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Consumer-Driven Virtual Power Plants: A Field Experiment on the Adoption and Use of a Prosocial Technology

Quentin Coutellier* Greer Gosnell† Zeynep Gürgüç‡ Ralf Martin§ Mirabelle Muûls¶

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Abstract

Demand response strategies that rely on individual behavior change have consistently demonstrated that flexibility in energy demand exists, but that there are constraints to demand shifting such as limited attention or rebound effects. This paper analyzes residential energy demand flexibility through a series of field experiments on adoption and usage of WiFi-enabled smart plugs that largely overcome the need for home dwellers' effort and attention altogether. With 144 active participants, we study the adoption and user interaction of devices for automated dynamic energy demand-side management. Our design allows us to explore whether and how devices and incentive systems may be designed and deployed to improve load balancing in the centralized energy grid. Such a system would reduce the need for inefficient and often carbon-intensive back-up power generators during periods of peak demand, and increase the possible share of energy supplied by intermittent renewable energy sources. Our results suggest that users are more inclined to participate if switch-off events are sufficiently long to provide a meaningful probability of winning lottery prizes, but that higher frequency of such events may reduce participation intensity. We also develop an algorithm to optimally schedule users' power demand and switch-off events. Applying this to high resolution user and power market data suggests that both costs and implied CO_2 impact could be reduced by nearly 10% for the average user with more efficient scheduling of demand.

Keywords: Behavioral intervention, field experiment, household energy demand, demand side management, load balancing.

JEL codes: C93, 031, Q21, Q41, Q54, Q55

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1 Introduction

Increasing attention to the threat posed by global climate change has underscored the need for rapid development and deployment of innovative solutions to catalyze a sustainable low-carbon energy transition. Policymakers' and practitioners' ability to reduce overall energy consumption and manage energy market volatility is becoming increasingly important in this context. As decarbonization of electricity supply will rely on large-scale deployment of variable renewable energy sources, smarter management of electricity consumption, i.e. demand-side management (DSM), will prove essential to reach the global targets set out in the Paris Agreement (Grunewald and Diakonova, 2018; Gielen et al., 2019).

Innovation and internet connectivity in electronic systems have opened the door for development of advanced DSM solutions to accommodate fluctuations in energy supply and demand. Such developments expand energy suppliers' and grid operators' toolkits beyond supply-side load balancing mechanisms that often themselves require continuous emissions to maintain ramping capabilities of back-up power plants. Excessive energy demand can be shifted from peak to off-peak hours, when electricity typically costs less, by switching off some appliances for limited periods of time.[1] Thus, residential and commercial consumers have the ability—and, under a growing number of dynamic retail energy plans, the incentive—to contribute to a more flexible energy grid (Carbon Trust and Imperial College London, 2016).

Our research considers the extent to which energy consumers' adoption of an inexpensive Internet of Things (IoT)[2] technology—specifically the smart plug—can allow for carbon and cost efficiency improvements through increased flexibility in energy demand given an embedded stock of energy-consuming goods and durables in the economy.[3] We posit that scaled utilization of such technology enables the formation of sizable and robust virtual power plants (VPPs). Frequently regarded as important elements of a net-zero carbon future, VPPs aggregate a network of distributed (often renewable) power sources, storage systems, and flexible energy consumers to optimize and dispatch generation or consumption in a smart energy grid. Flexibility on the demand side is particularly crucial during temporary periods of either high energy demand (i.e. peak load) or limited energy supply from variable renewable sources.

On the supply side, technologies such as IoT applications and smart meters can reveal crucial information about patterns and flexibility in households' and businesses' appliance-specific energy use. Suppliers and grid operators can use this information—and, given access, use direct load control[4]—to minimize inefficiency and waste while balancing electricity demand with available supply, with

[1] Energy consumption from buildings comprises about a fifth of global energy consumption, with the proportion expected to increase as residents of non-OECD countries adopt home electronics and appliances at increasing rates (U.S. Energy Information Administration, 2019). In anticipation of growing energy demand from the residential sector and increased electrification of cooking, heating, and cooling as well as automobiles (Ürge-Vorsatz et al., 2015; Gielen et al., 2019), understanding and managing patterns of electricity use is becoming ever more crucial to meeting global climate change mitigation objectives. Additionally, due to varying carbon intensity of the grid throughout the day, the time of the day at which this growing electricity demand occurs will impact its carbon footprint as well as grid reliability (Holland et al., 2016). Analysis of energy efficiency investments related to air conditioning in California demonstrates that the value to society of energy efficiency upgrades increases when time of use is taken into account (i.e. they are characterized by a "timing premium"), as peak savings occur during hours of high value to electricity markets (Boomhower and Davis, 2020).

[2] According to the Oxford Dictionary, IoT refers to "the interconnection via the Internet of computing devices embedded in everyday objects, enabling them to send and receive data."

[3] Our research is pertinent to the literature that provides evidence on "load shifting" behavior (Borenstein et al., 2002). Considering monetary incentives, recent experimental research supports the hypothesis that time-of-use (TOU) electricity pricing, dynamic pricing, and price elasticity signals—that is, reminding consumers how much electricity costs when it is being used—can strongly affect the timing of electricity consumption (Wolak, 2011; Jessoe et al., 2014; Bradley et al., 2016; Harding and Sexton, 2017), though evidence across all demand response programs is quite mixed (Parrish et al., 2019). Non-monetary incentives—which have been tested extensively in relation to overall energy consumption (Abrahamse et al., 2005; Buckley, 2020)—have also been tested in the context of load shifting (Alberts et al., 2016). Prest (2020) demonstrated that the effect of TOU electricity pricing, coupled with price signals, leads to a 10% reduction in peak electricity usage, and information provision via in-home displays augments these reductions to 15%. Typically, non-pecuniary messages significantly affect high users, while low users are more responsive to financial incentives (List et al., 2017).

[4] Interventions using direct load control, e.g., through smart thermostats, have shown to reduce peak demand by 10% to over 80% of reference load (Ivanov et al., 2013; Parrish et al., 2019).

minimal intervention into consumers' lifestyles. Furthermore, shaving peak load throughout the year can have a significant impact on suppliers' bottom lines, providing vast economic motivation for utilities to provide consumers with incentives—to date, usually embedded in rate design—to reduce consumption during these hours.[5] Thus, smart devices simultaneously create opportunities for cost savings and reduction in negative environmental externalities.

Widespread uptake of such technologies whose adoption creates benefits that extend beyond those internalized by the adopter—what we call "prosocial technologies"—is crucial for clean energy transitions. Prosocial technologies include, for example, residential solar photovoltaic panels or energy-efficient appliances, and they are increasingly being developed to target a variety of social aims, such as apps for tracing Covid-19 exposure, traffic warning devices, and vaccination trackers, among others. This paper considers the adoption and usage of such a prosocial technology in the residential energy domain.

When considering the potential of dynamic pricing in electricity, it has been recently assumed that enabling automation is of crucial importance given the tendency of households to be inattentive to electricity prices (Borenstein and Bushnell, 2019; Parrish et al., 2019), particularly over time (Houde et al., 2013; Gilbert and Graff Zivin, 2014) and when payments lack salience (Sexton, 2015).[6] This paper contributes to the limited literature that tests this conjecture in the field. IoT technologies—which create the potential to observe, disaggregate, and automate energy consumption—are becoming increasingly pervasive across the economy, with billions of electronics and appliances projected to be connected through IoT in the near future (Khajenasiri et al., 2017). This rapid IoT deployment has brought to the fore a number of concerns regarding the performance and reliability of the evolving smart energy system, as issues related to misuse, safety, transparency, and data leakage shake consumers' trust (Alaa et al., 2017; Nicholls et al., 2020; Parrish et al., 2020). As a consequence, the automation that is potentially necessary for effective implementation of demand response could be difficult to achieve.

We explore these issues by conducting a series of field experiments designed to explore the extent to which user behavior might constrain what is technically feasible—for example, users may have reservations when it comes to adopting "smart" or externally controlled devices—while also exploring how users might be incentivized to overcome such reservations.[7] Additionally, by observing users' tendencies to override our randomly timed smart plug switch-off events, we are able to gain insight into true energy demand flexibility; that is, we can understand which times of day or days of the week individuals may or may not be willing to turn off appliances.

We ran our experiments in university halls via an initiative called POWBAL (short for "power balancing")[8]. To facilitate the program, we developed a web platform that collects data on how much electricity is consumed through the plugs and allows us to remotely and briefly switch off POWBAL-branded smart plugs, through which users could connect a time-flexible appliance or electronic device. The program incentivized students to participate by offering them a free smart plug and the possibility of earning monetary rewards commensurate with plug usage. We also emphasized the prosocial element of participation by informing the user of the environmental

[5]As detailed in Pratt and Erickson (2020), a utility's demand during the annual peak hour determines the capacity cost it will be required to pay in the following year to ensure the same amount is available to them during the next annual peak hour (plus a reserve margin). This cost comprises a significant portion of a utility's capacity costs, which account for 25% of utilities' total wholesale market expense, a percentage that is trending upward. Hence, the ability to immediately shave peak load during particular hours of the year that are often difficult to forecast can lead to dramatic cost savings that, if passed to the customer, could provide additional incentive for consumers to accept direct load control mechanisms.

[6]Inattention severely impedes the benefits of dynamic pricing since active response to price changes is cognitively costly. Automation paired with dynamic pricing aims to enable lower-cost responses to price changes that can achieve at least three times larger reductions for households (Gillan and Gillan, 2017).

[7]In the context of climate change, any policy proposal to reduce emissions and energy demand will largely rely on an appropriate combination of behavioral, technological, and institutional capabilities. While technologies and institutions are often in the spotlight, influencing behavior is also crucial in tackling climate change (Stern, 2008). For instance, understanding the adoption behavior surrounding relevant technologies—such as home insulation or smart meters—is arguably as fundamental as developing the technology itself (Allcott and Mullainathan, 2010; Toft et al., 2014; Bugden and Stedman, 2019; Hmielowski et al., 2019).

[8]See Appendix A Figure 12 for a picture of the POWBAL plug.

benefits of energy demand flexibility.[9] Consenting participants each received a smart plug that allowed our research team (as well as the participants themselves) to control the power to the connected appliance remotely throughout the study period. Participants then accrued points in proportion to the energy use we displaced, which in turn determined their likelihood of winning monetary prizes in our fortnightly lotteries.

To gain insight into the role of energy service interruption in determining plug usage, participants were randomly assigned to treatments characterized by differing duration and frequency of our randomly-timed "switch-off events": (i) up to 15 or 30 minutes at a time, and (ii) either once or up to eight times a day. The higher risk of interrupted energy services in the 'higher intensity' treatments is compensated through increased probability of winning versatile digital gift cards in the fortnightly lotteries. We assess this trade-off through differences in plug adoption and usage conditional on treatment assignment.

From the perspective of internal validity, the chosen context (i.e. university student accommodation) allows us to largely disregard complex irrelevant factors—in particular energy cost considerations—and focus on the question at hand. From an external validity perspective, the university context may be limiting. On the other hand, we run the experiment at three different campuses comprising diverse student populations, allowing for assessment of generalizability to at least the UK student population. We centered our attention on a developed country context due to (i) these countries' extensive established centralized energy grid systems that are largely sourced with emissions-intensive power generators (though may accommodate more renewable energy sources, provided flexibility), and (ii) the prevalence of energy-intensive home appliances and electronics amenable to smart plug usage.[10] Nevertheless, these features suggest immense potential of such programs in the developing world—perhaps particularly in rapidly industrializing economies—going forward, as per capita energy use seeks parity with the developed world and the need for rapid energy transitions becomes increasingly urgent, in particular due to air quality and climate concerns.

Our results suggest that users are more inclined to participate if switch-off events are sufficiently long to provide a meaningful probability of winning lottery prizes, but that higher frequency of such events may reduce participation intensity. However, individuals with relatively long but less frequent switch-off events are also more inclined to override. We provide evidence that individuals are motivated to consume more energy via the smart plug—contributing more to load balancing—just after they have been randomly selected to receive a lottery reward.

We also develop a framework to optimally schedule users' switch-off events and hence their power demand. The algorithm takes into account high frequency power consumption data, users' responses to switch-offs, and wholesale electricity market data on power prices and carbon content. The framework suggests that for the average user, both implied carbon consumption and (wholesale) power costs could be reduced by 8%, and can be as high as 26% for some users.

The remainder of the paper is structured as follows. The next section describes the experimental setup and data. The third section outlines our stylized model and presents our results. Section 4 concludes.

[9] Several studies on energy flexibility and curtailment have demonstrated the importance of prosocial motivations (e.g., Asensio and Delmas, 2015; Pratt and Erickson, 2020).

[10] The energy demand displacement potential for large-scale systems of smart plugs in the residential sector is economically significant in developed countries. For example, should plugs be deployed on 30% of domestic refrigerators in the United Kingdom—each of which consumes between 150W to 400W on average—then a large coal-fired power station (2.4GW) could be entirely displaced during peak hours.

2 Research Design

2.1 Sample Recruitment

We conducted a series of field experiments focused on assessing individuals' willingness to adopt POWBAL smart plugs and their subsequent energy consumption via these plugs under three randomly assigned treatments. We recruited undergraduate and graduate students from five LSE student halls, and from one student hall each at Imperial College London and University of Reading. Eligibility was restricted to individuals living in single-occupancy rooms to ensure that usage of the plugs derived from the sole individual exposed to treatment, and to maintain comparability in the characteristics of the residences and residents within a given student hall. The invitation offered participation in a research study aimed at designing systems to manage peak demand and smooth household energy consumption, where the information provided to prospective participants varied only in the frequency and duration with which they would experience switch-off events, as in Table 1 (see Appendix A for recruitment materials).

Our sample of prospective participants comprised 1798 residents, where 262, 648, and 888 occupants from Imperial, LSE, and Reading (respectively) received an invitation to participate. From this sample, 231 experimental subjects (30, 93, and 108, respectively) consented to participate in the study and received plugs, of which 144 (21, 39, and 84, respectively) actively used the plugs. We recruited participants via several channels, including email, phone app, flyers, in-person, or welcome packs in their rooms upon move-in. We recruited a majority of our participants in person inside the residence halls, using a predetermined script to describe the study and solicit consent.[11]

Students registered to participate in the study by completing a brief consent survey in the Qualtrics survey software. The survey first asked individuals to read a one-page overview of the study's purpose and implications of participation, then check four boxes confirming that they had read the information sheet, understood their participation rights, and were aware that their plugs could be switched off for periods of time corresponding to their randomly assigned frequency and duration, which were stated explicitly and saliently in both the information sheet and the consent language (see Appendix A).

Using student halls as the context of study comes with advantages and drawbacks. Students are not typical households and use much of their household electricity outside of their rooms, for example in laundry or common dining rooms and kitchens. They therefore have a smaller range of appliances to which they can choose to connect their plugs, with laptop and phone chargers comprising the bulk of available electronics, followed by lamps and hair accessories, and only a handful of individuals reporting larger energy consumers such as refrigerators, TVs, or electric heaters (see Table 9). A back-of-the-envelope calculation suggests that total electricity consumption of student rooms in the UK accounts for a very small proportion of total domestic consumption.[12] On the other hand, the share of their overall electricity consumed via the smart plug is likely to be higher than would be the case in a regular household, so we likely capture a larger proportion of their potential behavioral response. Most importantly, our student participants do not pay for their energy usage, meaning we can test our incentive mechanisms in isolation (i.e. without any confounding of savings from reduced or time-shifted energy usage). The size of the rewards in relation to total budget is also likely to be greater for our participants than for the rest of the population.

[11] Previous research has linked social pressure to technology adoption, adding another dimension to this channel; we do not attempt to measure treatment or welfare effects from our channel of adoption (see Giaccherini et al., 2019), but acknowledge that there may be an effect on adoption that, if anything, would attenuate any treatment effects in our study.

[12] Students in Imperial residences consume on average 18kWh per week. Assuming similar consumption levels for the approximately 650,000 student rooms in the UK, university residents' consumption totals 11GWh per week which, under certain assumptions, can be produced by 40 wind turbines.

2.2 Experimental design

To discern the likelihood of adoption based on switch-off intensity, we used a simple randomization[13] to assign prospective participants into three groups differing in the frequency and duration of switch-off events. We implemented three cells of a 2x2 study design. The first dimension is the number of possible switch-off events in a given 24-hour period. Some invitees were told that the switch-off events may occur once per day, while others were told they may occur once every three hours (i.e., up to eight times in a 24-hour period). The second dimension is the duration of the switch-off events, which may be either 15 or 30 minutes. To bolster group-level sample size and maximize observed switch-off events, we exclude the 15-minute switch-off once per three hours cell of the 2x2 design, as shown in Table 1.

Table 1: Treatment Group Design

	3-hour intervals	24-hour intervals
15 minutes switch-offs		Treatment 1
30 minutes switch-offs	Treatment 3	Treatment 2

NOTES: This table describes the three treatments with switch-off events varying in both duration and frequency over a 24-hour period. A 3-hour interval means a switch-off event can occur once every 3 hours, i.e. up to eight times in a 24-hour period.

We distributed a free smart plug to all consenting participants that we used to remotely control electricity supply to their selected electronic device or appliance. Over the course of the study period, we administered randomly timed switch-off events in accordance with the switch-off intensity to which each participant had been assigned. Participants collected points based on the energy that had been displaced through these events, as measured by the amount of energy consumed through the plug (in Watts) immediately prior to the event multiplied by the event's duration.[14] Finally, in fortnightly intervals, we performed a lottery where participants with more points had a higher chance of winning monetary prizes.[15] Provided they accumulated at least one reward point during the two-week period, the lottery allocated each participant with a probability to win a voucher in proportion to their reward points.[16] Table 2 shows that we distributed £550 worth of versatile digital gift cards to 26 total winners, among which a vast majority (18) won only once, while three participants won 4 times.

2.3 Data

Data collection began in April 2019 and lasted until mid-March 2020. In addition to recruitment data, our dataset consists of energy consumption readings for all online POWBAL plugs at 5-minute intervals (1,323,888 observations), the timing of the random switch-off events, and the dates and amounts of prize money lottery winners received.

Figure 1 reports hourly figures of aggregate power consumption via the smart plugs. Out of the 231 prospective participants who signed up and received their plug, 144 went on to use it at least once. The LSE trial started in April 2019 and ended over the summer as students successively moved out of the halls, as reflected in the left-hand part of Figure 1. The Imperial trial initiated in October 2019 when students moved in, and the Reading trial began in January 2020 at the start

[13] We do not have data on characteristics of the subject pool, hence stratified randomization was not possible.

[14] To illustrate, if the power consumed by the plug prior to switch-off was 2 Watts, and the switch-off event lasted for 30 minutes (i.e. $\frac{1}{2}$ hour), the participant earned 2 Watts x $\frac{1}{2}$ hour = 1 reward point. If a participant overrode the switch-off event (i.e. by pressing the override button on the plug or via the app), we only rewarded the user for the amount of time that the plug was switched off before the override.

[15] Our prizes came in the form of digital gift cards, redeemable in a variety of high-street and online retailers as well as hospitality providers.

[16] The lottery worked as follows: the number of sub-lotteries for a £10 voucher was defined by the number of participants with non-zero reward points during a given fortnight, for example 100 sub-lotteries if there had been 100 such participants. Each voucher was given away by drawing the names of participants. The probability to win each of these draws was equal to 15% of that participant's share of the overall number of reward points accumulated in those two weeks.

Table 2: Lottery Results

	N	Vouchers won	Highest voucher won
One-time winners	18	£260	£30
2-times winners	4	£120	£50
3-times winners	1	£30	£10
4-times winners	3	£140	£20
Total	26	£550	£50

NOTES: This table reports the outcomes of the fortnightly lotteries, i.e how the payouts were distributed among lottery winners. Each line records how many participants won a given number of lottery draws, the total value distributed and highest value of vouchers won by x-times winners out of the entire voucher pool.

of term. The latter two trials ended on March 15, 2020 when the COVID-19 lockdown became imminent, which led many students to move out of the halls to be with their families.[17]

Table 3 reports descriptive statistics on the power consumption of all connected devices (outside of switch-off events) throughout the trials. The average power is 7.5 Watts, akin to that of a phone charger. However, this figure hides considerable heterogeneity both between and within users. Note that most plugs do not consume any electricity most of the time. Of the nearly 1.3 million data measurements we observe from our active users, only 22% report non-zero consumption, while in the remaining 78% of observations the plugs were connected to a socket without any devices consuming energy through them. However, there are several users who at times use up to 3 kW (about the power needed for 2 average electric space heaters).

Table 3: Descriptive Statistics of Power Consumption via Smart Plugs (Watts)

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
All online plugs	1,323,888	7.53	73.10	0	0	0	3,118
Plugs with non-zero power	288,653	34.53	153.53	3.10	6.40	25.10	3,118
Non-zero power in week	1,235,129	8.07	75.65	0	0	0	3,118

NOTES: This table reports descriptive statistics of power consumption over the duration of the experiment. Power consumption is recorded in Watts. The first row reports on all plugs that are online. The second row reports on plugs online with non-zero consumption. The third line reports on plugs that have at least one observation with non-zero consumption in a given week.

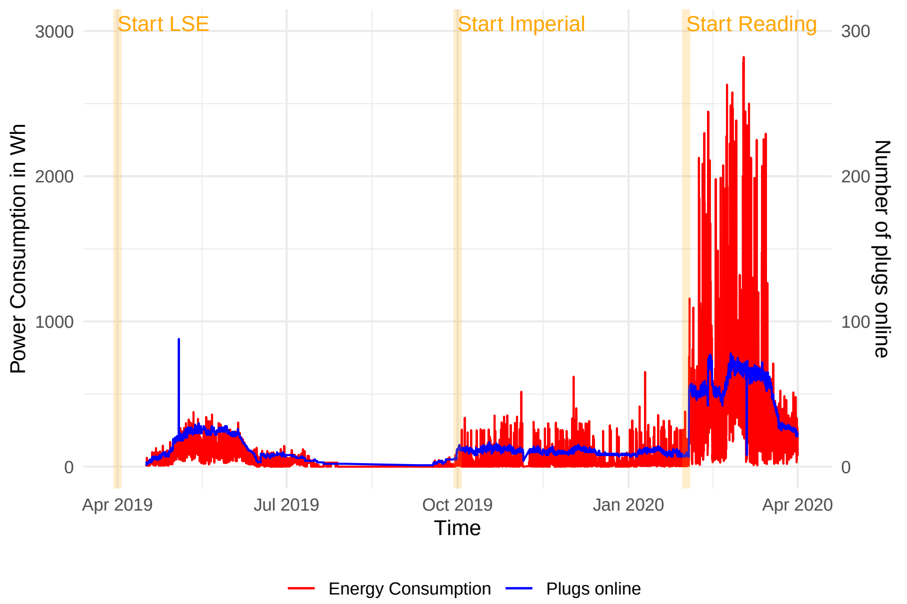
Within-plug consumption changes over time as users connect different devices, turn off the outlet, unplug the POWBAL plug, or toggle between switching a device off or on, which they can do remotely or via a button on the plug itself. The data on power drawn when power consumption is non-zero is reported in row 2 of Table 3, which reveals that average consumption is 34.5 Watts with the 75th percentile at 25.1 Watts, on the order of magnitude of a small laptop or tablet charger. This coincides with qualitative feedback from the debrief survey (see Appendix A). Figure 2 reports the distribution of measured power for plugs with non-zero consumption.

2.4 Consumption over the course of the day

Given the importance of optimizing and integrating VPPs in increasingly smart energy systems, demand fluctuations and VPP capacity throughout the day must be well understood. While variation is independent of the day of the week, Figure 3 shows that the average power usage via the plugs during different hours of the day varies substantially. During evening hours from 18:00

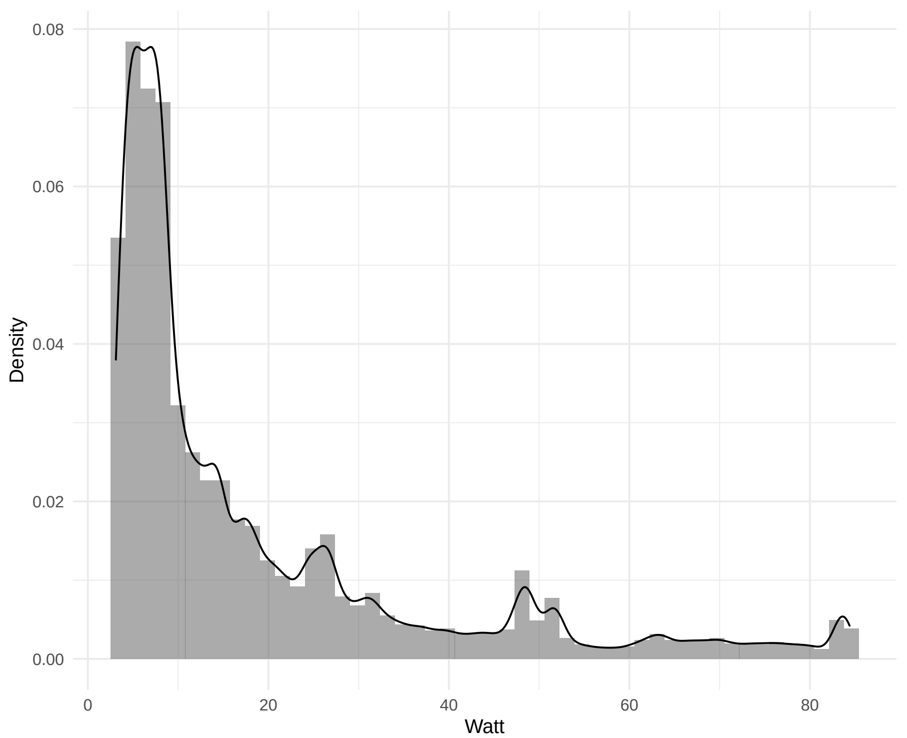
[17]In our pre-registry, we had indicated that trials would take place in 2018, and simultaneously. Logistical technicalities delayed rollout at two of our sites, and the opportunity to work with the University of Reading arose as we were preparing to implement the experiment at Imperial. Given lower than expected uptake in Imperial and LSE, we partnered with Reading to achieve our desired sample size of 200-250, as designated in the pre-registry, which can be found on OSF.

Figure 1: POWBAL Performance Over Time



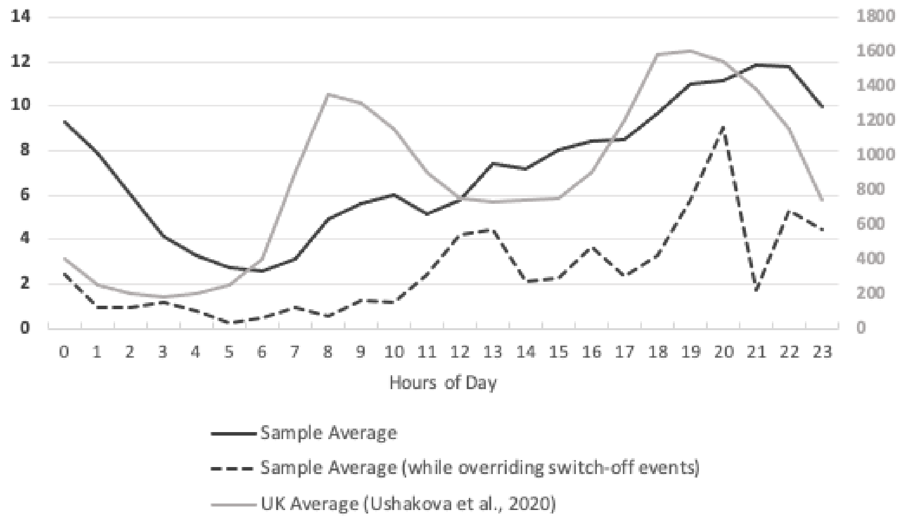
Notes: The graph reports hourly figures of aggregate power consumption in Watt hours (red curve) and the number of plugs online (blue curve) over the duration of the experiment. Data collection in LSE halls started in April 2019 and ended during the summer. Subsequent trials at Imperial College London and University of Reading initiated in October 2019 and January 2020 respectively and ended due to the emergence of COVID-19, which drew students home from March 2020.

Figure 2: Distribution of Power



Notes: The figure shows the fitted density plot of electricity consumption in Watts for non-zero consumption over the trial period, where the cutoff at the 99th percentile is 84.3 Watts.

Figure 3: Electricity Consumption Throughout the Day in Wh



Notes: The figure depicts average electricity consumed through plugs at each hour of the day, reported in Watt hours. Left-hand side y-axis denotes the Wh for the sample averages, whereas right-hand side y-axis denotes the Wh for the UK average. The hours of the day are noted on the x-axis. The average hourly consumption data for the UK was adapted from Ushakova and Jankin Mikhaylov (2020).

(6pm) onward, consumption is more than three times higher than during the lowest consumption period around 5:00 (5am). This pattern is comparable to within-day variations of consumption in typical UK households (Ushakova and Jankin Mikhaylov, 2020), with the notable difference that nighttime consumption is higher through the students' plugs and that the morning peak is not pronounced. Figure 3 illustrates that electricity consumption when overriding switch-off events remains low during peak load, with the exception of 8pm. These observations signify that the VPP's capacity generally follows typical electricity demand patterns, so that latent and untapped flexibility in the energy system is maximized during periods of peak load. Additionally, we see that the load remains relatively high in late evenings, which could be important if electric vehicle owners plug in their cars to charge at night, as incentivized in many electric vehicle energy plans.

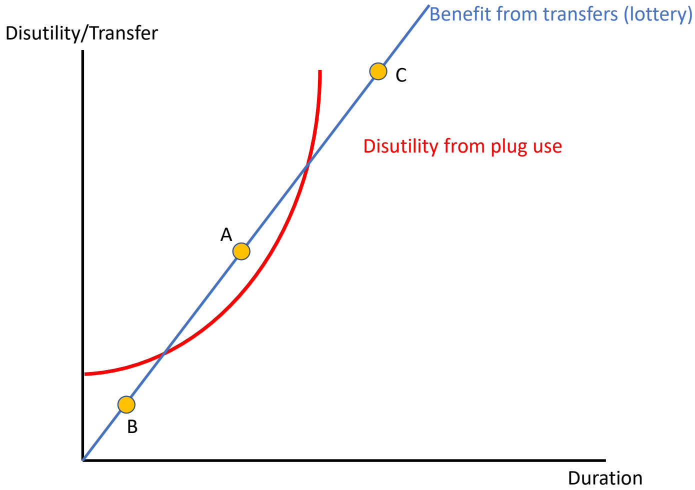
3 Empirical Specification and Results

In this section we address our primary experimental research question of how our treatments, and the switch-off intensity they embodied, affected the likelihood of adoption and use. To do so, we compare adoption (a binary measure of whether participants consumed any power through the plug at all) and use (a continuous measure of the energy consumption's contribution toward the VPP via the plug following adoption) across the three groups, using Treatment 2 as a reference group upon which to compare Treatments 1 and 3. We additionally explore the impact of receiving financial rewards on subsequent usage and rule out that participants are uniquely prosocially motivated.

3.1 Prosocial Technology Adoption: A Stylized Model

To frame our analysis, we develop a stylized model of prosocial technology adoption. POWBAL differs from many technology adoption experiences—for instance, purchasing and using a smart phone—in that there is no intrinsic utility for the user. The value of adoption arises exclusively as a positive externality; e.g., in our case it facilitates increased efficiency of the electricity grid. However, there is potentially disutility from adoption, for instance, setup costs, data sharing, and relinquished control over select energy services in the home. As a consequence, users may need to be compensated (Richter and Pollitt, 2018).

Figure 4: A Stylized Model



Notes: The figure models disutility from plug use (red curve) combined with benefits from transfers (blue curve) as a function of variations in duration of switch-off events. At point A, benefits form the the lottery exceed the disutility from adopting the plug. Conversely, at points B and C, disutility is larger than the potential benefits.

For simplicity, we assume that intensity of participation is unidimensional (e.g., frequency or duration of a switch-off event) and that there is a fixed disutility, or 'setup cost', from adoption. Moreover, with increasing switch-off intensity, the disutility of adoption increases at an accelerating rate, as in the red line of Figure 4. We also suppose that transfer payments (e.g., lottery prizes) increase linearly in consumption through the smart plug, as in the blue line of Figure 4. At point B, disutility exceeds benefits and the user will not adopt. At point A, benefits are higher than disutility so that a user will adopt. In our current setting, the user cannot choose switch-off intensity freely; rather, intensity is exogenously allocated. Hence, depending on the shape of the underlying functions in our experimental settings, individuals will either adopt and use the technology (as at point A) or choose not to adopt (as at points B or C).

In the next two sections, we first analyze how the different treatments, and the disutility from plug use that they represent, affect adoption rates. We then explore whether the rewards from the lottery (extrinsic motivation) interact with prosocial utility (intrinsic motivation).

3.2 Treatment effects on adoption

3.2.1 Empirical Specification

Our treatments allow us to explore two dimensions that could have an impact on subjects' decisions of whether to adopt the plugs: the duration and the frequency of energy service interruption. All else equal, we would assume that a user prefers lower frequency (i.e. a long gap between switch-off events) and shorter duration. However, shorter and less frequent switch-off events also translate to lower payoff likelihood, so the expected response to the different treatments is an empirical question.

To answer this question, we run regressions of two different measures of VPP participation on the treatments received, which vary in frequency and duration. The regressions take the following form:

$$Y_i = \beta_0 + \beta_1 T1 + \beta_2 T3 + H_i'\gamma + \epsilon_i \tag{1}$$

where Y_i is the measure of VPP participation. The first measure is the average electricity consumed per week (in kWh) through individual plugs. The second measure is the percentage of weeks that a plug is online, regardless of how much electricity is consumed through it. For example, if a user came online for the first time in week 1, and then only every other week until the end of the trial, the latter outcome would be 50%. $T1$ and $T3$ are binary variables set to 1 when a user is in a given treatment group. The reference group is T2, where users are exogenously assigned switch-off events of relatively long duration (30 minutes) and only once every 24 hours. H_i is a vector of residence hall dummies.

3.2.2 The effect of varying switch-off event frequency and duration

Figure 5 graphically explores two measures of adoption—weekly energy consumption and share of users that have their POWBAL plug online at least once during a given week—conditional on treatment assignment. It reports the β_d coefficients of the regression

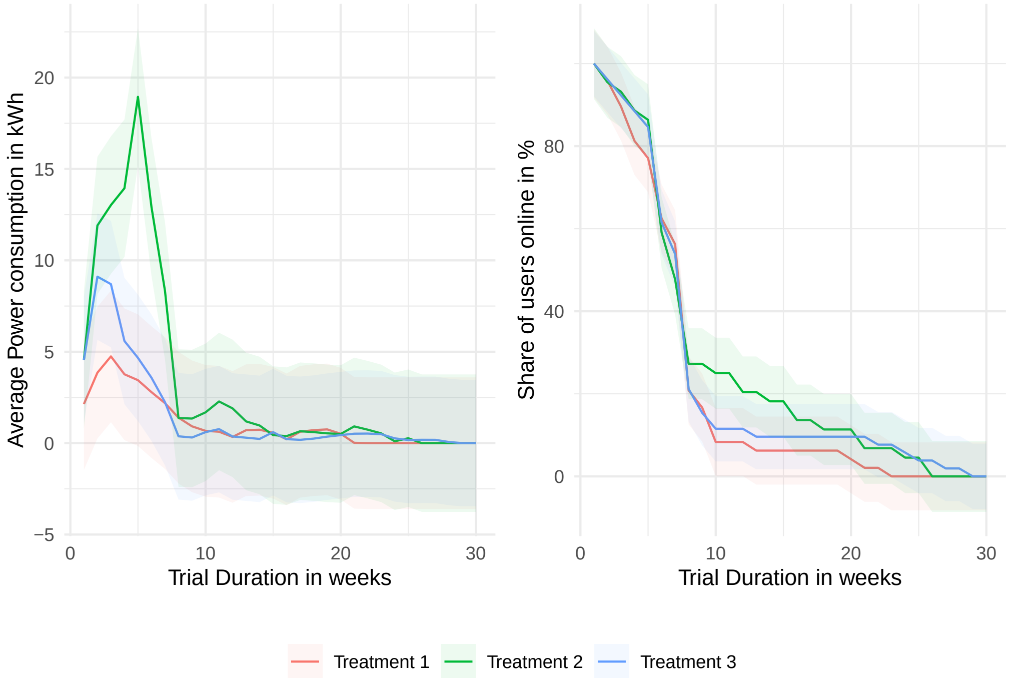
$$Y_{it} = \sum_d \beta_d DUR_{it} + \epsilon_{it}$$

where Y_{it} is either the weekly energy consumption (in kWh) of user i in week t (in the left panel of the figure) or a dummy equal to 1 if a user's plug came online in a given week (in the right panel). $DUR_{d,i,t}$ is a dummy equal to 1 if in week t user i has been participating in the trial for d weeks. The figure reveals that energy consumption via the plug tends to be highest for Treatment Group 2 (low frequency, long duration of switch-off event) particularly in the early weeks of the trial. Consumption is lowest for participants assigned to the least intrusive treatment, with the highest-intensity group in between.

In line with our discussion in section 3.1, one explanation for the low consumption in Treatment 1 may be that users do not view the disutility from switch-off events as worthwhile when prospective rewards—whether monetary or prosocial—are too low, so infrequent switch-off events lead to user disengagement. On the other hand, frequent switch-off events inconvenience the user, so that engagement is highest with long duration and low frequency events. Explicit regressions of consumption on treatment characteristics, as per equation 1, are presented in Table 4. They support this interpretation in that they suggest users with short duration switch-off events consume 3.3 kWh less on average over a week than the reference group, whereas high frequency reduces consumption by 2.8 kWh on average, as shown in column 1. The result holds when we do not control for the residence in which the user lives (column 2). When winsorizing the dependent variable at 1% (column 3), the magnitude and the significance of the coefficients are attenuated, but their sign is preserved, indicating the results are not solely driven by a few outliers.[18]

[18] This also holds when winsorizing at 5%. At 2% winsorization, the T1 and T3 coefficients are significant at 10%.

Figure 5: Treatment Effects on Plug Usage



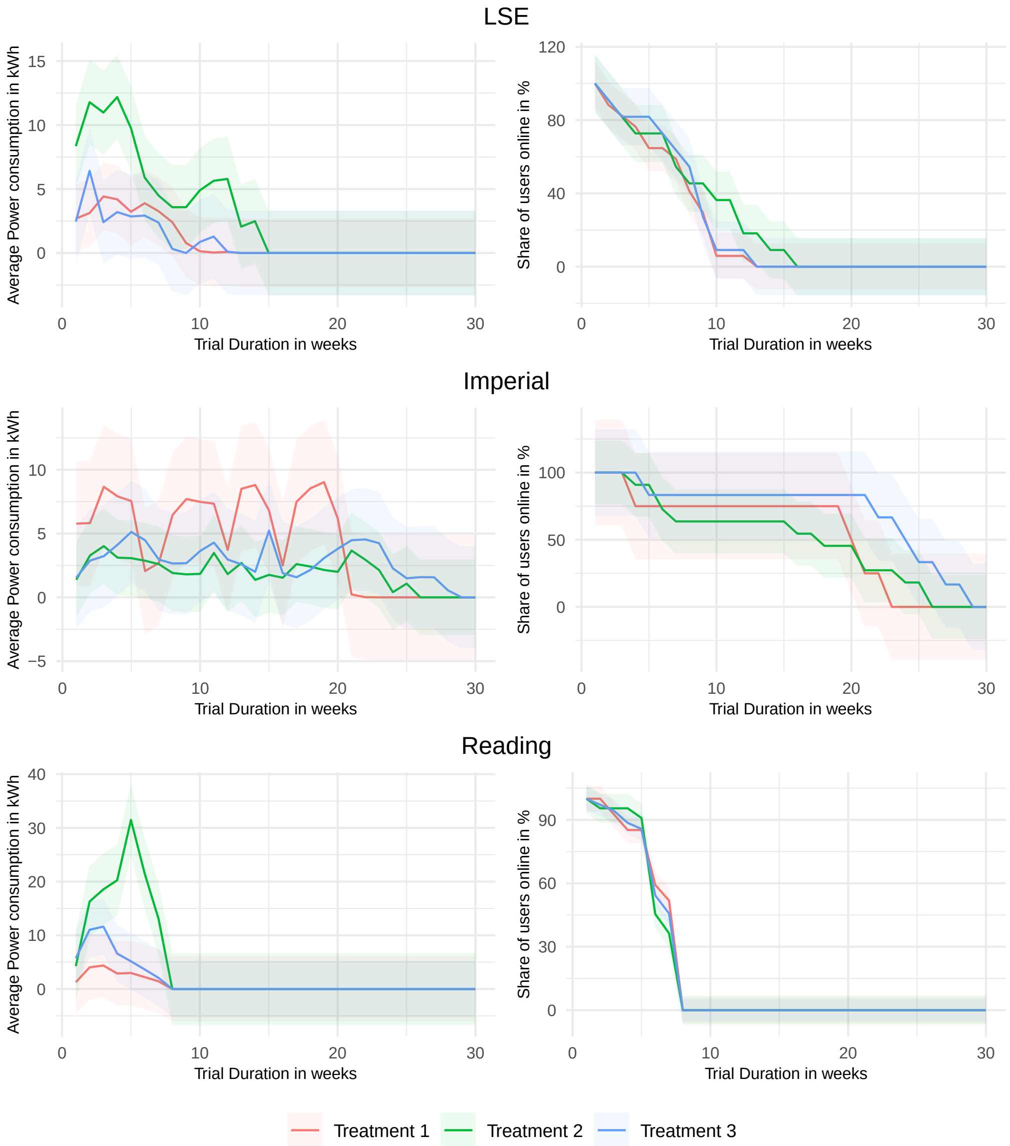
Notes: The left-hand side graph reports the average energy consumption in kWh consumed through the plugs for each treatment group across all sites over the trial duration measured in weeks where time 0 is when the user first uses the plug. The right-hand side graph reports the share in percent of users that come online at least once, even briefly, during a given week for each treatment group across all sites over the trial duration in weeks.

Additional results support this interpretation. The gap between Treatment Group 2 and the other groups becomes initially bigger as the trial proceeds. This is consistent with participants learning about their rewards: users in group 2 respond to higher rewards whereas users in group 1 lose interest because of their lower chance of receiving rewards. We also see that users in group 2 are, toward the end of the trial period, the most likely to remain engaged, leaving their plugs online for more weeks, as shown in the right panel of Figure 5. This effect is less pronounced than the consumption effect: in the last column of Table 4, we find that users with a shorter switch-off duration treatment are 7 percentage points less likely to continue participating compared to the reference group, though the effect is not statistically significant.

There are a number of caveats to this interpretation. First, Figure 5 illustrates powerfully that there is non-trivial attrition. By week 15 of the trial most users have abandoned adoption. It is however noteworthy that the observed drop is conflated by the end of term (in the LSE case) and the onset of the COVID-19 lockdown (in the Reading case), as illustrated by Figure 6, which repeats Figure 5 for our three trial sites separately. Likewise, 60% of debrief survey respondents expressed an interest in remaining involved in POWBAL initiatives in the future. Note that for the Imperial site where we had about 27 weeks of data before the lockdown began, attrition is much lower.

Interestingly, the relative performance of the treatment groups is different for the Imperial site compared to the others. Hence, we have to be cautious in drawing overly strong conclusions from the aggregated results. However, consistent with earlier results, group 1 comes lower in terms of participation likelihood toward the end of the trial. Hence, we can conclude with some confidence that the need to provide sufficient incentive to participate will dominate, within reason, factors such as the inconvenience of having plugs switch off too often or for too long.

Figure 6: Treatment Effects on Plug Usage by Site



Notes: The left-hand side graph reports the average energy consumption in kWh consumed through the plugs for each treatment group across the various sites over the trial duration measured in weeks. The right-hand side graph reports the share in % of users that come online at least once during a given week for each treatment group across LSE sites over the trial duration in weeks.

Table 4: Regressions on Treatment Characteristics

	Average Weekly Consumption (kWh)			
	(1)	(2)	(3)	Users Online
Short duration (T1)	-3.272^{*}	-3.289^{**}	-1.659^{*}	-7.036
	(1.671)	(1.628)	(0.944)	(4.942)
High Frequency (T3)	-2.768^{*}	-2.703^{*}	-1.327	-4.432
	(1.633)	(1.598)	(0.927)	(4.850)
Reference Group (T2)	4.809^{**}	4.874^{***}	3.124^{***}	40.682^{***}
	(1.848)	(1.176)	(0.682)	(3.570)
Observations	144	144	144	144
Site Controls	Yes	No	No	No
Winsorized	No	No	Yes	No
R^2	0.033	0.032	0.024	0.014
Adjusted R^2	0.005	0.018	0.010	0.0004
Residual Std. Error	7.853	7.802	4.524	23.679
F Statistic	1.182	2.305	1.716	1.031

Notes: These estimates are the result of OLS regressions. The table reports the effect of varying the duration and frequency of switch-off events on the weekly average electricity consumption in kWh, as well as the number of users whose plugs are online. Each coefficient represents the difference relative to the reference group so as to estimate the treatment effects of long duration and high frequency switch-off events. The dependent variable is average weekly electricity consumption in columns 1 through 3. In column 1, a set of dummies controls for the student residence in which the participant resides. In column 3, the average weekly electricity consumption is winsorized at 1%. In column 4, the dependent variable is the percentage of weeks that a given user was online at least once after their first connection. Robust standard errors are reported in parentheses. Significance levels are indicated as *p<0.1; **p<0.05; ***p<0.01

3.3 Participation motives

Despite the disutility from interruption of energy services, at least two advantages may drive users to adopt. A purely prosocial motivation may arise since POWBAL technology promises to enable clean energy generation, and users may desire to win lottery prizes.[19] If users are exclusively driven by prosocial motives, they should not respond to lottery wins by increasing their energy consumption through the plug to increase their chances of future wins. However, if they are driven solely by private rewards *and* if they update their expectations about those rewards according to observed lottery wins, we would expect to find a relationship between receiving rewards and participation intensity. In other words, a boost in VPP contributions in response to rewards being paid out is a sufficient condition for the presence of reward effects (although not a necessary one).

We develop a simple model to illustrate this phenomenon. Suppose users' utility is defined as

$$U = (\kappa r_i + s_i)\, e_i - e_i^{\eta} - \gamma$$

where e_i is participation intensity, r_i represents the financial reward, κ is the importance of rewards to users, s_i is the prosocial benefit, and γ is the fixed setup cost. We assume that $\eta > 1$, which implies increasing marginal disutility from higher participation intensity.

Hence optimal participation is defined by the first-order condition

$$U' = \kappa r_i + s_i - \eta e_i^{\eta-1} = 0$$

so that optimal participation intensity becomes

$$e_i^* = \left(\frac{\kappa r_i + s_i}{\eta}\right)^{\frac{1}{\eta-1}}$$

If there is uncertainty over rewards, consumers will maximize expected utility $E\{U\}$ which implies that optimal adoption becomes

$$e_{it}^* = \left(\frac{\kappa E_{it}\{r_i\} + s_i}{\eta}\right)^{\frac{1}{\eta-1}}$$

with $E_{it}\{r_i\}$ being users' expectation about rewards at time t. If we find that actual reward payouts in the past (e.g., r_{it-1}) drives current participation e_{it}, we can infer that users form their expectations about payouts on the basis of what they have actually received in the past:

$$E_{it}\{r_i\} = f(r_{it-1})$$

Hence, past payouts become an instrument for the effect of rewards on participation, though we do not directly observe $E_{it}\{r_i\}$. We can then write the reduced form effect in this setting as

$$\frac{\partial e_{it}}{\partial r_{it-1}} = \frac{1}{\eta-1}\left(\frac{\kappa E_{it}\{r_i\} + s_i}{\eta}\right)^{\frac{2-\eta}{\eta-1}} \frac{\kappa}{\eta} \times \frac{\partial f(r_{it-1})}{\partial r_{it-1}}$$

Consequently, a regression of e_{it} on r_{it-1} will provide the response of expectations to rewards times the marginal response to rewards. For an entirely prosocially driven user (with $\kappa = 0$) this

[19] Of 52 debrief survey responses, 28 (54%) claimed environmental benefits as their primary motive for participation, whereas 22 (42%) and 2 (4%) claimed that money and free technology were their primary motives, respectively.

marginal response would be zero. For users that are not exclusively prosocially driven, it seems plausible to assume that

$$0 < \frac{\partial f(r_{it-1})}{\partial r_{it-1}} < 1$$

i.e. in response to a very high payment, users would adjust their beliefs upward, but not excessively so. Consequently, a reduced form regression of the form

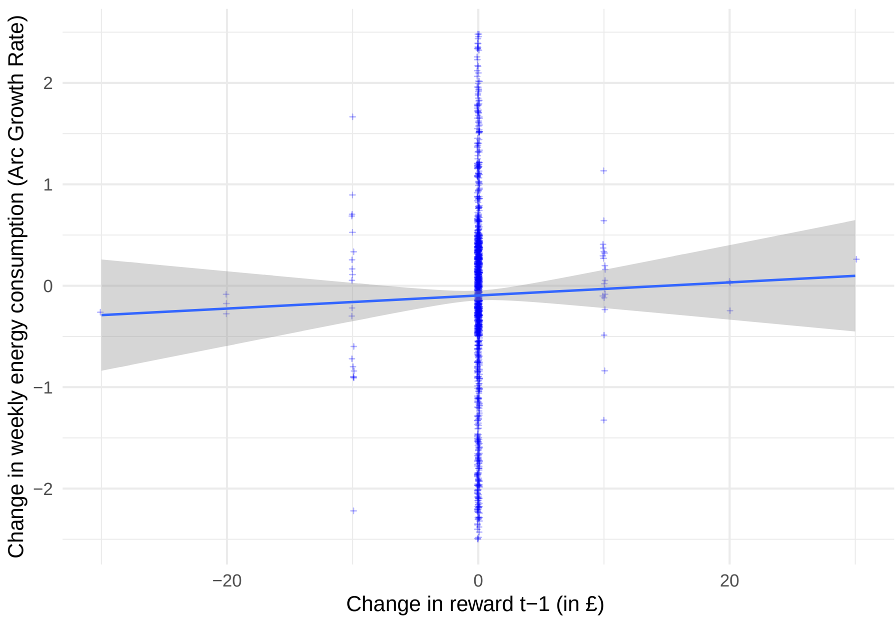
$$e_{it} = \beta r_{it-1} + \epsilon_{it}$$

provides a lower bound measure of the response of users to rewards, which in turn provides us with an upper bound of the prosocialness of our virtual power plant:

$$\frac{1}{\eta - 1}\left(\frac{\kappa E_{it}\{r_i\} + s_i}{\eta}\right)^{\frac{2-\eta}{\eta-1}} \frac{\kappa}{\eta} > \beta$$

Figure 7 plots the change in weekly energy consumption against the change in reward payments received. We find large variation in both variables. The figure also reveals a positive relationship between energy consumption at t and rewards at $t-1$, which suggests that more reward payments will encourage participants to increase the amount of electricity they consume through the plugs.

Figure 7: Effect of Change in Rewards on Usage



NOTES: The figure shows a scatter plot between percentage changes in weekly energy consumption and lagged changes in reward payouts (t-1). We see that a reward payout (in £) in the previous week (t-1) is associated with an increase in energy consumption via the plug.

We examine this response in greater detail by running regressions of the form 3.3 where we also assume that there is a user-specific fixed effect:

$$\epsilon_{it} = \alpha_i + \nu_{it}$$

To deal with unobservable user-specific variation we run the regression in first differences. Table 5 presents the results. Column 1 suggests that a reward payout in the previous week will increase consumption in the current week by 51Wh per £1 paid out. Column 2 includes both the rewards lagged at $t-1$ and $t-2$, which suggests that the consumption increase remains positive and significant two weeks after a payout. However, we also see that this additional boost disappears by the third week after receiving payout. Hence, our first column estimate seems to be a good representation of the net effect.

Table 5: Regressions of Energy Consumption on Reward Payouts

	Dependent variable:		
	Change in weekly energy consumption		
	(1)	(2)	(3)
Reward Week -1	52.404**	64.020**	86.218*
	(20.818)	(25.129)	(50.468)
Reward Week -2		48.868**	87.548**
		(23.507)	(39.620)
Reward Week -3		−7.469	−7.492
		(16.817)	(44.639)
Wh Week -1			−0.131
			(0.347)
Wh Week -2			0.095
			(0.230)
Wh Week -3			0.100
			(0.283)
Week controls	Yes	Yes	Yes
Observations	1458	1458	1458
Users	144	144	144

NOTES: These estimates are the result of OLS regressions. The dependent variable is the change in weekly electricity consumption in Wh from week t-1 to week t. The explanatory variables take the value 1 if the user received a reward in week t-1, t-2 or t-3, and zero otherwise. The table reports the effect of receiving a reward in previous weeks on the change in electricity consumption. Column 3 also includes as controls weekly electricity consumption in weeks t-1, t-2 and t-3. Robust standard errors are reported in parentheses. Significance levels are indicated as *p<0.1; **p<0.05; ***p<0.01

One concern could be that autocorrelation in users' consumption could be driving our effects; that is, if a user consumed more last week she might also consume more (or less) this week. Clearly last week's consumption is driving last week's reward payments due to our incentive structure. It is straightforward to account for this autocorrelation, however, by including the previous week's consumption levels as further controls and using a dynamic panel estimator (i.e. Arellano Bond) for the estimation. The results of such a specification, presented in column 3, show that autocorrelation has little effect on the qualitative conclusions drawn from columns 1 and 2. Indeed, it leads to a slightly larger estimated impact of rewards.

Based on these findings, what can we conclude about the importance of the financial motive in comparison to the prosocial motive in fueling our virtual power plant? As noted above, our estimates provide a lower bound on the financial motive (and, in turn, an upper bound on the prosocial motive). Considering the estimate in column 1 of Table 5, the analysis suggests that the response to winning £1 is an additional 52 Wh of consumption through the plug. Average weekly consumption is 539.94 Wh, and average payouts are 34 pence. Hence, not paying the average user would reduce her consumption by $52Wh \times 0.34 = 17.68Wh$. This amount corresponds to 3.3% of average consumption. Of course, rewards need to be determined in relation to marginal increases in either revenue or carbon reductions, which will be explored below.

3.4 Overriding

Our discussion thus far has focused on VPP participation and participation intensity, which are the primary outcomes of interest in our study. We explore a further dimension of participant response to the exogenous switch-off schedule: user overriding behavior (i.e. canceling the switch-off event after it has begun). Table 6 reports regressions where the dependent variable is a binary variable equal to 1 if a switch-off event is overridden by the user, and the independent variable of interest is treatment assignment. In total we observe 6,725 switch-off events.

At first glance, treatment assignment (i.e. switch-off intensity) appears to have little impact on overriding behavior—with overrides occurring during 5.5% of switch-off events in Treatment 2 (Reference Group) with a statistically insignificant effect of changes to variation and frequency. This low figure is due in part to many of the switch-off events occurring during periods where users are not consuming power via the plugs. Hence, in column 2, we only consider overrides in cases where a switch-off event occurs after at least five-minutes of non-zero plug load (in Watts). In this sample, overriding occurs in 7% to 17% of cases. Comparing the variation in overriding behavior between treatment groups leads to clear results: overriding is most prevalent in Treatment 2 with relatively long but infrequent switch-off events. On the other hand, the amount of overriding in Treatments 1 and 3 are very similar. One might have expected most overriding to occur in Treatment 3, wherein participants experience both long and frequent switch-off events. This result could be driven by users connecting different types of devices under the various treatments. Longer treatments may mean users ensure ex ante that any energy services from connected devices are time flexible and therefore better suited for withstanding switch-off events.

Columns 3 and 4 explore whether there is a relationship between pre-switch-off energy consumption and overriding. A positive relationship would be of concern as this would imply that the overriding behavior might substantially reduce the capacity of the virtual power plant. Column 3 includes the whole sample whereas in column 4 we only include the switch-off events with positive pre-switch-off power usage (as in column 2). The strong association between power usage and overriding in column 3 is not present in column 4. Hence, the effect in column 3 is entirely driven by the extensive margin of power users with positive usage.

3.5 Optimal operation and value of load balancing

The primary benefit of this load balancing technology adopted at scale would be system-wide cost reductions, which will increase substantially as larger shares of electricity derive from intermittent renewable generation (see Strbac, 2008). Nevertheless it is insightful to benchmark the performance of our emerging virtual power plant against the current performance of the UK electricity market. To do so, we need to determine the most efficient way to operate the plant; that is, we need to optimize the demand response automation by taking into account individuals' usage patterns as well as fluctuations in cost and/or carbon content of electricity generation over time.

Such optimization is not trivial as constraints on plug usage give rise to a real options problem: switching off a plug in period t will remove the option to switch off the plug for a number of subsequent periods. We develop an algorithm that accounts for this issue as well as for market data and user-specific behavioral data from our field experiments. We describe the highly personalized algorithm for plug control that results from it as "power doctoring". To derive the algorithm and simplify its exposition, we assume in what follows that an individual plug is under treatment 3, i.e. switch-off events last 30 minutes within 3 hourly (or 6 half-hourly) intervals, and that we are solving it for a week. The algorithm defines at any time t whether the plug should be switched off ($so_t = 1$) or not ($so_t = 0$). $\theta(t)$ characterizes which half-hour of the week t is at the start of, and therefore takes in this case values 1 to 336. We define the number of intervals (here, 336)

Table 6: Regressions of Override events

	Dependent variable:			
	Override event			
	(1)	(2)	(3)	(4)
Short duration (T1)	-0.031	-0.101^{***}	-0.030^{***}	-0.099^{***}
	(0.030)	(0.015)	(0.009)	(0.030)
High frequency (T3)	-0.021	-0.078^{***}	-0.021^{***}	-0.077^{***}
	(0.030)	(0.017)	(0.007)	(0.023)
Pre-switch-off power in W			0.0001^{***}	0.00004
			(0.00003)	(0.0001)
Reference Group (T2)	0.055^{**}	0.171^{***}	0.053^{***}	0.169^{***}
	(0.025)	(0.014)	(0.006)	(0.022)
Sample	All	Power>0	All	Power>0
Observations	6,725	1,485	6,725	1,485
R^2	0.002	0.009	0.005	0.010
Adjusted R^2	0.002	0.008	0.004	0.008
Residual Std. Error	0.184	0.298	0.184	0.299
F Statistic	6.616^{***}	6.827^{***}	10.750^{***}	4.759^{***}

Notes: These estimates are the result of OLS regressions. The table reports the propensity of participants to override switch-off events across treatment groups. The dependent variable is a binary variable equal to 1 when a switch-off event is overridden, while each coefficient represents the increased likelihood (in percentage points) of overrides in each of the three treatment groups. In columns 1 and 3, regressions are run on the entire dataset while columns 2 and 4 only include plugs with non-zero consumption immediately preceding switch-off events. The variable pre-switch-off power in columns 3 and 4 reports the effect of power consumption before a switch-off event on the likelihood of overriding the upcoming switch-off event. Robust standard errors are clustered at the user level and reported in parentheses. Significance levels are indicated as *p<0.1; **p<0.05; ***p<0.01

as Θ. The state variable K_t counts the number of half-hour periods the plug must "wait" before becoming eligible for another switch-off event. $\bar{K}$ represents the time window of the switch-off events, i.e. 6 (half-hours) in this case. We therefore formulate the value of operating an individual plug as follows:

$$V_{\theta(t)}(K_t) = \begin{cases} \max_{so_t} \left\{ -P_tC_t + \beta E\left[V_{\theta(t+1)}(0)\right], -P_tC_t(1+\pi_0) \right. \\ \left. -\sum_{f=1}^{\infty} \beta^f E\left[P_{t+f}C_t\pi_f\right] + \beta E\left[V_{\theta(t+1)}\left(\bar{K}\right)\right] \right\} & \text{if } K_t = 0 \\ \\ -P_tC_t + \beta E\left[V_{\theta(t+1)}(K_t - 1)\right] & \text{otherwise} \end{cases} \tag{2}$$

where the first expression represents the case where the plug can be switched off, i.e. $K_t = 0$. In that case, the algorithm compares two payoffs. First, in the case where the plug is not switched off, the cost of consumption C_t has to be borne and can be measured in monetary or carbon terms by multiplying it by price P_t.[20] One must then add the expected value of operating the plug in the following half-hour $\theta(t+1)$, with $K_{t+1} = 0$ given it has not been switched off at t. $\beta < 1$ is the discount factor. Second, we look at the case the plug is switched off. π_0 denotes the (percentage) change in demand when a switch-off event occurs. We assume that only $1 + \pi_0$ is consumed: if there is no overriding, $\pi_0 = -1$, meaning that the percentage change in consumption is 100%. π_0 could be less than 100% if users override, or if we were to apply our optimization to partial demand reduction (e.g., in the case of adjustments to the set points of smart thermostats).

Switching off also means that consumption will increase in subsequent periods $t + f$: π_f is the consumption change in f subsequent periods in response to a switch-off event. In addition, if $so_t = 1$, the option of switching off at $t+1$ is foregone as K_{t+1} is then equal to $\bar{K} = 6$. The second expression in equation 2 is the value of operating the plug when the plug cannot be switched off at t because $K_t \neq 0$. In that case the cost of consumption is borne. The expected value at $t+1$ depends on whether K_{t+1}, which is equal to $K_t - 1$, is equal to zero, i.e. if a switch-off is possible.

There are $\bar{K} + 1$ states, which includes $\bar{K}$ intervals that a plug must wait plus the state when the plug is eligible for a switch-off event. Therefore, we need to know $(\bar{K} + 1) \times \Theta$ values (7×336) of $E\left[V_\theta(K)\right]$ to calculate the value function and determine whether to switch off in a given period. We assume that wholesale costs and user-level consumption (in the absence of switch-off events) evolve as $P_t = \mu_{P,\theta(t)} + \epsilon_{P,t}$ and $C_t = \mu_{C,\theta(t)} + \epsilon_{C,t}$, taking a specific value for every period of the week θ.[21] As a result, from equation 2 we can derive for each of the 7 states of K:

$$E\left[V_\theta(K)\right] = \begin{cases} -E\left[P_\theta C_\theta\right] + \beta E\left[V_{\phi(\theta,1)}(0)\right] Pr(so_\theta = 0) \\ + \Big(E\left[-P_\theta C_\theta(1+\pi_\theta)\right] - \sum_{f=1}^{\infty} \beta^f E\left[P_{\phi(\theta,f)}C_\theta\pi_f\right] + \beta E\left[V_{\phi(\theta,1)}\left(\bar{K}\right)\right] \Big) \\ \times Pr(so_\theta = 1) & \text{if } K = 0 \\ \\ -E\left[P_\theta C_\theta\right] + \beta E\left[V_{\phi(\theta,1)}(K-1)\right] & \text{otherwise} \end{cases} \tag{3}$$

where $E\left[P_\theta C_\theta\right] = E\left[P_tC_t | \theta(t) = \theta\right]$. The function ϕ serves as a counter through the periods of the week, returning to 1 when 336 has been reached so that

$$\phi(\theta, f) = \begin{cases} \theta + f & \text{if } \theta + f \leq \Theta \\ \theta + f - \Theta & \text{otherwise} \end{cases}$$

[20] For simplicity, we assume here that the length of the time periods (indexed by t) within which we observe plug consumption is equal to the length of the switch-off. The algorithm could be adapted to include more frequent measurement of consumption.

[21] $\epsilon_{P,t}$ and $\epsilon_{C,t}$ could be correlated.

The probability of a switch-off event is defined as

$$
\begin{aligned}
Pr(so_\theta = 1) = E\Bigg[I\Bigg\{&-P_\theta C_\theta + \beta E\left[V_{\phi(\theta,1)}\left(0\right)\right] \\
&< -P_\theta C_\theta\left(1+\pi_0\right) - \sum_{f=1}^{\infty}\beta^f E\left[P_{\theta+f}C_\theta\pi_f\right] + \beta E\left[V_{\theta(t+1)}\left(\bar{K}\right)\right]\Bigg\}\Bigg]
\end{aligned}
\tag{4}
$$

and $Pr(so_\theta = 0) = 1 - Pr(so_\theta = 1)$. We can use the above equation system with $(\bar{K}+1)\times\Theta$ equations to solve for the $(\bar{K}+1)\times\Theta$ values $E\left[V_\theta\left(K\right)\right]$. The system may be difficult to solve outright both because it is non-linear and potentially large. For instance, if we were to solve this system for every 5-minute period of the year and allow for switch-off event gaps of 3 hours we would end up with nearly 4 million equations per plug. However, it also defines a contraction mapping so we can solve it recursively.[22] With a solution $E\left[V_\theta(K)\right]^{(*)}$ we can work out the optimal switch-off policy for different periods t as $so_t^{(*)}$.[23]

On this basis, one can then measure the impact of power doctoring on weekly costs or carbon emissions. To do so, we conduct the following counterfactual experiment at the level of specific users: considering the average energy consumption and energy prices/carbon content across our sample ($E[C_\theta]$, $E[P_\theta]$), what would be the reduction in weekly costs or carbon emissions if switch-off events were optimally scheduled?

To answer this question, we use wholesale energy prices and carbon content data from Electric Insights (2021). We then estimate π_f, the consumption change in periods following a switch-off event, through the following (Poisson) fixed effects regression

$$
C_{it} = \exp\left(\sum_l \pi_f so_{it-l} + \alpha_i + \alpha_{ht} + \alpha_{Treat,t} + \epsilon_{it}\right) \tag{7}
$$

where C_{it} is the electricity consumed by user i at time t, so_{it-l} are the randomized switch-off events in lagged periods, α_i are user fixed-effects, $\alpha_{H,t}$ are student hall×time controls, and $\alpha_{Treat,t}$ controls for the length of switch-off (15 or 30 minutes) entailed by the treatment, interacted with time.

Table 7 reports our regression results for various lags of so_{it}. The coefficients can be approximately interpreted as the percentage change in consumption during a given time period relative to consumption in the moments prior to the switch-off event. Hence the results suggest that a switch-off event on average leads to about a 50% reduction in power consumption followed by an increase of 15% in the subsequent period. We do not find significant effects beyond lag 1. In other words, a switch-off event reduces consumption via the plug by just over half, and some of that avoided energy consumption is displaced to the following period. Thus, the results imply not only a shifting of consumption but also a net reduction.

---

[22] That is, for arbitrary starting values $E\left[V_\theta(K)\right]^{(r)}$, we compute the next set of values as

$$
E\left[V_\theta(K)\right]^{(r+1)} = \begin{cases}
-E\left[P_\theta C_\theta\right] + \beta E\left[V_{\phi(\theta,1)}\left(0\right)\right]^{(r)} Pr(so_\theta = 0)^{(r)} & \\
+\left(E\left[P_\theta C_\theta\left(1+\pi_0\right)\right] - \sum_{f=1}^{\infty} E\left[P_{\phi(\theta,f)}C_\theta\pi_1\right] + \beta E\left[V_{\phi(\theta,1)}\left(\bar{K}\right)\right]^{(r)}\right) & \\
\times Pr(so_\theta = 1)^{(r)} & \text{if } K = 0 \\
& \\
-E\left[P_\theta C_\theta\right] + \beta E\left[V_{\phi(\theta,1)}\left(K-1\right)\right]^{(r)} & \text{otherwise}
\end{cases}
\tag{5}
$$

[23]

$$
\begin{aligned}
so_t^{(*)} = I\Bigg\{&-P_t C_t + \beta E\left[V_{\phi(\theta(t),1)}\left(0\right)\right]^{(*)} \\
&< -P_t C_t\left(1+\pi_0\right) - \sum_{f=1}^{\infty}\beta^f E\left[P_{t+f}C_t\pi_f\right] + \beta E\left[V_{\theta(t+1)}\left(\bar{K}\right)\right]^{(*)}\Bigg\}
\end{aligned}
\tag{6}
$$

Table 7: Changes in Energy Consumption During and After Switch-off Events

Dependent Variable:	Electricity Consumption in Wh		
Model:	(1)	(2)	(3)
Variables			
Switch off in t	-0.5240***	-0.5527***	-0.5547***
	(0.0676)	(0.0775)	(0.0774)
Switch off in t-1	0.1519**	0.1836**	0.1725**
	(0.0644)	(0.0771)	(0.0824)
Switch off in t-2		-0.0846	-0.0736
		(0.0845)	(0.0941)
Switch off in t-3			-0.0341
			(0.0662)
Fixed-effects			
User (56)	Yes	Yes	Yes
Treatment×t	Yes	Yes	Yes
Hall×t	Yes	Yes	Yes
Treatment×t	23,401	23,394	23,386
Hall×t	19,688	19,682	19,677
Pseudo R^2	0.67728	0.67739	0.67738
Observations	138,542	138,487	138,427

NOTES: The table reports Poisson fixed effects regressions of the amount of energy consumed by an individual user's plug in a 30-minute interval. We restrict the sample to users with at least 1 observation in a non-switch-off state for all 336 periods of 30 minutes in a week. Significance levels are indicated as *p<0.1; **p<0.05; ***p<0.01

In addition to the coefficients for π_0 and π_1 obtained from column 1 of Table 7, we calculate for each plug the user-specific values

$$E\left[P_\theta C_{\theta,i}\right] = \frac{\sum_{t \text{ with } \theta(t)=\theta \text{ \& } so_{it}=0} P_t C_{t,i}}{\#(t \text{ with } \theta(t) = \theta \text{ \& } so_{it} = 0)}$$

and

$$E\left[P_{\phi(\theta,f)} C_{\theta,i}\pi_1\right] = \frac{\sum_{t \text{ with } \theta(t)=\theta \text{ \& } so_{it}=0} \pi_1 P_{t+1} C_{t,i}}{\#(t \text{ with } \theta(t) = \theta \text{ \& } so_{it} = 0)}$$

These allow us to compute user-specific values $E\left[V_{i,\theta}\left(K\right)\right]^{(*)}$ and therefore plug switch-off rules $so_{it}^{(*)}$. We then compute for each user the cost ($TCOST_i$) and carbon impact ($TCO2_i$) of consuming for a typical week with and without power doctoring. The individual cost reductions in percent can be measured as:

$$\frac{TCOST_i^{powdr} - TCOST_i}{TCOST_i}$$

where

$$TCOST_i = \sum_\theta E[C_{\theta i}]E[P_\theta]$$

$$TCOST_i^{powdr} = \sum_\theta E[C_{\theta i}]E[P_\theta](1 + \pi_0 so_{i\theta}) + E[C_{\theta-1,i}]E[P_\theta]\pi_0 so_{i,\theta-1}$$

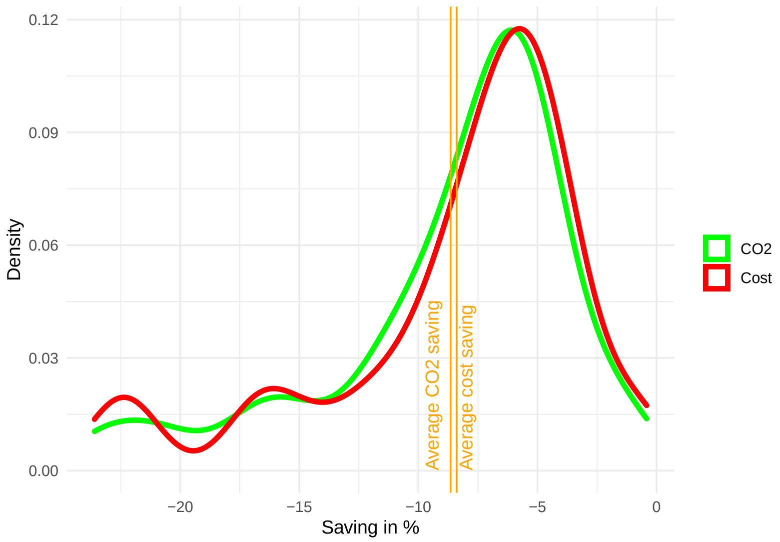
and equivalently for CO_2 reductions. $E[P_\theta]$ is equal to the average electricity price for period θ during our field experiment.

Figure 8 reports the distribution implied by these individual reductions and shows that optimal load shifting reduces both cost and emissions for the average user by about 8% with some users experiencing reductions as high as 26%.[24]

[24] If such reductions can be applied to all electronics and appliances in a household, these figures are substantially

Figure 9 provides further insight into the optimal power doctoring program. In panel (a) we report the share of users in our sample with a plug switch-off event being programmed ($so_{i\theta} = 1$) across periods θ of a week. It illustrates that at most 26% of users have their plug switched off in the same period. If users were not highly heterogeneous we would have all plugs being switched off at the same time. Also note that the optimal policy is different depending on the objective criterion (i.e. minimizing cost or CO_2) used, although there is a correlation between the two. Panel (b) shows how $E[P_\theta]$ varies across periods when measured as wholesale cost of electricity and carbon intensity. Panels (c) and (d) show that both high prices and high carbon intensities are positively correlated with optimally scheduled switch-off events. It should be noted that, given the importance of user-specific consumption profiles, the optimal policies often deviate substantially from a simple rule based on prices or CO_2 intensity.

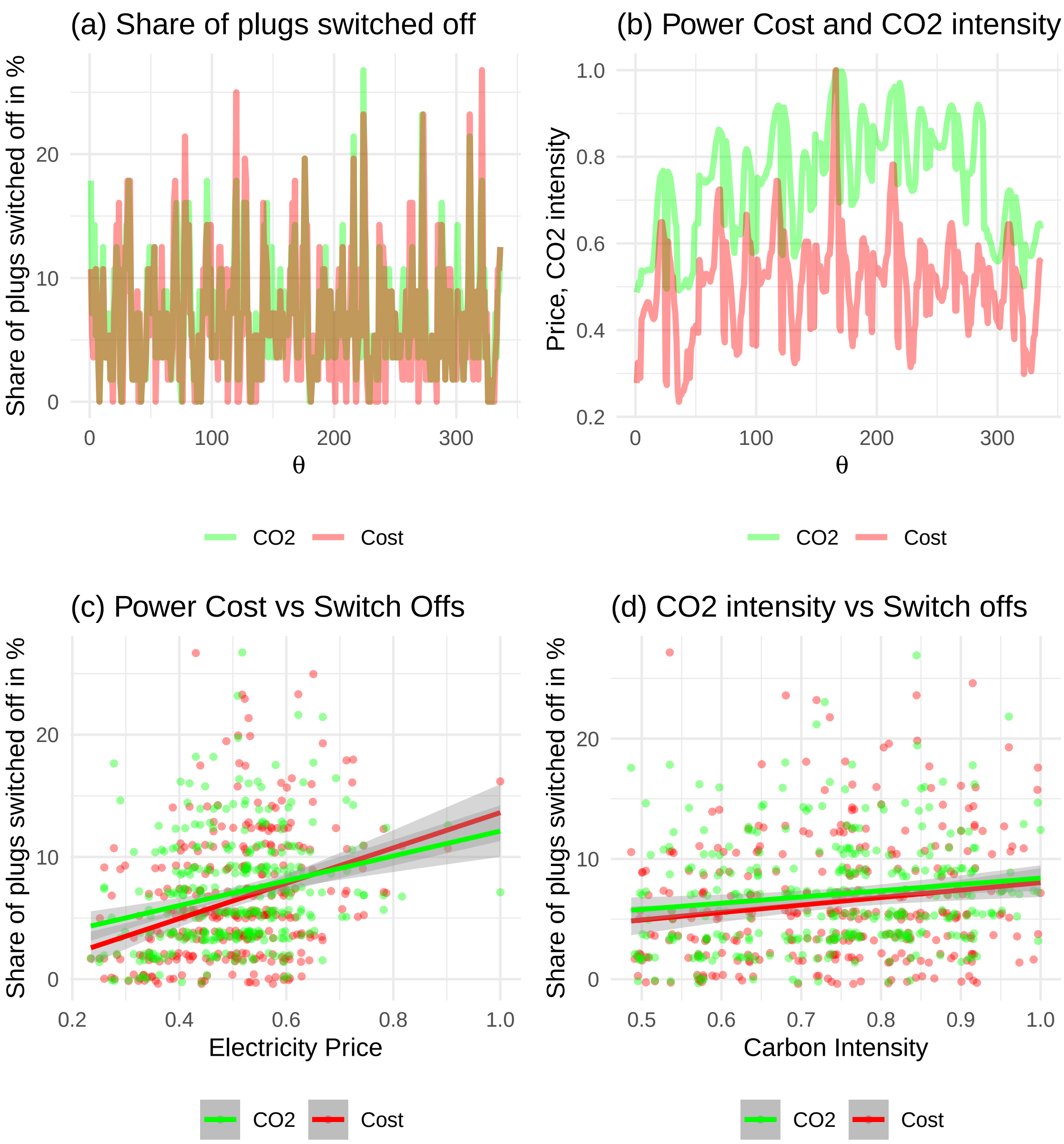
Figure 8: The Effect of Power Doctoring



Notes: The figure reports the density of user-level reductions in cost or carbon emissions that can be achieved by optimally using POWBAL plugs; i.e. we take into account a user's average consumption over 336 weekly 30-minute periods as well as the average fuel or carbon intensity in those same periods. We then apply the dynamic program outlined in equation 2 to find the optimal switch-off times $so_{it}^{(*)}$ and work out how much CO_2 reductions using CO_2 intensity as P in equation 2, or cost reductions using electricity prices as P.

larger than other interventions targeting end user demand; e.g., the UK Government assumes a household energy reduction of 2% from smart meter adoption, and a similar reduction occurs on average through oft-cited behavioral interventions (e.g., see Buckley, 2020). Moreover, these reductions occur during time windows that are optimal from a system-level perspective, and are devoid of costs to users associated with attention and effort.

Figure 9: Drivers of Power Doctoring



NOTES: Panel (a) reports the share (in %) of users whose plugs are switched off by the optimal policy rule over the 366 30-minute periods of an average week, using either CO_2 intensity or (wholesale) cost of electricity as objective criterion. Panel (b) shows an average index of electricity price and carbon intensity for the same periods. The maximum value for each series is normalized to 1. Panel (c) reports a scatter plot of the switch-off share (separately for CO_2 and electricity price criterion) versus the electricity price. Panel (d) reports a scatter plot of the switch-off share (separately for CO_2 and electricity price criterion) vs the carbon intensity.

4 Discussion and Conclusion

The development and adoption of new and often "prosocial" technologies will be critical to address climate change as well as other prominent societal issues, including economic growth and public health. Smart and connected IoT devices powered by artificial intelligence have become a central focus of technological advancement in recent years, and opportunities abound for these technologies to contribute toward social good.

In this paper, we introduce POWBAL, a new and original platform. Using internet-connected plug adapters, it allows remote device-level electricity consumption monitoring and switch-offs, an intervention we refer to as "power doctoring" when optimized to reduce cost or carbon emissions. We use this capability to conduct a series of field experiments on dynamic demand-side management.

Our research provides a first step in understanding mechanism design for virtual power plants fueled by smart plugs, an inexpensive IoT technology that can make any appliance or electronic "smart". While our focus on student halls in the United Kingdom limits the external validity of our results, a number of interesting findings emerge.

First, the duration and frequency of disruption to energy services matter. Users appear to respond to different treatment options (with different degrees of switch-off intensity) in a nonlinear way. That is, more intrusion does not necessarily lead to less participation, which may be rationalized via the trade-off between rewards and service interruption. Relatedly, we find that users who experience a more intensive switch-off regimen do not necessarily override the load-balancing efforts more frequently, which could indicate that these users are more considerate of the flexibility of devices they connect through their smart plugs.

Second, users clearly respond to reward payouts, suggesting that adoption is not purely driven by prosocial motives. Evidence of such varied motivations is good news for efforts to facilitate widespread adoption of such a technology, as prosocially motivated adopters tend to comprise only a small fraction of any population. Future research should further explore the vast array of competing motivations that determine adoption of prosocial technologies that can contribute toward such a virtual power plant—for instance, through tailoring of recruitment and switch-off approaches via user-specific algorithms—as well as the welfare implications for (vulnerable) users.

Finally, we develop an algorithm to optimally design switch-off events taking into account individual user behavior patterns, the state of the electricity grid, and option values that follow from plug usage constraints (i.e. if we switch off a plug we lose the option to switch it off again for several time periods). We fit our model to user profiles and wholesale electricity grid data and find that optimal dispatch depends significantly on user-specific consumption profiles, and that both the carbon and wholesale cost impact of users' consumption through the plug could be reduced by nearly 10% within the existing UK energy system, on average. These efficiency improvements are significant.

If such reductions can be applied to all electronics and appliances in a household, these figures are substantially larger than other interventions targeting end user demand (e.g., the UK Government assumes a household energy reduction of 2% from smart meter adoption). Moreover, these reductions occur during time windows that are optimal from a system-level perspective, and are devoid of costs to users associated with attention and effort. Therefore, the ultimate potential of such a technology, deployed at scale, lies in its ability to facilitate a future "smart" energy system with more clean generation assets and less conventional backup capacity. It allows for the conceptualization and actualization of a consumer-driven virtual power plant with instantaneous ramping capabilities, delivering dispatchable "negawatts" to the grid. There is also immediate potential in existing grid systems with predominantly conventional generation assets in shifting consumption to cleaner (less carbon-intensive) and/or cheaper time periods.

The emergence of IoT applications will continue to exponentially increase data availability across a number of sectors, creating an environment where harvesting information about the activities and behaviors of devices, consenting individuals, and physical phenomena becomes increasingly commonplace. Understanding which information and incentives are useful for achieving societal objectives, which IoT applications are likely to be adopted and influence energy consumption behavior, and how users respond to real-time feedback mechanisms is therefore critical to realize the full extent of social benefits these innovations have to offer.

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A Appendix

Figure 10: Participant Information Sheet

Participant Information Sheet

We are writing on behalf of POWBAL, a research project on energy consumption by Imperial College Business School and the London School of Economics and Political Science. We have organised a platform through which you can win versatile and easy-to-use e-vouchers* through your energy use.

How?
You can sign up to the study by reading this information sheet and agreeing to the consent form (by ticking all of the boxes in the Qualtrics sign-up survey). As a participant in the study, you will receive a smart plug, free of charge, which can be controlled and monitored remotely via the Internet.

You can attach this smart plug to your home electronics or appliances. The more energy you consume through the plug, the higher the likelihood that you will win e-vouchers. A handy Frequently Asked Questions document as well as further details on the project will be emailed to you after you sign up.

What is POWBAL all about?
In short, the plugs can be used to help balance the UK's electricity grid, allowing for cleaner electricity generation. By participating, you will allow us to switch off the plug for **30 minutes no more than once in any given 24-hour period.** Hence you should only connect certain devices for which brief switch-offs are unproblematic. For instance, you could use it to power devices with battery backup or that you regularly leave on standby (note that plugged-in electronics consume energy even when not in use). That said, you **always** remain in control. You will be able to easily override any switch-off if it happens at an inconvenient time via a button on the plug or on your web profile.

Why should you take part?
If we all use smart plugs in this way, it becomes much easier to balance the electricity grid by matching electricity supply and demand more efficiently. Such balancing is important if we want to have cleaner power from renewable sources such as wind and solar in the UK's energy mix. Hence, by taking part you can help to make the power system cleaner. And, of course, you can win rewards. In total, we have **£5000 worth of rewards to give away** over the course of the 2019-2020 academic year, and we anticipate around 250 participants.

For further details on the project or if you have any questions, please email us at powbal@imperial.ac.uk.

Yours faithfully,
The POWBAL team

*Rewards come in the form of Tango gift cards, which are currently redeemable to Amazon, Argos, Caffe Nero, Debenhams, Decathlon, Google Play, Halfords, iTunes, John Lewis, Marks & Spencer, New Look, Nike, Pizza Express, Starbucks, Steam Wallet, Tesco, The Great British Pub (i.e. all participating UK pubs), Ticketmaster, TK Maxx, Uber, and Zalanda.

Figure 11: Participation Consent Form

Thank you for your interest in **POWBAL: Power Balancing for a Sustainable Energy Transition**.

To sign up, please confirm that you have read the POWBAL Information Sheet and understand your rights as a participant by **ticking the boxes below**:

- ☐ I confirm that I have read and understood the POWBAL Information Sheet for the above study and have had the opportunity to ask questions which have been answered fully.
- ☐ I understand that my participation is voluntary and I am free to withdraw any time, without giving any reason, without my legal rights being affected.
- ☐ I understand that I will be asked to use a smart plug that can be switched on and off remotely. I also understand that my electricity usage data may be looked at by responsible individuals from Imperial College London and London School of Economics. I give permission for these individuals to access the data collected during this research and contact me via the email address I provide below.
- ☐ I have been informed about the compensation arrangements.
- ☐ I agree to take part in the above study and allow the POWBAL research team to switch off my smart plug up to 15 minutes no more than once in a given 24-hour period during my participation in this study.

Your preferred email address:

We will send a copy of our study FAQs and brief details on what comes next to the email address listed above. We will also use this email address as the username for your brand new POWBAL account (we'll take care of the setup for you!).

Table 8: Devices Connected via Smart Plugs (Debrief Survey Sample)

	Device 1	Device 2
Laptop charger	19 (36%)	14 (26%)
Phone charger	15 (28%)	11 (21%)
Lamp	6 (11%)	3 (6%)
Kettle	3 (6%)	0 (0%)
TV	2 (4%)	2 (4%)
LED or computer screen	2 (4%)	0 (0%)
Hair electronics (incl. shavers)	1 (2%)	3 (6%)
Refrigerator	1 (2%)	1 (2%)
Games Console	1 (2%)	1 (1%)
Bluetooth speaker charger	1 (2%)	0 (0%)
Electric heater	1 (2%)	0 (0%)
Printer	1 (2%)	0 (0%)
Plug-in diffuser	0 (0%)	1 (2%)
Speaker	0 (0%)	1 (2%)
No second device	N/A	15 (28%)
No Response	N/A	1 (2%)

NOTES: This table reports the participants' responses regarding the items that were connected via smart plugs. The column "Device 1" records the number of participants that selected a particular device they plugged in first. The column "Device 2" records the number of participants that stated a second device, where applicable.

Table 9: Self-reported Electronics and Appliances Available

	Quantity	Percent of survey sample
Laptop charger	38	65.5
Phone charger	38	65.5
Lamp	27	46.6
Hair electronics	20	34.5
Screen	8	13.8
Kettle	8	13.8
Refrigerator	5	8.6
TV	4	6.9
Electric heater	3	5.2
Fan	2	3.5
Speaker charger	1	1.7
Toothbrush charger	1	1.7
Decorative lights	1	1.7
Desktop computer	1	1.7
Printer	1	1.7
Total sample	58	100

NOTES: The table reports the total quantity as a percentage of debrief survey respondents who self-reported availability of electronic devices in their residence.

Figure 12: The POWBAL Plug