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Distributional effects of Time of Use tariffs based on electricity demand and time use

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Abstract

The introduction of Time of Use (ToU) tariffs may affect residential electricity consumers differently depending not only on their financial position but also time availability. The aim of this paper is to identify socio-demographic groups which may be financially advantaged or disadvantaged by the introduction of ToU tariffs. Assuming no behavioural change, we impose ToU tariffs on UK half hourly smart meter data and the synthetic demand profiles for different household composition generated using the 2014-2015 UK Time Use Survey data and optimisation of energy consumption per activity against the smart meter data. The distributional effects of ToU tariffs are obtained for customer segmentation and socio-demographic groups, and presented in terms of peak to off-peak ratios and impacts on the synthetic demand profiles. Findings on the distributional effects of ToU tariffs reveal regional differences (e.g. positive effects for high income groups in London) and household composition similarities (e.g. positive effects for households with children not in the high-income group).

Keywords: Distributional effects; Electricity demand; Flexibility; Time of Use tariffs; Time use.

1. Introduction

Smart meters have been rolled out in several developed countries as demand-side devices to be integrated with the changing configurations in electricity supply. Smart meters provide the means of collecting high-resolution energy demand data at end-use point. The costs of electricity smart meters are in part justified by balancing the electricity grid to reducing system costs, improving balancing between demand and renewables, to making the most of distributed energy systems and battery storage. One of the key attributes of smart meters consists of enabling the provision of tariffs which reflect more closely the cost of electricity generation, which is increasingly low when the share of renewable sources of electricity is high and high when additional generation is needed and demand is high.

Examples of these types of tariffs abound and include pricing based on power demand capacity, real-time pricing, critical peak pricing, and Time of Use (ToU). Suppliers in the UK will be incentivised to offer a range of these tariffs (Ofgem, 2016) and, indeed, some of the suppliers already offer real-time pricing (Octopus, 2020) and ToU tariffs to their customers (Bulb, 2020). ToU tariffs are the focus of this paper as in the UK the energy regulator, Ofgem, proposes to explore how to encourage their uptake as a demand side measure to achieve the Net Zero ambition for carbon emissions (Ofgem, 2020).

The majority of previous studies on ToU focus on the extent to which such tariffs cause changes in electricity consumption, including temporary reductions in electricity demand during peak periods and absolute net conservation effects. More recently, the distributional effects of these tariffs on different types of residential consumers have been analysed as it was recognised that changes in tariffs may create advantages to some socio-demographic groups, but also disadvantages to others (Hledik et al., 2017).

The introduction of ToU tariffs may affect residential electricity consumers differently depending not only on their financial but also time availability. Understanding how different socio-demographic groups may financially gain from the introduction of ToU tariffs calls for analyses which look simultaneously at highly granular metered electricity consumption data, socio-demographic information about consumers and timing of activities carried out in their homes. This paper sets out to address this research challenge by matching electricity demand profiles to time use activities and assessing the distributional effects of ToU on different income groups.

The main objective of this paper is to identify socio-demographic groups which may be financially advantaged or disadvantaged by the introduction of ToU tariffs. It applies literature-derived ToU tariffs to UK smart meter datasets from Low Carbon London (LCL; Schofield et al., 2015) and Customer Led Network Revolution (CLNR; Sidebotham & Northen Powergrid, 2015). This also enables to observe differences in the timing of energy demand across different regions. The 2014-2015 UK Time Use Survey data was used to connect electricity consumption to activities affected by ToU tariffs across several socio-demographic parameters. A time use approach (without the support of smart meter electricity data) was also used by (Torriti and Yunusov 2020), (Yunusov et al 2018) to cluster activities in relation to peak periods. Given the geographic attributes and diverging findings from the LCL and CLNR datasets in terms of ToU effects on different socio-demographic groups, the UK Time Use Survey data is utilised to derive synthetic load profiles which are nationally representative.

The main contribution of this paper focuses on the geographical and household composition (family structure and income) differences in distributional impact from ToU tariffs. These findings are achieved through a novel method for modelling household electricity demand based on time use data paired with smart meter demand profiles with matching socio-demographic parameters.

The paper reviews work on ToU tariffs as well as previous models connecting time use activities to load profiles (Section 2). It describes the overall methodological approach, the smart metering and time use data as well the research methods utilised for the analysis (Section 3). Findings are presented in terms of customer segmentation and estimation of impacts from activity profiles (Section 4). The paper concludes by discussing the implications and limitations of this study (Section 5).

2. Time of Use tariffs and time use

2.1 Time of Use tariffs

Under Time of Use tariffs customers are charged for their energy consumption during different periods of the day. Unit rates can be assigned to set periods of the day called 'time bands', in advance of the charging year to reflect the probability that the network will be congested during that period. Customers are consequently charged for the actual energy they consume during each time band on an ex-post basis. Possible variations to this basic option include seasonality, where charges during the 'peak' season are higher than during the rest of the year.

Existing studies can shed light on three critical aspects of ToU tariffs, i.e. average demand reduction in correspondence with peak periods, income effects and flexibility of practices. The literature shows that consumers tend to adapt electricity consumption patterns in response to ToU tariffs (Newsham & Bowker, 2010). There are large and unexplained variations in responsiveness to ToU tariffs across consumers (Cappers & Sheer, 2016). A review of 163 studies shows that peak reduction levels range from 0 to almost 60% (Faruqui and George, 2017). Findings show that with a peak to off-peak price ratio of 5:1, pricing only trials obtained a 13.8% peak reduction, whereas peak to off-peak price ratio of 10:1 pushed peak reduction to almost 16%. King & Delurey (2005) found an average of 4% energy savings in 24 studies on dynamic pricing mostly in North America and a few European studies. Time of Use tariffs in Ireland reduced peak consumption by 8.8% for specifically designed price bands (Darby & McKenna, 2012). In Italy, Time of Use tariffs have gradually been applied to Italian residential electricity users since the year 2010. The first pilot of ToU involved 4 million end users. A 2012 study finds a modest level of average peak reduction. When there is significant demand shifting this did not necessarily follow a price related logic (Torriti, 2012).

In the UK, despite the fact that about 5.5 million customers make use of multi-rate energy tariffs and 3 million specifically on Time of Use tariffs -the most popular being called 'Economy 7'- evidence on their effects is scarce as data is not available or published (Buryk et al., 2015). Some demand reductions at peak are inevitably intertwined with the performance of electric storage heating (Barton et al., 2013). This was integrated as heating in several residential buildings (especially in council housing blocks) as part of the nuclear power programme from the 1960's with the requirement for nuclear generators to operate continuously giving rise to low baseload and off-peak prices (Torriti, 2015). More recently, two DNO-led innovation projects tested the impact of ToU on the demand reduction during evening peak time: the Low Carbon London trial found average shifts reduction in peak energy demand of around 4.2% between 5% and 10% in response to dynamic ToU (UK Power Networks, 2014) and Customer Led Network Revolution found an average peak demand reduction of between 3.2% and 12.5%.

With regards to income effects and price elasticity, the literature is vast. A recent review points to residential electricity demand being almost price-inelastic and income-inelastic in the short-term (Zhu et al., 2018). The type of data used to understand the relationship between short-term changes in tariffs and electricity demand matters. On the one hand, a study making use of household panel data for homeowners finds that the income elasticity of short run demand for residential electricity is significant (Branch, 1993). On the other hand, a study based on a mixed panel of dwellings in urban areas finds that the price elasticity of electricity demand declines with income, but the magnitude of the effect is not large (Alberini et al., 2011). In the U.S., low-income groups have been associated with lower peak reduction than other groups (Faruqui and Sergici, 2013). Existing studies are not conclusive about the relationship between income variables and ToU tariffs (Stromback et al., 2011). Demand management interventions, including turning off lights, standbys or reducing the temperature of the home during absences cannot be related to income (Cayla et al., 2011). A meta-analysis of ToU uptake notes that existing studies do not show significant results across factors such as income because not enough studies collect income-related information about consumers (Nicolson et al., 2018).

A different approach from individual behaviour in response to price changes consists of work focusing on the timing of practices. Several empirical works emerging in the energy demand literature on flexibility point to different flexibilities of practices to ToU. Powells et al. (2014) analyse the flexibility of individual practices during peak hours in response to TOU pricing. They find that flexible practices (i.e. practices performed differently as a result of ToU tariffs) include laundry, household chores and dishwashing. Domestic cleaning practices, such as laundering, are considered to be relatively flexible in time in other studies (Jack, 2016). Smale et al. (2017) group practices in relation to appliances involved and issues around time the distinctions made above. They show that timing is critical for lighting, heating and cooling spaces; cooking, eating and leisure activities are time critical, whereas domestic cleaning is not seen as time critical. Households changed the performance of a number of practices only if these were not specifically tied to socially conventional times. In a Swedish study, practices which were regularly shifted from peak to off-peak hours included dishwashing and laundry (Öhrlund et al., 2019). Other practices such as showering, tumble drying, vacuum cleaning, bubble bathing and sauna bathing were also shifted from peak to off-peak hours on several occasions (though not as regularly as dishwashing and laundry).

Conversely, practices are identified as inflexible if they are not performed differently as a result of the introduction of ToU tariffs. Inflexible practices consist of cooking and watching TV according to Powells et al. (2014). Practices specifically tied to socially conventional times constrain their temporal flexibility. Lighting, heating and cooling of spaces are grouped as inflexible practices as they relate to comfort (Friis and Christensen, 2016). According to these studies, seasonality affects the daily rhythms of lighting and heating, which are otherwise considered highly inflexible. Light and warmth are seen as 'necessary' services. Cooking, eating and leisure activities can be clustered together. Food and entertainment are also considered to play an important role in shaping and maintaining social bonds between members of a household. Two explanations are presented for the inflexibility of eating practices. First, bodily needs and temporality seem to be more strictly defined when it comes to eating). Second, the timing of food (and entertainment practices) are a matter of (often complex) coordination between household members (Higginson, 2014). Electricity intensive forms of entertainment like watching TV and video gaming are two more examples of inflexible practices during which people relax and are typically less reflexive of energy issues (Smale et al., 2017).

This brief review shows the importance of expanding knowledge about the dynamics between ToU, socio-demographic variation and timing of practices whilst connecting different data on these relationships. The review reveals three key issues. First the lack of consistent evidence around the effects of ToU on electricity demand implies that assumptions around no-behavioural change have not yet been invalidated. Second, the need for approaches which capture social and spatial differences suggest that controlling for behaviour might be an effective research strategy to understand the financial effects of ToU *ceteris paribus* –in this case, if people carry on with everyday life regardless of ToU. Third, a practice approach involves first and foremost examining the ordering and timing of activities in everyday life as these are not all likely to change because of price. These observations brought about the decision to control for behaviour as explained as part of the methodological choices in Section 3.

2.2 Modelling load profiles through time use activities

Studies based on time use data consist of a growing body of work which typically relies on national time use surveys to either model electricity load profiles or infer energy-related proxies, such as occupancy. Early work comprises a study by Capasso et al (1994), who modelled 15-minute period consumption patterns based on appliance and homeowner variables; Wood and Newborough (2003), who used three characteristic groups to explain electricity consumption patterns in the household:

“predictable”, “moderately predictable” and “unpredictable”; Stokes et al (2004), who modelled domestic lighting with a stochastic approach, generating load profiles with a resolution of 1 minute from the 30 minute resolution of measured data in 100 households; and a study by Firth et al (2008) who analysed groups of electrical appliances (continuous and standby, cold appliances and active appliances) in terms of time of the day when they are likely to be switched on.

Richardson et al. (2008) make use of the National Time Use Survey to develop a model which generates occupancy data for UK households. The model consists of probabilistic approach to infer how many other occupants enter or leave the household between time intervals. The model is used in Richardson et al. (2010) and Ramírez-Mendiola et al. (2018) to simulate electricity demand. Other have used time use data to derive flexibility indices (Torriti et al., 2015). In a similar study, Blight et al. (2013), examined the occupant behaviour and its impacts on heating consumption in Passivhaus buildings. Using Richardson et al. (2008) model the authors developed occupancy, appliance-use and door-opening profiles, based on UK Time-Use-Survey, which describes time use at a 10-min resolution by 11,600 householders. Their finding suggests that the occupancy patterns are less significant factors to the total heating energy than other factors, such as set point temperature and appliance use.

Widén and Wäckelgård (2010) developed a model simulating households’ activities based on Swedish time use data. The timing of electricity demand is derived from time use data combined with appliance holdings, ratings and daylight distribution. The same author applied the same model to water heating (Widén et al, 2009a) and lighting (Widén et al, 2009b).

Duffy et al (2010) applied the same probabilistic modelling to five different dwelling types in Ireland. They compare the synthetic data generated by the model with metered electricity demand. Their findings show unusual peak loads during the day and night which do not correspond to existing load profiles.

López Rodríguez et al. (2013) used the Spanish National Time Use Survey to generate activity specific energy consumption profiles or to cluster consumers based on their states of occupancy. They used the generated profiles to identify appliances that were running during the occupancy. Aerts et al. (2014) using the Belgian time use data define a three-state probabilistic model to generate occupancy patterns. They combine socio-economic aspects of population with occupancy data in investigating the clustering of different occupancy patterns.

Others also consider socio-economic characteristics (such as age, employment status, income or main activity) to be powerful predictors of occupancy characteristics. For example, Dar et al. (2015) using the Norwegian Time Use Survey investigated the effect of occupant behaviour and family size on the energy demand of a building and the performance of the heating systems. They identify nine occupancy categories based on number of occupants and working hours.

3. Methodology

Since the aim of this paper is to identify groups of consumers who may be financially advantaged or disadvantaged by the introduction of ToU tariffs, the methodology is designed to produce peak to off-peak ratios of activities and impacts on synthetic electricity demand profiles. Previous studies reviewed in section 2.2 (e.g. López Rodríguez et al., 2013; Widén and Wäckelgård, 2010; and Richardson et al., 2008) model load profiles through data on time use activities as well as appliance ownership and energy use for the survey respondents. On the one hand, the methodological approach of these studies is consistent with the aim of this paper because of their focus on building occupancy and the timing on energy-related activities. On the other hand, the main limitations of this approach relate to the accuracy of the model in reproducing load profiles as information about electrical appliances, power efficiency and building properties are typically assumed (Torriti, 2014). In order to overcome these issues, this paper imposes ToU tariffs onto half hourly smart meter data and synthetic demand profiles as this enables a thorough identification of distributional effects through consumer segmentation and socio-demographic groups.

The methodological approach of this paper is presented in Figure 1. The tasks of the methodology of this paper are associated with smart metering data (in red in Figure 1), modelling (blue) and distributional analysis (purple).

We process smart meter electricity demand data and apply ToU tariffs on different income groups to derive groups that will be advantaged and disadvantaged from such tariffs. In parallel, we process activity data to determine number of energy related activities per household and extract socio-demographic information for each household, mapping the activity probability profiles to the socio-demographic groups.

Activity data are used to derive activity and occupancy probabilities by income groups and geographical location within the UK. This enables us to estimate the kWh value per activity and occupancy probabilities by income groups and, consequently model demand from activity and occupancy probabilities by optimising kWh values per activity against demand data for consumers with similar socio-demographic properties.

Finally, the comparison between electricity demand profiles and modelled demand from activities and occupancy leads to the application of ToU to matching demand profiles. This identifies those who will be advantaged and disadvantaged from ToU implementation both by income groups and geographical location.

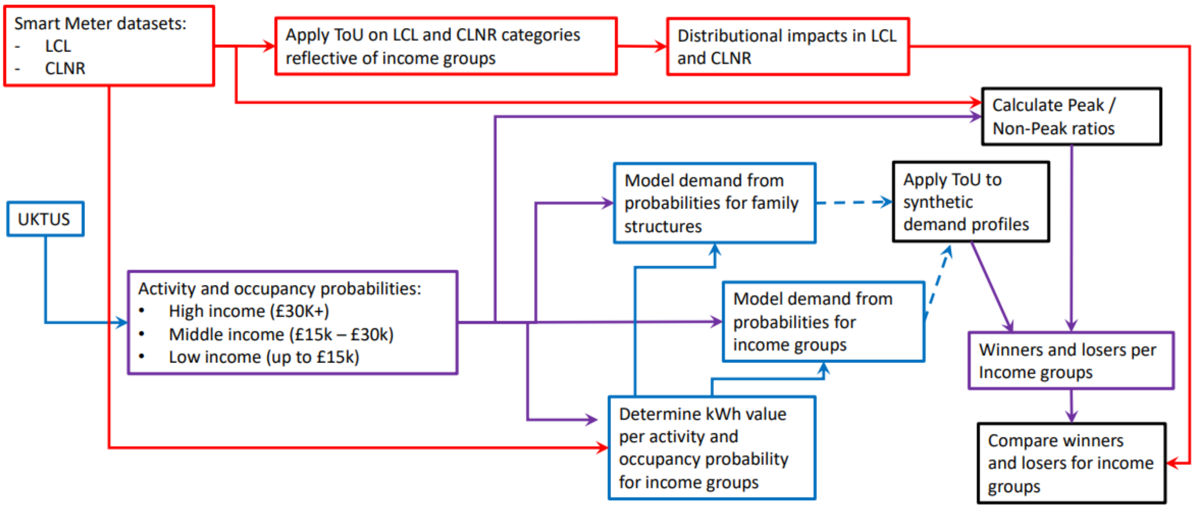

Figure 1 - Methodological approach of this study

3.1 Data

We used two UK smart meter datasets with socio-demographic information. First, the Customer-Led Network Revolution was carried out over 2011 to 2014 by Northern Power Grid (Sidebotham & Powergrid, 2015), which is based on 13,000 electricity customers in the North East of England to develop an understanding of electricity use patterns. Smart meter data is analysed for customers in different circumstances and in response to various interventions. For domestic customers this included a control set of basic demand profiling, and customers with Low Carbon Technologies, such as Air Source Heat Pumps and Electric Vehicles. Second, Low Carbon London was a UK Power Networks project encompassing energy consumption readings from 5,567 London households between 2011 and 2014 (Sun et al., 2016). Data is available for a control group and a group that were subject to dynamic ToU tariffs in 2013.

With regards to activity data and social-demographic information for the activity analysis, this was provided by the UK Time Use Survey (UKTUS). In total UKTUS comprises of over 1600 participants with 16 with 270 individual activity codes that the respondents could choose from to describe their activity. To reduce the computational requirements and to focus on electricity consumption associated with activities, the activity codes were grouped by similarity (e.g. "watching sports on TV" or "watching films on DVD" grouped as "watching TV") and whether activity is likely to be directly linked with electricity consumption. For each household, all energy related activities for each respondent to the activity diary were added together to get a profile containing the number of energy related activities in the household. For modelling purposes, the energy related profile for each household profile was normalised to per person in the household to focus the weights on the shape of the profile. The social-demographic information for each household was gathered from the individual survey and household survey. Combining two data sets gave a wider selection of the socio-demographic parameter for each household, which contains the following information: (i) number of children in the household (variable DM016 from UKTUS household survey); (ii) overall household income; (iii) property type; (iv) employment status of the residents of 16 years old and above: self-employed, employed, retired or unemployed; (v) number of residents in the full-time education; (vi) household type: single person, married or cohabiting couple with children (under 16), married or cohabiting couple without children, single parent with children (under 16), single parent without children, married or cohabiting couples in complex households, single parents in complex households and other households (e.g. unrelated or siblings); (vii) number of rooms in the household; and (viii) age of the residents.

3.2 Distributional impacts

3.2.1 Existing customer segmentation

Both LCL and CLNR projects have utilised commercially available customer segmentation provided by CACI's Acorn and Experian's Mosaic respectively. These customer segmentation mechanisms are based on a composite of a multitude of parameters and are aimed at evaluating commercial, financial and marketing preference features of the population by postcode areas. Although income is only one of the parameters in the segmentation, both segmentation approaches can be broadly mapped to income groups (Table 1).

Table 1 – Mapping of consumer segmentation groups from LCL and CLNR to income groups

Consumer income group	Acorn Groups (LCL)	Mosaic Groups (CLNR)
Low	KLMNOPQ	IJKLN
Middle	FGHIJ	DEFGHMO
High	ABCDE	ABC

To assess the impact of income level on the effects of ToU tariffs under a scenario of no change in behaviour, we apply the chosen ToU tariff on the demand profiles in each of the consumer segmentation groups and compare it against the flat tariff. By comparing the results between the two projects, we can compare the difference in effect of income across two regions: London and the North East of England.

3.2.2 Modelling demand from activity data

Whilst the UK Time use survey gives a representative picture across all regions in the UK, the analysis of the activity probability profiles between different socio-demographic groups may not be sufficient to determine the degree of impact from ToU tariffs. However, evaluating the ratio of activity probability at peak time against the non-peak time probability of activity can give an insight on which groups are more likely to carry out energy related activities at peak time and hence consume more energy at peak time.

In an attempt to further explore the distributional impacts of ToU tariffs, we require demand profiles with the corresponding singular or at most dual parameter socio-demographic information - e.g. household income and geographical location. Compensating for the lack of access to such data, we have set out to estimate the power consumption associated with the selected activities by creating synthetic profiles that match the demand for the customers with similar socio-demographic properties. The process for creating synthetic profiles is described in Table 2.

Table 2 – Process of generating synthetic demand profiles for household composition combined with income groups

1. Extract corresponding activity profiles	**2. Split LCL data by income**	**3. Optimise activity energy coefficient**	**4. Apply activity energy coefficient**
UKTUS data for households in London across income groups: • Low (under £15k) • Middle (£15k-£30k) • High (over £30k) Calculate probability profiles: Occupancy; Cooking; TV Watching; Laundry; Ironing and House cleaning	Split demand profiles for by income groups: • Low income - Acorn groups KLMNOPQ; • Middle income - Acorn groups FGHIJ; • High income - Acorn groups ABCDE.	For each demand profile in an LCL income group create matching synthetic profile by: • optimising activity energy coefficients for occupancy and activity profiles for corresponding income group to match LCL demand profile; • maintain proportion of daily energy per activity	For the corresponding income groups, energy coefficients are applied to activity data from other socio-demographic groups to generate demand profiles for distributional impact analysis.

The optimisation of the activity energy coefficient allows to derive the power demand associated with the probability of each activity corresponding to the income group. Here we assume that activity energy coefficients per income group are equal across the UKTUS geographical areas.

Formulation of the optimisation problem is given below:

$$\text{minimise } F(\boldsymbol{w}, p),$$

$$F(\boldsymbol{w}, p) = \sqrt{\sum_i^7 \left(p^t - w_i^t a_i^t\right)^4} \qquad (1)$$

Subject to

$$\sum_t^{48} \frac{w_i^t a_i^t}{2} = e_i \sum_t^{48} p^t \qquad (2)$$

$$w_1, w_2, w_3, w_7 \in [0\ 10] \qquad (3)$$

$$w_4, w_5, w_6 \in [0\ 2] \qquad (4)$$

Where $\boldsymbol{w}$ is the set of 48 energy coefficients per activity *i*, *p* is the target demand profile, a_i^t is the probability of activity *i* at time *t* and e_i is the activity *i* energy proportion of daily energy for profile *p.*

Equation (1) is the cost function of the optimisation designed to minimise the difference between the synthetic demand profile, $w_i a_i$, and the target demand profile, subject to maintaining the daily energy use per service, equation (2), and bounds for the energy coefficients per activity, equations (3) and (4). The proportions of energy use per service linked to activities are approximated from the Energy Consumption in the UK data (BEIS, 2018) and are as described in Table 3.

Table 3 - Proportions of total energy demand per activity

Activity number	Activity name	Proportion of total energy demand
1	Active occupancy	34%
2	Cooking	10%
3	Laundry	11%
4	TV watching	9%
5	Ironing	3%
6	House cleaning	3%
7	other	30%

The energy coefficients which were derived from the synthetic demand profiles with deviation from the target profiles by more than 1% have been excluded. The remaining energy coefficients were used to extract representative energy coefficients per income group, derived from customer categories. These representative energy coefficients are then used to generate synthetic demand for other socio-demographic groups with the corresponding income distribution from UKTUS.

3.2.3 Tariffs

To assess the impact of ToU tariff on each socio-demographic group two types of tariffs were chosen: standard flat tariff and static ToU tariffs. The tariff schedule and ratio of price levels for the tariffs were based on two studies by Centre for Sustainable Energy (2014) and by Hledik et al. (2017). In order to derive differences across socio-demographic groups, it is assumed that there is no change in behaviour and in demand as result of ToU tariff. Table 4 presents the timings and the price levels of the tariffs.

Table 4 - Flat and static ToU tariffs applied to assess the impact on bill costs

Source	Tariff	Peak Period	Peak Price p/kWh	Middle Period	Middle Price p/kWh	Off-Peak Period	Off-Peak Price p/kWh	Peak to Off-Peak Price Ratio
CSE	ToU-1	everyday 16:00-20:00	22.9	-	-	Everyday 20:00 -16:00	10.6	2.160
CSE	ToU-2	everyday 16:00-20:00	23.4	everyday 14:00 - 16:00 20:00 - 23:00	11.7	Everyday 20:00 -16:00	7	3.343
CSE	ToU-3	weekday 16:00-20:00	27.1	weekday 14:00 - 16:00 20:00 - 23:00	13.7	weekday 20:00 -16:00; weekend all day	8.1	3.346
CSE	Flat	-	-	All time	13.6	-	-	-
Brattle	Tou-1	weekday 16:00-20:00	18	-	-	weekday 20:00 -16:00; weekend all day	6	3.000
Brattle	Flat	-	-	All time	12	-	-	-

4. Findings

4.1 Customer segmentation and existing smart meter data

Figure 3 highlights the difference between mean demand profiles for the approximated income groups from consumer segmentation methods used in LCL and CLNR projects against the defined CLNR income categories. The key difference between LCL and CLNR mean demand profiles is the timing of the peak demand: residential demand in London peaks about 60-90 minutes later compared to demand in the North East England area. Demand for the CLNR approximated high-income group is higher than the CLNR high-income category and the peak demand in LCL high-income group. Otherwise, for the middle- and low-income groups, demand from LCL is similar to the corresponding CLNR approximated income groups and CLNR categories.

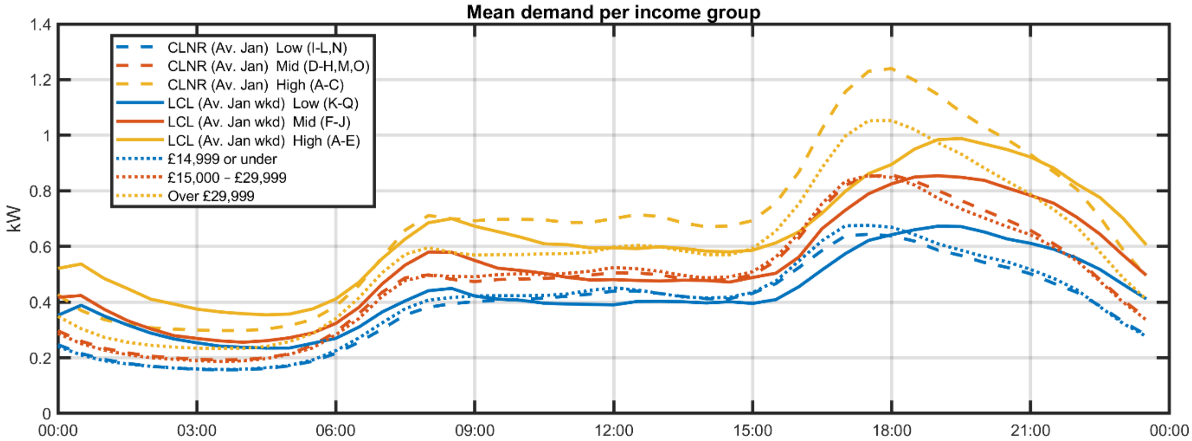

Figure 2 – Mean demand profiles for January per consumer segments mapped to income groups for LCL and CLNR datasets

Applying selected ToU tariff components generally have similar effects across all income groups. This is explained by the price ratio between peak and off-peak associated with the ToU tariffs. In order to understand the impact on low, middle- and high-income groups, Figure 4 shows the relative difference on the bill per tariff on average week demand based on the Mosaic segmentation of CLNR data.

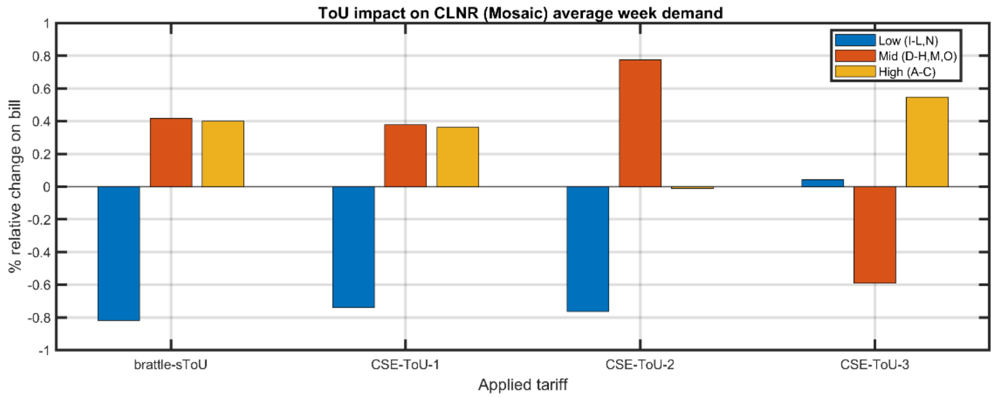

Figure 3- Relative effect of ToU tariffs on the bill of low, middle- and high-income groups based on CLNR data on average week demand and Mosaic customer segmentation

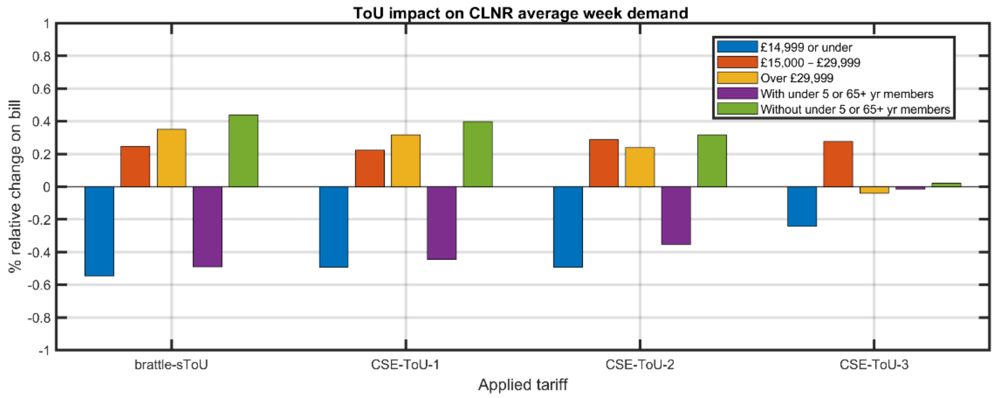

Figure 4- Relative effect of ToU tariffs on the bill of different categories of consumers based on CLNR data on average week demand

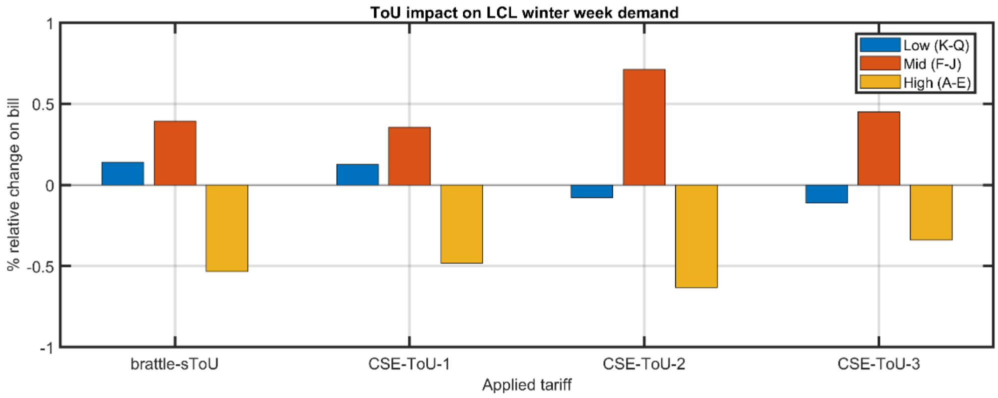

Figure 5– Relative effect of ToU tariffs on the bill of low, middle- and high-income groups based on LCL data on average winter week demand

According to Figure 4, the low-income group in the CLNR would be financially advantaged from all ToU tariffs except for CSE ToU-3 in which there is a very slight bill increase. For the same dataset, middle and high-income groups are generally disadvantaged from ToU. The CSE-ToU-2 tariff presents the highest bill increases for the high-income group and a neutral effect on the middle-income group. Figure 5 shows the relative effect of ToU tariffs on the bill of different categories of consumers based on CLNR data on average week demand. Households with either children under 5 years old or over 65 years old members would be advantaged from all tariffs -except CSE ToU-3. Reversely, households without either children under 5 years old or over 65 years old members would be disadvantaged from all tariffs -except CSE ToU-3. Figure 6 illustrates the relative effect of ToU tariffs on the bill of low, middle- and high-income groups based on LCL data on average winter week demand. The application of ToU tariffs generates positive effects on higher income households. In essence, Figure 4 and Figure 6 show different results between the mostly rural, North East England data and the London data. This disparity can be partly explained with the different occupancy levels as shown in the UK Time Use Survey data in Section 4.3, which is also reflected in the fact that electricity peak demand takes place on average one hour later in London compared with other parts of the UK (Snodin et al, 2019).

4.2 From activities to distributional impact

Figure 7 shows the levels of active occupancy for different income groups and different household compositions on weekdays (left column) and weekend (right column). The presence of children introduces a particular pattern in active occupancy on weekdays for all income groups. A spike in the morning around 7am is followed by a trough just after 8am and another spike around 4pm – all correlating with typical school run patterns. Overall low-income groups demonstrate higher occupancy during the day on the weekdays and single parent families are less likely to be actively occupying homes than bigger families for the same income groups. On the weekend, except for the single parent families, active occupancy also follows a similar pattern for all groups, whilst low-income groups remain with higher probabilities of active occupancy during the day.

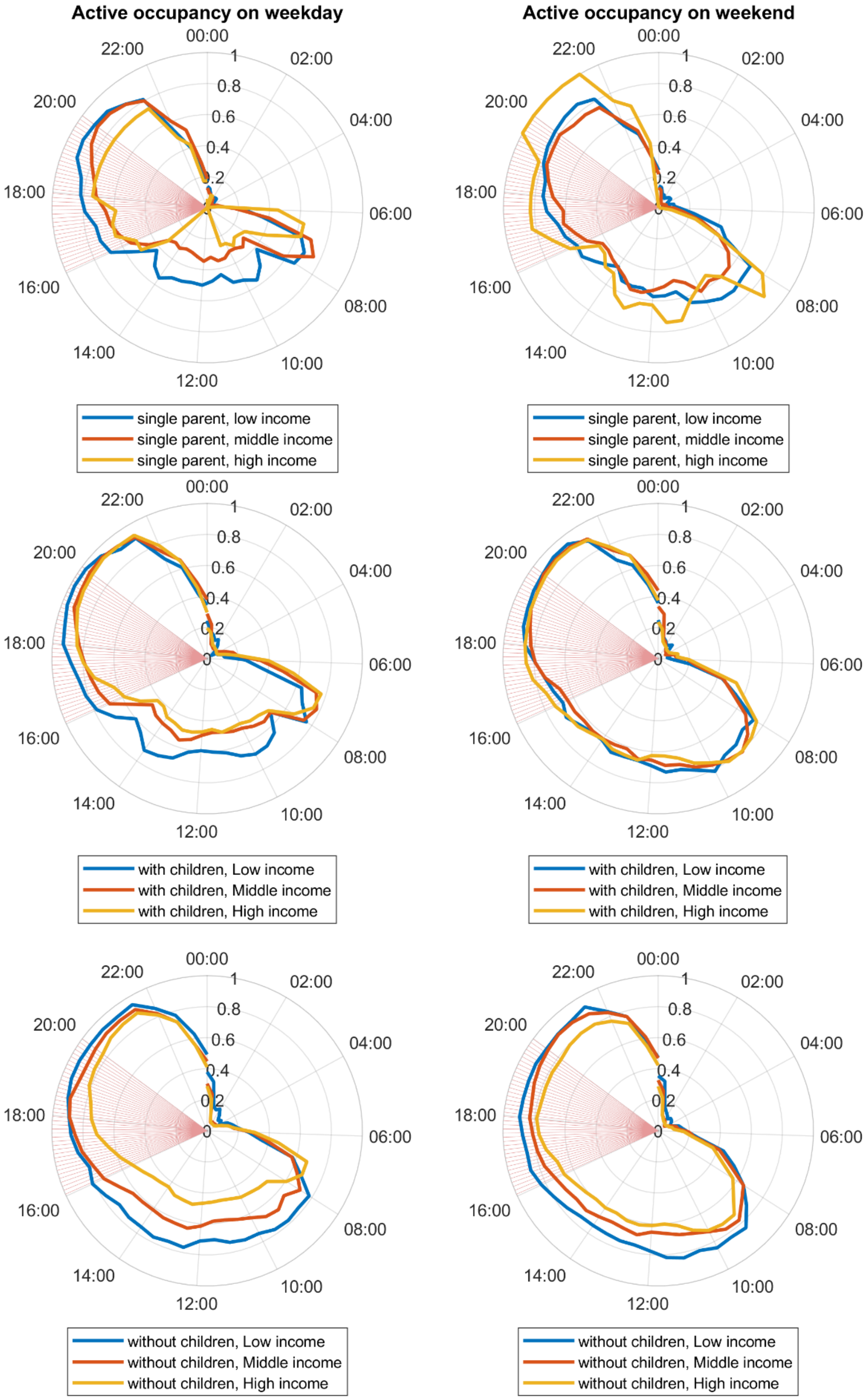

Figure 6– Active Occupancy probability on a weekday and weekend for household composition across income groups (the peak demand period is highlighted by the red-shaded area)

From a broader perspective, Figure 8 compares the peak to off-peak ratios of occupancy and energy-related activities by income group and household composition. Cooking is the activity which presents the highest peak to off-peak ratios for all income groups and household structures apart from single parents in the high-income group. Cooking features the highest peak to off-peak ratios in correspondence with household with children and either middle or high income. In Figure 8 only activities with ratios below 1 are performed during off-peak period compared to the peak time. For example, the laundry takes place mostly off peak for single parents in the middle-income group, retired couples, and households without children in the low-income group.

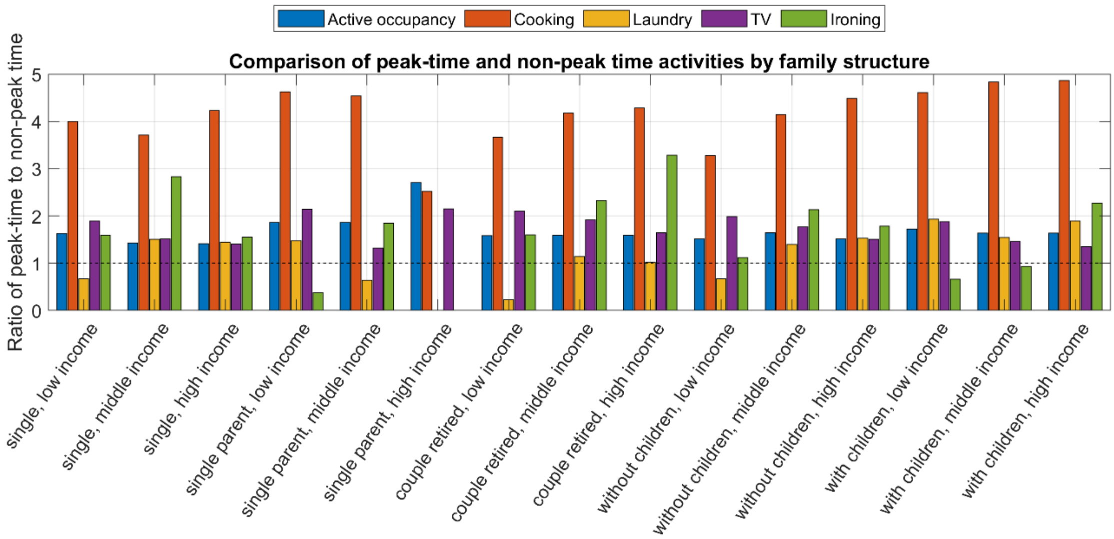

Figure 7- Peak to off-peak ratios of occupancy and energy-related activities by income group and household composition

In attempt to summarise, Figure 9 compares the product of peak to off-peak ratios of active occupancy and energy-related activities across three regions and income groups. The highest products of peak to off-peak ratios are associated with regions North and Scotland, high income. This means that the collective probability of active occupancy and energy-related activities for these categories is significantly higher than other categories. Conversely, London, high income features a low product of ratios compared to the low-income group in London. This partly explains the divergence in results in Figure 4 and Figure 6. In practice however, low-income group are likely to benefit from greater from savings from ToU tariffs due to higher active occupancy, which offers an opportunity to shift demand away from peak period (e.g. laundry).

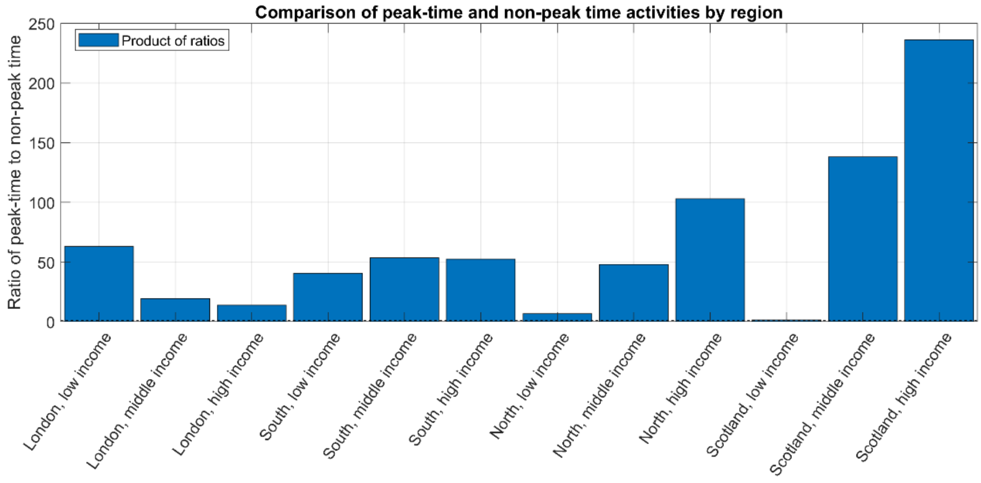

Figure 8– Product of peak to off-peak ratios of occupancy and energy-related activities across three regions combined with income groups

Applying similar approach, Figure 10 compares the product of peak to off-peak ratios of occupancy and energy-related activities by income group and household composition. Households with children and high income feature the highest product of ratios. From the other end of spectrum, low-income retired couples and families without children are associated with the lowest product of ratios. Within the household compositions, except for the families with children, middle income groups tend to have highest product of ratios.

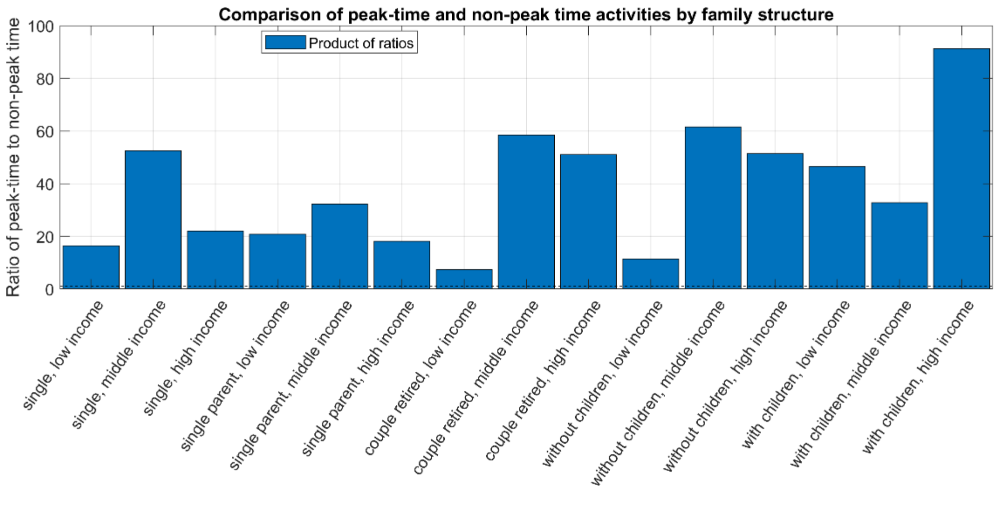

Figure 9– Product of peak to off-peak ratios of occupancy and energy-related activities by income group and household composition

In an attempt to define the distributional impact of ToU more precisely than the peak-to-off-ratio, we derived a set of energy coefficients that can be applied to occupancy and activity probabilities to model demand and extrapolate ToU impact to income groups across the geographical coverage of UKTUS.

Figure 11 illustrates the distribution of energy coefficients associated with occupancy per income group. For instance, the occupancy median reaches the highest levels during the night hours – which is a side effect of low overnight active occupancy. In line with the active occupancy probabilities in Figure 6, low-income groups have higher energy coefficient for active occupancy during the day.

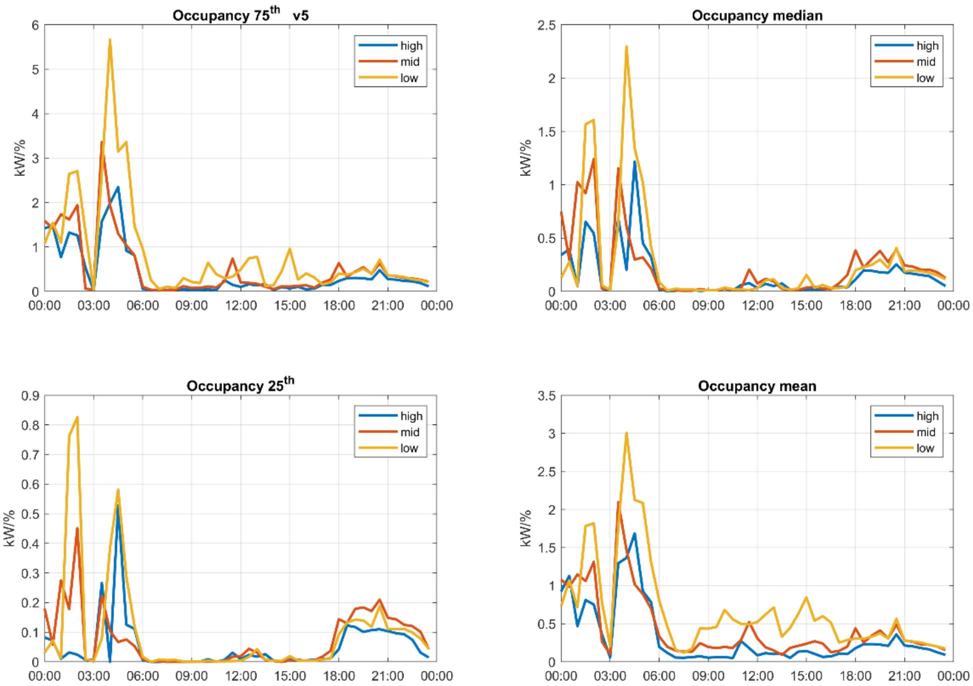

Figure 10– Distribution of energy coefficients associated with active occupancy per income group.

As a result of applying activity energy coefficients, Figure 12 shows the synthetic demand profiles generated from activity data divided by household composition and income groups. For instance, across income groups single parents feature distinctive demand patterns, with higher demand in early mornings and lower afternoon demand -particularly for the high-income group. The medium income group presents consistent peaks in the morning and evening across different household compositions and a generally low electricity demand at lunch time. Whist these profiles do not accurately model the demand profiles associated with the income groups, the key features of demand in the context of ToU are represented.

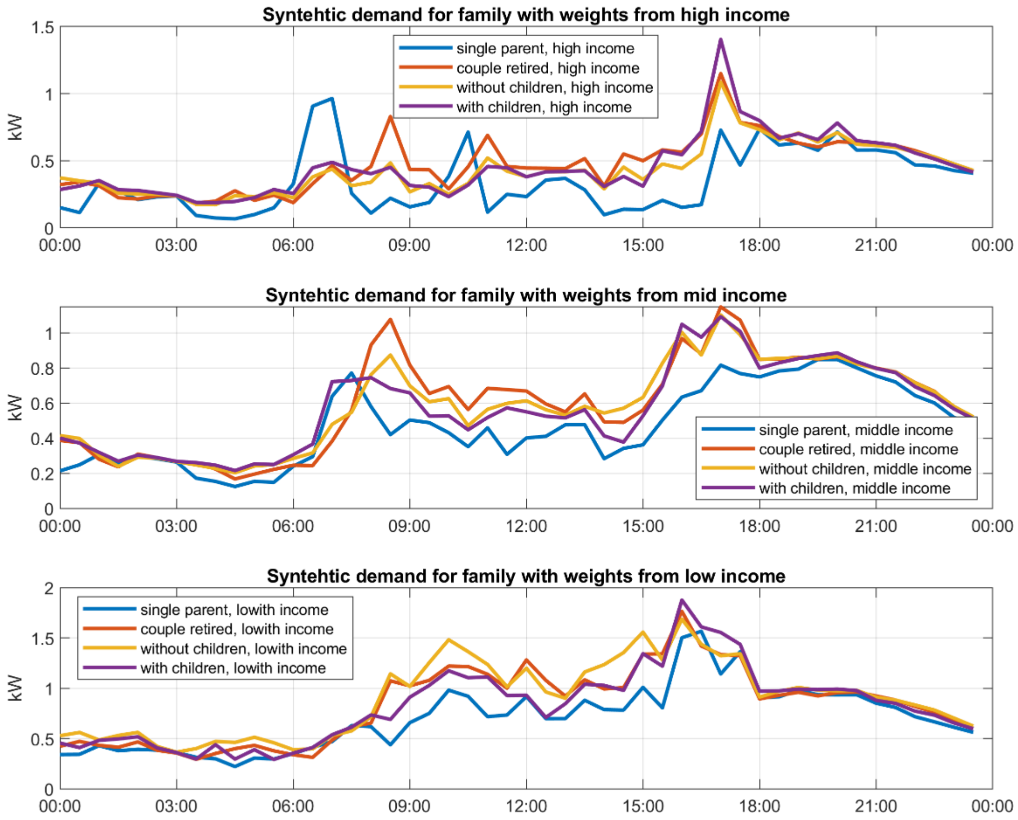

Figure 11– Synthetic demand profiles (in kW) generated from activity data for household composition and income groups with activity energy coefficients from income groups.

Figure 13 presents findings on the impact of ToU tariffs on synthetic profiles combining household composition and income groups. The results are based on the synthetic profiles generated from energy coefficients by activity corresponding to the London income groups. Single parents are approximated to consume less compared to other groups with the same energy coefficients per activity. Any ToU tariff of those applied in this paper brings about bill increases on high income for both households with and without children. Marginally lower bill increases would affect middle income households without children and middle-income retired couples. Single parents in the low-income group are the category which would be financially most advantaged from the introduction of any ToU tariffs. With the exception of the high-income group, there is consistency in the effects of ToU for households with the same household composition (irrespective of whether they are in the middle of low-income group).

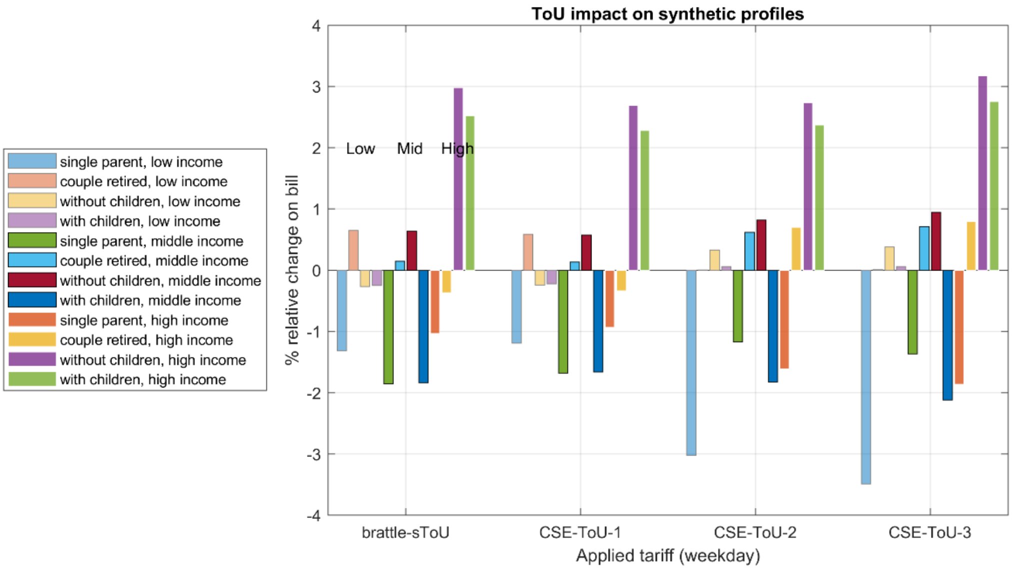

Figure 12- Relative difference of bill impact across household composition and income groups for synthetic profiles

5. Conclusion and Policy Implications

The opportunities for dynamic pricing and enhanced flexibility associated with smart meters need to be considered in terms of their effects on residential consumers. This paper presents findings on the application of ToU tariffs across different income groups and household compositions. The emphasis is on time availability as it is recognised that active occupancy and the timing on energy-related activities vary significantly across the population. For this reason, we analysed both highly granular metered electricity consumption data, socio-demographic information about consumers and timing of activities carried out in their homes. Occupancy and activity probabilities for each household type were used to generate synthetic electricity demand profiles. Synthetic demand profiles demonstrated variability in electricity demand aligned with the changes in energy-related activities during the peak time. Whist the synthetic demand only approximates the energy use by different household compositions, it is sufficient to indicate potential impact from ToU on household structures and incomes.

Findings on smart meter data show diverging results. For instance, the low-income group in the North East England (CLNR data) would be financially advantaged from the analysed ToU tariffs, whereas in London (LCL data) the application of ToU tariffs generates positive effects on higher income households. This is reflected in the fact that electricity peak demand takes place on average one hour later in London compared with other parts of the UK. Our analysis shows some evidence that the static ToU tariff periods may not align with actual peak demand periods, as there are regional variations in residential electricity demand and time use. In its current format, UK smart metering data alone is not sufficient to understand distributional effects of ToU tariffs unless it is enriched by socio-demographic parameters which are currently not contained in publicly available sources. Time use data analysis partially fills the gap in understanding the distributional effects of ToU tariffs – at least from the perspective of distribution of activities between peak and off-peak time.

These regional differences are evidenced by time use data, showing that in the North high-income groups have higher product ratios in terms of active occupancy and energy-related activities compared with any other region and income group. On the opposite, Londoners in the high-income category present low product of ratios and are consequently less likely to be negatively affected by ToU tariffs. Time bands set in advance may over-reward high income users in London for two reasons which are presented in this paper. First, currently their occupancy levels are relatively low at peak time –arguably because of different work and leisure/social patterns compared with other parts of the UK (Jarvis, 2005). Second, smart metering data shows that high income users in London are better off with any of the ToU tariffs applied in this paper. The over-rewarding effect could only be compensated if ToU tariffs instigate significant behavioural change in lower income groups and non-urban areas. Studies applying behavioural estimates to aggregate socio-demographic groups find that under ToU tariffs on average all, except some of the most affluent groups, would save on their annual bills (Cambridge Economic Policy Associates, 2017).

Whenever variations in energy bill impacts from ToU tariff are represented in absolute values these are also the result of volumes associated with different residential consumers. Higher responses are more likely to take place with larger residential users. In general, households vary significantly in the amount of energy they use. These variations could be attributed to differences in engineering and economic factors, energy type and household characteristics (family size, age of household members, etc.). However, when these factors are controlled or set, large variations in the amount of energy use in individual houses remain. The large variations and the non-linear responsiveness to price signals relate to non-energy factors of electricity demand. Both baseline and ToU intervention load profiles are affected by the rhythms of everyday life (office opening hours, school times, shops opening hours) more than price. Formally, variables like occupancy and weather might have a strong explanatory power, but are not often captured in ToU studies partly because of difficulty/cost of collecting this type of data.

The policy implications of research on the effects of ToU tariffs in distributional and spatial terms are extremely significant. In the UK, regulatory reform of ToU tariffs has been estimated to bring about estimated aggregate bill savings for UK residential customers of between £1.6 billion and £4.6 billion over a period of two to three decades (Ofgem 2020). In parallel, the locational granularity of charges for most users may move away to a simple regional charge for those connected at the lower voltages.

Regional charges might be combined with time bands to vary by charging zone so that higher charges for their demand customers' usage during winter peak periods in areas of the distribution network where peaks take place. Charges would be highest for customers in areas where the network is more expensive. Increasing block pricing has precedent elsewhere and could offer a cost-reflective alternative to other forms of charging in combination with ToU. The literature in this area is mixed with regards to the extent to which progressive tariffs bring about higher efficiency and mitigate distributional effects of charge (Kahn and Wolak, 2013).

The regional differences combined with the absence of publicly available information on the socio-demographics of metered use emphasise the importance of attempting to model at high temporal and spatial scales the distributional effects of ToU. High-resolution models such as those reviewed in Section 2.2 fall short of differentiating demographically load profiles. This is because, in the example of the most used activity-based model in the UK -CREST (Richardson et al., 2008)- the variation is given by the number of occupants irrespective of any socio-demographic characteristics. The model we introduce in this paper estimates the power consumption associated with the selected activities by creating synthetic profiles that match the demand for the customers with similar socio-demographic properties. The model findings show that ToU tariffs lead to bill increases for high income consumers in both households with and without children. Bill increases are milder for middle income households without children and middle-income retired couples. ToU tariffs would benefit financially single parents in the low-income group. With the exception of the high-income group, there is consistency in the effects of ToU for households with the same household composition (irrespective of whether they are in the middle of low-income group).

To enhance the relevance of the findings to the policy makers and the practicality of distributional impact outcomes, the methodology presented in the paper would benefit from the inclusion of energy use datasets with granular socio-demographic information. Furthermore, information describing the socio-demographic composition of consumers on commercially available ToU tariffs in the UK could be used to refine the model and validate the outcomes of the analysis.

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