



Investigating UK consumers' heterogeneous engagement in demand-side response

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Received: 31 October 2018 / Accepted: 30 January 2020
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Abstract Demand-side response (DSR), the incentivised time-shifting of energy use by consumers away from peak times, is regarded as a potentially effective measure to balance electricity supply and demand. This will be even more important in the low-carbon energy system of the future, with a high share of non-dispatchable power, such as variable renewable energy and nuclear power. Most DSR programmes require consumers' active engagement in shifting end-use activities. Previous studies have, however, rarely revealed socio-demographic factors influential for consumers' willingness-to-shift specific end-use activities. This study thus aims to fill this research gap and, using a multinomial logistic model to analyse a nationwide survey, identify factors influential for DSR-related decisions. The

nationwide survey for 1004 respondents was carried out to collect data about consumers' willingness-to-shift their daily activities. We focused on the activities that constitute the major part of domestic energy consumption, i.e. cooking, dish-washing, entertainment, heating, laundry and showering. According to the results, consumers' original timing of the end-use activities, socio-demographic factors, ownership of specific appliances and level of concern for energy-saving are influential for their willingness-to-shift activities. These findings can not only help policymakers make more targeted DSR promotion plans but also help to improve broader modelling tools to better consider consumers' willingness-to-shift their demand.

Keywords Flexibility · Demand response · Consumer behaviour · Multinomial logistic model

Highlights

- Consumers' willingness-to-shift demand was explored using multinomial logistic models.
- Focus was on the willingness-to-shift various energy using activities to two off-peak periods.
- The timing of consumers' end-use activities consistently influences their choices.
- Socio-demographic factors strongly affect consumers' willingness-to-shift activities.
- Ownership of appliances also significantly influences consumers' decisions.

Introduction

The UK has set in the UK Climate Change Act (HM Government 2008) an ambitious, legally binding target to reduce greenhouse gases (GHGs) emissions to at least 80% below 1990 levels by 2050. To achieve the requisite emission reductions, the whole energy system needs to be dramatically transformed over the coming decades.

As the electricity generation sector is one of the major sources of GHG emissions, accounting for 25% of total emissions in 2016 (BEIS 2018a), it should be largely decarbonised through the adaptation of low-carbon power production technologies. In fact, it's estimated

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that the carbon intensity of the power sector needs to drop below 100 gCO₂/kWh by 2030, followed by full decarbonisation by 2050 (CCC 2015). A combination of low-carbon technologies, such as nuclear, renewable energy and thermal power plants with CCS, therefore needs to be deployed at scale. Given the recent cost reductions for renewables, such as wind turbines and solar photovoltaic (PV) (IEA 2017), the share of these intermittent generation sources is likely to keep increasing. According to estimates, the capacity of such variable renewable energy (VRE) sources could increase to 89 GW, providing about 46% of total electricity generation by 2050 (National Grid 2017). However, high share of variable renewable energy poses challenges to a balanced electricity system, due to their intermittent nature of the production. For instance, an unexpected, sharp increase in wind speed over a short period of time could lead to a surplus of electricity; an unpredicted, sudden drop of wind speed at another period in time could cause a supply deficit.

The system balance challenge can become even more demanding due to the expected high level of electrification in the end-use sectors. Electrification is generally seen as a way to decarbonise many of the sectors (e.g. space heating, hot water and transport) that currently mostly rely on energy vectors other than electricity. According to estimates (CCC 2015; Usher and Strachan 2010), the level of electricity consumption in 2050 could be 50% to 135% higher than the current level. Installation of heat pumps could increase to 16.7 million units (National Grid 2017), or approximately 49% of households, by 2050. Similarly, electrification could play a substantial role in the transport sector (CCC 2015), with up to 25 million electric vehicles (EVs) deployed to replace conventional passenger vehicles by 2050, together consuming 35 TWh/year of electricity (National Grid 2017). Increasing electrification in the end-use sectors could lead to higher fluctuations (the difference between peak and average demand) in the daily demand profile. Consequently, this further increases the challenge of moving from dispatchable generation to more intermittent, or less responsive, generation. Dispatchable plants, such as gas-fired power plants, and storage systems can be deployed to balance electricity supply and demand across time periods, in order to cope with the intermittency. However, these technologies are either carbon-intensive or, for the time being, costly (Deane et al. 2015; Teng et al. 2016).

Demand-side response (DSR), also known as demand response, from the end-use sectors is regarded as a promising, additional mechanism to balance the electricity system (Bradley et al. 2013; Cappers et al. 2012; Grünewald et al. 2014; Strbac 2008; Strbac et al. 2015). Both time-based and incentive-based DSR programmes (Parrish et al. 2019) can contribute to system balancing by shifting or shedding loads to match with the electricity supply profile (Cappers et al. 2012). However, as suggested by Cappers et al. (2012), DSR programmes with time-based retail rates might have less potential as the granularity in the prices of these programmes is usually not sufficient to affect consumers' electricity consumption to reflect detailed system conditions. For example, time-of-use (TOU) pricing, critical peak pricing (CPP) and critical peak rebate (CPR) only have a limited number of time-differentiated prices fixed for specific blocks of hours in a day. Real-time pricing (RTP), which allows the price to differ on an hourly level, can be more effective in changing consumers' behaviours based on the system conditions in place. On the other hand, incentive-based programmes that reward consumers for their willingness to alter their consumption in response to system events could have a significant potential to accommodate higher shares of VRE. For example, direct load control (DLC) programmes can control appliances, such as air conditioners and water heaters, via smart grid automatically, without consumers' direct interventions.

For time- and incentive-based programmes, both consumers' participation and engagement play a central role in influencing the potential of these programmes for integrating higher shares of VRE. Time-based schemes, such as TOU, require consumers to adjust their energy consumption behaviour in response to pricing signals. The potential of the incentive-based schemes, such as DLC, heavily depends on consumers' acceptance of the interruptions to their daily routines (Cappers et al. 2012; Parrish et al. 2019). Consumers are cautious about losing control over appliances and comfort, and would thus prefer to have the right to override smart control of appliances (Fell et al. 2015; Lopes et al. 2016; M. Nicolson et al. 2017; Xu et al. 2018). On the other hand, it has also been noted that recruitment approach (opt-in and opt-out) influences consumers' willingness to engage in DSR schemes. A higher average response to various DSR schemes has been observed when consumers participated in DSR schemes on their own initiative (opt-in recruitment), in comparison to cases in

which consumers were automatically enrolled in DSR schemes, with a possibility to opt-out (opt-out recruitment) (Parrish et al. 2019). For example, Power System Engineering (2012) ran a critical peak pricing (CPP) pilot test on different consumer groups in the USA to investigate their responses to CPP rates. The test found the opt-in group had on average 12% deeper demand reduction than the opt-out group did. Similarly, in another test carried out in CA, USA (Potter et al. 2014), opt-in customers also had higher average demand reduction rates than opt-out customers, for both CPP and TOU pricing signals (with 12% and 7% more, respectively). Moreover, opt-in recruitment can sometimes result in higher aggregate peak load reduction than opt-out recruitment, even when the former has a lower enrolment rate (Ida and Wang 2015). Therefore, understanding consumers' heterogeneous engagement with DSR programmes is crucial for policymakers and utilities, so that they can target their DSR promotion schemes especially towards those who are most likely to engage with it and help increase system flexibility effectively in the early stage (Faruqui and George 2005).

There have been numerous studies aiming to explore consumers' engagement in DSR programmes. Most of them focused on consumers' aggregated reactions to pricing signals, such as static TOU tariff or dynamic pricing, but did not consider the possible influences of numerous socio-demographic factors (Asadinejad et al. 2018; Roldán Fernández et al. 2017). It has, however, been suggested that, in addition to financial incentives, socio-demographic backgrounds might also play a crucial role in consumers' decisions to participate in DSR (He et al. 2012; Horne and Kennedy 2017; Xu et al. 2018). There are, however, currently only a limited number of studies exploring consumers' heterogeneous acceptance of DSR based on their socio-demographic characteristics. Moreover, those few studies that did consider socio-demographic elements all focused on aggregate use of electricity alone and did not assess the willingness to adjust specific domestic end-use activities, such as cooking and heating, as a function of the socio-demographic indicators (Fell et al. 2015; M. Nicolson et al. 2017; Xu et al. 2018). As consumers' acceptance of DSR programmes could vary dramatically for different end-use activities (Carmichael et al. 2014; Li et al. 2017), the estimation of future benefits of DSR in system balancing based on aggregated engagement with DSR (Teng et al. 2016) could be misleading. Moreover, the lack of understanding of

consumer behaviour and the capacity to adjust end-use activity has also been suggested to be a significant barrier to the design and deployment of effective DSR programmes (Gyamfi et al. 2013).

The UK residential sector can, in principle, provide substantial potential for DSR, accounting for about 30% of total final energy consumption and 36% of total electricity consumption (108 TWh) in 2016 (BEIS 2018b). Cooking, dish-washing, entertainment (e.g. watching TV), heating, laundry and showering are the major drivers of energy use in the sector, as is shown in Fig. 1. Natural gas accounted for about 76% of fuels used for heating, but heat decarbonisation in the future is expected to increase the share of electricity use.

This study aims to use a nationwide survey to explore the influential factors for consumers' willingness-to-shift loads for a set of domestic end-use activities. We will focus on the six end-use activities listed above and will use multinomial logistic models (MNLMS) to explore the impact of a wide range of factors on consumers' willingness-to-shift the six end-use activities to two off-peak periods, namely late night (20:01~0:00) and early morning (0:01~7:00) periods, when the electricity consumption is lower according to the historical electricity demand profile, with the lowest consumption in the early morning (Gavin 2014). Besides providing information on the determinants of consumers' acceptance, or non-acceptance, of DSR, the developed MNLMS can also be further incorporated in other modelling frameworks, such as agent-based models, to better reflect consumers' heterogeneous engagement with DSR programmes. However, it should be noted that various DSR designs are not taken into account in this study; we only focus on the general willingness to engage with DSR.

The paper is structured as follows: the "Literature review" section reviews literature on consumers' reactions to DSR measures. The "Methodology" section describes the methodology and the nationwide survey on consumers' willingness-to-shift, if lower energy prices or a flexible device is available, and the multinomial logistic model applied to explore the influential factors for consumers' decisions. The results, i.e. the identified influential factors for the six end-use activities and the implications of the findings on shifting demands, are then discussed in the "Results and discussion" section. Finally, the "Conclusions and policy implications" section draws out the main conclusions from the study.

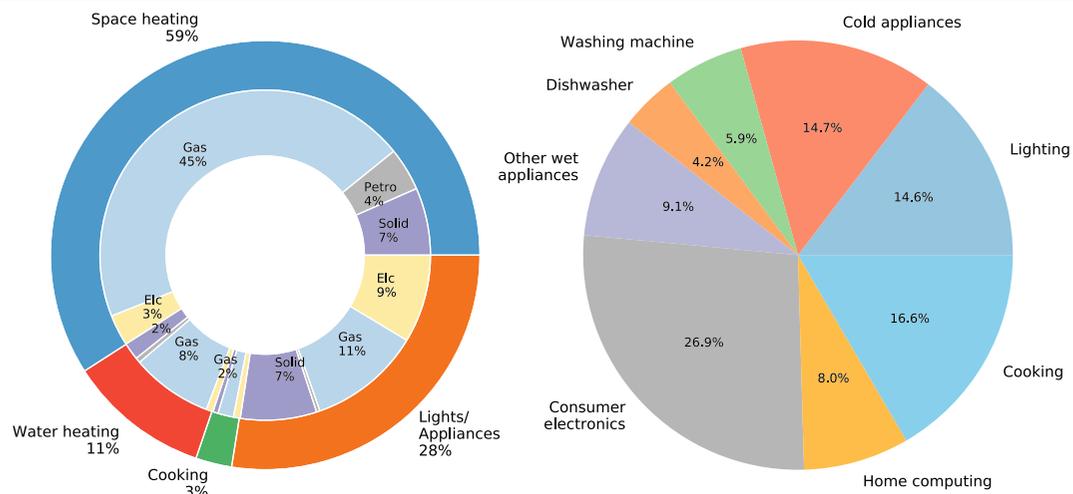


Fig. 1 Domestic energy consumption by energy use and fuel type and electricity consumption by domestic appliances (excluding heating technologies) in 2016 (BEIS 2018b)

Literature review

During the past few years, DSR has been identified as a promising measure for, among others, providing system flexibility to reduce electricity demand, shifting peak demand, providing reserve capacity for unforeseen events, balancing electricity supply and demand and reducing congestion of the network and thus avoiding additional investments in new plants and network reinforcements (Bradley et al. 2013; Strbac 2008). As a result, there are numerous studies focusing on consumers' reactions to pricing rates of various DSR schemes, such as static TOU, dynamic TOU and DLC (Asadinejad et al. 2018; Bradley et al. 2016; D'hulst et al. 2015; Faruqui and George 2005; Roldán Fernández et al. 2017; Thorsnes et al. 2012). For instance, BC Hydro's residential TOU/CPP pilot study in British Columbia found that higher price ratio between peak and off-peak rates increased customers' reduction of energy use (Woo et al. 2013).

The influence of non-monetary factors on customers' aggregate engagement with DSR has also been explored in previous studies. As suggested by Parrish et al. (2019), consumers' engagement might be affected by enabling technologies, such as in-home displays, ownership of specific appliances, recruitment measure and level of commitment from the organisers of the scheme. For example, Hydro One's trial on TOU in Toronto, Canada, showed that customers with in-home displays reduced their energy use 1.8% more than those without displays (Hydro

One 2008). Xcel Energy (Faruqui and Sergici 2010) carried out a CPP trial in CO, USA, and found that peak load reduced 6.4% more when an autonomous control technology was offered to customers. California's state-wide CPP pilot trial revealed that customers who owned air conditioners reduced 8.4% more load in peak periods than those who did not own air conditioners (Faruqui and George 2005).

However, previous studies mostly did not investigate how consumers' heterogeneous engagement with DSR is correlated with their socio-demographic characteristics, even though understanding the various responses among different social groups of consumers can be useful from both policy and marketing perspectives (Faruqui and George 2005). The few identified studies that did do this are reviewed as follows.

Some studies on DSR programmes considered how social group membership affects engagement with DSR programmes, but did not differentiate between the various end-use activities. For instance, Ipsos MORI (2012) used an online survey to interview 602 UK respondents who had adopted static TOU programmes about their characteristics and attitudes towards the tariffs. The survey found that middle-aged consumers with higher income were more likely to participate in the static TOU programmes. These participants were also more likely to live in specific geographic regions, such as South East, East Midlands and Eastern regions in England. However, acceptance of load-shifting in terms of various, specific appliances across different social groups was not investigated.

Other studies investigated consumers' heterogeneous engagements with DSR trials, exploring the influence of generally only a limited number of socio-demographic characteristics and not differentiating between the different end-use activities. Carmichael et al. (2014) investigated the responses of 1119 London residents, divided into 17 different social groups (reflecting a handful of socio-demographic attributes, such as wealth, living area and race), to low and high price signals in a dynamic TOU trial. The acceptance of the dynamic TOU was found to be generally fairly strong, with an in-home display showing the energy price found the most useful measure to help consumers react to the dynamic TOU. Consumers with higher incomes or more family members were also found to be more responsive to the programme. Potter et al. (2014) carried out DSR trials in a municipal district in CA, USA, for 2 years, in order to explore the impacts of various pricing schemes (including CPP and static TOU), recruitment approaches (opt-in and opt-out) and in-home display on customers' energy use. However, customers' socio-demographic characteristics were not taken into account. Opt-in customers had a higher average load reduction than opt-out customers, while low-income customers were found to be more likely to opt in the trial and less likely to drop out. The customers with lower income level were, however, also less willing to shift consumption from peak to off-peak period under both pricing plans. None of the studies reviewed here considered participants' responses in terms of different end-use activities.

Online surveys are the most often adopted approach for exploring consumers' heterogeneous engagement with DSR. Even though respondents' stated preferences could be different from their revealed preferences, this approach is seen as an efficient way to investigate consumers' possible behaviours (Helveston et al. 2018). Moreover, unlike participants of DSR trials who opt in, respondents of an online survey are more likely to represent the general public as a whole, as they have not been screened by DSR recruitment mechanisms. Some studies using online surveys are reviewed as follows.

For example, Mert et al. (2008) conducted online surveys in five EU countries (Austria, Germany, Italy, Slovenia, and the UK), in order to better understand consumers' appliance specific acceptance of load-shifting (washing machine, tumble drier, dishwasher, air conditioner, refrigerator, electric water heater, electric space heater and heat pump were considered). It was found that the acceptance of smart operation of appliances was heterogeneous across the countries, e.g.

respondents in Slovenia had a higher willingness to accept smart control of space heating while the UK respondents were more likely to accept smart control of heat pumps. Consumers' acceptance of load-shifting by their socio-demographic characteristics within these countries was not considered, however.

Denski et al. (2013), in turn, carried out a nationwide online survey to investigate UK public's stated acceptance of various remote control strategies related to their electricity use. Autonomous turn-off of standby digital boxes, TVs and computers had the highest acceptance, while about half of respondents also accepted remote control of their washing machines and showers. Fewer respondents, about 30%, were willing to accept remote control of their boilers and fridges. Again, the impact of socio-demographic characteristics was not considered in the study.

Oseni et al. (2013) used an online survey to investigate UK consumers' stated attitudes towards three scenarios of shifting, through smart appliances and dynamic supplier intervention, the energy use of cold appliances, wet appliances and cooking. Load shifting of cold appliances had the highest acceptance rate; whereas, respondents were less likely to accept the use for wet appliances (dishwashers and washing machines) to be interrupted. The diverse level of engagement among social groups of respondents—defined based on their gender, age and income—was also investigated. Only the influence of age was identified as significant by the study. Other major end-use activities, such as heating and showering, were not considered.

Using an online survey, Fell et al. (2015) explored the factors affecting UK consumers' willingness to adopt specific DRS programmes (static TOU tariff, static TOU with automated response to price changes, dynamic TOU, dynamic TOU with automated response to price changes and DLC). DLC was found acceptable in principle (within tight bounds and with override ability). Dynamic TOU with automated response to price changes and static TOU had a similar level of acceptance. Several socio-demographic factors, such as age and housing tenure, were included in a multiple linear regression to identify the relationship between respondents' acceptance of DSR programmes and the predictor variables, but no influential socio-demographic factors were revealed or discussed in the study. Instead, only the influences of perceived usefulness, perceived ease of use, spending control and general control were reported.

Nicolson et al. (2017) used a survey experiment to study UK consumers' willingness to switch to a 3-tiered

TOU tariff. Consumers' willingness was found to be influenced by loss-aversion, ownership of demand flexible appliances, age of the respondent, household lifestyle and household size. How consumers' willingness-to-shift depends on the original end-use time (e.g. morning, evening) and the specific end-use activity, such as heating and cloth-washing, was not examined in the study.

Li et al. (2017), in turn, explored, with the help of an online survey, users' willingness in the Netherlands to adopt smart appliances and to shift the use time of the appliances. Socio-demographic characteristics, dwelling characteristics, household energy use, familiarity with smart technologies and energy attitude were taken into account in a linear regression formulation, to identify the consumers' heterogeneous willingness to change their end-use behaviours. These behaviours included the use of smart technologies, postponing the start times of appliances, turning off heating or air-conditioning and lowering the indoor temperature. Willingness-to-shift other major end-use activities, such as cooking, cloth-washing and showering, was not considered, neither was the influence of the original timing of the activities.

Horne and Kennedy (2017) conducted three online experiments to explore the influences of social norms, such as positive behaviour visible to others, on US consumers' willingness to reduce energy consumption and carbon emissions. Non-monetary strategies, such as normative pressure, were identified as efficient in influencing consumers' energy consumption behaviours. However, the considered socio-demographic factors, including political orientation, gender, age and education, were not found statistically significant in influencing consumers' decision on adopting smart technologies to shift end-use times.

Most recently, Xu et al. (2018) used an online survey to investigate US consumers' acceptance of DLC with and without financial incentives and an override option. The relationship between consumers' socio-demographic characteristics and their decisions was also explored. About half of the participants were found willing to accept DLC without any conditions, and the existence of an override option was found to increase acceptance by further 20%. Respondents who were younger, Democrats, non-Whites, had higher education levels, lived in larger dwellings and lived with more people were more likely to adopt DLC. The authors, however, only considered consumers' acceptance for the two DLC programmes to control air conditioners, but did not consider any other end-use activities.

Overall, a fairly limited range of socio-demographic characteristics, such as age, education level, ethics, political orientation, homeownership and dwelling characteristics, were considered in the previous studies. More importantly, consumers' heterogeneous willingness to change the time of major residential energy end-use activities, such as heating and cloth-washing, as a function of their socio-demographic characteristics has not been explored. Understanding better the potential for shifting various residential demands, and the acceptable timing for those shifts, is crucial for understanding the system flexibility that may be available to accommodate increasing share of VRE.

In view of the identified research gap, this study thus aims to consider a wider range of potentially influential factors, including the original end-use time for a specific activity, ownership of appliances and consumers' attitude towards energy-saving, into account to assess consumers' heterogeneous willingness-to-shift their end-use time of all major energy consumption activities. Consumers' choices of shifting to specific two off-peak periods, late night (20:01~0:00) and early morning (0:01~7:00), are explicitly considered.

Methodology

Nationwide survey

An existing nationwide survey (Xenitidou 2016) was adopted as it includes data about UK consumers' willingness-to-shift individual end-use activities, while simultaneously reporting on a wide range of respondents' socio-demographic attributes. The nationwide survey was conducted to collect respondents' choices about three shifting options, "would not shift," "shift to early morning (0:01~7:00)" and "shift to late night (20:01~0:00)". The survey was carried out in 2015 among UK adults aged 18–65 by a market research firm using an online questionnaire. Rim-weighting (Sharot 1986) was then used to correct any imbalances in the sample profile achieved during the survey. The variables that were weighted were age, gender, region, number of people in a household, education, income, working status and tenure (for more detailed information regarding the design of the survey, refer to Xenitidou (2016)).

The following question was presented to respondents for each of the six end-use activities, i.e. cooking, dish-

washing, entertainment, heating, cloth-washing and showering:

If there was a time in the day/night when the following activities could be done in a cheaper or more energy efficient way (e.g. flexible use option, ecological or economy programme or device, cheaper gas/electricity rate), would you shift the time in the day that the following activities are done in your home?

As specific DSR programme implementations and monetary measures were not included in the survey, the responses only reflect consumers' general willingness, or non-willingness, to shift their activities. In other words, we measure how consumers' choices are affected by their socio-demographic and other considered characteristics, but different price signals are outside the scope of our research.

Along with the question regarding willingness-to-shift, the questionnaire also comprised a long list of questions regarding respondents' original timing of activities, socio-demographic background, dwelling characteristics, ownership of appliances and eco-attitudes towards energy-saving. Up to 51 attributes were collected through the survey, as shown in Table 1. These attributes were then treated as potentially influential factors on respondents' willingness-to-shift. Only some attributes were regarded as continuous variables, e.g. number of residents and number of children in a household. The rest of the attributes were regarded as dummy variables, i.e. binary variables representing respondents' specific socio-demographic characteristics, such as being male or living in a detached house, in the analysis in which influential factors were identified. These attributes were taken into account because previous studies had suggested they might be influential for DSR or other consumer behaviour issues, such as heating technology choices (Decker and Menrad 2015; Michelsen and Madlener 2012).

Multinomial logistic model

This study applies an MNLM to investigate the factors affecting the choice of whether to shift energy use or not. An MNLM explains choice behaviour as a set of preferences where the consumer is assumed to choose the most preferred available outcome in order to maximise one's own utility (Ben-Akiva and Lerman 1985). MNLMs

have thus been adopted widely in many studies that investigate factors influencing consumers' choice of, for example, residential heating technologies and transport technologies (Byun et al. 2018; Decker and Menrad 2015; Hackbarth and Madlener 2013; Laureti and Secondi 2012; Lillemo et al. 2013; Michelsen and Madlener 2012; Rouvinen and Matero 2013; Ruokamo 2016; Scarpa and Willis 2010; Willis et al. 2011). The question regarding consumers' willingness-to-shift is also a choice problem, comprising, in our case, of three alternative options: not willing to shift, willing to shift to early morning (0:01~7:00) and willing to shift to late night (20:01~0:00). Even though there are other approaches, such as simple descriptive statistics (Demski et al. 2013; Tjørring et al. 2018) and ordinary least squares regression analysis (M. L. Nicolson et al. 2018), that have been applied in some previous studies, those approaches are not able to represent consumers' preferences for multiple options in parallel, in order to compare their choice preferences on the same statistical basis. Furthermore, the constructed MNLMs can estimate the probability of consumers' choices based on their multiple characteristics. Such models can then be used to evaluate DSR potential of a target group of consumers, in order to support policymaking. Therefore, the MNLM is adopted also in this study to explore consumers' preferences for demand-shifting of end-use activities.

The utility (U) for shift alternative i (i.e. no shift, shift to late evening, shift to early morning) for activity j (i.e. cooking, dish-washing, entertainment, heating, cloth-washing, showering) for individual n ($n = 1, 2, \dots, N$) can be expressed as follows:

$$U_{nij} = V_{nij} + \varepsilon_{nij} \quad (1)$$

V_{nij} is the systematic observable component or mean utility value of the alternative i for activity j for an individual n . ε_{nij} is the random error component associated with an alternative i for activity j for an individual n . The observable systematic utility, V_{nij} , is given by:

$$V_{nij} = \alpha_{ij} + \beta_{ijk} X_{nk} \quad (2)$$

where X_{nk} is a vector of the explanatory variables ($k = 1, 2, \dots, K$), such as consumer n 's age, household income, dwelling type and ownership of appliances, β_{ijk} is a vector of the unknown parameters associated with the explanatory variables X_{nk} and α_{ij} is the alternative-specific constant, which also reflects the average (system-specific) impacts of factors that are not observed and included in the model.

Table 1 Respondents' attributes collected from the survey

Category	Attribute
Time of use	Cooking, dish-washing, entertainment, heating, laundry, showering in 5 intraday periods, including 0:01~7:00, 7:01~9:00, 9:01~18:00, 18:01~20:00, 20:01~0:00
Socio-demographic	Gender, age range (younger than 17, 18~24, 25~34, 35~44, 45~54, 55~64, older than 65), regions (North East, North West, York and Humber, East Midlands, West Midlands, East of England, London, South East, South West, Wales, Scotland), number of residents*, number of children*, education level (GCSE or similar, A-levels, degree level, professional/work related, none), household income (less than 15,000, 15,000~29,999, 30,000~79,999, more than 80,000), employment status, work from home (yes/no, days*, hours*), pay bill
Dwelling characteristics	House type (detached, semi-detached, terraced, flat, studio), number of bedrooms*, ownership, house age*
Ownership of appliances/devices	Energy-efficient appliances, smart meter, CFL, LED, PV, heat pump, wood stove, wood pellet boiler, home insulation solution, dishwasher, vacuum cleaner, TV, home cinema audio system, DVD player, game console, audio system, computer, electric storage heater, central heating, space heater, continuous water heater, instantaneous water heater, tumble drier, washing machine, iron, shower, cooker, microwave, fridge, freezer
Eco-attitude	Level of concern for energy-saving*

Only those with * are continuous variables. The rest are dummy variables

The probability of consumer n 's choice of a specific shifting option m can be represented as follows:

$$P(y_{nj} = m | X_{nk}) = \frac{\exp(\beta_{ijk} X_{nk})}{\sum_{i=1}^3 \exp(\beta_{ijk} X_{nk})} \quad (3)$$

where y_{nj} is consumer n 's choice of willingness-to-shift for activity j . As there are three shifting options considered in this study for each activity j , the denominator thus comprises the summation of the exponential function for the three options.

The coefficients of the model and their significance were estimated using the PythonBiogeme package,

which uses maximum likelihood estimation to determine those coefficients (Ben-Akiva and Lerman 1985; Bierlaire 2016). The considered socio-demographic factors were introduced into the model sequentially as explanatory variables to investigate their significance in influencing consumers' choices. Only those statistically significant enough factors, whose p values¹ are less than 0.1, were retained and are discussed in the following sections. Changes of these statistically significant factors are likely to lead to changes in the prediction of respondents' willingness-to-shift. Therefore, these factors could be meaningful for understanding respondents' heterogeneous engagement with DSR.

Results and discussion

Respondents' end-use activities and overall willingness-to-shift

In total, 1004 respondents completed the survey, and the descriptive statistics of these respondents are given in Appendix 1. Compared to ONS (2017), the age and gender profile of the respondents is very similar to that of UK population. According to a standard statistical formula for sample size design suggested in Pani and Sahu (2019), the sample size of this study corresponds to a confidence level of 99%. The confidence level represents the percentage of replies that can reflect the opinions of the whole population. Moreover, the sample size also leads to a margin of error of about 4%, which is the percentage of error that could exist in the estimated parameters compared to real parameters. Both statistics are better than default statistical settings used for the sample size design (Raosoft Inc. 2004). Similar sample sizes have also been reported in other survey-based studies (Lillemo et al. 2013; Ruokamo 2016; Willis et al. 2011). The revealed relationship between consumers' characteristics and their shifting choices in this study is thus statistically meaningful.

The temporal distribution of the various end-use activities as obtained from the survey is shown in Fig. 2, to illustrate the contribution of individual activities to hourly residential energy consumption. This information,

¹ P values are measures to tell how likely it is the corresponding explanatory variables have a meaningful influence on the response variables. The lower the p value is, the higher the chance of the explanatory variable correlating with response variables is.

together with the identified willingness-to-shift that will be discussed in the following sections, will allow the potential for DSR to be evaluated based on consumers' characteristics. Percentage of respondents carrying out activities in the five time-slots (0:01~7:00, 7:01~9:00, 9:01~18:00, 18:01~20:00 and 20:01~0:00) is distributed evenly for each hour within each time-slot. It should be noted that each respondent might carry out a specific activity several times a day and do several activities during a specific time-slot, which means the summation of the percentages of respondents over all time-slots for an activity, or over a specific time-slot for all activities, can both be larger than 100%. Since the magnitude of the y -axis represents the percentage of respondents, the profile of activities only illustrates the frequency of activities in each time-slot, rather than the amount of energy consumed. Cooking takes place more frequently both during the morning (7:01~9:00) and the evening (18:01~20:00) peaks. Dish-washing follows a similar trend as that of cooking. Entertainment (e.g. watching TV), on the other hand, happens mostly in later time-slots, such as 18:01~20:00 and 20:01~24:00. Finally, heating, laundry and showering all have two peaks: one in the morning (7:01~9:00) and another one in the evening (18:01~20:00). Overall, activities are generally taken less often in early morning (0:01~7:00). These results are consistent with those found by Torriti (2017).

The timings of individual activities are correlated to each other, as the correlation coefficient matrix in Appendix 2 shows. This suggests that respondents can have specific combinations of how the end-use activities are timed. Also, it is often found that the timing of an activity also influences the likelihood of performing that same activity at another point during the day. For example, statistically speaking, when one cooks during daytime (9:01~18:00), it is less likely that one would cook during the evening peak (18:01~20:00). For laundry and showering, this applies for all time-slots, i.e. once the activity is taken in a specific time-slot, it's less likely to be carried out in any other time-slot. Moreover, some activities are likely to happen together. For instance, cooking time has a positive correlation with dish-washing during the same time-slot, implying that these two activities often occur side-by-side (as opposed to, for example, one happening after the other). Results also suggest that a respondent who cooks during the evening peak (18:01~20:00) also has a higher chance to watch TV during the evening peak (18:01~20:00) and night (20:01~0:00) than a respondent who cooked at a different time.

The overall willingness-to-shift for the six end-use activities is presented in Fig. 3. Cooking, entertainment, heating and showering are the least likely to be shifted, with, depending on the specific activity, 73–88% of respondents not willing to shift. Dish-washing and laundry, in turn, are the two activities that respondents are more willing to shift; 45% would be willing to shift the timing of their dish-washing and 58% the timing of laundry. The high willingness to change dish-washing and laundry time is in line with the findings in previous studies (Carmichael et al. 2014; Li et al. 2017; Power System Engineering 2012; Smale et al. 2017). In general, respondents tend to shift the end-use time to late night (20:01~0:00) rather than early morning (0:01~7:00) to avoid noises from the operation of appliances (Carmichael et al. 2014; Friis and Haunstrup Christensen 2016).

Multinomial logistic models

Six MNLMs were constructed to identify influential factors for respondents' willingness-to-shift the timing of the six activities. The overview for the importance of specific factor groups in influencing respondents' willingness-to-shift end-use activities is shown in Table 2, with the colour of the circles reflecting the number of individual influencing factors (darker circles equals a higher share of all factors in the group being influential). This table is used to summarise how influential the different factor groups are for each of the end-use activities. The underlying, more disaggregated individual factors are then discussed further in the following sections.

The coefficients of the identified influential factors in six MNLMs, one for each specific activity, have also been compiled into Table 6 in Appendix 4 for cross comparison. The definitions of the variables shown in Table 6 can be found in Appendix 3. Each end-use activity, such as cooking and dish-washing, has its own MNLM, with coefficients representing the influences of the corresponding variables on respondents' choices of shifting (including no shift, to 0:01~7:00 (early morning) and to 20:01~0:00 (late evening)). A positive coefficient in the table implies the corresponding variable increases respondents' tendency of choosing the corresponding shifting option; a negative coefficient suggests the opposite. For variables represented by binary variables (e.g. male vs female), the larger the coefficients, the higher the influences the corresponding variables have on respondents' decisions. For example, the positive coefficient 0.39 for variable male in the

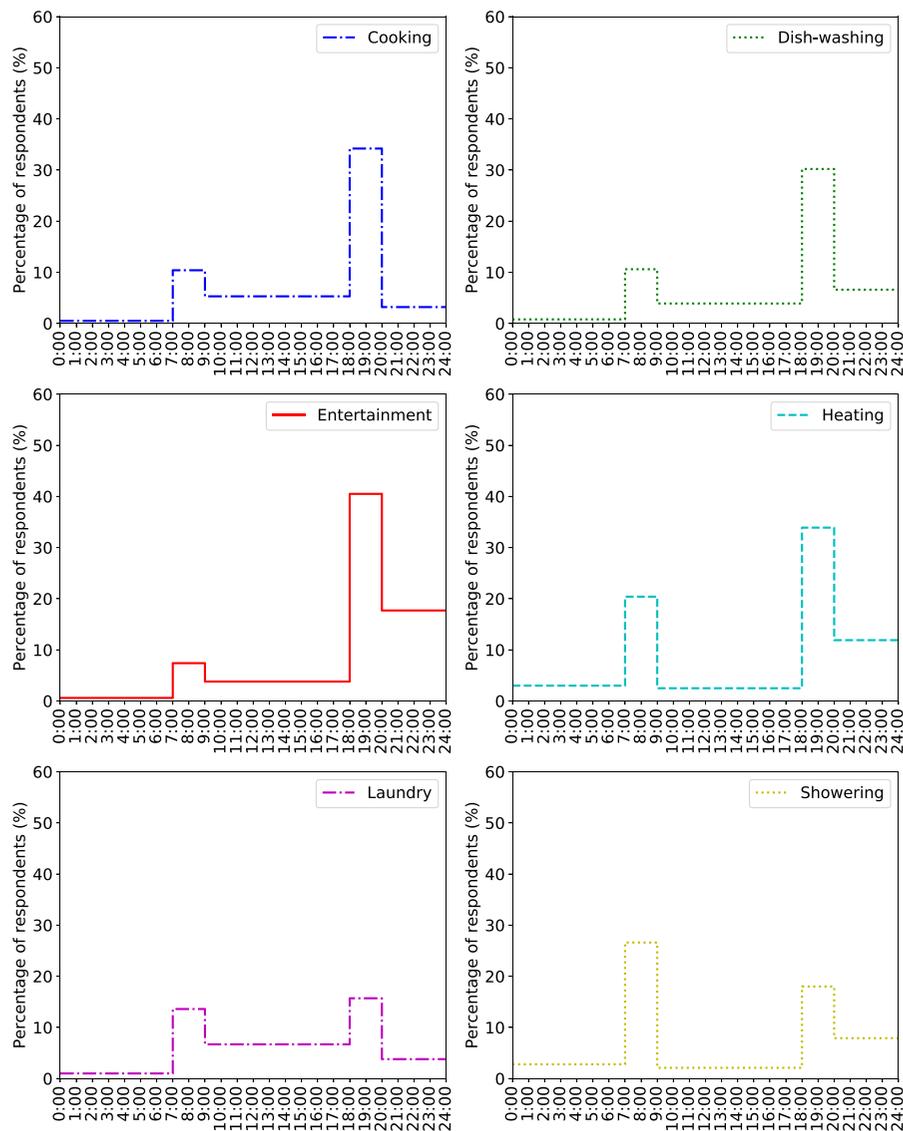


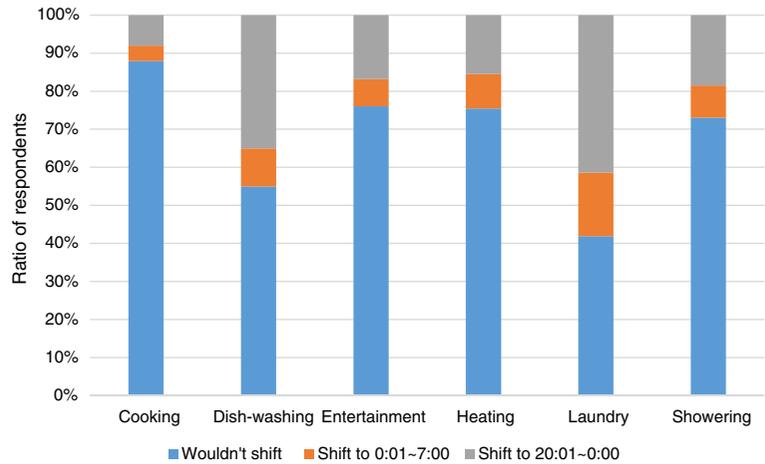
Fig. 2 Temporal distribution of domestic energy consumption activities

column indicating the choice of switching “to 20:01–0:00” for cooking activity suggests that male respondents agree to shift cooking to late evening more often than women do. For the continuous variables, such as the number of residents or house age, the influence is evaluated by multiplying the coefficients with the variable values. For example, as shown in Table 6 in Appendix 4, living in a house with 5 bedrooms (variable “No. of bedrooms”) increases the likelihood to shift dish-washing time to the early morning more than doing cooking in the early morning does, as their coefficients are 0.306 and 1.08 respectively (variables “No. of bedrooms” and CK0to7). Finally, the variables with no

coefficients reported in the table are not influential for the specific activity and are discarded from the MNLM. For example, living in London does not affect the likelihood for shifting cooking in any way.

Overall, the current timing of activities is consistently found influential on respondents’ willingness-to-shift. More importantly, the original timing of an activity not only affects the general willingness-to-shift the activity, but also the original timings of the other activities often play a role. Furthermore, respondents’ age also shows substantial correlations with their shifting tendency for most of end-use activities, e.g. older respondents were often found less likely to be willing to shift their usual

Fig. 3 Willingness-to-shift of domestic energy consumption activities



timings of activities. Likewise, the ownership of appliances and devices is also identified as strong explanatory factors on respondents' decisions, even in cases when the specific appliance is not directly linked to the activity (e.g. respondents who own washing machines have lower intention to shift the timing of dish-washing). Strong influences of respondents' eco-attitudes on predicting respondents' willingness-to-shift were identified, but are limited to dish-washing, entertainment and laundry. Finally, consumers' other socio-demographic attributes,

such as gender and education level, can also affect their willingness-to-shift for certain activities, e.g. house type is particularly influential for heating. The identified influential factors for each end-use activity are discussed in more detail in the following sections.

End-use time

Timing of the end-use activities was consistently found to be an influential factor on consumers' willingness-to-

Table 2 Importance of variable groups in influencing respondents' shifting choices for six end-use activities

Variable group	Cooking	Dish-washing	Entertainment	Heating	Laundry	Showering
End-use time	●	●	●	●	●	●
Gender					●	
Age	○	●	●	●	●	●
Region of the UK	○	○	●	○	○	●
Education level	○	●	○	○	●	○
No. of residents				●		●
Household income		○		●		
Work from home					●	●
Bill payer	●					
House type			●	●	○	
House ownership					●	
No. of bedrooms		●			●	
Ownership of appliances	●	●	●		●	○
Eco-attitude		●	●		●	○

●: high relevance; ●: medium relevance; ○: low relevance

shift the activities. The timing of an activity can be influential for the willingness-to-shift the same activity—or another activity. As an example for the former, consumers are more likely to shift their end-use activity, if they originally carried out the specific activity in the time-slot right before or after the new time-slot. Dish-washing, laundry and showering belong to this category; respondents who wash dishes in the morning (7:01~9:00) or the evening (18:01~20:00) peak were more willing to shift dish-washing to a little earlier (0:01~7:00) or later (20:01~0:00). The same applies to doing the laundry. This suggests that respondents would be more likely to change end-use time if the changes are not very large and the new timing of the end-use activity remains close to the original slot. According to our results, this is especially the case for dish-washing, laundry and showering.

In contrast, for some activities, respondents would clearly prefer to keep activities at their original slots. This is especially evident for the respondents who heat their homes between 7:01 and 20:00 (and even more clearly, 9:01~18:00). The same applies to the respondents who shower in the morning (7:01~9:00), as also shown in Table 6 in Appendix 4.

As noted, significant correlations also exist between the timings of different activities. For example, the timing of respondents' cooking and showering has clear relationships with consumers' willingness-to-shift other activities. Dish-washing, for example, is more likely to be shifted after or to the same time-slot as cooking time, as the coefficient of variable CK0to7 (cooking in the early morning) for the choice of shifting dish-washing to early morning is positive (1.08). A range of similar dynamics can be observed, for example, for laundry and showering (showering preferred to be shifted to the period before laundry) and laundry and entertainment (entertainment preferred to be shifted to the period after laundry). While some of these, such as the connection between cooking and dish-washing, appear understandable, others are less obvious, might reflect some other underlying characteristics and would require further research.

Finally, activities taking place in daytime (9:01~18:00) have been found to increase the likelihood of consumers being unwilling to shift their activities. For example, respondents who cook during daytime (9:01~18:00) are less likely to be willing to shift their timing for dish-washing, laundry and showering. This could be due to those activities being also carried out in the daytime (9:01~18:00), as cooking does (see the correlation coefficient matrix in

Appendix 2). Timings of heating and showering have similar influences, as heating houses during the daytime increases respondents' unwillingness-to-shift their cooking time, as does showering for dish-washing and laundry.

Socio-demographic factors

A wide range of significant socio-demographic factors has also been identified and discussed as follows.

i. Age

Age of respondents is found to be very relevant to their willingness-to-shift, as is shown in Table 6 in Appendix 4. The respondents who are older than 55 are more likely to express their unwillingness-to-shift any of the six activities. Furthermore, respondents aged between 45 and 54 are also identified to be less willing to shift certain activities. Conversely, being younger than 44 increases the likelihood to be willing to shift various end-use activities (dish-washing, heating, laundry and showering). The influences of age on respondents' switching choices are also shown in Fig. 4. The varying, age-dependent willingness-to-shift activities has also been confirmed by other studies (Li et al. 2017; Xu et al. 2018). Nicolson et al. (2017) did find that UK consumers older than 65 would be more likely to switch to smart TOU tariff, but as our study did not consider that age group, our findings do not contradict those of Nicolson et al. (2017) either. As elderly consumers are more vulnerable to cold weather (Alexander 2010; Gyamfi et al. 2013), one could speculate that they might be less willing to shift heating due to health-related concerns.

ii. Gender

In the previous survey-based studies, gender has not been found influential on consumers' engagement with DSR (Mert et al. 2008; Oseni et al. 2013), but this could be due to considering the end-use activities in a more aggregated manner, rather than individually. When individual appliances are taken into account, the differences of willingness-to-shift between male and female respondents were found in a DSR trial (Tjørring et al. 2018).

This study found that male respondents were more likely to shift their cooking and heating time than their female counterparts (for laundry, this is reversed), as

shown in both Table 6 in Appendix 4 and Fig. 5. For example, male respondents were found more likely to shift their cooking and heating time to late night (20:01~0:00) and early morning (0:01~7:00) respectively. About 10% more of the male respondents showed their unwillingness-to-shift their laundry time than their female counterparts did.

The lower willingness-to-shift laundry shown by male respondents has also been confirmed by Tjørring et al. (2018), who reported female respondents were more likely to respond to pricing signals by shifting laundry time in a dynamic TOU trial in Denmark. Due to other activities linked to laundry, such as hanging up clothes, the involved series of activities thus lowers the ease of shifting laundry time (Tjørring et al. 2018).

iii. Geographic region

According to the influential geographic variables in the MNLMs, as shown in Table 6 in Appendix 4, the geographical regions of the UK in which the respondents reside also affect consumers' views on shifting their activities. Respondents from North East, North West, West Midlands and London expressed a higher willingness-to-shift activities. For example, respondents from London are more likely to shift their dish-washing and showering time to the early morning (0:01~7:00) and respondents from York and Humber are more likely to shift heating time to the early morning (0:01~7:00). Furthermore, those from North East and North West expressed higher willingness-to-shift their showering time to the early morning (0:01~7:00).

The existing participants of static TOU programmes in the UK are mostly from East Midlands, West Midlands, East of England and the South East (Ipsos MORI 2012). In view of the identified higher willingness-to-shift of respondents from other regions, there might be potential to promote DSR programmes in those regions further.

iv. Education

Education qualification has also been identified as influential, but no clear tendency can be identified, as shown in Table 6 in Appendix 4 and Fig. 6. For example, respondents with a degree-level education (higher education qualification) are more likely to shift their timing of cooking and laundry but not their showering time. Those with professional/work-related qualifications, in turn, are more willing to shift their dish-washing and

entertainment time to the early morning. The influences of education qualification have also suggested in the previous studies (Faruqui and George 2005; Xu et al. 2018), which concluded consumers with higher education qualification are more willing to engage in DSR programmes. Our study, in turn, suggests that the willingness-to-shift of higher educated respondents was more heterogeneous across the various activities.

v. Household size

Furthermore, respondents from households with a higher number of occupants have a higher willingness-to-shift their cooking, heating and showering time. Higher occupancy and higher electricity consumption in these households might motivate the respondents to be more flexible, as households with higher baseline electrical demand usually have larger responses in DSR programmes (Parrish et al. 2019). For example, respondents were more willing to shift their showering time to the late night (20:01~0:00), if a higher number of occupants lived in the house. Also, respondents living in homes with more bedrooms have shown a higher willingness-to-shift their dish-washing and laundry time. Since the number of bedrooms is highly correlated to household size (DCLG 2015), this could also imply those households with more residents might also tend to shift their dish-washing and laundry time.

Similar findings have also been reported in previous studies. An online survey in the USA showed that respondents who were more likely to adopt DLC programmes without any financial incentive or override option usually had a larger household size (Xu et al. 2018). Furthermore, higher responsiveness of larger households to pricing signals has also been reported in a dynamic TOU trial in the UK (Carmichael et al. 2014).

vi. Household income

Household income was also found to be influential for respondents' willingness-to-shift, as is shown in Table 6 in Appendix 4. Respondents with lower household incomes are more likely to consider shifting the timing for heating. For example, those earning less than 15,000 GBP/year were more likely to shift heating time to the early morning (0:01~7:00), as were, to a lesser extent, those with incomes between 15,000 and 29,999

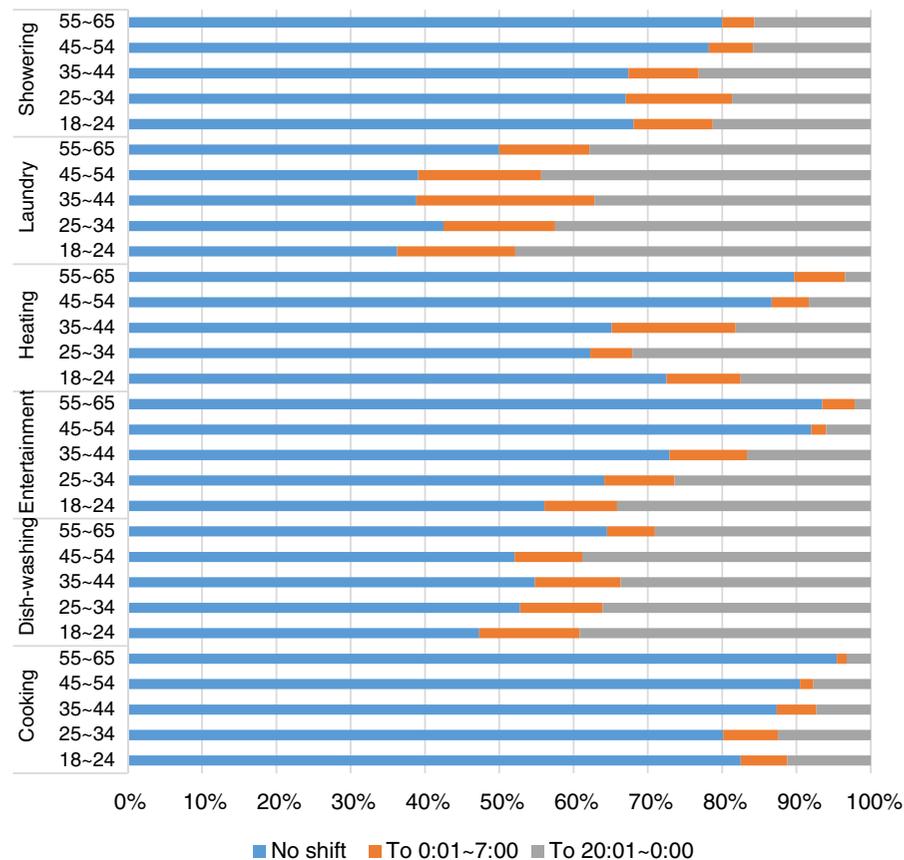


Fig. 4 Respondents' shifting choice against age for six end-use activities

GBP/year. The higher willingness-to-shift heating is also illustrated in Fig. 7. In contrast, the figure further reveals that respondents with the highest income level showed their higher willingness-to-shift timing of other activities, such as dish-washing and laundry.

Gyamfi et al. (2013) have suggested the lower income households are more responsive to a higher price and thus more likely to reduce energy consumption during peak load events. Low-income households might not have the capacity to pay the high peak prices (Alexander 2010), leading to stronger engagement. Our results suggest that the responsiveness is, however, also a function of the specific activity to which the energy consumption is related, with lower income households being more responsive to shift certain activities and high-income households others.

vii. Working from home

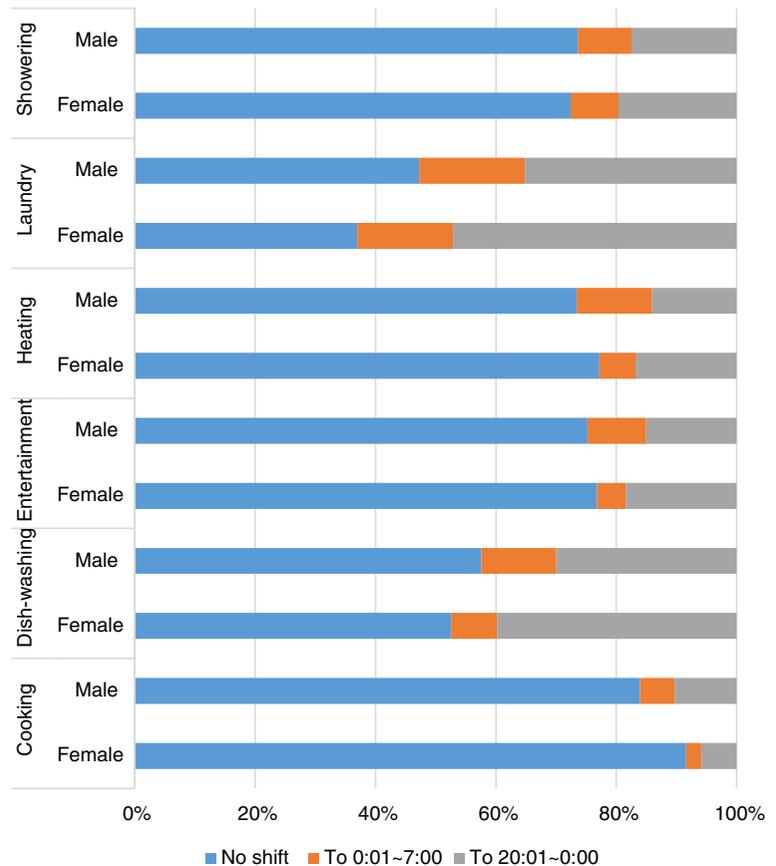
Finally, working from home has not often been recognised as an influential factor on consumers'

decisions to shift the timing of activities. According to the survey, respondents who worked from home were already more likely to carry out these activities during the off-peak time-slots (e.g. 20:01~0:00 and 0:01~7:00) and are therefore unable to shift those activities to these slots. Showering is the only activity that might be positively influenced by this working arrangement. However, those who work from home have also been found less likely to shift their usual laundry time as they already wash clothes more frequently in the late night (20:01~0:00) and early morning (0:01~7:00). Therefore, according to this finding, the change of working arrangement, i.e. working from home more frequently, might not be a crucial factor for demand flexibility.

Dwelling type

Likewise, dwelling type has a strong relationship with respondents' willingness-to-shift activities, as is shown in Table 6 in Appendix 4 and Fig. 8. Respondents living in detached houses expressed more frequently their

Fig. 5 Respondents' shifting choice against gender for six end-use activities



unwillingness-to-shift their heating time. In contrast, those living in semi-detached and terraced houses showed a higher willingness-to-shift entertainment and heating time.

Furthermore, flat dwellers are found more likely to shift heating time, but less likely to shift their laundry time. The unwillingness-to-shift laundry time could be related to their dwelling characteristics as the operation of washing machines could be too noisy during the night (Carmichael et al. 2014).

Ownership of appliances and devices

Those with smart meters were found to be more willing to shift their end-use activities, including cooking, dish-washing, entertainment, laundry and showering, as shown in Table 6 in Appendix 4 and Fig. 9. In fact, it has been reported that about 80% of owners of smart meters with in-home displays change their behaviour to reduce energy use (BEIS 2018c). This might be due to the better information they have about their electricity consumption and costs that the in-home displays, rolled out

to UK homes under current regulation (Ofgem 2010), provide. A separate investigation would be needed to confirm a causal relationship, however. In contrast, as heating in the UK is still largely provided by gas boilers, better information about electricity use might thus not affect respondents' decisions about shifting the timing of heating. The benefits of information disclosure with in-home displays in motivating consumers' responses to dynamic TOU pricing signals have been previously reported by Carmichael et al. (2014), as smart metering can act as a reminder and motivator to drive consumers to engage in DSR (Carroll et al. 2014). Participants in a dynamic TOU trial in the UK claimed the in-home displays are helpful for them to respond to pricing signals (Carmichael et al. 2014). Therefore, rolling out smart meters with in-home displays could increase UK consumers' willingness-to-shift their end-use activities.

Furthermore, respondents who owned electric storage heaters were more likely to be willing to shift end-use time of other unrelated activities, such as cooking. This tendency has also been shown by the fact that participants

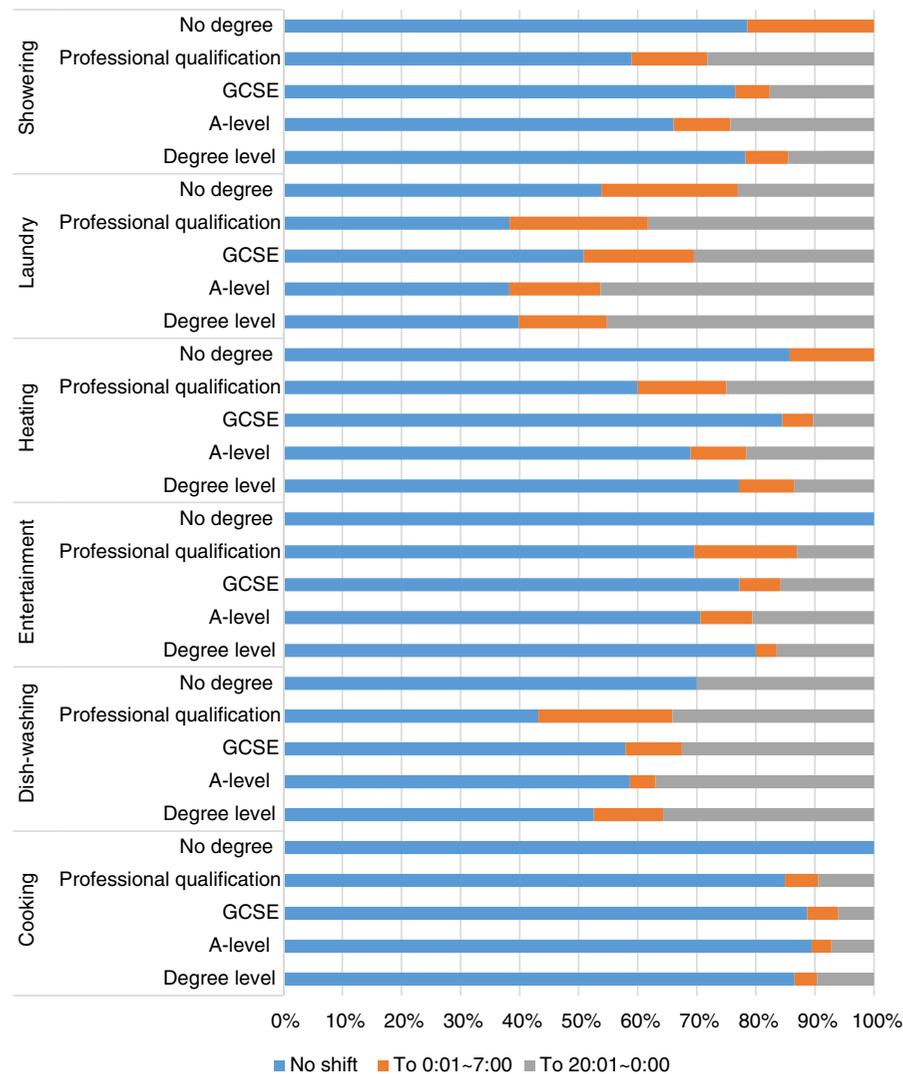


Fig. 6 Respondents' shifting choice against education qualification for six end-use activities

of a static TOU programme (Economy 7) in the UK are more likely to have electric storage heaters in their households, in order to exploit the low electricity price during the night (Bradley et al. 2016). Higher demand reduction from electric storage heater owners has also been observed by Carroll et al. (2014) in a static TOU trial.

Nonetheless, owning energy-efficient or energy-saving technologies does not always imply that the owners would be more willing to shift the timing of their activities. For example, as shown in Table 6 in Appendix 4, LED users showed less willingness-to-shift their cooking time. PV owners have also expressed their unwillingness to shift their laundry time. Similar influences can be found for energy-efficient appliances on shifting

entertainment time. The negative correlation between energy-saving behaviours, such as using energy-saving bulbs, and acceptance of smart appliances for DSR has also been reported for the UK by Mert et al. (2008). This tendency, however, is opposite to that found for other countries, such as Slovenia (Mert et al. 2008).

Overall, appliance ownership can be an important indicator for revealing customers' willingness to shift their end-use activities.

Attitude towards energy-saving

Finally, the concern for energy-saving (an attitudinal variable) could also motivate consumers to adjust their routines

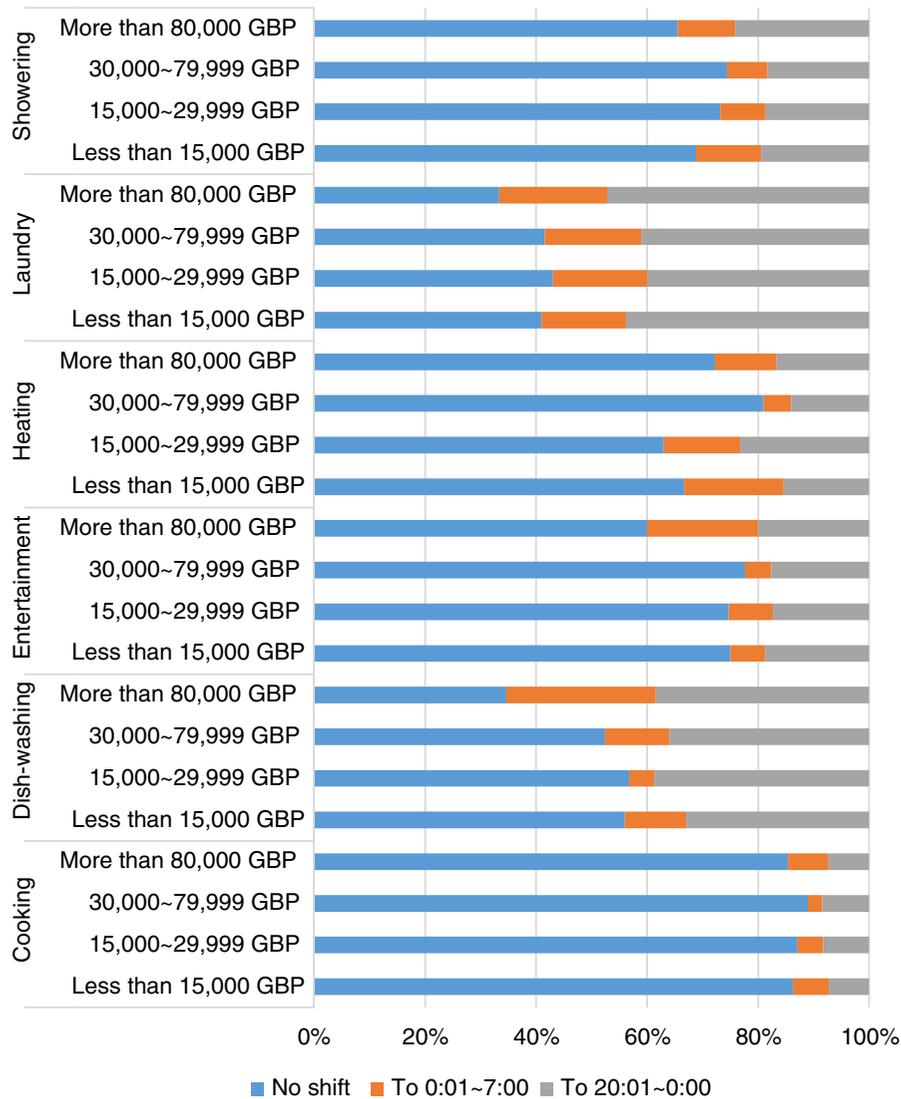


Fig. 7 Respondents' shifting choice against household income for six end-use activities

for the end-use activities, as is shown in Table 6 in Appendix 4 and Fig. 10. This has been found relevant for dish-washing and laundry. For example, respondents with higher concern for energy-saving are more likely to shift their dish-washing and laundry time to the two off-peak time-slots, i.e. the late night (20:01~0:00) and the early morning (0:01~7:00). However, respondents who agreed that they are very concerned about energy-saving were less willing to shift entertainment time, as is shown in Fig. 10.

Overall, the identified influence of energy-saving attitude is in line with other studies. Customers who took part in a DSR trial in the UK stated that environmental benefits motivated them to participate (Bradley

et al. 2014). Respondents with higher ecological awareness were also found to be more willing to accept smart appliances for DSR (Mert et al. 2008). Therefore, consumers' attitudes could also be related to their energy use behaviour (Abrahamse and Steg 2009; Bradley et al. 2014; Hong et al. 2019; Thøgersen 2018).

Conclusions and policy implications

This study adopted a UK-wide survey that collected data on consumers' stated willingness to shift their end-use time for six major energy using activities: cooking, dish-washing, entertainment, heating, laundry and showering. An

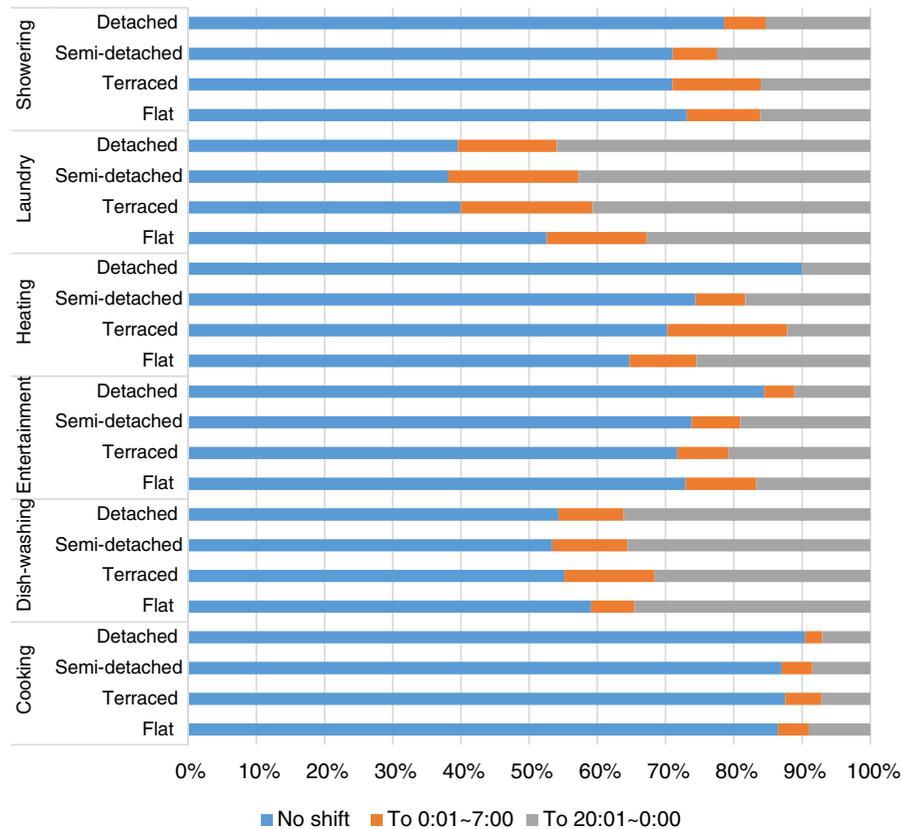


Fig. 8 Respondents' shifting choice against house types for six end-use activities

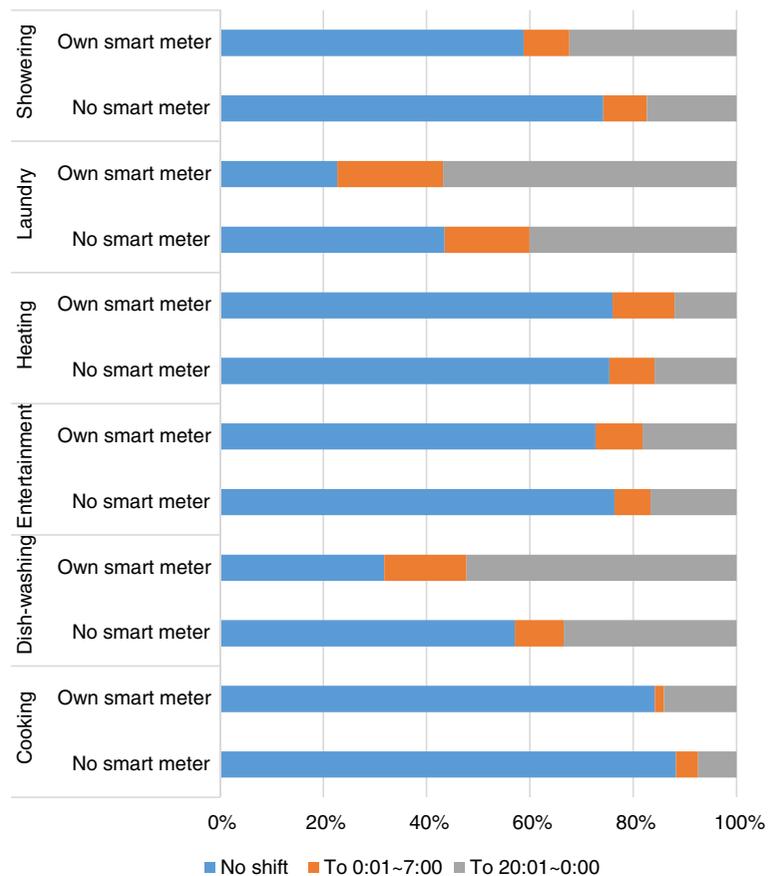
MNLM was then used to identify the influential factors for respondents' decisions on whether to agree to shift demand. Six MNLMs were constructed for the factor identification, one for each end-use activity, and influential factors for consumers' stated willingness to shift the timing of each specific end-use activity were separately assessed. This study thus contributes to the existing knowledge with a more detailed analysis of consumers' heterogeneous willingness to shift various end-use activities to off-peak periods, based on their stated willingness to do so.

Overall, the original timings of activities were found to be influential for consumers' stated shifting decisions. Not only does the original timing of the activity under consideration have a strong influence on the outcome, but also those of other activities are frequently found significant. Respondents are more willing to shift loads when the new time-slot is closer to original timing of the end-use activity. In addition, respondents' stated willingness-to-shift of end-use activities is highly correlated to many socio-demographic characteristics, such as age, gender, geographic region, education qualification, household size and household income. For

example, older respondents are less likely to be willing to shift loads. Male respondents are more willing to shift cooking and heating. Some geographic regions, such as North East, where respondents show a higher willingness to shift, might be ideal for promoting DSR programmes. Respondents with higher education qualification are also more willing to shift their loads. Similarly, those with larger household size show higher intention to change their end-use activities. Low-income respondents, on the other hand, are more likely to shift heating time. Respondents living in flats are more likely to shift their heating time. Furthermore, the ownership of appliances was also found to affect respondents' decisions. For example, electric storage heater owners are more likely to shift their loads. Finally, respondents with a higher level of concern for energy-saving expressed a higher intention to shift their activity time more frequently.

By revealing factors influencing consumers' stated decisions, our results could help policymakers understand better the bottlenecks and opportunities and perhaps focus during the early stages of DSR schemes on the

Fig. 9 Respondents' shifting choice against ownership of smart meter for six end-use activities



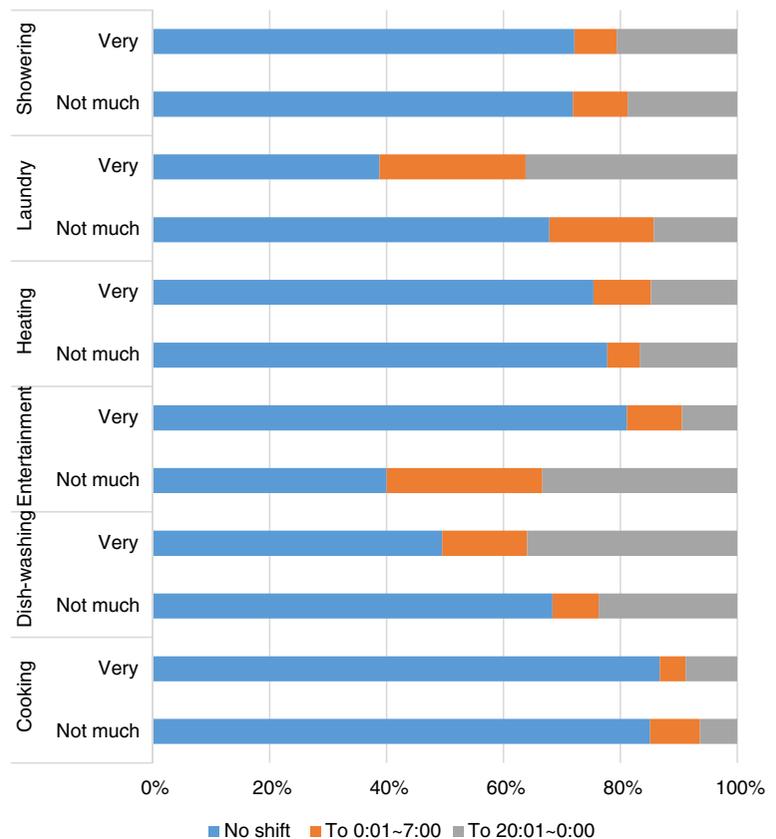
consumers who appear to be more willing to shift the timing of their activities. For example, consumers living in terraced houses have higher willingness-to-shift. Income also plays a role, and it may be households with a higher income should be targeted first as they generally have a higher willingness to shift their several end-use activities, with a higher capability of having flexible technologies. Nonetheless, the status of vulnerable households with lower disposal income should also be taken into account carefully, to avoid negative impacts (e.g. discomfort) on them (Powells and Fell 2019). DSR promotion strategies can also be designed based on different genders' willingness to shift different types of appliances. For example, flexible operation of washing machines for DSR is specifically appealing to female consumers and could be incorporated in the promotion materials to target those who are in charge of using relevant appliances (Tjørring et al. 2018).

Consumers accessing smart meters have been found to be more willing to shift residential energy loads, possibly due to their higher awareness of electricity consumption

via in-home displays, which consumers in the UK get together with their smart meters. Until the end of 2018, however, there were only 12.8 million smart meters operating across Great Britain (BEIS 2018c). To increase demand-side flexibility, the government should strengthen the implementation plan to ensure the rollout of smart meters to every household as soon as possible. Meanwhile, more active, transparent and accessible channels, such as text messaging, mobile applications and social media, could be exploited to enhance consumers' knowledge of their electricity expenditure and to inform how bills could be reduced with DSR schemes.

Concern for energy-saving has also been found influential on consumers' stated willingness-to-shift. Since information policies have proved to be effective in influencing consumers' energy-saving attitude and even behaviour (Henryson et al. 2000; Hong et al. 2019; Lindén et al. 2006), the government could thus consider to campaign for energy-saving along with the promotion of DSR programmes. This matches with the suggestion made by Faruqui and Sergici (2010) to blend

Fig. 10 Respondents' shifting choice against level of concern for energy-saving for six end-use activities (very, very concerned about energy-saving; not much, not concerned about energy-saving)



DSR programmes with education initiatives to increase the demand impact.

Furthermore, understanding what affects people's stated decisions can also help policymakers assess the potential of DSR and how it could contribute to e.g. balancing VRE cost-effectively. Combining the understanding of the electricity demand profiles for the six major end-use activities with the penetration rates of electricity-using appliances and survey outcomes for the share of electricity consumption that may be possible to shift, an approximation can be developed for the potential of DSR to shift demand to the late night or the early morning timeslots. The probability of shifting, and thus DSR potential, can be determined on a disaggregated level using the developed six MNLMs, with e.g. the residents' socio-demographic attributes.

This study has already taken a wide range of potential factors into account, such as socio-demographic factors and dwelling characteristics. Nonetheless, more relevant factors, such as price signal and neighbours' adoptions of DSR measures, can be considered in the future to explore the potential drivers for consumers' DSR participation, so

that policymakers can consider those in the process of policymaking. Furthermore, choice experiments with various pricing signals and DSR programmes, such as DLC, can also be incorporated in the future survey. As this study focused on consumers' stated willingness, future studies can consider consumers' revealed willingness to shift to further verify the findings in this study based on responses of participants in DSR trials and programmes.

Finally, the revealed influential factors can be included in agent-based models or energy system models to reflect consumers' heterogeneous preferences for DSR to determine more cost-effective decarbonisation pathways.

Funding information This work was financially supported by the wholeSEM project funded by the Engineering and Physical Science Research Council (EPSRC) (EP/K039326/1) and the REEEM project from the European Union's Horizon 2020 research and innovation programme under grant agreement 691739.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Appendix 1. Sample statistics

Table 3 Descriptive statistics of respondents

Factor	Statistics										
Gender	Male	Female									
	492	512									
Age	49%	51%									
	18~24	25~34	35~44	45~54	55~65						
	144	222	214	221	203						
	14.3%	22.1%	21.3%	22%	20.2%						
Education	GCSE or similar	A-levels or similar	Degree level	work-related qualifications	None						
	208	264	423	83	26						
Dwelling type	20.7%	26.3%	42.1%	8.3%	2.6%						
	Flat	Semi-detached	Detached	Terraced	Other						
	210	252	313	193	34						
	20.9%	25.1%	31.2%	19.2%	3.4%						
No. of bedrooms	1	2	3	4	5 or more						
	97	290	430	139	48						
	9.7%	28.9%	42.8%	13.8%	4.8%						
Geographical region	North East	North West	York and Humber	East Mid	West Mid	East Eng	South West	London	South East	Wales	Scotland
	180	112	88	74	92	88	138	146	138	50	91
	15.7%	9.8%	7.7%	6.5%	8%	7.7%	7.5%	20.9%	12.1%	4.4%	7.9%
No. of Residents	1	2	3	4	5 or more						
	178	338	195	171	122						
	17.7%	33.7%	19.4%	17%	12.2%						
Household income (GBP/year)	15,000 or less	15,000~29,999	30,000~79,999	80,000 or more	Not reply						
	180	289	374	64	97						
	17.9%	28.8%	37.3%	6.4%	9.7%						

Appendix 2. Correlation between end-use times

Table 4 Correlation coefficients between end-use times

	CK0to7	CK7to9	CK9to18	CK18to20	CK20to0	DS0to7	DS7to9	DS9to18	DS18to20	DS20to0	EN0to7	EN7to9	EN9to18	EN18to20	EN20to0	HT0to7	HT7to9	HT9to18	HT18to20	HT20to0	LD0to7	LD7to9	LD9to18	LD18to20	LD20to0	SW0to7	SW7to9	SW9to18	SW18to20	SW20to0
CK0to7	1.00	-0.08	-0.04	0.05	0.02	0.17	0.00	-0.06	0.06	-0.04	0.16	-0.02	-0.03	0.01	0.01	0.11	-0.04	0.02	0.02	0.00	0.09	0.02	-0.05	0.02	0.04	0.22	-0.06	-0.04	0.00	0.05
CK7to9	-0.08	1.00	0.06	0.06	0.00	0.02	0.21	0.07	0.03	0.03	0.02	0.25	0.11	0.05	-0.03	0.09	0.10	0.02	0.01	-0.01	0.05	0.11	0.02	0.05	-0.01	-0.01	0.16	0.03	0.11	0.00
CK9to18	-0.04	0.06	1.00	-0.38	-0.10	-0.05	0.14	0.38	0.04	-0.10	0.04	0.07	0.37	0.17	0.02	-0.03	0.05	0.24	0.03	-0.04	-0.02	0.04	0.27	-0.07	-0.09	-0.09	0.05	0.26	0.21	-0.02
CK18to20	0.05	0.06	-0.38	1.00	-0.04	0.01	0.02	-0.09	0.22	0.18	0.02	0.04	-0.08	0.25	0.26	0.12	0.09	-0.03	0.18	0.18	0.01	0.07	0.05	0.21	0.10	0.09	0.15	-0.04	0.05	0.18
CK20to0	0.02	0.00	-0.10	-0.04	1.00	0.03	-0.01	-0.01	-0.01	0.24	0.09	0.01	0.03	-0.01	0.17	0.03	0.02	0.04	-0.01	0.12	-0.01	0.00	0.02	0.11	0.15	0.00	-0.03	0.07	0.03	0.17
DS0to7	0.17	0.02	-0.05	0.01	0.03	1.00	-0.08	-0.08	-0.08	0.00	0.04	0.00	-0.06	0.04	0.00	0.15	0.01	-0.01	0.00	-0.02	0.32	0.02	-0.09	-0.04	0.03	0.21	-0.05	-0.05	0.02	0.01
DS7to9	0.00	0.21	0.14	0.02	-0.01	-0.08	1.00	0.03	0.13	-0.08	0.01	0.22	0.08	0.08	0.04	0.02	0.10	0.06	0.09	0.04	0.07	0.27	0.01	0.06	0.00	-0.01	0.15	0.00	0.10	0.10
DS9to18	-0.06	0.07	0.38	-0.09	-0.01	-0.08	0.03	1.00	-0.12	-0.17	-0.05	0.03	0.35	0.10	0.02	-0.03	-0.01	0.22	-0.01	0.00	-0.04	-0.01	0.25	-0.01	-0.03	-0.10	0.07	0.26	0.18	-0.02
DS18to20	0.06	0.03	0.04	0.22	-0.01	-0.08	0.13	-0.12	1.00	-0.33	0.04	0.01	0.05	0.25	0.12	0.04	0.05	0.05	0.17	0.05	-0.01	0.05	0.09	0.17	-0.01	0.07	0.07	0.04	0.16	0.07
DS20to0	-0.04	0.03	-0.10	0.18	0.24	0.00	-0.08	-0.17	-0.33	1.00	0.03	0.02	-0.10	0.04	0.18	0.06	0.10	-0.04	0.07	0.15	-0.07	0.04	-0.02	0.16	0.23	0.02	0.08	-0.06	-0.05	0.20
EN0to7	0.16	0.02	0.04	0.02	0.09	0.04	0.01	-0.05	0.04	0.03	1.00	-0.03	-0.08	0.01	0.03	0.10	-0.04	-0.02	0.04	0.04	0.02	-0.02	-0.04	0.08	0.10	0.11	-0.03	0.03	0.02	-0.02
EN7to9	-0.02	0.25	0.07	0.04	0.01	0.00	0.22	0.03	0.01	0.02	-0.03	1.00	0.09	0.04	-0.10	0.04	0.16	0.04	-0.02	-0.04	0.07	0.11	0.03	0.03	0.01	-0.03	0.11	-0.01	0.08	0.03
EN9to18	-0.03	0.11	0.37	-0.08	0.03	-0.06	0.08	0.35	0.05	-0.10	-0.08	0.09	1.00	0.09	-0.06	0.01	0.06	0.24	0.02	-0.07	0.00	0.03	0.23	0.00	-0.03	-0.09	0.06	0.24	0.18	-0.02
EN18to20	0.01	0.05	0.17	0.25	-0.01	0.04	0.08	0.10	0.25	0.04	0.01	0.04	0.09	1.00	0.13	0.09	0.15	0.07	0.32	0.12	0.03	0.11	0.18	0.17	0.03	0.04	0.19	0.00	0.20	0.10
EN20to0	-0.01	-0.02	0.02	0.26	0.17	0.00	0.04	0.02	0.12	0.18	0.03	-0.08	-0.06	0.13	1.00	0.06	0.14	0.05	0.17	0.32	-0.01	0.05	0.14	0.15	0.14	0.03	0.18	-0.02	0.03	0.21
HT0to7	0.11	0.09	-0.03	0.12	0.03	0.15	0.02	-0.03	0.04	0.06	0.10	0.04	0.01	0.09	0.06	1.00	-0.12	-0.12	0.00	0.12	0.06	0.06	-0.05	0.05	0.05	0.30	-0.02	-0.11	-0.01	0.06
HT7to9	-0.04	0.10	0.05	0.09	0.02	0.01	0.10	-0.01	0.05	0.10	-0.04	0.16	0.06	0.15	0.14	-0.12	1.00	0.01	0.26	0.05	0.07	0.13	0.10	0.06	0.04	-0.09	0.28	-0.06	0.03	0.08
HT9to18	0.02	0.02	0.24	-0.03	0.04	-0.01	0.06	0.22	0.05	-0.04	-0.02	0.04	0.24	0.07	0.05	-0.12	0.01	1.00	0.11	-0.10	0.01	0.00	0.19	0.03	0.00	-0.06	0.06	0.27	0.06	-0.01
HT18to20	0.02	0.01	0.03	0.18	-0.01	0.00	0.09	-0.01	0.17	0.07	0.04	-0.02	0.02	0.32	0.17	0.00	0.26	0.11	1.00	0.08	0.00	0.13	0.09	0.11	0.11	0.05	0.15	-0.01	0.12	0.02
HT20to0	0.00	-0.01	-0.04	0.16	0.12	-0.02	0.04	0.00	0.05	0.15	0.04	-0.04	-0.07	0.12	0.32	0.12	0.05	-0.10	0.08	1.00	-0.05	-0.02	0.06	0.10	0.20	0.04	0.07	-0.06	0.04	0.17
LD0to7	0.09	0.05	-0.02	0.01	-0.01	0.32	0.07	-0.04	-0.01	-0.07	0.02	0.07	0.00	0.03	-0.01	0.06	0.07	0.01	0.00	-0.05	1.00	-0.05	-0.10	-0.09	-0.04	0.11	-0.02	-0.03	0.05	-0.04
LD7to9	0.02	0.11	0.04	0.07	0.00	0.02	0.27	-0.01	0.05	0.04	-0.02	0.11	0.03	0.11	0.05	0.06	0.13	0.00	0.13	-0.02	-0.05	1.00	-0.06	-0.04	-0.05	0.10	0.14	-0.05	0.04	0.05
LD9to18	-0.05	0.02	0.27	0.05	0.02	-0.09	0.01	0.25	0.09	-0.02	-0.04	0.03	0.23	0.18	0.14	-0.05	0.10	0.19	0.09	0.06	-0.10	0.20	1.00	-0.10	-0.05	-0.11	0.14	-0.18	0.12	0.00
LD18to20	0.02	0.05	-0.07	0.21	0.11	-0.04	0.06	-0.01	0.17	0.16	0.08	0.03	0.00	0.17	0.15	0.05	0.06	0.03	0.11	0.10	-0.09	-0.04	-0.10	1.00	0.18	0.08	0.08	-0.01	0.11	0.15
LD20to0	0.04	-0.01	-0.09	0.10	0.15	0.03	0.00	-0.03	-0.01	0.23	0.10	0.01	-0.03	0.03	0.14	0.05	0.04	0.00	0.11	0.20	-0.04	-0.05	-0.10	0.18	1.00	0.05	0.03	-0.05	0.05	0.12
SW0to7	0.22	-0.01	-0.09	0.09	0.00	0.21	-0.01	-0.10	0.07	0.02	0.11	-0.03	-0.09	0.04	0.03	0.30	-0.09	-0.06	0.05	0.04	0.11	0.10	-0.11	0.08	0.05	1.00	-0.08	-0.15	-0.09	0.05
SW7to9	-0.06	0.16	0.05	0.15	-0.03	-0.05	0.15	0.07	0.07	0.08	-0.03	0.11	0.06	0.19	0.18	-0.02	0.28	0.06	0.15	0.07	-0.02	0.14	0.14	0.08	0.03	-0.08	1.00	-0.15	-0.11	-0.03
SW9to18	-0.04	0.03	0.26	-0.04	0.07	-0.05	0.00	0.26	0.04	-0.06	0.03	-0.01	0.24	0.00	-0.02	-0.11	-0.06	0.27	-0.01	-0.06	-0.03	-0.05	0.18	-0.01	-0.05	-0.10	-0.15	1.00	-0.01	-0.14
SW18to20	0.00	0.11	0.21	0.05	0.03	0.02	0.10	0.10	0.16	-0.05	0.02	0.08	0.18	0.20	0.03	0.01	0.03	0.06	0.12	0.04	0.05	0.04	0.12	0.11	0.05	-0.09	-0.11	-0.01	1.00	-0.10
SW20to0	0.05	0.00	-0.02	0.18	0.17	0.01	0.10	-0.02	0.07	0.20	-0.02	0.03	-0.02	0.10	0.21	0.06	0.08	-0.01	0.02	0.17	-0.04	0.05	0.00	0.15	0.12	0.05	-0.03	-0.14	-0.10	1.00

CK cooking, DS dish-washing, EN entertainment, HT heating, LD laundry, SW showering

Appendix 3. Definition of considered explanatory variables in the MNLMs

Table 5 Definition of explanatory variables in the MNLMs

Variable	Definition
CK0to7	Whether cook during 0:00~6:59 (1 if yes; 0 otherwise)
CK7to9	Whether cook during 7:00~8:59 (1 if yes; 0 otherwise)
CK9to18	Whether cook during 9:00~17:59 (1 if yes; 0 otherwise)
CK18to20	Whether cook during 18:00~19:59 (1 if yes; 0 otherwise)
CK20to0	Whether cook during 20:00~23:59 (1 if yes; 0 otherwise)
DS0to7	Whether wash dishes during 0:00~6:59 (1 if yes; 0 otherwise)
DS7to9	Whether wash dishes during 7:00~8:59 (1 if yes; 0 otherwise)
DS9to18	Whether wash dishes during 9:00~17:59 (1 if yes; 0 otherwise)
DS18to20	Whether wash dishes during 18:00~19:59 (1 if yes; 0 otherwise)
DS20to0	Whether wash dishes during 20:00~23:59 (1 if yes; 0 otherwise)
EN0to7	Whether entertain, such as watching TV, during 0:00~6:59 (1 if yes; 0 otherwise)
EN7to9	Whether entertain, such as watching TV, during 7:00~8:59 (1 if yes; 0 otherwise)
EN9to18	Whether entertain, such as watching TV, during 9:00~17:59 (1 if yes; 0 otherwise)
EN18to20	Whether entertain, such as watching TV, during 18:00~19:59 (1 if yes; 0 otherwise)
EN20to0	Whether entertain, such as watching TV, during 20:00~23:59 (1 if yes; 0 otherwise)
HT0to7	Whether turn on space heating during 0:00~6:59 (1 if yes; 0 otherwise)
HT7to9	Whether turn on space heating during 7:00~8:59 (1 if yes; 0 otherwise)
HT9to18	Whether turn on space heating during 9:00~17:59 (1 if yes; 0 otherwise)

Table 5 (continued)

Variable	Definition
HT18to20	Whether turn on space heating during 18:00~19:59 (1 if yes; 0 otherwise)
HT20to0	Whether turn on space heating during 20:00~23:59 (1 if yes; 0 otherwise)
LD0to7	Whether wash clothes during 0:00~6:59 (1 if yes; 0 otherwise)
LD7to9	Whether wash clothes during 7:00~8:59 (1 if yes; 0 otherwise)
LD9to18	Whether wash clothes during 9:00~17:59 (1 if yes; 0 otherwise)
LD18to20	Whether wash clothes during 18:00~19:59 (1 if yes; 0 otherwise)
LD20to0	Whether wash clothes during 20:00~23:59 (1 if yes; 0 otherwise)
SW0to7	Whether take a shower during 0:00~6:59 (1 if yes; 0 otherwise)
SW7to9	Whether take a shower during 7:00~8:59 (1 if yes; 0 otherwise)
SW9to18	Whether take a shower during 9:00~17:59 (1 if yes; 0 otherwise)
SW18to20	Whether take a shower during 18:00~19:59 (1 if yes; 0 otherwise)
SW20to0	Whether take a shower during 20:00~23:59 (1 if yes; 0 otherwise)
Male	Male, 1; female, 0
Age (younger than 17)	Whether respondent is younger than 17 years old (1 if yes; 0 otherwise)
Age (18~24)	Whether respondent's age is between 18 and 24 years old (1 if yes; 0 otherwise)
Age (25~34)	Whether respondent's age is between 25 and 34 years old (1 if yes; 0 otherwise)
Age (35~44)	Whether respondent's age is between 35 and 44 years old (1 if yes; 0 otherwise)
Age (45~54)	Whether respondent's age is between 45 and 54 years old (1 if yes; 0 otherwise)
Age (55~65)	Whether respondent's age is between 55 and 64 years old (1 if yes; 0 otherwise)
Age (older than 65)	Whether respondent is older than 65 years old (1 if yes; 0 otherwise)
North East	Whether live in North East (1 if yes; 0 otherwise)
North West	Whether live in North West (1 if yes; 0 otherwise)
York and Humber	Whether live in York and Humber (1 if yes; 0 otherwise)
East Midlands	Whether live in East Midlands (1 if yes; 0 otherwise)
West Midlands	Whether live in West Midlands (1 if yes; 0 otherwise)
East England	Whether live in East England (1 if yes; 0 otherwise)
London	Whether live in London (1 if yes; 0 otherwise)
South East	Whether live in South East (1 if yes; 0 otherwise)
South West	Whether live in South West (1 if yes; 0 otherwise)
Wales	Whether live in Wales (1 if yes; 0 otherwise)
Scotland	Whether live in Scotland (1 if yes; 0 otherwise)
GCSE or similar	Whether highest education level is GCSE or similar (1 if yes; 0 otherwise)
A-levels	Whether highest education level is A-levels (1 if yes; 0 otherwise)
Degree level	Whether highest education level is degree level (1 if yes; 0 otherwise)
Professional qualification	Whether highest education level is professional qualification (1 if yes; 0 otherwise)
No degree	Whether no education degree (1 if yes; 0 otherwise)
No. of children	Number of children
No. of residents	Number of residents
HI15kless	Whether household income is less than 14,999 GBP (1 if yes; 0 otherwise)
HI15k~29k	Whether household income is between 15,000 and 29,999 GBP (1 if yes; 0 otherwise)
HI30k_79k	Whether household income is less than 30,000~79,999 GBP (1 if yes; 0 otherwise)
HI80kmore	Whether household income is more than 80,000 GBP (1 if yes; 0 otherwise)
Employment	Whether respondent is employed (1 if yes; 0 otherwise)
Work from home	Whether respondent occasionally works from home (1 if yes; 0 otherwise)

Table 5 (continued)

Variable	Definition
Days working from home	Number of days in a week working from home
Hours working from home	Number of hours in a week working from home
Not pay bill	Whether respondent is not responsible for paying bills (1 if not; 0 otherwise)
Flat	Whether live in a flat (1 if yes; 0 otherwise)
Terraced house	Whether live in a terraced house (1 if yes; 0 otherwise)
Detached house	Whether live in a detached house (1 if yes; 0 otherwise)
Semi-detached house	Whether live in a semi-detached house (1 if yes; 0 otherwise)
Studio	Whether live in a studio (1 if yes; 0 otherwise)
Other house type	Whether live in an other type of house (1 if yes; 0 otherwise)
House age	House age
Own house	Whether own a house (1 if yes; 0 otherwise)
No. of bedrooms	Number of bedrooms in the house
Dishwasher	Whether own a dishwasher (1 if yes; 0 otherwise)
Vacuum cleaner	Whether own a vacuum cleaner (1 if yes; 0 otherwise)
TV	Whether own a TV (1 if yes; 0 otherwise)
Home cinema	Whether own a home cinema (1 if yes; 0 otherwise)
DVD player	Whether own a DVD player (1 if yes; 0 otherwise)
Game console	Whether own a game console (1 if yes; 0 otherwise)
Audio system	Whether own an audio system (1 if yes; 0 otherwise)
Computer	Whether own a computer (1 if yes; 0 otherwise)
Central heating	Whether own a central heating system (1 if yes; 0 otherwise)
Space heater	Whether own a space heater (1 if yes; 0 otherwise)
Continuous water heater	Whether own a continuous water heater (1 if yes; 0 otherwise)
Tumble drier	Whether own a tumble drier (1 if yes; 0 otherwise)
Instantaneous water heater	Whether own an instantaneous water heater (1 if yes; 0 otherwise)
Washing machine	Whether own a washing machine (1 if yes; 0 otherwise)
Iron	Whether own an iron (1 if yes; 0 otherwise)
Shower	whether own a shower room (1 if yes; 0 otherwise)
Cooker	Whether own a cooker (1 if yes; 0 otherwise)
Microwave	Whether own a microwave (1 if yes; 0 otherwise)
Fridge	Whether own a refrigerator (1 if yes; 0 otherwise)
Freezer	Whether own a freezer (1 if yes; 0 otherwise)
Efficient appliances	Whether own energy-efficient appliances (1 if yes; 0 otherwise)
Smart meter	Whether own a smart meter (1 if yes; 0 otherwise)
CFL	Whether own a CFL (1 if yes; 0 otherwise)
LED	Whether own a LED (1 if yes; 0 otherwise)
PV	Whether own a PV panel (1 if yes; 0 otherwise)
Electric storage heater	Whether own an electric storage heater (1 if yes; 0 otherwise)
Heat pump	Whether own a heat pump (1 if yes; 0 otherwise)
Wood stove	Whether own a wood stove (1 if yes; 0 otherwise)
Wood pellet boiler	Whether own a wood pellet boiler (1 if yes; 0 otherwise)
Insulation	Whether house has insulation (1 if yes; 0 otherwise)
Concern energy-saving	Level of concern for energy-saving (1, not at all, to 5, very concerned)

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