Price Responsive Demand in Great Britain's Electricity Market

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25 November 2021

Abstract

Electricity markets balance supply and demand with price. Historically, this price response has come almost entirely from supply. However, when much of supply is intermittent or inflexible, price responsive demand becomes essential for reliability and resiliency. We measure how responsive consumers are to price in Great Britain from July 2020 to July 2021 with half-hourly individual-household data. Our sample includes customers with a dynamic rate that tracks wholesale cost, as well as flat-rate customers used to control for weather and other factors. A one percent increase in price reduces demand by 0.26 percent. This elasticity is larger for consumers owning low-carbon technologies. This price response is sufficient to maintain system balance in extreme events even when most consumers are unresponsive. Regulators can encourage price responsive demand through retail choice and subsidize enabling technologies. Regulators can protect consumers with mandated hedging in dynamic plans. Low-income households benefit most from such policies.

Introduction

Households and businesses generally pay a flat rate per electricity kilowatt-hour irrespective of market conditions. A flat rate, say $0.15/kWh, is simple and limits variation in bills. Still, it is inefficient in today's electricity markets, where the social cost varies from -$0.02 to $9.00/kWh depending on time and location. Consumers do not see or feel this real-time generation cost. Supply must provide the flexibility to balance the system every second. The disconnect between retail rates and the real-time electricity price adversely affects reliability and system costs. The regulator must intervene to create short- and long-term supply incentives to ensure resources offer sufficient flexibility. Focusing solely on supply is much like tying a knot with one hand. It is much easier to use both hands. A better solution is to let both supply and demand respond to price. Exposing some customers to the electricity price enables price responsive demand, which improves the electricity system's resiliency and accelerates and lowers the cost of the energy transition.

Many markets have widespread adoption of smart meters, and some markets allow rates that track the wholesale electricity price. We use Great Britain customer-level data from Octopus Energy to estimate electricity demand response to day-ahead prices. We find that a one percent price increase reduces consumption by 0.26 percent. Also, the elasticity is larger for households owning low-carbon technologies,

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particularly electric vehicles. While this effect may partly reflect self-selection, rapid innovation in demand-response technologies will likely increase adoption and enable greater price responsive demand going forward.

Regulators can promote price responsive demand while benefitting consumers and society at large. Low-income households would benefit most from dynamic rates but are more exposed to the financial risk of volatile bills and may lack the resources to invest in innovative home technologies. We argue that regulators should allow retail choice while monitoring consumer rate plans and mandating hedging. Hedging enables consumers to enjoy the upside of dynamic rates, protects consumers from the downside, and preserves incentives to act in a socially beneficial manner. Regulators can subsidize the adoption of innovative home technologies, particularly for low-income households. These policies support clean energy goals and the electrification of other sectors.

Previous studies on the electricity consumption response to prices focused on industrial customers or residential pilot programs limited in duration and number of participants. Zhu et al. (2018) report a mean elasticity of -0.228 in a literature review for residential consumption. We use half-hourly data from actual residential contracts offered to Great Britain customers, including customers with a rate that tracks the wholesale cost. The large size of the sample allows us to study the effect of technology ownership. Both features are crucial to understanding the scope for price responsive demand in practice.

Consumer engagement for reliability, resiliency, and the energy transition

Electricity markets are organized for reliability. Power must be available whenever the end-user demands it. The spot market has features to ensure supply can respond to demand variations in almost all circumstances. For example, the system requires the availability of responsive reserves that can quickly balance supply and demand.

At times, this supply response may be insufficient to match demand, resulting in controlled outages. Rolling outages are an administrative response to a shortage caused in part by end-users failing to reduce non-essential consumption, despite a social cost that is 300 times the typical electricity price. Rolling outages are coarse and produce pent-up demand exacerbating the need for rolling outages. A family without power cannot heat their home, whereas a family with power may over-heat their home, anticipating a rolling outage. By contrast, prices are a coordination mechanism directing electricity towards most critical social uses, heating both houses as necessary.

The lack of price-responsive demand also produces long-term reliability issues. When supply and demand do not balance, the price is undefined. The price signal is absent precisely when it should convey the inadequacy of generation and storage resources. The lack of price formation leads to the so-called missing-money problem at the root of underinvestment in electricity markets (Joskow 2008). Regulators address this issue by defining an administrative shortage price and an administrative demand curve for reserves. These scarcity prices quickly approach the value of lost load as a market nears shortage (Hogan 2013). Some markets go further and coordinate investments and retirement decisions by procuring capacity resources years in advance on behalf of load (Cramton et al. 2013).

Price responsive demand is critical for resiliency. Resiliency is the ability to withstand systemwide events disrupting supply and demand, such as extreme weather. The 2021 Texas cold snap caused widespread outages of conventional generation and a simultaneous demand spike, resulting in a gap of approximately

30GW in a system with a winter peak of 58GW (Busby et al. 2021). The system operator ordered rolling outages for four days. Hundreds of lives were lost; the economic loss was $130 billion. In Bobbio et al. (2021), we use the demand model estimated in this paper to show that if 44% of end-users had been price responsive, no outages would have been necessary. The $9/kWh shortage price would have induced households to reduce their energy consumption enough to balance supply and demand. Demand response is a powerful way to improve resiliency.

Finally, price responsive demand is essential to speed the energy transition and lower its cost. A zero-emission resource mix will have a high share of solar, wind, storage, and possibly nuclear. Solar and wind generation is highly variable. These intermittent resources require substantial flexibility from other resources. Nuclear has limited flexibility, hence the need for significant investments in storage. However, the demand side can be another source of flexibility. Unlike storage, enhancing price responsive demand is low-cost and improves the electricity system along other dimensions, reducing system costs while fostering reliability and resiliency.

Promoting price responsive demand within a well-regulated framework will save consumers money, especially low-income households. It will incentivize the innovation and adoption of low-carbon technologies, like energy efficiency, smart homes, and electric vehicles. The complementarity with electric vehicles is fundamental. Steinberg et al. (2017) estimate electric vehicles will raise energy consumption by 25% by 2050. Smart charging is crucial to avoid overloading the grid. Passenger cars are parked most of the time. Electric vehicles could service the grid by storing excess energy and discharging when electricity demand is high relative to supply from intermittent resources. Deploying vehicle-to-grid (smart charging and discharging) would reduce dramatically the need to invest in transmission and utility-scale storage to operate a zero-emission grid reliably. It would also be low cost. However, end-users paying flat electricity rates have no incentives to engage in vehicle-to-grid. Exposing end-users to prices that reflect the electricity spot price is crucial to coordinate charging decisions and to motivate the socially efficient use of vehicle batteries to smooth intermittent generation.

Empirical findings on the consumption response to prices from Great Britain household data

We use household-level data from Octopus Energy to estimate how consumers who signed up for dynamic rates respond to electricity prices. These customers pay half-hourly retail rates based on the day-ahead wholesale price. Every day at about 16:00, they learn prices for the following day. We employ half-hourly smart meter readings that measure electricity consumption from July 2020 to July 2021.

Our regression analysis includes time segment fixed effects to control periodicity and trends in electricity consumption. A *time segment* is defined as the combination of year, month, day of the week, and half-hour interval. For example, consumption and prices on Mondays at 7:30 in March behave similarly, regardless of whether it is the first or second Monday of March 2021. We can, therefore, think of the joint distribution of prices and consumption as approximately stable for a particular *time segment.* We use the consumption of Octopus customers on flat-rate plans to control for demand shocks like the weather.

Figure 1 displays the price elasticity coefficients of our baseline regression model. The coefficients describe how households react when electricity prices marginally increase in period 0h. The figure's x-axis shows the seventeen half-hourly periods before and after the price increase. The time lags and leads capture whether households shift consumption to adjacent periods in response to a price increase in 0h. The y-axis depicts the price elasticity of electricity consumption.

The left panel of Figure 1 reveals that a one percent price increase induces customers on a dynamic plan to reduce consumption by 0.265 percent in the same period. This behavior is in line with findings in previous studies on the demand elasticity to prices. Espey and Espey (2004) report a mean own-price elasticity of -0.35 and a median of -0.28 in their meta-analysis of 36 studies.

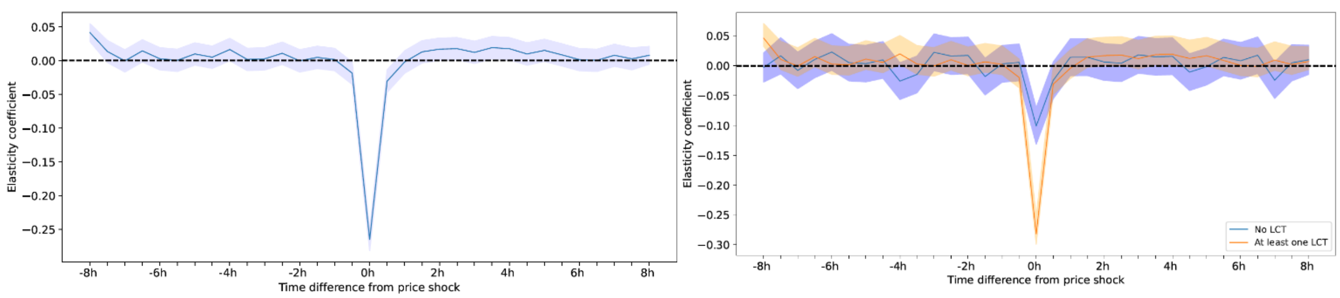
The left side of Figure 1 suggests that customers modestly increase demand in adjacent periods when the price increases in period 0h. However, these cross-price elasticities are generally not statistically significant—see Table A-1 in the appendix. Thus, customers' willingness or ability to shift consumption over time appears to be limited.

Table A-1 also reveals that customers' response to prices only moderately differs across seasons. Own-price elasticities are slightly stronger in summer and winter when average consumption is higher than in spring and fall. In contrast, the consumption response varies substantially by time of day. Customers seem less willing to adjust their electricity usage in the morning and afternoon. Postponing electricity-consuming activities during these times of day might be impractical and too costly due to fixed working hours.

Low-carbon technologies

Octopus Energy surveys customers who sign up for a dynamic plan and collects ownership information of low-carbon technologies (LCT). We use this data to analyze if customers with LCTs react more or less strongly to price changes. We consider five LCTs: 1) electric heating, 2) smart thermostats, 3) electric vehicles, 3) residential solar, and 4) battery storage.

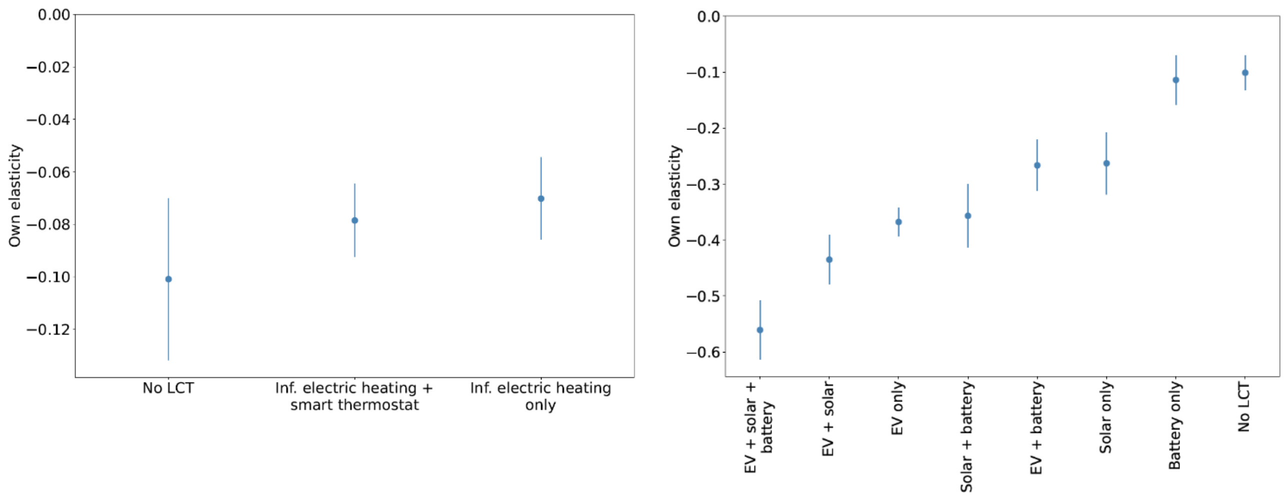
Figure 1: Consumption response due to price shock at period 0h



The right graph of Figure 1 shows that customers owning at least one LCT are almost three times as price responsive as customers who do not own any LCT. No-LCT customers have an own-price elasticity of -0.101 compared to -0.282 for customers with at least one LCT.

Next, we consider specific combinations of LCTs. For conciseness, Figure 2 only shows the own-elasticity coefficients. Table A-1 in the appendix displays the complete estimation results. The left side of Figure 2 indicates that low-carbon heating technologies do not increase customers' price responsiveness. The own-price elasticities are nearly the same for customers with electric heating, or electric heating and smart thermostats (and no other LCT) as for customers without LCTs.

Figure 2: Consumption response by low-carbon technology ownership status



On the right side of Figure 2, we focus on the effect of the remaining LCTs, namely electric vehicles, solar PV, and batteries.[2] The own-price elasticity of customers who only have an electric vehicle (EV only) is more than three times larger than the elasticity of customers without any LCT. Electric cars require substantial amounts of energy, motivating consumers to charge when electricity is cheaper. Pairing electric vehicles with solar and batteries increases the price-responsiveness even further.

Solar PV ownership also has a substantial effect on price responsiveness. Perhaps surprisingly, batteries alone do not make customers more price responsive than customers without any LCT. Moreover, customers who pair batteries with electric vehicles or solar PV are not significantly more price responsive than customers who only use an EV or a solar panel. Batteries are not yet endowed with software to take advantage of price changes because dynamic rates remain rare.

Our findings add to the literature that examines how consumers respond to dynamic electricity prices (Dutta und Mitra 2017; Espey und Espey 2004). Most of this literature focuses on industrial and commercial customers since dynamic prices are only offered to business customers in many countries (Boisvert et al. 2007; Herriges et al. 1993; Taylor et al. 2005; Patrick und Wolak 2001). Empirical evidence on residential customers' price responsiveness largely relies on pilot programs and small-scale experiments (Allcott 2011; Faruqui and Sergici 2010). Some of these pilot studies also evaluate the effect of low-carbon technologies like smart thermostats (Faruqui and George 2005) and electric vehicles (Limmer 2019) on demand response. Our study contributes to this literature in three ways. First, we employ a large sample of observational household consumption data. Second, our large sample allows us to stratify our dataset by low-carbon technology (LCT) ownership to analyze the effects of different LCTs on price responsiveness. Third, we study how the combination of multiple LCTs influences customer behavior.

[2] To increase the size of our sub-samples, we do not control for ownership of the low-carbon heating technologies. For instance, "EV only" customers have an electric vehicle, no solar PV, and no battery, but they may have electric heating or own a smart thermostat. Low-carbon heating technologies do not have a significant effect on price responsiveness, as discussed above.

Policy levers and consumer protection

Dynamic rates are beneficial to consumers. They allow households to shift their electricity consumption to times when supply is abundant relative to demand and electricity is cheap, thus saving money. Potential savings are particularly significant for low-income households who spend a larger share of their income on electricity.

Dynamic rates are now feasible. Innovation in information technology has solved the problem of conveying real-time prices to consumers. Regulators are supporting the adoption of smart meters in many countries. Also, technical and social trends will increase the appeal of dynamic rates. Households will spend a larger share of their income on electricity due to electrification. Drivers who now drive to the cheapest pump along their daily commutes will select plans that allow them to charge their electric vehicles at the lowest price. Better user interfaces and algorithms will enable households to take advantage of real-time price variations at little cognitive cost.

Regulators can take significant steps to promote price responsive demand. First, regulators should allow retail choice and encourage the adoption of dynamic rates. Sophisticated providers may take advantage of consumers, as is true in many markets. The solution is to regulate and monitor the plans that providers offer. While dynamic rates allow consumers to save on average, they can lead to steep bills when wholesale prices remain high for an extended period, as occurred during the 2021 Texas winter storm. Regulators often employ price caps to shield customers from high wholesale prices—£0.35/kWh in Great Britain—but price caps are problematic. They limit demand response when it is most socially valuable and increase providers' bankruptcy risk.

Regulators should instead protect customers by mandating hedging of dynamic rates or making a certain level of hedging the default option. The provider purchases a household's expected consumption, say one month forward. The consumer pays the real-time price only for deviations from the expected consumption. Hedging reduces the risk of high bills while preserving incentives to respond to prices. If the real-time price is high, the household can reduce its consumption. The household automatically gets a credit equal to the price difference (real-time price minus forward price) times the reduction in quantity. With hedging, real-time price volatility is purely advantageous to consumers. A price cap becomes not only unnecessary but harmful to consumers, in addition to increasing providers' bankruptcy risk.

Hedged dynamic rates do not require households to become sophisticated traders. The regulator could simply state that household rates be capped at double the rate in the same month of the previous year. The provider would then do the hedging on behalf of the consumer. The consumer would earn money by reducing consumption when the real-time price is high—and allow other households to have power for critical uses. The consumer would always have the option of a flat-rate plan. But many consumers would choose dynamic rates and receive compensation for the flexibility they provide to the system.

Regulators should support the adoption of dynamic rates with grants for low-income households to purchase energy-efficient and smart electric devices. These investments often are beneficial, yet low-income households lack the resources to pay the upfront costs. Some electric vehicles already have a lower total user cost than the cheapest gas alternatives (Miotti et al. 2016), but the purchase price remains substantially higher. These technologies produce environmental benefits directly, enable consumers to respond to real-time prices, and strengthen the response, bringing many social benefits as discussed in section two. Thus, it is socially efficient for regulators to subsidize their development and adoption.

Conclusions

Price responsive demand is fundamental for reliable and resilient electricity. It should also be part of any least-cost strategy to decarbonize the electricity sector and reduce emissions in other sectors of the economy. It supports investments in intermittent renewable resources and nuclear power. It is a precondition for smart charging and discharging of electric vehicles that support clean energy investments and transport decarbonization. Electricity, heat, and transport account for over 60% of global emissions (EPA 2021). Price responsive demand strengthens incentives to adopt home low-carbon technologies.

Using Great Britain customer-level data, we showed that households' electricity consumption responds to wholesale prices. The price elasticity of demand is -0.265, which is sufficient for electricity markets to be resilient to extreme storms, even when most consumers are unresponsive. Ownership of low-carbon technologies is associated with an even stronger response, particularly in the case of electric vehicles, suggesting that price responsive demand will be increasingly important as these technologies improve.

Regulators need to take an active stance to make dynamic rates attractive for consumers while enhancing retail competition.

Data Sources

UK Octopus Energy provided anonymized, half-hour electricity smart meter customer readings on three types of pricing rates: Flat-rate, dynamic (wholesale-linked), and electric vehicle (EV) plans.

Our sample of 15,000 customers consists of approximately 5,000 consumers randomly sampled from each plan type. All had smart meters since at least July 2020. Each consumer is associated with up to one year of smart meter readings from July 2020 to July 2021. As users are free to switch plans across this period, users may belong to multiple groups across the whole period. For instance, a user on a dynamic plan may choose to migrate onto an EV plan at any point. A small proportion of users participate in export plans, which are structured as separate plans. A user may be in multiple plans at the same point in time in this instance.

Dynamic plan

The dynamic plan reflects day-ahead auction prices for electricity. The final price also reflects distribution costs and a peak-time premium, as explained in this blog. Octopus designed the plan to encourage consumers to shift their consumption outside the 4-7 pm peak. Customers have forward notice of these half-hourly prices, which are made available every evening between 4-8 pm for the next day. A negative wholesale price can result in a negative customer price, known as plunge pricing. However, a cap at 35p/kWh—roughly double a flat-rate plan—protects customers from surge pricing.

EV plan

EV plans offer electricity at two rates: an off-peak price during fixed charging hours, such as 00:30 - 04:30, and otherwise a peak price approximately three times higher. Pricing depends slightly on geographic location. Octopus designed the plan to incentivize consumers to charge their electric vehicles in the off-peak window.

For our analysis above, we only focus on customers on dynamic and flat-rate plans.

Low-carbon technology ownership survey data

When users sign up for a dynamic plan, Octopus Energy asks them to complete a survey to indicate their ownership of various low-carbon technologies (LCTs). The survey queries information on four LCTs: 1) smart thermostats, 2) electric vehicles, 3) residential solar, and 4) battery storage. Boolean flags indicate the stated ownership of these technologies. In addition, we add information on electric heating ownership that is not survey-based but inferred from the lack of a gas contract with Octopus Energy—households generally purchase electricity and gas from the same provider in Great Britain.[3]

Table 1 shows the number of customers on dynamic and flat-rate plans by ownership of low-carbon technologies (LCTs). We only have information on LCT ownership for a subsample of households since many households did not participate in the survey.

Table 1: Number of customers by customer groups and plan types

	Customer groups	**Dynamic tariff**	**Fixed tariff**
1	All customers	4148	5904
3	At least one LCT	2593	647
2	No LCT	99	12
4	Inferred electric heating only	414	162
5	Inferred electric heating + smart thermostat	411	94
6	EV only	1025	352
7	Solar only	138	27
8	Battery only	49	12
9	EV + solar	280	45
10	EV + battery	66	16
11	Solar + battery	124	21
12	EV + solar + battery	177	20

Methodology

We employ a time segment fixed effects regression model to estimate price elasticities of electricity demand. A time segment is defined as the combination of year, month, day of the week, and half-hour interval.

The fixed effects control for periodicity and trends. They capture how consumption and prices move relative to one another after accounting for their characteristic values in a particular time segment. Electricity consumption and prices are positively correlated and vary systematically across years, seasons, and throughout the day. Consumption and prices are higher in the early morning than at night, and the afternoon peak occurs later in the summer than in the winter. However, their joint distribution is likely approximately stable for a particular time segment. For example, consumption and prices on Monday at

[3] Our indicator of electric heating ownership is relatively imprecise. Some customers who do not have a gas contract with Octopus Energy might purchase gas from another supplier or might use oil heating. Therefore, we might falsely assume some gas heating owners use electric heating. This imprecision will likely lead to a downward bias of our estimates for electric heating ownership because gas heating owners are arguably less responsive to electricity prices than electric heating owners.

7:30 behave similarly, regardless of whether it is the first or second Monday of March 2021. In essence, we can view each time segment as a repeated experiment where we draw four or five consumption-price pairs—depending on the number of weeks in a month.

Using fixed effects for these time segments, we estimate the following model by OLS:

$$\ln(C_t^d) = c^{s(t)} + \sum_{j=-16}^{16} \gamma_j \ln(P_{t+j}) + \ln(C_t^f) + \varepsilon_t$$

t denotes time in half-hour increments. C is the average consumption of households on dynamic plans (superscript d) and flat-rate plans (superscript f); P is the average retail price paid by households on dynamic rates. $c^{s(t)}$ denotes the fixed effect for time segment $s(t)$. ε is the error term, which we assume is independently and identically distributed and uncorrelated with regressors P and C^f.

The specification assumes that the demand curve is isoelastic—if the price increases by *x%,* consumption varies by $\gamma \times x\%$ regardless of the consumption and price level. Households may respond to a higher price by shifting consumption to other time intervals when the price is lower—run the dishwasher or charge the electric vehicle earlier or later. At 16:00, households on dynamic plans learn prices for the following day. Thus, the model includes the contemporaneous price and earlier and later prices, spanning a ±8-hour window for a total of 33 elasticity coefficients γ_j, $j = -16,\ldots, +16$.

The model includes the average consumption of households on a flat rate as a control for demand shocks. A positive demand shock increases the price, affecting households' consumption on dynamic plans both directly and indirectly—via the price. Failure to control for demand shocks positively biases the contemporaneous elasticity coefficient. Interestingly, the response to prices turns out to be sufficiently strong; estimating the model without control delivers a statistically and economically significant negative coefficient. As expected, introducing the control increases the coefficient's magnitude in absolute value. Finally, the estimated coefficient on the control is not statistically different from one, indicating that demand shocks similarly affect customers on dynamic and flat-rate plans.

Our analysis first examines how households on dynamic plans respond to prices. Then, we stratify the analysis by low-carbon technology (LCT) ownership status. For example, we estimate the model by restricting attention to households that own electric vehicles.

One drawback of our analysis is that many households did not participate in the LCT survey. Moreover, only customers who switched to a dynamic rate were asked to fill the survey. Therefore, we only have LCT information for households on flat-rate plans if they switch to a dynamic plan at some point in time. These customers on flat-rate plans might differ from flat-rate plan customers who never switched to a dynamic plan.

We drop all households without LCT ownership information for all regressions that analyze the effect of owning an LCT. This filtering leaves only a few observations for some LCTs, especially flat-rate plans (see Table 1). For example, we only have twelve customers on flat-rate plans that have no LCTs. Thus, we estimate the model using a generic control group with all 5,904 households on flat-rate plans, irrespective of LCT ownership status. As a robustness check, we also run the model using smaller LCT-group-specific control groups. Our results are robust to using these narrower control groups compared to using the generic group. Results for the LCT-group-specific controls are available upon request.

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Appendix

Table A-1: Fixed effects regression results

Regressors	All customers	winter	spring	summer	fall	night (0-6)	morning (6-12)	afternoon (12-18)	evening (18-24)
const	-0.002***	-0.001	-0.001	-0.000	-0.004***	-0.003**	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
-8h	0.042***	0.017	0.026*	0.040**	0.057***	0.037***	0.011	0.004	0.005
	(0.007)	(0.011)	(0.016)	(0.016)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
-7.5h	0.014*	0.024*	0.012	0.027	0.009	-0.001	0.003	0.001	0.014
	(0.008)	(0.014)	(0.020)	(0.019)	(0.014)	(0.014)	(0.013)	(0.013)	(0.012)
-7.0h	-0.000	-0.000	-0.008	-0.009	0.001	0.001	-0.002	-0.001	-0.004
	(0.008)	(0.014)	(0.020)	(0.020)	(0.014)	(0.014)	(0.013)	(0.013)	(0.012)
-6.5h	0.015*	0.008	0.024	-0.004	0.015	0.019	0.010	0.007	0.014
	(0.008)	(0.014)	(0.020)	(0.020)	(0.014)	(0.014)	(0.013)	(0.013)	(0.012)
-6h	0.003	0.009	0.005	-0.034*	0.000	-0.006	-0.003	0.005	0.037***
	(0.008)	(0.015)	(0.020)	(0.020)	(0.014)	(0.014)	(0.013)	(0.013)	(0.012)
-5.5h	0.001	0.004	0.023	0.009	-0.002	0.017	-0.009	0.015	0.019
	(0.008)	(0.015)	(0.020)	(0.020)	(0.014)	(0.014)	(0.013)	(0.013)	(0.012)
-5.0h	0.010	0.003	0.032	0.008	-0.000	0.009	0.016	-0.001	0.011
	(0.008)	(0.015)	(0.020)	(0.020)	(0.014)	(0.014)	(0.013)	(0.013)	(0.012)
-4.5h	0.005	0.012	-0.013	0.011	0.004	0.013	0.004	0.004	-0.008
	(0.008)	(0.015)	(0.020)	(0.020)	(0.014)	(0.014)	(0.013)	(0.014)	(0.012)
-4h	0.017**	0.015	0.001	0.014	0.013	0.024*	0.007	0.006	-0.001
	(0.008)	(0.015)	(0.020)	(0.020)	(0.014)	(0.014)	(0.013)	(0.013)	(0.012)
-3.5h	0.002	0.014	-0.005	-0.007	0.007	0.003	0.011	0.022	-0.000
	(0.008)	(0.015)	(0.020)	(0.020)	(0.014)	(0.014)	(0.013)	(0.013)	(0.012)
-3.0h	0.003	0.006	-0.006	-0.003	0.004	0.019	0.011	0.004	0.000
	(0.008)	(0.015)	(0.020)	(0.020)	(0.015)	(0.014)	(0.013)	(0.013)	(0.012)
-2.5h	0.011	0.017	0.029	0.016	0.008	0.015	0.008	0.018	-0.004
	(0.008)	(0.015)	(0.020)	(0.020)	(0.015)	(0.014)	(0.013)	(0.013)	(0.012)
-2h	-0.000	0.003	0.008	0.002	0.000	0.003	0.009	0.010	-0.012
	(0.008)	(0.015)	(0.020)	(0.020)	(0.015)	(0.014)	(0.013)	(0.014)	(0.012)
-1.5h	0.005	-0.000	-0.012	-0.001	-0.004	0.004	0.007	0.022	-0.013
	(0.008)	(0.015)	(0.020)	(0.020)	(0.015)	(0.014)	(0.013)	(0.014)	(0.012)
-1.0h	0.002	0.012	0.029	-0.003	0.002	0.021	0.020	0.020	0.010
	(0.008)	(0.015)	(0.020)	(0.020)	(0.015)	(0.014)	(0.013)	(0.014)	(0.012)
-0.5h	-0.018**	-0.006	-0.035*	0.003	-0.029**	-0.007	0.025*	-0.011	-0.022*
	(0.008)	(0.015)	(0.020)	(0.020)	(0.015)	(0.014)	(0.013)	(0.014)	(0.012)
0h	-0.265***	-0.273***	-0.246***	-0.297***	-0.223***	-0.302***	-0.154***	-0.157***	-0.240***
	(0.008)	(0.015)	(0.020)	(0.020)	(0.015)	(0.014)	(0.013)	(0.014)	(0.012)
0.5h	-0.030***	-0.030**	-0.035*	0.017	-0.029**	-0.060***	0.006	-0.020	0.046***
	(0.008)	(0.015)	(0.020)	(0.020)	(0.015)	(0.014)	(0.013)	(0.014)	(0.012)
1.0h	-0.002	-0.007	-0.004	0.027	0.002	0.003	0.022*	0.022	0.026**
	(0.008)	(0.015)	(0.020)	(0.020)	(0.015)	(0.014)	(0.013)	(0.014)	(0.012)
1.5h	0.013	0.010	-0.002	0.016	0.016	-0.011	-0.003	0.001	0.032**
	(0.008)	(0.015)	(0.020)	(0.020)	(0.015)	(0.014)	(0.013)	(0.014)	(0.012)
2h	0.017**	0.008	0.019	0.026	0.005	0.030**	0.002	0.010	0.042***
	(0.008)	(0.015)	(0.020)	(0.020)	(0.015)	(0.014)	(0.013)	(0.014)	(0.012)
2.5h	0.018**	0.021	0.001	0.019	0.012	0.019	0.024*	0.009	0.004
	(0.008)	(0.015)	(0.020)	(0.020)	(0.015)	(0.014)	(0.013)	(0.014)	(0.012)
3.0h	0.012	0.001	0.052**	0.006	0.015	0.009	0.016	0.018	0.003
	(0.008)	(0.015)	(0.020)	(0.020)	(0.015)	(0.014)	(0.013)	(0.013)	(0.012)
3.5h	0.019**	0.018	0.025	0.026	0.028*	0.012	-0.001	0.007	0.016
	(0.008)	(0.015)	(0.020)	(0.020)	(0.015)	(0.014)	(0.013)	(0.013)	(0.012)
4h	0.018**	0.005	0.001	0.044**	0.019	0.011	-0.007	-0.004	0.019
	(0.008)	(0.015)	(0.020)	(0.020)	(0.015)	(0.014)	(0.013)	(0.014)	(0.012)
4.5h	0.010	0.014	0.017	-0.003	0.003	0.005	0.001	-0.001	0.010
	(0.008)	(0.015)	(0.020)	(0.020)	(0.015)	(0.014)	(0.013)	(0.014)	(0.012)
5.0h	0.015*	0.026*	0.003	-0.011	0.010	-0.019	0.014	-0.012	0.017
	(0.008)	(0.014)	(0.020)	(0.020)	(0.014)	(0.014)	(0.013)	(0.014)	(0.012)
5.5h	0.009	0.004	-0.009	-0.009	0.003	-0.022	0.004	0.001	0.018
	(0.008)	(0.014)	(0.020)	(0.020)	(0.014)	(0.014)	(0.013)	(0.014)	(0.012)

6h	0.002	0.003	0.011	-0.013	-0.000	0.002	-0.022*	0.019	0.007
	(0.008)	(0.014)	(0.020)	(0.020)	(0.014)	(0.014)	(0.013)	(0.014)	(0.012)
6.5h	0.001	-0.001	0.013	-0.013	0.003	0.003	0.010	-0.005	-0.005
	(0.008)	(0.014)	(0.020)	(0.020)	(0.014)	(0.014)	(0.013)	(0.013)	(0.012)
7.0h	0.008	-0.000	-0.010	0.023	0.012	-0.001	-0.013	0.005	0.007
	(0.008)	(0.014)	(0.020)	(0.020)	(0.014)	(0.014)	(0.013)	(0.013)	(0.012)
7.5h	0.003	-0.004	-0.003	-0.013	0.014	0.012	0.012	0.016	-0.009
	(0.008)	(0.014)	(0.020)	(0.019)	(0.014)	(0.014)	(0.013)	(0.013)	(0.012)
8h	0.008	0.033***	-0.005	-0.010	-0.006	0.015	0.035***	0.003	-0.001
	(0.007)	(0.011)	(0.016)	(0.016)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
delta_ln_watt_fixed	1.008***	1.226***	1.043***	0.838***	0.804***	0.568***	1.112***	1.055***	0.899***
	(0.009)	(0.016)	(0.015)	(0.021)	(0.022)	(0.031)	(0.014)	(0.009)	(0.020)
Observations	17,105	4,200	4,247	4,295	4,263	4,233	4,257	4,260	4,257
R2	0.484	0.657	0.570	0.354	0.362	0.434	0.628	0.784	0.415
Adjusted R2	0.483	0.655	0.567	0.348	0.357	0.429	0.625	0.782	0.410
Residual Std. Error	0.070 (df=17070)	0.063 (df=4165)	0.061 (df=4212)	0.054 (df=4260)	0.090 (df=4228)	0.098 (df=4198)	0.054 (df=4222)	0.042 (df=4225)	0.062 (df=4222)
F Statistic (omitting all regressors)	471.336*** (df=34; 17070)	235.063*** (df=34; 4165)	164.230*** (df=34; 4212)	68.553*** (df=34; 4260)	70.542*** (df=34; 4228)	94.636*** (df=34; 4198)	209.497*** (df=34; 4222)	451.391*** (df=34; 4225)	88.134*** (df=34; 4222)
F Statistic (omitting time leads and lags)	58.241** (df=32; 17070)	21.934** (df=32; 4165)	10.757** (df=32; 4212)	6.900** (df=32; 4260)	13.258** (df=32; 4228)	18.206** (df=32; 4198)	9.938** (df=32; 4222)	11.865** (df=32; 4225)	11.228** (df=32; 4222)

Note: *p<0.1; **p<0.05; ***p<0.01

Regressors	No LCT	At least one LCT	Inf. electric heating only	Inf. electric heating + smart thermostat	EV only	Solar only	Battery only	EV + solar
const	-0.001	-0.002***	-0.001**	-0.001*	-0.002**	-0.003	-0.001	-0.003**
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.002)	(0.001)	(0.001)
-8h	-0.003	0.046***	0.011*	-0.003	0.060***	0.028	0.011	0.087***
	(0.013)	(0.007)	(0.006)	(0.006)	(0.010)	(0.022)	(0.018)	(0.018)
-7.5h	0.017	0.011	-0.005	0.014**	0.004	0.024	0.015	0.009
	(0.016)	(0.009)	(0.008)	(0.007)	(0.013)	(0.028)	(0.022)	(0.022)
-7.0h	-0.008	-0.001	-0.003	-0.012*	-0.002	0.004	0.033	0.007
	(0.016)	(0.009)	(0.008)	(0.007)	(0.013)	(0.028)	(0.022)	(0.022)
-6.5h	0.011	0.015*	0.002	0.003	0.012	0.010	-0.007	0.030
	(0.016)	(0.009)	(0.008)	(0.007)	(0.013)	(0.028)	(0.022)	(0.022)
-6h	0.023	0.003	0.004	0.008	0.010	-0.027	-0.026	0.020
	(0.016)	(0.009)	(0.008)	(0.007)	(0.013)	(0.028)	(0.022)	(0.022)
-5.5h	0.005	0.001	-0.002	-0.007	0.008	-0.006	0.017	-0.004
	(0.016)	(0.009)	(0.008)	(0.007)	(0.013)	(0.028)	(0.022)	(0.022)
-5.0h	0.004	0.011	-0.000	0.015**	0.010	0.009	0.003	0.027
	(0.016)	(0.009)	(0.008)	(0.007)	(0.013)	(0.028)	(0.022)	(0.022)
-4.5h	0.010	0.006	-0.002	-0.001	0.011	0.012	-0.001	-0.001
	(0.016)	(0.009)	(0.008)	(0.007)	(0.013)	(0.028)	(0.022)	(0.022)
-4h	-0.026	0.020**	0.010	-0.014*	0.029**	0.015	0.001	0.029
	(0.016)	(0.009)	(0.008)	(0.007)	(0.013)	(0.028)	(0.022)	(0.022)
-3.5h	-0.015	0.003	-0.003	0.002	-0.001	0.001	-0.018	0.011
	(0.016)	(0.009)	(0.008)	(0.007)	(0.013)	(0.028)	(0.022)	(0.022)
-3.0h	0.022	-0.000	0.002	0.014**	-0.008	0.014	0.021	-0.007
	(0.016)	(0.009)	(0.008)	(0.007)	(0.013)	(0.028)	(0.022)	(0.022)
-2.5h	0.016	0.010	0.009	0.006	0.005	0.020	0.026	0.021
	(0.016)	(0.009)	(0.008)	(0.007)	(0.013)	(0.028)	(0.022)	(0.022)
-2h	0.017	0.000	0.000	-0.001	-0.001	0.013	-0.010	0.001
	(0.016)	(0.009)	(0.008)	(0.007)	(0.013)	(0.028)	(0.022)	(0.022)
-1.5h	-0.018	0.006	-0.002	-0.005	0.003	0.011	0.024	0.014

	(0.016)	(0.009)	(0.008)	(0.007)	(0.013)	(0.028)	(0.022)	(0.022)
-1.0h	0.003	0.002	-0.000	0.001	-0.002	0.033	-0.005	-0.009
	(0.016)	(0.009)	(0.008)	(0.007)	(0.013)	(0.028)	(0.022)	(0.022)
-0.5h	0.006	-0.020**	-0.014*	-0.008	-0.022*	-0.006	-0.039*	-0.044**
	(0.016)	(0.009)	(0.008)	(0.007)	(0.013)	(0.028)	(0.022)	(0.022)
0h	-0.101***	-0.282***	-0.070***	-0.079***	-0.368***	-0.263***	-0.114***	-0.435***
	(0.016)	(0.009)	(0.008)	(0.007)	(0.013)	(0.028)	(0.022)	(0.022)
0.5h	-0.024	-0.031***	-0.007	-0.028***	-0.018	-0.060**	-0.041*	-0.047**
	(0.016)	(0.009)	(0.008)	(0.007)	(0.013)	(0.028)	(0.022)	(0.022)
1.0h	0.014	-0.004	-0.001	-0.002	-0.012	0.026	0.006	-0.001
	(0.016)	(0.009)	(0.008)	(0.007)	(0.013)	(0.028)	(0.022)	(0.022)
1.5h	0.014	0.014	0.018**	0.000	0.002	0.050*	0.017	0.027
	(0.016)	(0.009)	(0.008)	(0.007)	(0.013)	(0.028)	(0.022)	(0.022)
2h	0.006	0.017*	0.003	0.013*	0.008	0.043	0.030	0.027
	(0.016)	(0.009)	(0.008)	(0.007)	(0.013)	(0.028)	(0.022)	(0.022)
2.5h	0.004	0.018**	0.001	0.005	0.016	0.046	0.013	0.033
	(0.016)	(0.009)	(0.008)	(0.007)	(0.013)	(0.028)	(0.022)	(0.022)
3.0h	0.018	0.012	-0.005	0.000	0.007	0.021	0.056**	-0.005
	(0.016)	(0.009)	(0.008)	(0.007)	(0.013)	(0.028)	(0.022)	(0.022)
3.5h	0.015	0.019**	0.003	0.003	0.023*	0.021	0.030	0.028
	(0.016)	(0.009)	(0.008)	(0.007)	(0.013)	(0.028)	(0.022)	(0.022)
4h	0.016	0.019**	0.007	-0.004	0.031**	0.007	0.012	0.023
	(0.016)	(0.009)	(0.008)	(0.007)	(0.013)	(0.028)	(0.022)	(0.022)
4.5h	-0.011	0.012	0.007	0.011	0.017	-0.007	0.003	0.023
	(0.016)	(0.009)	(0.008)	(0.007)	(0.013)	(0.028)	(0.022)	(0.022)
5.0h	-0.002	0.017*	0.008	0.001	0.014	0.019	0.005	0.025
	(0.016)	(0.009)	(0.008)	(0.007)	(0.013)	(0.028)	(0.022)	(0.022)
5.5h	0.014	0.009	-0.003	0.009	0.014	0.016	-0.009	0.020
	(0.016)	(0.009)	(0.008)	(0.007)	(0.013)	(0.028)	(0.022)	(0.022)
6h	0.008	0.001	-0.011	-0.003	0.005	-0.011	0.024	-0.008
	(0.016)	(0.009)	(0.008)	(0.007)	(0.013)	(0.028)	(0.022)	(0.022)
6.5h	0.018	-0.001	-0.005	-0.009	-0.002	-0.015	0.022	0.004
	(0.016)	(0.009)	(0.008)	(0.007)	(0.013)	(0.028)	(0.022)	(0.022)
7.0h	-0.024	0.009	-0.001	-0.003	0.018	0.010	0.013	0.002
	(0.016)	(0.009)	(0.008)	(0.007)	(0.013)	(0.028)	(0.022)	(0.022)
7.5h	0.005	0.002	-0.006	-0.002	0.005	-0.013	-0.010	-0.004
	(0.016)	(0.009)	(0.008)	(0.007)	(0.013)	(0.028)	(0.022)	(0.022)
8h	0.010	0.007	0.013**	0.005	0.017*	-0.048**	0.017	-0.012
	(0.013)	(0.007)	(0.006)	(0.006)	(0.010)	(0.022)	(0.018)	(0.018)
delta_ln_watt_ fixed	1.331***	0.965***	0.766***	0.716***	0.709***	2.176***	2.223***	1.183***
	(0.017)	(0.009)	(0.008)	(0.008)	(0.014)	(0.030)	(0.023)	(0.024)
Observations	17,049	17,105	17,054	17,105	17,096	17,105	17,049	17,105
R2	0.286	0.455	0.335	0.354	0.266	0.245	0.361	0.193
Adjusted R2	0.285	0.454	0.334	0.353	0.264	0.243	0.360	0.191
Residual Std. Error	0.128 (df=17014)	0.073 (df=17070)	0.065 (df=17019)	0.059 (df=17070)	0.106 (df=17061)	0.233 (df=17070)	0.181 (df=17014)	0.183 (df=17070)
F Statistic (omitting all regressors)	200.905*** (df=34; 17014)	419.567*** (df=34; 17070)	252.189*** (df=34; 17019)	274.979*** (df=34; 17070)	181.800*** (df=34; 17061)	162.757*** (df=34; 17070)	282.433*** (df=34; 17014)	119.738*** (df=34; 17070)
F Statistic (omitting time leads and lags)	6.026** (df=32; 17014)	56.016** (df=32; 17070)	2.351** (df=32; 17019)	3.605** (df=32; 17070)	35.602** (df=32; 17061)	6.944** (df=32; 17070)	10.674** (df=32; 17014)	20.466** (df=32; 17070)

Note: *p<0.1; **p<0.05; ***p<0.01

Regressors	EV + battery	Solar + battery	EV + solar + battery
const	-0.002	-0.003	-0.003*
	(0.001)	(0.002)	(0.002)
-8h	0.029	0.065***	0.073***
	(0.019)	(0.023)	(0.021)
-7.5h	0.007	0.015	0.070***
	(0.023)	(0.028)	(0.026)
-7.0h	0.015	0.025	0.010
	(0.023)	(0.028)	(0.026)
-6.5h	0.031	0.026	0.021
	(0.023)	(0.028)	(0.026)
-6h	-0.006	-0.019	0.013
	(0.023)	(0.029)	(0.027)
-5.5h	0.015	-0.006	-0.005
	(0.023)	(0.029)	(0.027)
-5.0h	-0.004	0.014	0.010
	(0.023)	(0.029)	(0.027)
-4.5h	0.010	-0.008	-0.010
	(0.023)	(0.029)	(0.027)
-4h	0.015	0.005	0.030
	(0.023)	(0.029)	(0.027)
-3.5h	0.011	-0.006	0.003
	(0.023)	(0.029)	(0.027)
-3.0h	0.015	-0.004	0.017
	(0.023)	(0.029)	(0.027)
-2.5h	0.005	0.047	0.018
	(0.023)	(0.029)	(0.027)
-2h	-0.004	0.024	0.016
	(0.023)	(0.029)	(0.027)
-1.5h	0.010	0.022	-0.001
	(0.023)	(0.029)	(0.027)
-1.0h	0.014	0.066**	0.036
	(0.023)	(0.029)	(0.027)
-0.5h	-0.044*	-0.035	-0.019
	(0.023)	(0.029)	(0.027)
0h	-0.266***	-0.357***	-0.561***
	(0.023)	(0.029)	(0.027)
0.5h	-0.066***	-0.046	-0.069**
	(0.023)	(0.029)	(0.027)
1.0h	0.013	0.051*	0.045*
	(0.023)	(0.029)	(0.027)
1.5h	0.016	0.032	0.053**
	(0.023)	(0.029)	(0.027)
2h	0.029	0.045	0.043
	(0.023)	(0.029)	(0.027)
2.5h	0.040*	0.037	0.074***
	(0.023)	(0.029)	(0.027)
3.0h	0.059**	0.086***	0.065**
	(0.023)	(0.029)	(0.027)
3.5h	0.028	0.009	0.049*
	(0.023)	(0.029)	(0.027)
4h	0.020	-0.012	-0.000
	(0.023)	(0.029)	(0.027)
4.5h	0.011	0.026	-0.003
	(0.023)	(0.029)	(0.027)
5.0h	0.016	0.023	0.027
	(0.023)	(0.029)	(0.027)
5.5h	0.015	-0.022	0.014
	(0.023)	(0.029)	(0.027)
6h	0.002	-0.003	-0.012
	(0.023)	(0.029)	(0.027)
6.5h	0.000	0.014	0.000
	(0.023)	(0.028)	(0.026)

7.0h	0.002 (0.023)	0.015 (0.028)	0.008 (0.026)
7.5h	0.003 (0.023)	0.030 (0.028)	-0.014 (0.026)
8h	0.004 (0.019)	-0.042* (0.023)	-0.006 (0.021)
delta_ln_watt_ fixed	1.357*** (0.025)	2.516*** (0.031)	1.987*** (0.028)
Observations	17,101	17,105	17,105
R2	0.174	0.304	0.267
Adjusted R2	0.172	0.302	0.266
Residual Std. Error	0.193 (df=17066)	0.237 (df=17070)	0.220 (df=17070)
F Statistic (omitting all regressors)	105.696*** (df=34; 17066)	218.937*** (df=34; 17070)	183.060*** (df=34; 17070)
F Statistic (omitting time leads and lags)	16.329** (df=32; 17066)	15.527** (df=32; 17070)	28.579** (df=32; 17070)

Note: *p<0.1; **p<0.05; ***p<0.01