The Impact of Solar and Battery on Energy Demand*

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Abstract

Solar and batteries have been proposed as technologies to decarbonize the energy sector, yet we lack causal evidence quantifying their benefits to households, the grid, and society. We run a natural field experiment, randomly contacting customers to receive a free solar and battery installation. We use these random encouragements as an instrument for installation. Installation of solar and batteries had large effects, reducing weekly imported electricity by 45 percent and weekly net grid imports by 91 percent, translating into bill savings of approximately 71 percent. Treatment effects vary substantially by season, with monthly bill reductions peaking in June when there is abundant solar generation, and narrowing but not fully closing in December. Not only did it provide private benefits to the households, installation reshaped intraday consumption profiles in ways that benefit the grid: overnight imports increased as batteries charged during off-peak hours, while evening peak imports fell by 59 percent. This pattern persists even in winter when solar generation is minimal. Exploiting exogenous variation in battery feasibility across properties, we decompose the marginal contribution of storage: batteries are responsible for 33% for the total customer bill savings.

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1 Introduction

The transition to a low-carbon economy will dramatically increase demand for electricity. Electrifying cars, heating, and other end uses shifts energy consumption onto the grid, but building the infrastructure needed to support this shift is slow and difficult. New transmission lines can take over a decade to deliver, and large-scale generation projects face similar delays (Davis et al., 2023; IEA, 2025), with some powerful lobbying against such market moves (Hausman, 2025). As a result, the pace of decarbonization may ultimately be constrained not by technology, but by the speed at which infrastructure can be built.

One way to ease this constraint is to move some of the energy system closer to the end consumer, through distributed energy resources. Among these distributed technologies, rooftop solar has seen especially rapid adoption, driven by dramatic cost declines; panel prices have fallen by over 90% since 2010 (Our World in Data). A large empirical literature has documented that rooftop solar reduces household bills and grid dependence, and displaces carbon emissions (Siler-Evans et al., 2013; Kattenberg et al., 2024; Borenstein, 2017; Beppler and Oliver, 2021; Aydın et al., 2023; Gillingham and Watten, 2024; Bollinger et al., 2025).

But solar alone has an important limitation: it produces when the sun shines, not when households need it most. Batteries address this mismatch. They allow households to store excess daytime generation and use it later, increasing the usefulness and value of solar while also smoothing demand on the grid. Fortunately, the economic case for this pairing has accelerated rapidly, as battery costs have declined by 97% over the past decade (Our World in Data). Despite the potential benefits of batteries and their growing adoption, empirical evidence on these impacts remains limited. Most existing studies rely on structural models and observational data from self-selected early adopters, a group with stronger environmental preferences, higher incomes, and greater technological sophistication than the broader population (Kaps and Netessine, 2025; Sun et al., 2025; Bollinger et al., 2025).

We address this gap with a natural field experiment, providing one of the only experimental estimates of the impact of residential solar, and the first for solar combined with battery storage. In partnership with Octopus Energy Limited, the UK's largest electricity supplier, we conducted a randomized encouragement design involving 38,821 customers eligible for the Warm Home Discount (WHD) Industry Initiative Scheme — a government

program that targets households on means-tested benefits, in fuel poverty, or vulnerable to cold-related illness. In 2024, 12% of UK residents were WHD eligible. Under this initiative, Octopus Energy received government approval to provide solar panels and in-home batteries to eligible customers at no cost over two program years, running April 2024 to March 2026.

To estimate the causal effect of solar and battery installation on household consumption, we embedded a randomized encouragement design into the program's rollout. Eligible customers were randomly assigned to batches, and batch contact order was randomized. The program team contacted batches sequentially until the government budget was projected to be fully allocated; uncontacted customers serve as a pure control group. Among contacted customers, 725 have received an installation after completing a multi-stage screening process. We instrument installation with randomized encouragement to recover the local average treatment effect on electricity consumption and bills. This paper presents results from the first program year; the second year of installations is nearly complete, and we will soon have results across both years. This study was pre-registered through the AEA RCT Registry (AEARCTR-0014148).

1.1 Primary findings

We report four main sets of findings. First, solar and battery installation substantially reduced household electricity consumption and bills. Using encouragement assignment as an instrument for installation, we estimated that installation reduced weekly imported electricity by 29 kWh (a 45 percent decline relative to the control group mean) and weekly net grid imports (imports minus exports) by 57 kWh, a 91 percent reduction in net reliance on the grid. These consumption reductions translated into bill savings of approximately £12.50 per week, or roughly £650 per year, a 71 percent reduction relative to the control group.

Second, treatment effects varied substantially by season. Installation reduced monthly bills by up to £110 in June, when solar generation peaks, with installed households' bills falling close to zero during summer months. In winter, when solar output diminishes, bill reductions narrowed to approximately £26 per month. We observed a similar seasonal pattern in import and net consumption.

Third, installation reshaped the intraday electricity profile in ways that benefit the grid. Among customers with smart meters at baseline, we found that installations in-

creased overnight imports, consistent with battery charging during off-peak periods, while reducing daytime imports. Importantly, during the evening peak (17:00–20:00) period, imports decreased by 59%. This pattern of load shifting persisted even in winter months when solar generation is minimal, indicating that the battery alone contributes to demand flexibility by charging from the grid overnight and discharging during the day. Installation also triggered substantial tariff switching: roughly one quarter of installed customers moved onto solar-specific time-of-use tariffs within two months of installation, suggesting that a complementary solar-specific tariff can provide additional savings.

Fourth, exploiting additional variation from the two-year staggered rollout, we decomposed the impact of solar panels alone from solar-plus-battery. Across the two program years, 645 customers received both technologies while 80 received solar panels only. Using a difference-in-differences event study, we found that solar-plus-battery reduced weekly imports by 24 kWh compared to 16 kWh for solar alone, and reduced weekly bills by £11.6 versus £7.72 — implying that battery storage delivers an additional £202 per year in savings. Additionally, intraday analysis shows that households with batteries charge overnight and discharge during the evening peak, reducing peak demand far more than solar-only customers. Batteries thus shift demand away from the hours when electricity is most expensive and grid stress is highest.

In addition to these analyses, we have two major extensions underway. First, this paper presents results from the first program year. However, the second year of installations is nearly complete, and we will soon exploit the full two-year staggered rollout in a pooled instrumental variables framework, increasing statistical power and enabling richer heterogeneity analysis.

Second, we are collecting three additional datasets to extend our analysis. Our first new dataset will link installations to credit records, allowing us to test whether energy savings translate into measurable improvements in household financial health such as reduced debt, higher savings, or shifts in spending. Second, we are acquiring validated solar generation data to construct a household-level generation model, allowing us to decompose consumption estimates into genuine demand reductions and rebound effects. For our final new dataset, we are administering a willingness-to-pay survey using a Becker-DeGroot-Marschak mechanism to both low-income and general customers. This will allow us to estimate the subsidy required to close adoption gaps across the income distribution and test whether adoption barriers and realized benefits vary across regions.

1.2 Relevant literature

Our main contribution is to the nascent literature on the value of residential battery storage. The closest paper to ours is Kaps and Netessine (2025), who develop a structural model of German prosumer households and find that storage reduces grid dependence by 38 percent but increases total consumption. Sun et al. (2025) simulate the economic and backup viability of solar-plus-battery for over 500,000 US households, but their analysis is a model-based feasibility assessment rather than an estimate of realized treatment effects. There is also related work by Bollinger et al. (2023), who focus on adoption and estimate a dynamic model of solar and storage co-adoption using U.S. administrative data and find strong demand complementarities: 20 percent of co-adopters would not have adopted either technology alone. We provide the first experimental estimates of how solar-plus-battery causally affects household consumption and bills, and separately identify the marginal contribution of storage by exploiting property-level variation in battery feasibility.

Second, we contribute to the broader literature on the impacts of energy technologies on household consumption and private benefits. A large literature shows that solar adoption leads to substantial reductions in net electricity consumption and bills, but also induces rebound effects, with households increasing consumption in response to lower marginal costs on the order of 20–30% (Beppler and Oliver, 2021; Oliver et al., 2025; Aydın et al., 2023). Financial returns to solar depend critically on tariff structures and policy design, including tax incentives (Borenstein, 2017; Gillingham and Watten, 2024). Environmental benefits arise from displacing conventional generation, but vary substantially across locations depending on the marginal generation mix (Siler-Evans et al., 2013; Brown and O'Sullivan, 2020; Callaway et al., 2018; Sexton et al., 2021; Reguant, 2019). These estimates all rely on observational comparisons of adopters and non-adopters. Our paper is most closely related to Kattenberg et al. (2024), who exploit a randomized subsidy lottery in the Netherlands and find that the ITT effect of solar subsidy receipt reduces household electricity consumption by 7 percent. We build on this work by providing experimental evidence on the combined effects of solar and battery adoption.

Third, we relate to the large literature on solar adoption and subsidy design. Financial incentives have been shown to be powerful drivers of installation rates (Hughes and Podolefsky, 2015; Crago and Chernyakhovskiy, 2017; Gillingham and Tsvetanov, 2019; De Groote and Verboven, 2019; Burr, 2016; Cass et al., 2025). Social interactions, through

peer effects, messaging, and campaign design, play a complementary role in accelerating diffusion and use (Bollinger and Gillingham, 2012; Bollinger et al., 2020; Carattini et al., 2024; Bollinger et al., 2024; Bollinger and Gillingham, 2014; List et al., 2024; Parkins et al., 2018). Our paper takes the adoption decision as given and focuses on a question this literature has not been able to answer with experimental evidence: what are the downstream consumption and bill effects of installation?

Fourth, we contribute to the literature on the distributional effects of solar policy and energy poverty. Existing solar subsidies disproportionately benefit higher-income households (Borenstein and Davis, 2016; Sarikaya and Qiu, 2024; Dorsey and Wolfson, 2024; Dauwalter and Harris, 2023), and several papers have studied subsidy and tariff designs that could improve equity (Feger et al., 2022; Colas and Reynier, 2024). On the question of whether solar and storage can alleviate energy insecurity, Kerby et al. (2025) find that these technologies can substitute for two-thirds of the bill savings that low-income U.S. households currently achieve through severe energy-limiting behaviors. We provide the first causal evidence that solar and battery installation substantially reduces bills for fuel-poor household by roughly 69 percent, filling a gap in a literature that has documented the regressivity of existing programs but lacks experimental evidence on the magnitude of benefits when these technologies are delivered to the households that need them most.

2 Research design

This section describes the design and implementation of our natural field experiment. We begin by detailing the eligibility criteria under the Warm Home Discount Industry Initiative Scheme that define our sampling frame. We then describe the randomisation procedure used to generate exogenous variation in encouragement status. Next, we outline the solar and battery installation process, including the multi-stage screening and the property-level constraints that determined whether customers received solar alone or solar-plus-battery. We conclude by summarising the timeline of the experiment, the data sources used in the analysis, and checks on experimental integrity.

2.1 Sampling frame: eligibility for Warm Home Discount Industry Initiative

The Warm Home Discount (WHD) is a UK government scheme introduced in 2011 to reduce energy costs for low-income and vulnerable households. In England and Wales, it provides an annual £150 rebate on electricity bills during winter, applied directly to eligible customers' accounts. Eligibility is primarily determined through means-tested benefits and assessed high energy costs.

In addition to the core bill rebate, the scheme includes an "Industry Initiative" component, which allows energy suppliers to fund broader forms of support for household in or at risk of fuel poverty; examples include energy advice, debt relief, and energy efficiency measures. Under this initiative, Octopus Energy Limited received government approval to provide solar panels and in-home batteries to eligible customers at no cost for the duration of two program years, running April 2024 to March 2026.

The sampling frame for this study thus consisted of 19,411 Octopus Energy customers eligible for the WHD Industry Initiative Scheme, identified prior to randomization using administrative and linked external data. Customers were included if they:

1. Received the Warm Home Discount the year prior (2023–2024). This includes customers (or their partners) on a state run pension scheme (i.e., Guaranteed Pension Credit), or those on qualifying means-tested benefits and identified as living in a high energy cost property based on Valuation Office Agency data

2. Met additional vulnerability and fuel poverty targeting criteria, including: (1) being located in the top 20% most fuel-poor Lower Layer Super Output Areas (LSOAs), (2) registered on the Priority Services Register, and, (3) other commercially sensitive criteria determined by Octopus Energy

2.2 Randomization

The WHD team operated under a fixed budget approved by the government (£8.8 million over the two Service Years) and was required to minimize both overspending and underspending.[1] Because installation take-up rates and per-installation costs were

[1] Ofgem (the Office of Gas and Electricity Markets) is the independent energy regulator for Great Britain and oversees supplier compliance with social and environmental policy schemes, including the Warm Home Discount.

uncertain ex ante, contacting all eligible customers simultaneously would have created substantial financial risk. We thus implemented the encouragement design in a manner that accommodated the program's binding budget constraint.

To facilitate precise budget management while preserving random assignment, we randomly allocated customers to 78 "batches" of approximately 500 customers each. We used stratified randomization to improve balance across observable characteristics. Specifically, customers were stratified by (i) Grid Supply Point (GSP) group (14 geographic electricity network regions) and (ii) Estimated Annual Consumption (EAC), categorized into four groups based on quartiles of the sample distribution. Within each stratum defined by the cross of GSP group and EAC category, customers were randomly assigned to batches.

Following randomization, the WHD team contacted batches sequentially, beginning with the lowest randomly assigned batch numbers. Batches were released gradually over time so that the team could monitor realized conversion rates and installation costs and stop contacting additional batches once the available budget was expected to be fully allocated. Customers in contacted batches received an email encouraging them to complete an online screening form to initiate the process of obtaining a free solar panel and battery installation. Customers in batches that were never contacted received no communication about the program and served as the control group.

Because batch order was randomly assigned, variation in whether customers were ever contacted and in the timing of contact was random. This design generated exogenous variation in encouragement status (ever contacted versus never contacted), allowing us to estimate the intent-to-treat effect of being offered the opportunity to participate in the installation program.

2.3 Solar and battery installation details

Customers in contacted batches received an email inviting them to participate in the WHD Industry Initiative and encouraging them to complete an online screening form via Typeform to begin the process of obtaining a free solar panel and battery installation.

Completing the online form was the first active step in the customer journey. The form collected information necessary to assess preliminary installation feasibility, including home ownership status, property characteristics (e.g., roof type, insulation, and available space), and other features relevant to installation suitability. Customers who did not

complete the form took no further part in the installation process.

Among those who completed the form, the supplier assessed installation feasibility. Installation-eligible customers were those who, based on self-reported information and internal review, appeared to own their property and have a property type compatible with the supplier's standard solar and battery installation program. Customers deemed non-eligible exited the installation pathway at this stage.

Installation-eligible customers proceeded to a more detailed screening stage. This included additional data validation steps conducted by Octopus, such as property-level checks using satellite imagery (e.g., Google Earth), assessment of roof orientation and shading, and follow-up phone calls to confirm property suitability and collect any further required technical information. This stage was designed to ensure compliance with Microgeneration Certification Scheme (MCS) requirements and operational constraints.

Customers who passed this more detailed screening were then scheduled for installation. Installations were carried out by certified installation teams and typically involved fitting rooftop solar panels, installing an in-home battery system, and integrating the system with the household's existing electricity meter. The full funnel—from initial contact to completed installation—typically spanned approximately 16 to 20 weeks, depending on customer responsiveness, property characteristics, and installation scheduling constraints.

At each stage, participation remained voluntary. Customers could discontinue the process without penalty, and not all customers who began the journey ultimately received an installation due to screening failures, logistical constraints, or non-response during later stages of the process.

In some cases, customers received solar panels without an accompanying battery. Although the program was designed to install both technologies jointly, battery installation was subject to additional technical and regulatory constraints. The two main reasons batteries were not installed were (i) manufacturer guidelines—for example, Enphase batteries could not be placed in direct sunlight, which ruled out installation where only a south-facing wall was available; and (ii) compliance with electrical safety standards set by the UK Department for Energy Security and Net Zero (DESNZ), which in some homes left no viable battery location that met required regulations.

2.4 Timeline and data

The primary batch of installations unfolded, with encouragement emails sent sequentially to randomly assigned batches beginning in September 2024 and continuing until the available budget was expected to be fully allocated. Installations for customers who proceeded through the screening and eligibility stages occurred between December 2024 and March 2025.

Our main analysis uses administrative daily electricity consumption data for both smart meter and traditional meter customers. For customers with traditional (non-smart) meters, energy consumption data is typically recorded during manual meter readings, which often occur at irregular intervals (e.g., every few months). However, Octopus Energy's billing system automatically estimates daily (and thus weekly) consumption, and we use these estimated daily consumption figures as the main outcome measure for these customers. For customers with smart meters, we also have half-hourly consumption data. We combine this consumption data with customer characteristics drawn from supplier records (e.g., baseline consumption, meter type, EPC rating, tariff, and tenure).

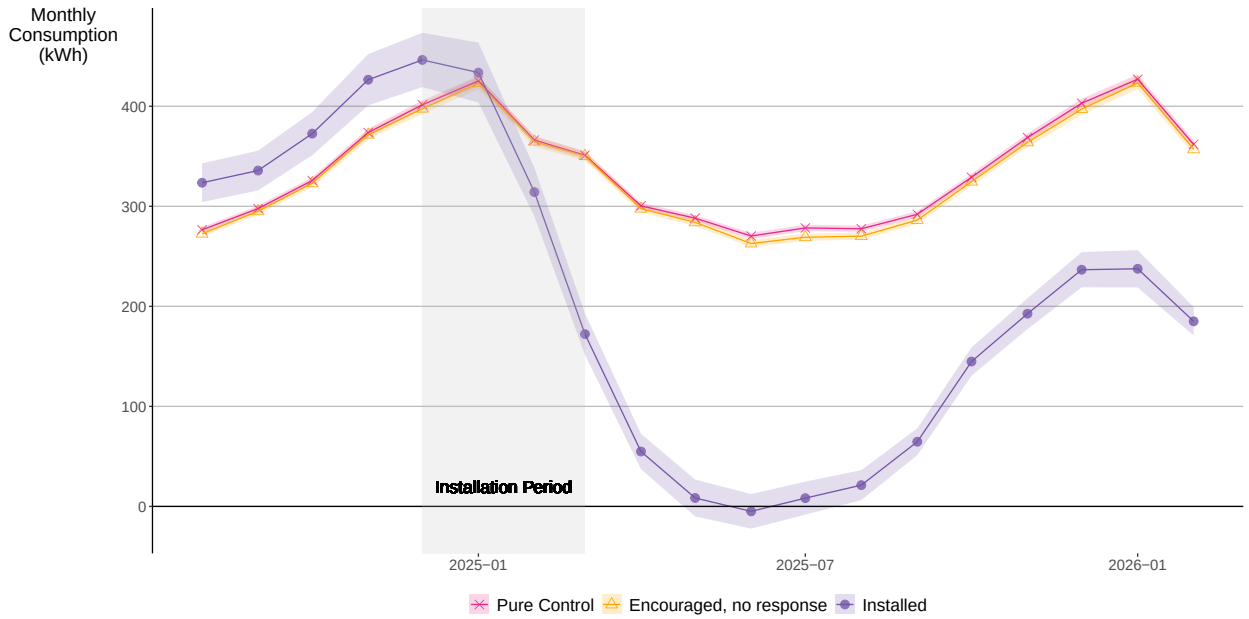
Figure 1 shows raw monthly electricity consumption across three groups over the study period. The control and encouraged groups track each other closely throughout, consistent with successful randomization. Among those who eventually received an installation, pre-period consumption is visibly higher than in the control group, suggesting positive selection on baseline energy use. Following installation, the installed group exhibits a sharp and sustained decline in net consumption, falling close to zero during summer months when high solar generation can offset grid draws.

2.5 Experimental integrity

Balance: Table A1 reports baseline balance between encouraged and control groups. Overall, observable characteristics were well balanced across the groups. These results are consistent with successful randomization.

Attrition: Attrition here is defined as a customer leaving Octopus Energy. Attrition is low (4% in the control group) and balanced between never-contacted controls and encouraged customers (Table A2, row 1). However, customers who received an installation exhibit lower attrition rates than those who did not receive an installation (Table A2, row 2). This is perhaps unsurprising, given that there are two potential forces: (1) a mechanical effect,

Figure 1: Net monthly consumption



Notes: Monthly net (imports minus exports) electricity consumption (kWh) for (1) never contacted control group, (2) encouraged but not installed customers, and (3) customers who received installation, plotted from September 2024 to December 2025. The shaded grey band indicates the installation period (December 2024 – March 2025). Shaded ribbons around each series denote 95% confidence intervals.

whereby customers remain with Octopus through the installation process to receive the technology, and (2) a residual loyalty effect from receipt of a high-value asset at no cost.

Attrition is also negatively correlated with Octopus tenure, so customers who have been with Octopus longer and less likely to attrite, and customers with higher energy ratings are more likely to attrite. Attrition is also related to baseline characteristics. It is negatively correlated with tenure at Octopus, and positively correlated with higher Energy Performance Certificate (EPC) ratings.

In subsequent drafts, we plan to address potential bias from selective attrition using three complementary approaches: (i) ex post matching to rebalance observable characteristics, (ii) imputation of post-exit consumption outcomes, and (iii) compute nonparametric bounds on treatment effects in the presence of differential attrition (Lee, 2009).

Pre-analysis plan: This study was pre-registered through the AEA RCT Registry, as AEARCTR-0014148.

3 Results

This section presents our main empirical findings. We begin by describing the instrumental variables specification used to estimate the causal effect of installation on household electricity outcomes. We then report aggregate treatment effects on electricity consumption and bills, followed by an analysis of how these effects vary across seasons. Next, we examine how installation reshaped intraday consumption profiles using half-hourly smart meter data. We conclude by documenting tariff switching behaviour among installed customers.

3.1 Empirical specification

To estimate the causal effect of installation on electricity consumption, we used instrumental variable approach that exploited randomized encouragement as an instrument for treatment take-up. Let I_{it} denote an indicator for whether household i had received the installation by time t, and let E_{it} denote an indicator for whether the household had been encouraged to fill out a survey to start the "customer journey" to obtain a free installation. In the first stage, we estimated

$$I_{it} = \pi_0 + \pi_1 E_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{1}$$

where μ_i is household fixed effects and δ_t is time fixed effects. The coefficient π_1 captured the effect of encouragement on the probability of installation. In the second stage, we estimated

$$Y_{it} = \beta_0 + \beta_1 \widehat{I_{it}} + \gamma_i + \phi_t + \epsilon_{it}, \tag{2}$$

where Y_{it} was the outcome of interest and $\widehat{I_{it}}$ was the predicted installation status from the first stage.

Y_{it} is one of our three main outcome variables: net electricity consumption (import minus export), import consumption, and bill, for customer i in week t. Note that our main specification includes both smart meter and traditional meter customers. For customers with traditional (non-smart) meters, energy consumption data is typically recorded during manual meter readings, which often occur at irregular intervals (e.g., every few months). However, Octopus Energy's billing system automatically estimates daily (and thus weekly)

consumption, and we use these estimated weekly consumption figures as the outcome measure for these customers.

As we pre-specified, we exclude the rollout period entirely, removing all customer-week observations from December 2024 through March 2025, which corresponds to the primary installation window. This exclusion is designed to preserve the exogeneity of treatment timing. During the rollout period, installations occur at different times across customers, and the timing itself may be endogenous; for example, if customers more eager or better positioned to benefit from the installation self select into early treatment.

3.2 Main results: impact of solar and battery on consumption and bills

Solar and battery installation substantially reduces household grid consumption and electricity bills. Table 1 presents the results of estimating Equation (2), using encouragement assignment as an instrument for installation. The first-stage relationship was strong (Wald statistic = 389.34).

Installation reduced imported electricity by 28.00 kWh per week (column 1), a 44 percent decline relative to the control mean. When accounting for exports, net grid imports fell by 57.65 kWh per week (column 2), implying a 91 percent reduction in net reliance on the grid. These consumption reductions translated into substantial financial savings. Column (3) shows that treated households experienced a £12.50 reduction in weekly electricity bills—approximately 71 percent relative to the control group, or about £650 annually. The smaller proportional reduction in bills compared to net consumption reflects asymmetric pricing: households pay retail rates for imports but receive lower compensation for exports.

The existing literature has documented rebound effects on the order of 20-30 percent following solar adoption (Beppler and Oliver, 2021; Oliver et al., 2025; Aydın et al., 2023). Our estimates of reduced grid imports therefore likely understate the total change in electricity generation, as some solar output is absorbed by higher consumption. While we do not currently observe solar generation for our sample, we are in the process of acquiring validated generation data that will allow us to construct a generation model for these households and estimate the magnitude of the rebound.

Table 1: Effect of solar and battery installation on consumption and bills

Dependent Variable Model:	Import kWh (1)	Net kWh (2)	Bill (£) (3)
Variables			
Received Install	-29.34***	-57.27***	-12.33***
	(7.69)	(7.83)	(1.85)
Fixed-effects			
Household	Yes	Yes	Yes
Week	Yes	Yes	Yes
Fit statistics			
Control Mean	65.06	64.96	17.88
Observations	1,512,137	1,512,137	1,512,137
Wald (1st stage), treated	351.19	351.19	351.19

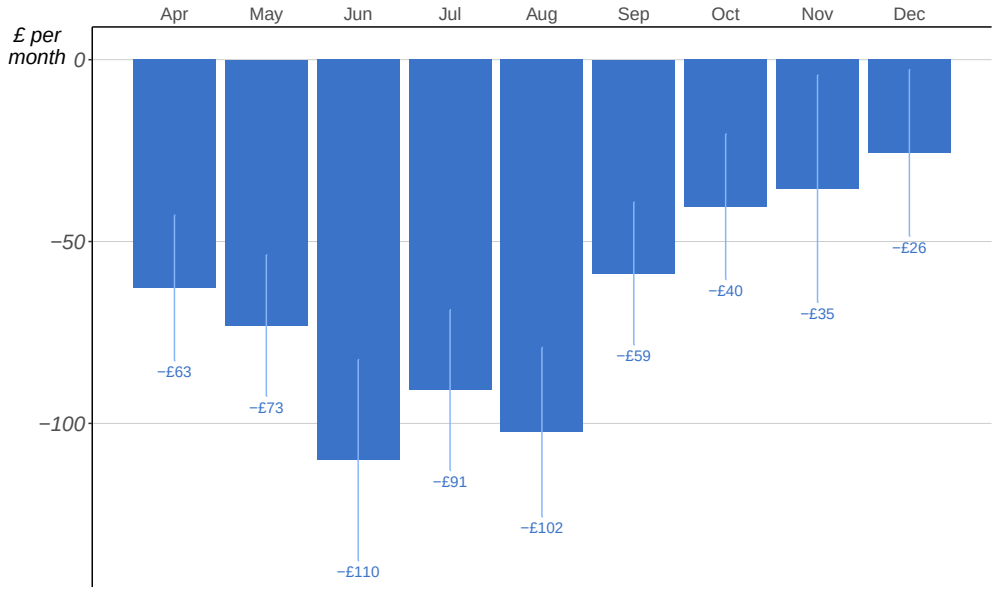
Clustered (Household) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: This table reports IV estimates from Equation (2) of the effect of receiving a solar panel and battery installation on weekly household electricity outcomes. Installation status is instrumented using randomized encouragement assignment. All specifications include household and week fixed effects. The dependent variables are weekly imported electricity (kWh) in column (1), weekly net grid imports (imports minus exports, kWh) in column (2), and weekly electricity bills (£) in column (3). Standard errors are clustered at the household level and reported in parentheses. Control means are calculated using the never-contacted control group. The reported Wald statistic corresponds to the first-stage F-statistic on the excluded instrument.

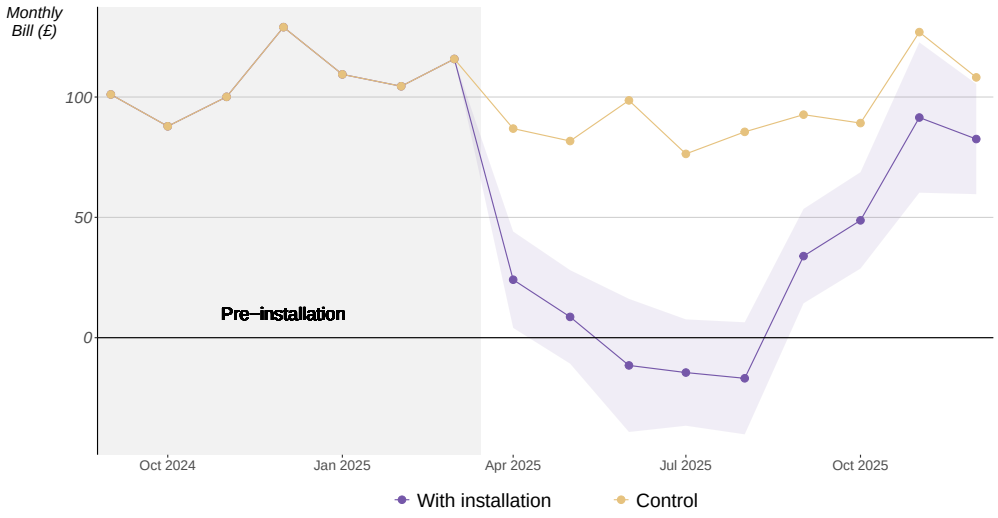
3.3 Seasonal treatment effects

Treatment effects differ substantially by season. Figure 2 illustrates this pattern. Figure 2a reports estimates from a specification interacting installation status with month-of-year indicators, allowing the treatment effect to vary flexibly across the calendar year. The effects are negative throughout and largest in summer, peaking at -£110 in June when solar generation is highest. Figure 2b translates these estimates into levels by adding the month-specific treatment effects from Figure 2a to the observed mean monthly bills of the control group, giving an implied time path of bills for an installed customer. This shows that installed households' bills fall close to zero in summer months, before recovering toward the non-installed group's level in winter as solar output diminishes. We observe a similar seasonal pattern in import and net consumption, as shown in Figure A1 and Figure A2.

Figure 2: Impact on bills by month of the year



(a) Month-of-year IV estimates



(b) Implied monthly bills

Notes: Panel (a) reports month-of-year IV estimates of the effect of installation on monthly electricity bills (£), from a specification interacting installation status with month-of-year indicators. Confidence intervals are shown at the 95% level. Panel (b) plots implied monthly bills for installed customers alongside observed mean monthly bills for the control group. The "With installation" series is constructed by adding the month-specific treatment effects from panel (a) to the control group mean in each month. The shaded grey region in panel (b) denotes the installation period (December 2024 – March 2025). Shaded ribbons denote 95% confidence intervals.

3.4 Intraday impacts

Our sample includes both smart meter and traditional meter customers. To examine how installation affected the intraday consumption profile, we restrict the sample to customers with half-hourly smart meter data. Importantly, we limit this analysis to customers who had a smart meter at baseline. Treatment increased smart meter adoption (Table A4), so conditioning on post-treatment smart meter status would introduce selection bias by restricting the sample to an outcome affected by treatment.

Note also that treatment effects are heterogeneous by baseline smart meter status. In particular, effects are larger among customers who had a smart meter at baseline. For example, relative to their respective control groups, customers without a baseline smart meter experienced a 48 percent reduction in electricity bills, whereas customers with a baseline smart meter experienced a 70 percent reduction (Table A5). These differences may reflect underlying differences in household characteristics correlated with early smart meter adoption, such as engagement with energy usage. Given this, we note that this analysis is likely not reflective of the intraday effects over the whole sample.

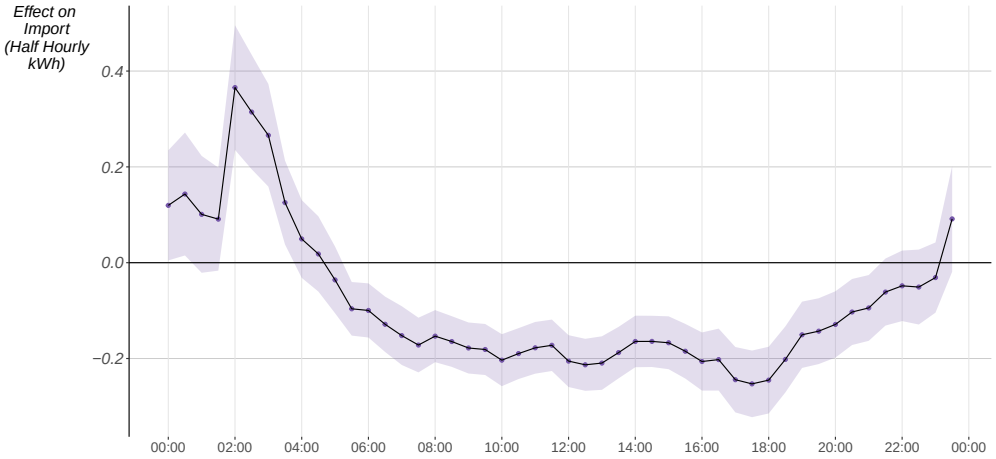
Among customers with smart meters at baseline, installation substantially reshaped the intraday electricity import profile in ways that benefit the grid. Interacting installation status with hour-of-day indicators shows that installations increased overnight imports (consistent with battery charging) and reduced daytime imports, including during the evening peak (Figure 3a). This suggests that solar and battery installations not only reduced costs for individual households but would also lower system-wide costs by shifting demand away from peak periods.

We further decompose the intraday treatment effects by estimating month-specific hourly profiles. Specifically, we interact installation status with hour-of-day indicators and estimate separate regressions for each month of the year. This approach allows the treatment effect to vary flexibly both within the day and across seasons. We also show exports by hour-of-day and month. We report descriptive hourly averages rather than IV estimates, as electricity exports are mechanically zero in the absence of installation.

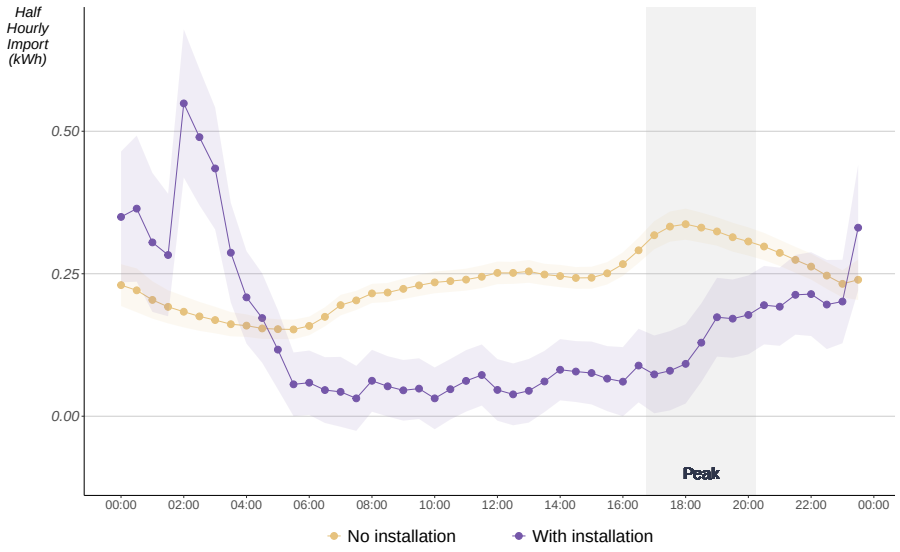
Intraday import profiles show a consistent pattern across all months: overnight imports rise sharply while daytime imports fall substantially (Figure A3). Notably, this pattern persists even in winter months when exports are near zero, indicating that the battery alone contributes to load shifting, even without solar genereation. In these months, customers appear to charge their batteries from the grid during overnight off-peak periods

Figure 3: Impact on import consumption by hour of the day

(a) Hour-of-day IV estimates



(b) Implied intraday consumption profiles



Notes: Panel (a) reports IV estimates of the effect of installation on half-hourly electricity imports (kWh), from a specification interacting installation status with half-hour-of-day indicators. The sample is restricted to customers with smart meters at baseline. Shaded ribbons denote 95% confidence intervals. Panel (b) plots implied half-hourly import profiles for installed and non-installed customers, constructed by adding the half-hour-of-day treatment effects from panel (a) to the control group mean at each half-hour interval. The shaded grey region denotes the evening peak period (17:00–20:00).

and discharge them to meet daytime demand, reducing grid imports throughout the day.

3.5 Tariff switching

The intraday load-shifting documented above requires not just battery storage, but price incentives to charge overnight and discharge during peak periods. Octopus offers a large range of tariffs, some of which are tailored to customers with solar and battery; we describe these solar-specific tariffs in Figure 4. We examine whether installation induces customers to switch toward import tariffs that provide such incentives, and find that installation triggers significant tariff switching, helping to explain the intraday patterns.

Figure 4: Tariff options for customers with solar



Table A6 shows that installation causes customers to move away from non-LCT tariffs toward solar-specific tariffs. The probability of being on a non-LCT tariff falls by 0.28 (from a control mean of 0.95), while the probability of being on a solar tariff rises by 0.24; roughly one quarter of installed customers switch onto a solar-specific tariff following installation.

Solar tariff adoption typically occurs within two months after (Figure A4a). Panel (a) of Figure 5 shows that approximately 30% of switchers adopt a solar tariff within the first month post-installation, and a further 45% within the second, with the distri-

bution declining sharply thereafter. This concentration of switching in the immediate post-installation period suggests that tariff switching is driven mostly by the installation event itself, rather than gradual learning or delayed awareness.

In calendar time, adoption clusters sharply around April 2025 (Figure A4b), though this pattern reflects two coincident forces: the concentration of installations completing in late 2024 and early 2025, and the onset of the UK solar generation season in spring. We cannot separately identify why the April spike is mechanical (reflecting the distribution of installation dates) or whether customers are more likely to switch upon first observing meaningful solar generation on their bills.

Table A7 reveals that these tariff switches are toward price schedules that incentivize intraday consumption shifting. Installation reduces the probability of being on a fixed tariff by 0.26 (from a control mean of 0.83), with offsetting increases in new TOU tariffs (+0.18) and managed TOU tariffs (+0.12).

While installation induces substantial tariff switching, 57% of installed customers remain on fixed tariffs, suggesting inertia or switching costs in tariff choice. These customers may therefore not fully capture the potential gains from their solar and battery systems. We cannot test this directly, however, because tariff choice is endogenous to installation. Any comparison of bill savings between switchers and non-switchers would conflate the causal effect of the tariff with selection into switching.

A similar pattern is evident in export tariff choice: among installed customers, 60% select a fixed export tariff, 20% a time-of-use tariff, and 10% a dynamic pricing tariff, indicating that most installed customers opt for simplicity on both sides of the meter.

4 Value of battery in addition to solar

A central question for policymakers designing subsidies for low-income households is whether battery storage adds meaningful value beyond solar panels alone. Solar panels reduce grid imports during daylight hours, but without storage, surplus generation is exported immediately, and households remain fully reliant on grid imports overnight and during peak periods. Batteries can, in principle, capture daytime surplus for later use, enabling further reductions in grid dependence and allowing households to exploit time-of-use tariff structures. Yet few studies have been able to separately identify the marginal contribution of battery storage in a setting with credible counterfactuals.

We exploit variation in who received solar-only versus solar-plus-battery to quantify the additional value of a battery. Amongst our installations, 80 households (12% of installations) received only solar panels, whilst the rest received solar and battery. Importantly, the absence of a battery was not a customer choice. All installations were designed to include both technologies. However, property-level constraints outside the control of the customer prevented battery installation in a subset of cases. Two constraints were primarily responsible: (i) the battery manufacturer guidelines prohibit battery placement in direct sunlight[2], ruling out properties where only a south-facing wall was available; and (ii) Department for Energy Security and Net Zero (DESNZ) electrical installation regulations impose placement requirements that some properties could not satisfy. We exploit this variation to estimate the incremental effect of battery storage on household electricity consumption and bills.

While customers do not choose whether to receive a battery, the property features that determine battery feasibility are correlated with broader household characteristics. Table A8 confirms that the two groups differ on observables: solar-only customers have lower property values (£271,081 versus £323,928), higher EPC ratings (4.17 versus 3.82), fewer panels installed (8.09 versus 9.17), and lower estimated annual consumption (3,600 kWh versus 4,172 kWh).

To account for these baseline differences, our identification strategy relies on a parallel trends assumption: in the absence of installation, solar-only and solar-plus-battery customers would have followed the same consumption trajectory over time. Since assignment to solar-only was determined by physical property constraints (wall orientation, regulatory compliance) rather than by customer behavior or energy use decisions, it is that the two groups were on diverging consumption paths prior to installation. We test this assumption directly using the event study described below, which allows us to inspect whether the two groups exhibit differential trends in the pre-installation period.

4.1 Event study analysis

We restrict the sample to customers who received an installation and use not-yet-treated customers, households who ultimately received an installation but had not yet done so in week t, as the control group. To estimate the dynamic effects of installation

[2] All batteries were manufactured by Enphase.

and assess pre-trends, we estimate:

$$Y_{it} = \alpha_i + \gamma_t + \sum_{\substack{k=-40 \\ k\neq -1}}^{30} \left[\beta_k^{\text{Solar}} \cdot D_{it}^k \cdot \text{Solar}_i + \beta_k^{\text{SolarBattery}} \cdot D_{it}^k \cdot \text{SolarBattery}_i \right] + \varepsilon_{it} \tag{3}$$

where Y_{it} is the outcome for household i in calendar week t (weekly import kWh, net kWh, or electricity bill); α_i and γ_t are household and calendar-week fixed effects; $D_{it}^k = \mathbf{1}[t - t_i^* = k]$ indicates that household i is k weeks from its installation date t_i^*; and Solar_i and SolarBattery_i are indicators for solar-only and solar-plus-battery households, respectively. The omitted reference period is $k = -1$, with all event times before -40 binned. The coefficients β_k^{Solar} and $\beta_k^{\text{SolarBattery}}$ trace out the weekly treatment-effect paths for each technology group relative to the pre-installation baseline. Standard errors are clustered at the household level.

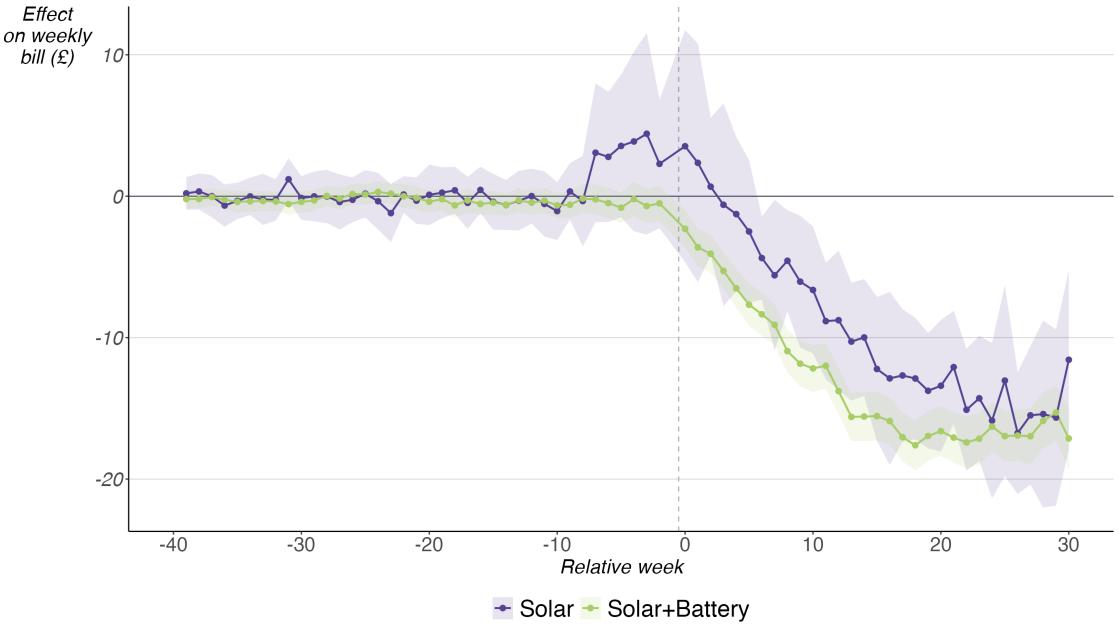
Additionally, we construct inverse propensity score weights (IPW) to reweight the solar-only battery group to match the covariate distribution of the solar-and-battery group. The propensity score is estimated via logistic regression using the number of solar panels installed, property value, and baseline estimated annual consumption. IPW-weighted estimates serve as our primary specification.[3] The key covariate motivating this reweighting is panel count. Because generation scales approximately linearly with the number of panels, any distributional imbalance between groups induces a mechanical difference in net consumption reductions unrelated to the battery. In the appendix, we show that unweighted estimates exhibit no differential pre-trends but produce noticeably larger post-installation treatment effects (Figures A6 and A7), consistent with the solar-and-battery group having more panels on average. IPW removes this compositional confound, isolating the marginal contribution of the battery.

Figure 5 plots the impact on weekly bills. In the 40 weeks prior to installation, treatment-effect estimates for both groups hover around zero with no systematic divergence, supporting the parallel trends assumption. At the point of installation, both series drop sharply, but the solar-plus-battery trajectory falls more steeply and remains consistently below the solar-only trajectory throughout the post-installation period. This pattern is also observed for import and net consumption, as shown in Figure A7.

Next, we collapse the event-time variation into a single post-installation indicator.

[3] Augmenting the propensity score model with energy performance rating, baseline smart meter status, and Octopus tenure leaves results largely unchanged. We prefer the parsimonious specification to limit overfitting risk given the small solar-only sample (n=80n=80 n=80).

Figure 5: Event study: impact of solar versus solar-plus-battery on weekly bills



Notes: This figure reports IPW-weighted TWFE event study estimates of the effect of installation on weekly bills, separately for solar-only and solar-plus-battery customers. The sample is restricted to customers who received an installation, with not-yet-treated customers serving as the control group. Shaded ribbons denote 95% confidence intervals. Standard errors are clustered at the household level.

Both technologies substantially reduce electricity consumption and bills, but the addition of a battery amplifies the effect across all outcomes. Solar-plus-battery installation reduces weekly electricity imports by 24.2 kWh, compared to 15.9 kWh for solar alone; the battery contributes an additional 8.3 kWh per week in avoided grid imports. On bills, battery storage delivers an additional £3.88 per week in savings (£11.6 versus £7.72), or roughly £202 per year.

For net consumption (imports minus exports), adding a battery delivers an additional reduction of 7.6 kWh per week (57.1 versus 49.5 kWh). Comparing solar-only to solar-plus-battery systems involves two opposing forces. Batteries introduce efficiency losses, which could dampen overall savings. But without a battery, households may be unable to use or export excess generation, especially if they are not on an export tariff, meaning that some solar output is effectively wasted. In practice, we find noisier and more modest differences between the two groups, with somewhat larger reductions for solar-plus-battery systems. This suggests that avoiding wasted generation outweighs efficiency losses, consistent with the fact that around 30% of customers are not on an export tariff.

Table 2: Impact of solar versus solar+battery

Model:	Import kWh (1)	Net kWh (2)	Bill (£) (3)
Variables			
Solar post-install	-15.9***	-43.6***	-7.72***
	(5.81)	(8.53)	(1.50)
Solar+Battery post-install	-24.2***	-55.7***	-11.6***
	(1.81)	(2.29)	(0.442)
Fixed-effects			
Household	Yes	Yes	Yes
Week	Yes	Yes	Yes
Fit statistics			
Baseline Mean	69.8	69.6	18.9
Observations	103,954	103,954	103,954

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

Note: This table reports IPW-weighted difference-in-differences estimates of the effect of installation on weekly household electricity outcomes, separately for solar-only and solar-plus-battery customers. The sample is restricted to customers who received an installation, with not-yet-treated customers serving as the control group. All specifications include household and calendar-week fixed effects. Standard errors are clustered at the household level and reported in parentheses.

4.2 Intraday load shifting

The event study captures the aggregate impact of batteries on weekly consumption and bills, but leaves open two questions. First, how do batteries affect the electricity grid; do they simply reduce total demand, or do they also shift demand away from peak periods when system costs are highest? Second, through what mechanism do batteries generate additional household savings: by increasing self-consumption of solar generation, by enabling arbitrage across time-of-use pricing periods, or both? To address these questions, we exploit half-hourly smart meter data to examine how batteries reshape within-day consumption and export profiles.

We restrict the sample to customers with smart meters at baseline, and estimate separate difference-in-differences regressions for each half-hour of the day, with household and week fixed effects. This yields a treatment-effect curve across the 48 half-hour periods, separately for solar-only and solar-plus-battery customers. For exports, we balance the panel by filling unobserved household–half-hour cells with zeros, reflecting the fact that zero grid export is the economically relevant counterfactual for periods without surplus generation.

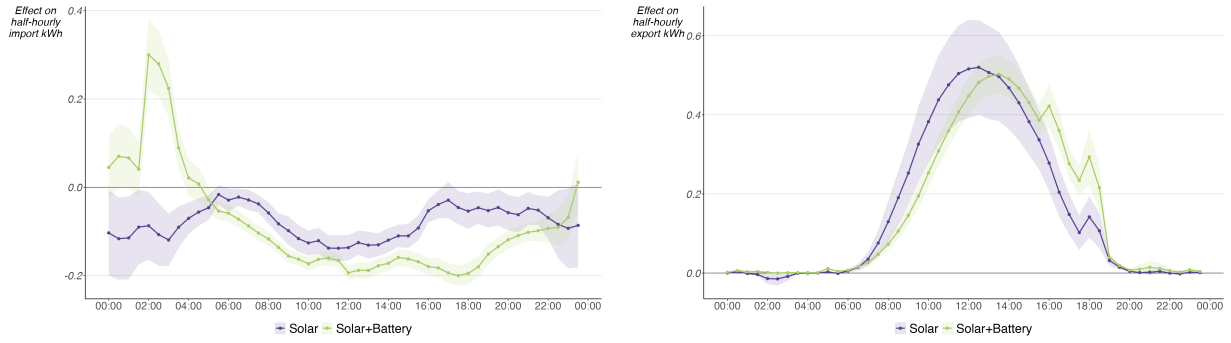
Figure 6 presents the results. Panel (a) shows that solar-only and solar-plus-battery

customers exhibit similar reductions in daytime imports (roughly 08:00–16:00), consistent with both groups self-consuming solar generation during daylight hours. However, the two groups diverge markedly at other times of day. Solar-plus-battery customers show increased overnight imports (roughly 00:00–05:00), consistent with battery charging during off-peak periods, and reduced imports during the evening peak (roughly 16:00–19:00), consistent with battery discharge substituting for grid imports when prices are highest.

Panel (b) shows the mirror image on the export side: solar-only customers export substantially more during midday hours, while solar-plus-battery customers retain this generation in their battery for later use. The net effect is that batteries convert a "generate-and-export" profile into a "generate-store-and-discharge" profile that both reduces the household's bill (by avoiding peak import prices and reducing reliance on lower-valued export rates) and benefits the grid (by reducing demand during the system peak).

Notably, this load-shifting pattern persists even in winter months (as documented in the month-by-month intraday profiles in Figure A3), when solar generation is minimal. During these months, customers appear to charge their batteries from the grid during cheap overnight periods and discharge during the day, suggesting that the battery's value extends beyond solar time-shifting to include pure grid-arbitrage benefits.

Figure 6: Impact on electricity import by month of the year



(a) Imports (b) Exports

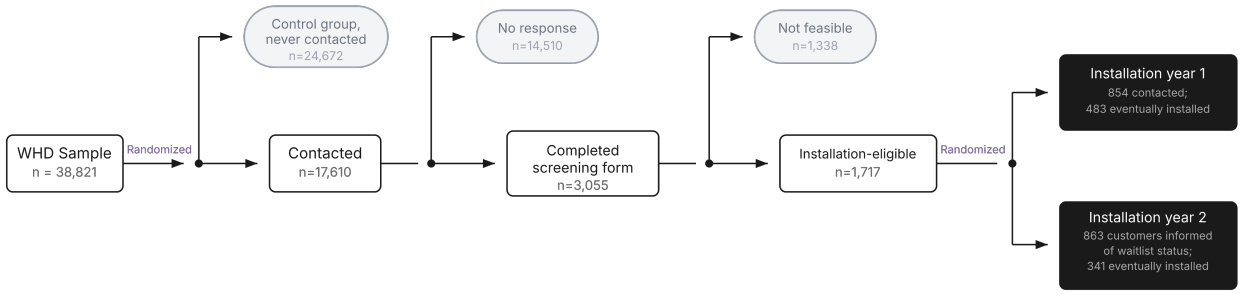
Notes: Panel (a) reports month-of-year IV estimates of the effect of installation on import consumption , from a specification interacting installation status with month-of-year indicators. Confidence intervals are shown at the 95% level. Panel (b) plots implied monthly import consumption for installed customers alongside observed mean monthly net consumption for the control group. The "With installation" series is constructed by adding the month-specific treatment effects from panel (a) to the control group mean in each month. The shaded grey region in panel (b) denotes the installation period (December 2024 – March 2025). Shaded ribbons denote 95% confidence intervals.

5 Extended analysis of second program year

The analysis in Section 2 estimated the effect of solar and battery installation on energy consumption using a randomised encouragement design applied to a subset of customers drawn from a larger pool of 38,821 eligible households. In practice, however, installations occurred over the course of two program years: the first beginning in December 2024 and the second in September 2025. This staggered rollout provides an additional source of experimental variation that we can exploit. While installations from the second year are still ongoing and we intend to wait for a fuller post-installation observation period before conducting a comprehensive pooled analysis, we present some interim descriptive results here that illustrate the promise of this second source of variation.

The full sample of 38,821 eligible customers was first randomized into two installation years before any encouragement emails were sent. Regardless of their assigned installation year, all encouraged customers were contacted during the same period in April 2024 and followed the same screening process. Customers completed the online intake form, underwent feasibility assessment, and were deemed installation-eligible without any knowledge of which year they had been assigned to. Only after a customer was confirmed as eligible were they informed whether they would receive their installation immediately or be placed on a waitlist for the following year. This sequencing ensures that the decision to engage with the program, and the screening outcomes themselves, were not contaminated by knowledge of waitlist status. Crucially, assignment to Installa-

Figure 7: Full randomisation strategy



tion Year 1 versus Year 2 is random and orthogonal to the encouragement randomisation within each year. This means that rather than treating the two installation years as separate experiments requiring distinct analyses, we can pool the full sample and exploit all of the variation — both across encouraged versus control customers and across in-

stallation years — in a single estimation framework. The year-of-installation assignment provides additional temporal variation for the encouragement instrument.

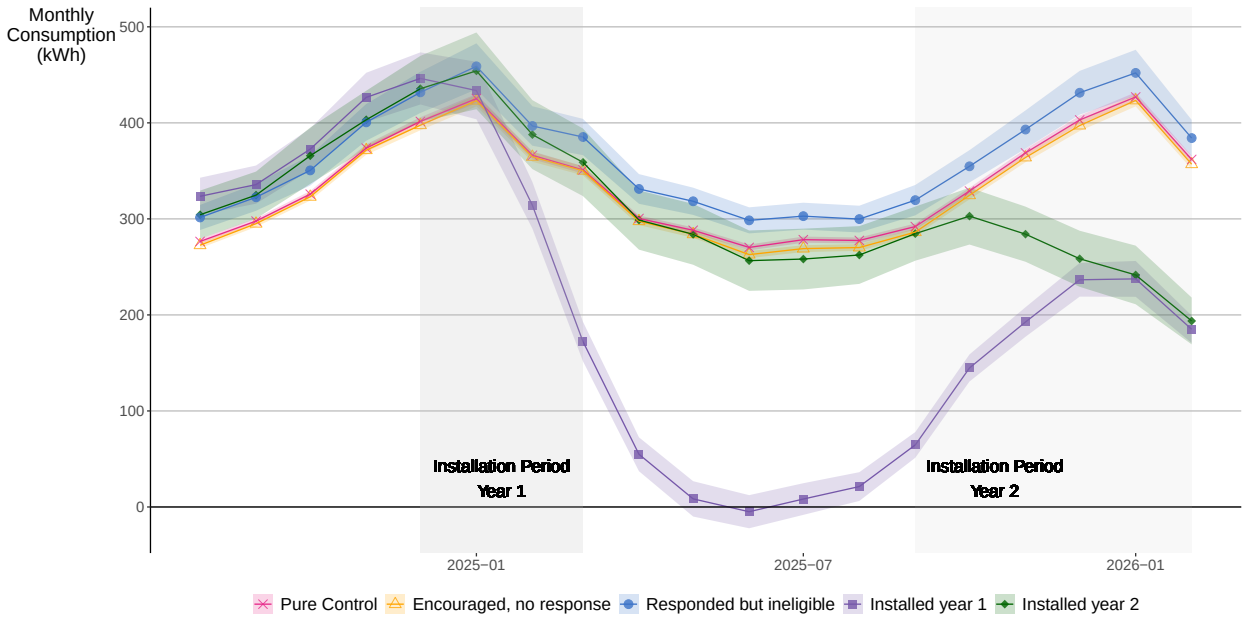
For this interim analysis, we focus on a descriptive comparison of net monthly electricity consumption across five groups defined by the randomisation and screening outcomes: (1) the pure control group, who were never contacted; (2) customers who were encouraged but did not respond to the screening invitation; (3) customers who responded and showed interest but were found to be ineligible for installation; (4) customers who were eligible and received their installation in the first program year; and (5) customers who were eligible and received their installation in the second program year.

Figure 8 plots monthly net electricity consumption (imports minus exports, in kWh) for each of these groups from October 2024 through to the latest available data. Several patterns are worth noting. Prior to any installations, all five groups track each other closely, exhibiting the same seasonal pattern of higher winter consumption and lower summer consumption — consistent with the randomisation having successfully balanced observable and unobservable characteristics across groups. The pure control group, the non-responders, and the responded-but-ineligible group remain tightly bundled throughout the observation period, suggesting that encouragement alone (without installation) does not materially shift consumption behaviour.

The most striking feature is the behaviour of the Year 2 installation group, who had been deemed eligible but were waiting for their installation. Throughout the spring and summer of 2025 — while Year 1 households saw their net consumption fall close to zero as solar generation offset imports — the Year 2 group continued to consume at levels comparable to the control groups. As the second installation period begins from September 2025 onwards, the Year 2 group's net consumption drops, and matches closely the net consumption of the Year 1 group's net consumption.

We defer formal estimation of treatment effects using the pooled two-year sample to the final analysis, when the Year 2 installation group will have accumulated a full year of post-installation data and we can exploit the complete set of randomised variation in a single instrumental variables framework. For now, the raw consumption trajectories provide encouraging evidence that the installations are delivering substantial reductions in net electricity consumption for participating households.

Figure 8: Net monthly consumption - two installation years



Notes: Monthly net (imports minus exports) electricity consumption (kWh) for (1) never contacted control group, (2) customers who were invited, but did not respond, and (3) customers who responded and showed interest, but were ineligible for an installation, (4) customers who were eligible and received an installation in the first year of rollout, and (5) customers who received an installation in the second year of rollout. The shaded grey band indicates the installation periods (December 2024 – March 2025 for the first year, and September 2024-March 2026 for the second year). Shaded ribbons around each series denote 95% confidence intervals.

6 Conclusions and further extensions

In this paper, we have shown that solar and battery installations have large benefits. Installation reduced net grid reliance by 91 percent and cut electricity bills by approximately £650 per year — a 71 percent reduction for households. These effects vary substantially across seasons, with bills falling close to zero in summer months before recovering in winter as solar output diminishes. Crucially, the benefits extend beyond individual households to the wider grid: installation reshaped intraday consumption profiles, with batteries charging overnight during off-peak periods and discharging during the evening peak, reducing peak imports by 59 percent. This load-shifting pattern persists even in winter when solar generation is minimal, demonstrating that batteries provide demand flexibility independently of solar output.

By exploiting property-level variation in battery feasibility, we separately identify the marginal contribution of storage. Adding a battery to solar panels delivers an additional

£202 per year in bill savings and shifts demand away from the hours when electricity is most expensive and grid stress is highest. This finding has direct implications for subsidy design: programs that pair solar with battery storage generate meaningfully larger private and system benefits than solar alone.

We also document important behavioral responses to installation. Roughly one quarter of installed customers switched to solar-specific time-of-use tariffs within two months, enabling them to capture additional savings through price-responsive charging and discharging. At the same time, over half of installed customers remained on fixed tariffs, suggesting that inertia or switching costs may prevent some households from fully realising the value of their systems. This points to a complementary role for default tariff design or nudges alongside technology provision.

This paper presents results from the first program year, and we have two major extensions underway. First, the second year of installations is nearly complete, and we will soon exploit the full two-year staggered rollout in a pooled instrumental variables framework, increasing statistical power and enabling richer heterogeneity analysis.

Second, we are collecting three additional datasets to enrich our existing analyses. We are integrating extremely rich credit data for all participating households, which will allow us to trace whether the financial savings from reduced energy bills translate into measurable improvements in broader financial health, such as reduced debt, increased savings, or changes in spending patterns. We are also acquiring validated solar generation data, which will enable us to construct a household-level generation model and decompose our consumption estimates into genuine demand reductions and rebound effects, sharpening the interpretation of our main findings. In our last data collection effort, we are administering a willingness-to-pay survey using a Becker-DeGroot-Marschak mechanism to both vulnerable and general customers. These incentive-compatible valuations will allow us to estimate the subsidy required to close adoption gaps across the income distribution, and to test whether the relationship between adoption barriers and realized benefits varies across regions.

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Appendix

A Tables

Table A1: Balance Table

Variable	Control Mean	Encouraged	N
Property Value (£)	291,331.60	-2,855.43	38,734
	[171,705.36]	(86,909.44)	
Octopus Tenure (years)	4.24	0.76	38,794
	[1.47]	(0.74)	
Estimated annual consumption (kWh)	3,746.34	1,918.62	38,310
	[2,575.41]	(1,275.63)	
Has Smart Meter	0.64	-0.12	38,804
	[0.48]	(0.24)	
Energy rating	3.95	1.00	25,477
	[0.90]	(0.90)	
Joint F-Test		0.67	

Note: This table reports baseline balance between households assigned to encouragement and control groups. The *Control Mean* column reports the mean in the never contacted control group; standard deviations are in brackets. The *Encouraged* column reports the coefficient of an OLS regression of the covariate on encouragement status with randomization-block fixed effects; standard errors are in parentheses. *N* is the number of non-missing observations used in each row-specific regression. The *Joint F-Test* row reports the p-value from a test that all listed covariates are jointly unrelated to treatment assignment within panel. Estimated Annual Consumption is measured in kWh. Current energy rating is based on the official A–G efficiency scale and is mapped to a numerical value for analysis.

Table A2: Attrition

Variable	Control	Received intervention	Difference	p-value
Lost supply, encouraged	0.04	0.05	0.00	0.26
	(0.21)	(0.21)		
Lost supply, treated	0.05	0.00	-0.04	<0.01***
	(0.21)	(0.07)		

Note: This table reports attrition rates, defined as the proportion of customers who left Octopus Energy during the study period. Row 1 compares attrition between the never-contacted control group and all encouraged customers; Row 2 compares customers who received an installation with those who did not. The Control and Received Intervention columns report group means, with standard deviations in parentheses. The Difference column reports the raw difference in means, and the p-value column reports the result of a two-sided t-test for equality of means.

Table A3: Attrition and Customer Covariates

Model:	(1)
Variables	
Octopus tenure (years)	-0.01**
	(0.00)
Estimated annual consumption (kWh)	0.00
	(0.00)
Has smart meter	0.00
	(0.01)
Energy rating	0.00*
	(0.00)
Property value (£)	0.00
	(0.00)
Fit statistics	
Control Mean	0.05
Observations	25,111

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

Note: This table reports OLS estimates from a regression of an indicator for attrition (leaving Octopus Energy during the study period) on baseline customer characteristics. The sample includes all customers in the encouraged group. Standard errors are clustered at the allocation (batch) level and reported in parentheses.

Table A4: Take-up of smart meters

Model:	(1)
Variables	
Received Install	0.15***
	(0.05)
Fixed-effects	
Household	Yes
Date	Yes
Fit statistics	
Control Mean	0.70
Observations	24,055,939

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

Note: This table reports IV estimates of the effect of receiving a solar and battery installation on the probability of having a smart meter, using randomised encouragement assignment as an instrument for installation. The dependent variable is a binary indicator equal to one if the customer has a smart meter on a given date. All specifications include household and date fixed effects. Standard errors are clustered at the household level and reported in parentheses. The control mean of 0.70 indicates that 70 percent of never-contacted customers had a smart meter during the study period.

Table A5: IV x Baseline Smart Meter

Dependent Variable	Import kWh	Net kWh	Bill (£)
Model:	(1)	(2)	(3)
Variables			
Received Install x No Smart Meter	-6.46	-33.23	-4.72
	(39.87)	(40.06)	(9.44)
Received Install x Has Smart Meter	-25.84**	-54.18***	-11.45***
	(12.25)	(12.32)	(2.77)
Has Smart Meter	4.30***	4.21***	0.58***
	(0.72)	(0.72)	(0.17)
Fixed-effects			
Week	Yes	Yes	Yes
Fit statistics			
Control Mean, No Smart Meter	57.99	57.93	16.68
Observations	1,512,141	1,512,141	1,512,141

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

Note: This table reports IV estimates of the effect of installation on weekly household electricity outcomes, allowing the treatment effect to vary by baseline smart meter status. Installation status is interacted with an indicator for whether the customer had a smart meter prior to the installation period, and both interactions are instrumented using the corresponding interactions of encouragement assignment with baseline smart meter status. The dependent variables are weekly imported electricity (kWh) in column (1), weekly net grid imports (imports minus exports, kWh) in column (2), and weekly electricity bills (£) in column (3). All specifications include week fixed effects. Standard errors are clustered at the household level and reported in parentheses. Control means are calculated for customers without a baseline smart meter in the never-contacted control group.

Table A6: Tariff Switching - tehchnology-specific

Model:	No LCT Tariff (1)	Heat Pump Tariff (2)	EV Tariff (3)	Solar Tariff (4)
Variables				
Received Install	-0.28***	0.00	0.03	0.24***
	(0.04)	(0.01)	(0.04)	(0.02)
Fixed-effects				
Household	Yes	Yes	Yes	Yes
Week	Yes	Yes	Yes	Yes
Fit statistics				
Control Mean	0.95	0.00	0.04	0.00
Observations	1,537,008	1,537,008	1,537,008	1,537,008

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

Note: Each column reports IV estimates of the effect of installation on a binary indicator for tariff type, using encouragement assignment as an instrument. Tariff categories are mutually exclusive and defined as: (1) fixed tariff, (2) classic time-of-use tariffs (Economy 7 and Economy 10), which offer a fixed number of overnight off-peak hours at a reduced rate, (3) new time-of-use tariffs, with clearly defined peak and off-peak pricing windows, and (4) dynamic pricing tariffs, which track day-ahead wholesale prices. All specifications include household and week fixed effects. Standard errors are clustered at the household level.

Table A7: Tariff Switching - ToU

Model:	Fixed (1)	Classic TOU (2)	New TOU (3)	Managed TOU (4)
Variables				
Received Install	-0.24***	-0.06**	0.18***	0.12***
	(0.05)	(0.02)	(0.03)	(0.04)
Fixed-effects				
Household	Yes	Yes	Yes	Yes
Week	Yes	Yes	Yes	Yes
Fit statistics				
Control Mean	0.83	0.11	0.01	0.05
Observations	1,594,278	1,594,278	1,594,278	1,594,278

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

Note: Each column reports IV estimates of the effect of installation on a binary indicator for low-carbon technology (LCT) tariff type, using encouragement assignment as an instrument. Tariff categories are: (1) no LCT tariff, (2) heat pump tariff, (3) electric vehicle tariff, and (4) solar tariff. All specifications include household and week fixed effects. Standard errors are clustered at the household level.

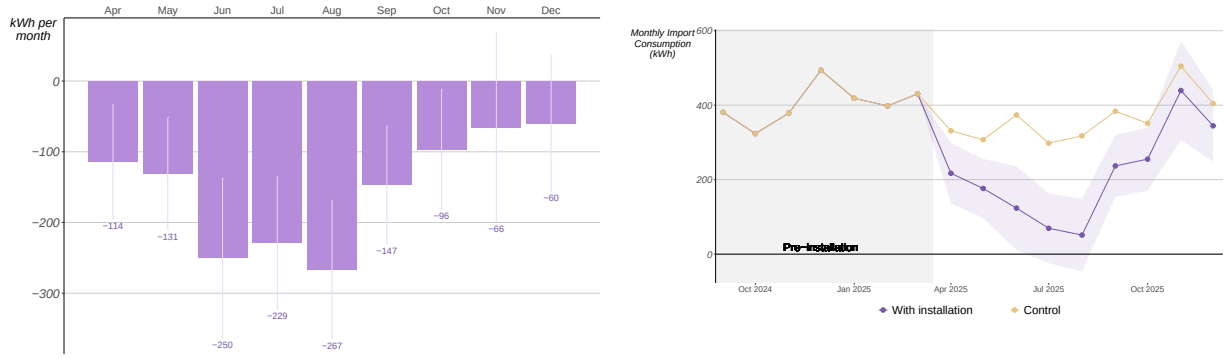
Table A8: Balance between solar only installations and solar+battery installations

Variable	Control	Solar Only	Difference	p-value
Property Value (£)	323,927.91	271,081.16	-52,846.75	<0.01***
	(162,815.59)	(117,497.02)		
Octopus Tenure (years)	4.27	4.07	-0.20	0.23
	(1.52)	(1.42)		
EAC (kWh)	4,171.55	3,599.75	-571.80	0.02**
	(2,670.97)	(1,972.11)		
Has Smart Meter	0.77	0.79	0.01	0.78
	(0.42)	(0.41)		
EPC	3.82	4.17	0.35	<0.01***
	(0.80)	(0.84)		
Number of Panels	9.17	8.09	-1.08	0.01**
	(4.08)	(3.41)		

Note: This table compares baseline characteristics of customers who received solar panels with a battery (Control column) and customers who received solar panels only (Solar Only column). Standard deviations are reported in parentheses. The Difference column reports the raw difference in means, and the p-value column reports the result of a two-sided t-test for equality of means.

B Figures

Figure A1: Impact on electricity import by month of the year

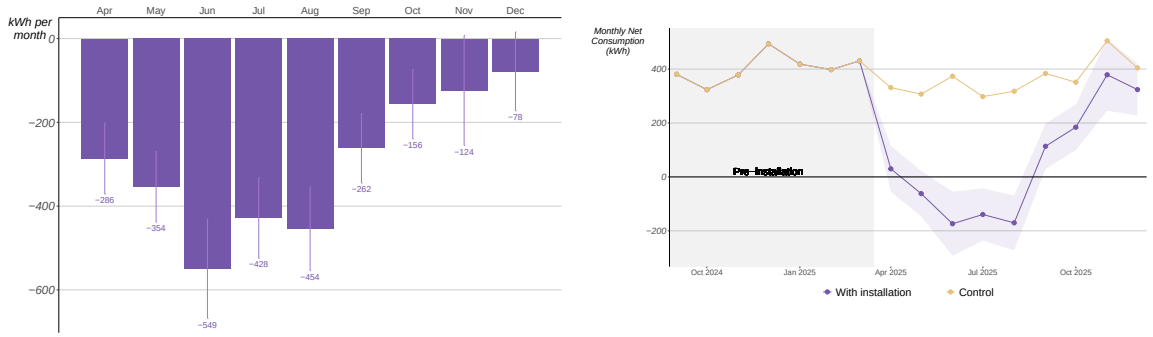


(a) Month-of-year IV estimates

(b) Implied monthly import consumption

Notes: Panel (a) reports month-of-year IV estimates of the effect of installation on import consumption , from a specification interacting installation status with month-of-year indicators. Confidence intervals are shown at the 95% level. Panel (b) plots implied monthly import consumption for installed customers alongside observed mean monthly net consumption for the control group. The "With installation" series is constructed by adding the month-specific treatment effects from panel (a) to the control group mean in each month. The shaded grey region in panel (b) denotes the installation period (December 2024 – March 2025). Shaded ribbons denote 95% confidence intervals.

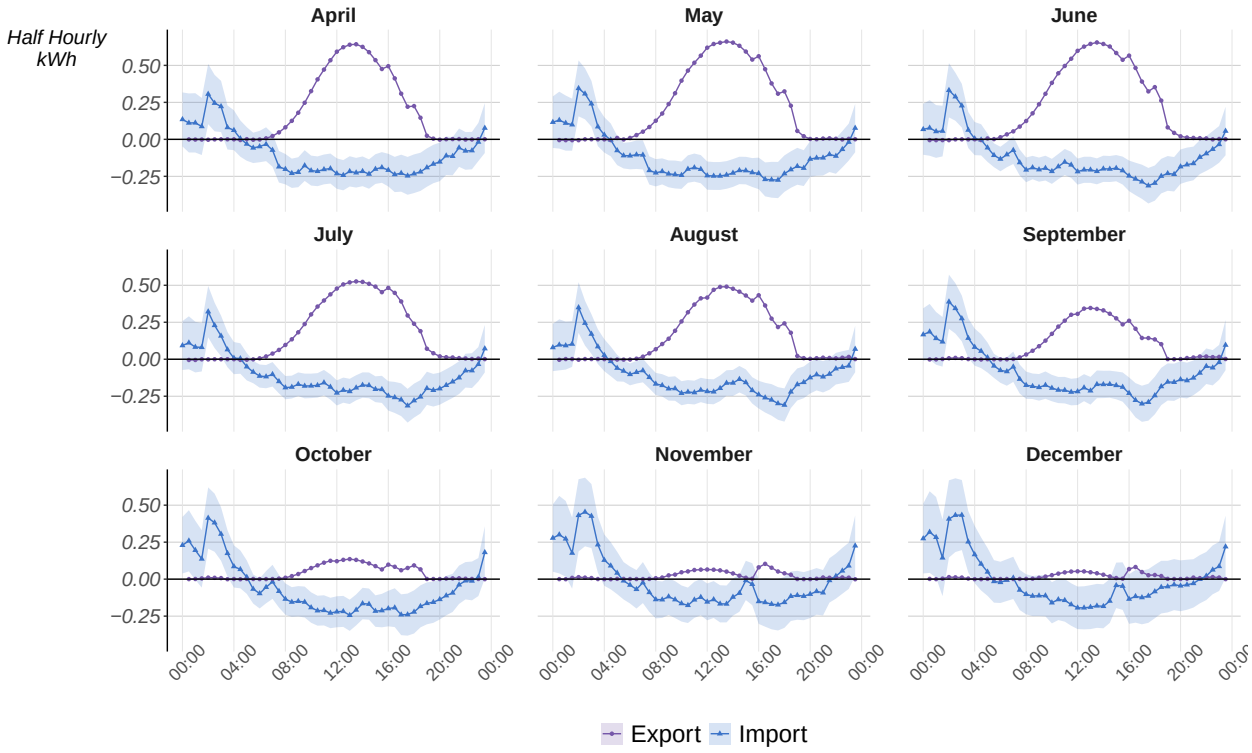
Figure A2: Impact on net consumption by month of the year



(a) Month-of-year IV estimates (b) Implied monthly net consumption

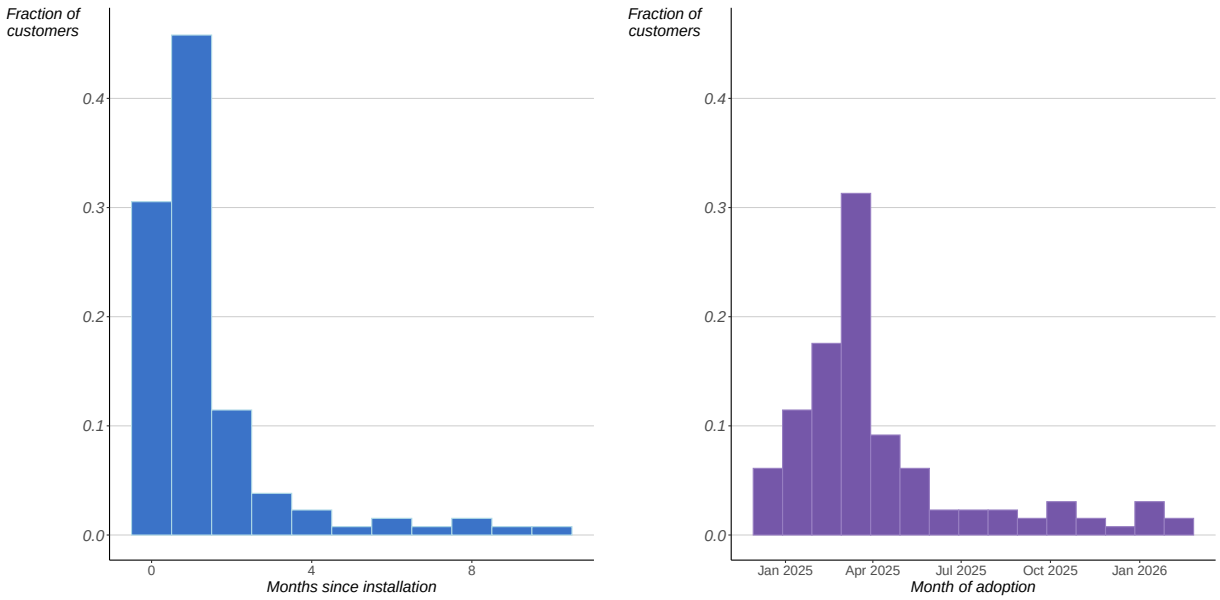
Notes: Panel (a) reports month-of-year IV estimates of the effect of installation on net consumption (import minus export), from a specification interacting installation status with month-of-year indicators. Confidence intervals are shown at the 95% level. Panel (b) plots implied monthly net consumption for installed customers alongside observed mean monthly net consumption for the control group. The "With installation" series is constructed by adding the month-specific treatment effects from panel (a) to the control group mean in each month. The shaded grey region in panel (b) denotes the installation period (December 2024 – March 2025). Shaded ribbons denote 95% confidence intervals.

Figure A3: Intraday treatment effects, by month



Notes: Each panel reports IV estimates of the effect of installation on half-hourly electricity imports (kWh, blue) from a regression interacting installation status with half-hour-of-day indicators, estimated separately for each calendar month. The export series (purple) plots mean half-hourly exports for installed customers; exports are not instrumented since, absent installation, exports are mechanically zero. The sample is restricted to customers with smart meters at baseline. Shaded ribbons denote 95% confidence intervals. Errors are clustered at the customer level

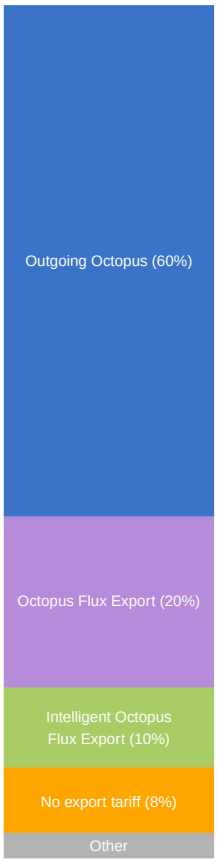
Figure A4: When do customers adopt a solar import tariff



(a) Causal impacts (b) Compare to not encouraged group

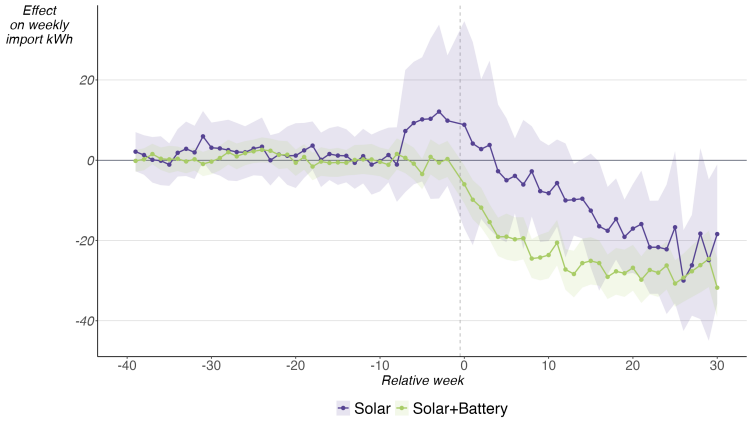
Notes: Panel (a) plots the distribution of months elapsed between installation and solar tariff adoption, among installed customers who switch to a solar tariff. Panel (b) plots the fraction of solar tariff adoptions occurring in each calendar month, among the same sample. The spike in April 2025 reflects both the concentration of installations completing in the preceding months and the onset of the UK solar generation season.

Figure A5: Export tariff choice among installed customers

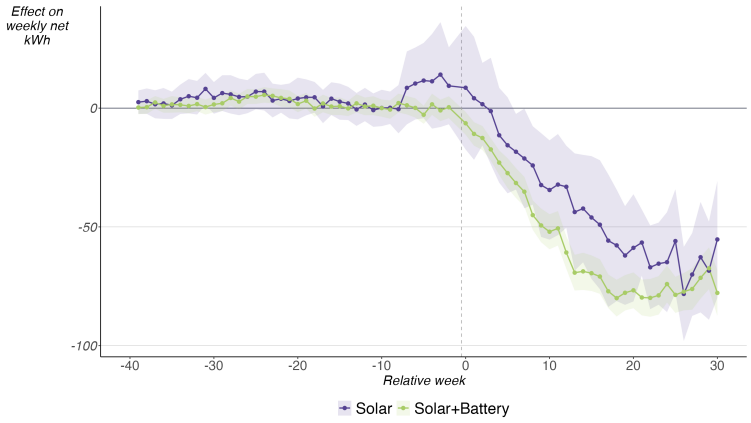


Notes: The figure plots the distribution of export tariff types among customers who received a solar and battery installation. "Outgoing Octopus" is a fixed export tariff paying a flat rate per kWh exported. "Octopus Flux Export" a TOU export tariff with three pricing periods, with peak rates between 16:00–19:00 and cheapest rates between 02:00–05:00 Octopus Energy, which customers manage manually. "Intelligent Octopus Flux Export" is a smart time-of-use tariff where Octopus takes control of the customer's battery, automatically scheduling charging when prices are lowest and exporting during the peak period between 16:00–19:00. "No export tariff" indicates customers who have not registered for an export tariff despite having an installation. Shares are calculated as a fraction of all installed customers.

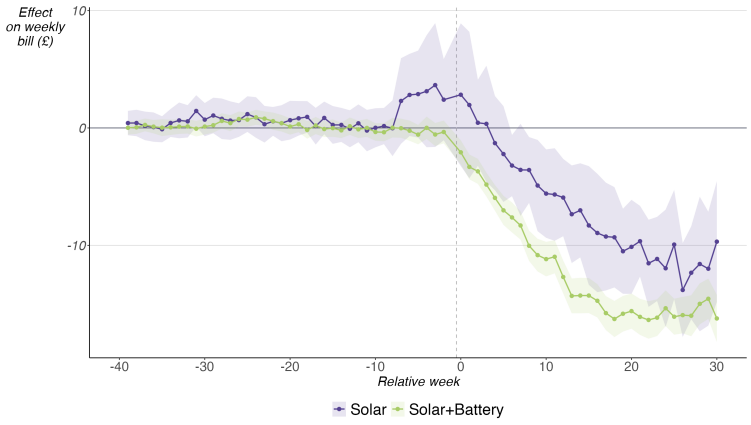
Figure A6: Solar versus solar-plus-battery: unweighted TWFE event study



(a) Import



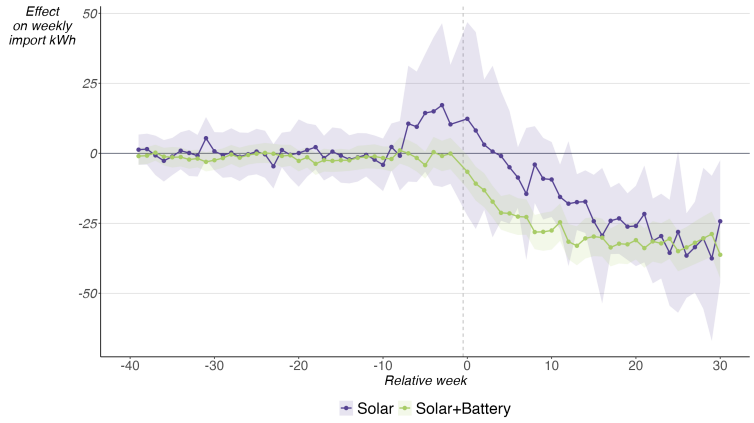
(b) Net



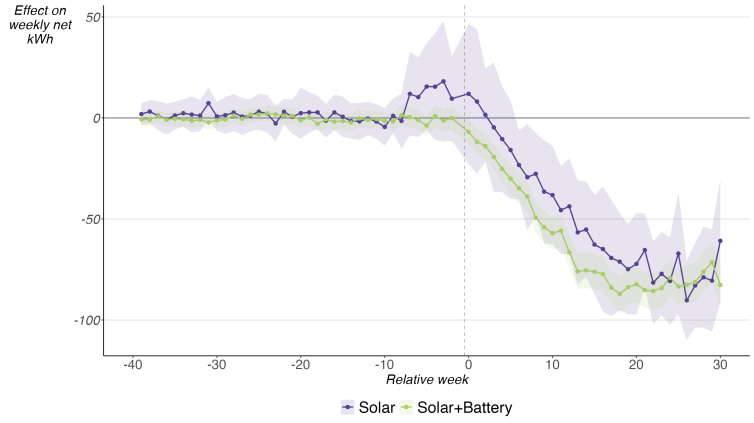
(c) Bills

Notes: This figure reports unweighted two-way fixed effects (TWFE) event study estimates of the effect of installation on weekly electricity outcomes, separately for solar-only and solar-plus-battery customers. Panel (a) shows effects on weekly imported electricity (kWh), panel (b) on weekly net grid imports (imports minus exports, kWh), and panel (c) on weekly electricity bills (£). The sample is restricted to customers who received an installation, with not-yet-treated customers serving as the control group. All specifications include household and calendar-week fixed effects. The omitted reference period is one week prior to installation.

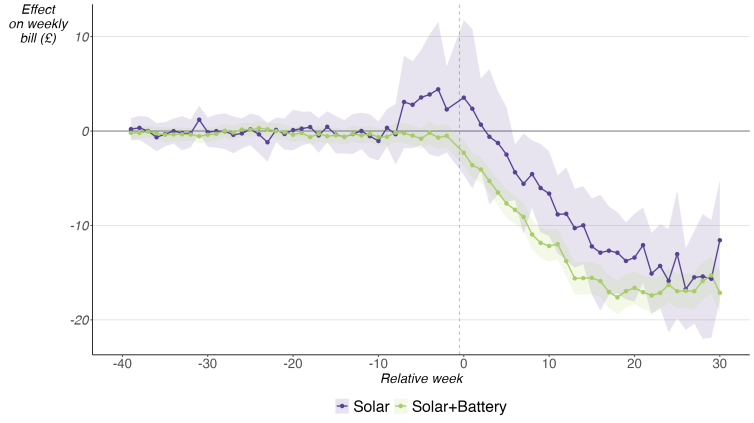
Figure A7: Solar versus solar-plus-battery: weighted TWFE event study



(a) Import



(b) Net



(c) Bills

Notes: This figure reports inverse propensity score weighted (IPW) two-way fixed effects (TWFE) event study estimates of the effect of installation on weekly electricity outcomes, separately for solar-only and solar-plus-battery customers. Panel (a) shows effects on weekly imported electricity (kWh), panel (b) on weekly net grid imports (imports minus exports, kWh), and panel (c) on weekly electricity bills (£). The sample and specification are identical to Figure A6, but observations are reweighted using inverse propensity scores estimated via logistic regression on the number of solar panels installed, property value, and baseline estimated annual consumption. IPW reweighting adjusts for the distributional imbalance in observable characteristics between the two groups (property value, baseline estimated annual consumption, and number of installed solar panels), isolating the marginal contribution of battery storage.