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# What is the effect of weather on household electricity consumption? Empirical evidence from Ireland

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ABSTRACT

We explore the links between weather variables and residential electricity consumption using high-resolution smart metering data. While weather factors have been used for grid-level electricity demand estimations, the impact of different weather conditions on individual households has not been fully addressed. The deployment of smart meters enables us to analyse weather effects in different periods of the day using hourly panel datasets, which would previously have been impossible. To conduct the analysis, fixed-effects models are employed on half-hourly electricity consumption data from 3827 Irish household meters. We demonstrate that temperature has robust and relatively flat effects on electricity demand across all periods, whereas rain and sunshine duration show greater potential to affect individual behaviour and daily routines. The models show that the most sensitive periods differ for each weather variable. We also test the responses to weather factors for weekends and workdays. Weather sensitivities vary with the day of the week, which might be caused by different household patterns over the course of the week. The methodology employed in this study could be instructive for improving understanding behavioural response in household energy consumption. By using only weather indicators, this approach can be quicker and simpler than traditional methods – such as surveys or questionnaires – in identifying the periods when households are more responsive.

## 1. Introduction

In recent years, there has been an increase in residential smart meter installations in many jurisdictions as they move to modernise their electricity networks (Eid et al., 2017). The old mechanical metering systems usually record monthly energy consumptions of households, which limit the possibility of understanding residential electricity consumptions in depth. Besides, dynamic pricing of electricity is impossible using current metering infrastructures, due to the technical constraints of having no real-time usage data. In light of these concerns, the deployment of Advanced Metering Systems can potentially be part of the solution to achieve greater energy efficiency. There is one significant advantage of smart metering that is widely accepted — The new technologies record high-resolution data of household electricity usage and increase the visibility of energy consumption. As a consequence, the availability of high volumes of data enables more fine-grained studies of residential behaviour and consumption patterns (Razavi et al., 2019).

Thus, one area that particularly benefits from the installation of smart meters is the study of the effects of pricing structures on electricity consumption. Previous studies in this area have focused either on longer-time frames, such as monthly household usage, or relatively shorter periods (daily consumption) but at the regional level (Pardo et al., 2002; Davies, 1958; Atalla and Hunt, 2016; Trotter et al., 2016). High-frequency individual usage data makes it possible to examine the price effects during a specific short period during a day rather than using daily or monthly time steps. Although the results of the efficiency of different price schemes can be contradictory, increasingly studies have been done in the field to examine the effects from different perspectives.

However, the influence of weather in residential electricity consumption is one area that has not been extensively studied, although it has been widely accepted as an important factor affecting energy demand. The exploration of the relationship between energy consumption and weather is often seen in two sets of studies: (1) weather as control variables in models focusing on price or on socio-economic effects (Wangpattarapong et al., 2008; Newsham and Bowker, 2010; Cosmo and O'hora, 2017); (2) alternatively, weather has been used as the main independent variables but only when investigating the relationship between daily or even monthly regional demand and weather

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variables (Moral-Carcedo and Vicéns-Otero, 2005; Costa and Kahn, 2010; Blázquez et al., 2013). Weather variables such as temperature, precipitation, relative humidity, wind speed, cloud cover, and sun duration are the most common variables used in both types of research. In spite of interest in the relationship between electricity consumption and weather, few studies have studied the possible association during different periods of the day due to limitations on the frequency of energy use data (Davies, 1958). Would specific findings hold in every period? For example, will residential customers reduce their consumption in every period of a sunny day? Are the weather responses, in fact, period-dependent? A better understanding of the weather impact on electricity can assist researchers, policymakers and energy companies. A study of how residential customers respond to weather in different periods can provide insights into daily patterns of household behaviour, e.g during which periods a family is more likely to be active or often go out.

We examine here the weather response at different times of day using fixed-effects models on high-frequency usage data from Ireland's Smart Metering Electricity Behavioural Trial (Commission for Energy Regulation (CER), 2012a) combined with weighted weather data from five weather stations in Ireland. Due to the half-hourly data available from smart meters, we are able to investigate the household response to weather during different periods. We aim to provide evidence that the weather sensitivities are indeed period-dependent and that weather factors may be good proxies for household behaviour patterns in different periods of a day. In addition, this paper explores the impact of weather on the differences in electricity demand between weekends and workdays, thereby demonstrating that the relationships between weather and energy demand are not universal.

The paper continues by reviewing the related literature of weather effects in Section 2 and the details of the dataset used are specified in Section 3. The two main models used and the explanation of variable selection are described in Section 4. Results of the models are presented in two parts in Section 5, and Section 6 provides a discussion of potential implications and offers some conclusion.

## 2. Literature review

### 2.1. Weather effects on demand in general

The discussion of weather variables often appears in two sets of studies in this field: one is model establishments for electricity consumption forecasting and usually at an aggregated regional/national level. For example, Mirasgedis et al. (2006) summarise the studies paying particular attention to short-term forecasting and the role of weather variability. They claim that based on the experience of utilities, the main weather factors affecting electricity consumption are temperature, humidity, and precipitation in decreasing order of importance, while wind speed and solar radiation is not significant for the Greek mainland. Therefore, they only include the two weather variables (temperatures and relative humidity) in the models predicting the mid-term electricity consumption in Greece. Instead of using outdoor temperatures directly, heating degree days (HDD) and cooling degree days (CDD) are used to reflect the non-linear relationship between temperature and demand, which is particularly common in electricity demand studies (Bessec and Fouquau, 2008; Alberini and Filippini, 2011; Boogen et al., 2017). However, in these studies the effects of weather are based on total consumption including all sectors, not just on residential consumption specifically. Thus, the importance of these factors still needs to be examined with a particular focus on residential electricity demand. The second type of research where weather variables are often included is in studies of the determinants of regional electricity consumption. Such studies rarely focus solely on residential electricity demand but rather on total regional consumption. Trotter et al. (2016) examined the relationship between climate and daily electricity demand in Brazil where the only weather factors used are CDD, HDD, and the lag effects of CDD and HDD. One compelling argument they make is that the effect of temperature on the weekend is slightly different than on working days. Furthermore, a model based on aggregated monthly or annual data might not be able to reveal differences between the two cases. In addition to temperature, rainfall is another common variable examined. Hor et al. (2005) investigated monthly electricity demand from 1983 to 1995 in the UK and found a very weak negative relationship between rainfall and monthly demand. However, they argued that the correlation between demand and rainfall should be stronger but that the weak unexpected negative coefficient is mainly because they used only national-level data, while rainfall is very location-specific. Davies (1958)'s work considered aggregated country-level electricity demand in England and Wales arguing that five meteorological elements affect demand: temperature, wind speed, cloudiness, visibility, and precipitation. Temperature allied with wind speed determines the need for heat, while the remaining variables determine the level of daylight illumination, affecting lighting demand. The study divides daily demand into eight three-hour periods of demand to verify whether the effect of weather is the same across different periods of a day. The results show that temperature has a peak influence on demand around 9:00 and a lower coefficient during the 17:00 period. However, the direct effects of rainfall are only evident at 17:00. The findings indicate that the effect of a weather variable is not constant through a day, and it could be interesting to examine the differences in the residential sector specifically. Many researchers (Pardo et al., 2002; Räsänen et al., 2010; Albert and Rajagopal, 2013) agree with Davies (1958) that weather indices such as humidity, wind speed, cloudiness, and barometric pressure are suitable explanatory factors for weather sensitivity, although those variables may have less significant influence on electricity demand than temperature, rainfall and sun duration.

As discussed above, studies involving weather effects have paid more attention to total electricity consumption in a region. There has been a lack of panel data to support deeper studies of the residential electricity sector — current panel studies concerning weather and residential electricity are primarily based on aggregated regional panel data. Atalla and Hunt (2016) looked at the residential electricity demand in six Gulf Cooperation Council countries using a panel dataset of annual demand in slightly different periods from country-to-country. CDD and HDD are the only weather indicators used but do not necessarily have significant impacts on demand. It depends on geographic locations and whether there is variation in the weather variable. Blázquez et al. (2013) used aggregate monthly panel data at the province level for 47 Spanish provinces from 2000 to 2008. The authors acknowledge that in panel data analysis, fixed-effects models (FE) or random-effects models could be helpful to control unobserved heterogeneity, however, neither of these was appropriate for their study since they include a lagged dependent variable in their model. Again, CDD and HDD are also the only weather conditions considered, which is common in panel studies of regional residential electricity consumption. Due to the lack of data at household level, very little research has been done based on non-aggregate residential consumption. Henley and Peirson (1998) studied residential energy demand and the interaction of price and temperature based on a Time-of-Use (TOU) trial with 150 households between April 1989 and March 1990. Through a fixed-effects model, they found that the effect of temperature is negative and non-linear, and the magnitudes vary for different periods. Alberini and Towe (2015) attempted to estimate residential electricity usage savings from energy efficiency programmes. They assembled a panel dataset of monthly electricity usage and bills for a sample of about 17,000 households in Maryland from 2008 to 2012. They used Difference-in-Difference" and fixed-effects models to capture annual and seasonal household effects, and season-by-year effects. Weather effects are not the focus of the study, but CDD and HDD were included for monthly consumption control.

### 2.2. Weather effects in studies using smart metering data

In light of the trend of smart meter installation around the world, availability of household-level consumption data has begun to change. One of the main innovations brought by smart meters is that electric utilities can obtain huge volumes of high-resolution household usage data. A daily load profile of a household that depicts daily consumption trends from midnight to 11:59 p.m can now be easily drawn. High sampling frequencies provide operators with the opportunity to better understand consumption patterns of their residential customers. The availability of household consumption data enables researchers to identify the determinants of residential demand and the difference of effects on the demand of different periods of a day in more depth. One main strand of the literature using smart meter data investigates the effects of socio-economic and house-specific variables on load profiles. Anderson et al. (2017) summarised the existing evidence of household characteristics linked to load profiles and categorised those variables into three subgroups: (1) household features, such as number of persons, number of children, and age distribution (Yohanis et al., 2008; Beckel et al., 2015); (2) dwelling status: e.g. dwelling type, household tenure, number of rooms (Firth et al., 2008; McLoughlin et al., 2012); and (3) householder characteristics: employment status, social status, age and gender. Other Householder variables, such as education level, ethnic group, marital status and household income are also found to have significant impact on demand and load profiles (McLoughlin et al., 2012; Carroll et al., 2014). Nevertheless, research into electricity demand and household features have rarely paid attention to weather variables. There is little evidence of weather effects on residential demand from household-level data. Kavousian et al. (2013) examine structural and behavioural determinants of residential consumption using a dataset of 10-minute interval smart meter readings from 1628 households in California. They prove that weather and location are among the most important determinants of residential electricity use. However, the only weather variables, they include in their models are outdoor temperature and climate zone.

Another set of studies use smart metering data and consider weather variables to identify the effectiveness of time-of-use tariffs. Torriti (2012) took advantage of data from a TOU and smart metering trial in Northern Italy involving quarter-hourly readings from 1446 households from 1 July 2009 to 30 June 2011. The findings show that peak load shifting took place for morning peaks and created a split into two peaks for evening periods, while total consumption increased by 13.69%. The only weather variable, temperature, is used to control for the effect of weather variation, but the effect is not discussed in details. Other studies have used data from the large-scale trial smart metering experiment or Consumer Behavioural Trial (CBT) carried out by the Irish Commission for Energy Regulation (CER). Cosmo et al. (2014) utilise the CBT panel data of over 4000 households to explore whether the designed TOU is efficient in reducing peak demand. Two weather variables – sunshine duration and heating degree days – are included. Their results show that HDD are positively associated with consumption, while the opposite relationship is found for sunshine duration for the three periods considered (day, peak, and night). They only used the weather data from Dublin Airport weather station, as detailed information on household location is not available. However, considering that the selected households were drawn from across the country, a population-weighted weather dataset from different weather stations would be more accurate for a study of weather effects. In addition, the time periods may be too long since weather effects could change dramatically over the course of a period lasting as long as 10 h.

From the review above It can be easily seen that little research has focused on weather effects and weather influences are usually introduced as control variables for other research objectives. Generally, temperature is the main weather factor considered and other variables, such as precipitation, wind speed, and sun duration, have not been explored extensively. Furthermore, weather impacts are commonly discussed at an aggregate level, e.g., daily or monthly level. However, as proposed in some studies (Davies, 1958; Henley and Peirson, 1998), the impact of weather indices might differ depending on the time of a day. The lack of research could be due to the limited availability of high-frequency household-level data. Even with greater access to detailed household usage data, the focus of studies using smart meter data has been on time-of-use tariffs, rather than weather effects. Therefore, a comprehensive study of the weather effects on residential electricity demand and household behaviour patterns during different periods of the day would be helpful to filling the gap.

**Table 1**
Residential Time-of-Use tariffs 1st January to 31st December 2010.

| Cents per kWh | **Night** 23.00–8.00 | **Day** 8.00–17.00 19.00–23.00 weekdays 17.00–19.00 weekends and bank holidays | **Peak** 17.00–19.00 (Mon to Fri), excluding bank holidays |
|---|---|---|---|
| Tariff A | 12.00 | 14.00 | 20.00 |
| Tariff B | 11.00 | 13.50 | 26.00 |
| Tariff C | 10.00 | 13.00 | 32.00 |
| Tariff D | 9.00 | 12.50 | 38.00 |

## 3. Data

### 3.1. Residential electricity consumption data

The smart meter dataset used in this paper was collected as part of Ireland's Electricity Smart Metering Consumer Behavioural Trial, which includes 4000 residential customers (Commission for Energy Regulation (CER), 2012a).

Half-hourly readings of usage were recorded by meters installed in the trial from 15 July 2009 to 31 December 2010. During the benchmark period (July 2009 to Dec 2009) all households were charged a fixed tariff. From 1 January 2010, those who were selected into treatment groups were charged time-of-use (TOU) tariffs. There were 4 TOU tariff periods: peak (17:00-18:59 Monday–Friday, excluding public holidays), day (08:00–16:59; 19:00–22:59 Monday–Friday, plus 17:00–18:59 public holidays, Saturday and Sunday) and night (23:00–07:59) periods. The tariff structure is shown in Table 1. In order to control the effects caused by the price incentives, our research only includes data recorded from 1 January 2010 onward, where tariffs are constant across all households during that period. In addition, homes with average daily consumption of more than 54 kWh are also removed because these outliers may not be residential consumers, but are more likely to be small enterprises or home-based enterprises[1]

### 3.2. Weather data

To generate daily weather observations at specific times of day, hourly weather data provided by the Irish Meteorology Office (Met Éireann) are matched with household electricity consumption data. Recorded hourly observations are dry-bulb (air) temperature (° C), relative humidity (%), wind speed (kph), and fraction of sunshine per hour (%). Since location information is not provided by CER due to privacy concerns, a population-weighted weather dataset should be considered to reflect consumption response to weather from families living across Ireland (Valor et al., 2001; Auffhammer and Aroonruengsawat, 2012). As a result, four weather stations, Dublin Airport, Valentia Observatory,

[1] Furthermore, the impacts of daylight saving time (31st October 2010 and 25th March 2010) are taken into account. The data from the second 2 am (end of DST) is deleted from the dataset to avoid double counting.

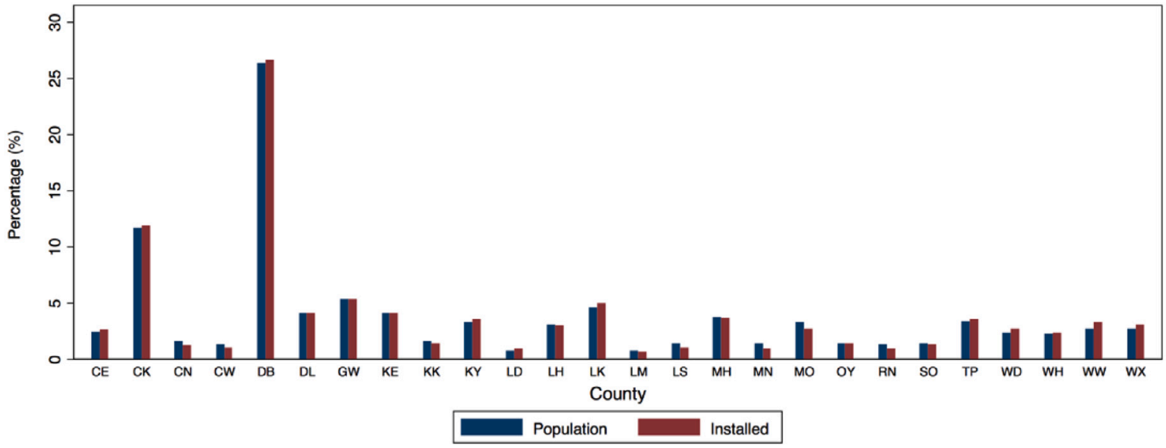


**Fig. 1.** Comparison of county level distribution between acceptances and total population.

**Table 2**
Average correlations between weather variables and household demands.

| Observatory stations | Rain | Temperature | R. Humidity | Wind Speed | Sun Duration |
|---|---|---|---|---|---|
| Belmullet | 0.051 | −0.274 | 0.088 | −0.031 | −0.088 |
| Cork Airport | 0.016 | −0.274 | 0.091 | 0.049 | −0.090 |
| Dublin Airport | 0.047 | −0.267 | 0.194 | 0.041 | −0.132 |
| Valentia | 0.024 | −0.265 | −0.026 | 0.000 | −0.076 |
| Weighted | 0.051 | −0.271 | 0.165 | 0.020 | −0.129 |

Belmullet and Cork Airport, were chosen. The first three synoptic stations are the choices of Met Éireann for regular Irish weather statements (Met Éireann, 2018) and Cork was selected to ensure enough sufficient regional representation because a significant number of participating households live in Cork (See Fig. 1). Since the distribution of the final acceptances onto the trial was similar to the total population at county-level (Fig. 1), the population ratios around the four stations are aggregated and calculated as weights to create a new dataset to match with the consumption data.

The weights of the population ratios used are 0.535 for Dublin, 0.175 for Cork, 0.16 for Belmullet and 0.11 for Valentia. The method of how to draw the boundaries of each station is not ideal due to the absence of household location information. For example, County Clare (CE in Fig. 1) can be associated with Cork station or Belmullet station. However, as the weather in Ireland is relatively similar, the boundaries/weights hardly change the final results as we tried different weights for the analysis.

We investigated which datasets could better reflect the consumption responses to weather changes through correlation analysis. First, we calculated the correlation coefficients of each household to the weather variables separately. Secondly, the average correlation coefficients for the weather factors were obtained for each weather dataset and shown in Table 2. The weighted method seems the most balanced dataset that is with higher correlations across different weather variables.

The descriptive statistics for the weather variables are described in Table 3.[2]

### *3.3. Time use study data*

In order to help divide hourly data into several discrete periods, the Irish National Time-Use Survey 2005 (McGinnity et al., 2005) is used. It collected detailed national time-use statistics on over 1000 adult participants' daily activities, which includes two complete diaries of their activities over a 24-hour period — one for a weekday and another for a weekend day. It provides a comprehensive view of daily life in Ireland and possible behaviour during every 15-minute slot of a day. As a result, the findings of the survey can be particularly helpful in two ways: (1) to divide hourly data more accurately and avoid splitting one major daily activity into two periods, which may distort the actual response by either exaggerating or underestimating the effects. For instance, separating 12:00–14:00 into two different periods may cancel out part of the impacts of lunchtime; (2) to better understand how people respond to weather changes. For example, if people are less sensitive to rainfall during 12.00–14.00, it could be a lunchtime effect. Therefore, this survey data provides a supplementary tool to explain and confirm the results obtained from the proposed models.

## 4. Methodology

As seen in the literature review in Section 2, studies of the effects of weather variables have mainly focused on relationships between daily electricity consumption and daily weather change. It is not clear that how households respond to weather change at different times of day. To investigate the weather sensitivities in different periods of a day, it is reasonable to assume that households will not change their behaviour immediately when the weather changes. In order to capture the lagged effects, the hourly data is aggregated and divided into periods based on patterns of daily activities, rather than using raw hourly data directly. Although autoregressive models can be used on hourly data to control lagged effects, it might complicate the situation and the lag lengths suitable for weather effects are not clear and there is no agreed lag time in the literature.

Two rules are employed in separating the time periods: (1) To control for possible price effects caused by the TOU tariffs, the time periods chosen should not cross over two different tariffs (i.e., the tariff structure shown in Table 1); and (2) A period does not split major activities. On the basis of these rules, the tariffs provides natural breaks at the early morning, peak and night periods. However, the day price period (see Table 1) is much longer than the other periods, which may obscure the real response, and so needs to be sub-divided. In the end, 9 periods are set as follow with the help of the time use study: early morning (6:00–8:00), day_1 (8:00–10:00), day_2 (10:00–12:00), day_3 (12:00–15:00), afternoon/day_4 (15:00–17:00), peak (17:00–19:00), early evening/evening_1 (19:00–21:00), evening_2 (21:00–23:00) and night (23:00–3:00). The summary of weather variables in these periods can be seen in Table 3. The period of night_2 from 3:00 to 6:00 is not discussed in the main analysis, since no major activities occur during that period and that the estimates for weather variables are generally less than 0.5% (seen in Table 5). The descriptions of the four main activities with the highest proportions of people doing on workdays and weekends are shown in Table 4. The numbers in each cell represent

[2] The rules of how these periods are divided will be introduced in Section 4.

**Table 3**
Descriptive Statistics for the weather variables.

| | | Morning | Day_1 | Day_2 | Day_3 | Day_4 | Peak | Evening_1 | Evening_2 | Night |
|---|---|---|---|---|---|---|---|---|---|---|
| Temperature (°C) | Mean | 7.23 | 8.64 | 10.18 | 11.03 | 10.75 | 9.83 | 8.75 | 7.91 | 7.20 |
| | Std. Dev. | 5.42 | 5.56 | 5.37 | 5.33 | 5.71 | 5.88 | 5.63 | 5.32 | 5.25 |
| | Min | −7.49 | −7.49 | −5.16 | −2.84 | −3.60 | −4.98 | −5.20 | −5.85 | −6.33 |
| | Max | 17.52 | 18.09 | 19.94 | 20.57 | 20.78 | 19.82 | 18.69 | 17.52 | 17.09 |
| Rel. Humidity (%) | Mean | 89.26 | 84.43 | 77.98 | 74.21 | 74.97 | 78.61 | 83.04 | 86.48 | 88.75 |
| | Std. Dev. | 5.08 | 7.54 | 9.74 | 10.48 | 11.10 | 10.39 | 8.42 | 6.21 | 4.75 |
| | Min | 64.67 | 62.83 | 51.77 | 46.53 | 47.57 | 51.18 | 57.25 | 64.74 | 71.44 |
| | Max | 97.52 | 97.14 | 96.15 | 96.32 | 96.53 | 96.91 | 97.27 | 97.22 | 97.28 |
| Wind speed (knots) | Mean | 8.24 | 9.04 | 10.06 | 10.67 | 10.46 | 9.60 | 8.61 | 8.05 | 8.02 |
| | Std. Dev. | 3.56 | 3.55 | 3.72 | 3.77 | 3.84 | 3.87 | 3.82 | 3.89 | 3.78 |
| | Min | 2.03 | 2.54 | 2.91 | 3.46 | 2.66 | 2.86 | 1.75 | 1.47 | 2.06 |
| | Max | 27.16 | 27.87 | 27.07 | 29.03 | 28.93 | 29.79 | 28.83 | 27.93 | 24.34 |
| Sun duration (% per hour) | Mean | 0.14 | 0.36 | 0.48 | 0.46 | 0.33 | 0.20 | 0.07 | 0.00 | 0.00 |
| | Median | 0.04 | 0.31 | 0.50 | 0.45 | 0.25 | 0.03 | 0.00 | 0.00 | 0.00 |
| | Std. Dev. | 0.23 | 0.30 | 0.31 | 0.30 | 0.31 | 0.29 | 0.15 | 0.00 | 0.00 |
| | Min | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | Max | 0.97 | 0.98 | 0.98 | 0.98 | 0.98 | 0.98 | 0.91 | 0.03 | 0.00 |
| Rainfall (mm) | Mean | 0.08 | 0.07 | 0.08 | 0.08 | 0.10 | 0.13 | 0.12 | 0.10 | 0.10 |
| | Median | 0.01 | 0.01 | 0.01 | 0.01 | 0.00 | 0.01 | 0.00 | 0.00 | 0.01 |
| | Std. Dev. | 0.19 | 0.18 | 0.18 | 0.18 | 0.23 | 0.31 | 0.29 | 0.23 | 0.22 |
| | Min | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | Max | 1.40 | 1.34 | 1.32 | 1.71 | 1.96 | 2.27 | 1.93 | 1.84 | 1.82 |

**Table 4**
Percentage of four main activities for workdays and weekends.

| | *1st* | | *2nd* | | *3rd* | | *4th* | |
|---|---|---|---|---|---|---|---|---|
| | Workdays | Weekends | Workdays | Weekends | Workdays | Weekends | Workdays | Weekends |
| Morning 6.00–8.00 | *Sleep* 46.3–91.9 | *Sleep* 72.9–92.4 | *Personal Care* 1.7–12.4 | *Personal care* 1.2–6.2 | *Eating* 0.3–9.7 | *Paid Employ* 0.6–4 | *Travel* 0.6–9 | *Travel* 0.4–3.1 |
| Day_1 08.00–10.00 | *Paid Employ* 11.6–35.8 | *Sleep* 26.4–61.5 | *Sleep* 8.8–32 | *Eating* 5.5–14.2 | *Travel* 9–16 | *Perscare* 8.1–11.5 | *Personal care* 4.6–15.9 | *Paid Employ* 5.6–10.9 |
| Day_2 10.00–12.00 | *Paid Employ* 33–39 | *Sleep* 6.7–18 | *Cleaning* 7.4–9.1 | *Eating* 4.5–12.4 | *Eating* 3.1–9 | *Paid Employ* 9.1–10.8 | *Travel* 6.3–8.3 | *Cleaning* 6.2–10.3 |
| Day_3 12.00–15.00 | *Paid Employ* 17.9–38.7 | *Eating* 5.6–23.7 | *Eating* 3–26.2 | *Paid Employ* 6.8–12.4 | *Breaks* 1.8–14.5 | *Cooking* 7.2–11.9 | *Shopping* 3.4–5.7 | *Travel* 5.3–8.9 |
| Day_4 15.00–17.00 | *Paid Employ* 34.9–38.6 | *Eating* 3.8–16.3 | *Eating* 2.2–9.6 | *Paid Employ* 9.2–11 | *Travel* 5.3–7.1 | *Travel* 7–9.1 | *Cleaning* 4.2–6.6 | *Shopping* 7.3–8.5 |
| Peak 17.00–19.00 | *Paid Employ* 18.2–35.9 | *Paid Employ* 9.1–10.5 | *Travel* 8–13.9 | *Chatting* 6.6–9.6 | *Cooking* 4.3–11.9 | *Travel* 6.1–8.8 | *Eating* 2.6–9.7 | *TV/Vdieos* 7.6–8.8 |
| Evening_1 19.00–21.00 | *Eating* 6.5–20.3 | *TV/Videos* 10–18.3 | *TV/Videos* 7.8–19.2 | *Eating* 6.6–17.8 | *Paid Employ* 8.3–12.7 | *Travel* 5.2–9.8 | *Travel* 4.9–11.9 | *Chatting* 7.2–9 |
| Evening_2 21.00–23.00 | *TV/Videos* 18.4–33.2 | *TV/Videos* 16–26.8 | *Resting* 8.6–10.8 | *Eating out* 5.2–12.4 | *Chatting* 6.8–8.5 | *Resting* 8.7–11.3 | *Eating* 2.4–6.9 | *Chatting* 8–9.7 |
| Night 23.00–03.00 | *Sleep* 37.2–90.1 | *Sleep* 26.1–81.3 | *TV/Videos* 0.4–18.3 | *TV/Videos* 10–17.7 | *Resting* 0.8–6.6 | *Eating out* 6.5–16.3 | *Chating* 0.3–5.3 | *Resting* 0.9–6.5 |

the minimum and maximum percentages of people doing the activities during each period of a day.

As panel data allows for the exploitation of both time and cross-section dimensions, it has the potential to eliminate unobserved heterogeneity in the data (Asteriou and Hall, 2011). As a result, given the nature of the panel dataset, two fixed-effect models are employed. Although random-effects (RE) models are also used in the related literature, fixed effects (FE) models better suit the purposes of this study.

With FE models, the focus is given to weather variables, while the effects of variables whose values are consistent across time (Wooldridge, 2013), such as demographics, housing conditions, and electric appliance ownership, are captured in a single fixed-effects estimator since the focus of the study is not on household characteristics. In addition, the results of the Hausman test imply that FE models are more suitable, since the null hypotheses of RE models is rejected (p-values of 0.0000).

The first model (Model 1) explores the effects of selected weather variables on electricity consumption and is as follows:

$$\log\left(q_{i,t}^{h}\right) = \alpha_i^h + \sum_{p=1}^{5} \delta_p^h W_{p,t} + \sum_{m=2}^{12} \lambda_m^h M_{m,t} + \sum_{j=2}^{7} \theta_j^h D_{j,t} + \zeta_y^h H_y + \varepsilon_{i,t}^h \quad (1)$$

where $h = 1 - -9$ for each of the 9 periods. $\log(q_{i,t}^h)$ denotes the logarithm of household $i$'s daily electricity consumption in kilowatt-hours during one period of day $t$. As discussed above, there are 9 periods in a day. The model therefore is run for each period separately; $W_{p,t}$ are the five weather variables; $M_{m,t}$ are dummies of month indicators, and January is selected as the baseline (when $m$=1) ; $D_{j,t}$ indicate day of week and the reference category is Monday (where $j$=1); the coefficient $\delta$ represents the expected weather effect on consumption, while the coefficients $\lambda$ and $\theta$ quantify the consumption differences between the expected effect (the month $i$ and the day $j$) and the baseline (January and Monday); $H_y$ is the public holiday dummy; $\alpha_i^h$ are household fixed effects and $\varepsilon_{i,t}^h$ is a stochastic disturbance term. There may also be

**Table 5**
Estimated coefficients from Model 1 of weather effects.

| Variables | (1) Morning 6.00–8.00 | (2) Day_1 8.00–10.00 | (3) Day_2 10.00–12.00 | (4) Day_3 12.00–15.00 | (5) Day_4 15.00–17.00 | (6) Peak 17.00–19.00 | (7) Evening_1 19.00–21.00 | (8) Evening_2 21.00–23.00 | (9) Night 23.00–03.00 | (10) Night_2 3.00–6.00 |
|---|---|---|---|---|---|---|---|---|---|---|
| **Weather** | | | | | | | | | | |
| Temperature | −0.001792*** | −0.005751*** | −0.01291*** | −0.01402*** | −0.01326*** | −0.01307*** | −0.01216*** | −0.01015*** | −0.009062*** | −0.0007606*** |
| Rainfall | −0.0002214 | 0.04434*** | 0.04876*** | 0.01696*** | 0.04374*** | 0.01897*** | 0.009795*** | 0.009304*** | 0.004056 | 0.001362*** |
| Sun duration | 0.01921*** | 0.01038*** | 0.002493 | 0.01257*** | −0.03527*** | −0.04913*** | −0.09356*** | / | / | / |
| Relative humidity | −0.001364*** | −0.0007425*** | 0.001294*** | 0.002896*** | 0.001511*** | 0.001598*** | 0.001377*** | 0.0006098*** | 0.001433*** | 0.001433*** |
| Wind speed | −0.0006325** | −0.00001235 | 0.002379*** | 0.003416*** | 0.003632*** | 0.002928*** | 0.003103*** | 0.002508*** | 0.002866*** | 0.0002630* |
| ***Weather coefficients above in a readable form*** | | | | | | | | | | |
| Temperature | −0.2% | −0.6% | −1.3% | −1.4% | −1.3% | −1.3% | −1.2% | −1.0% | −0.9% | −0.1% |
| Rainfall | | 4.4% | 4.9% | 1.7% | 4.4% | 1.9% | 1.3% | 1.0% | 0.4% | 0.1% |
| Sun duration | 1.9% | 1.0% | 0.2% | 1.3% | −3.5% | −4.9% | −9.4% | \ | / | / |
| Relative humidity | −0.1% | −0.1% | 0.1% | 0.3% | 0.2% | 0.2% | 0.1% | 0.1% | 0.1% | 0.1% |
| Wind speed | −0.1% | | 0.2% | 0.3% | 0.4% | 0.3% | 0.3% | 0.3% | 0.3% | 0.0% |
| **Time** | | | | | | | | | | |
| Sunday | *Ref* | *Ref* | *Ref* | *Ref* | *Ref* | *Ref* | *Ref* | *Ref* | *Ref* | |
| Monday | 0.2519*** | 0.06085*** | −0.3173*** | −0.2831*** | −0.06142*** | 0.1199*** | 0.07258*** | 0.07611*** | 0.009453*** | −0.03566*** |
| Tuesday | 0.2891*** | 0.08829*** | −0.3536*** | −0.3214*** | −0.08644*** | 0.1056*** | 0.06893*** | 0.08320*** | 0.06792*** | 0.06792*** |
| Wednesday | 0.2855*** | 0.09368*** | −0.3522*** | −0.3289*** | −0.1049*** | 0.07815*** | 0.04770*** | 0.06515*** | 0.01134*** | −0.04373*** |
| Thursday | 0.2928*** | 0.09713*** | −0.3717*** | −0.3506*** | −0.1207*** | 0.06379*** | 0.03537*** | 0.06527*** | 0.02789*** | −0.04102*** |
| Friday | 0.2727*** | 0.09912*** | −0.3376*** | −0.3145*** | −0.1003*** | 0.03893*** | 0.008178*** | 0.02278*** | 0.1039*** | −0.02955*** |
| Saturday | 0.05649*** | 0.08121*** | −0.07385*** | −0.09508*** | −0.003968 | 0.05539*** | 0.00417 | −0.02833*** | 0.09864*** | −0.01729*** |
| Non-holiday | *Ref* | *Ref* | *Ref* | *Ref* | *Ref* | *Ref* | *Ref* | *Ref* | *Ref* | *Ref* |
| Holiday | −0.08155*** | −0.04648*** | 0.1033*** | 0.09791*** | 0.01649*** | −0.06722*** | −0.03440*** | −0.02201*** | 0.04221*** | 0.03038*** |
| **Month** | | | | | | | | | | |
| January | *Ref* | *Ref* | *Ref* | *Ref* | *Ref* | *Ref* | *Ref* | *Ref* | *Ref* | *Ref* |
| February | 0.01436*** | −0.003099 | −0.07754*** | −0.09040*** | −0.1293*** | −0.1381*** | −0.04967*** | −0.05712*** | −0.07450*** | −0.05259*** |
| March | −0.008113** | −0.03512*** | −0.08563*** | −0.09903*** | −0.1810*** | −0.2989*** | −0.1011*** | −0.08255*** | −0.1096*** | −0.06409*** |
| April | −0.08523*** | −0.08503*** | −0.07490*** | −0.1029*** | −0.2316*** | −0.4113*** | −0.3512*** | −0.1131*** | −0.08343*** | −0.07262*** |
| May | −0.08081*** | −0.09148*** | −0.09447*** | −0.1194*** | −0.2253*** | −0.4209*** | −0.4227*** | −0.2038*** | −0.07287*** | −0.06053*** |
| June | −0.07489*** | −0.08472*** | −0.04169*** | −0.06096*** | −0.1848*** | −0.4117*** | −0.4391*** | −0.3027*** | −0.03034*** | −0.01912*** |
| July | −0.1195*** | −0.1150*** | −0.01284** | −0.04466*** | −0.2042*** | −0.4413*** | −0.4714*** | −0.2942*** | −0.04733*** | −0.01373*** |
| August | −0.1254*** | −0.1164*** | −0.003654 | −0.03843*** | −0.2074*** | −0.4392*** | −0.4451*** | −0.2142*** | −0.05090*** | −0.01801*** |
| September | 0.006025 | −0.05519*** | −0.06729*** | −0.07816*** | −0.1684*** | −0.3890*** | −0.2414*** | −0.1378*** | −0.09302*** | −0.02973*** |
| October | −0.02453*** | −0.04794*** | −0.07490*** | −0.09983*** | −0.1810*** | −0.3057*** | −0.1271*** | −0.1383*** | −0.1027*** | −0.06576*** |
| November | 0.01848*** | −0.01011*** | −0.09065*** | −0.1065*** | −0.06440*** | −0.05878*** | −0.08408*** | −0.09882*** | −0.1026*** | −0.06209*** |
| December | 0.05976*** | 0.1034*** | 0.1129*** | 0.05702*** | 0.09065*** | 0.01957*** | 0.007024* | 0.02495*** | 0.03491*** | 0.0847207*** |
| **Constant** | −0.2103*** | 0.2800*** | 0.5056*** | 0.9000*** | 0.5277*** | 0.8759*** | 0.8964*** | 0.7818*** | 0.4845*** | −0.103125*** |
| **Obeservations** | 1495843 | 1496318 | 1495849 | 1496196 | 1496368 | 1496948 | 1497084 | 1497236 | 1497783 | 1497123 |
| **R2** | 0.5637 | 0.4846 | 0.4322 | 0.4735 | 0.4702 | 0.5116 | 0.523 | 0.5553 | 0.6319 | 0.6722 |

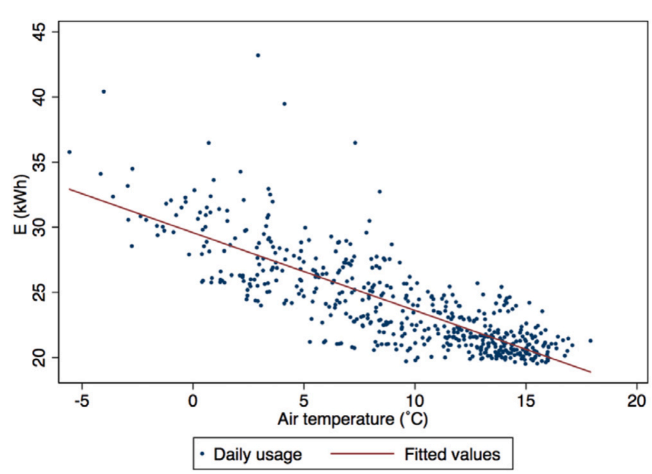


**Fig. 2.** Average daily electricity consumption per household.

unobserved household-specific differences in consumer demand, for example, presence of electric dryers or other appliances. The fixed-effects estimator used can handle it well as this household-level heterogeneity is constant over time.

Although weather has been identified in many studies as an essential factor, no agreement has been reached on which weather variables and in what form they should be added into the modelling. However, heating/cooling degree days, hours of sunshine, rainfall, wind speed and relative humidity are five leading variables that have been used in the relevant research. Model 1 employs all these variables, apart from heating degree days (HDD) and cooling degree days (CDD), which are replaced by air temperature in the equation. The reason for this substitution is that HDD and CDD are used to reflect the non-linear relationship between daily electricity demand and daily temperature. However, although a non-linear response is found in other studies (Woods and Fuller, 2014; Auffhammer and Mansur, 2014), there is no clear non-linear relationship, but rather a linear correlation in Irish houses (Fig. 2). One reason may be that the temperature range in Ireland is relatively flat and air conditioning uncommon in Ireland. In addition, Model 1 examines the weather during different periods of the day, rather than daily changes, so the using CDD and HDD would not suit the case.

The second model (Model 2) is based on Model 1 but streamlined to focus on estimating how differently households respond to weather changes on weekends and weekdays. The different consumption patterns can be seen in Fig. 3.

To estimate the differences, the following model is tested:

$$\log\left(q_{i,t}^{h}\right) = \alpha_i^h + \vartheta^h D_x + \zeta_y^h H_y + \sum_{p=1}^{3} \delta_p^h W_{p,t} + \sum_{p=1}^{3} \beta_i^h W_{p,t} \times D_x + \sum_{m=2}^{12} \lambda_m^h M_{m,t} + \varepsilon_{i,t}^h \tag{2}$$

The model is similar to Model 1, apart from the following changes:

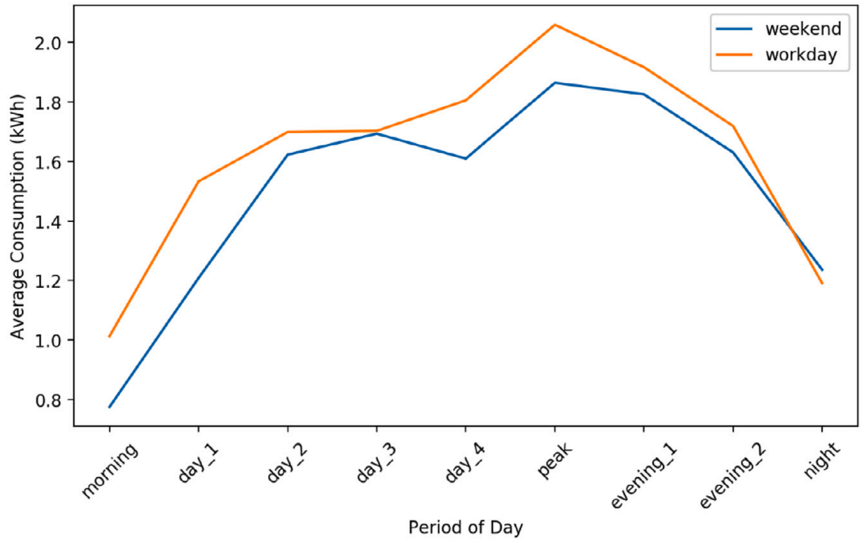


**Fig. 3.** Average daily electricity consumption per household.

1. Day of week dummies are replaced by a workday dummy $D_x$ to estimate the difference between workdays and weekends. It should be highlighted that the definition of working days varies depending on the period of the day. Before 19:00 (peak period), the definition remains the same as the typical sense that Monday to Friday are working days. However, the definitions of working days from 19:00–03:00 are slightly different. For the evening_1 and evening_2, periods workdays are defined as Monday to Thursday, which means 3 days for each weekend because it is sensible to treat Friday evening as the start of a weekend. Additionally, before 23:00 on a Sunday can also be regarded as part of a weekend. However, it may be logical to assume that the behaviour/life pattern for the night period (23:00–3:00) on a Sunday is more similar to a workday. During late evenings/evening_2 on weekends eating out is still the second most common activity (Table 4) and so Sunday evenings should not be treated as workdays. Therefore, the definition of workdays for the night period is Sunday to Thursday. The analysis for holidays/public holidays applies the same rule.
2. Only three weather variables are included in this model. Wind speed and relative humidity are excluded as they have less impact on demand. In addition, the objectives of this model are to examine the differences in response in the main weather factors between weekdays and weekends. Adding variables that have limited effect can overfit the model and may lead to biased results. As a result, Model 2 only keeps three weather variables. It is because: (a) the results shown in Model 1 prove that humidity and wind speed have the least and almost negligible effects on demand. A model including the two variables would weaken the model; (b) To ensure no significant variables are missed, we tested the model with all five weather variables and their interactions, which shows that with or without relative humidity and wind speed included, the results for the other three variables remain almost the same. Therefore, the more concise model with better explanatory power is employed.

In Model 2, the main coefficients of concern are $\beta_i^h$ and $\delta_p^h$. $\beta_i^h$ represents the difference in demand between workdays and weekends/holidays caused by weather variable $W_{p,t}$. $\delta_p^h$ indicates the possible effects of weather variable $W_{p,t}$ on weekends/holidays. Note that together holidays plus weekends act as the reference category and that holidays are not separated from weekends because less than 10 days in a year are treated as holidays. Results from the interaction between the holiday dummy and weather factors may be biased due to the limited sample size.

## 5. Results

### 5.1. General relationships between weather factors and demands

Analysing the weather sensitivities on periods of day basis will allow us to answer different questions. First, do consumers change their behaviour alongside changes in weather and the seasons? And if so, which weather variables affect the consumption behaviour most significantly? Is there any particular period in which the effect of one specific weather factor dominates? The weather effects on electricity consumption in Ireland do not reflect behaviour change related to heating demand since natural gas is the main heating source in Ireland and electric heating appliance ownership is low, around 10% (Commission for Energy Regulation (CER), 2012a). Instead, the changes in demand reflect how weather factors will affect households' daily behaviour for electricity-intensive activities such as lighting, cooking, and other household appliances (washing machines, dishwashers, dryers, televisions, etc.) and so will reflect both variation in household chores and activities as well as whether people are at home or whether have gone outside or away from home.

As the dependent variable is log transformed, the coefficients of independent variables present the percentage change in demand (the dependent variable) for a one unit increase in that variable. The table presents the estimated coefficients from the models for the ten periods (Table 5). We keep the coefficients in this form to show the significance level and original results. To make the results more readable, we converted the coefficients into percentages and showed them below the original results. For example, a coefficient of −0.01291 indicates the demand decreases by almost 1.3%.

#### 5.1.1. Temperature

Temperature always has a negative effect on household electricity consumption. This is in line with many previous research findings (Blázquez et al., 2013; Cosmo et al., 2014) that daily electricity demand decreases when the daily temperature rises. This result holds across all periods, not just for average daily consumption. The reduction in demand with rising temperature could be caused by various drivers including engaging in more outdoor activities and lower heating demand. Considering that the Irish heating system largely depends on natural gas (Commission for Energy Regulation (CER), 2012b), with a higher possibility that the reduction from temperature is from spending more time outside. By contrast, the reason for the negative effect on mornings (6:00-8:00) may be different, since most households should be still asleep or in the bed. The response to temperature can be seen as the sensitivity of the activities in this period to temperature change (warm/cold weather. Hence, a higher sensitivity represents the activities/behaviour in that period are more likely to be outdoor activities. From Table 5, it can be seen that night (23:00-03:00), and especially early morning (6:00-8:00) are far less sensitive than other periods with less than a 2% reduction. The highest coefficient is in the early afternoon (12:00-15:00), which indicates that the activities in that period can be most sensitive to warmer weather.

#### 5.1.2. Rain

In terms of rainfall, our prior expectations were that higher rainfall could be associated with an increase in electricity demand for all periods. It seems reasonable that the heavier it rains the less likely that people would go outside. As expected, all periods show a positive relationship between rainfall and consumption, except for mornings (6:00-10:00) and late nights. The reversed sign in the early mornings (6:00-8:00) may indicate that the households wake up later when it is raining outside. Moreover, the electricity usage in mornings (8:00-10:00) and late nights are rarely affected by rain. By the time many people have left home to work, while those who stay at home may not be ready to go out immediately for shopping or exercises after breakfasts. Relatively few households are awake after 23:00, most households tend to go to bed earlier on workdays and even on weekends many households will not stay up beyond midnight. This assumption can be verified by the Time-Use Survey in Ireland (McGinnity et al., 2005), which showed that more than 50% percent of people are sleeping at 23:00–23:59. The figure soars to 85% for 0:00–1:00.

#### 5.1.3. Sun

The results of sun duration suggest two clear patterns over the course of a day. The turning point seems to be 15:00, which is consistent with the findings of Harold et al. (2015) and Cosmo and O'hora (2017). The more sunshine observed In that period, the less electricity consumed by households. Before 15:00 it has an opposite effect with the model producing a positive coefficient. The positive effect may be due to the different nature of the activities during the two periods. Since, as discussed, electricity consumption does not reflect heating demand, the results would indicate that more indoor activities (e.g chores, DIY, gardening) tend to occur over 6:00-15:00 whereas there was greater chance of outdoor activities (e.g., shopping, sports) occurring in the late afternoon and early evening. Furthermore, the larger coefficients in the early evening (17:00-21:00) reveal that for the half year that has sunshine in the early evening (mainly late Spring and summer), willingness to go out is particularly sensitive to sunshine during that period.

#### 5.1.4. Humidity and wind speed

Relative humidity and wind speed show similar patterns in affecting residential electricity demand. They increase demand for electricity for all periods after 10:00. In terms of wind speed, it has limited impact on electricity demand in the early mornings (6:00-10:00) with less than a 0.005% reduction in demand during 6:00-8:00 and with an insignificant coefficient at 8:00-10:00. On the other hand, relative humidity has a negative relationship with consumption during the same period. Humidity have a compounding effect with temperature, where air temperature with higher humidity may give a colder apparent temperature. However, all the impacts from humidity and wind speed are of negligible magnitude with under 0.5% change in demand. Therefore, these two variables will be removed in the following model where the focus is to identify the differences between weekdays and weekends for each of the main weather factors.

### 5.2. Behaviour difference between weekends and workdays

Based on the overview of the effects of the weather factors, this section attempts to identify and answer the following questions: are there differences in demand between weekends and workdays in weather sensitivities? What differences in daily routine between weekends and workdays can cause any discrepancies? Estimated results are shown in Table 6. Here, the interactions of weather variables and workday dummies indicate the differences between workdays and weekends. Likewise, to make the results easier to understand, we calculated and converted them into percentage (%) form for estimates. The workday results are calculated by adding the differences between weekends and workdays, (i.e coefficients for workdays) to the baseline/reference (i.e, coefficients for weekends). For example, the response to temperature on workday mornings (−0.002) equals to the coefficient for weekends (0.002524) plus the coefficient for workdays (−0.004587). The transformed results are shown below the original results.

#### 5.2.1. Temperature

As expected, the results suggest that temperature have a negative effect on the demand among both weekends and workdays of all periods. However, the exception is weekend early mornings. The reason for this unexpected impact of temperature is not particularly clear. Of all periods, early weekend mornings (6:00-10:00) have the least impact, which suggests that the early morning is the most insensitive period. The behaviour during that period is robust and less likely to be changed by temperature.

Furthermore, weekends are in general more sensitive to temperature change than weekdays. This difference can be explained by more activities occurring indoors. However, the difference in the early evening (19:00–21:00) seems negligible. It could be explained by that limited activities would occur during the post-dinner time on both weekends and workdays, since many would enjoy an indoor relaxing time after dinner. The largest difference appears at night (23:00–3:00), which is in line with expectations. People would be more likely to go out later and stay out later on weekends/holidays, especially on warmer days, whereas people tend to go to sleep earlier on workdays even on warmer days.

#### 5.2.2. Rainfall

The effects of rain represent to what percentage the electricity demand would change by the rainfall. From the results it is possible to infer how flexible plans or activities are in a given period. A period with higher sensitivity to rain that there may be more outdoor activities or households prefer to go out during that period.

The midday (10:00-15:00) and early evening (19:00-21:00) periods on workdays are the only time slots with greater sensitivities than their counterparts on weekends. It is noteworthy that the sensitivities during the midday period (10:00-15:00) on weekdays are exceptionally higher than any other period in either weekends or workdays. It indicates that stay-at-home family members tend to go out during that period on weekdays. While on weekends, the households may not be able to go out early due to more chores and family care. This period actually shows the largest gap between weekends and workdays, which indicates the large underlying difference in daily routines between weekends and workdays are in the midday period. For example, people might regularly go out on workdays while stay at home on weekends during this period. Likewise, the significant high coefficients of over 0.1 are also found on weekend mornings (8:00-10:00) and nights (23:00-3:00). The unusually high sensitivities on weekend mornings may be due to more chores done or sports activities.

Interestingly, in spite of a smaller difference compared to the 10:00-15:00 period, workdays in the early evening (19:00-21:00) are surprisingly more sensitive than on weekends, whereas a plausible hypothesis would be that evenings should be more sensitive on weekends. It could be a result of the timing of outdoor activities on weekdays since people

**Table 6**
Estimated coefficients from Model 2 Workday and Weekend differences.

| Variables | (1) **Morning** 6.00–8.00 | (2) **Day_1** 8.00–10.00 | (3) **Day_2** 10.00–12.00 | (4) **Day_3** 12.00–15.00 | (5) **Day_4** 15.00–17.00 | (6) **Peak** 17.00–19.00 | (7) **Evening_1** 19.00–21.00 | (8) **Evening_2** 21.00–23.00 | (9) **Night** 23.00–03.00 |
|---|---|---|---|---|---|---|---|---|---|
| **Weather** | | | | | | | | | |
| Temperature (weekend as ref) | 0.002524*** | −0.003289*** | −0.01518*** | −0.01767*** | −0.01343*** | −0.01192*** | −0.01074*** | −0.009082*** | −0.01038*** |
| Temperature * Workday | −0.004587*** | −0.003138*** | 0.002516*** | 0.005478*** | 0.001465*** | 0.0008027** | 0.0003072 | 0.001683*** | 0.005085*** |
| Rainfall (weekend as ref) | 0.04134*** | 0.1401*** | 0.02043** | 0.03680*** | 0.08389*** | 0.04746*** | 0.03440*** | 0.04573*** | 0.1062*** |
| Rainfall * Workday | −0.07466*** | −0.1499*** | 0.1075*** | 0.09673*** | −0.02118*** | −0.01767*** | 0.01490*** | −0.02919*** | −0.09189*** |
| Sun duration (Weekend as ref) | 0.04544*** | 0.04637*** | 0.03262*** | −0.004638 | −0.07735*** | −0.08104*** | −0.09148*** | \ | \ |
| Sun duration * Workday | −0.02227*** | −0.04787*** | −0.05150*** | −0.01570** | 0.02682*** | 0.009996 | −0.04168*** | \ | \ |
| ***Weather coefficients above in a readable form*** | | | | | | | | | |
| Temperature (weekend as ref) | 0.25% | −0.33% | −1.52% | −1.77% | −1.34% | −1.19% | −1.07% | −0.91% | −1.04% |
| Temperature * Workday | −0.46% | −0.31% | 0.25% | 0.55% | 0.15% | 0.08% | 0.03% | 0.17% | 0.51% |
| Rainfall (weekend as ref) | 4.13% | 14.01% | 2.04% | 3.68% | 8.39% | 4.75% | 3.44% | 4.57% | 10.62% |
| Rainfall * Workday | −7.47% | −14.99% | 10.75% | 9.67% | −2.12% | −1.77% | 1.49% | −2.92% | −9.19% |
| Sun duration (Weekend as ref) | 4.54% | 4.64% | 3.26% | −0.46% | −7.74% | −8.10% | −9.15% | s | \ |
| Sun duration * Workday | −2.23% | −4.79% | −5.15% | −1.57% | 2.68% | 1.00% | −4.17% | \ | \ |
| **Time** | | | | | | | | | |
| Weekend | *Ref* | *Ref* | *Ref* | *Ref* | *Ref* | *Ref* | *Ref* | *Ref* | *Ref* |
| Workday | 0.3123*** | 0.1146*** | −0.3311*** | −0.3451*** | −0.1178*** | 0.04710*** | 0.05132*** | 0.06453*** | −0.1198*** |
| Holiday | 0.04419*** | −0.01954*** | −0.03182*** | −0.02297*** | −0.01975*** | −0.02584*** | −0.01376*** | 0.000299 | −0.0006169 |
| **Month** | | | | | | | | | |
| January | *Ref* | *Ref* | *Ref* | *Ref* | *Ref* | *Ref* | *Ref* | *Ref* | *Ref* |
| February | 0.004319 | −0.008879** | −0.07065*** | −0.09739*** | −0.1371*** | −0.1472*** | −0.05878*** | −0.06146*** | −0.08921*** |
| March | −0.004226 | −0.02927*** | −0.1076*** | −0.1486*** | −0.2024*** | −0.3194*** | −0.1171*** | −0.08663*** | −0.1314*** |
| April | −0.1016*** | −0.08898*** | −0.07714*** | −0.1317*** | −0.2542*** | −0.4451*** | −0.3794*** | −0.1315*** | −0.1149*** |
| May | −0.1026*** | −0.09503*** | −0.09476*** | −0.1480*** | −0.2462*** | −0.4544*** | −0.4558*** | −0.2277*** | −0.1127*** |
| June | −0.1000*** | −0.09125*** | −0.03643*** | −0.08592*** | −0.2083*** | −0.4538*** | −0.4787*** | −0.3347*** | −0.07309*** |
| July | −0.1447*** | −0.1189*** | 0.002915 | −0.05617*** | −0.2208*** | −0.4777*** | −0.5048*** | −0.3240*** | −0.07985*** |
| August | −0.1503*** | −0.1238*** | 0.0003798 | −0.05829*** | −0.2266*** | −0.4726*** | −0.4770*** | −0.2396*** | −0.09119*** |
| September | −0.01313*** | −0.05696*** | −0.05770*** | −0.09163*** | −0.1853*** | −0.4187*** | −0.2734*** | −0.1618*** | −0.1238*** |
| October | −0.04151*** | −0.05426*** | −0.06378*** | −0.1088*** | −0.1861*** | −0.3289*** | −0.1444*** | −0.1533*** | −0.1291*** |
| November | 0.007114** | −0.01446*** | −0.08299*** | −0.1136*** | −0.06349*** | −0.06272*** | −0.09159*** | −0.1012*** | −0.1115*** |
| December | 0.04578*** | 0.09784*** | 0.1216*** | 0.06538*** | 0.08648*** | 0.01402*** | 0.001041 | 0.02436*** | 0.02734*** |
| **Constant** | −0.3460*** | 0.2122*** | 0.6075*** | 1.1735*** | 0.7033*** | 1.0694*** | 1.0534*** | 0.8668*** | 0.8850*** |
| **Observations** | 1495843 | 1496318 | 1495849 | 1496196 | 1496368 | 1496948 | 1497084 | 1497236 | 1493682 |
| **R2** | 0.5647 | 0.4844 | 0.4323 | 0.4732 | 0.4699 | 0.5106 | 0.5227 | 0.5549 | 0.6315 |

would only be able to go out during that period on weekdays while they could choose other time periods on weekends. In addition, households may have dinner at a slightly later period on weekends. For many, this period may be post-dinner on workdays (19:00-21:00) but may actually be dinner time for weekends. Therefore, whether there is rain or not may have a greater effect on workdays, due to the lower probability of going out in the evenings on workdays.

The only negative effects are for early mornings (6:00-10:00) on workdays. It is possible that the heavier it rains, the earlier people may feel to leave houses to avoid the traffic jam, although the effect significantly drops from −3.3% to −0.8% at 8:00-10:00. It is a solid proof that the negative effect mainly comes from the behaviour of workers in the house since the effect falls to nearly zero when it reaches the start of work hours.

### *5.2.3. Sun*

The prior expectation was that longer sun duration should be associated with decreased electricity demand, as people are more likely to go out on a sunny day. However, contrary to this expectation, the opposite findings are found in the weekend mornings (6:00–12:00) and the early mornings on workdays (6:00–8:00). The increased consumption in sunny early mornings for both weekends and workdays could be partly explained by a relatively early wake-up times. This effect is especially clear on weekends since on workdays people are more likely to maintain their routines in the early mornings and may not change their behaviour easily in response to greater sunlight.

In the mornings, from 8:00 until 12:00, interesting and unusual differences between weekends and workdays appear. While sunshine hours now have a negative effect on workdays, the positive effects continue on weekends during this period. The increased demand reverse the common idea that families or individuals are more willing to spend time outside, especially on a sunny weekend. However, this may be capturing an effect of preferences of specific activities/routines on weekend mornings. The positive results could be due to the fact that households have propensities to carry out housework on weekend mornings, before heading out in the afternoons. Additionally, some types of chores are more likely to give a rise to electricity consumption on a sunny day. For example, roughly 30% of households do not own a dryer (Leahy et al., 2012), so they would choose to do laundry on a sunny day and even households with dryers might choose to reduce their bills and dry their clothes outside. Thus, the positive effects may reflect the behavioural habits on weekend mornings. It should be highlighted that the positive impacts are decreasing from the 8:00-10:00 morning period and becomes insignificant by mid-afternoon (12:00-15:00), which is the only insignificant period. The reason may be that on weekends, family meals are common at lunchtime and sun duration does not affect these behaviour patterns. After that point, sun sensitivities on weekends gradually increase from −7.6% to −9% during the 15:00–21:00 period. This may indicates more sun-related outdoor activities later on weekend days, compared to "housework mornings".

On the other hand, negative effects are seen during almost every weekday period. However, it is still important to note that compared to a relatively constant sensitivity of −1.8% in the period 8:00-15:00 on workdays, a clear increasing pattern is shown for the period after 15:00. The sensitivities are much higher than during the first half of day, with values over 5%. This provides strong evidence that similar to behavioural patterns on weekends, afternoons are generally more flexible on workdays. Higher negative coefficients imply that the households have more free or flexible time and are more likely to go out. Nevertheless, it should be pointed out that a weaker sensitivity to sunshine duration does not necessarily mean that people are less likely to go out during that period. Unlike for rain, whether or not there is sunshine would generally not affect people's movements or activities. For instance, if one is used to shopping for groceries for the family in the morning, he/she would not cancel or delay the shopping just because of cloudy weather. Therefore, a relatively smaller sensitivity should be interpreted as a higher possibility that one's time is occupied by regularly scheduled plans, which could be either indoors or outdoors.

Similar to the results shown in the rain effects above, early evening (19:00-21:00) is the only period when workdays are more sensitive than holidays. It should be kept in mind that only half of a year (mainly late spring and summer) has sunshine during the period. The findings in this period therefore largely limit and reflect the behaviour in summer. As suggested in the rain section, only in this evening period are people still able and more willing to go out on workdays, compared to late evenings and nights. Another interesting finding is that sun duration in this period (19:00-21:00) of workdays has the largest effect among all other sunshine effects on encouraging people to go out. Note that as no sunshine exists after 21:00, no sun effect can be tested for those periods.

## 6. Discussion and conclusion

This study set out to examine the behaviour of residential customers exposed to different weather conditions in different periods of a day using unbalanced panel data from the Irish Smart Metering Electricity Consumer Behavioural Trial (Commission for Energy Regulation (CER), 2012a). To conduct the analysis, half-hourly electricity consumption data from 3827 household meters over one year were aggregated into daily usage for every period of a day. Together with the weather variables, fixed-effects models with robust standard errors clustered at the household level were used to control for unobserved household-specific factors, which gives a better understanding of households' response to weather factors at different times of the day.

Overall, this paper has demonstrated from the first model that in general although temperature has robust and relatively flat effects on electricity demand across all periods, rain and sunshine duration show greater potential to affect individual behaviour and daily routines. The demand response to temperature could be interpreted as warm/cold sensitivities of the activities in that period. As expected, the periods from 10:00–21:00 present higher sensitivities than early mornings and nights, since more activities occur in those periods. Although night time periods (21:00–3:00) have smaller sensitivities than daytime, they are still much more sensitive than early mornings. Not many activities occur over 6:00–10:00 when most people are getting up and going off to work. The rainfall sensitivity may act as an indicator of whether outdoor activities occur more often in that period. It should be noted that the results mainly reflect the behaviour of the households who are in the house during day-time, and the proportion of these households account for over 68% of the sample. One of the lowest rainfall sensitivities appears at 12:00–15:00 which is cooking and lunchtime that the possibility of going outdoor would be relatively small. This finding is consistent with the Irish Time Use Survey (Table 3) that for those who are not working (61%–82%), eating is one of the main activities. Apart from the similar pattern of lower sensitivities at the start and end of a day, the relatively high coefficients at two periods 10:00–12:00 and 15:00–17:00 reveal that individuals could be more used to or prefer going out during these periods. On the other hand, the impact of sunshine on households' behaviour differs from rainfall, although both affect the chances of going out. Negative sunshine sensitivities represent the time availability and willingness to go out of households, in other words, how flexible the period so that one can response to good weather. The results strongly support the interpretation that the sensitivity gradually increases from late afternoon (15:00) and peaks in early evening (19:00–21:00), compared to the small and positive sensitivities shown in the mornings.

The responses to weather factors for weekends and workdays are tested in the second model. The differences are caused by different household patterns between weekends and workdays. In terms of temperature sensitivities, weekends are more sensitive than workdays because households have more available time to spend, while the sensitivity difference is minimal. The biggest difference is seen on the night period (23:00–3:00), where people would care less about the cold weather and be more likely to go out on weekends. Moreover, the rainfall results suggest two clear patterns: before 15:00 workdays are more sensitive than weekends, although the effects of workday mornings are insignificant; after 15:00, weekends show higher sensitivities than workdays, apart from 19:00–21:00. The findings imply that more rain-sensitive activities occur before mid-afternoon during weekdays, while these activities (e.g. outdoor activities) occur at 15:00 afterward in general. The difference in life patterns between workdays and weekends are also revealed by sun duration. In the mornings (6:00–12:00), while sunlight has positive effects on weekends: the longer the duration of sunshine, the greater the consumption during those periods on the weekend. It could be associated with more sun-sensitive chores on the weekend mornings. The pattern changes after 15:00 — households seem more flexible at this time on weekends. And both weekends and workdays reveal increasing sensitivities during that period, especially workdays, which soars after 15:00 from −1.6% to a maximum of 13%. One especially interesting finding is that early evening (19:00–21:00) is the one period when weekends are less sensitive to all weather factors than workdays. This may be unexpected but could be explained by the fact: Compared to weekends, early evenings on weekdays might be the most flexible time where outdoor activities are possible, especially for those employed households, so the period is more sensitive to weather.

The study could be instructive for understanding household energy consumption behaviour. First, the weather sensitivity analysis provides an overview of households' behaviour/life pattern without the assistance of a survey. Especially, sunshine and rain sensitivities may be considered as proxies of whether a period is with more flexibility and whether people tend to leave home (or use less) at certain periods respectively. Furthermore, analysing the differences in patterns between weekdays and weekends can help identify which periods on weekends or workdays are more sensitive and flexible. With more knowledge of people's life pattern among different periods the tariff structure design could be more efficient in shifting energy demand. Secondly, with deeper analysis on individual level, for example, combing the attitude and behaviour data in the survey with the weather sensitivity patterns, it could create an initial profile of a family's daily activities. For instance, if a family displays relatively higher weather sensitivities, this may reflect greater flexibility in their living patterns. A target tariff aimed at those families may help shift peak electricity demand. These potential implications lead to possible future research in improving residential customers' consumption profiles. It would be interesting to categorise the households by their weather sensitivities and to examine if the weather sensitivities are associated with certain demographic factors, which may provide a cheaper and faster means of understanding a household's social-economic profile. Data mining tools are helpful in this case to cluster and classify the residential customers, which offers a new angle to summarise and depict customers' activity patterns by using only weather and consumption data. By using only weather indicators this approach can be faster and simpler than traditional methods – such as surveys or questionnaires – in identifying which period are more flexible at the household level.

## CRediT authorship contribution statement

**Jieyi Kang:** Conceptualisation, Methodology, Software, Validation, Formal analysis, Data curation, Writing – original draft, Visualisation. **David M. Reiner:** Writing – review & editing, Supervision.

## Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.eneco.2022.106023.

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