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John A. List, Ioannis C. Pragidis, and Michael K. Price

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THE UNIVERSITY OF CHICAGO
BECKER FRIEDMAN INSTITUTE FOR ECONOMICS

5757 S. University Ave.
Chicago, IL 60637
Main: 773.702.5599
bfi.uchicago.edu

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ABSTRACT

Prosumers are becoming increasingly important in global energy consumption and production. We partner with an energy service provider in Sweden to explore the economics facing such agents by conducting a natural field experiment over a 32-month period. As a policy instrument, we explore how simple nudges affect choices on both the consumption and production sides. Importantly, with the added flexibility to influence both sides of the market, and with a rich data set that permits an analysis of intraday, intraweek, and seasonal variation, we can detail effects on overall conservation efforts, intertemporal substitution, load shifting, and net purchases from the grid. The overarching theme is that nudges have the potential to have an even greater impact on the energy market with prosumers compared to their portmanteau components.

John A. List
Department of Economics
University of Chicago
1126 East 59th
Chicago, IL 60637
and Australian National University
and also NBER
jlist@uchicago.edu

Ioannis C. Pragidis
Democritus University of Thrace
gpragkid@econ.duth.gr

Michael K. Price
Department of Economics, Finance,
and Legal Studies
The University of Alabama
250 Alston Hall
Box 870224
Tuscaloosa, AL 35487
and Australian National University
and also NBER
mkprice2@ua.edu

A randomized controlled trials registry entry is available at:
https://www.socialscienceregistry.org/trials/11882

Introduction

The import of prosumers—an individual or business that both produces and consumes within a specific market—have increasingly grown in modern economies. Experts argue that within the energy sector, prosumers are essential for promoting future sustainable energy practices and transitioning toward a greener future. This is because such actors can provide grid stability, accelerate adoption of renewable energy sources, and have experienced considerable growth in recent years. For example, investments in residential photovoltaic (PV) systems have increased rapidly over the past decade; as of 2022, it was estimated that residential distributed PV rooftop systems account for more than 23% of total installed PV capacity around the globe [1]. Expert projections suggest that the share of PV capacity amongst residential consumers in developed countries will increase significantly over the next several years [2].

For their part, governments around the globe have recognized the value of prosumers and are increasing subsidies for the installation of rooftop PV systems. At the grid level, the installation of such systems can lead to reductions in greenhouse gas emissions and help to stabilize electricity distribution networks – particularly during periods of peak load [3]. At the household level, the installation of such systems can lead to lower expenditures on electricity and increased home values [4]-[7]. Implicitly, many of these benefits rest on the assumption that households do not adjust consumption patterns following the adoption of a PV system.

Unfortunately, there is a growing body of empirical work documenting *increased consumption* following the installation of residential PV systems. This phenomenon has been labeled the “solar rebound” effect with estimates of the change in consumption ranging from 5.8 to 41 percent [8]-[15]. Conceptually, there are multiple channels that could underlie both the existence and magnitude of “solar rebound” [16]. Some of these channels, e.g., remuneration schemes and relative differences in the price of electricity bought from and sold to the grid, are neoclassical in nature. Other channels, e.g., moral licensing, inattention, and peer influence, are behavioral in nature [16]-[22].

In this study, we step back from this debate to explore the economics of prosumers more generally. To do so we use a common tool in the economics literature on energy conservation – a home energy report – to explore behavioral effects on the household electricity production and use with rooftop PV systems. We leverage the home energy report by conducting a natural field experiment in collaboration with an energy services provider in Sweden.[1] Our experimental approach provides a secondary benefit in that although there is a large literature exploring the effect of peer comparisons on residential energy use [24]-[30], we are unaware of any prior work exploring the use of such strategies to manage the actions of prosumers. Given the rapid diffusion of rooftop PV systems and the pervasiveness of "solar rebound", this is an important gap in the literature.

A key aspect of our study is that we observe hourly data on electricity consumption, purchases from the grid, and sales back to the grid for over 700 of the company's clients. The data span a 32-month period starting in December 2020. Households in the experiment were randomized into either a treatment or control group. Starting in December of 2021, households in the treatment group were sent an electronic Home Energy Report (eHER) on a bi-weekly basis. The eHER contained both descriptive and injunctive information regarding both overall electricity consumption and electricity purchased from the grid.

Results from our field experiment provide evidence that HERs are an effective strategy to manage the energy use of prosumers and thus moderate "solar rebound". Households receiving the eHER reduce average weekly consumption by approximately 9.80 percent. Yet, the estimated Average Treatment Effect (ATE) masks substantial heterogeneity across seasons. For example, the average treatment effect is significantly greater during periods of increased production – April to September. During winter months, the impact of the eHER is substantially lower and, in many weeks, is statistically insignificant.

We observe similar heterogeneity when examining the effect of the eHER on behavior across the different hours of the day. During the overnight and early morning hours – 1am to 6am – the estimated hourly treatment effects are negative but statistically insignificant. During the morning and early afternoon hours – 7am to 3pm – the estimated

[1] We label our work as a natural field experiment following the nomenclature in Harrison and List [23]. Sweden is a key test case country because the share of PV capacity coming from residential households is more than twice the world's average, accounting for more than half of the grid-connected PV power. This provides the variation possible to explore the economics of prosumers.

hourly treatment effects are statistically significant and correspond to approximate 5 percent reductions in average hourly consumption. The estimated hourly treatment effects increase substantially in the late afternoon and evening hourly. Between 4pm and midnight, the estimated average hourly effects fluctuate in the range of 7 to 10 percent and reach a peak during the 6pm hour.

As a final set of results, we examine changes in sales to, and purchases from, the grid over the course of the day. Relative to counterparts in the control group, treated customers increase sales to the grid during daylight hours – 5am to 5pm – and reduce sales in the evening and pre-dawn hours – 7pm to 4am. We observe the opposite pattern when examining purchases from the grid. Treated customers purchase significantly more from the grid during the late evening/early morning hours – 11pm to 3am – than counterparts in the control group. In contrast, we observe a significant reduction in purchased electricity during daylight hours – 5am to 6pm. Viewed in its totality, such patterns suggest that the observed hourly treatment are driven by a combination of load shifting and conservation.

The remainder of our study proceeds as follows. Section II describes the natural field experimental design. Section III summarizes the empirical results. Section IV concludes.

II. Field Experiment

Our natural field experiment was implemented in collaboration with a Swedish company specializing in metering and IT systems for energy efficiency and renewable energy. Data from the experiment were drawn from a sample of 705 residential customers who were randomized into either a treatment (488 households) or control (217 households) group. Figure 1 provides a timeline of the experiment. Households in the treatment group were sent an electronic Home Energy Report (eHER) via email on a bi-weekly basis starting in December 2021. In total, customers in the treatment group received 36 eHER's with the final report delivered on August 13th, 2023. Supplementary Table 1 provides information on the number of eHERs delivered in each month of the experiment.[2]

[2] The eHER was sent every third week during Christmas and the summer holidays. Supplementary Figure 2 displays the spatial distribution of households in our experiment; the majority of which reside in the southern portion of the country.

Appendix Figure 1 provides a sample of the eHER which is comprised of different sections, each of which provides information on the customer's energy consumption and efficiency along with a set of energy-savings tips. The main feature of the eHER was a section providing both descriptive and injunctive information about the household's overall electricity consumption and purchases from the grid. The descriptive information compared the household's overall electricity consumption and purchases from the grid over the last 8 weeks with that from two distinct reference groups – a set of similar customers and a set of the most energy efficient customers.[3]

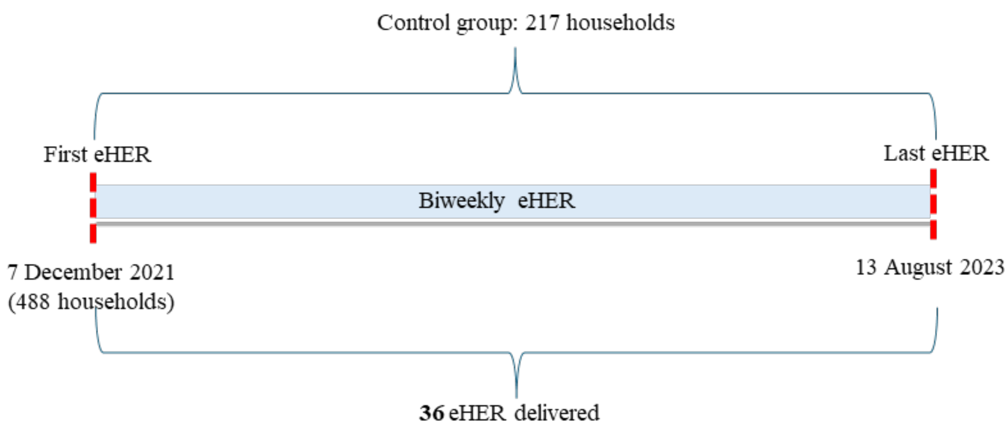

Fig. 1 | Overview of the timeline in the experiment. The treatment group was randomly assigned in December 2021. eHERs are delivered via email every second week.

The descriptive norm was conveyed as two distinct messages. The first provided a comparison of the customer's average consumption compared to that of their most efficient neighbours. Specifically, the first message read

On average, you consumed XX% more energy than your most efficient neighbours

The second message displayed how the household's average consumption ranked relative to the set of like households. The message was displayed in a colored box with different icons and background colors, and read

Your rank: AA out of BB similar households

[3] The set of similar customers included at least 20 other households who lived in the same geographic area as the recipient. The set of the most energy-efficient customers was based on the 15th percentile of users.

The color of the text box depended on the household's relative rank. For consumers whose average consumption fell within the top 25% of referential others, the text box was illuminated in green. For those whose average consumption fell in the 25^{th} to 75^{th} percentiles, the text box was illuminated in blue. And for those whose average consumption was in the upper quartile, the text box was illuminated in red.

The injunction norms were similarly conveyed in two forms. The first was one of three emojis – a winking face (Great - green), a slightly smiling face (Good - blue), and a neutral face (Moderate - red) – based upon the household's average weekly consumption over the past eight-week period relative to the set of like and efficient neighbours. Customers whose average consumption was less than the efficient neighbour received the winking face (Great) emoji. Customers whose consumption fell between that of the efficient and average neighbour received the smiling face (Good) emoji. And those whose average consumption over the eight-week period exceed that of the average neighbour received the neutral face (moderate) emoji.

The second part of the injunctive norm was a general message

> Is saving energy important to you? For more than 80% of our customers saving energy important value. Even little deeds can have a large impact. Discover our tips to consume less and better.

The statement was designed to convey the importance of energy conservation and remind households that even small actions can matter. In this regard, the statement shares similarity with fund-raising appeals reminding donors that every penny counts [31]-[32].

The final section of the eHER offered tailored information providing tips for saving energy. The tips focused on two distinct behaviors (a) curtail strategies to manage everyday consumption and (b) investments for improving the energy efficiency of the home. An example curtailment message is the following;

> *A microwave takes 15 minutes to do the same job as 1 hour in an oven. Use a microwave instead of your oven 4 times a week and save money.*

A typical message focusing on energy efficient investments is;

> *Add insulation to walls of your building to improve energy efficiency.*

The number of tips provided to each household was endogenously determined, with the most efficient households receiving fewer tips.

We have access to data on hourly electricity consumption, purchases from the grid, production, and sales back to the grid from December 7th, 2020, to August 13th, 2023. We also had access to some demographics, such as home size, number of household members, the age of the homeowner, and the zip code. However, it should be noted that demographics were not available for all households in our sample. Based on the analysis of the pre-treatment period presented in the supplementary material, households in the treatment group had higher consumption on average than households in the control group. We address this issue in the empirical analysis by using fixed effects in the regression model and showing parallel trends pre-treatment.

III. Field Experimental Results

Weekly effects

We estimate heterogenous treatment effects through a difference-in-differences setting. Our approach builds upon recent advances in the economics literature, which allow the researcher to estimate models that include multiple treatments and effects that are allowed to differ across multiple time periods [33]-[36]. The analysis aims to examine our intervention's effect on energy efficiency (average weekly consumption) and demand response (consumption across different hours of the day).

Figure 2 displays time-varying estimates for the effect of our treatment on average weekly consumption over each of the 88 weeks of the post-intervention period. The figure displays two distinct patterns. First, evaluated over the course of the experiment, the estimated ATE corresponds to an approximate 9.8 percent decrease in average weekly electricity use. The estimated treatment effect is significantly larger than the range of estimates for similar programs in Europe [24], [37] and the United States [38]. The estimated treatment effect is also larger than the weighted average in [39] for studies reporting estimates from interventions utilizing some form of a social comparison but comparable to effects reported in [40] for weekly social comparison reports amongst households residing in apartments in India’s National Capital Region.

There are several potential reasons why the effect sizes we observe are larger than those in prior work. First, the average home size for households in our sample is 178 square meters, approximately 45 percent larger than the average size (122 square meters) for a one- or two-dwelling building in Sweden. We observe similar differences in average weekly consumption amongst households in our sample (~35 kWh/week) and the average Swedish household (~24.09 kWh/week). Past work has documented that peer-comparisons' effect is larger amongst the highest user groups [37]. We would thus expect larger average treatment effects in our setting than those observed in prior work.

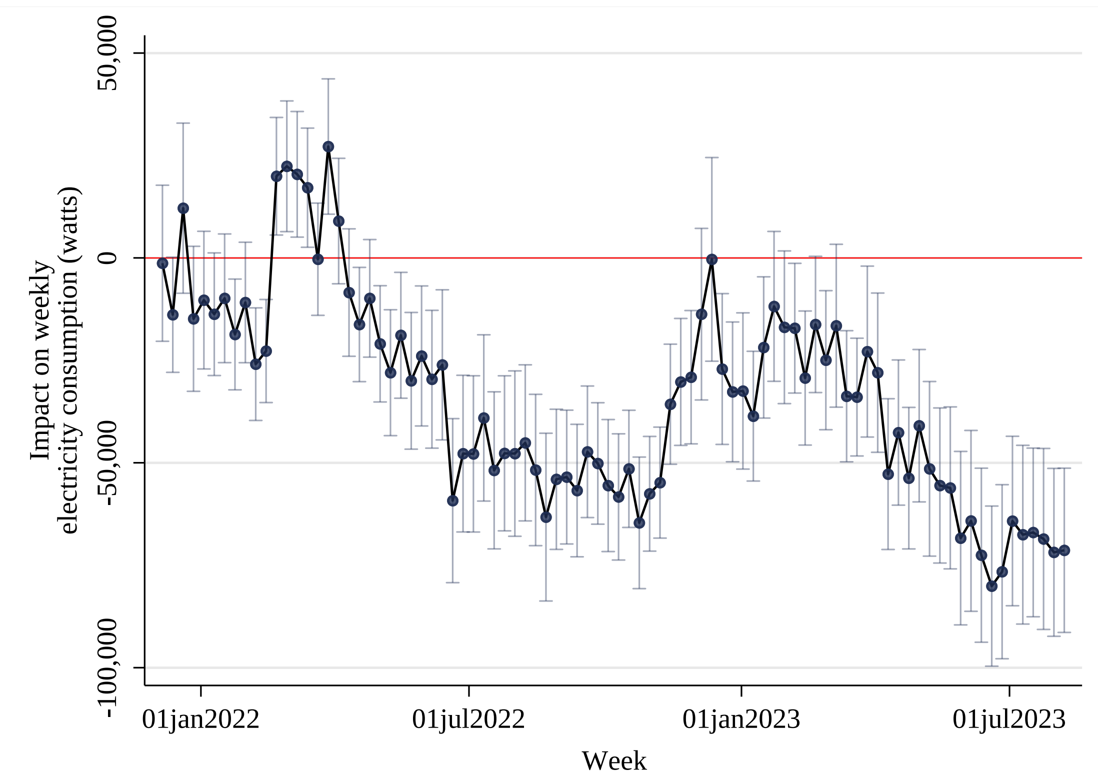

Fig. 2 | ATT on electricity consumption. The graph shows the ATT on electricity consumption (in watts) weekly. The period of analysis is from 07 December 2021 to 13 August 2023.

Second, past work has documented a direct relationship between the frequency with which customers observe peer comparisons and the resulting treatment effect. For example, [41] shows significant differences in the effect of monthly vs quarterly HERs. Given that households in our study received the eHER every other week, it is not surprising that the effects we observe are larger than those in past work where peer-comparisons were delivered on a less frequent basis. Finally, we cannot rule out that households in our sample increased electricity consumption following the installation of the solar PV system. Mechanically, any such "solar rebound" effect would distort counterfactual consumption and provide an additional margin for the eHER to induce change, mitigation of distortions related to "solar rebound".[4]

The second distinct pattern observed in Figure 1 is marked seasonal differences in the effect of the eHER on weekly consumption. During the late Fall through early Spring months (November through March), peer comparisons have little to no impact on observed consumption patterns. For example, over these months, the estimated weekly treatment effects range from an approximate 7.8 percent increase in consumption during the week of the 28th of March 2022 to a 15.7 percent decrease in consumption during the week of the 7th of November 2022. Moreover, fewer than 50 percent (18 out of 38) of the estimated weekly effects are statistically significant at the $p < 0.05$ level.

Peer comparisons, in contrast, have a more pronounced impact on average weekly consumption during the mid-Spring through mid-Fall months (April through October). For example, over this period, 92 percent (46 out of 50) of the estimated weekly treatment effects are statistically significant at the $p < 0.05$ level. The median treatment effect over this sample is a 15,6 percent decrease in consumption, while the largest estimated treatment effect is a 22,7 percent reduction in use amongst treated households in the week of 19^{th} of June 2023.

The seasonality observed in the estimated treatment effects mirrors seasonal differences in daylight hours and, hence, the amount of electricity produced by the rooftop PV systems of the households in our sample. As displayed in Figure 3, the average watts/hour produced in the pre-intervention period by households during the months of November through March is approximately one-half to one-eighth of that produced from April through August. However, the estimated seasonality runs counter to differences in both average wholesale (day ahead) prices and aggregate electricity

[4] Such argument shares similarity with findings in [42] which decomposes the estimated effect of a critical peak pricing experiment into distortions in consumption on counterfactual (non-CPP) days and reductions in use that would have arisen in the absence of such distortions.

demand in Sweden across different months of the year. The estimated effects are also counter to prior work in Finland [26] documenting that peer comparisons have a greater impact on average monthly consumption during winter months.

In part, such differences may capture an "income effect" whereby prosumers perceive energy conservation as an opportunity for financial gain by selling excess electricity back to the grid. Mechanically, such opportunities are directly related to solar PV production and inversely related to the need for energy intensive activities such as heating. Intuitively, one would thus expect prosumers to perceive the potential for financial gain to be more pronounced (salient) during summer months.

Yet, it is important to note that such perceptions are misguided. Under net metering, there is a broader set of financial gains from conservation efforts – even during winter months or other periods where consumption exceeds production. During such periods, conservation efforts and increased reliance upon self-produced electricity allow prosumers to forego on VAT (25%) and a 5 cent per MWh energy tax imposed on grid-purchased electricity. From a policy perspective, such misperception and the dampened incentive to conserve during winter months is concerning as aggregate domestic production and corresponding average wholesale prices spike during the winter months.[5]

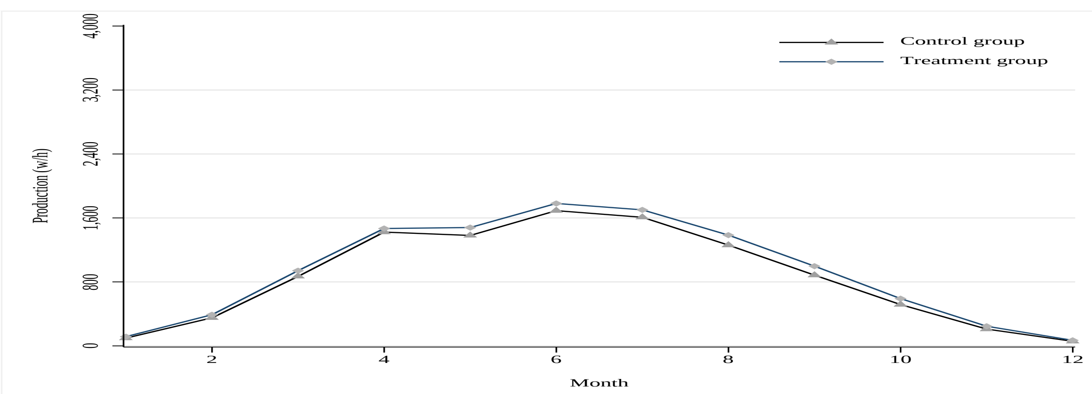

Fig. 3 | Electricity production from PV systems by month and treatment group. The graph shows the electricity production from PV panels (in watts) by month and treatment group. The analysis period is pre-treatment, from 07 December 2020 to 06 December 2021.

[5] For example, whereas aggregate domestic electricity production in the first month of our treatment period (January 2022) exceeded 16.5 terawatt hours, aggregate domestic production was approximately 31 percent lower (~11.43 terawatt hours) in June 2022 and more than 39 percent lower (~9.98 terawatt hours) in June 2023 [43].

Hourly treatment effects

We next explore the effect of our treatment on intraday patterns of consumption and how these reflect changes in both purchases from and sales back to the grid. Figure 4 displays average intraday electricity production by the households in our sample (Panel A) and the estimated hourly average treatment effects (ATEs) of the eHER on hour-by-hour electricity consumption. As noted in Panel A, average hourly electricity production varies widely over the course of a day. For example, average hourly production is effectively zero in the evening and overnight hours (19:00 to 03:00) and peaks in the late morning between the 09:00 and 12:00 hours.

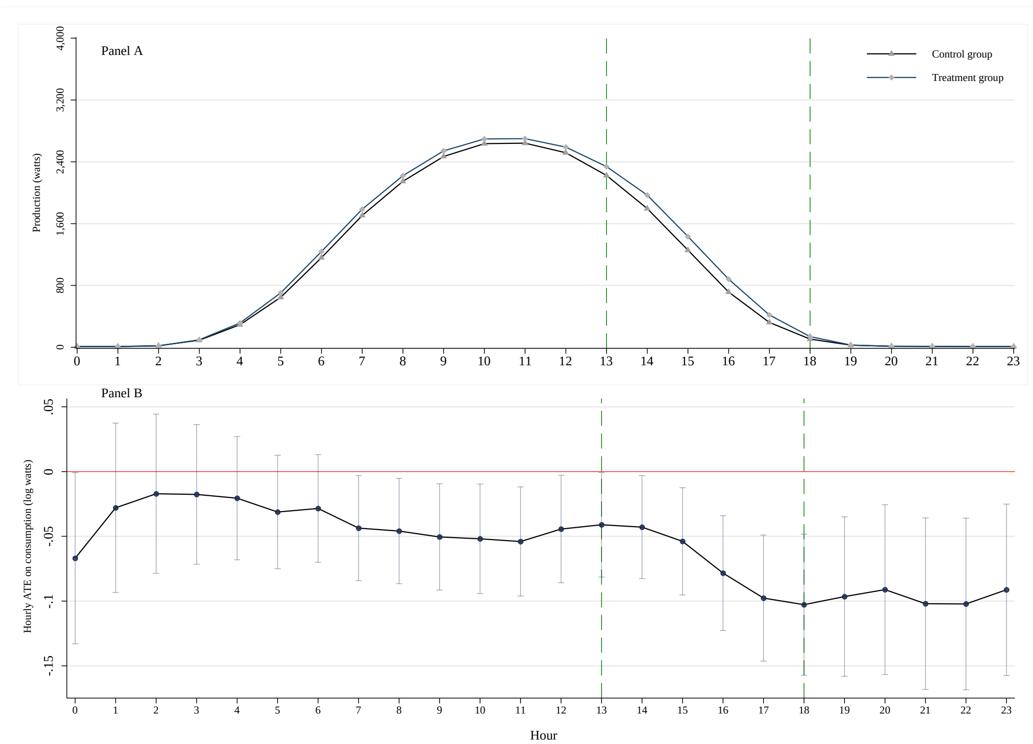

Fig. 4 | Electricity production and ATE on electricity consumption. The first panel of the graph shows the average electricity production from PV panels (in watts) by hour of the day and by treatment group. The second panel shows the ATE on electricity consumption (in watts) by hour of the day. The period of analysis is from 07 December 2021 to 13 August 2023.

Panel B of Figure 4 displays temporal variation in the estimated hourly treatment effect – as measured by differences in log watt/hours consumed – over the course of the day. During the overnight and early morning hours (01:00 to 06:00), the hourly average treatment effects are small in magnitude – approximately 2 to 2.5 percent reductions in consumption – and statistically insignificant. Starting with the 07:00 hour, the estimated treatment effects nearly double and remain relatively constant until the mid-afternoon (15:00 hour). During this period, treated households consume approximately 5 percent less in every hour than counterparts in the control; differences that are statistically significant at the $p < 0.05$ level. The estimated hourly treatment effects steadily increase during the 16:00 and 17:00 hours and subsequently stabilize through the midnight hour. Over these evening hours, treated households consume approximately 10 percent less per hour than counterparts in the control group; differences that are statistically significant at the $p < 0.05$ level.

It is interesting to note that those hours with the largest estimated treatment effects are distinct from hours with greatest average solar PV production. This suggests that the intraday impacts of the eHER are not driven entirely by desires to increase sales to the grid. To better understand factors that determine the observed hourly impacts, we next explore the effect of the eHER on intraday patterns of purchases from and sales to the grid and the extent to which these changes reflect intraday differences in the average spot market price for electricity. As many of the households in our sample have in-home battery storage systems, there is a financial incentive to purchase electricity for storage during periods with low electricity prices and to consume produced and stored electricity in periods with highest prices.[6] As noted earlier, such intraday shifts allow prosumers to forego paying a VAT (25%) and an additional 5 cents per MWh energy tax imposed on grid-purchased electricity.

Figure 5 and Figure 6 display intraday estimates of the hour-by-hour ATEs for sales back to and purchases from the grid, respectively. As displayed in the figures, the estimated impacts vary substantially across hours of the day. For example, relative to counterparts in the control group, treated customers reduce sales back to the grid in the evening and overnight (19:00 to 03:00) hours. However, such customers sell approximately 8 to 23 percent more electricity back to the grid between the 05:00 and 17:00 hours with the estimated difference spiking in the afternoon (13:00 to 16:00) hours.

[6] Unfortunately, we do not have information on which households in our sample have in-home battery storage systems. We only know that a large majority of our partner's customers, elect to bundle the purchase of the rooftop solar PV and in-home battery storage systems.

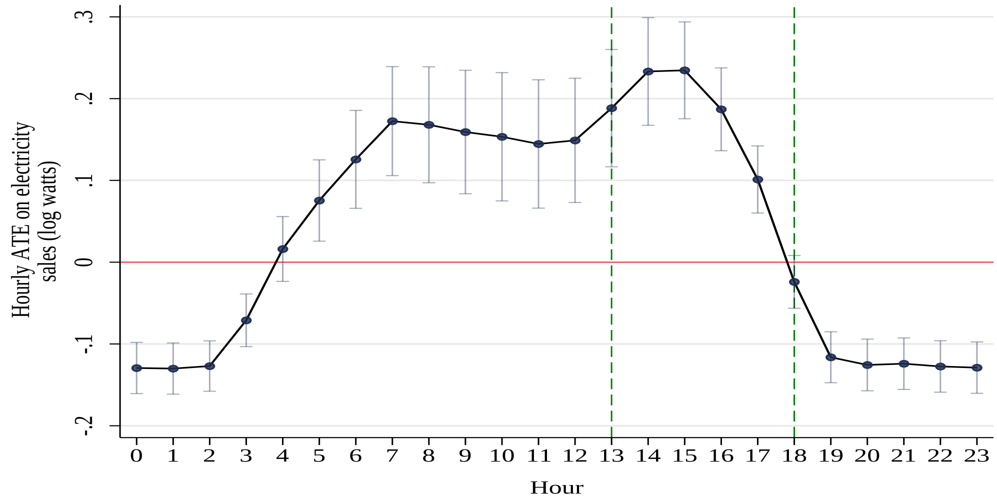

Fig. 5 | Hourly ATE on electricity sales back to the grid. The graph shows the ATT on electricity sales (in watts) back to the grid by hours of the day. The period of analysis is from 07 December 2021 to 13 August 2023.

Figure 6 plots the estimated hourly average treatment effects for purchases from the grid. As displayed in the figure, the intraday pattern of ATEs is opposite that for sales back to the grid. For example, relative to counterparts in the control group, treated households purchase approximately 3 to 8 percent more electricity in the late evening and overnight (21:00 to 03:00) hours than counterparts in the control groups; differences that are statistically significant at the $p < 0.05$ level from the 23:00 to the 02:00 hour. Starting with the 05:00 hour treated households purchase significantly less electricity from the grid than counterparts in the control group; a pattern that lasts throughout the 18:00 hour. During this time period, the estimated treatment effects correspond to reductions in purchases from the grid in the range of 8 to 24 percent. As with sales back to the grid, the estimated treatment effects are relatively stable from the 07:00 to 12:00 hours and peak during the 14:00 and 15:00 hours.

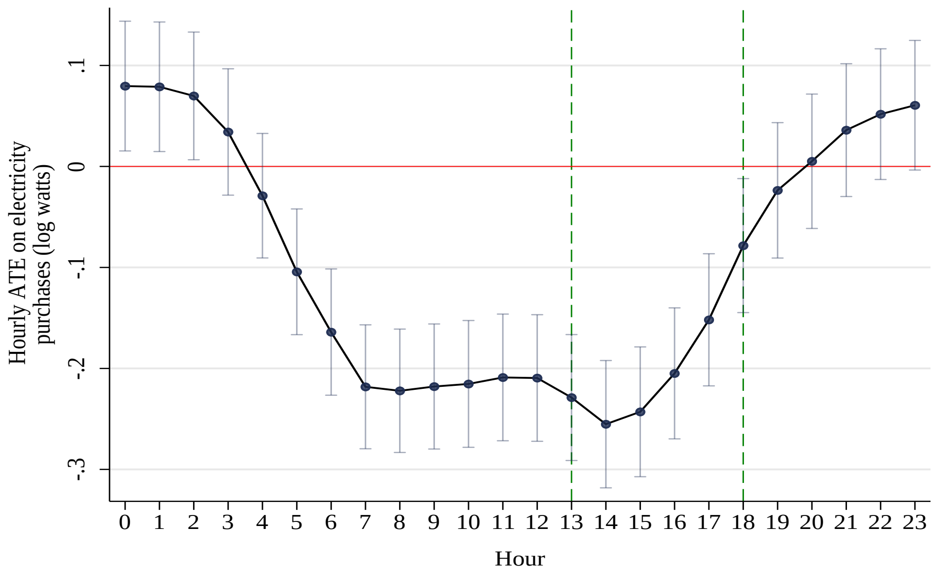

Fig. 6 | Hourly ATE on electricity purchases from the grid. The graph shows the ATT on electricity purchases (in watts) from the grid by day hours. The period of analysis is from 07 December 2021 to 13 August 2023.

A natural question arises: what drives the observed intraday patterns of treatment effects on sales to and purchases from the grid? Under net metering, there is financial incentive for households to reduce purchases from the grid during hours of the day where the spot market price for electricity is high. To do so, there are multiple strategies that a prosumer can follow. One possible strategy is to intertemporally substitute consumption between periods of high and low prices. A second strategy is to intertemporally substitute consumption from periods with low levels of solar PV production to periods with higher levels of production. A third strategy, for households with in-home battery storage systems, is to charge the battery during periods of low spot prices either through storage of produced electricity or purchases from the grid and to consume the stored electricity during peak periods when prices are highest.

Given that we observe significant reductions in overall electricity consumption and reductions in consumption every hour of the day, we can rule out intertemporal substitution as a primary driver of the observed intraday dynamics on purchases from and sales back to the grid. To better discern the relative importance of the remaining two strategies, it is important to document intraday variation in electricity prices. Figure 7 presents average hourly prices over the course of our experiment for both the pre- and post-intervention periods.

As noted in the figure, spot market prices were significantly higher in the post-intervention period than those observed in the pre-intervention period for all hours of the day; an impact driven by the Russian invasion of Ukraine and subsequent reductions in supplies of natural gas to the European Union. Yet, the observed differences reflect a level shift but have no discernible impact on the intraday pattern of price variation. In both periods prices spike and peak twice during the day and subsequently fall in the overnight hours. The first spike occurs in the mornings and peaks around the 08:00 hours; a period that coincides with individuals waking up and getting ready for work/school. The second spike occurs in the late afternoon and peaks around the 18:00 hour; a period that coincides with individuals returning from work/school. Although prices dip by approximately 30-40 percent between the two peaks, average hourly prices during these hours are significantly higher than those observed in the overnight hours.

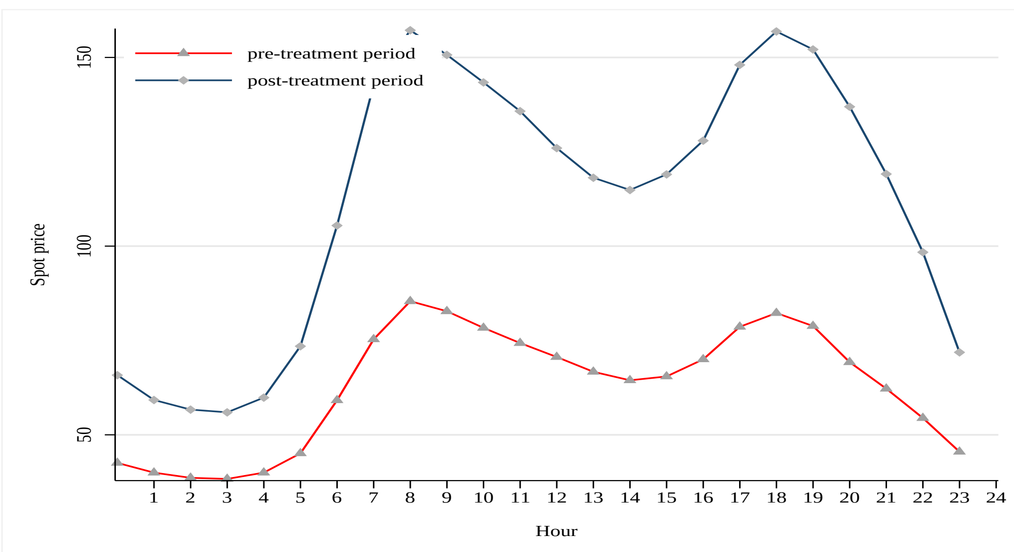

Fig. 7. Intraday variation of electricity spot prices by treatment period. This figure shows the changes in the intraday variation of electricity spot prices between the pre-and post-treatment periods.

Given observed intraday variation in spot market prices, there is financial incentive for households to charge batteries in the overnight hours to store energy for use later in the day – e.g., periods where the household would otherwise be a net consumer of electricity from the grid. To the extent that receipt of the eHER increases the salience of such financial incentives, we would thus expect to observe simultaneous increases in purchases from the grid and reductions in sales back to the grid during the overnight hours – a pattern documented in Figures 5 and 6.

By a similar line of reasoning, there is financial incentive for households to intertemporally substitute consumption from evenings when in-home production is relatively low but spot market prices are still high to morning and afternoon hours when both in-home production and spot market prices are relatively high. Given that we observe an overall reduction in consumption in all hours of the day, we would expect such impacts to be less pronounced in the morning and afternoon hours than during the evening hours (particularly between the 17:00 and 19:00 hours which correspond to the evening price peak). This is the precise pattern of intraday variation in the hourly ATEs displayed in Panel B of Figure 4.

Viewed in its totality, the intraday pattern of treatment effects observed in Figures 4 through 6 suggest that receipt of the eHER makes financial incentives afforded prosumers more salient. In doing so, the eHER not only induces overall conservation efforts but also intertemporal substitution in both overall consumption and net purchases from the grid. That intraday conservation decisions are so responsive to financial incentives is noteworthy given that observed variation in conservation efforts across seasons. As noted early, such effects are less pronounced in winter and early spring months. Given that aggregate electricity production and average wholesale prices spike during these months, the financial returns to conservation efforts in such months are greater than those afforded in months with lower average prices.

IV. Conclusions

We explore the economics of prosumers through the lens of a natural field experiment amongst Swedish households. A key aspect of our study is that we observe hourly data on electricity consumption, purchases from the grid, and sales back to the grid for over 700 households. By using a home energy report as our policy instrument to affect behavioral change, we are permitted a unique exploration into the choices of prosumers. More narrowly, we view our results as also having implications for the design and use of peer comparisons as a tool to manage resource use. Specifically, our findings suggest that such interventions lead to economically meaningful and statistically significant reductions in overall electricity consumption. In this regard, our paper contributes to a growing body of work exploring the use of behavioural interventions to influence the use of energy-efficient technologies to minimize rebound effects [18].

More broadly our empirical findings have implication for settings whereby households can use storage to facilitate load shifting via new/greater intertemporal substitution possibilities. In this regard, our findings speak to a growing body of work exploring the impact of real-time pricing on consumer well-being and intraday patterns of electricity consumption [28], [44]-[48]. Specifically, our findings suggest that peer comparisons and similar programmes influence intraday patterns of consumption by making salient opportunities for financial gain associated with (i) shifting use from periods with low levels of solar PV production to periods with higher levels of production and (ii) charging in-home storage systems during periods with low spot prices and subsequently using the stored electricity during peak periods when prices are greatest.

Of course, our results may be specific to the context that we study; particularly features of the eHER and characteristics of the households in our sample. For example, households in our sample are larger and use more electricity than the median household in Sweden. Prior work has documented heterogeneity in the effect of HERs on energy use with the impacts more pronounced for the highest users [37]. Similarly, households in our sample are drawn disproportionately from the two southern bidding zones in Sweden and face higher average prices than counterparts in the northern parts of the country.[7]

Intuitively, one would expect that the impact of peer comparisons on energy consumption would depend, in part, on the underlying marginal price of a kWh. Yet, we are unaware of studies that systematically explore how prices impact the efficacy of social comparisons. Further investigations in this area is needed to verify the generalizability of our findings and the promise of HERs as a tool to attenuate ‘solar rebound’. Likewise, such patterns depend on regulatory context defining the relative preferences and beliefs

[7] The electricity grid in Sweden is divided into four bidding zones (or regions) for which prices on both the day-ahead and spot market can vary. Prior to 2020, prices across the four zones were approximately equal. Since then, prices in the two southern zones have been 2 to 2.5 times higher than those in the two northern regions.

prosumers' face when purchasing electricity from and selling electricity back to the grid [49]. The extent to which our results generalize to settings with differential incentives is an open question. Yet, we should note that our policy instrument has features that are conducive to scaling [49]. Future work should explore this question as it speaks directly to the design of tariff systems and the benefits that arise through the adoption of rooftop solar PV systems.

Moreover, it is important to caveat that we find no evidence that the eHER makes salient differences in savings associated with conservation efforts across seasons. In percentage terms, we observe lower rates of conservation in winter months even though consumers face significantly higher prices than during spring and summer months. Further investigation is needed to understand why we observe differences in the salience of intraday and inter-seasonal variation in prices on the efficacy of the eHER. One possibility for this divergence is differences in the time horizon over which prices fluctuate. Conceptually, time preference and discounting could have differential impacts on the perceived benefits of load shifting when facing intraday variation in pricing and energy efficiency when facing inter-seasonal variation in average monthly prices. Alternately, reduced conservation in winter months could reflect preferences for comfort and the inelasticity of demand for heating.

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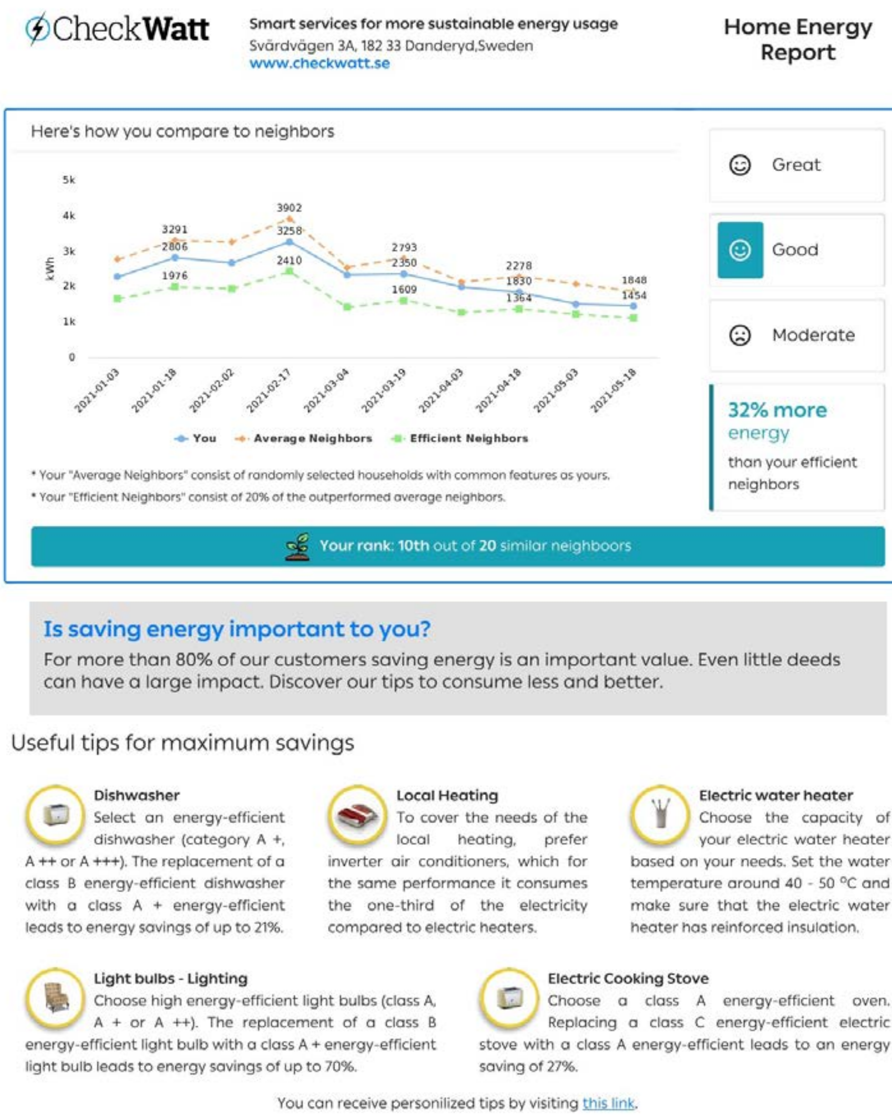
Appendix

Experimental design

The company has a customer base of over 5,000 individuals, though only 800 have opted to share their electricity consumption and production data. While our partnering company can access production data, prosumers' consumption data can only be accessed through electricity utilities with written consent. App. Fig. 1 displays the eHER that the customers received via email.



App. Fig. 1 | Home energy report. The figure shows the HER that consumers receive translated into English.

Methodology

Econometric estimation

To estimate the average treatment effect (ATE) and considering potential heterogeneity, we estimate a fixed effects panel regression using as controls the time-varying treatment indicator, $T_{i,t}$, interacting it with the hour of the day and weekly indicator variables following Wooldridge [27]:

$$y_{i,t} = a_i + w_t + T_{i,t} + X_{i,t} + h_t + \sum_{i=1}^{140} w_t * T_{i,t} + \sum_{i=1}^{24} h_t * T_{i,t} + e_{i,t}$$

where $y_{i,t}$ is the output of interest (e.g., electricity consumption in levels), a_i and w_t are individual and time-fixed effects (weeks), respectively, w and h are indicator variables for weeks and hours of the day, respectively, $X_{i,t}$ is the electricity production, and $e_{i,t}$ is the error term. Thus, we saturated all possible treatment combinations and times corresponding to an effectively treated unit.

A key point from this new literature is that the classic difference-in-differences method extended for many periods and units produces biased estimators for the treatment effect in staggered settings and the presence of heterogeneity. For mitigating potential biases, Wooldridge[8] [27] proposes to allow for sufficient heterogeneity by interacting the time-varying treatment indicator and simply interacting it with other time indicator variables like hour and week. To test robustness, we estimate the weekly effect using other similar methodologies [28], and the results remain similar qualitatively.

Table A1 shows the estimated average treatment effect on a weekly basis for the entire experimental period. Electricity consumption decreases by 34,344 watts per week. This translates to approximately a 9.8% decrease (the percentage decrease is estimated by dividing 34,344 by the average weekly electricity consumption of the treatment group, 350,013 watts).

[8] We thank Jeffrey Wooldridge for providing valuable suggestions regarding the estimated model.

Table A1: Estimation of the Average Treatment Effect

	Delta method			
	coefficient	std. err.	[90% conf. interval]	
ATE	-34,344.15	5,199.64	-42,896.80	-25,791.50

Supplementary information

Data

The company collects hourly data regarding electricity production and sales back to the grid and receives information from utility companies for the electricity a household purchases from the grid. Thus, electricity consumption is not directly observed; instead, it is derived from the:

$$consumption_t = production_t + purchases_t - sales_t$$

To deal with potential data mismeasurements and outliers, we keep only data between the lower 5^{th} and higher 95^{th} percentile.

Supplementary Table 1. shows the distribution of eHERs by month.

Month	# of eHERs	Month	# of eHERs
December 2021	1	November 2022	2
January 2022	2	December 2022	2
February 2022	2	January 2023	2
March 2022	2	February 2023	2
April 2022	2	March 2023	2
May 2022	2	April 2023	2
June 2022	2	May 2023	2
July 2022	1	June 2023	2
August 2022	1	July 2023	1
September 2022	2	August 2023	1
October 2022	1		

Pre-treatment period

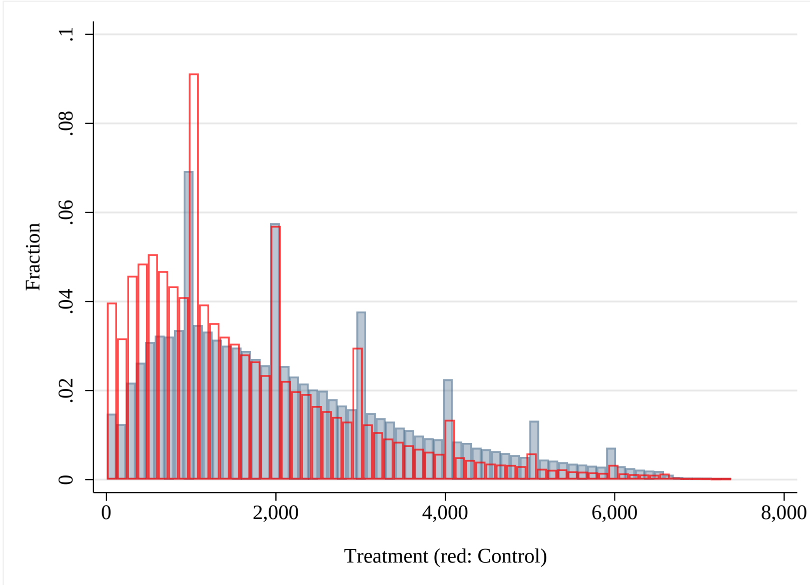
Supplementary Table 2 summarizes the statistics for the control and treatment groups during the pre-treatment period from 07 December 2020 to 06 December 2021. The results indicate that the control and treatment groups are well-balanced regarding electricity production and demographics. However, there is a statistically significant difference in electricity consumption, purchases, and sales. The treatment group consumes more electricity than the control group, leading them to purchase more electricity from the grid and sell less to the grid. Fixed effects should be included in the panel estimation to account for household differences.

Supplementary Table 2. Summary statistics by control and treatment group

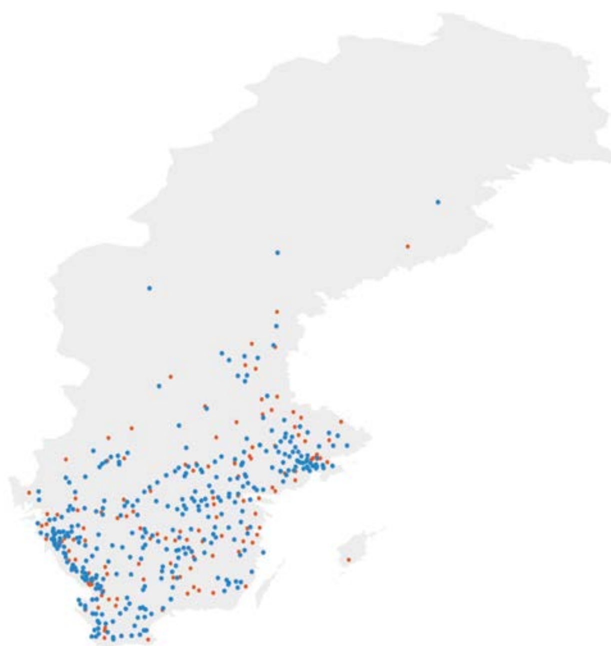
	Control			Treatment		
	Mean	std	Obs.	Mean	std	Obs.
Electricity consumption (w/h)	1,787.37	1,756.33	1,506,008	2,264.86	1,764.12	3,947,466
Electricity production (w/h)	844.12	1,728.54	1,506,008	906.05	1,801.12	3,947,466
Electricity purchases (w/h)	1,468.71	1750.622	1,506,008	1,861.97	1,819.60	3,947,466
Electricity sales (w/h)	525.46	1,350.24	1,506,008	503.20	1,310.37	3,947,466
House size (sq. meters)	177.17	63.58	1,126,252	178.31	52.49	2,893,965
Household members	2.83	1.13	723,263	2.87	1.21	2,322,917
Age of homeowner (years)	57.79	9.95	845,854	59.05	11.68	1,547,736

Notes: The table shows descriptive statistics between the control and treatment groups for the pre-treatment period, 07 Dec. 2020 – 05 Dec. 2021. Variables include the hourly amount of electricity (in watts/hours) a household Consumes, Produces, Sells back to the grid, and Purchases from the grid. It also presents summary statistics for three control variables: home size, Household members, and homeowner age. We don’t have observations for these three variables from all households since some didn’t respond to the company’s survey.

Supplementary Fig. 1 shows the distribution of electricity consumption between the treatment and control groups, revealing that the distribution, apart from the mean, shares common characteristics. Supplementary Fig. 2 illustrates that nearly all households are in southern Sweden and that the spatial distribution between the two groups is evenly distributed.

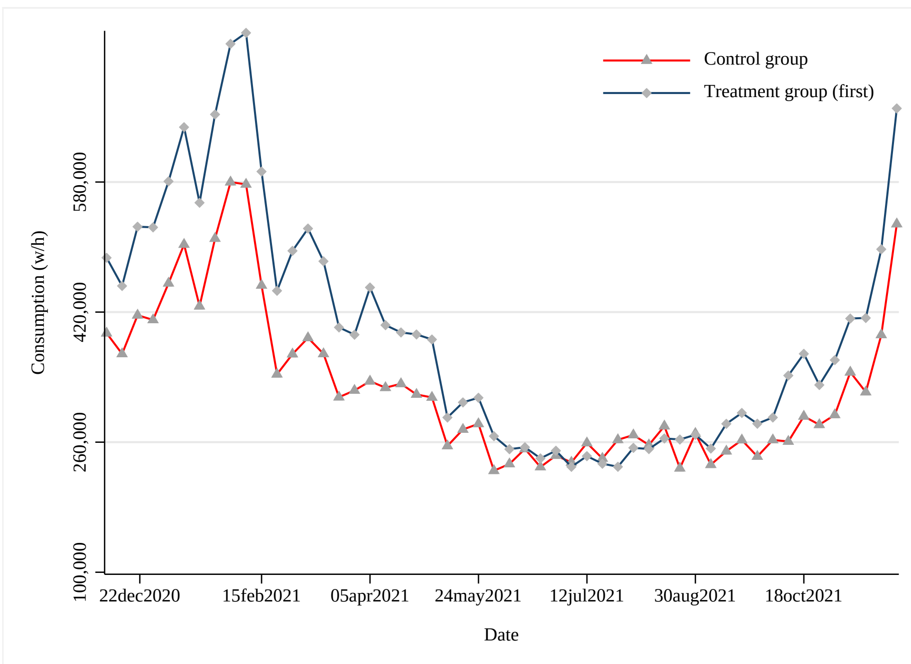


Supplementary Fig. 1. Electricity consumption histogram by control and treatment group. The graph shows the probability distribution of households' hourly electricity consumption (in watts) for the pre-treatment period, 07 Dec. 2020 – 06 Dec. 2021.



Supplementary Fig. 2. Spatial distribution of control (red) and treatment (blue) groups. The graph shows the spatial distribution across Sweden of control (in red color dots) and treatment groups. Each dot in the map indicates a household.

Supplementary Figure 3 presents a visual representation of the electricity consumption of both the control and treatment groups during the pre-treatment period. The figure highlights that the electricity consumption of both groups follows a similar trend, which substantiates the validity of the parallel trend assumption. Maintaining a constant difference in the outcome variable between the control and treatment groups is crucial to identifying the treatment effect accurately. Therefore, the parallel trend assumption confirms that the groups were comparable before the treatment was administered, and any observed differences in outcomes can be attributed to the treatment effect.



Supplementary Fig. 3. Parallel trend assumption between control and treatment group. The graph shows the evolution of the hourly electricity consumption (in watts) by the control and treatment groups from 07 Dec. 2020 to 06 Dec. 2021 (pre-treatment period) to test the parallel trend assumption.

Customers' reactions to eHER

Case 1: A customer shared an interesting experience with us. He received his first rounds of electronic Health Records (eHERs) and activated a new service for his heat pump. The service was supposed to optimize the use of the heat pump at the spot price of electricity. However, he noticed that his energy performance had worsened compared to his group's. Upon investigation, he discovered that the service was running the heat pump at night when the spot price was low, but the pump's efficiency was also low due to low outside temperatures. On the other hand, the service did not run the heat pump during the daytime when the price was high. As a result, the direct electricity heating function is triggered, leading to higher energy consumption.