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

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Abstract

In an attempt to shift peak electricity demand, the introduction of Time of Use (ToU) tariffs may affect residential electricity consumers differently depending not only on their financial 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. We impose ToU tariffs on UK half hourly smart meter data and the synthetic demand profiles for different family structures generated using the 2014-2015 UK Time Use Survey 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 impact 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; Time of Use tariffs; Time use; Electricity demand.

1. Introduction

The national rollouts of smart metering in several countries is in part motivated 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. However, there are uncertainties about how higher levels of demand-side flexibility, in this context, will be delivered. In the past, commercial and industrial end-users have been contributing to demand side flexibility mainly via interruptible load programmes (Torriti et a., 2010). In the future, it is expected that time of day tariffs will be extended to significant portions of the residential sector as a way of mitigating peaks in electricity demand and potentially increase demand during off-peak periods.

Examples of these types of tariffs abound and include tariffs based on actual capacity, tariffs based on agreed capacity, real-time pricing, critical peak pricing, critical peak rebates and block pricing and Time of Use (ToU) tariffs. Suppliers in the UK will be incentivised to offer a range of these tariffs (Ofgem, 2016) and some of the suppliers already offer real-time pricing (Octopus, 2020) and ToU tariffs to their customers (Bulb, 2020). ToU tariffs are analysed in this paper as in the UK the energy regulator proposes to explore how to encourage the uptake of ToU tariffs and stimulate necessary change in consumer behaviour 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 Time of Use 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 & Powergrid, 2015). The 2014-2015 UK Time Use Survey data was used to identify activities differently affected by ToU tariffs across several socio-demographic parameters. 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 paper reviews work which analysed the distributional effects of Time of Use tariffs as well as previous models connecting time use activities to load profiles (Section 2). It describes the overall methodological approach, the different smart metering and time use datasets as well the research methods utilised for the analysis. Findings are presented in terms of customer segmentation, peak to off-peak ratios and synthetic 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 activities

2.1 Time of Use tariffs

Under Time of Use tariffs customers are charged for their actual consumption during different periods of the day. Different unit rates can be assigned to set periods of the day called 'time bands', in advance of the charging year and 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 either seasonality – where charges during the 'peak' season are higher than during the rest of the year.

Existing studies can shed light on two critical aspects of Time of Use tariffs, i.e. average demand reduction in correspondence with peak periods and distributional effects.

With regards to average demand reductions, a review of 163 reviewed studies shows that peak reduction levels range from next to 0 to almost 60% (Faruqui and George, 2005). Findings show that 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%.

Time of Use tariffs in Ireland reduced peak consumption by 8.8% for specifically designed price bands (Darby and McKenna, 2012). In France Time of Use tariffs were combined with weather inputs, with days differentiated based on price signals for peak and off-peak hours. It was estimated that for a typical household with a 1 kW average load, the Tempo tariff brought about a reduction in consumption in the region of between 15% and 45% with customers saving 10% on average on their electricity bills (Torriti et al., 2010). In Italy, Time of Use tariffs have gradually been applied to Italian residential electricity users since the year 2010. The first pilot of Time of Use (dual tariff) involved 4 million end users. Lower tariffs are applied to weekends and to weekdays from 7.00 PM to 8.00 AM. The two tariffs (initially set at 0.09 cent/kwh and 0.07 cent/kwh for peak and off-peak respectively) were originally designed to yield savings for the end-user whose consumption is concentrated for more than 66% during the lower tariff periods. 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. For example, in the Northern Italy data a third peak emerged in the middle of the afternoon bringing about lower consumption before the change in tariffs at 7.00 PM (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 of 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). However, the Low Carbon London trial found average shifts in energy demand of around 4.2% (UK Power Networks, 2014).

With regards to distributional effects, existing studies are not conclusive about the relationship between socio-demographic variables and response to ToU tariff (Hledik et al, 2017). In the U.S., low-income groups are associated with lower peak reduction than other groups (Faruqui and Sergici, 2013). In the UK, ToU being about diffused and relatively minor reductions in bills, some increases of up to 20% (Centre for Sustainable Energy, 2014). Age, gender, housing tenure, employment status, education, income and social grade do not explain the uptake of ToU tariffs (Nicholson et al. 2017).

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

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. From the smart meter data, we normalise profiles in terms of peak demand and mean demand; carry out correlation per weekday/weekend winter demand and match metered demand profiles to activity data.

Activity data are used to derive activity and occupancy probabilities by income groups and household composition. This enables us to determine the kWh value per activity and occupancy probabilities by income groups and, consequently model demand from activity and occupancy probabilities.

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 and losers from ToU implementation both by income groups and household composition.

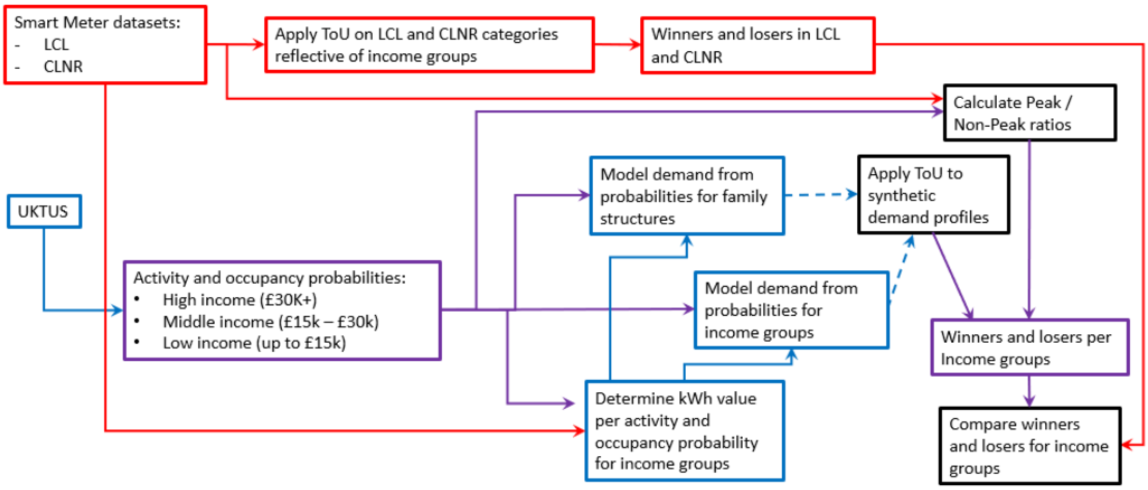

Figure 1 - Methodological approach of this study

3.1 Data

We used two UK smart meter datasets with socio-demographic information. First, the Consumer-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 form the individual survey and household survey. Combining two data sets gave a wider selection of the socio-demographic parameter for each household, contains the following information: (i) number of children in the household (variable DM016 from UKTUS household survey); (ii) overall household income (variable Income from UKTUS household survey); (iii) property type (variable Accom from UKTUS household survey); (iv) employment status of the residents of 16 years old and above: self-employed, employed, retired or unemployed (variable WorkSta from UKTUS individual survey); (v) number of residents in the full-time education (value 7 from variable WorkSta from UKTUS individual survey); (vi) household type (variable dhhtype from UKTUS individual survey): 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 (variable NumRooms from UKTUS household survey); and (viii) age of the residents (variable DVAge from UKTUS individual survey).

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 segmentations 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 approaches can be broadly mapped to income (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

The income groups are relative to the socio-demographic categories and do not represent income groups in monetary terms. Demand profiles in each of the groups are assessed on the impact of ToU tariffs. Unlike LCL dataset with individual demand profiles, LCNR data set only contains average demand for each customer group, therefore reducing the variation which might occur within an income group.

3.2.2 Peak to off-peak ratio

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 which groups are more likely to carryout energy related activities in peak time and hence consume more energy at peak time.

3.2.3 Building up synthetic demand

Probability of activities, on their own, can only show the likelihood of an activity occurring during peak time. To understand the distributional impact of ToU tariffs, we require demand profiles with the corresponding singular or at most dual parameter socio-demographic information - e.g. family structure or composite of 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 family structures combined with income groups

1. Extract corresponding activity profiles	2. Split LCL data by income	3. Optimise activity weights	4. Apply weights
UKTUS data for households in London across income groups: • Low (under £15k) • Middle (£15k-£30k)	Split demand profiles for by income groups: • Low income - Acorn groups KLMNOPQ;	For each demand profile in LCL income group create matching synthetic profile by: • optimising weights for occupancy and	For the corresponding income groups, weights are applied to activity data from other socio-demographic groups to generate demand

• High (over £30k) Calculate probability profiles: Occupancy; Cooking; TV Watching; Laundry; Ironing and House cleaning	• Middle income - Acorn groups FGHIJ; • High income - Acorn groups ABCDE;	activity profiles for corresponding income group to match LCL demand profile; • maintain proportion of energy per activity	profiles for distributional impact analysis.

The optimisation of the activity weights allows us to find the power demand for probability of each activity corresponding to the income group. Here we assume that power consumption weights 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 ***w*** is the set of 48 weights 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, subject to maintaining the daily energy use per service, equation (2), and bounds for the weights per activity, equations (3) and (4). The proportions of energy use per activity 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%

Once the activity weights are determined for all demand profiles per income group, we remove weights that have produced synthetic profile with error over 0.01. The remaining weights we use to extract representative weights per income group, derived from customer categories, these representative weights are then used to generate synthetic demand for other socio-demographic groups with the corresponding income distribution from UKTUS.

3.3 Tariffs

To assess the impact of ToU tariff on each socio-demographic groups two tariffs were chosen: standard flat tariff and price varying static 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). Figure 2 depicts the timings and the price levels of the tariffs. Three static ToU were analysed in Centre for Sustainable Energy (2014) (CSE): (i) ToU-1 is a two level tariff with peak time pricing applied daily (both weekday and weekend) between 4PM and 8PM; (ii) ToU-2 consists of a three level tariff with peak time pricing applied daily (both weekday and weekend) between 4PM and 8PM, mid-level pricing applied from 7AM to 4PM and 8PM to 11PM and the remainder of the time with the lower price; and (iii) ToU-3 is also a three level tariff, however, the peak-time pricing and mid-level pricing is only applied to weekdays. The ratios of the price level are adjusted accordingly to ensure revenue neutrality. Similarly to CSE ToU-2, static ToU used in Hledik et al. (2017) (hereafter referred to as Brattle-sToU) is a two level tariff with the peak time pricing applied between 4PM and 8PM daily, including weekend. Previous works in the literature have studied the impact on ToU on the consumer behaviour and the shift in electricity demand. In this paper, it is assumed that there is no change in behaviour and in demand as result of ToU tariff. This is equivalent to assuming that there is no significant difference across socio-demographic groups in terms of response to changes in tariffs.

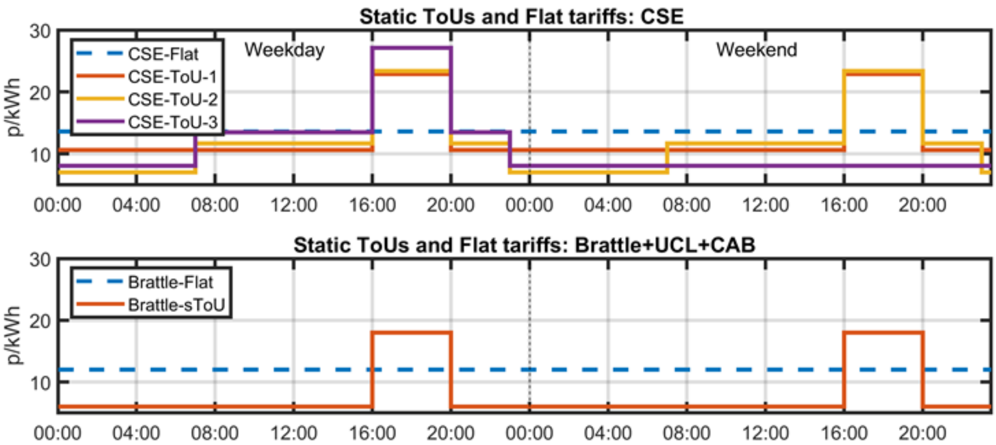

Figure 2-Flat and static ToU tariffs applied to assess the impact on bill costs

Similarly to CSE ToU-2, static ToU used in Hledik et al. (2017) is a two level tariff with the peak time pricing applied between 4PM and 8PM daily, including weekend. Previous works in the literature have studied the impact on ToU on the consumer behaviour and the shift in electricity demand. In this paper, it is assumed that there is no change in behaviour and in demand as result of ToU tariff. This is equivalent to assuming that there is no significant difference across socio-demographic groups in terms of response to changes in tariffs.

4. Findings

4.1 Customer segmentation

Figure 3 highlights the difference between mean demand profiles for the approximated income groups from consumer segmentations 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 CLRN area (North East of England). 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.

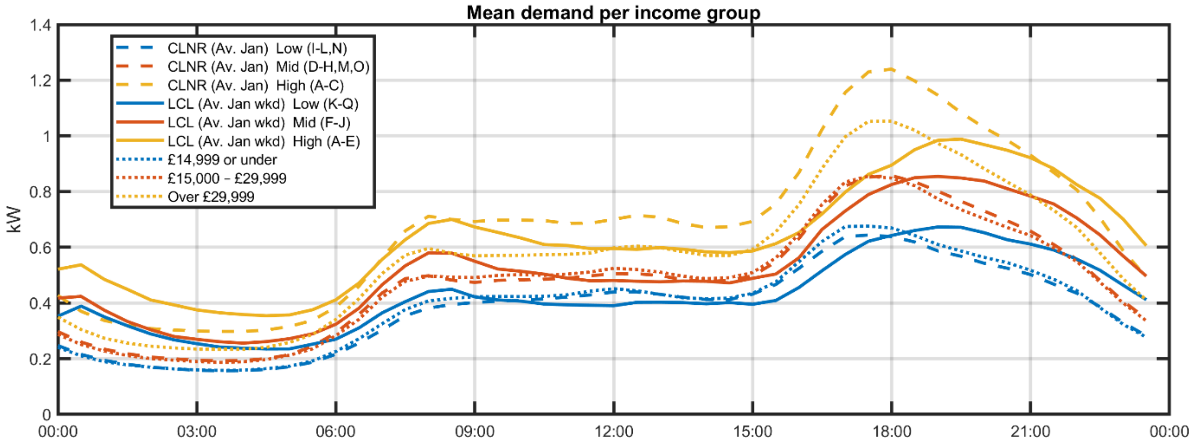

Figure 3 – Mean demand profiles for January per consumer segments mapped to income groups for LCL and CLNR datasets

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.

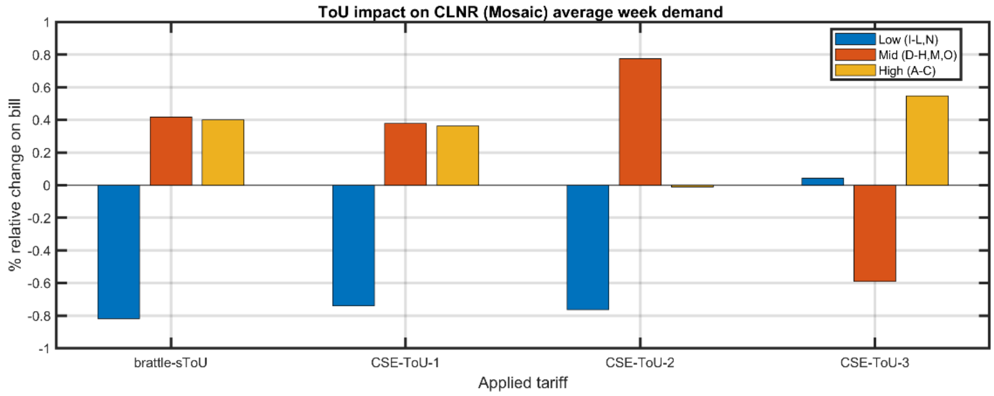

Figure 4- Relative effect of ToU tariffs on the bill of low, middle- and high-income groups based on CLNR data on average week demand and Mosaic customer segmentation

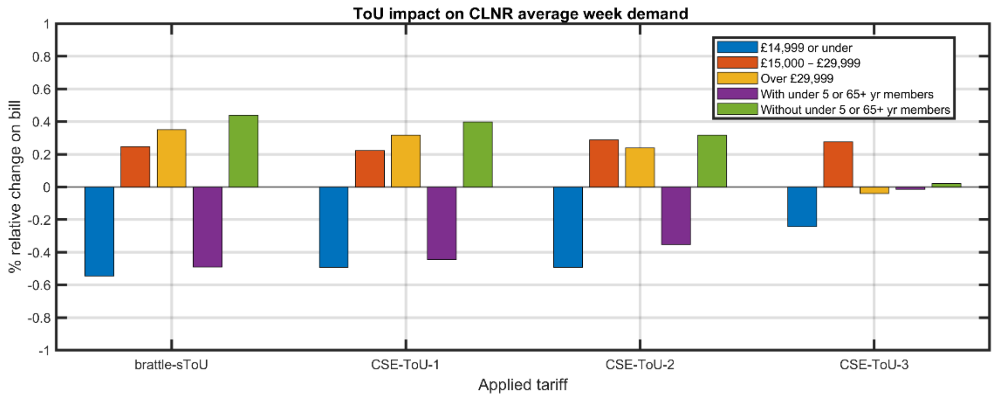

Figure 5- Relative effect of ToU tariffs on the bill of different categories of consumers based on CLNR data on average week demand

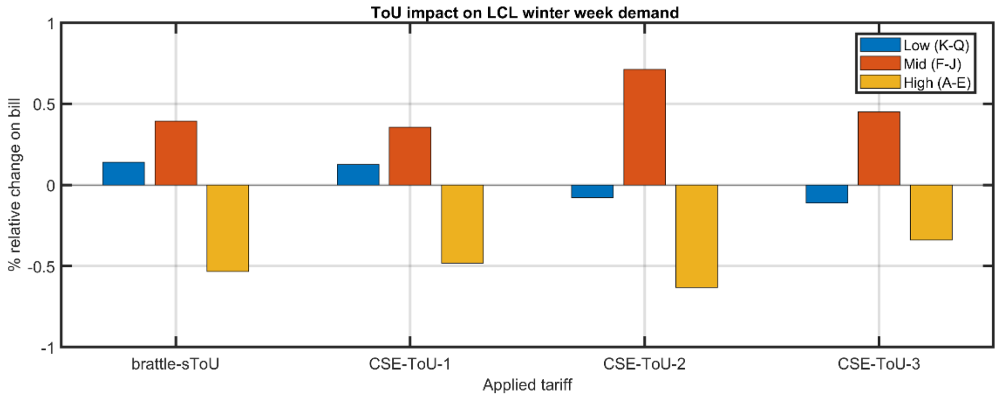

Figure 6– Relative effect of ToU tariffs on the bill of low, middle- and high-income groups based on LCL data on average winter week demand

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 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, Northern England CLNR 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 Peak to off-peak ratios

Figure 7 shows the levels of active occupancy on weekdays for different income groups separating households without children (graph on the left) and households with children (graph on the right). In households with children occupancy is higher during weekday for lower income groups regardless of income. In households with children their occupancy levels are similar for different income groups.

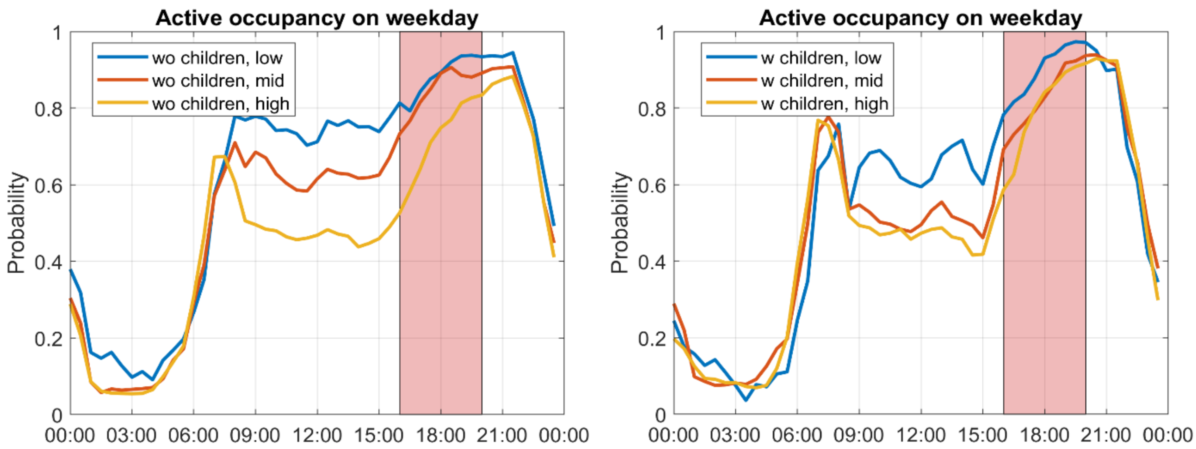

Figure 7– Active Occupancy probability on a weekday for family structures with and without children across income groups

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 present 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 mostly performed off-peak compared with 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.

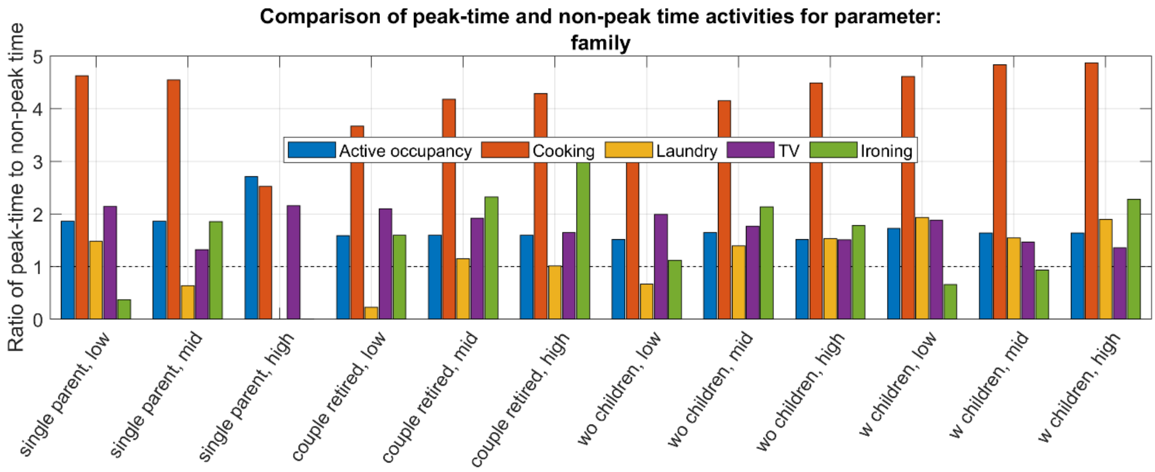

Figure 8- Peak to off-peak ratios of occupancy and energy-related activities by income group and household composition

Figure 9 compares the product of peak to off-peak ratios of active occupancy and energy-related activities (cooking, laundry, TV & Ironing) across three regions and income group. The highest products of peak to off-peak ratios are associated with region North, high income. This means that the collective probability of active occupancy and energy-related activities for this category is significantly higher than other categories. Conversely, London, high income features a low product of ratios. This partly explains the divergence in results in Figure 4 and Figure 6.

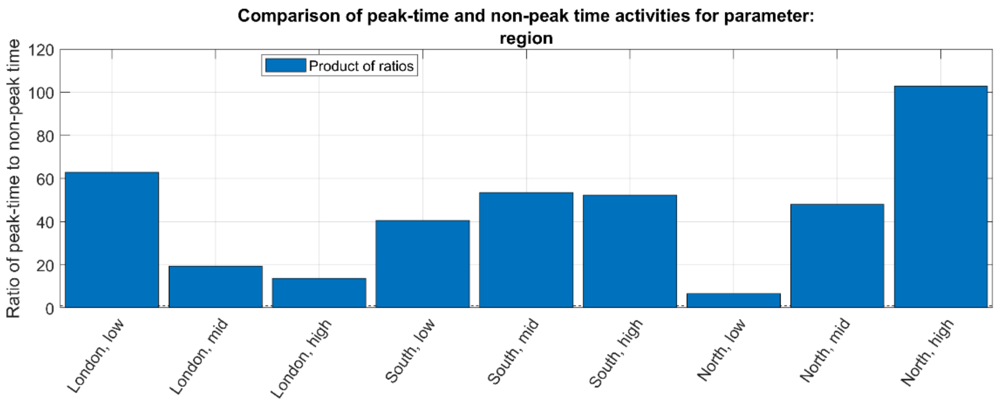

Figure 9– Product of peak to off-peak ratios of occupancy and energy-related activities across three regions combined with income groups

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. The opposite applies to single parents on high income, who are associated with the lowest product of ratios.

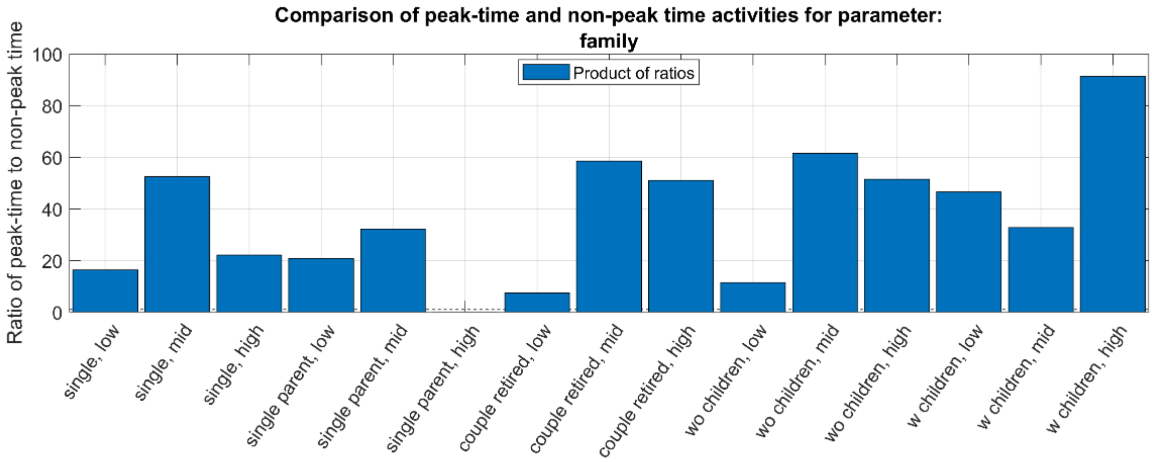

Figure 10– Product of peak to off-peak ratios of occupancy and energy-related activities by income group and household composition

4.3 Synthetic profiles

This section presents findings on ToU effects at the UK national level based on the simulation of demand profiles -as explained in Section 3.3. Figure 11 shows an example of matching synthetic profile to the target profile from middle income group. In this comparison of demand profiles, the resultant profile following the optimisation process matches the target profile. Weights are assigned to each activity across the day, including occupancy, cooking, laundry, TV, ironing, household cleaning and other. The highest weights are associated with occupancy and cooking, with the latter varying significantly based on the time of the day. The demand profiles per activity follow profile-level patterns as indicated by time use data.

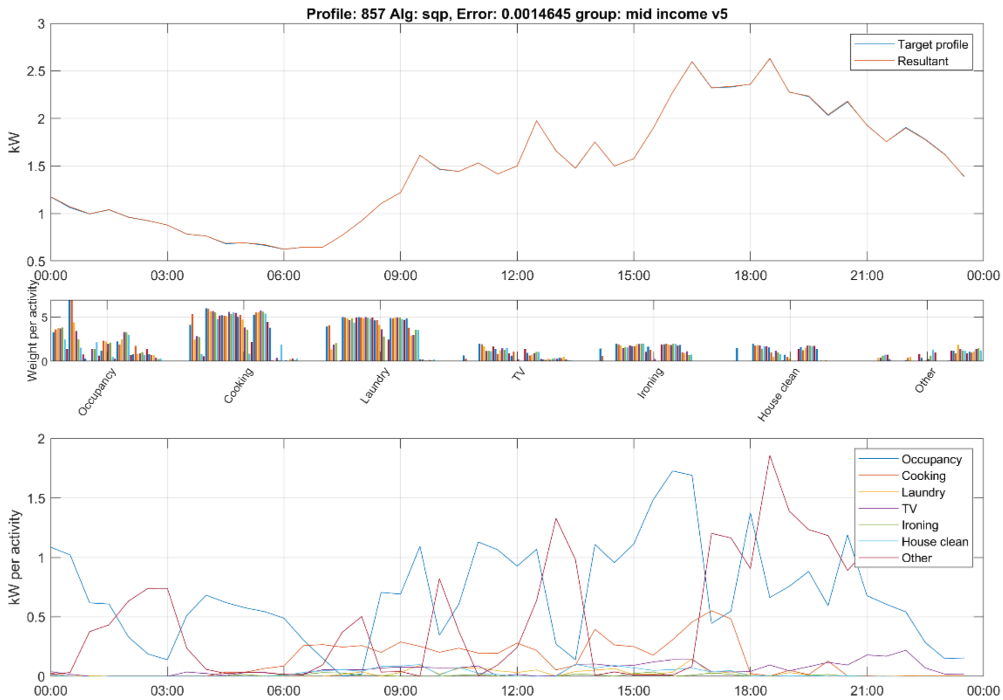

Figure 11– Example of matching synthetic profile to the target profile from middle income group. Top: demand profiles comparison (target and resultant from optimisation). Middle: weights assigned to each activity across the day. Bottom: resultant demand profiles

Figure 12 illustrates the distribution of power consumption weights associated with occupancy per income group. For instance, the occupancy median reaches the highest levels during the night hours. The higher income group comprises higher consumption weights in the late evening.

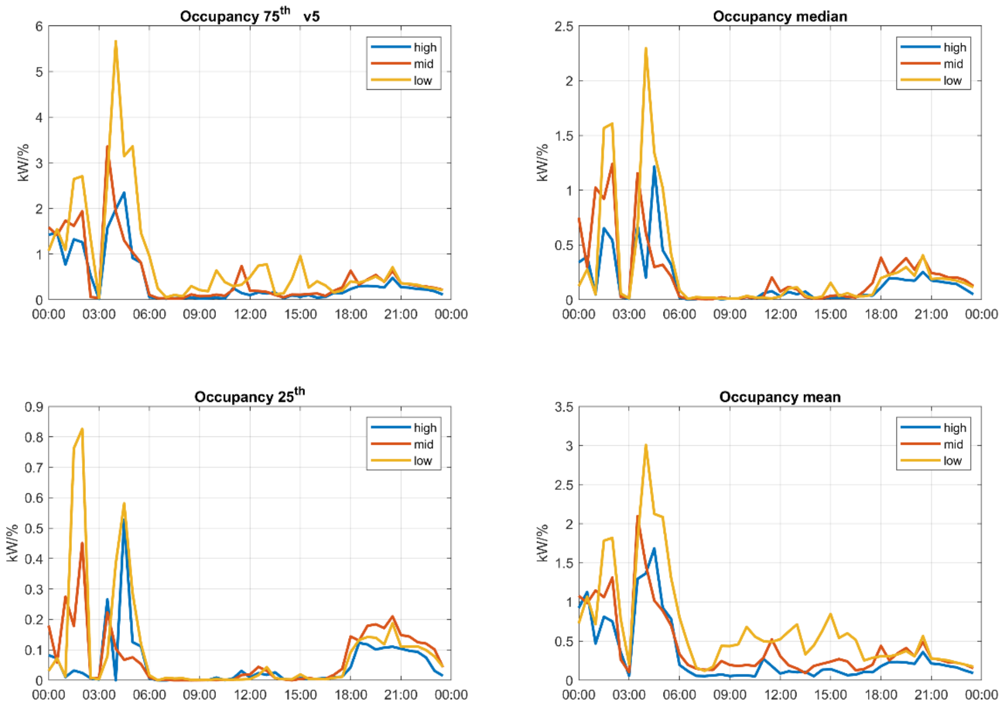

Figure 12– Distribution of power consumption weights associated with occupancy per income group

Figure 13 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.

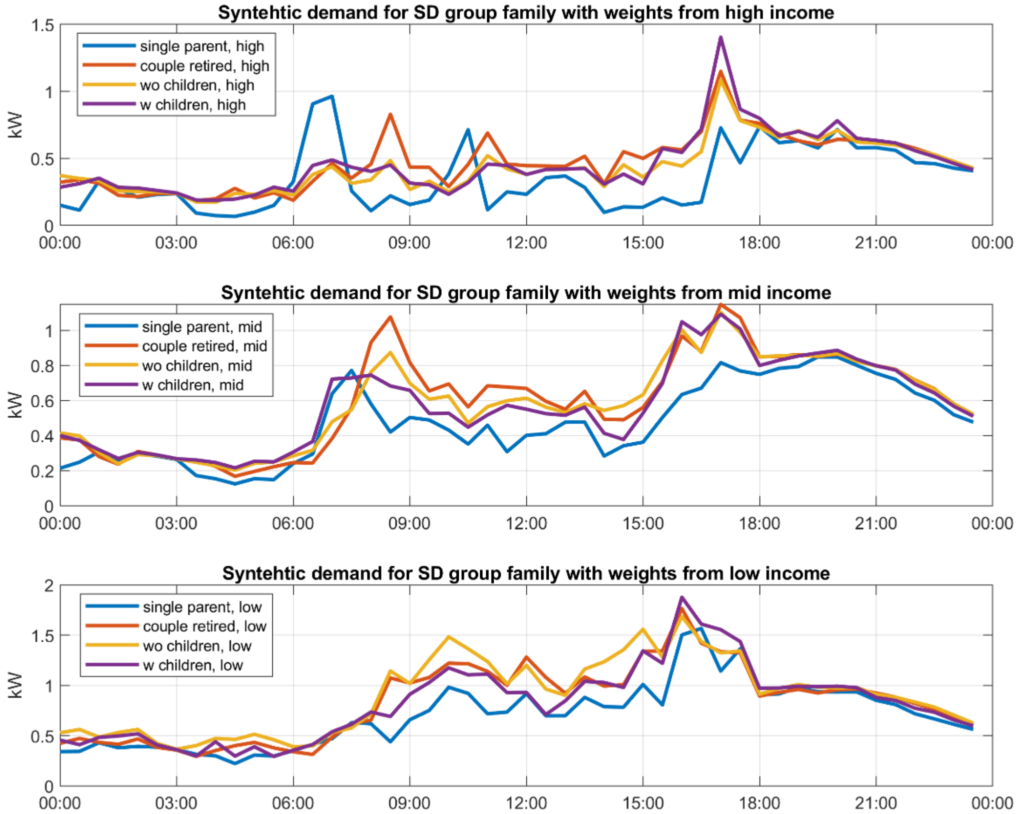

Figure 13– Synthetic demand profiles (in kW) generated from activity data for family structures and income groups with activity weights from income groups

Figure 14 presents findings on the impact of ToU tariffs on synthetic profiles for combination of family structures and income groups. The results are based on the synthetic profiles generated from weights per activity corresponding to London income groups. Single parents are approximated to consume less compared to other groups with the same weights 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).

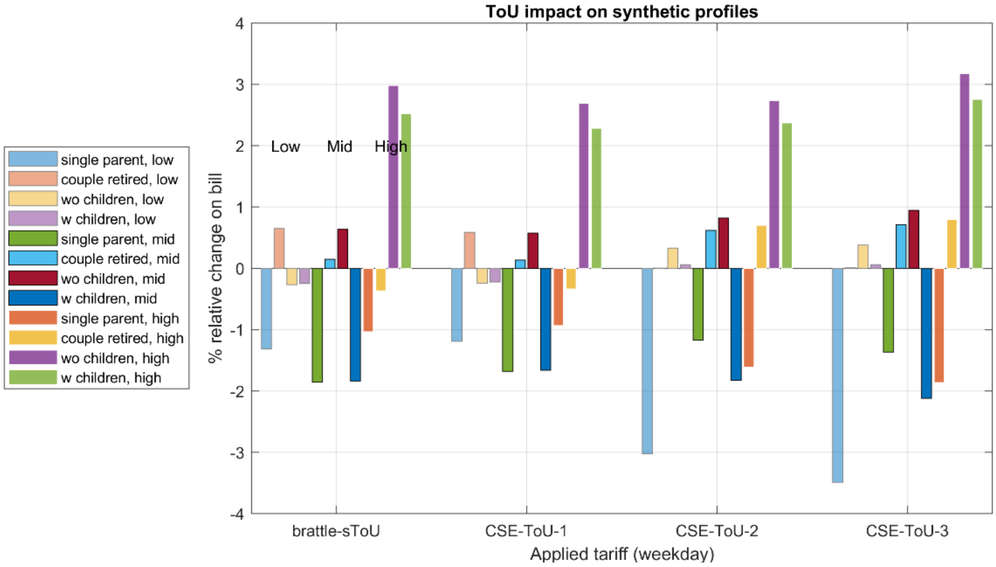

Figure 14- Relative difference of impact on the bill across household composition and income groups for synthetic profiles

5. Conclusion and Policy Implications

The 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 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.

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. Findings on smart meter data show diverging findings. For instance, the low-income group in the CLNR data would be financially advantaged from most 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 static time-of-use periods may not align with actual peak periods, as there are regional variations in residential electricity demand and time use. In turn, this may result in inefficient network usage.

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, Londoner 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 as currently their occupancy levels are relatively low at peak time and smart metering data shows that they are better off with any of the ToU tariffs applied in this paper.

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 nationally 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).

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