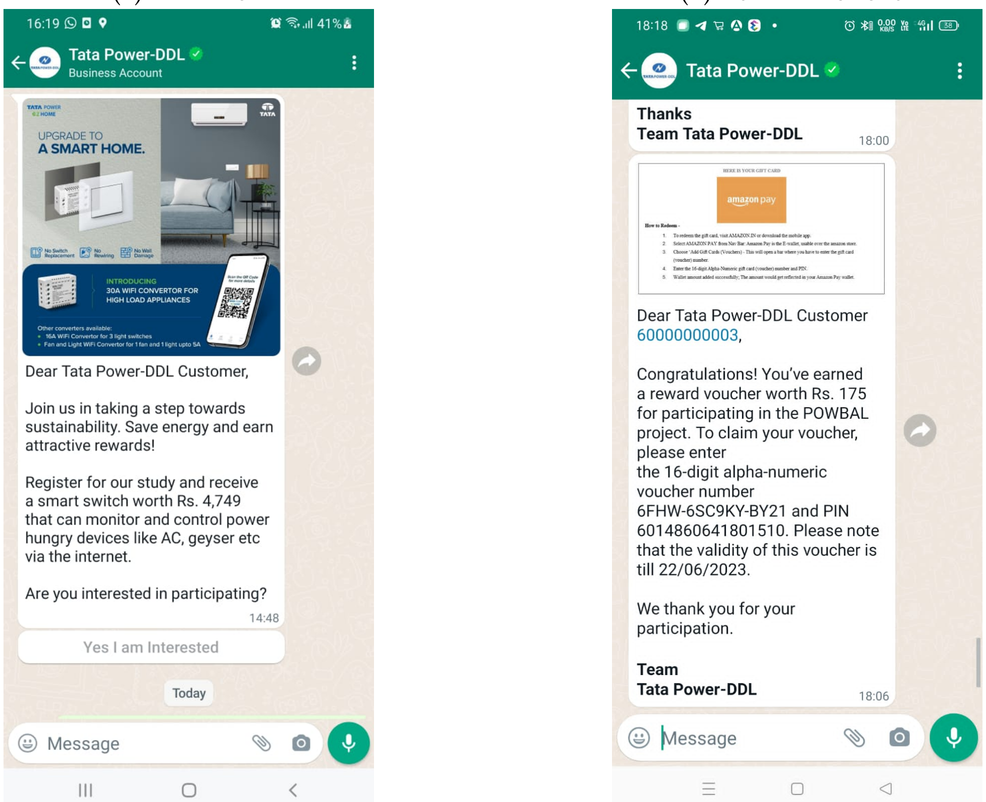
Reward voucher:

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#}.

B WhatsApp notifications

Figure 24: 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.

C 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