Journal of Environmental Economics and Management 121 (2023) 102845

Contents lists available at ScienceDirect

Journal of Environmental Economics and Management

journal homepage: www.elsevier.com/locate/jeem

The spillover effect of peak pricing

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ARTICLE INFO

JEL classification:
D10
D91
L94
Q41

Keywords:
Pricing
Demand response
Dynamic tariffs
Inattention

ABSTRACT

Understanding consumer behaviours is important in designing dynamic tariffs, which are usually considered the first-best solution when the conventional flat tariff does not reflect the varying cost of electricity generation. I estimate households' own- and cross-price elasticities using dataset from a smart metering project, and investigate which household specific characteristics determine the impact of peak prices on electricity consumption. I find peak prices (17:00–20:00) reduce peak and post-peak consumption (20:00–23:00), indicating a spillover effect of peak prices. The underlying mechanisms that could be generating the spillover effect have been further discussed and investigated. Finally, I estimate dynamic tariffs' distributional and welfare effects, and demonstrate that the spillover effect is crucial in determining the cost effectiveness of a smart metering programme.

1. Introduction

When addressing energy and environmental issues, most economists consider market-based approaches as the first-best solution. Such instruments can be theoretically appealing if one can effectively predict how consumers respond to prices. Understanding the full context in which consumer behaviours are formulated is crucially important in designing market-based instruments that aim to cost-effectively achieve economic efficiency in the energy market and broader environmental goals. In liberalised electricity markets, retailers purchase electricity in the wholesale market (from generators) and then sell it in the retail market (to consumers).[1] As the conventional flat tariff in the retail market does not reflect the variation of electricity generation costs, economic inefficiency arises (Steiner, 1957; Williamson, 1966). Borenstein and Holland (2005) estimated the monetary value of this inefficiency to be at least 5%–10% of wholesale energy costs.

The first-best solution to this economic inefficiency might be market-based approaches that adjust retail prices intraday based on the varying wholesale prices that reflect the marginal costs of electricity generation. This is known as a real-time pricing (RTP) tariff and may vary at a (half-)hourly frequency. However, RTP tariffs might lose their efficacy if the implementation or cognitive cost (i.e., time and effort) is too high for consumers to understand and respond (Wolak, 2011; Sallee, 2014). An alternative is a related but simpler tariff scheme known as (dynamic) time-of-use (TOU) tariff that charges cheaper rates at certain times of the day or night when demand is at its lowest, and higher rates at popular times. Dynamic tariffs (including TOU and RTP tariffs, as well as critical peak pricing, or CPP tariffs to be discussed later) can improve efficiency by aligning retail prices with the marginal cost of electricity generation and can be attractive to retailers by improving their demand flexibility (Nilsson et al., 2018), thereby

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[1] In the wholesale market, only flexible power plants (such as combined-cycle gas turbines) with higher marginal costs (than baseload generating plants, such as nuclear energy) can ramp up sufficiently fast to meet various electricity demands (Chyong et al., 2020), resulting in time-varying wholesale prices. In the retail market, however, most domestic consumers pay a time-invariant electricity tariff (or a flat tariff) for each unit of electricity used.

https://doi.org/10.1016/j.jeem.2023.102845
Received 1 September 2022
Available online 5 July 2023

increasing retail profitability (Nojavan et al., 2017). Further, dynamic tariffs can also shift peak load to off-peak periods, thereby lowering (usually underinvested) capital investments required on 'peaking' generation capacity. Moreover, the increasing renewable penetration requires a more flexible electricity system and time-varying tariffs[2] can accommodate the integration of renewable energy into the grid. The phenomenon of electricity consumers adjusting their power consumption during specific periods to relieve stress on the grid is also known as demand response.

This study builds on the existing literature that explores the impact of time-varying electricity tariffs on residential electricity consumption behaviours. The implementation of dynamic tariffs may alter consumer behaviours via two channels: (1) price signals and (2) information and automation. Economists believe that 'getting the price right' is crucial in solving the peak demand problem (Harding and Sexton, 2017). As asserted by Joskow (2012) [p. 40], 'using appropriate prices to provide consumers with an incentive to cut peak demand during a small number of hours can reduce generating costs significantly in the long run'. Moreover, dynamic tariffs are usually accompanied by ancillary facilities such as information technologies (e.g., smart meters and in-house displays) that can provide consumers with advanced price notification (e.g., one-day-ahead of the real time) (Di Cosmo et al., 2014; Jessoe and Rapson, 2014), and automated technologies (e.g., smart household appliances and thermostats) that can be programmed to respond to time-varying prices (Harding and Lamarche, 2016; Bollinger and Hartmann, 2020). Thus, information and automation technologies can increase responsiveness, either by lowering the cost of acquiring information about prices or automating consumer behaviours (Prest, 2020).

Although most studies found statistically significant demand response, implied elasticities are generally lower than 0.20 in absolute value, indicating low residential price responsiveness to the introduction of time-varying electricity tariffs (Harding and Sexton, 2017). For example, Allcott (2011) investigated the first ever RTP programme and estimated that the overall price elasticity of demand among Chicago households was about −0.10. The author also estimated that the programme increased consumer surplus by $10, which may not be sufficient to override the cost of conservation and metering technology. However, the author illustrated that it might be beneficial to invest in retail Smart Grid applications that could potentially encourage consumers to be more elastic, thereby boosting the consumer surplus. In surveying 15 pilots, experiments, and full-scale implementations of time-varying electricity tariff, Faruqui and Sergici (2010) estimated that TOU tariffs induced a drop in peak demand between 3%–6%, and CPP tariffs[3] induced a drop in peak demand between 13%–20%. Likewise, Wolak (2011) found that regular households in the District of Columbia, US, were more responsive to CPP than RTP tariffs. However, households with electric heating responded to CPP and RTP tariffs similarly. Herter and Wayland (2010) also found the merit of CPP pricing in achieving statistically significant peak demand reduction. In studying heterogeneous consumer responses, they found that households who consumed more electricity and lived in the coldest climate zone were more sensitive to prices.

Much related research has also emphasised the importance of information on consumers' demand response. Among recent literature, Prest (2020) applied a machine-learning method on an Irish smart metering trial and found that information provision was one of the most important sources of heterogeneity. Although the installation of smart meters and in-house displays lowers consumers' costs of obtaining information about consumption and prices (Martin and Rivers, 2018), economists are usually interested in the fundamental driver of households' responses to time-varying tariffs. For example, Shin (1985) and Ito (2014) argued that households might not know the marginal price they faced in any instance. Therefore, marginal prices may not be the only driver of demand response; instead, the average price might be the key determinant of households' consumption decisions. Jessoe and Rapson (2014) studied a randomised control trial in Connecticut and found that as the window of advanced notification shrunk, households no longer responded to prices. Specifically, they estimated that households with day-ahead notification of prices had an elasticity of −0.10, whereas households with 30-minute-ahead notification of prices had statistically insignificant price elasticity. In analysing data from a field experiment in the southern United States, Bollinger and Hartmann (2020) found that households who only used an online portal to obtain information about prices had an elasticity of only −0.04. However, households with a programmable communicating thermostat were more elastic at −0.21. Therefore, they emphasised the important role of automation technology in dynamic tariff schemes. Other research found that frequent information about electricity consumption (Gans et al., 2013; Jessoe and Rapson, 2014) and reminding households about their electricity expenditure (Gilbert and Zivin, 2014) can also reduce peak demand.

A growing body of literature has emphasised the role of behavioural science in understanding consumers' decision-making about electricity consumption. In studying the participation of dynamic tariff schemes, Fowlie et al. (2021) found that over 90% of households who were initially randomly allocated into a time-varying tariff programme chose to retain the enrolment and respond to dynamic tariffs. However, only 20% of the (randomly allocated) households who initially paid a flat rate actively opted in, although the differences in the cost of opting in and out was negligible. They explained this phenomenon as the 'default effect' — decision-makers tend to maintain the default and do not change their decision-making choices. They further demonstrated that the default effect is most likely due to consumers being inattentive to prices and benefits when making their participation decisions. DellaVigna (2009) argued that when processing new information, households may exhibit rational or irrational inattention to electricity prices and consumption information, probably due to cognitive constraints. It might be rational for consumers to be imperfectly informed or not fully deploy full cognitive efforts in the face of information acquisition or cognition costs (Simon, 1955). Therefore, households may find the structure of time-varying tariffs and the noisy signals about energy consumption to be complicated, and thus may ignore information on prices, resulting in a reduction of the effectiveness of price signals (Jessoe et al., 2014). Finally, in a field

[2] In this study, the phrase 'time-varying tariff' will be used interchangeably with 'dynamic tariff'.

[3] CPP tariffs only vary peak prices across days; on most days, prices in peak periods are higher than other periods.

experiment, Ito et al. (2018) found that behavioural incentives such as moral suasion[4] only had short-run effects, whereas economic incentives such as CPP tariffs reduced consumer peak demand and induced strong habit formation in energy conservation.

Unlike most related research that has focused on the treatment effect of time-varying tariffs and smart metering programmes (e.g., Jessoe and Rapson, 2014; Ito et al., 2018; Bollinger and Hartmann, 2020; Fowlie et al., 2021), in this study, I focus on households' price elasticities. Elasticities provide estimates regarding how consumers would react to different price rates, thereby guiding the design of dynamic tariffs to achieve market efficiency. Whereas treatment effects usually ignore the importance of cross-prices, I demonstrate that the magnitude of cross-price elasticities (i.e., the percentage change in the quantity demand of one period in response to one percentage change in the price of another period) can be compatible with the magnitude of own-price elasticities (i.e., the percentage change in the quantity demanded divided by the percentage change in the price of the same period). I adopt a dataset from the Low Carbon London (LCL) project, where more than a thousand households are opt-in recruited to receive the dynamic TOU tariff that was in effect throughout 2013. This study makes four primary contributions to the literature, which have key implications for economic and energy policy.

First, it extends the existing literature that estimates households' price elasticities and adds new evidence to the growing literature demonstrating that households are inattentive to price information (Wolak, 2011; Jessoe et al., 2014; Fowlie et al., 2021). Economic theory suggests that consumers respond to high prices by consuming less, resulting in negative own-price elasticities. In addition, as dynamic tariffs aim to shift peak demand to other periods, one would expect positive cross-price elasticities. My estimates demonstrate that the own-price elasticities are significantly negative, but the magnitude is small (lower than 0.1). Further, the estimated cross-price elasticities are even smaller in values than (but compatible in magnitudes with) the estimated own-price elasticities, consistent with related empirical literature (Allcott, 2011; Harding and Sexton, 2017). Nevertheless, households may not always respond to retail electricity prices as economists would generally predict — I find strong evidence that peak prices negatively affect post-peak electricity consumption. In other words, a high peak price would not only lower peak consumption but also 'spillover' and lower the post-peak consumption. Therefore, I call this the spillover effect of peak prices. Moreover, notably, this study is not unique in finding a positive effect of peak prices on non-peak consumption. Other evidence can also be found from relative literature such as Harding and Lamarche (2016), Ito et al. (2018), and Fowlie et al. (2021). Nonetheless, this is the first study that focuses on this positive effect and investigates its underlying mechanism and welfare effects.

The second contribution is to extend the research on households' heterogeneous responses to electricity price signals across time (Gillingham et al., 2009; Gerarden et al., 2017) and amongst households (Herter and Wayland, 2010; Wolak, 2011; Prest, 2020). Identifying which households are more sensitive to prices has multiple co-benefits. For example, as most domestic consumers are risk-aversive and dislike varying prices, TOU (and dynamic) tariff schemes usually suffer from low participation rates. Understanding which households are more sensitive to price signals (hence which households would potentially benefit more from dynamic tariffs) allows retailers to target those households, thereby increasing participation rates. In this study, I investigate which time and household specific characteristics determine the impact of peak prices on households' electricity consumption. This is manifested via a machine-learning model selection technique called post-Lasso regressions. The results suggest that number of occupants and family structure are key determinant of own- and cross-price elasticities, and the spillover effect is less salient among households with old-aged adults than others. This is because old-aged adults usually sleep earlier than others and barely respond to price signals during post-peak periods. The post-Lasso regressions also demonstrate that the impact of peak prices on peak consumption is greater among households with electric hobs, when a typical household prepares dinner. Finally, I find that the impact of peak prices is more salient among households who are more concerned about the environment, and that month of year and day of week are key determinants for the heterogeneous impact of peak prices.

The third contribution of this study is that it provides new evidence to the limited literature on energy and environmental economics focusing on consumer inattention (Ito, 2014; Fowlie et al., 2021). After eliminating the possibility that the spillover effect is due to electricity consumption between peak and post-peak periods being complementary, I argue that the spillover effect is due to households being inattentive to varying price signals. Investigating further, I decline the explanation that the spillover effect is due to households responding to average instead of marginal prices, but could not reject the hypothesis that it is due to households overreacting to peak prices. Furthermore, I find evidence supporting the posit that the overreaction is due to cognitive strain. In the LCL project, households mostly paid the base rate (of £0.1176/kWh). The evidence demonstrates that for any period when the own-price is equal to the base rate, households become more rational when responding to cross-prices; whereas when the own-price deviates from the base rate, households tend to behave more irrationally, and that is when overreaction occurs.[5] I argue that in the former case, households are more rational because they are experiencing repeated events and are less cognitively strained, whereas in the latter case, households are irrational because they are experiencing unfamiliar events, resulting in cognitive strain.

Fourth, my study contributes to the literature on the distributional and welfare effect of time-varying electricity tariffs (Borenstein and Holland, 2005; Holland and Mansur, 2008; Guo and Weeks, 2022). I find that (relative to the conventional flat tariff) the arbitrarily designed dynamic tariff scheme applied in the LCL project transferred a significant amount of consumer surplus to the electricity retailer, and that the net benefit from implementing dynamic tariffs is negative. Therefore, I re-design the dynamic tariffs to align prices with households' electricity consumption and find that the re-designed tariffs would no longer harm consumer surplus, and the net benefit from implementing dynamic tariffs become positive. I also demonstrate that as ignoring the spillover

[4] Households receive messages requesting voluntary energy conservation during peak hours.

[5] Here, 'rational' means more positive (or less negative) cross-price elasticities of demand.

effect could underestimate the energy conservation effect of dynamic tariffs, the spillover effect could be a key determinant of the cost-effectiveness analysis of smart metering programmes.

The remainder of this article proceeds as follows. Section 2 introduces the LCL project. The empirical analysis of the price elasticities is described in Section 3. Section 4 examines the underlying mechanism of the spillover effect, and the distributional effect and welfare analysis of the dynamic tariffs is provided in Section 5. Finally, Section 6 concludes the article.

2. The Low Carbon London project

The Low Carbon London (LCL) project was designed to investigate the potential impact of dynamic tariffs on London's electricity system and the social impact of dynamic tariffs on residential consumers. A total of 1,122 households were opt-in recruited to receive the dynamic tariff that came into effect for the entire year of 2013. While this study focuses on estimating households' price elasticities, I shall leave the examination of treatment effects to future research.

Smart meters were installed in all households to record their half-hourly electricity consumption. The dynamic tariff comprised three rates — the 'base' rate at £0.1176/kWh, the 'high' rate at £0.6720/kWh, and the 'low' rate at £0.0399/kWh, whereas the outside option for the households is to pay a flat tariff rate at £0.14228/kWh. Households were informed about the electricity prices one day ahead of the delivery via the smart-meter-linked in-house displays (IHD). They also had the option of having alerts sent to mobile as text message. Those notification messages include information on prices and pricing periods. An example message reads, 'From 5 am Thurs 21st to 5 am Friday 22nd your rate is LOW except HIGH 7 am–10 am'. Meanwhile, the price rate in real time was displayed on the IHD (Schofield et al., 2014). These arrangements ensured that once households had noticed price changes, they were also supposed to be aware of the time period for the changes. Price events occurred in the case of system balancing (SB) or distribution network constraint management (CM). The former arbitrarily took place throughout the year, while most of the latter events occurred arbitrarily in winter months.[6]

Other arrangements were also made to limit inconvenience to households. For example, there were at most three event days and one 'double tariff band change' (i.e., directly from high to low or from low to high) in a week. Besides, all households received monthly feedback reports. Consequently, in a post-project survey that assessed attitudes and behaviour change related to dynamic electricity pricing, more than 75% of households found the information via the IHD useful for responding to prices and about 85% of them found the information via the IHD unit clear (Carmichael et al., 2014). Therefore, it is reasonable to make the statement that households were fully aware of the rules and mechanisms of the TOU prices.

I define noon periods as 11:00–14:00, pre-peak periods as 14:00–17:00, peak periods as 17:00–20:00, post-peak periods as 20:00–23:00, and midnight periods as 23:00–02:00(+1). By design, in each day, there is no variation in price rates within each period, but prices may differ across periods.[7] This simplifies the analysis by aggregating the half-hourly data to three-hourly data.[8] Table 1 illustrates the number of days that electricity prices are equal to different rates in different periods. For most periods, households paid the base rate. However, there were 30 days for which households paid the high rate during peak periods. Therefore, although price events arbitrarily took place across days, high-price events took place more frequently at peak periods.

Table 1
Number of days for each price rates.

	Prices £/kWh	Noon 11:00–14:00	Pre-peak 14:00–17:00	Peak 17:00–20:00	Post-peak 20:00–23:00	Midnight 23:00–02:00(+1)
Low rate	0.0399	35	36	18	36	33
Base rate	0.1176	317	317	317	317	323
High rate	0.6720	13	12	30	12	9

Households also participated in an appliance survey of necessary demographic information (number of occupants, age categories, etc.), residence information (number of rooms, etc.), and the number of appliances owned (television, refrigerator, etc.). In total, 990 submissions were completed. More detailed information on the LCL project and the associated surveys are provided in Appendix A.1 and Schofield et al. (2015).

3. Estimating price elasticities

In this section, I first apply panel data analyses to estimate the own- and cross-price elasticities among households participating in the LCL project. Then, I adopt post-Lasso fixed-effect models as a model selection technique to investigate which household demographic characteristics determine the magnitudes of elasticities and the impact of months and days of the week on elasticities.

[6] Notably, in reality, high-price events are supposed to take place when the load is unusually high or low; however, in the LCL project, the price events took place arbitrarily by design. I will discuss this issue further in Section 5 when analysing the distributional and welfare effects of dynamic tariffs.

[7] In this study, I only focus on electricity consumption in pre-peak, peak, and post-peak periods because the fundamental purpose of dynamic tariffs is to reduce peak load.

[8] In my analysis, I do not consider the morning period between 02:00–11:00 because, by design, electricity prices during the morning period may change hourly (instead of three-hourly), which would complicate the matter if I included the morning time-varying prices. I also assume that the prices in the morning period have a negligible effect on pre-peak, peak, and post-peak consumption. This can be proved from the empirical results demonstrating that noon prices have an insignificant effect on pre-peak consumption, and midnight prices have an insignificant effect on post-peak consumption (see Table 2).

3.1. Estimating elasticities

I assume that household i's electricity consumption $C_{i,d,t}$ is characterised by

$$C_{i,d,t} = \lambda_{i,d,t} \cdot P_{d,t-1}^{\beta_t} \cdot P_{d,t}^{\gamma_t} \cdot P_{d,t+1}^{\delta_t}, \tag{1}$$

where subscript $i = 1, \ldots, n$ represents individual households, $d = 1, \ldots, D$ represents days, and $t = 1, \ldots, T$ represents periods within the day. In this case, t may represent pre-peak, peak, and post-peak periods (defined as in Table 1), and $t-1$ (and $t+1$) represents the three-hour period before (and after) period t.

In (1), $C_{i,d,t}$ denotes household i's electricity consumption on day d during period t, and $P_{d,s}$ for $s \in \{t-1, t, t+1\}$ denotes electricity prices on day d during period s. I assume constant price elasticities; hence, γ_t denotes own-price elasticity, and β_t and δ_t denote cross-price elasticities[9] — the impact of percentage change in prices in periods $t-1$ and $t+1$ on the percentage change of demand in period t, respectively. Notably, as the time-varying electricity prices are identical across households, there is no subscript i for prices.

To estimate price elasticities, I take the natural logarithms on both sides of Eq. (1) and develop the following panel data specification

$$\ln C_{i,d,t} = \alpha_t + \beta_t \ln P_{d,t-1} + \gamma_t \ln P_{d,t} + \delta_t \ln P_{d,t+1} + \boldsymbol{\omega_t X_{i,d,t}} + \eta_{i,t} + \varepsilon_{i,d,t}, \tag{2}$$

where $\boldsymbol{X_{i,d,t}}$ is a vector of control variables comprising short-term time-invariant household-specific variables (such as the number of occupants, frequency of teleworking, and the number of rooms), day-specific variables (such as dummy variables for months, days of the week, and public holidays), and day- and period-specific weather variables (such as temperature and wind speed). Tables 2 and A.3 provide complete lists of the control variables. $\boldsymbol{\omega_t}$ is a vector of slope coefficients representing the impact of the control variables on the percentage change in electricity consumption ($\ln C_{i,d,t}$).

Finally, $\eta_{i,t}$ is the unobserved household-specific effect on its electricity consumption in period t, and $\varepsilon_{i,d,t}$ is an unobserved error term. If $\eta_{i,t}$ is independent of electricity prices ($\ln P_{d,s}$) and the observed control variables $\boldsymbol{X_{i,d,t}}$, a random-effect (RE) model would be more efficient.[10] If $\eta_{i,t}$ is correlated with explanatory variables (either $\ln P_s$ or $\boldsymbol{X_{i,d,t}}$), the RE model would be biased and inconsistent, and a fixed-effect (FE) model would be preferable. The FE model treats $\alpha_t + \eta_{i,t}$ as household-specific intercepts (or household-specific dummy variables), which would be perfectly collinear with time-invariant household-specific variables (such as number of appliances) in $\boldsymbol{X_{i,d,t}}$. Hence, time-invariant household-specific variables are excluded from regressions of the FE models.

The consistency of specification (2) relies on independent variables being exogenous. According to Schofield et al. (2015), the system balancing (SB) events were *'scattered randomly throughout the 365 days of the trial year'*, and the constraint management (CM) events took place *'during predominantly winter months'*. As I have included monthly dummy variables in the regressions, I could safely treat time-varying electricity prices as exogenous variables. Furthermore, all control variables in $\boldsymbol{X_{i,d,t}}$ can be taken as exogenous because in the short run, households' electricity consumption does not determine households' demographics, in-house appliances, time, or weather.

Specification (2) aims to estimate the own- and cross-price elasticities. I apply specification (2) for pre-peak, peak, and post-peak electricity consumption. Table 2 presents the baseline regression results from FE and RE models. Notably, in the baseline regressions, I assume temperature having a linear effect on electricity consumption. In Table A.4, I also attempt polynomial and spline functions to capture the non-linear impact of temperature as temperature and prices might be correlated, depending on time of day. The results suggest that my estimates on own- and cross-price elasticities are consistent despite the variation in the functional form of temperature in the regression.

All regression results indicate negatively significant own-price elasticities of demand, consistent with the demand theory — a higher price lowers demand. The magnitude of the estimates is comparable with Harding and Sexton (2017), who reviewed related literature and summarised that the empirical estimates of households' elasticities are usually lower than 0.2 in magnitude. The own-price elasticities in pre-peak and peak periods are much higher in magnitude than those in post-peak periods. This is probably because some households sleep early and would be less sensitive to electricity prices during post-peak periods.

Most of the estimates on cross-price elasticities are either positive or not significantly different from zero. Specifically, I find that peak price has a significant and positive effect on pre-peak consumption. On average, a 100% increase in peak prices results in a 0.9% increase in pre-peak consumption from the FE estimates or a 1.2% increase from the RE estimates. The effects of pre- and post-peak prices on peak consumption are also significantly positive. From the FE estimates, a 100% increase in pre-peak (or post-peak) prices will raise peak consumption by 0.6% (or 2.9%).

Perhaps surprisingly, I find negative effects of peak prices on post-peak consumption. This is counter-intuitive because one would expect a high peak price to shift peak load to other periods, resulting in positive cross-price elasticities. I call this counter-intuitive phenomenon the spillover effect of peak prices. Further investigation demonstrates that the spillover effect holds consistently across regression specifications. In Table A.5, I present alternative specifications for post-peak consumption, where all estimates suggest negative effects of peak prices on post-peak consumption.[11] I will investigate the underlying mechanism of the spillover effect in Section 4.

[9] The subscripts $s \in \{t-1, t, t+1\}$ represent the period to which the associated electricity price belongs.

[10] The RE model treats $\eta_{i,t} + \varepsilon_{i,d,t}$ as the error term and uses generalised least square (GLS) to estimate β_s and $\boldsymbol{\omega_t}$.

[11] One may also be curious about the impact of prices in period $t \pm 2$ on electricity consumption in period t. These results are reported in Table A.6, where whenever the effect of prices in period $t \pm 1$ on consumption in period t is significant in Table 2, I add prices in period $t \pm 2$ to the regression specification. The results are similar to Table 2 and most importantly, the spillover effect of peak prices still exists.

Table 2
The impact of electricity prices on consumption.

	Pre-peak		Peak		Post-peak	
	FE	RE	FE	RE	FE	RE
Noon price	0.0039	0.0047				
	(0.0040)	(0.0046)				
Pre-peak price	−0.0694***	−0.0747***	0.0064**	0.0062*		
	(0.0041)	(0.0046)	(0.0025)	(0.0028)		
Peak price	0.0093***	0.0116***	−0.0731***	−0.0817***	−0.0158***	−0.0175***
	(0.0021)	(0.0024)	(0.0044)	(0.0050)	(0.0040)	(0.0045)
Post-peak price			0.0285***	0.0320***	−0.0189***	−0.0219***
			(0.0044)	(0.0050)	(0.0040)	(0.0045)
Midnight price					−0.0017	−0.0002
					(0.0025)	(0.0028)
Temperature	−0.0100***	−0.0101***	−0.0093***	−0.0093***	−0.0063***	−0.0064***
	(0.0004)	(0.0004)	(0.0003)	(0.0004)	(0.0003)	(0.0004)
Wind speed	0.0014***	0.0015***	0.0006*	0.0006*	0.0005	0.0006*
	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0003)
Pub. holiday$_d$	0.0262**	0.0293**	−0.0730***	−0.0723***	−0.0639***	−0.0607***
	(0.0083)	(0.0095)	(0.0082)	(0.0093)	(0.0075)	(0.0084)
Month$_d$	YES	YES	YES	YES	YES	YES
Day of week$_d$	YES	YES	YES	YES	YES	YES
Demographics		YES		YES		YES
R^2	0.0635	0.0660	0.1015	0.1040	0.0474	0.0504
No. Obs.	368,341	286,347	368,349	286,350	368,341	286,346
B-P test	✓	✓	✓	✓	✓	✓
Hausman	✓		✓		✓	

Notes: * refers to significance at the 5% level; ** refers to significance at the 1% level; *** refers to significance at the 0.1% level. All price variables and the dependent variables (i.e., electricity demand) are in a natural logarithm. Variables with the subscript d are dummy variables. Dependent variables are log electricity demand during pre-peak (first two columns), peak (middle columns), and post-peak (last two columns) periods. The number of observations in RE models is smaller than that in FE models because not all households submitted the appliance survey.

Finally, for all periods, the Breusch–Pagan Lagrangian Multiplier tests for individual effects prefer RE models over pooling Ordinary Least Square (OLS) models, and Hausman tests prefer FE models over RE models. Therefore, for the remainder of the paper, I only apply FE models for further analysis.

3.2. Heterogeneous impacts of peak prices

Households may exhibit heterogeneous elasticities of demand. By comparing a model for the full sample and a model based on estimating an equation for each household, I can reject the hypothesis that elasticities are identical across households.[12] Therefore, in this section, I investigate the impact of time (e.g., months and days of the week) and household-specific characteristics (e.g., households' demographic information and in-house appliances) on the impact of peak prices. The reason that I focus on peak prices is that the fundamental purpose of smart metering programmes is to shift peak consumption to other periods. To this end, I consider the following specifications:

$$\begin{aligned}\ln C_{i,d,Pre} &= \alpha_{Pre} + \beta_{Pre}\ln P_{d,Noon} + \gamma_{Pre}\ln P_{d,Pre} + g_{Pre}(\boldsymbol{D_i}, \boldsymbol{T_{d,Pre}})\ln P_{d,Peak} \\ &\quad + \boldsymbol{\psi_{Pre}}\boldsymbol{T_{d,Pre}} + \eta_{i,Pre} + \varepsilon_{i,d,Pre},\end{aligned} \tag{3}$$

$$\begin{aligned}\ln C_{i,d,Peak} &= \alpha_{Peak} + \beta_{Peak}\ln P_{d,Pre} + g_{Peak}(\boldsymbol{D_i}, \boldsymbol{T_{d,Pre}})\ln P_{d,Peak} + \delta_{Peak}\ln P_{d,Post} \\ &\quad + \boldsymbol{\psi_{Peak}}\boldsymbol{T_{d,Pre}} + \eta_{i,Peak} + \varepsilon_{i,d,Peak},\end{aligned} \tag{4}$$

$$\begin{aligned}\ln C_{i,d,Post} &= \alpha_{Post} + g_{Post}(\boldsymbol{D_i}, \boldsymbol{T_{d,Pre}})\ln P_{d,Peak} + \gamma_{Post}\ln P_{d,Post} + \delta_{Post}\ln P_{d,Midnight} \\ &\quad + \boldsymbol{\psi_{Post}}\boldsymbol{T_{d,Pre}} + \eta_{i,Post} + \varepsilon_{i,d,Post},\end{aligned} \tag{5}$$

where $\ln C_{i,d,\tau}$ for $\tau \in \{Pre, Peak, Post\}$ represents the electricity consumption for household i during the period τ of day d, which is determined by electricity prices in that period, electricity prices in the three-hour period before and after period τ, as well as other control variables. $g_\tau(\boldsymbol{D_i}, \boldsymbol{T_{d,\tau}})$ are functions of time-invariant household-specific variables $\boldsymbol{D_i}$ and time and weather variables $\boldsymbol{T_{d,\tau}}$. Therefore, $[\boldsymbol{D}'_i, \boldsymbol{T}'_{d,\tau}] = \boldsymbol{X}'_{i,d,t}$ in specification (2). $g_\tau(\boldsymbol{D_i}, \boldsymbol{T_{d,\tau}})$ can be interpreted as the slope coefficients for $\ln P_{d,Peak}$ or the elasticities estimating the impact of peak prices on pre-peak, peak and post-peak consumption, whose value depends on $\boldsymbol{D_i}$ and $\boldsymbol{T_{d,\tau}}$.

For simplicity, I assume $g_\tau(\boldsymbol{D_i}, \boldsymbol{T_{d,\tau}})$ to be linear functions of $\boldsymbol{D_i}$ and $\boldsymbol{T_{d,\tau}}$. If this is the case, specifications (3)–(5) are equivalent to adding interaction terms between the control variables (i.e., $\boldsymbol{D_i}$ and $\boldsymbol{T_{d,\tau}}$) and peak prices $\ln P_{d,Peak}$. However, one potential issue

[12] The test compares the FE model with a variable coefficients model where a different model is estimated for each household. The p-value for the F test is 0.00.

with specifications (3)–(5) is that it gives redundant coefficients to interpret, making it difficult to identify which variables are the most influential in determining the spillover effect.

To deal with this issue, I follow Belloni and Chernozhukov (2013) and implement the post-Lasso (least absolute shrinkage and selection operator) fixed-effect model. The model operates in the following two steps. First, I run specifications (3)–(5) with Lasso. Instead of minimising the residual sum of squares (RSS), Lasso forces the sum of the absolute values of the regression coefficients to be less than a fixed value and forces specific coefficients (i.e., the less significant coefficients) to be set to zero.

Next, I run regressions that minimise the RSS but only with variables with non-zero coefficients from the first-step Lasso. Therefore, the first-step Lasso is treated as a genuine model selection technique. The reason for using the post-Lasso regression instead of Lasso is that a Lasso regression would induce an attenuation bias that the post-Lasso regression can alleviate. For more details, see Appendix A.4 and Belloni and Chernozhukov (2013).

The regression results are reported in Table 3. In regressions (i), (iv), and (vii) I focus on when would the impact of peak prices be more or less salient; hence, only variables that capture time changes $\boldsymbol{T}_{d,\tau}$ are included in $g_\tau(\cdot)$. In regressions (ii), (v), and (viii), I focus on which types of households are more likely to be affected by the peak prices; hence, only time-invariant household-specific variables $\boldsymbol{D}_i$ are included in $g_\tau(\cdot)$. Finally, regressions (iii), (vi), and (ix) follow specifications (3)–(5), where both $\boldsymbol{D}_i$ and $\boldsymbol{T}_{d,\tau}$ are included in $g_\tau(\cdot)$. For all regressions in Table 3, I do not penalise the coefficients for price variables as they are the coefficients of interests. In other words, in regressions (i)–(ix), $\boldsymbol{\psi}_\tau$ and coefficients for the interaction terms between $\ln P_{d,Peak}$ and $\boldsymbol{D}_i$ (and/or $\boldsymbol{T}_{d,\tau}$) are penalised by Lasso.

Note that in Table 3, the estimated coefficients for peak prices (i.e., the third row of the table) only represent price elasticities for a particular group of households in a particular period of time instead of all households across the sample period. The coefficients for the interaction terms estimate the impact of the corresponding variables on the own- and cross-price elasticities. Overall, among regressions for each time period, the results are consistent across regressions in terms of the signs and magnitudes of the coefficients and the variables selected from the first-step Lasso regressions.

Regressions (i)–(iii) investigate the heterogeneous impact of peak prices on pre-peak consumption. The results suggest that the cross-price elasticities are less heterogeneous among households as no household-specific variable is selected into the post-Lasso regressions. Instead, wind speed becomes a key determinant for cross-price elasticities — the heavier the wind, the smaller (in magnitude) the impact of peak prices on pre-peak consumption. The reason might be that on windy days, households are more often staying at home which weakens the load-shifting effect of peak prices. This explanation can be supported by regression results reported in Table 2, which suggest that the impact of wind speed on electricity consumption is positively statistically significant.

Regressions (iv)–(vi) study the heterogeneous impact of peak prices on peak consumption, whereas regressions (vii)–(ix) examine the heterogeneous impact of peak prices on post-peak consumption, i.e., the spillover effect. Both groups of regressions suggest that the number of occupants and family structure (i.e., whether the household has children, mid- and old-aged adults) are the key determinants of the own- and cross-price elasticities. More specifically, the impact of peak prices is decreasing (in magnitude) with number of occupants, which is intuitive because one would expect big families to be less elastic to electricity prices due to coordination issues. The same logic applies to households with children. The results also suggest that the spillover effect is more salient among households with middle-aged adults, and it disappears among households with old-aged adults. One explanation is that old-aged adults usually sleep earlier than others and are less sensitive to electricity prices during post-peak periods. This explanation is supported by Fig. A.4, which compares the average load pattern for middle- and old-aged households. During post-peak periods, the electricity consumption for old-aged households declines substantially, whereas it is not the same case for middle-aged households. Not surprisingly, household with electric hobs are more sensitive to peak prices in peak periods, when a typical British household prepares and enjoys dinner. Finally, households who claim to be 'very interested in micro-generation' are more sensitive to peak prices during post-peak periods. One possible reason is that when joining the LCL project, households were told that responding to peak prices by reducing electricity load would 'help the environment'. Therefore, households who are interested in micro-generation are more likely to be concerned about the environment and thus would be more sensitive to peak prices. This is supported by the regression results from Table A.7, which estimates the spillover effect among households who claimed themselves to be 'not at all', 'not very', 'don't know', 'fairly', and 'very' interested in micro-generation. The results demonstrate that the magnitude of the spillover effect indeed depends on households' interests in micro-generation.

While my analysis on peak and post-peak consumption suggests that household specific characteristics are the major determinants of the heterogeneous impact of peak prices, my earlier analysis on pre-peak consumption suggests not, indicating that the households who increase their pre-peak consumption following a high peak price are not the same households that later show a reduction in post-peak consumption. Therefore, it is necessary to further investigate the underlying mechanisms of the spillover effect.

The regression results for all three groups suggest that month of year is a key determinant for the heterogeneous impact of peak prices on pre-peak, peak, and post-peak electricity consumption. In particular, the impact of the peak prices on peak and post-peak consumption is more salient in the first and fourth quarters of the year and becomes less substantial in the second and third quarters.[13] The reason might be that in Great Britain (GB), electricity consumption in winter is much greater than that in summer. When demand is high, it is more beneficial for households to be more sensitive to electricity prices, resulting in greater own- and cross-price elasticities. This explanation can be further verified by Fig. A.5, which illustrates that, on average, the peak and post-peak electricity consumption for a household is much lower in the second and third quarters than in the first and fourth

[13] To save space, the detailed results for month and day of week are not reported in Table 3, but are available upon request.

Table 3
Heterogeneous elasticities across time and amongst households.

	Pre-peak consumption			Peak consumption			Post-peak consumption		
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)
Noon price	0.0008	−0.0007	0.0007						
	(0.0040)	(0.0040)	(0.0040)						
Pre-peak price	−0.0657***	−0.0666***	−0.0654***	0.0075**	0.0056*	0.0066*			
	(0.0041)	(0.0041)	(0.0041)	(0.0025)	(0.0027)	(0.0028)			
Peak price	0.0061*	0.0077***	0.0117***	−0.0719***	−0.0888***	−0.0918***	−0.0123**	−0.0231**	−0.0308***
	(0.0025)	(0.0021)	(0.0025)	(0.0047)	(0.0068)	(0.0070)	(0.0046)	(0.0070)	(0.0074)
Post-peak price				0.0193***	0.0290***	0.0227***	−0.0276***	−0.0312***	−0.0300***
				(0.0044)	(0.0048)	(0.0048)	(0.0040)	(0.0043)	(0.0044)
Midnight price							−0.0052*	−0.0024	−0.0047
							(0.0025)	(0.0027)	(0.0027)
Control variables	YES	YES	YES	YES	YES	YES	YES	YES	YES
Peak price ×									
Wind speed	−0.0006***		−0.0008***						
	(0.0001)		(0.0001)						
No. occupants					0.0086***	0.0086***		0.0078***	0.0094***
					(0.0023)	(0.0023)		(0.0022)	(0.0019)
Children$_d$					0.0219*	0.0220*		0.0146	
					(0.0093)	(0.0093)		(0.0091)	
Mid-age adults$_d$								−0.0178***	−0.0206***
								(0.0051)	(0.0048)
Old-age adults$_d$								0.0162**	0.0159***
								(0.0051)	(0.0048)
Elec. hob$_d$					−0.0232***	−0.0233***			
					(0.0048)	(0.0048)			
Very interested in micro-generation$_d$								−0.0142**	
								(0.0051)	
Month$_d$	YES		YES	YES		YES	YES		YES
Day of week$_d$				YES		YES	YES		YES
R^2	0.0627	0.0614	0.0615	0.1009	0.1033	0.1028	0.0451	0.0471	0.0473
Num. obs.	368,341	368,341	368,341	368,349	301,305	301,305	368,341	302,395	302,395

Notes: The dependent variable is the natural logarithm of electricity consumption. The results in the second half of the table are estimates of the coefficients for the interaction terms between peak prices and time and household-specific variables. The full regression results are available upon request.

quarters. This also indicates that temperature might be a key determinant for the magnitude of elasticities, although it is not selected by the first-step Lasso.

The regression results also suggest that the impact of peak prices on peak and post-peak electricity consumption becomes more salient on Mondays and Tuesdays, and less so on Saturdays. One possible reason might be that on Saturdays, more households may stay outside (than Sundays) and hence would be less sensitive to price signals. This can be further verified from Fig. A.6, which indicates that on Saturdays, the peak and post-peak electricity consumption for an average household is indeed lower than those on Sundays and weekdays. The reason for the much greater impact of peak prices on Monday and Tuesday is unclear, and one untestable guess would be the 'Blue Monday' effect — households with jobs are usually in a worse mood at the beginning of a week and are more likely to make irrational decisions when responding to electricity prices.[14]

To summarise, the results from the post-Lasso fixed-effect models suggest that when demand is high, households turn out to be more sensitive to peak prices, resulting in greater magnitude of own- and cross-price elasticities. The findings are consistent with other empirical literature studying consumers' heterogeneous responses to electricity prices. For example, Herter and Wayland (2010) found that households with high electricity demand are more sensitive to prices than others.

4. Explanations for the spillover effect

I next investigate the underlying mechanisms that could be generating the spillover effect of peak prices. I give three possible explanations: peak and post-peak electricity consumption being complementary, consumers responding to average instead of (or as well as) marginal prices, and households overreacting to peak prices. I assess these explanations in light of the empirical facts from the LCL dataset. I argue that these empirical facts are more consistent with the mechanism where households overreact to peak prices than with other explanations. Further investigation demonstrates that households' overreaction is likely due to cognitive strain — when the own-price deviates from the base rate that households mostly pay, they are experiencing unfamiliar events, resulting in cognitive strain. In such cases, households may behave irrationally when responding to price signals, resulting in overreaction to peak prices.

[14] In Section 4, I failed to reject the hypothesis that the spillover effect is due to overreaction, resulting from cognitive strain. The theory of cognitive strain may also explain the 'Blue Monday' effect.

4.1. Peak and post-peak consumption are complements

My first suggested explanation is that peak and post-peak consumption are complementary. This explanation is probably counter-intuitive because the fundamental purpose of introducing time-varying prices is to encourage consumers to shift their peak consumption to other periods. If so, one would expect electricity consumption between peak and non-peak periods to be substitutes, and a high peak price would increase households' electricity demand in post-peak periods, resulting in positive cross-price elasticities. However, this explanation could be intuitive — households may use electricity continuously, such as watching television, doing laundry, and (electric) heating and air conditioning. When high price events took place, some households may decide to not stay at home to avoid consuming electricity, resulting in lower electricity consumption in peak and post-peak periods.

In economic theory, if two goods are complementary, increasing the price of one good would result in a decline in demand for the other, and this effect is supposed to be bilateral. However, the empirical results from Table 2 do not support this explanation — I find that while increasing peak prices reduces post-peak consumption, a raise in post-peak prices significantly increases peak consumption. One may also argue that if the spillover effect only exists in some particular demographic groups of households, such as households with middle-aged adults suggested by Table 3, My assessment should probably only focus on those groups of households. Therefore, I separate the data into two groups — a group consisting of households with middle-aged adults and a group consisting of other households — and apply the FE model on each sub-sample of the data. The results are reported in Table A.8. Similarly, I find that the impact of peak prices on post-peak consumption is significantly negative, whereas the impact of post-peak prices on peak consumption is significantly positive. Therefore, I fail to explain the spillover effect of peak prices as a result of electricity consumption in peak and post-peak periods being complementary.

4.2. Households respond to average prices

Inspired by Ito (2014), my second explanation is that households respond to average prices instead of (or as well as) marginal prices.[15] Households may find it cognitively difficult to understand time-varying tariffs and are inattentive to complex price schemes. Consequently, they may respond to their perceived prices (which are less cognitively costly to understand than marginal prices) as an approximation of marginal prices. In the LCL project, the high rate is substantially greater than the low and base rates. Therefore, when a high-price event takes place and if the perceived prices are some (weighted) averages of marginal prices across several periods (which include the high-price period), the perceived price would also be significantly increased. As the high rate took place more frequently in peak than other periods (recall Table 1), one may observe peak prices negatively affecting non-peak consumption.

To examine whether consumers respond to average prices, Ito (2014) used the encompassing test, which compares a model where households only respond to marginal prices against one where they respond to perceived prices as well. However, in my case, the encompassing test raises identification concerns because the average price (i.e., the 'perceived price') is a function of marginal prices, resulting in multicollinearity. That is, the fact that households respond to cross-prices can be interpreted as households responding to some weighted averages of marginal prices in different periods. Therefore, it would be impossible to identify both in a single regression.

Despite this, I find this suggested explanation implausible based on the following observed facts. First, if households respond to average prices, then there is no reason to believe that they only respond to average prices in post-peak periods and not in other periods. If this is the case and if peak prices are the key components of the average prices to which households respond, peak prices would not only negatively affect post-peak consumption, but also pre-peak consumption. However, my results from Table 2 do not support this analysis because I found that peak prices have a significantly positive impact on pre-peak consumption.

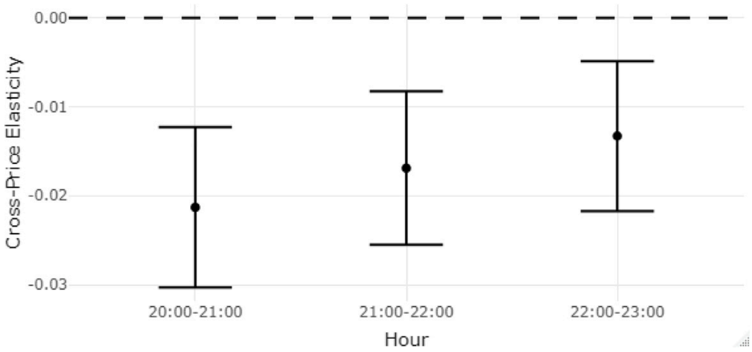
Second, if households respond to average prices, then there is no reason that the formula of average prices should be substantially different in different periods. If this is the case, the spillover effect of peak prices indicates that the marginal price in $t-1$ is a key component of the average price that households respond to in period t, resulting in negative cross-price elasticities. However, the results from Table 2 do not support this analysis because they show that pre-peak prices significantly positively affect peak consumption.

Third, one may argue that the aforementioned two analyses may not be necessary conditions for the explanation that households respond to average prices, because the average prices that households respond to could be more complicated than some general algebraic forms. However, recall that the rationale for the suggested explanation is that the average price is less cognitively costly to understand. Therefore, even if it is true that the average prices that households respond to is complicated, it contradicts the underlying reason for households responding to average prices, making this explanation less plausible.

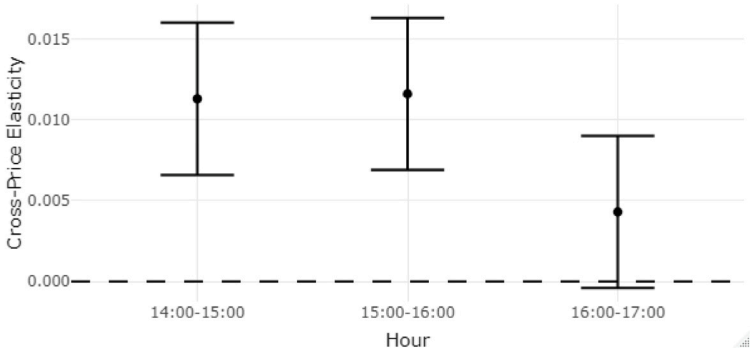
4.3. Households overreact to peak prices

Inspired by Greenwood and Shleifer (2014), who found that in stock markets, people will overreact to past returns by extrapolating excessively, my third proposed explanation is that households overreact to peak prices when making post-peak consumption decisions. Intuitively, households' peak consumption is usually substantially greater than other periods. Hence, they are likely to be more sensitive to peak prices and might be too sensitive, resulting in an overreaction to peak prices in post-peak

[15] It is noteworthy that Ito (2014) did not study consumers' responses to dynamic tariffs. Instead, the author investigated how consumers respond to non-linear price schedules, where the marginal price of electricity depends on the accumulative electricity consumption within that month.



(a) Post-peak consumption



(b) Pre-peak consumption

Fig. 1. The impact of peak prices on pre- and post-peak consumption. **Notes:** these figures report the estimates on the spillover effects on hourly sub-periods pre- and post-peak. The error bars capture 95% confidence intervals of the estimates.

periods. In this subsection, I investigate if it is plausible to argue that overreaction is the underlying mechanism of the spillover effect and, if so, what caused households to overreact. A simple model of overreaction can be expressed as

$$\tilde{P}_{d,t} = mP_{d,t-1} + (1-m)P_{d,t},$$

where $\tilde{P}_{d,t}$ denotes households' subjective price in period t of day d, which depends on post-peak prices as well as peak prices. Note that in my particular case and in the rest of this subsection, t denotes post-peak periods. m denotes the degree of overreaction, which would be greater if households are more extrapolative. Subsequently, households may lower their post-peak consumption when the peak price is high and *vice versa*.

The next step is to identify whether overreaction does exist, and the best identification strategy might be replacing $P_{d,t}$ in specification (2) by $\tilde{P}_{d,t}$ and test whether m is significantly positive (and meanwhile the estimate of β_t is no longer significantly positive). However, this regression cannot simultaneously identify both m and γ_t, hence other strategies are preferred to investigate overreaction. Here, I propose and apply two alternative strategies.

The first strategy is based upon the intuition that if overreaction does exist, the degree that households overreact would depend on the time gap between peak periods and the time where electricity is consumed. For example, as peak periods range between 17:00–20:00, I would expect the degree of overreaction to be more substantial during 20:00–21:00 than 21:00–22:00, and so forth.

To verify this intuition, I separate post-peak periods into three hourly sub-periods, namely 20:00–21:00, 21:00–22:00, and 22:00–23:00. I then investigate the impact of peak prices on electricity consumption in those hourly periods. The results with 95% confidence intervals are reported in Fig. 1(a),[16] which verifies my guess — the impact of peak prices on hourly post-peak consumption declines as the time gap between peak periods and the time where electricity is consumed becomes wider. However, the impact remains significantly negative until 22:00–23:00, suggesting that the overreaction persists for at least three hours after peak periods.

I also implement the same technique on pre-peak consumption, to check whether the spillover effect of peak prices also applies to pre-peak consumption, especially when time approaches peak periods. The results are reported in Fig. 1(b), which suggest that as time approaches peak periods, the impact of peak prices on pre-peak consumption turns from significantly positive to

[16] The complete regression results that I use to plot Figs. 1–3 are reported in Tables A.9–A.11.

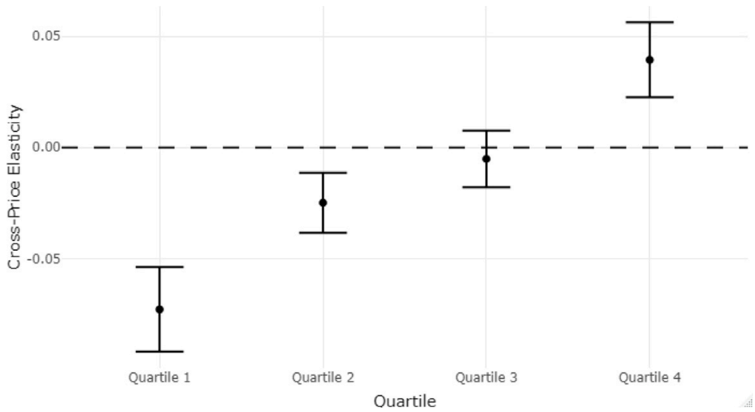


Fig. 2. The impact of peak prices on post-peak consumption for different quartiles. **Notes:** this figure reports the estimates on the spillover effects for different quartile groups, where each quartile is determined by the own-price elasticities in peak periods estimated for each household. Quartile 1 contains households who are most sensitive to peak prices, and Quartile 4 contains households who are least sensitive to peak prices. The error bars capture 95% confidence intervals of the estimates.

insignificant. This indicates that households' overreaction to peak prices may not only impact post-peak consumption, but also pre-peak consumption, though the degree might be much smaller.

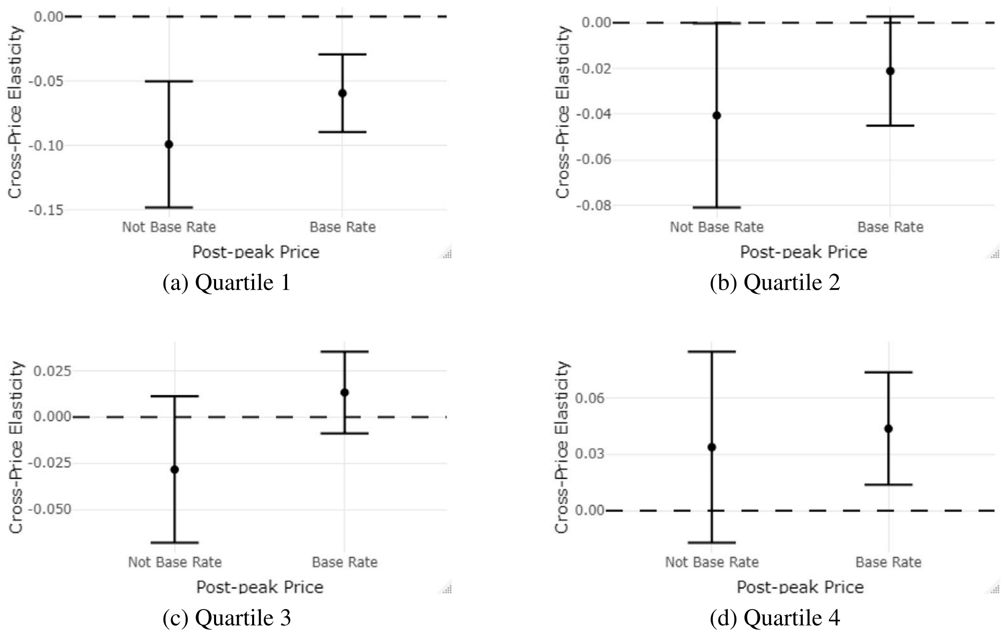
The second strategy is based on the intuition that if the spillover effect is due to overreaction, I would expect households who are sensitive to peak prices during peak periods to also be sensitive to peak prices during post-peak periods. This has already been partially supported by results from Table 3, which suggest that the number of occupants and family structure are key determinants for the impact of peak prices on both peak and post-peak consumption. Another way to investigate overreaction is to separate households into several sub-groups based on their own-price elasticities during peak periods and test whether households with greater own-price elasticities overreact more substantially to peak prices during post-peak periods. Therefore, I first apply OLS regressions on each household to estimate their own-price elasticities during peak periods and then separate the data into quartiles based on the value ranking of the estimated own-price elasticities. Next, I study the impact of peak prices on post-peak consumption by applying FE models to each sub-group of households.

Fig. 2 reports the estimated impact of the peak prices on post-peak consumption, for each quartile of households. It suggests that the spillover effect is indeed more salient among households in the first quartile (i.e., households who are most sensitive to peak prices during peak periods). It gradually declines and disappears among households in the second and third quartiles. In the fourth quartile, the impact of peak prices on post-peak consumption becomes positive, indicating that these households are no longer overreacting.

Now that I have demonstrated that the spillover effect of peak prices is likely due to households overreacting to peak prices, my next question is what causes households to overreact. As overreaction is due to people having limited attention (Gabaix, 2019), I would assume that if the cognitive cost for responding to prices reduces, households would behave more rationally (i.e., being less overreactive or not overreacting at all). In the LCL project, households pay the base rate of £0.1176/kWh most of the time (recall Table 1). Therefore, I may expect that whenever electricity prices are equal to the base rate, households are experiencing repeat events, which require less cognitive cost, and households may behave more rationally. This concept is also known as 'cognitive ease'; that is, people feel 'ease' towards things that are familiar, easy to understand, and easy to see or read (Kahneman, 2011). Conversely, households may experience 'cognitive strain' if the own-price deviates from the base rate, resulting in irrational behaviours such as overreacting. This argument can be supported by further separating each quartile based on whether the post-peak price is equal to the base rate and then applying FE models on post-peak consumption. Recall that once conditional on months, these price events took place arbitrarily across days; hence, separating the data based on tariff rates will be unlikely to generate sample selection bias.

The results reported in Fig. 3 support the theory of cognitive strain. When the post-peak price is equal to the base rate, the quartile of households with high own-price elasticities during peak periods (i.e., Fig. 3(a)–3(b)) overreacted less to peak prices. Conversely, the spillover effect becomes salient when the post-peak price deviates from the base rate, suggesting a greater level of overreaction. Notably, households with low own-price elasticities during peak periods (i.e., Fig. 3(c)–3(d)) are also becoming more rational when the post-peak price is equal to the base rate, given that their cross-price elasticities were becoming more positive and significant (than when the post-peak price deviates from the base rate).

If overreaction is due to cognitive strain when the own-price is equal to the base rate, I may also observe households behaving differently during pre-peak and peak periods, conditional on whether the own-price is or is not equal to the base rate. This argument can be tested by separating the data based on whether the pre-peak (or peak) price is equal to the base rate and then studying the impact of prices on households' pre-peak (or peak) consumption. The regression results are reported in Table A.12, which also supports the theory of cognitive strain. During pre-peak and peak periods, households are becoming more rational when the own-price is equal to the base rate, where 'more rational' refers to the cross-price elasticities becoming more positive and significant. Although the evidence provided in this section does not allow me to draw conclusions that the spillover effect is indeed caused by



(a) Quartile 1 (b) Quartile 2

(c) Quartile 3 (d) Quartile 4

Fig. 3. The impact of peak prices on post-peak consumption, by separating the data based on whether peak-peak prices equal to the base rate, for different quartiles. **Notes:** these figures report the estimates on the spillover effects for different quartile groups, when the own-price is or is not equal to the base rate. Each quartile is determined by the own-price elasticities in peak periods estimated for each household. Quartile 1 contains households who are most sensitive to peak prices, and Quartile 4 contains households who are least sensitive to peak prices. 'Not Base Rate' refers days when the own-price (i.e., post-peak prices in this case) differs from the base rate, and 'Base Rate' refers to days when the own-price equals to the base rate. The error bars capture 95% confidence intervals of the estimates.

overreaction due to cognitive strain, my findings raise the possibility which may need to be verified through some more careful experimental designs in future research.

4.4. Other explanations for the spillover effect

There might be other possible explanations for the spillover effect. For example, Ito et al. (2018) found that on treatment days, economic incentives would reduce peak and non-peak consumption. This is known as the spillover effect of treatments and it is argued that it might be due to a change in households' lifestyles. Another possible explanation is that households may have a mental account of their daily electricity expenditure. Therefore, on days when the peak price is high, they may reduce electricity usage during non-peak periods to retain a balanced daily expenditure. Although these explanations are worth discussing, I find them either difficult to test in my context or implausible. For example, it might be challenging to test Ito et al.'s theory, and having a mental account of electricity expenditure, which is only an extremely small proportion of households' total consumption, seems to be implausible. More importantly, in this study, I failed to reject the explanation that the spillover effect is due to overreaction, and I found evidence supporting the posit that overreaction is due to households' cognitive strain.

5. Distributional and welfare effects

The conventional flat tariff could not reflect the varying cost of electricity generation, resulting in market inefficiency. Subsequently, the fundamental purpose of dynamic tariffs is to fix this inefficiency by charging higher rates when the system load is high and lower rates otherwise. The implication of dynamic tariffs will change market outcomes, raising concerns about how more efficient tariff structures would influence different market entities.

In this section, I first investigate the impact of dynamic tariffs implemented by the LCL project on consumers, producers, and the market as a whole relative to a counterfactual flat tariff. I conclude that the LCL project resulted in an increase in the retailer profit in sacrificing consumer welfare due to a failure in the initial tariff design. Therefore, I re-design a dynamic tariff scheme and use my earlier results to estimate households' electricity consumption under the new tariff scheme. I demonstrate that relative to a flat tariff, the re-designed tariff scheme would have a negligible impact on consumer and producer surpluses.

Demand response would also affect social welfare, which will mainly include changes in the cost of energy and capacity, and the social value of reduced emissions. Therefore, in the second part of this section, I estimate the improvement in social welfare from dynamic tariffs and answer the question of whether the spillover effect of peak prices affects social welfare. The results demonstrate that the spillover effect can be vital in determining whether the benefit overwhelms the cost in a smart metering project.

5.1. Distributional effects

To estimate the distributional effects of dynamic tariffs, I focus on a representative household whose electricity consumption equals the average of all participants of the LCL project. I first construct a counterfactual scenario where households only pay a flat tariff, and for the sake of parsimony, the household's electricity consumption under the flat tariff is estimated from the FE regression results reported in Table 2.[17]

Then, I compare the household's electricity consumption under the dynamic tariffs against that under the counterfactual flat tariff and estimate the distributional effects of dynamic tariffs. Details in calculating consumer and producer surpluses and other variables are given in Appendix A.5. The estimation results are shown as Scenario 1 in Table 4. I find the average electricity price in the LCL project being greater than the flat rate, resulting in a substantial loss in consumer surplus (about 4%–5% of its annual electricity bill), which is transferred to the electricity retailer. Surprisingly, in 2013, dynamic tariffs increased the total peak consumption for the representative household by around 2 kWh; this is because the LCL project does not charge substantially higher prices during peak periods compared to other periods. Therefore, I argue that the LCL project might be qualified to investigate households' responses to dynamic tariffs but is a bad example of the design of dynamic tariffs.

Table 4
Distributional effects of dynamic tariffs.

Variables	Unit	Dynamic tariffs				Flat tariff
		Scenario 1	Scenario 2	Scenario 3	Scenario 4	
Electricity bill	£/year	250.52	251.45	239.92	240.03	238.05
Retailer profit	£/year	153.57	154.61	143.48	143.55	141.72
Δ Consumer surplus	£/year	−10.75	−12.02	−0.77	−0.74	–
Δ Producer surplus	£/year	11.85	12.90	1.76	1.84	–
Δ Market surplus	£/year	1.10	0.87	0.99	1.09	–
Average price	£/kWh	0.1487	0.1494	0.1427	0.1427	0.14228
Pre-peak price	£/kWh	0.1235	0.1235	0.0969	0.0969	0.14228
Peak price	£/kWh	0.1582	0.1582	0.2022	0.2022	0.14228
Post-peak price	£/kWh	0.1586	0.1608	0.1176	0.1176	0.14228
Δ Average price	£/kWh	0.0064	0.0072	0.0005	0.0004	–
Δ Pre-peak price	£/kWh	−0.0187	−0.0187	−0.0454	−0.0454	–
Δ Peak price	£/kWh	0.0159	0.0159	0.0599	0.0599	–
Δ Post-peak price	£/kWh	0.0163	0.0186	−0.0247	−0.0247	–
Total demand	kWh/year	1684.90	1682.54	1680.83	1681.81	1673.10
Pre-peak demand	kWh/year	469.56	469.56	477.28	477.28	461.91
Peak demand	kWh/year	627.30	627.30	616.14	616.14	625.43
Post-peak demand	kWh/year	588.05	585.68	587.41	588.39	585.76
Δ Total demand	kWh/year	11.80	9.44	7.73	8.71	–
Δ Pre-peak demand	kWh/year	7.64	7.64	15.37	15.37	–
Δ Peak demand	kWh/year	1.87	1.87	−9.29	−9.29	–
Δ Post-peak demand	kWh/year	2.29	−0.07	1.65	2.63	–

Notes: In Scenario 1, households pay the LCL tariff and the spillover effect is anticipated by policymakers. In Scenario 2, households pay the LCL tariff but the spillover effect is not anticipated by policymakers. In Scenario 3, households pay the re-designed dynamic tariff and the spillover effect is anticipated by policymakers. In Scenario 4 households pay the re-designed dynamic tariff but the spillover effect is not anticipated by policymakers. Δ refers to the difference between dynamic and flat tariffs.

To increase consumer welfare, I re-design the dynamic tariff scheme based on the following two principles. First, I will ensure that households are not significantly worse off from participating in the dynamic tariff, and this requires the re-designed scheme to have less high-price periods and/or more low-price periods. Second, I will ensure that the high- and low-price events take place whenever necessary (instead of arbitrarily), and this requires the re-designed scheme to be related to households' electricity consumption. Therefore, I rank the household's pre-peak, peak, and post-peak consumption from high to low (hence, there are 1095 periods in total). After several attempts, the re-designed scheme is structured as follows:[18] for the 45 periods with the highest consumption, I set the tariff rate to the high rate; for the 120 periods with the lowest consumption, to the low rate; and for the remaining 930 periods, to the base rate.[19] I retain the same noon and midnight prices as the LCL project.[20] Finally, I estimate households' electricity

[17] Recall that households who do not participate in the LCL project paid a flat rate of £0.14228/kWh.

[18] The design of the optimal dynamic tariff remains an open question, and I shall leave this for future research.

[19] The high, base, and low rates are identical with the LCL projects. Here, the number of high-rate periods does not have to be 45. I chose a number below but close to 54, which is the total number of high-price periods during peak-peak, peak, and post-peak periods from the original scheme (recall Table 1). The total number of low-price periods is also greater than that in the original scheme.

[20] Here, I only re-designed the pre-peak, peak, post-peak prices and keep the prices in other periods as they were in the original scheme. One reason is that these periods are the main battlefields of demand response. Another reason is that re-designing prices in other periods would also affect consumption in those periods, which would complicate my comparisons between the original and re-designed dynamic tariff schemes (although the re-designed pre-peak, peak, and

consumption under the re-designed scheme and calculate the associated distributional effects. The results are reported as Scenario 3 in Table 4.

I demonstrate that unlike the LCL project, the re-designed scheme no longer has an unpleasant distributional effect. The consumer surplus for an average household is barely affected relative to the flat tariff, although the electricity retailer no longer makes much greater profit from dynamic tariffs. The most significant difference between the two tariff schemes is the average pre-peak, peak, and post-peak prices — the re-designed scheme has a much higher average price during peak periods than the pre- and post-peak periods. Consequently, the impact of dynamic tariffs on peak load reduction is substantial — for an average household in 2013, the total peak consumption has been reduced by 11.16 kWh, most of which are shifted to pre-peak periods.

Finally, to investigate the impact of the spillover effect on the market outcome, I consider two counterfactual scenarios where households do not overreact to peak prices and that the impact of peak prices on post-peak consumption is positive.[21] These can be considered as *ex-ante* scenarios where before the implementation of dynamic tariffs, policymakers were unaware of the spillover effect and its underlying mechanisms, and they would anticipate market outcomes assuming that households have positive cross-price elasticities. In the first counterfactual scenario denoted as Scenario 2 in Table 4, I assume that households participate in the LCL project but do not overreact to peak prices. In the second counterfactual scenario denoted as Scenario 4 in Table 4, I assume that households participate in the re-designed scheme but do not overreact to peak prices.

Owing to the spillover effect, a high peak price will reduce peak and post-peak consumption. Therefore, if the spillover effect were ignored, policymakers would underestimate the impact of high peak prices on energy conservation. The results suggest that when the dynamic tariff is poorly designed (i.e., Scenarios 1 and 2), ignoring the spillover effect would result in households over-reducing electricity usage, resulting in lower consumer and market surpluses than policymakers anticipate. On the other hand, if the dynamic tariff is carefully designed (i.e., Scenarios 3 and 4), ignoring the spillover effect would not substantially change the distributional effect of dynamic tariffs. This further verifies the importance of tariff design.

5.2. Welfare effects

Thus far, I have analysed the distributional effects of dynamic tariffs from the perspective of different market entities (i.e., households and the retailer). I now estimate the social benefit of dynamic tariffs from the perspective of policymakers. Specifically, I investigate whether the shifted and reduced (peak) load from dynamic tariffs can benefit society to offset the cost of a smart metering project.

To this end, I use a data-driven method developed by Ovaere and Gillingham (2019) and quantify the benefit of dynamic tariffs along the different stages of electricity supply. Subsequently, the main benefits from dynamic tariffs should include the reduced (or increased) cost from electricity generation, the value of the reduced need for peaking plants, and the social value of reduced (or increased) greenhouse gas emissions. Notably, there are some additional benefits such as the reduced cost of balancing the system, reduced cost of congestion and losses, and reduced distribution line and loading. However, I argue that these benefits would be considerably smaller than the main benefits listed above and are hence ignored from my analysis. Given these, I may underestimate the social benefits of dynamic tariffs.

The detailed estimation processes are provided in Appendix A.5. Table 5 presents the estimated social benefits from implementing dynamic tariffs on an average household, where I take 2013 as the year of reference because the LCL project was implemented in that year.

The re-designed dynamic tariff scheme (Scenarios 3 and 4) outperforms the LCL tariff scheme (Scenarios 1 and 2) in both saved energy costs and capacity investments. The reason is simply that the re-designed scheme aims at reducing peak load whereas in the LCL tariff scheme, high-price events took place arbitrarily across days. This reflects the crucial importance of the design of dynamic tariffs in achieving greater social benefits.

I find that in all scenarios, the introduction of dynamic tariffs do not reduce the total cost of electricity generation. The reason is that although dynamic tariffs reduced peak consumption, in all scenarios, the total consumption increased (recall Table 4). Put another way, the saved energy from peak periods is offset by the increased energy consumption in other periods. Notably, there is always a trade-off between energy conservation and consumer welfare — energy conservation requires the average price under dynamic tariffs to be greater than the flat rate, which in turn harms consumer welfare. In such cases, households may find dynamic tariffs less attractive and return to the original flat tariff. Therefore, energy conservation is never the fundamental purpose of implementing dynamic tariffs.

In Scenarios 3 and 4, most benefits come from saved capacity, but the difference between the two scenarios is that in Scenario 3, a high-price event in peak periods would reduce not only peak but also post-peak consumption, meaning that the need for both peaking and normal plants is reduced.[22] Hence, the results suggest that the saved capacity would be underestimated if policymakers are unaware of the fact that households may overreact to peak prices. Despite that, in both scenarios, the value for the saved peaking

post-peak prices may also change consumption in other periods, I argue that those impacts would be small because prices in most periods would still follow the base rate at £0.1176/kWh).

[21] Here, in estimating the counterfactual electricity consumption, I simply assume that the impact of peak prices on post-peak consumption is the inverse of the estimated negative elasticities.

[22] As consumption in post-peak periods is greater than that in all periods other than peak periods, a reduction in post-peak consumption indicates that the need for normal (non-peak) plants is reduced.

Table 5
Social benefit of dynamic tariffs, £/year/household.

	Scenarios			
	1	2	3	4
Saved energy	−0.62	−0.50	−0.11	−0.15
Saved capacity	0.65	−0.04	8.11	5.44
Saved emissions	−0.24	−0.19	−0.18	−0.20
Total benefits	−0.21	−0.73	7.82	5.09

Notes: In Scenario 1, households pay the LCL tariff and the spillover effect is anticipated by policymakers. In Scenario 2, households pay the LCL tariff but the spillover effect is not anticipated by policymakers. In Scenario 3, households pay the re-designed dynamic tariff and the spillover effect is anticipated by policymakers. In Scenario 4 households pay the re-designed dynamic tariff but the spillover effect is not anticipated by policymakers.

capacity can still be substantial, suggesting that a small number of peak hours drives costly generating capacity expansions, and reducing peak consumption avoids the investment to construct and maintain these peaking plants.

Further, notably, the benefits from saved emissions can be negative. This is because in 2013, the carbon prices in GB's electricity industry were low (at around £10/tCO_2), and the marginal cost of generation from coal was lower than that from combined-cycle gas turbines (CCGTs); hence, CCGTs are the marginal plants operating in peak hours. As the emission factor of CCGTs is much smaller than that of coal plants, the marginal emissions in peak hours are lower than those in non-peak hours. As dynamic tariffs shifted peak consumption to non-peak periods, total emissions will be (slightly) increased due to the higher marginal emissions in non-peak hours. However, suppose the carbon prices were sufficiently high (such as after 2015, at £25/tCO_2 or above); to make the marginal cost of electricity generated from coal higher than gas, coal plants would more often be the marginal plants operating in peak hours, resulting in higher marginal emissions in peak periods compared to non-peak periods. In such a case, shifting households' peak consumption to non-peak hours would result in reduced emissions, and the benefits from saved emissions will be positive, resulting in greater benefits.

Although I do not have information about the cost of the LCL project, I can infer from Fowlie et al. (2021) that the cost of a US smart metering programme is approximately \$6–7/household/year (or £5–6/household/year), assuming that the dynamic tariff would run for ten years. This suggests that the total benefits of a smart metering project could be lower than the costs if the design of dynamic tariffs is problematic. Furthermore, if the costs of a smart metering project in GB were at somewhere between £5.1 and £7.8/household/year (which is possible given its costs in the US), and if policymakers ignore overreaction, they may anticipate a smart metering project to be uneconomical while it is actually cost-effective.

My cost–benefit analysis is also supported by an official report from the Department for Business, Energy & Industrial Strategy (BEIS) of the United Kingdom, which estimated that the British Smart Metering Implementation Programme would 'deliver significant benefits for households and small businesses in Great Britain'. The total benefits are estimated to be £19.5 billion, substantially greater than the estimated total costs of £13.4 billion (BEIS, 2019).

Finally, the ideal design of dynamic tariffs should aim to maximise social welfare. However, neither the LCL project nor my re-designed tariff takes social welfare as the objective function in maximising. In other words, if a dynamic tariff scheme is carefully designed to maximise social welfare, the net benefits of dynamic tariffs will be further increased. However, finding the optimal dynamic tariff could be challenging as the social value of dynamic tariffs should be carefully estimated. Therefore, I leave this important topic for future research.

6. Conclusions and policy implications

This study used data from the Low Carbon London (LCL) project to investigate households' responses to time-varying electricity tariffs. I found that households are inelastic to electricity prices with own-price elasticities of demand lower than 0.1, though this price effect is statistically significant. I found that a high peak price not only reduces peak consumption, the negative impact also 'spills over' to post-peak periods, reducing post-peak consumption. Therefore, I call this the spillover effect of peak prices. I failed to reject the hypothesis that the spillover effect is due to overreaction, and found evidence supporting the posit that the overreaction is due to households' cognitive strain when facing unfamiliar pricing events. I found that relative to a flat tariff scheme, the LCL tariff scheme substantially increased retailer profit by sacrificing households' welfare. Further, if the design of the dynamic tariff is arbitrary, the total benefit of a dynamic tariff scheme could be lower than the cost of a smart metering project, resulting in a failure in achieving a more efficient retail market. Therefore, I re-designed the dynamic tariff and demonstrated that under the re-designed scheme, both households' welfare and the market surplus could be improved, and the total benefits of a smart metering project surpasses its total costs. These findings reflect the importance of tariff design in a smart metering project.

As described in the data section, one important limitation of this study is that households in the LCL project do not formulate a random sample of the population. Consequently, my estimates of households' price elasticities may not be representative of all British households. However, the participating households are representative of London citizens in terms of demographic distributions (Schofield et al., 2015). I also illustrated that the estimated price elasticities are similar to those found in previous research and that evidence on the spillover effect can be found from the related literature, suggesting that my results are unlikely to be substantially different from the population in terms of households' responses to prices. Another limitation is that even though I found evidence that the underlying mechanism for the spillover effect is overreaction due to cognitive strain, the LCL project is not designed to study this type of consumer behaviour. Therefore, a future smart metering trial that specifically investigates overreaction and cognitive strain would be preferable.

Economic and energy policy may induce significantly different distributional and welfare effects depending on the design of the policy. Notably, the re-designed tariff scheme substantially improved consumer welfare as well as social benefits, but the re-design process is informal as the price rates completely depend on households' electricity consumption. This means that if the dynamic tariff scheme could be designed more carefully, both consumer surplus and net benefits from implementing dynamic tariffs could be further improved. Furthermore, understanding how consumers respond to prices can also be vitally important in a cost–benefit analysis about whether a new policy should be implemented. Misunderstanding consumer responses may underestimate the net benefit of a policy, resulting in a failure in improving cost effectiveness. Finally, once the concept of cognitive strain when facing unfamiliar price rates has been fully understood in the context of a smart metering project, policymakers can take advantage of it to achieve better social outcomes.

Acknowledgments

I am indebted to David Newbery, Li Su, Lunyu Xie, the anonymous referees and the editor for helpful comments. Financial support from the National Natural Science Foundation of China (No. 72203218) is gratefully acknowledged.

Appendix

A.1. More information about the Low Carbon London project

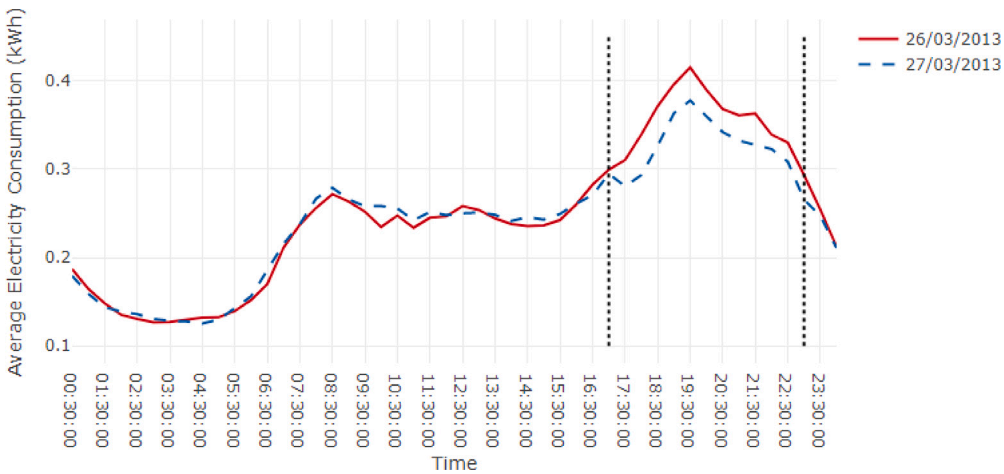


Fig. A.1. Average daily load patterns on 26 and 27 March 2013 across all households. **Notes:** prices for 26 March 2013 were £0.1176/kWh from 00:00 to 24:00, and prices for 27 March 2013 were £0.6720/kWh from 17:00 to 23:00 and £0.0399/kWh otherwise.

Fig. A.1 plots the average electricity load patterns across all households participating in the LCL project for two consecutive working days between 26 and 27 March 2013. On the first day, households pay the base rate throughout the day, and on the second day, households face a CM event, paying the high rate from 17:00–23:00 and the low rate for the rest of the day. Electricity consumption has been substantially reduced during the period with a high rate (i.e., the segment between the dotted vertical lines). However, there is limited evidence on demand shifting from high-rate to low-rate periods by simply comparing the two daily load curves. In the empirical section, I formally investigate the quantitative impact of prices on demand and demand shifting.

Fig. A.2 presents pie charts for household demographic characteristics in terms of the number of occupants, the frequency of teleworking (i.e., work from home), and the number of rooms.[23] It also plots the survey on participants' attitudes towards renewable energy, micro-generation, and global warming. As the survey participants claim themselves to be 'at least jointly responsible for decisions' regarding their household energy consumption, I consider their answers to be representative of the entire household.

Most households (above 75%) have only one or two occupants, and households with five occupants or above only comprise less than 4% of the entire sample. Approximately 70% of households never teleworked, and only less than 8% of households had at least

[23] The survey questions are as follows: 'how many people currently live in your household?'; 'do you or anyone else in your household work from home during a normal week?'; 'how many rooms (include kitchens, living rooms, utility rooms, bedrooms, studies, conservatories, and outbuildings/garden buildings with electricity) are there in your home?'.

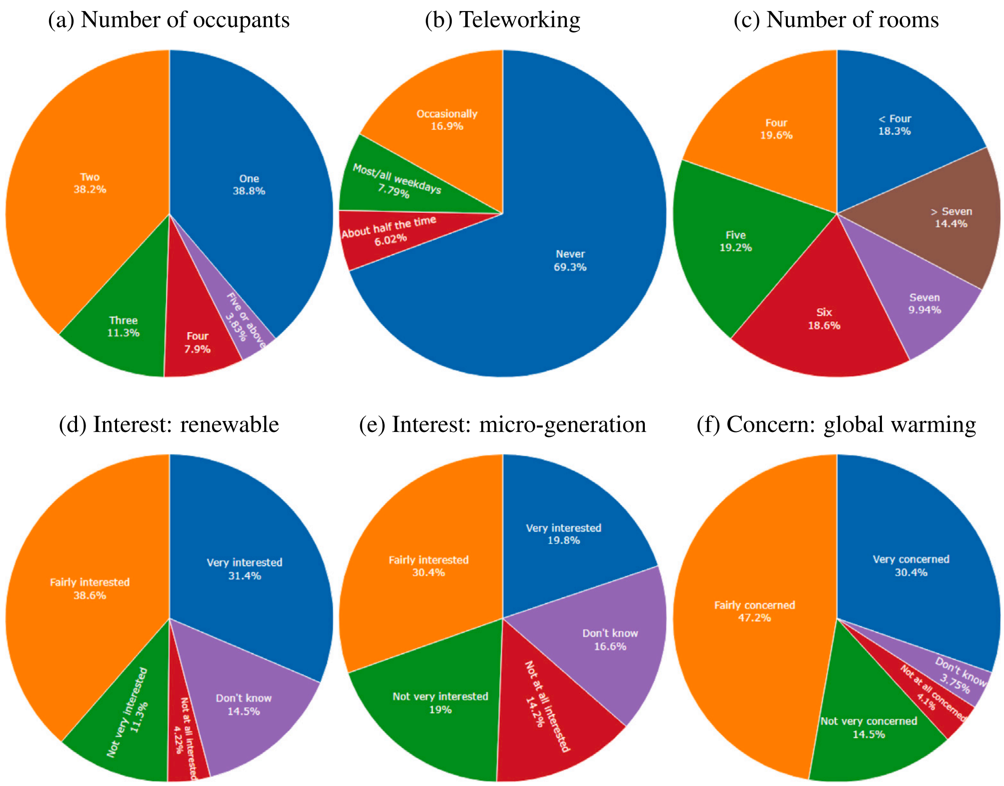


Fig. A.2. Demographic information and households' attitudes towards renewable energy, micro-generation, and climate change.

one occupant teleworking during most/all normal weekdays. The number of rooms is rather evenly distributed across the sample, with more than a half of households living in accommodation with four, five, or six rooms.

More households demonstrate an interest in renewable energy than micro-generation (such as solar photovoltaics or PVs), probably because households treat micro-generation as their own investment and make micro-generation decisions with caution. Finally, in general, households are more aware of global warming than renewable energy and micro-generation, reflecting that households are concerned about the issue but are less certain about which actions to take.

Table A.1 lists some more demographic information about the apartment ownerships, apartment types, heating systems, and household structures. Specifically, it presents the percentage of households who own their accommodation, the percentage of accommodations that are houses or bungalows (relative to flats or apartments), and the proportion of households that use electricity for central heating and water boiling. It also lists the proportion of households that comprise children (younger than 12), teenagers (13–18), young adults (19–44), middle-aged adults (45–64), and old-aged adults (older than 65).

Table A.1
Apartment ownerships, apartment types, heating systems, and household structures.

	True	False		True	False
Ownership	29.8%	70.2%	Children	9.6%	90.4%
House	63.0%	37.0%	Teenagers	8.1%	91.9%
Electric heating	5.1%	94.9%	Young adults	33.5%	66.5%
Electric boiler	10.9%	89.1%	Middle-age adults	50.4%	49.6%
Electric hob	31.1%	68.9%	Old-age adults	48.0%	52.0%

Note: 'Ownership = True' means that the household owns or partly owns the property. 'House = True' means that the accommodation is a whole house or bungalow. 'Electric Heating = True' means that the household uses an electric central heating system. 'Electric Boiler = True' means that the household uses an electric immersion heater to heat household water.

Perhaps surprisingly, approximately 70% of households in the survey do not own their accommodation. Additionally, 63% of households live in a house or bungalow, and I would expect them to consume more electricity mainly because the floor area of a house is normally greater than that of an apartment. Few households use electricity for heating and/or boiling, and I expect them to consume more electricity than others. In terms of household structures, less than 10% of households have at least one child, and less than 10% of households have at least one teenager. However, most households comprise at least one middle-aged adult and/or one old-aged adult.

Table A.2
Summary statistics for the number of major appliances in a household.

	Mean	S.D.	Min.	Max.
Fridge	0.41	0.60	0	4
Freezer	0.44	0.62	0	3
Fridge-freezer	0.74	0.52	0	2
Electric oven	0.70	0.57	0	3
Microwave	0.85	0.39	0	2
Washing machine	0.77	0.43	0	2
Dryer	0.30	0.46	0	1
Washer-dryer	0.16	0.37	0	1
Dishwasher	0.44	0.50	0	2
Electric shower	0.33	0.55	0	4
Television	1.68	1.05	0	6
Desktop	0.58	0.74	0	6

Finally, Table A.2 lists the summary statistics for the number of major appliances[24] in a household. I expect households who own washing machines, dryers, and dishwashers to be more elastic to electricity prices because they can choose to turn on those machines in low-price periods.

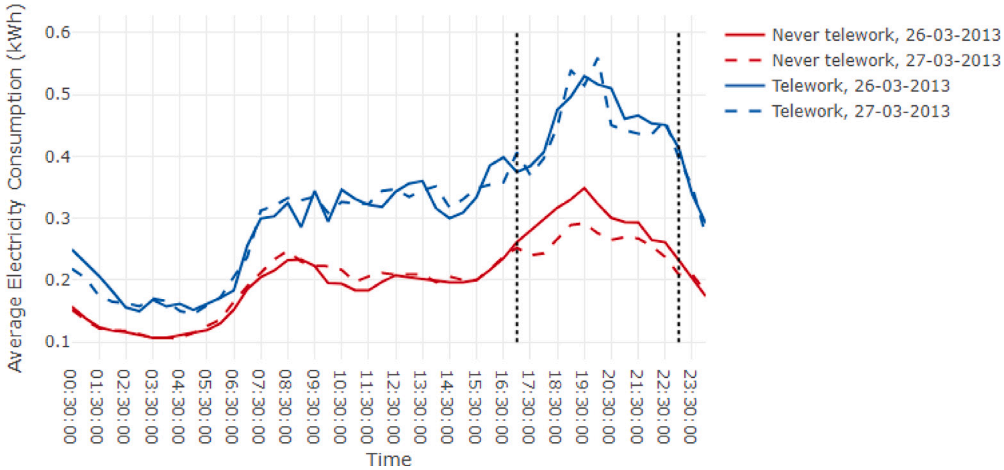


Fig. A.3. Average load patterns on 26 and 27 March 2013 for households who have never teleworked against those who have teleworked at least 'about half the time'. **Notes:** prices for 26 March 2013 were £0.1176/kWh from 00:00 to 24:00, and prices for 27 March 2013 were £0.6720/kWh from 17:00 to 23:00 and £0.0399/kWh otherwise. In total, 575 households (57%) have never teleworked, 115 households (11%) have teleworked often, and the rest have either teleworked 'occasionally' or did not participate in the trial (or categorised themselves as 'NA'). 'Telework' refers to telework 'About half the time' or 'Most/all' weekdays.

Households with different social and economic backgrounds may exhibit heterogeneous responses to electricity prices, thereby formulating different own-price and cross elasticities. Fig. A.3 illustrates the average load patterns for households who claimed they had 'never' teleworked against those who teleworked at least 'about half the time' on 26 and 27 March 2013, the same dates as in Fig. A.1. Not surprisingly, I observe distinctive consumption patterns — households who 'never' teleworked consume much less electricity than others, even during non-working hours. This is probably because households with an option to telework are more likely to be in management positions or self-employed and hence earn a higher income and live in larger accommodation. Perhaps surprisingly, I also observe a reduction of peak load among households who 'never' teleworked, while households who teleworked at least 'about half the time' did not seem to respond to the price signals. The possible reason is that households with an option to telework are likely to be wealthier than others. Hence, they are less aware of price signals as electricity bills only require a small proportion of their income.

In addition to teleworking, other demographic information may also influence household load patterns and price responses. It would be extremely tedious to investigate their impact individually, and some more comprehensive regression techniques are preferable, as given in the main body of this study.

A.2. Table appendix

Table A.3 lists all control variables and their associated coefficients estimated from the RE models. The results illustrate that apartment types, number of occupants, and number of major appliances significantly affect electricity consumption.

[24] Major appliances refer to large machines in home appliances used for routine housekeeping tasks such as cooking and laundry and dishwashing.

Table A.3
Continuation of Table 2, random-effect models.

	Pre-peak	Peak	Post-peak		Pre-peak	Peak	Post-peak
Ownership$_d$	0.1378**	0.0653	0.0254	**Meter location**			
	(0.0513)	(0.0483)	(0.0471)	Hallway	−0.3257	−0.2258	0.0442
House$_d$	0.1695**	0.2141***	0.2141***		(0.2173)	(0.2043)	(0.1994)
	(0.0583)	(0.0548)	(0.0535)	Kitchen	−0.3137	−0.1497	0.0917
No. rooms	0.0062	0.0086	0.0111		(0.2114)	(0.1988)	(0.1940)
	(0.0091)	(0.0085)	(0.0083)	Living room	−0.1892	−0.0537	0.2032
No. occupants	0.1877***	0.2046***	0.1884***		(0.2145)	(0.2017)	(0.1969)
	(0.0355)	(0.0334)	(0.0326)	Other	−0.2774	−0.1294	0.1514
Fridge	0.1343*	0.0999	0.1244*		(0.2173)	(0.2043)	(0.1995)
	(0.0546)	(0.0513)	(0.0501)	Don't know	0.0151	0.2891	0.4964
Freezer	0.2118***	0.1929***	0.1691***		(0.3472)	(0.3265)	(0.3187)
	(0.0454)	(0.0427)	(0.0416)	**Interest in renewable**			
Fridge-freezer	0.2806***	0.2798***	0.2514***	Very	−0.5394	−0.2817	−0.1473
	(0.0625)	(0.0588)	(0.0574)		(0.3400)	(0.3197)	(0.3121)
Elec. oven	0.0623	0.0961*	0.0552	Fairly	−0.5219	−0.2209	−0.1050
	(0.0436)	(0.0410)	(0.0400)		(0.3397)	(0.3194)	(0.3118)
Microwave	−0.0943	−0.0875	−0.1217*	Not very	−0.5803	−0.3433	−0.1832
	(0.0599)	(0.0563)	(0.0550)		(0.3457)	(0.3250)	(0.3173)
Wash. machine	0.4076***	0.3079***	0.2947***	Not at all	−0.5955	−0.2654	−0.0971
	(0.0818)	(0.0770)	(0.0751)		(0.3555)	(0.3343)	(0.3263)
Dryer	0.2478***	0.2127***	0.1730***	Don't know	−0.4404	−0.1678	−0.0259
	(0.0525)	(0.0493)	(0.0481)		(0.3447)	(0.3241)	(0.3164)
Wash-dryer	0.4886***	0.3838***	0.3926***	**Interested in micro-generation**			
	(0.0897)	(0.0844)	(0.0824)	Very	0.0915	−0.0921	0.0104
Dishwasher	0.1594**	0.1659***	0.1892***		(0.2795)	(0.2628)	(0.2565)
	(0.0500)	(0.0470)	(0.0459)	Fairly	0.1750	−0.0203	0.0450
Elec. shower	0.0160	0.0120	−0.0005		(0.2784)	(0.2618)	(0.2555)
	(0.0409)	(0.0384)	(0.0375)	Not very	0.1983	0.0041	0.0304
Television	0.0705**	0.0742***	0.0473*		(0.2785)	(0.2619)	(0.2556)
	(0.0235)	(0.0221)	(0.0216)	Not at all	0.1963	0.0087	0.0793
Desktop	0.1466***	0.1225***	0.1259***		(0.2807)	(0.2640)	(0.2577)
	(0.0315)	(0.0297)	(0.0289)	Don't know	0.1283	−0.0690	−0.0360
Children$_d$	0.0987	0.0834	0.0204		(0.2831)	(0.2662)	(0.2598)
	(0.0994)	(0.0935)	(0.0912)	**Concern about global warming**			
Teenagers$_d$	−0.1305	−0.1560	−0.2039*	Very	0.1725	−0.1179	−0.4651
	(0.1033)	(0.0971)	(0.0948)		(0.4257)	(0.4003)	(0.3908)
Young adults$_d$	−0.0812	−0.0821	−0.0243	Fairly	0.2090	−0.1037	−0.4404
	(0.0721)	(0.0678)	(0.0662)		(0.4233)	(0.3980)	(0.3885)
Mid-age adults$_d$	−0.0008	−0.0197	−0.0336	Not very	0.2211	−0.1119	−0.4961
	(0.0635)	(0.0597)	(0.0582)		(0.4280)	(0.4024)	(0.3928)
Old-age adults$_d$	0.0710	−0.0103	−0.0558	Not at all	0.3572	−0.0561	−0.4387
	(0.0683)	(0.0642)	(0.0627)		(0.4407)	(0.4144)	(0.4045)
Elec. cent. heat.	0.0398	0.0727	0.0787	Don't know	0.3414	−0.0224	−0.3546
	(0.1213)	(0.1141)	(0.1114)		(0.4427)	(0.4162)	(0.4063)
Elec. boiler	0.4023***	0.3545***	0.2631***	**Teleworking**			
	(0.0821)	(0.0772)	(0.0754)	Most/all	−0.1928	−0.1468	0.0066
Elec. hob$_d$	0.0235	0.0808	0.0238		(0.2068)	(0.1944)	(0.1898)
	(0.0538)	(0.0506)	(0.0494)	Half	−0.2646	−0.1942	−0.0433
(Intercept)	−0.9691*	−0.4540	−0.6463		(0.2117)	(0.1991)	(0.1943)
	(0.4426)	(0.4161)	(0.4062)	Occasionally	−0.2957	−0.1926	0.0101
					(0.2000)	(0.1881)	(0.1836)
				Never	−0.3997*	−0.2929	−0.1770
					(0.1924)	(0.1809)	(0.1766)

Table A.4 tests whether some more complex functional forms on temperature would result in different estimates on own- and cross-price elasticities. In regressions using polynomial functions on temperature, I gradually increase the degree (of polynomial parts) until the newly added polynomial term becomes statistically insignificant. I choose the same degree (as polynomial functions) for spline functions. As the estimates on elasticities are extremely similar to those which adopt linear functional form of temperature, for simplicity and interpretability I assume temperature linearly affects electricity consumption in the rest of the paper.

Table A.5 serves as supplements for the spillover effect of peak prices. In all specifications (A.i)–(A.iv), the impact of peak prices on post-peak consumption is estimated to be significantly negative, suggesting that the spillover effect is consistent across regression specifications.

Table A.6 adds $t \pm 2$ specifications to investigate the impact of own and cross prices on electricity consumption, the results approve the consistency of the earlier results and the spillover effect of peak prices still exists.

Table A.7 serves as a supplement for Table 3, where I find that households who claimed themselves to be 'very' interested in micro-generation are more sensitive to peak prices in post-peak periods. The results from Table A.7 illustrate that households are

Table A.4
The impact of electricity prices on consumption with more complex functional forms on temperature.

	Pre-peak		Peak		Post-peak	
	Polynomial	Spline	Polynomial	Spline	Polynomial	Spline
Noon price	0.0035	0.0040				
	(0.0040)	(0.0040)				
Pre-peak price	−0.0719***	−0.0726***	0.0070**	0.0068**		
	(0.0041)	(0.0041)	(0.0025)	(0.0025)		
Peak price	0.0087***	0.0089***	−0.0738***	−0.0738***	−0.0158***	−0.0158***
	(0.0021)	(0.0021)	(0.0045)	(0.0045)	(0.0041)	(0.0041)
Post-peak price			0.0292***	0.0294***	−0.0196***	−0.0196***
			(0.0044)	(0.0044)	(0.0040)	(0.0040)
Midnight price					−0.0022	−0.0021
					(0.0025)	(0.0025)
Temperature(1)	−42.6765***	−0.1371***	−44.5551***	−0.1540***	−27.7097***	−0.0808***
	(1.6185)	(0.0206)	(1.6387)	(0.0177)	(1.4887)	(0.0157)
Temperature(2)	13.2743***	−0.1679***	4.2346***	−0.1192***	7.1631***	−0.1013***
	(0.9508)	(0.0124)	(0.9485)	(0.0109)	(0.8520)	(0.0100)
Temperature(3)	5.0913***	−0.3651***	5.5486***	−0.3137***	2.2009**	−0.2091***
	(0.8098)	(0.0183)	(0.7974)	(0.0170)	(0.7173)	(0.0157)
Temperature(4)	1.7994*	−0.3273***	5.1111***	−0.3622***	1.7930*	−0.2117***
	(0.7800)	(0.0186)	(0.7973)	(0.0169)	(0.7198)	(0.0159)
Temperature(5)	−2.3097**	−0.2694***	−3.4787***	−0.2749***	−1.7445**	−0.1549***
	(0.7507)	(0.0212)	(0.7356)	(0.0189)	(0.6676)	(0.0189)
Wind speed	0.0019***	0.0019***	0.0008**	0.0008**	0.0008**	0.0009***
	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Pub. holiday$_d$	0.0248**	0.0265**	−0.0629***	−0.0610***	−0.0623***	−0.0621***
	(0.0084)	(0.0085)	(0.0084)	(0.0084)	(0.0076)	(0.0076)
Month$_d$	YES	YES	YES	YES	YES	YES
Day of week$_d$	YES	YES	YES	YES	YES	YES
R^2	0.0643	0.0643	0.1019	0.1020	0.0477	0.0477
No. Obs.	368,341	368,341	368,349	368,349	368,341	368,341

Notes: * refers to significance at the 5% level; ** refers to significance at the 1% level; *** refers to significance at the 0.1% level. All price variables and the dependent variables (i.e., electricity demand) are in a natural logarithm. Variables with the subscript *d* are dummy variables. Dependent variables are log electricity demand during pre-peak (first two columns), peak (middle columns), and post-peak (last two columns) periods. The numbers in the parenthesis following variable "Temperature" denote the degree of polynomial parts. All regressions adopt FE models.

Table A.5
Alternative specifications to estimate the impact of prices on post-peak consumption.

	Post-peak consumption			
	FE			FGLS
	(A.i)	(A.ii)	(A.iii)	(A.iv)
Peak price	−0.0164***	−0.0290***	−0.0148***	−0.0095***
	(0.0040)	(0.0039)	(0.0040)	(0.0021)
Post-peak price	−0.0055	−0.0194***	−0.0165***	−0.0241***
	(0.0040)	(0.0039)	(0.0040)	(0.0026)
Midnight price	−0.0279***	−0.0067**	−0.0001	−0.0029**
	(0.0025)	(0.0024)	(0.0025)	(0.0014)
Temperature		−0.0177***		−0.0049***
		(0.0001)		(0.0003)
Wind speed		0.0007**		0.0002
		(0.0002)		(0.0001)
Public holiday$_d$			−0.0612***	−0.0413***
			(0.0075)	(0.0045)
Month$_d$			YES	YES
Day of week$_d$			YES	YES
R^2	0.0006	0.0383	0.0465	–
No. Obs.	368,341	368,341	368,341	368,341

Notes: The dependent variable is the natural logarithm of electricity consumption during post-peak periods. FE is the abbreviation for fixed effects models, and FGLS refers to general feasible generalised least square estimation. General FGLS estimators are based on a two-step estimation process: first, an OLS model is estimated, and then its residuals are used to estimate an error covariance matrix more general than the random effects one for use in an FGLS analysis.

indeed becoming increasingly sensitive to peak prices during post-peak periods if they are more interested in micro-generation. The reason might be that households who were 'very' interested in micro-generation had also installed domestic solar PVs, which usually require flexible consumption. Therefore, these households would be more sensitive to prices under dynamic tariff schemes.

Table A.6
Alternative specifications to estimate the impact of electricity prices on consumption.

	Pre-peak		Peak		Post-peak	
	FE	RE	FE	RE	FE	RE
Noon price	0.0039	0.0047	0.0002	0.0019		
	(0.0040)	(0.0046)	(0.0040)	(0.0045)		
Pre-peak price	−0.0694***	−0.0747***	0.0075	0.0061	0.0070**	0.0070**
	(0.0041)	(0.0046)	(0.0041)	(0.0047)	(0.0024)	(0.0027)
Peak price	0.0039	0.0081	−0.0733***	−0.0818***	−0.0153***	−0.0171***
	(0.0045)	(0.0051)	(0.0044)	(0.0050)	(0.0040)	(0.0045)
Post-peak price	0.0061	0.0039	0.0284***	0.0319***	−0.0187***	−0.0217***
	(0.0044)	(0.0050)	(0.0044)	(0.0050)	(0.0040)	(0.0045)
Midnight price			−0.0038	−0.0044	−0.0045	−0.0030
			(0.0029)	(0.0033)	(0.0027)	(0.0030)
Temperature	−0.0100***	−0.0101***	−0.0094***	−0.0093***	−0.0063***	−0.0064***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0004)
Wind speed	0.0014***	0.0015***	0.0006*	0.0007*	0.0005	0.0007*
	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0003)
Pub. holiday$_d$	0.0261**	0.0292**	−0.0738***	−0.0732***	−0.0639***	−0.0608***
	(0.0083)	(0.0095)	(0.0082)	(0.0094)	(0.0075)	(0.0084)
Month$_d$	YES	YES	YES	YES	YES	YES
Day of week$_d$	YES	YES	YES	YES	YES	YES
Demographics		YES		YES		YES
R^2	0.0635	0.0660	0.1015	0.1040	0.0475	0.0505
No. Obs.	368,341	286,347	368,349	286,350	368,341	286,346

Table A.7
The impact of 'interest in micro-generation' on households' responses to peak prices in post-peak periods.

	Post-peak consumption			
	(A.ix)	(A.x)	(A.xi)	(A.xii)
Peak price × Interested in micro-generation				
Not at all	−0.0037	−0.0038	−0.0038	−0.0038
	(0.0071)	(0.0069)	(0.0069)	(0.0069)
Not very	−0.0078	−0.0079	−0.0079	−0.0079
	(0.0065)	(0.0064)	(0.0064)	(0.0063)
Don't know	−0.0105	−0.0106	−0.0106	−0.0106
	(0.0068)	(0.0067)	(0.0066)	(0.0066)
Fairly	−0.0153**	−0.0154**	−0.0154**	−0.0154**
	(0.0059)	(0.0057)	(0.0057)	(0.0057)
Very	−0.0294***	−0.0294***	−0.0294***	−0.0294***
	(0.0065)	(0.0063)	(0.0063)	(0.0063)
Peak price	−0.0046	−0.0172**	−0.0030	−0.0039
	(0.0057)	(0.0056)	(0.0057)	(0.0057)
Post-peak price	−0.0055	−0.0194***	−0.0165***	−0.0189***
	(0.0040)	(0.0039)	(0.0040)	(0.0040)
Midnight price	−0.0279***	−0.0067**	−0.0001	−0.0017
	(0.0025)	(0.0024)	(0.0025)	(0.0025)
Temperature		−0.0177***		−0.0063***
		(0.0001)		(0.0003)
Wind speed		0.0007**		0.0005
		(0.0002)		(0.0002)
Public holiday$_d$			−0.0612***	−0.0639***
			(0.0075)	(0.0075)
Month$_d$			YES	YES
Day of week$_d$			YES	YES
R^2	0.0007	0.0384	0.0466	0.0475
No. Obs.	368,341	368,341	368,341	368,341

Notes: The dependent variable is the natural logarithm of electricity consumption during post-peak periods. The FE model is applied in all regressions. The interaction term between peak prices and 'interest in micro-generation' estimates the impact of households' interests in micro-generation on their responses to peak prices in post-peak periods.

Table A.8 serves as a supplement for Section 4.1. It separates the data by demographic groups and applies FE models on each group to investigate the impact of prices on peak and post-peak consumption. The results from Table A.8 illustrate that the peak and post-peak consumption are not complements.

Tables A.9–A.11 serve as supplements for Section 4.3. Table A.9 estimates the impact of peak prices on the hourly consumption, to investigate whether the spillover effect gradually disappears with time. Table A.10 studies impact of peak prices on post-peak consumption, by separating households base on their peak-period own-price elasticities. It suggests that households who are the

Table A.8
Applying the FE model on different demographic groups of households.

	Mid-age adults		Others	
	Peak	Post-peak	Peak	Post-peak
Pre-peak price	0.0061		0.0061	
	(0.0035)		(0.0041)	
Peak price	−0.0931***	−0.0174**	−0.0666***	−0.0157*
	(0.0063)	(0.0057)	(0.0074)	(0.0067)
Post-peak price	0.0350***	−0.0322***	0.0279***	−0.0103
	(0.0063)	(0.0057)	(0.0074)	(0.0066)
Midnight price		−0.0040		0.0022
		(0.0035)		(0.0041)
Temperature	−0.0095***	−0.0063***	−0.0092***	−0.0064***
	(0.0005)	(0.0005)	(0.0006)	(0.0006)
Wind speed	0.0012***	0.0011**	−0.0000	0.0003
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Public holiday$_d$	−0.0460***	−0.0587***	−0.1015***	−0.0667***
	(0.0118)	(0.0107)	(0.0138)	(0.0124)
Month$_d$	YES	YES	YES	YES
Day of week$_d$	YES	YES	YES	YES
R^2	0.1176	0.0528	0.0929	0.0474
No. Obs.	152,494	152,489	149,906	149,906

Notes: The dependent variable is the natural logarithm of electricity consumption during peak and post-peak periods. The FE model is applied in all regressions. 'Middle-aged adults' includes households with at least one middle-aged adult and 'others' refers to other households.

Table A.9
The impact of peak prices on hourly post-peak consumption.

Panel A			
	Post-peak consumption		
	20:00–21:00	21:00–22:00	22:00–23:00
Peak price	−0.0213***	−0.0169***	−0.0133**
	(0.0046)	(0.0044)	(0.0043)
Post-peak price	−0.0149**	−0.0151***	−0.0151***
	(0.0046)	(0.0043)	(0.0043)
Midnight price	−0.0037	−0.0014	0.0003
	(0.0028)	(0.0027)	(0.0026)
Control variables	YES	YES	YES
R^2	0.0604	0.0370	0.0221
No. Obs.	368,370	368,362	368,370
Panel B			
	Pre-peak consumption		
	14:00–15:00	15:00–16:00	16:00–17:00
Noon price	−0.0056	0.0058	0.0069
	(0.0045)	(0.0045)	(0.0045)
Pre-Peak price	−0.0586***	−0.0682***	−0.0608***
	(0.0045)	(0.0045)	(0.0045)
Peak price	0.0113***	0.0116***	0.0043
	(0.0024)	(0.0024)	(0.0024)
Control variables	YES	YES	YES
R^2	0.0362	0.0435	0.0681
No. Obs.	368,349	368,365	368,376

Notes: The dependent variable is the natural logarithm of electricity consumption in each hour during post-peak and pre-peak periods.

most sensitive to peak prices in peak periods are also the households who overreact the most to peak prices in post-peak periods. Table A.11 separates each quartile further based on whether the post-peak price (i.e., the own-price for post-peak periods) equal to the base rate that households usually pay, to investigate whether unfamiliar price events are the main reason for overreaction.

Table A.12 serves as a supplement for Section 4.3. Table A.12 illustrates that when the own-price is equal to the base rate, households become more rational in response to cross-prices (i.e., the cross-price elasticity becomes more positive and significant). This supports the argument that overreaction is due to cognitive strain when the own-price deviates from the base rate, as households would face unfamiliar events.

Table A.10
The impact of households' peak-period own-price elasticities on the spillover effect.

	Post-peak consumption			
	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Peak price	−0.0727***	−0.0248***	−0.0051	0.0394***
	(0.0097)	(0.0069)	(0.0065)	(0.0086)
Post-peak price	−0.0241*	0.0004	−0.0121	−0.0397***
	(0.0097)	(0.0068)	(0.0064)	(0.0086)
Midnight price	0.0054	−0.0048	−0.0059	−0.0013
	(0.0060)	(0.0043)	(0.0040)	(0.0053)
Control variables	YES	YES	YES	YES
R^2	0.0701	0.0532	0.0378	0.0391
No. Obs.	91,944	92,299	91,917	92,181

Notes: The dependent variable is the natural logarithm of electricity consumption during post-peak periods. The whole sample is separated into four sub-groups based upon each household's own-price elasticity during peak periods. Quartile 1 contains households with the lowest value of own-price elasticities (hence are most elastic), and Quartile 4 contains households with the highest value of own-price elasticities (hence are least elastic).

Table A.11
The impact of 'cognitive strain' on households' post-peak consumption.

Panel A				
	Quartile 1		Quartile 2	
	Non-base	Base	Non-base	Base
Peak price	−0.0991***	−0.0595***	−0.0406*	−0.0211
	(0.0250)	(0.0154)	(0.0206)	(0.0122)
Post-peak price	−0.0024		0.0111	
	(0.0225)		(0.0185)	
Midnight price	0.0194	−0.0119	0.0118	−0.0200*
	(0.0182)	(0.0109)	(0.0150)	(0.0087)
Control variables	YES	YES	YES	YES
R^2	0.0413	0.0480	0.0219	0.0346
No. Obs.	12,092	79,852	12,138	80,161
Panel B				
	Quartile 3		Quartile 4	
	Non-base	Base	Non-base	Base
Peak price	−0.0284	0.0133	0.0338	0.0437**
	(0.0202)	(0.0113)	(0.0260)	(0.0153)
Post-peak price	0.0072		−0.0373	
	(0.0182)		(0.0233)	
Midnight price	−0.0004	−0.0133	0.0093	−0.0072
	(0.0147)	(0.0080)	(0.0189)	(0.0109)
Control variables	YES	YES	YES	YES
R^2	0.0120	0.0238	0.0175	0.0224
No. Obs.	12,088	79,829	12,127	80,054

Notes: The dependent variable is the natural logarithm of electricity consumption during post-peak periods. The whole sample is separated into eight sub-groups based on households' own-price elasticity during peak periods and whether the post-peak price equals to the base rate. "Quartile 1" contains households with highest own-price elasticities, and "Base" and "Non-base" respectively refer to whether the post-peak price is or is not equal to the base rate of £0.1176/kWh.

A.3. Figure appendix

Figs. A.4–A.6 serve as supplements for Section 3, which presents households' heterogeneous responses to peak prices in post-peak periods. Figs. A.4–A.6 illustrate that the heterogeneity is mostly due to households having different load patterns.

A.4. Post-Lasso regression

The post-Lasso regression is manifested via the following two steps. First, I implement Lasso on each of the regressions (3)–(5), which solves the following problem:

$$\min_{\beta} \quad \frac{1}{nD}\mathrm{RSS} + \frac{\lambda}{nD}\|\psi'\beta\|_1, \tag{6}$$

Table A.12
The impact of cognitive strain on households' pre-peak and peak consumption decisions.

	Pre-peak		Peak	
	Non-base	Base	Non-base	Base
Noon price	0.0081	−0.0035		
	(0.0104)	(0.0073)		
Pre-peak price	−0.0690***		0.0068	0.0114**
	(0.0098)		(0.0095)	(0.0042)
Peak price	0.0066	0.0141**	−0.0636***	
	(0.0059)	(0.0043)	(0.0105)	
Post-peak price			0.0113	0.0410***
			(0.0112)	(0.0073)
Temperature	−0.0041*	−0.0105***	−0.0098***	−0.0093***
	(0.0019)	(0.0005)	(0.0022)	(0.0004)
Wind speed	−0.0027*	0.0017***	0.0007	0.0011**
	(0.0012)	(0.0003)	(0.0011)	(0.0003)
Public holiday$_d$	0.0216	0.0344**	−0.0460	−0.0628***
	(0.0388)	(0.0110)	(0.0417)	(0.0108)
Month$_d$	YES	YES	YES	YES
Day of week$_d$	YES	YES	YES	YES
R^2	0.0477	0.0407	0.0542	0.0725
No. Obs.	48,443	319,898	48,440	319,909

Notes: The dependent variable is the natural logarithm of electricity consumption during pre-peak and peak periods. The whole sample is separated into two sub-groups based on whether the pre-peak (or peak) price is equal to the base rate. 'Base' and 'Non-base' refer to whether the own-price is or is not equal to the base rate of £0.1176/kWh, respectively.

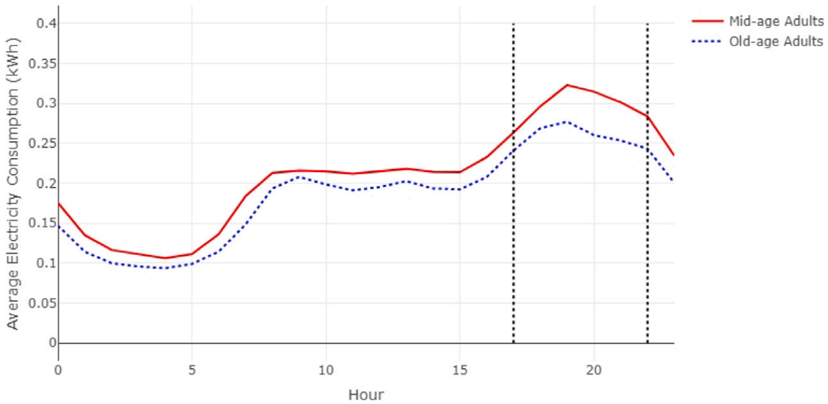


Fig. A.4. Load patterns for an average middle-aged *v.s.* old-aged household.

where RSS denotes the residual sum of squares, and $\boldsymbol{\beta}$ is a $p \times 1$ vector of slope coefficients in the corresponding regression specification; p represents the total number of slope coefficients. The difference between Lasso and the conventional least squares method is that in addition to the RSS, I also penalise non-zero slope coefficients via adding the penalty term $\lambda/nD \cdot \|\psi \boldsymbol{\beta}\|_1$, where λ is the overall penalty level, $\boldsymbol{\psi}$ is a $p \times p$ diagonal matrix with each parameter on the diagonal representing a coefficient-specific penalty level, and $\|.\|_1$ denotes the l_1 norm, or $\|\boldsymbol{x}\|_1 = \sum_j |x_j|$.[25]

There are several approaches to select the penalty levels λ and $\boldsymbol{\psi}$. In this paper, I adopt the theory-driven approach introduced by Belloni et al. (2012), who demonstrate that if the penalty loadings are set to

$$\lambda = 2c\sigma\sqrt{nD}\Phi^{-1}(1 - \frac{\gamma}{2p}), \quad \psi_j = \sqrt{\frac{1}{nD}\sum_i \sum_d x_{j,i,d}^2} \tag{7}$$

[25] $\boldsymbol{x}$ is a $q \times 1$ vector, and $j = 1, \ldots, q$.

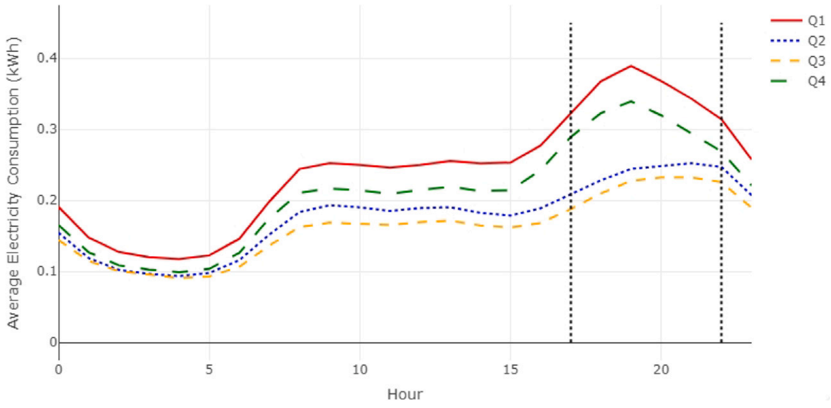


Fig. A.5. Load patterns for an average household in four quarters.

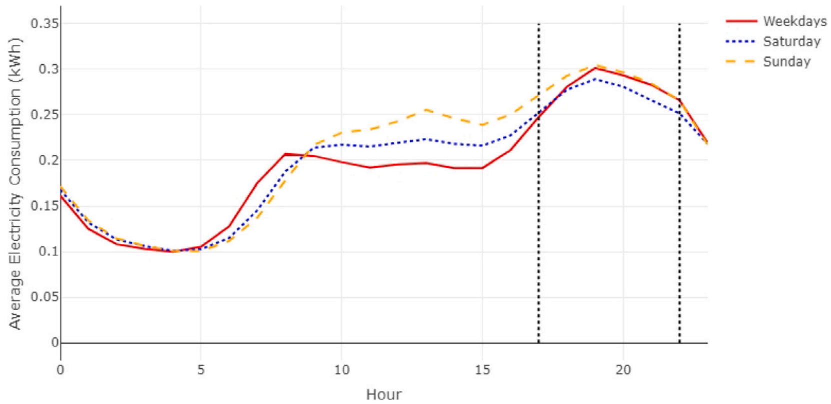


Fig. A.6. Load patterns for an average household on weekdays, Saturdays, and Sundays.

in the case of homoeoskedatic error terms and

$$\lambda = 2c\sqrt{nD}\Phi^{-1}(1 - \frac{\gamma}{2p}), \quad \psi_j = \sqrt{\frac{1}{nD}\sum_i \sum_d x^2_{j,i,d}\varepsilon^2_{i,d}} \tag{8}$$

in the case of heteroskedastic error terms, the post-Lasso estimates are consistent.[26]

Owing to the additional penalty term in (6), Lasso forces certain coefficients (most likely, the less significant coefficients) to be set to zero. The second step, therefore, is to regress the dependent variable on control variables with non-zero coefficients in the first-step Lasso and minimise the RSS of the regression.

A.5. Distributional and welfare effects: supplementary materials

Estimating the distributional effects

The consumer *electricity bill* is calculated as the sum of the product between consumption and electricity tariffs, or $\sum_t d_t \cdot \pi_t$, where d_t denotes electricity demand for a representative household, and π_t denotes the electricity tariff. The subscript t denotes all pricing periods in 2013.

[26] Two alternatives for selecting the penalty level of λ are information criteria and cross-validation. The difference is that the theory-driven approach allows robust estimation that accounts for heteroskedasticity.

The *retailer profit* is the difference between consumer electricity bill and the cost of purchasing electricity from the wholesale market, or $\sum_t d_t \cdot (\pi_t - \pi_t^s)$, where π_t^s denotes the British day-ahead wholesale price in 2013, which is collected from Bloomberg.

The consumer surplus is the area between households' aggregate demand curve and the average electricity price they paid. Subsequently, the impact of dynamic tariffs on consumer surplus, or *Δ consumer surplus*, is the shaded trapezoid area in Fig. A.7, where I assume the households' total demand curve to be linear at the margin. Algebraically, *Δ consumer surplus* can be expressed as $1/2 \cdot (D_f + D_d) \cdot (\bar{\pi}_d - \bar{\pi}_f)$, where D_f and D_d denote the household's total demand under flat and dynamic tariffs, and $\bar{\pi}_d$ and $\bar{\pi}_f$ denote the average electricity prices under flat and dynamic tariffs, respectively. Notably, this method gives a simple estimate of consumer surplus. (A more precise and complicated method would plot pre-peak, peak, and post-peak demand in different graphs, and a change in cross-prices would shift the demand curve.)

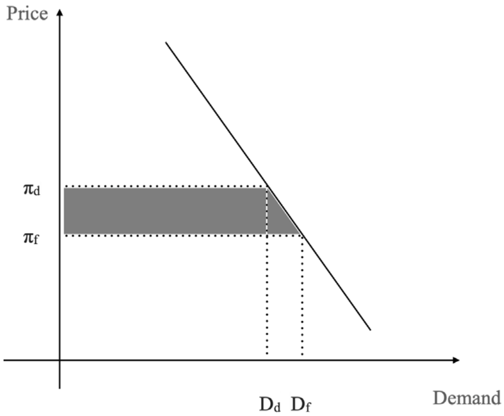


Fig. A.7. The change in consumer surplus from flat to dynamic tariffs.

The producer surplus is defined as the retailer profit, assuming the retailer to be risk neutral. Subsequently, *Δ producer surplus* is the difference in the retailer profit between dynamic and flat tariffs.

Finally, the average price is the household's total demand divided by electricity bill, and *Δ average price* refers to the difference in average prices between dynamic and flat tariffs.

Estimating the welfare effects

The total benefits from implementing dynamic tariffs mainly include saved energy, saved capacity, and saved emissions.

To estimate the value of the *saved energy*, I assume that the British electricity wholesale market to be workably competitive (CMA, 2016; Guo and Castagneto Gissey, 2021), such that the wholesale price reflects the marginal cost of electricity generation. Subsequently, the value of saved energy can be estimated by taking the difference of the wholesale costs between dynamic and flat tariffs, or $\sum_t (d_t - d_t^f) \cdot \pi_t^s$, where d_t^f denotes electricity demand under the flat tariff. One key assumption is that the wholesale price is exogenous, which is true if demand response from dynamic tariffs is not sufficiently substantial to change wholesale prices.

The *saved capacity* mostly comes from the reduced peak load, such that peaking technologies (reciprocating diesel and gas and open-cycle gas turbines (OCGT) at 500 h per year) will no longer be needed. Due to the spillover effect of peak prices, post-peak consumption may also be reduced; therefore, the saved capacity may also come from the saved normal load, such that CCGTs (at normal load factors) will no longer be needed. Based on Section 6 of BEIS (2020), which lists the annual cashflows required to finance the pre-development, construction, and fixed costs for a generic plant, I assume the capacity cost is equal to the cost of an 'OCGT 300 MW 500 hr' at £70/kW and the capacity cost of normal plants equal to the cost of a 'CCGT H Class 2015' at £75/kW and a 'CCGT H Class 2015' at £90/kW. The capacity cost is then multiplied by the difference of the maximum peak load between dynamic and flat tariffs. For example, the maximum peak load in Scenario 3 occurred on 20 Jan 2013 at 0.782 kW, whereas the maximum peak load under the flat tariff also occurred on 20 Jan 2013 at 0.882 kW, then the value for the saved peaking capacity is (0.882–0.782)× 70=£7. Meanwhile, the saved normal capacity is £1.12, hence the estimated total saved capacity is £8.12 (in Table 5 it is 8.11 due to rounding).

Whether dynamic tariffs reduce emissions depends on the marginal electricity generation emissions in peak and non-peak periods. Therefore, to estimate the *saved emissions* from dynamic tariffs, I first need to estimate marginal emissions of electricity generation in GB. I collect hourly electricity 'generation by fuel types' data in 2013 from Elexon and calculate emissions from electricity generation for each hour, using the emission intensities listed below in Table A.13 from Thomson et al. (2017).

Table A.13
Emission intensities of supply types in GB in 2013, tCO_2/MWh.

Coal	CCGT	OCGT	Oil	Other	IFA
1.123	0.475	0.511	1.019	0.179	0.098
Moyle	BritNed	EWIC	Nuclear	Hydro	Wind
0.571	0.498	0.571	0.008	0.004	0.011

Table A.14
Marginal emissions in different periods in 2013, tCO_2/MWh.

	Δ Emissions		
	Pre-peak	Peak	Post-peak
(Intercept)	−33.208***	18.824	−70.914***
	(9.657)	(12.613)	(18.212)
Δ Demand	0.407***	0.372***	0.469***
	(0.008)	(0.006)	(0.006)
Δ Renewable	−0.516***	−0.411***	−0.630***
	(0.032)	(0.035)	(0.048)
Hourly dummies	YES	YES	YES
R^2	0.893	0.895	0.871
No. Obs.	1,095	1,095	1,095

Subsequently, I estimate marginal emissions based on Hawkes (2010) and Thomson et al. (2017), who suggested the following regression specification:

$$\Delta E_t = a\Delta D_t + b\Delta R_t + c_t + \varepsilon_t, \tag{9}$$

where ΔE_t denotes the marginal change of greenhouse gas emissions from electricity generation in period t, and ΔD_t and ΔR_t denote the marginal changes of electricity demand and wind generation in period t, respectively. c_t is a constant representing other system effects, and, in my case, I use hourly dummy variables as a proxy for c_t. Subsequently, a represents the marginal emissions of electricity generation.

I adopt a seemingly unrelated regression (SUR) model to estimate specification (9), which will contain three regression equations, each representing pre-peak, peak, and post-peak periods. I use SUR instead of separately estimating each equation because SUR allows error terms across equations to be correlated, and in such cases, the standard OLS is generally not as efficient as the SUR method.

The regression results are reported in Table A.14, which illustrates that the marginal emissions in peak periods are lower than non-peak periods. Subsequently, I use the regression results to estimate the value of saved emissions, assuming the social cost of carbon to be £60/tCO_2, equivalent to the EU allowance price in mid-2021. Notably, the GB carbon prices are included in the wholesale cost of electricity generation. If one considers the carbon price of £10/tCO_2 in 2013 as the social cost of carbon, there is no need to estimate the value of saved emissions because in that case, the social cost of carbon is already included in the wholesale price of electricity generation, which is used to estimate the value of saved energy from dynamic tariffs. However, if one argues that the carbon prices in 2013 seriously underestimates the social cost of carbon as I do, then it would be necessary to estimate the value of saved emissions using a much higher value for the social cost of carbon. In my case, I assume the social cost of carbon to be £60/tCO_2. Hence, to estimate the value of saved emissions, I first calculate the difference in emissions between dynamic and flat tariffs and then multiply the difference by £50/tCO_2, which is the difference between the social cost of carbon and the carbon prices that GB implemented in 2013.

For example, in Scenario 3, the pre-peak, peak, and post-peak consumption of a representative household were 0.477 MWh, 0.616 MWh, and 0.587 MWh, respectively. Subsequently, the total emissions were 0.477×0.407+0.616×0.372+0.587×0.469=0.699. Under the flat tariff, the total emissions were 0.695; hence, the value of the total saved emission is negligible at £−0.20/household/year (in Table 5 it is −0.18 due to rounding).

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