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ORIGINAL ARTICLE

Household activities underlying residential electricity demand: who does what during the evening peak?

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Abstract Growing the proportion of electricity generated from renewable sources is an important goal. But periods of high energy demand are not always aligned with renewable supply, necessitating greater reliance on other sources such as fossil fuels. In Ireland, like many other countries, electricity demand typically peaks in the evening, driven largely by residential demand. Reducing or shifting household activities away from this evening peak period can thus increase the proportion of electricity generated from renewable sources. Understanding the flexibility potential of residential electricity demand requires knowing which household activities happen most during peak times, and what groups of people are most likely to perform them at those times, as well as understanding what might facilitate and motivate behaviour change. To investigate these questions, we use a behavioural science approach that is activity specific. Using a large dataset from an Irish tracking survey that adapts the day reconstruction method (Kahneman et al., 2004), we first record the time of day at which a range of activities – water heating and showering, laundry, dishwashing, and cooking, among others – take place. Focusing on the evening peak between 4 and 7 pm, we then investigate sociodemographic, household, and psychological variables associated with timing activities during this period rather than other times of day. We show that the factors associated with time of use (e.g., tariff structure, reported effort to avoid evening use, and household composition) vary by activity. We discuss the implications of our findings and note their value for demand side management mechanisms.

Keywords Demand flexibility · Household consumption · Time of use · Behavioural science

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Introduction

Background and motivation

Several countries are making substantial efforts to increase the share of electricity demand that is met via renewable sources (International Energy Agency (IEA), 2024). Renewable generation, being largely weather dependent, is not as reliable as fossil fuel generation. Generally, timing of demand and generation do not align particularly well, and current storage technology cannot fully bridge the gap. Fossil fuel generation is thus still relied upon, particularly during peak demand. Meanwhile, overall demand is growing owing to, amongst other factors, the increased electrification of heat (Rosenow et al., 2022) and transport

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(Kapustin & Grushevenko, 2020). The upshot is that balancing (increasingly renewable) generation and demand is becoming progressively more difficult (Lew et al., 2020; Rosales-Asensio et al., 2024) and there is increased attention on demand side management (D'Ettorre et al., 2022).

If consumer demand were more flexible, the size of demand peaks could be reduced, and demand overall would align better with renewable generation. A higher proportion of overall demand would thus be met using renewable sources. Demand side flexibility can be achieved through a number of different means (including curtailment contracts, technological solutions, behaviour change) to achieve different intermediary goals (reducing load during peak events, shifting electricity use towards times with higher availability of renewables). Shifting use away from the evening peak period – a time when demand is usually particularly high – is an important goal. This evening peak period is the primary focus of this paper.

To understand what causes variation in evening peak period household demand, we need to identify which activities and practices happen during that period and to what extent, and then investigate the factors that are associated with their timing. Measures of consumption alone do not provide explanations for variation in or timing of consumption (Stelmach et al., 2020) – it is at the level of human behaviour and activity that we set our study aims. Because different factors are associated with doing different energy-consuming activities (Trotta, 2018) and in different ways (Sustainable Energy Authority of Ireland (SEAI), 2023), it is useful to investigate timing factors separately for different activities and practices – in other words, to use a behaviour-oriented approach.

This approach underpins the development of interventions to increase flexibility that are targeted by audience, and communications that are action-specific – features that improve their effectiveness (de Vries, 2020). Communications around shifting habits and demand side management mechanisms should be targeted to the activities and people that will be most amenable to flexibility, and/or will make the largest impact. One reason that this is necessary is that lay intuitions about the energy intensity of different activities are inaccurate (Attari et al., 2010; Lesic et al., 2018; Timmons & Lunn, 2022; White & Sintov, 2018). Without effective, specific communication to consumers, mechanisms such as demand response programmes (e.g. time-of-use tariffs) will not work optimally because people have errant beliefs about how best to reduce consumption at the relevant times.

Aim and research questions

This paper is based on data from Ireland's Behavioural and Energy Travel Tracker (BETT) survey (SEAI, 2023). BETT gathers accurate and granular data about travel and home energy behaviours in Ireland. The survey is novel in its use of the Day Reconstruction Method (DRM; Kahneman et al., 2004), which prompts participants to recount recent experience accurately, and in a more ecologically valid manner (Lades et al., 2022). It also collects data on factors that may be related to energy behaviours, such as psychological factors and sociodemographic characteristics.

The data were collected from a large nationally representative sample, and precisely quantify a comprehensive range of electricity-consuming activities, allowing for robust statistical modelling to surmise the relationship between doing the activities during the evening peak and a wide range of other variables. Data were collected monthly throughout 2023 providing built-in seasonality.

We take a behavioural, activity-specific approach to answering the following research questions:

RQ1: What household activities are most responsible for electricity consumption during the evening peak in Irish homes?

RQ2: What household, sociodemographic, and seasonal factors are associated evening peak period electricity uses?

RQ3: How much effort do people in Ireland report to shift electricity use away from peak times? Is this self-reported effort correlated with behaviour?

RQ4: What motivates people to shift their activities away from the evening peak? Does electricity tariff structure affect behaviour?

Literature review

Household activities during peak demand periods

There is substantial variation in electricity demand within and between households (Sekar et al., 2016;

Yilmaz et al., 2017), and attributing consumption to different appliances and activities is difficult (Carlson et al., 2013). Some work has attempted to describe evening peak period demand activities using meter data. One UK study involved 135 households attaching consumption monitors to their meters and recording activities on an app (Satre-Meloy, 2019; Satre-Meloy et al., 2020). Focusing on 4 pm – 9 pm, it showed that the highest frequency peak activities were eating a hot meal, watching TV, cooking, socialising, and computer use. Timing of oven and hob use in particular was strongly associated with the timing of the peak. The study sample was small, however, and the data were collected on a single day for each participant, which varied across seasons and day of the week.

The 2010—11 English Household Electricity Survey comprehensively recorded consumption by activity in 250 owner-occupied households (Palmer et al., 2013). It found that cooking was responsible for the largest share of peak consumption, and that there was substantial potential peak reduction in shifting laundry, dishwashing, and water heating. However, they could not robustly investigate sociodemographic or other associations with timing of demand due to the small sample size.

Other studies have relied on self-reporting of activities without accompanying meter data to access larger samples, several of which are referenced in the following paragraphs. Importantly, empirical comparisons of meter data with associated diary entries have shown that people report their activities accurately (Suomalainen et al., 2019). Time-use data has been used successfully to construct electricity load profiles via simple conversion schemes that were subsequently validated using specific end-use electricity measurements (Widén et al., 2009).

Indeed, peak period *timing* of activity in particular has been investigated using diary survey methods (Anderson, 2016; Anderson & Torriti, 2018). A UK study that conducted interviews with 100 households reported eating and watching television as the most common evening peak activities (Powells et al., 2014). A recent study identified patterns (as well as large diversity) in dishwashing and laundry habits in Germany (Barsanti et al., 2024); which are also relatively prevalent during the evening time (Ozaki, 2018), and amenable to time-shifting (Muttaqee et al., 2024; Öhrlund et al., 2019).

Stelmach et al. (2020) arrived at the same conclusions about the timing of dishwashing and laundry, having asked 337 people which activities they regularly do during the evening peak period, which they defined as 3 pm to 9 pm. However, the authors note that their questions were open to interpretation of the meaning of "regular" – in other words, the prevalence of various activities were not recorded with precision. They also note that their results were open to recency bias – the study was conducted in summer, which likely influenced responses related to heating for example. And while the sample was larger than most works on this topic, it was still too small to make reliable statistical inferences about the factors that may or may not be associated with the timing of separate activities and practices during the evening peak period.

Factors affecting timing and flexibility of household activities

Routine

Routine is relevant to peak-period timing of activities in at least two ways. On a more general level, routines that involve more time spent outside the home are less amenable to flexibility in the timing of household activity (Parrish et al., 2020). This depends of course on the times of day that the person is most likely to be outside the home: if one is not home during the evening peak window, their household activity does not contribute to it.

On a more specific level, routines can be outcomes of constraints on the timing of certain activities, and some activities are much more tightly constrained by time considerations than others (Powells et al., 2014; Shove & Cass, 2018). For instance, relative to cooking, the timing of laundry activity is (generally) less constrained by routine. Cleaning is more likely to be undertaken when time allows and not necessarily planned. People are most likely to indicate a willingness to shift laundry and dishwashing activities (Muttaqee et al., 2024; Stelmach et al., 2020). Using load profile data from two homes, Pipattanasomporn & Teklu (2014) rank laundry, dishwashing, and water heating amongst the most flexible activities, while stating oven use has no demand response potential. Others note some flexibility potential for cooking however (Palmer et al., 2013).

Seasonal and sociodemographic factors

Extensive work has focused on identifying seasonal and sociodemographic factors that influence electricity demand generally (Abrahamse & Steg, 2011; Wilson and Dowltabadi, 2007; Jones & Lomas, 2015), but relatively little has focused on factors that influence the timing of activities that underlie demand. Existing evidence shows a high degree of variation between households, greater daytime use in households in which someone is working from home (Cetin et al., 2014; Curtis, 2021), and seasonal differences (Kaur & Gabrijelčič, 2022; Palmer et al., 2013). Peaks are smaller at weekends compared with the working week and household size is also influential (Curtis, 2021; Trotta, 2020). There are conflicting results about the impact of having children on the flexibility of household activity (Friis & Christensen, 2016; Torriti et al., 2015).

A common approach is to use smart meter data for cluster analyses that identify types of households that use more. Much of this work is characterised by small samples however, and it is rarely concerned with contributions of individual activities to the overall load profile. For example, Satre-Meloy et al. (2020) linked peak period demand to clustered household characteristics; for example, households with older occupants and more large appliances were more likely to contribute to early evening peaks in demand. The authors note, however, that their clustering techniques are susceptible to error in light of the sample size, and they could not account for seasonal variation. They also did not model the timing of activities separately but note that their results contribute to targeting interventions along sociodemographic dimensions.

Other clustering studies (Azaza & Wallin, 2017; Smith et al., 2012; Torriti & Yunusov, 2020; Yilmaz et al., 2019) produce similar and useful findings, but lack appliance-level specificity that is important for making conclusions about the flexibility potential of individuals and households (Barsanti et al., 2024). Furthermore, existing time-use surveys (e.g. Bellagarda et al., 2020; Palm et al., 2018), do not always probe relevant details, such as, for example, the settings used on appliances, or whether laundry was done by hand or using a machine (McKenna et al., 2017; Barsanti et al., 2024).

Motivational factors

Work on motivations in this area has taken a distinctly economic starting point and focused on switching from standard tariffs to tariffs with different rates for different times of day (ToU tariffs). People usually state monetary benefits as their motivation for doing so; some have found added benefits of an environmental frame (Barjaková et al., 2024), others have not (Fell et al., 2015). There is a tacit assumption that people will meaningfully change behaviour once on a ToU tariff, but this is far from clear. While larger ratios between peak and off-peak rates appear to be related to their effectiveness (Faruqui & Sergici, 2013), findings overall are mixed (Hobman et al., 2016; Burns & Mountain, 2021). Moreover, real-world uptake is consistently lower than hypothetical willingness to switch (Nicolson et al., 2018).

Environmental concerns may also act as motivation to reduce peak period use. People who are highly worried about the climate are less likely to use energy wastefully (SEAI, 2023), and environmental concerns are often more predictive of energy behaviour than financial factors, particularly when financial rewards are small (Asensio & Delmas, 2015; Dogan et al., 2014; Schwartz et al., 2015). It follows that environmental concern might also influence electricity use at peak times, provided the link between demand management and renewable supply is understood.

As mentioned earlier, people tend to have poor intuitions about the energy intensity of different activities. It follows that intentions and motivations to shift demand from peak times will not be as influential as they could be – i.e. because people have misconceptions about the activities that use most energy, they will not adapt their consumption optimally, even if they want to (White & Sintov, 2018). Indeed, mechanisms to show people how much electricity they are using in (near) real-time, such as in-home displays (IHDs) are consistently effective in producing reduced consumption (Yun, 2009; Hargreaves et al., 2010; Commission for Energy Regulation (CER), 2011; McKerracher & Torriti, 2013; Zhang et al., 2019), though not always (Barnicoat & Danson, 2015). Prior motivations and attitudes have been shown to be important prerequisites for IHDs to work (Oltra et al., 2013).

Methods

Sampling and data collection

We use data from Ireland's Behavioural and Energy Travel Tracker (BETT) survey (SEAI, 2023). The survey is ongoing, but the data used for this analysis were collected monthly from December 2022 through November 2023 (12 waves). Each wave was run online with a sample of 1,000 participants, recruited by a market research company, that were approximately representative of the Irish population on gender, age, geographical region, and social grade, resulting in a total sample size of n= 12,000. Participants could complete multiple waves but not consecutive waves. They were paid €4 and typically took about 15–20 min to complete the survey. For each wave, data were collected over a week period to control for day-of-week effects. The survey was programmed using Gorilla Experiment Builder (Anwyl-Irvine et al., 2019) and made available on all device types to minimise any selection bias.

Survey design

A full description of BETT is available elsewhere (see SEAI, 2023). Here we describe only the parts of BETT directly relevant to the current paper.

Day reconstruction & energy behaviour

BETT adapts the Day Reconstruction Method (DRM) to measure energy behaviours performed on a given day (the day preceding data collection). We prompt participants to split the previous day into three "episodes": morning, afternoon, and evening. Participants note their energy-related behaviours during each episode in open text boxes. We do not analyse these responses – they serve only to improve recall for subsequent parts of the survey.

Participants are asked to indicate what times of day they were at home on the preceding day (Before 8am, 8am – 4 pm, 4 pm – 7 pm, After 11 pm). Unless they had not been home at any point, they then respond to detailed questions about heating, hot water use, cooking, and appliances, with branching used to ensure participants only answer questions of relevance to them.

For each activity, other than space and water heating, we ask participants how many instances occurred. If there was more than one, we record detail (including time of use) about one randomly chosen instance.

We record the following data regarding electricity use:

1. Space heating (electric boilers, electric portable heaters, electric underfloor heating): total duration; time(s) of day (as above).
2. Immersion water heating: total duration; time(s) of day.
3. Electric shower use (one instance): approximate duration; setting used (regular or eco); time of day.
4. Cooking (one instance): type of appliance (oven, hob, steamer, fryer, slow cooker, grill); duration; temperature setting; time of day.
5. Washing machine use (one instance): cycle (standard, eco, or quick), temperature setting (20 °C, 30 °C, 40 °C, 50 °C, 60 °C, 90 °C); time of day.
6. Tumble dryer use (one instance): duration; time of day.
7. Dishwasher use (one instance): cycle (standard, eco, or quick); time of day.
8. Ironing (one instance): duration; time of day.
9. Hair appliance use (one instance): time of day.
10. Vacuum cleaning (one instance): duration; time of day.
11. Electric blanket use (one instance): duration; time of day.

BETT also captures use of heat pumps, but we do not include this in the analysis due to low prevalence as well as increased complexity in making conclusions about time of use.

We do not record an exhaustive list of electricity-consuming activities, with attention being focused on those appliances that consume the most electricity and that people make more of a conscious effort to use. For instance, we do not ask about refrigeration or lighting. Further, while we do record use of dehumidifiers, TVs, computers, kettles/coffee machines, and toaster/sandwich makers, we do so with insufficient detail to include them in the current analysis.

Additional variables

Once participants have completed the day reconstruction, we measure several psychological variables.

Using a series of 7-point rating scales, participants indicate the effort they make to save energy at home and to shift electricity use away from peak times. They also rate the efforts of the average Irish person. Participants who report making some effort then rank their motivations for doing so (to save money, to help the environment, to help avoid shortages or blackouts).

We then measure worry about climate change, cost of living, and energy/fuel shortages on 7-point scales from “not at all worried” to “very worried”.

We record dwelling type, location (county and whether it is urban or rural), household composition (living alone, living as a couple, living as a family, or living with others), education level, employment status, income, electricity meter and tariff type, solar PV ownership, EV ownership and previous charging location and time of day.

Data analysis

Descriptives

The results section begins with an overview of sociodemographic, household, and psychological characteristics of the sample, for which we report simple descriptives. We then report time-of-use of activities measures by proportion at each time of day. When reporting time-of-use, we group the first and last of the time windows listed above (“Before 8am” and “After 11 pm”) into an “Overnight” category.

We create population level estimates of the contribution of each activity recorded to the total amount of electricity used at peak (in kWh). To do so, we sourced average usage figures for each type of activity, and different ways of doing them – see supplementary material for figures used. The level of granularity in our questions allowed to us account for activity duration and different possible settings or system types.

Modelling

We create binary outcome variables for each activity that denote whether they were undertaken during the peak period of 4 pm – 7 pm or not. Thus, the question being addressed is: if an activity happens during the day, what factors make it more or less likely to occur during the peak period?

Additionally, in cases where a participant conducted multiple instances of an activity, but we ask about only one, it is possible that if the instance asked about was not during the peak period, that another instance was during peak.[1] Therefore, if a participant has done an activity more than once but the asked about instance was not during peak, we exclude the participant from the model.

We conduct separate multiple logistic regressions for each activity to investigate associations between doing an activity at peak and the other recorded variables listed above. We account for seasonal and day-of-week effects. We categorise study waves into a “season” variable: waves that occurred during April, May, June, July, August, or September are labelled “Brighter months” while the remainder are labelled “Darker months”. This approximately reflects a difference in daylight hours in Ireland. Participants who completed the day reconstruction about a Saturday, Sunday, or bank holiday were categorised “weekend”. The remainder were “weekday”. We categorised tariff types into standard or pay-as-you-go (PAYG), time-of-use tariffs, or night-savers.

Further, we categorise the effort and worry responses into high and low/medium based on median splits. Models include only those participants who did the activity in question at some point in the day. We model peak immersion use, peak laundry activity, peak dishwashing, peak cooking, and peak showering.

We do not model peak heating activity, EV charging, electric blanket use or ironing due to a small number of cases of each – less than 4% of the sample had conducted each of these on a given day. We do not model vacuuming due to its low energy intensity.

[1] BETT was not developed for the purpose of comprehensive time of use profiling. For heating we cannot assess the definite duration of activity during the peak period because we ask for total duration during the day. Further, for most activities, we ask about one instance of each activity. For activities that were carried out more than once by a single activity, we cannot know for sure an instance that wasn’t asked about happened outside of the peak period. We return to these study limitations in the discussion section.

Results

We begin this section with a brief summary of sample characteristics, before describing the psychological measures recorded. We then describe evening peak period (defined as 4 pm – 7 pm) activity in terms of share of each activity that happens during peak, proportion of the population that do each activity at peak, and the estimated contribution of each recorded activity to peak demand. Finally, we model the likelihood of doing various activities during the evening peak period window rather than some other time and day, as well the absolute level of evening peak period activity recorded.

Sample characteristics

Sociodemographic, household, and dwelling characteristics

A full description of the sample, as well as household and dwelling characteristics is included in Appendix 1. The sample was broadly nationally representative across all waves, with a slight underrepresentation of younger age groups and lower social grades.

Only 4% of the sample owned an electric boiler. Another 4% had storage heaters. A further 4% used heat pumps as their main heating source. Given these small proportions, we exclude heating from some sections of the analysis.

A national roll-out of smart meters was underway during the study period. The proportion of participants who reported having a smart meter increased from 41% in December 2022 to 51% in November 2023. Uptake of ToU tariffs in Ireland remains low. While about 16% of smart meter owners reported being on a ToU tariff in the most recent data collection period (November 2023), this is likely an overstatement. A more reliable figure based on supplier reporting is less than 10%.

Psychological factors

Most participants reported making effort to shift their electricity use away from peak times (Fig. 1). Three quarters of participants responded at or above the mid-point of the scale, and almost a fifth reported doing everything possible; the overall mean was 4.67 (SD = 0.02). The average did not change across the study period. The perceived efforts of other people to shift use away from peak was consistently lower (M = 3.90, SD = 0.01).

To address RQ4 we also look at the top-ranked motivations participants cite for making an effort to shift their use away from peak periods, assuming they are making at least some effort to do (i.e., responding 2 or above). By far the most frequently top-ranked motivation was to save money, with helping the environment and avoiding shortages being a distant second and third respectively. Avoiding shortages was ranked more highly than helping the environment for just the first two waves, a time at which the energy crisis was prominent in the media.

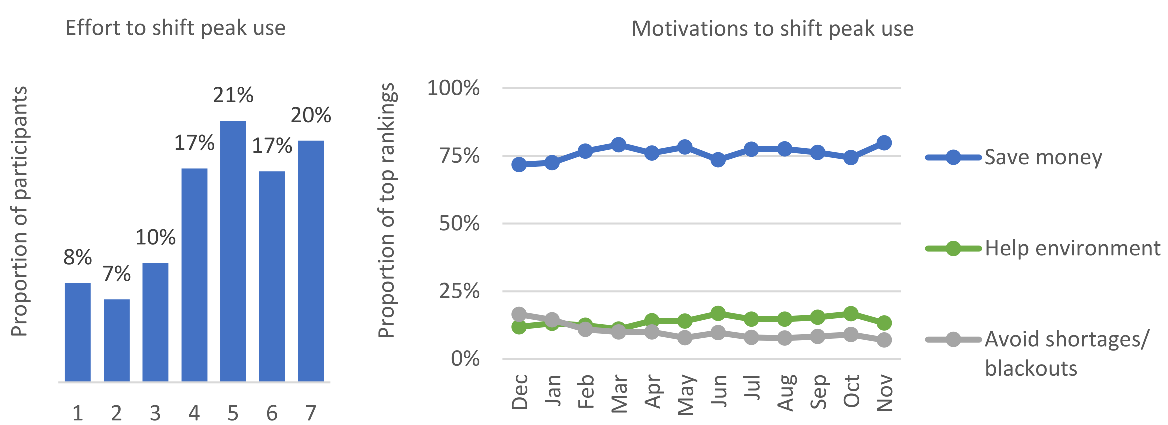


Fig. 1 Left: Self-reported efforts to shift electricity use away from peak times on a scale from 1 (Not making an effort) to 7 (Doing everything possible). Right: top-rated motivations by those making some effort over time

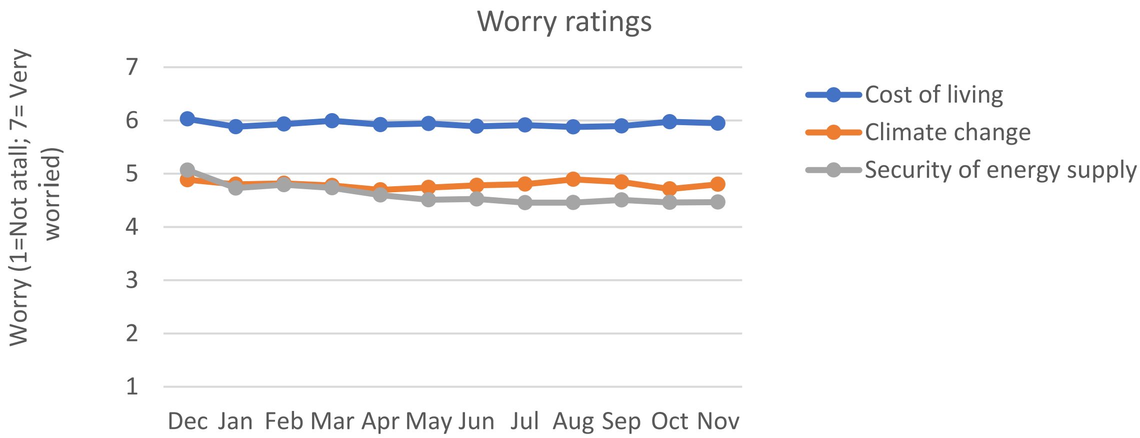


Fig. 2 Self-reported ratings of worry about cost of living, climate change, and security of energy supply

On average, more than three quarters of participants who reported making some effort said that saving money was their top priority. However, far fewer than that had a tariff that would allow them to save money by reducing peak-period consumption. Indeed, the proportion of people on standard meters reporting saving money as their motivation was only a couple of percentage points lower than the overall average. Conversely, there were no substantial reported motivational differences between people making a high degree of effort and those making a smaller effort.

We measured worry about climate change, energy security, and cost of living on separate 7-point scales (Fig. 2). Across the course of the study period, people were most worried about cost of living. Worry about security of the energy supply was highest during the first months of the study period, a time when related risks were prominent.[2] Worry about climate change was consistent at about 4.8 out of 7 on average, and after the risks to energy supply had dissipated, remained the second biggest worry to most people after cost of living.

Time of use profiles for electricity-consuming activities

In this section we present descriptive results regarding the share of different electricity consuming household activities that happens during the evening peak period.

[2] The energy crisis – largely caused by the Russian invasion of Ukraine – was prominent in Irish media at the time and was having a significant impact on energy prices.

Figure 3 displays time-of-use profiles for each of the electricity-consuming activities we tracked. The period of most interest to the current paper – the evening peak from 4 to 7 pm – is highlighted in each case. Note that for most of these activities, we only asked about the timing of one instance of each activity, even if they engaged in the activity more than once (except for space and water heating, for which we ask participants to select all the times of day they were used). However, by randomly choosing which instance to ask about, we gain a representative picture of the average share of use for each activity according to time of day.

Unsurprisingly, cooking was the activity most tied to the evening peak period – 46% of the instances that we asked about happened between 4 and 7 pm. About a quarter of vacuuming happened at peak, and about a fifth of water heating, electric space heating, and ironing. The use of laundry appliances (washing machine, tumble dryer, iron), dishwashers, electric showers and hair appliances was less likely to occur during the evening peak window, with most of these activities happening earlier in the day except for dishwashers, which were more likely to be used after the evening peak window. However, the share of these activities that occurred during the peak period was non-negligible (ranging from about 11% to 16% of instances). Electric vehicle charging at home and use of electric blankets were far less likely to occur at peak times compared with other times of day.

Whereas the figure above shows the proportion of instances of each activity occurring in each time

Fig. 3 Share of each electricity-consuming activity occurring at different times of day

window, Table 1 instead shows the proportions of all participants doing each activity in each time window in a given day, and therefore gives an indication of proportion of people to whom each activity is relevant. As noted above, the survey asks about heating times-of-day somewhat differently to other activities. Participants can indicate multiple time windows during which they used the heating (space and water). For all other activities, participants are asked about one instance, and what time of day that instance occurred. Therefore, the proportions in the table below are slight underestimations because some participants did activities more than once a day.

The ranking of activities by share that happens during the evening peak window is similar to the ranking of absolute prevalence during the peak window. EV charging and electric blanket use are lowest, cooking is highest – three in ten cooked using electrical appliances. We delve more into cooking in the next section. On an average given day, 7% of the full sample put on a wash at peak, 4% used the tumble dryer, and

Table 1 Average proportion of total sample engaged in each activity at each time window

	Overnight	8am – 4 pm	4 pm – 7 pm	7 pm – 11 pm
Cooking	2.5%	20.2%	**29.2%**	11.4%
Vacuuming	1.0%	23.8%	**9.3%**	4.0%
Washing machine use	7.2%	29.9%	**7.1%**	7.8%
Dishwasher use	6.8%	10.5%	**5.9%**	13.5%
Immersion water heating	8.9%	7.1%	**5.5%**	6.0%
Electric shower use	8.3%	17.0%	**4.6%**	10.1%
Tumble dryer use	1.8%	26.7%	**4.2%**	4.7%
Hair appliance use	5.2%	13.3%	**3.5%**	5.9%
Electric heating	3.1%	3.4%	**3.0%**	4.4%
Ironing	1.7%	6.0%	**2.9%**	2.6%
Elec blanket use	4.1%	0.3%	**0.3%**	5.0%
EV charging	0.8%	0.4%	**0.1%**	0.3%

6% used the dishwasher. About 6% of the population use electricity to heat water during the evening peak period. While a large portion of electric space heating happens at peak, it is uncommon in Irish households overall.

Contributions of different activities to peak period electrical load

In addition to looking at what activities occur during peak periods, we estimate consumption in kWh for these and deduce what share of peak electricity consumption each type of activity is responsible for (of the electricity consumption that we track) addressing RQ1 (Fig. 4). Sources for average kWh figures for each activity and a detailed account of the variable construction can be found in Supplementary Material. It is important to re-emphasise that we do not measure all household activities that use electricity. Among the excluded electricity uses are refrigeration, lighting, TV, computer, and kettle use.

Of the activities that we measure, cooking accounts for almost half of demand in the window from 4 pm – 7 pm. Despite being only the second most commonly used cooking appliance during the peak times, ovens account for almost two thirds (64%) of cooking electricity demand owing to their high intensity. Over a fifth (22%) of cooking electricity demand is from hob use, and a further 10% from fryers (primarily air fryers).

Laundry activity accounts for the next largest share of evening peak period electricity consumption (15%). About 60% of this is produced by tumble dryers despite their use being much less common than washing machines, which account for about a fifth of laundry-related demand. The remaining 13% comes from ironing.

Water heating also accounts for about 15% of measured evening peak period demand. Use of electric showers at peak times is relatively rare—about two thirds of measured water heating related electricity demand comes instead from immersion use.

Despite only a small proportion of the sample using various types of electric space heating, it still accounts for a sizeable chunk of evening peak period electricity demand, at 13%, owing to its high intensity. Dishwasher use accounts for 6% of the total activity we measure. The other appliances – vacuums, hair appliances – account for 2% each.

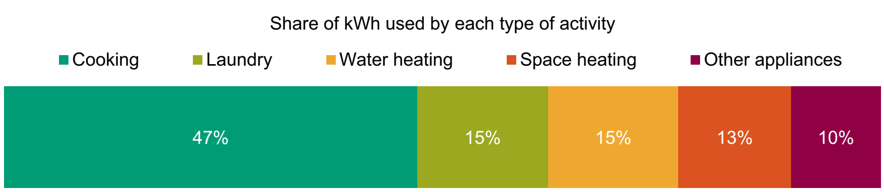


Fig. 4 Contribution of each activity type to total peak electricity consumption tracked in BETT

Factors affecting time of use

In this section, we model the likelihood of doing the following activities during the period between 4 and 7 pm: cooking, immersion water heating, tumble dryer use, electric shower use, dishwasher use, and washing machine use. If vacuuming were ignored, these would constitute the six most prevalent peak activities we record, and if space heating were ignored, they would constitute the six most peak electricity demanding activities. We do not model vacuuming due to the minute amount of electricity it uses, and we do not model electric space heating because of its lack of prevalence and the fact that is not particularly ripe for demand flexibility given the lack of heat pumps amongst our sample. These models address RQ2, RQ3 and RQ4.

We report results of logistic regressions that model the likelihood of doing each of the six activities during the peak period rather than some other time of day. Thus, the question being addressed is: if an activity happens, what factors make it more or less likely to occur during the evening peak period?[3] We report odds ratios and 95% confidence intervals for factors with a statistically significant association with each activity occurring at peak below. Full model outputs are in Table 2.[4]

Cooking

Cooking is more likely to occur at peak during darker months of the year compared to when daylight is more plentiful (OR =1.24, 95% CI [1.10, 1.38]), and less likely at the weekend compared to weekdays (OR =0.65, 95% CI [0.58, 0.73]). Participants living with family were significantly more likely to cook during peak compared to living alone (OR =1.37, 95% CI [1.14, 1.65]); there was no difference between couples and people living alone. Apartment dwellers (OR =0.58, 95% CI [0.48, 0.70]) and males (OR =0.84, 95% CI [0.75, 0.96]) were significantly less likely to do their cooking at peak, as were those educated to degree level (OR =0.84, 95% CI [0.75, 0.96]), while middle aged (OR =1.41, 95% CI [1.22, 1.64]) and older (OR =1.51, 95% CI [1.27, 1.8]) groups were more likely to relative to under 35 s. There were no statistically significant differences between people with different electricity tariff structures. The level of effort for avoiding peak period electricity use also showed no association with the timing of cooking, and nor did level of worry about climate, cost of living, or energy security.

Immersion use

Unlike cooking, there were no seasonal or weekday associations with timing of immersion water heating. Those living as a couple were significantly more likely to use their immersion between 4 and 7 pm rather than another time compared to those living alone (OR =1.86, 95% CI [1.28, 2.76]), as were those living as a family (OR =2.24, 95% CI [1.58, 3.24]). Additionally, people on night saver tariffs were significantly less likely to use their immersion at during the evening compared to those on standard and PAYG tariffs (OR =0.69, 95% CI [0.52, 0.90]), as were those who reported making substantial effort to shift activity away from peak periods compared those who did not (OR =0.76, 95% CI [0.62, 0.94]), but there was no effect of being on a time of use tariff.

Electric shower use

Showering during the evening peak period was relatively rare, but some factors were associated with an increased likelihood of doing so. Being male was one (OR =1.30, 95% CI [1.07, 1.57]), as was being in the youngest age group compared to both the middle aged (OR =0.75, 95% CI [0.60, 0.94]) and older group (OR =0.54, 95% CI [0.41, 0.71]). Being on a night-saver meter was associated with a reduction in the odds of showering during the evening peak period compared to being on standard or PAYG tariffs (OR =0.67, 95% CI [0.47, 0.93]),

[3] In cases where a participant conducted multiple instances of an activity, but we ask about only one, it is possible that if the instance asked about was not during the peak period, that another instance was during peak. Therefore, if a participant has done an activity more than once but the asked about instance was not during peak, we exclude the participant from the model.

[4] Table 2 displays results for the full models. We first ran models that included only sociodemographic and household variables. The coefficients do not materially differ. Results of those models are in Appendix 2.

Table 2 Logistic regression models of whether an individual performed a given activity during peak hours (4 pm – 7 pm), given they performed that activity at some point in a given day

	Cooking	Immersion	Electric shower	Washing machine	Tumble dryer	Dishwasher
	B (SE) ***OR***	***B (SE)*** ***OR***	***B (SE)*** ***OR***	***B (SE)*** ***OR***	***B (SE)*** ***OR***	***B (SE)*** ***OR***
Home during day	0.08 (0.06) 1.09	0.10 (0.1) 1.11	0.08 (0.1) 1.08	− 0.45*** (0.08) 0.64	− 0.31** (0.12) 0.73	− 0.03 (0.09) 0.97
Darker months	0.21*** (0.06) 1.24	− 0.06 (0.09) 0.94	− 0.04 (0.09) 0.97	0.19* (0.08) 1.20	0.17 (0.11) 1.18	− 0.14. (0.08) 0.87
Weekend	− 0.44*** (0.06) 0.65	− 0.11 (0.1) 0.89	− 0.04 (0.1) 0.97	0.16. (0.08) 1.17	0.23* (0.11) 1.26	0.15. (0.09) 1.16
Household composition (ref. = living alone)						
Couple	0.04 (0.1) 1.04	0.62** (0.2) 1.86	0.08 (0.18) 1.09	− 0.07 (0.16) 0.94	− 0.22 (0.25) 0.80	0.16 (0.21) 1.18
Family	0.32*** (0.1) 1.37	0.81*** (0.18) 2.24	0.19 (0.16) 1.21	0.19 (0.15) 1.21	0.2 (0.23) 1.22	0.21 (0.2) 1.23
Others	− 0.16 (0.15) 0.86	0.56* (0.26) 1.75	− 0.31 (0.26) 0.73	0.13 (0.23) 1.14	− 0.01 (0.32) 0.99	− 0.01 (0.31) 0.99
Apartment	− 0.55*** (0.1) 0.58	− 0.43** (0.16) 0.65	0.09 (0.18) 1.10	0.08 (0.14) 1.08	− 0.02 (0.22) 0.98	0.21 (0.19) 1.24
Male	− 0.17** (0.06) 0.84	− 0.19. (0.1) 0.83	0.26** (0.1) 1.30	0.12 (0.08) 1.13	− 0.1 (0.11) 0.90	0.16. (0.09) 1.17
Age (ref. = 18–34)						
35–54	0.35*** (0.08) 1.41	0.20. (0.11) 1.22	− 0.29* (0.11) 0.75	− 0.24* (0.09) 0.79	− 0.40** (0.13) 0.67	− 0.11 (0.11) 0.90
55 +	0.41*** (0.09) 1.51	− 0.13 (0.14) 0.88	− 0.62*** (0.14) 0.54	− 0.59*** (0.12) 0.55	− 0.63*** (0.18) 0.53	− 0.24. (0.13) 0.78
Degree	− 0.17** (0.06) 0.84	− 0.09 (0.1) 0.92	− 0.29** (0.11) 0.75	− 0.22* (0.09) 0.80	− 0.09 (0.12) 0.91	− 0.19* (0.09) 0.83
Employed	− 0.1 (0.07) 0.91	− 0.16 (0.11) 0.85	0.09 (0.11) 1.10	0 (0.09) 1.00	− 0.02 (0.13) 0.98	− 0.15 (0.1) 0.86
Monthly household income (ref. = < 2 k)						
2 k—4 k	0.21** (0.07) 1.23	0.02 (0.12) 1.02	0.02 (0.12) 1.02	− 0.18. (0.1) 0.84	− 0.03 (0.14) 0.97	0.02 (0.11) 1.02
4 k +	0.10 (0.09) 1.10	− 0.14 (0.14) 0.87	− 0.05 (0.15) 0.95	− 0.09 (0.12) 0.91	− 0.06 (0.17) 0.94	− 0.41** (0.14) 0.67
Tariff (ref. = standard/PAYG)						
Night-saver	0.05 (0.09) 1.05	− 0.38** (0.14) 0.69	− 0.41* (0.17) 0.67	− 0.43** (0.14) 0.65	− 0.74*** (0.2) 0.48	− 0.55*** (0.15) 0.57
Other ToU	0.13 (0.11) 1.14	− 0.16 (0.17) 0.85	− 0.04 (0.17) 0.96	− 0.2 (0.15) 0.82	0.06 (0.2) 1.07	− 0.36* (0.17) 0.70
Hi effort to shift—self	− 0.06 (0.07) 0.94	− 0.27* (0.11) 0.76	− 0.14 (0.11) 0.87	− 0.34*** (0.09) 0.71	− 0.49*** (0.12) 0.61	− 0.42*** (0.1) 0.66
Hi effort to shift—others	0.04 (0.07) 1.04	0.06 (0.11) 1.06	0.07 (0.11) 1.07	− 0.03 (0.09) 0.97	0.17 (0.12) 1.19	0.22* (0.1) 1.25
Hi worry—energy security	0.09 (0.06) 1.09	0.02 (0.11) 1.02	− 0.03 (0.1) 0.97	0.15. (0.09) 1.17	0.24. (0.13) 1.28	0.09 (0.09) 1.09
Hi worry—cost of living	− 0.06 (0.07) 0.94	− 0.14 (0.11) 0.87	0.15 (0.11) 1.16	− 0.03 (0.09) 0.97	− 0.18 (0.13) 0.84	− 0.24* (0.1) 0.79

Table 2 (continued)

	Cooking	Immersion	Electric shower	Washing machine	Tumble dryer	Dishwasher
Hi worry—climate	0.07 (0.06) 1.07	0 (0.1) 1.00	− 0.09 (0.1) 0.91	− 0.01 (0.08) 0.99	− 0.21. (0.12) 0.81	0.03 (0.09) 1.03
Observations (N)	5,507	2,729	4,511	5,193	1,883	4,113

as was being educated to degree level (OR = 0.75, 95% CI [0.61, 0.92]), but being on a time of use tariff had no effect.

Washing machine use

Washing machine use was somewhat less likely to occur at peak during the darker months (OR = 1.20, 95% CI [1.04, 1.40]). The youngest group was more likely to do their washing at peak compared to both the middle aged (OR = 0.79, 95% CI [0.66, 0.95]) and older groups (OR = 0.55, 95% CI [0.44, 0.70]). As with most other activities we recorded, people on night-saver tariffs were less likely to do their washing at evening peak times (OR = 0.65, 95% CI [0.49, 0.84]), as were those who reported substantial effort to avoid peak time use of energy (OR = 0.71, 95% CI [0.60, 0.85]), and people with a degree (OR = 0.80, 95% CI [0.67, 0.95]).

Tumble dryer use

There were fewer instances (n = 1,883) of tumble dryer use in our data. Nonetheless, we observe statistically significant associations between our age, tariff structure, and effort variables and likelihood of evening peak period use. Middle aged (OR = 0.67, 95% CI [0.52, 0.87]) and older (OR = 0.53, 95% CI [0.37, 0.75]) people were substantially less likely to use their tumble at peak compared to the younger group. Being on a night-saver tariff was associated with a 52% reduction in the odds of using the tumble dryer during the peak period compared to being on a standard or PAYG tariff (OR = 0.48, 95% CI [0.32, 0.70]), making this the activity most affected by tariff structure, although there was no statistically significant difference between those on other ToU tariffs and those on standard or PAYG tariffs. Participants who reported higher effort to shift use away from evening peak periods were also markedly less likely to use their tumble dryer during the window (OR = 0.61, 95% CI [0.48, 0.78]).

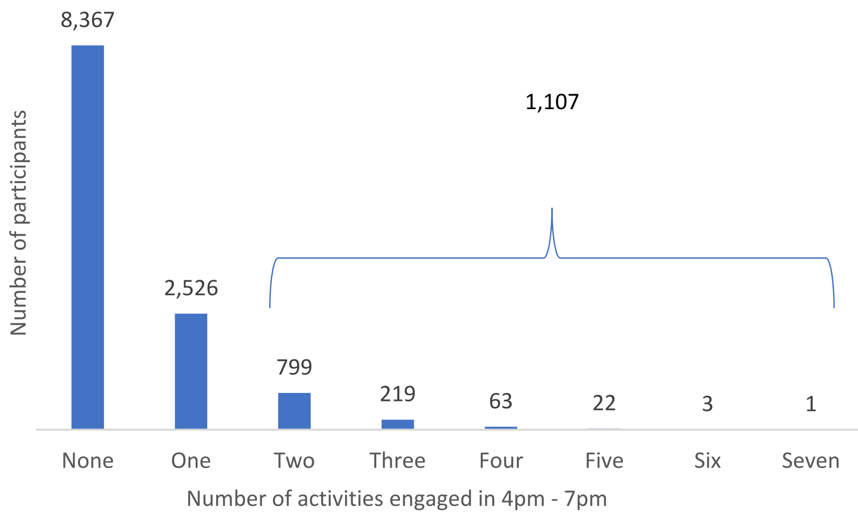
Dishwasher use

A similar association was detected between being on a night-saver tariff and using the dishwasher during the evening peak period (OR = 0.57, 95% CI [0.42, 0.77]). Of the activities we modelled, dishwasher use was the only one people on ToU tariffs were significantly less likely to perform at peak, compared with those on a standard or PAYG tariff (OR = 0.70, 95% CI [0.50, 0.96]). This was also true of those who indicated a higher degree of worry about the cost of living (OR = 0.79, 95% CI [0.65, 0.96]). Those on the highest income level were less likely to their dishwashing at peak compared to those on the lowest (OR = 0.67, 95% CI [0.51, 0.87]). Self-reported effort was associated with lower odds of peak dishwashing (OR = 0.66, 95% CI [0.54, 0.79]), though participants who perceived a high national average effort to shift use away from peak were more likely use to the dishwasher at peak compared to those who did not (OR = 1.25, 95% CI [1.04, 1.51]).

Factors associated with overall electricity consumption during the evening peak

The models in the preceding section answer the question: *if the activity happens at some time of the day, what makes it more likely that time is the evening peak period (4 pm – 7 pm)?* They do not necessarily pinpoint the factors that contribute to overall peak demand. We constructed a variable that is a count of all activities carried out at peak by each

Fig. 5 Number of tracked electricity-consuming activities engaged with during the evening peak in a given day (excluding cooking)



participant (of those activities that we track). The distribution is shown in Fig. 5. The bracketing illustrates a three-level categorisation of that variable (no peak-period activity, one peak-period activity, and two or more peak-period activities), which we use for modelling. We exclude cooking activity from these models.[5]

Table 3 shows the results of two ordinal logistic regressions to investigate associations between number of activities performed during the 4 pm – 7 pm window, and several of the measures taken in BETT. The first model includes everyone, and thus illustrates the associations between the predictor variables and level of peak-period activity for the population. It was necessary to exclude the age and home-at-day-time variables from this model to satisfy the assumption of parallel odds. The second model excludes people who were not at home during the peak period. It thus addresses the more specific question: if a person is home, what factors are associated with greater peak time activity.

For both models, there was no association between the number of evening peak period activities and the season or day of the week. There were also no gender differences, and no income differences were observed in model 1.

Household composition showed the most substantial impact on the odds of more peak time activity. Compared to living alone, living as a couple, family, or with others increased the odds of doing additional activities during the evening peak period substantially. Living as a family more than doubled the odds of higher activity counts (OR = 2.44, CI 95% [2.11, 2.81]).

Being on a night-saver tariff is associated with less peak-period activity when only people at home during the window are included (OR = 0.85, CI 95% [0.73, 0.99]), and not when everyone is included. A slightly larger proportion of that cohort was at home compared to people on standard tariffs. No difference in peak activity level was observed between those on ToU tariffs and those on standard or PAYG tariffs.

There were no differences either between those with high and medium/low levels of worry about the climate or cost of living, or between participants who perceived high average national effort to shift use away from peak and those who did not. There was a statistically significant difference with high worry about energy security and those with medium or low worry – those with a high level of worry displayed a slightly higher level of peak activity (OR = 1.13, CI 95% [1.02, 1.25]).

[5] When including cooking, the models do not pass the brant test of the proportional odds assumption. It appears that the influences of household composition, age, apartment dwelling, and weekend are not constant at each level of the dependent variable. What this likely indicates is that timing of cooking is associated with different factors to timing of most other activities. This contention is supported by the results of individual activities modelling.

Table 3 Ordinal logistic regression model of the number of electricity consuming activities performed by an individual during the evening peak (none, one, two or more)

	Full sample	People home at peak
	B (SE) OR	**B (SE) OR**
Home during day		− 0.32 (0.05) 0.73
Dark season	− 0.03 (0.04) 0.97	− 0.05 (0.05) 0.95
Weekend	0.03 (0.04) 1.03	0.09. (0.05) 1.10
Household composition (ref. = living alone)		
Couple	0.51*** (0.08) 1.67	0.47*** (0.09) 1.61
Family	0.89*** (0.07) 2.44	0.75*** (0.08) 2.11
Others	0.51*** (0.11) 1.66	0.44** (0.13) 1.55
Apartment	− 0.1 (0.07) 0.91	− 0.1 (0.08) 0.9
Male	− 0.07 (0.04) 0.93	− 0.05 (0.05) 0.95
Age (ref. = 18–34)		
35–54		− 0.14* (0.06) 0.87
55 +		− 0.43*** (0.07) 0.65
Degree	− 0.1* (0.04) 0.90	− 0.19*** (0.05) 0.83
Employed	0.02 (0.04) 1.02	0.07 (0.05) 1.07
Monthly household income (ref. = < 2 k)		
Income 2 k—4 k	0.05 (0.05) 1.06	0.12* (0.06) 1.12
Income 4 k +	0.04 (0.06) 1.04	0.03 (0.07) 1.03
Tariff (ref. = standard/PAYG)		
Night-saver	− 0.11. (0.07) 0.90	− 0.16* (0.08) 0.85
Other ToU	0.01 (0.07) 1.01	− 0.03 (0.08) 0.97
Hi effort	− 0.27*** (0.05) 0.76	− 0.26*** (0.05) 0.77
Hi effort—others	0.02 (0.05) 1.02	0.03 (0.05) 1.03
Hi worry—energy security	0.1* (0.05) 1.10	0.13* (0.05) 1.13
Hi worry—cost of living	0.07 (0.05) 1.07	0.04 (0.05) 1.04
Hi worry—climate	− 0.01 (0.04) 0.99	− 0.02 (0.05) 0.98
Observations (N)	12,000	8,444

Including solar PV ownership in the model does not affect this finding. Participants who reported making substantial effort to shift use away from peak did exhibit less peak-period activity than those who did not report as much effort (OR = 0.76, CI 95% [0.69, 0.85]), but there was no effect of the perceived effort of others.

Discussion

We have presented a representative, detailed, and comprehensive picture of the timing and prevalence of several electricity-using household activities that occur in Ireland, focusing on the evening peak period, defined here as 4 pm – 7 pm. In addition to finding the share of each of the activities that occur during the important peak window, we have estimated approximate population-level proportions of peak demand that each of the activities we record is responsible for. Moreover, we have described a wide range of factors differentially associated with doing household activities during the evening peak instead of another time of day, as well as different levels of peak-period activity overall. We now discuss our findings in the context of related work and its implications for demand side management practice and policy.

Household activities responsible for peak electricity use

We report specific estimates of proportions of the population that do different activities on a single average day. Direct comparisons with previous studies are complicated, but our findings broadly align with previous arguments that some activities are more constrained by routine than others (Powells et al., 2014) and support previous evidence regarding cooking being particularly responsible for peak consumption (Satre-Meloy et al., 2020).

We illustrate evening peak-period use in three different ways: we show the proportion of the full sample that do each activity during the evening peak window on a given day; we show the share of each activity that happens during this window; and we estimate the contribution of each activity to peak-period demand. For all three of these of these, cooking comes out on top. About 29% of the sample cooked a meal during the peak window on a given day; 46% of cooking activity happened during the peak; and it accounted for approximately 47% of the peak electricity demand of activities that we measured.

Despite being the greatest contributor to peak demand of the activities we measure, cooking was one of the only activities that had no relationship with self-reported effort to shift demand away from peak times. Assuming people are at least somewhat aware that cooking consumes electricity, this supports the contention that timing of cooking is less flexible than that of other activities. The importance of considering all available mechanisms for reducing peak demand is thus crucial. For example, shifting people to different cooking *appliances* rather than cooking *times* is one possible avenue – significant peak savings could be achieved through substitution of oven use with air fryers. Another mechanism would be to encourage batch cooking. Different mechanisms will suit different people.

Aside from cooking, immersion water heating, space heating and tumble dryer use also account for a substantial share of evening peak electricity use. Washing machine and dishwasher use are responsible for smaller shares, but their contributions are non-negligible, and these activities are quite amenable to shifting mechanisms (Ozaki, 2018; Öhrlund et al., 2019; Barsanti et al., 2024). Using the electric shower during peak is relatively rare but is in the top half of activities we measure both in terms of prevalence and share of electricity demand.

Seasonal and sociodemographic factors

Our results support findings that peak-period activity is less at weekends (albeit in relation only to cooking activity) and higher in larger households, and that it shows some seasonal variation (Cetin et al., 2014; Curtis, 2021; Kaur & Gabrijelčič, 2022; Trotta, 2020). Conversely, our results differ somewhat to those of Curtis (2021) in that we do find some associations between peak-period use and age, income, and education.

Those living with others, especially those living as a family, engaged in more peak-period household activity across the board, while degree-level education was generally associated with less activity. The remainder of the sociodemographic factors we used in our models have both positive and negative associations across the different activities examined, underscoring the value of modelling these activities separately (Stelmach et al., 2020). For example, older people were more likely to cook between 4 and 7 pm compared with under 35 s, but were less likely to shower or do laundry during those hours.

Clearly, as Satre-Meloy (2019) notes, different types and groups of people have varying degrees of curtailment or flexibility potential. Moreover, these contrasts are different according to the specific activity in question. Our results can inform both detailed targeting of all types of mechanisms and inform the design or development or indeed selection of mechanisms, of which there are many (see Grunewald & Diakonova, 2018), from the get-go. For instance, addressing peak laundry activities might require different mechanisms to cooking activities, and addressing cooking activities among older groups might require different mechanisms to addressing cooking activities among younger groups.

Motivational factors

The level of self-reported effort to shift use of electricity away from peak was high – close to 60% of the sample gave a 5 or above on the 7-point scale, while just 8% indicated making no effort at all. This is perhaps surprising given that it is unclear that people know why such efforts might matter, but a high degree of effort was indeed a reliable negative predictor of peak-period timing of most activities. Perception of other peoples' effort was not predictive of activity levels.

There is some evidence that people who use more energy at peak are aware of it. We found a somewhat higher amount of activity amongst people who were highly worried about energy security. One explanation is that they aware of their dependence on energy, or that they require a considerable amount, perhaps particularly during the peak period.

Despite a high degree of worry about the climate, helping the environment was not a prevalent stated motivation for shifting use away from peak and high climate worry did not predict peak activity. It seems likely that people are simply unaware of the connection. Climate worry was a predictor of engaging in fewer wasteful behaviours recorded by BETT more generally (SEAI, 2023).

Compared to monetary reasons to avoid peak-period consumption (with a ToU tariff), the environmental benefit of increasing the share of renewable generation has received little attention (Parrish et al., 2020). Research on the effectiveness of framing information about demand flexibility in terms of its environmental benefits is mixed (Barjaková et al., 2024). It appears that *awareness* of the benefit can be a stronger predictor of reduced peak-period use than monetary factors (Parag, 2021). Framing is not always successful in getting a message to permeate, particularly when it is complex, non-obvious, and/or new. There may therefore be potential in promoting demand flexibility through making people aware of the environmental benefits of shifting their demand. This is a hypothesis requiring greater attention and experimental methods that ensure participants understand the relevant concepts.

When people are asked, the most common motivation to shift use from peak periods is saving money (Parrish et al., 2020), and the majority of our participants reported this as their primary motivation. Interestingly though, only a small percentage of that group reported being on a tariff that allows for such saving, indicating a knowledge gap. We have also previously uncovered a misperception that electricity is more expensive during peak hours for anyone with a smart meter (SEAI, 2023).

Overall, we do not find evidence to support that ToU tariffs are associated with reduced electricity consumption during the evening peak in Ireland. This echoes previous real-world observations (Burns & Mountain, 2021) that have not found the same desired effects that trials of ToU tariffs (e.g. CER, 2011) and other studies have (Faruqui & Sergici, 2013).

We do find consistent differences in consumption patterns between people on night-saver tariffs and those on standard tariffs such that night-savers are significantly less likely to do their activities during the peak window. However, the only statistically significant difference between those on standard tariffs and those on other ToU tariffs is in dishwashing activity. Interestingly, a campaign run by the grid operator in Ireland to reduce peak demand used an image of a person looking at their dishwasher. It is noteworthy that night-saver tariffs are much more established in the Irish market; other ToU tariffs are relatively new and do not typically offer significant savings. Previous research has shown that the size of the difference between peak and off-peak rates moderates the effect on consumption change (Faruqui & Sergici, 2013).

Study limitations

BETT was not designed for time-of-use profiling and thus there are noteworthy limitations to the present study. First, BETT asks only about the previous day. Most people do not do more than one or two of the activities that we record on any given day. For this reason, we miss out on several potential data points compared to if we, say, asked about a week period. The substantial benefit however is that our straightforward factual questions about the most recent day (which we prompt participants to reconstruct) provide accurate accounts at a population level.

A related issue is that we only ask detailed questions – including time of use – about one instance of each activity. This results in what amounts to missing data as we must exclude people who did activities multiple times but were not asked about instances carried out at peak from the present analysis. Nonetheless, the use of randomisation allows us to gain a representative overall picture. And asking about only one instance allowed us to probe granular details of the behaviour that other time-use surveys have not accessed (Barsanti et al., 2024).

The analysis presented in this paper relates to data collected in 2023, during a global energy crisis. It is possible that energy behaviour was changed during this period due to heightened energy prices. However, any deviation from the norm is likely to be reflected in the overall level of electricity consumption rather than the time of day at which different activities are performed.

Lastly, we use survey data without accompanying monitoring data. Thus, we cannot cross-check the validity of participant responses, and the population estimates for demand contributions of each activity should be considered with some caution. However, we note that previous work has shown that time-use data can be used to build accurate and valid consumption profiles, and that people do report their activities accurately (Suomalainen et al., 2019; Widén et al., 2009). There are of course occasions where people do not report perfectly – we did not use the demand estimates that we calculated to make individual inferences. And where aggregate population level estimates deviate from reality, it has been due to non-representativeness of samples (Widén et al., 2009). Our sample was representative of the population. Further, our survey instrument (the DRM; Kahneman et al., 2004) was designed to validly capture participant daily time allocation while reducing recall biases (Lades et al., 2022).

Conclusion

Increasing demand flexibility requires first knowing what is used when and by who, and what may prompt people to change their behaviour. This paper paints a comprehensive and representative picture of evening peak time use in Ireland and charts several sociodemographic and household influences on consumption patterns at an activity-specific level. We have shown that the characteristics of people most likely to do a given activity during the typical evening peak window differ according to the activity in which they are partaking. Moreover, making an effort to shift use away from peak does not have the same impact for all activities. It is imperative that careful consideration is given to the design and implementation of interventions such that they are activity-specific and the full menu of means of achieving flexibility – including shifting, scheduling, shaving, efficiency, microgeneration, and storage – is considered. Our results provide the means to target efforts to increase demand side flexibility in ways specific to several activities and sociodemographic dimensions. It has also uncovered significant misconceptions and awareness gaps about demand flexibility among the public that subsequent work should investigate further.

Authors' contribution Both authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by both. The first draft of the manuscript was written by Ciarán Lavin and further edited by both authors. Both authors read and approved the final manuscript.

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Data availability The data used in the current study are available here: https://www.seai.ie/data-and-insights/behavioural-insights/publications/bett-dataset.

Appendix

Table 4 Sample characteristics

		Proportion
Gender	Female	54%
	Male	46%
	Other	0.3%
Age	18–34	24%
	35–54	43%
	55 +	33%
Region	Leinster	55%
	Munster	28%
	Connacht/Ulster	18%
Area type	Urban	63%
	Rural	37%
Social grade[1]	ABC1	50%
	C2DEF	50%
Education	Degree or above	38%
	Below degree	62%
Employment	Employed full time	44%
	Employed part time	16%
	Self-employed	4%
	Homemaker/carer	11%
	Student	2%
	Unemployed	4%
	Unable to work	4%
	Retired	15%
Net monthly income	Under 2k	29%
	2k—4k	38%
	4k +	22%
	Unknown	11%
Living situation	Living alone	14%
	Couple	26%
	Family	55%
	Unrelated/Mix	5%
Dwelling type	Detached house	40%
	Semi-detached/end of terrace house	36%
	Terraced house	14%
	Apartment/flat/bedsit	11%
	Mobile home/caravan/temporary building	0.4%
Dwelling tenure	Own home outright	33%
	Own home with loan/mortgage	31%
	Renting (private landlord)	19%
	Renting (local authority or housing association)	9%
	Living rent-free (e.g. with parents or friends)	8%

Table 4 (continued)

		Proportion
Electricity meter type	Standard (24 h) meter	30%
	Pay as you go	8%
	Day & night (Night-saver) meter	9%
	Smart meter	46%
	Don't know	6%
Tariff type	Standard	56%
	Pay as you go	8%
	Night-saver	12%
	Time-of-use	8%
	Don't know	16%

[1]Social grade is defined by the occupation of the chief earner in the household. ABC1 includes those categorised as being in managerial, supervisory, or clerical roles (administrative or professional). C2DEF includes manual workers, state pensioners, casual workers, farmers, and unemployed people receiving state benefits

Table 5 Models of peak activities with sociodemographic and household variables

	Cooking B (SE) OR	Immersion B (SE) OR	Electric shower B (SE) OR	Washing machine B (SE) OR	Tumble dryer B (SE) OR	Dishwasher B (SE) OR
Home during day	0.09 (0.06) 1.09	0.120 (0.1) 1.12	0.080 (0.1) 1.08	- 0.43*** (0.08) 0.65	- 0.3** (0.11) 0.74	- 0.01 (0.09) 0.99
Dark season	0.22*** (0.06) 1.24	- 0.06 (0.09) 0.94	- 0.04 (0.09) 0.96	0.19* (0.08) 1.21	0.18. (0.11) 1.2	- 0.14 (0.08) 0.87
Weekend	- 0.44*** (0.06) 0.65	- 0.11 (0.1) 0.89	- 0.03 (0.1) 0.97	0.15. (0.08) 1.16	0.24* (0.11) 1.28	0.15. (0.09) 1.16
Household [ref. = single]						
Couple	0.04 (0.1) 1.04	0.62** (0.2) 1.86	0.09 (0.18) 1.09	- 0.09 (0.16) 0.91	- 0.25 (0.25) 0.78	0.12 (0.21) 1.13
Family	0.3** (0.1) 1.36	0.8*** (0.18) 2.23	0.2 (0.16) 1.23	0.16 (0.15) 1.18	0.13 (0.22) 1.14	0.14 (0.2) 1.15
Others	- 0.17 (0.15) 0.85	0.58* (0.26) 1.78	- 0.31 (0.26) 0.74	0.1 (0.23) 1.1	- 0.04 (0.31) 0.97	- 0.08 (0.31) 0.93
Apartment	- 0.55*** (0.1) 0.58	- 0.44** (0.16) 0.65	0.1 (0.18) 1.1	0.07 (0.14) 1.07	- 0.03 (0.22) 0.97	0.21 (0.19) 1.23
Male	- 0.17** (0.06) 0.84	- 0.16 (0.1) 0.86	0.26** (0.1) 1.3	0.13 (0.08) 1.14	- 0.11 (0.11) 0.89	0.18* (0.09) 1.2
Age [ref. = 18—34]						
35—54	0.34*** (0.08) 1.41	0.17 (0.11) 1.18	- 0.3** (0.11) 0.74	- 0.28** (0.09) 0.76	- 0.41** (0.13) 0.66	- 0.14 (0.11) 0.87
55 +	0.42*** (0.09) 1.52	- 0.18 (0.14) 0.84	- 0.65*** (0.14) 0.52	- 0.64*** (0.12) 0.53	- 0.69*** (0.18) 0.5	- 0.28* (0.13) 0.75
Degree	- 0.17** (0.06) 0.85	- 0.06 (0.1) 0.94	- 0.3** (0.1) 0.74	- 0.22* (0.09) 0.81	- 0.09 (0.12) 0.91	- 0.18. (0.09) 0.83
Employed	- 0.1 (0.07) 0.91	- 0.17 (0.1) 0.85	0.09 (0.11) 1.09	0 (0.09) 1	- 0.04 (0.13) 0.96	- 0.16 (0.1) 0.85
Monthly income [ref. = < 2k]						
2k—4k	0.21 (0.07) 1.23	0.02 (0.12) 1.03	0.02 (0.12) 1.02	- 0.17 (0.1) 0.85	- 0.02 (0.14) 0.98	0.03 (0.11) 1.03
4k +	0.1. (0.09) 1.11	- 0.11 (0.14) 0.9	- 0.06 (0.14) 0.94	- 0.07** (0.11) 0.93	- 0.03 (0.16) 0.97	- 0.37** (0.14) 0.69
Night-saver	0.05 (0.09) 1.05	- 0.41** (0.14) 0.66	- 0.44* (0.17) 0.64	- 0.51*** (0.13) 0.6	- 0.79*** (0.2) 0.45	- 0.61 (0.15) 0.54
Other ToU	0.12 (0.11) 1.13	- 0.23 (0.17) 0.8	- 0.07 (0.17) 0.93	- 0.27. (0.15) 0.76	- 0.05 (0.2) 0.95	- 0.43*** (0.16) 0.65

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