Unravelling load patterns of residential end-uses from smart meter data

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Abstract

With increasing shares of intermittent renewable energy sources in the power mix, managing residential loads is seen as an emerging option for balancing supply and demand in the system, reducing the need for investments in additional electricity generation and transmission infrastructure. At the same time smart meters endow a growing number of utilities and system operators with detailed information on individual households' load profiles, but they usually provide no information on the actual end-use activities. Understanding residential electricity usage patterns, however, is critical for designing effective energy efficiency and load management programs. Thus, the aim of this paper is to elicit load patterns of individual end-uses from smart metering household data and to assess their implication for national energy system management.

This paper combines half-hourly load records with survey data from 4,200 households participating in a representative smart meter project in Ireland to econometrically estimate end-use-specific load profiles, controlling for demographic and buildings characteristics. For each of nine "typical days", representing combinations of different seasons and days of the week, we estimate 48 reduced form electricity demand equations. It was found that distinguishing load profiles between workdays and weekends proved essential, in particular for electric stoves, dishwashers and TVs. Calibrating our estimated load profiles for five household end-uses to the actual load curve of Ireland in 2011, we are able to explain up to 40 % of the total system load. Our estimates imply that that lighting and electric account for about a third of the winter evening peak load in the Irish power system, but their load profiles differ substantially between seasons.

To reduce the Irish system load peak energy efficiency policies should focus on lighting and thermal insulation. We find that energy efficient lighting and a wide-ranging technology switch from electric heating to heat pumps may lead to a reduction in the winter evening peak load by 17 %. Finally, policies promoting load-shift should address electric heating before targeting other end uses like driers or dishwashers.

Introduction

Gaining a better understanding of the factors governing electricity load patterns is conducive to effective power system management and capacity planning. For example, end-use-specific load profiles help grid operators and utilities to understand electricity usage behaviour and to identify the drivers of system load peaks, in particular when these profiles exhibit high temporal resolution. They also allow identifying and estimating the potential of different end-uses for load management or designing tariff programmes aimed at lowering or shifting loads in the residential sector (e.g. Bradley et al. 2012; Cappers et al. 2012; Torriti et al. 2010). Generating end-use-specific load profiles, however, may be costly, since this typically involves direct metering of individual end-uses in a large number of households over a sufficiently long period. In contrast, deriving end-use-specific load profiles from measuring households' total load via smart meters is less expensive, since each household then only requires a single recording device. Due to the Electricity Directive (European Union 2009), metered customer data with high temporal resolution will be readily available in most

Table 1. Overview of studies applying CDA to generate load profiles for end-uses.

	Aigner et al. (1984)	Brodsky et al. (1988)	Bartels et al. (1992)	Blaney et al. (1994)	Firth et al. (2008)	Morch et al. (2013)
Survey-related information						
Temporal resolution	15 min	hourly	15 min	hourly	5 min	hourly
Observation period [months]	3 (over 3 years)	24	15	12	24	n/a
Sample size	80–132	n/a	400	181	72	75
Country	USA	USA	AUS	USA	UK	NO
Regression/load profile-related information						
Number of end-uses	9	7	10	15	4	5
Use of sub-metered data	no	Yes	no	yes (monthly)	No	yes (1-minute)
Temporal resolution	hourly	hourly	hourly	hourly	5 min	hourly
Distinction of seasons	summer only	none	12 individual months	4	n/a	4
Distinction of weekdays*	none	WD/WE	WD/WE	WD/WE	n/a	WD/WE

* WD = weekday, WE = weekend

EU countries in the near future. Italy and Sweden have already completed a full roll-out and 14 countries aim to equip at least 80 % of all customers with smart meters by 2020 (CEER 2013)[1]. In general though, smart meter data provides no information on the actual end-use activities. Such information, however, is vital for designing effective load management, energy efficiency or energy rebate programs.

Conditional demand analysis (CDA) may be employed to transform household-level metered load data into end-use specific load profiles. For each time interval, household electricity demand is regressed on a set of explanatory variables including appliance stock and usage time, weather data, socio-economic information, and building characteristics. The parameter estimates for the different time intervals may then be used to to construct load profiles for the different end-use activities. The majority of these studies were conducted in the USA (see Table 1). Aigner et al. (1984) employ hourly measured data to generate a daily load profile for nine end-uses employing 24 regressions, i.e. one for each hour of a day. However, since load data was only available for three metered months spread over three years, their findings cannot be generalized. The remaining studies in Table 1 rely on observation periods of at least one year. In addition to household-level data, Brodsky et al. (1988), Blaney et al. (1994) and Morch et al. (2013) benefit from sub-metered data for selected end-uses, such as refrigerators or washing machines. While sub-metered data enables precise measurements of selected end-uses, such data is costly and only available for a small sample of households, thus limiting the generalization of findings. In general, studies vary by the number of end-uses and by the types of days (weekdays versus weekend days) considered. Most CDA-based load profile studies rely on household level data but suffer from a low sample size, or a short observation period, which does not allow for load profiles which differ across seasons.[2] None of the existing studies provides sub-hourly end-use load profiles based on a large sample size.

In this study, we estimate end-use specific load profiles with high temporal resolution for households in Ireland, capturing half-hourly, weekly and seasonal differences. These profiles are based on econometric analyses employing data from a smart metering pilot project, which included more than 4,200 households. In this pilot project, half-hourly load records were metered over the course of 17 months in 2009/2010.[3] Using half-hourly data our analysis is supposed to represent real consumption patterns more accurately compared to hourly assessments. Relying on hourly data, for example, is likely to underestimate peak loads, which tend to occur for a fraction of an hour only. That means, the higher the temporal resolution of the load data, the lower the error of averaging. To assess the potential of end-use-specific energy efficiency improvements and load shifting, we relate our estimated load profiles to the observed Irish electricity demand in 2011, and quantify the contribution of key measures to reducing peak demand.

The remainder of this paper is organized as follows: First, we describe the data and the methodology employed. Subsequently, we present the results of the econometric analysis, the end-use specific load profiles, the validity checks and our application to the total load in the Irish power system. Last, we discuss the major findings and highlight the policy implications.

1. Member States may carry out a cost-benefit analysis prior to implementing smart metering systems (European Commission 2012). See (Jennings 2013) for an assessment of the Irish strategy.

2. In their survey of empirical studies, Swan and Ugursal (2009) conclude that a CDA only provides reliable insights if data from hundreds or even thousands of households is used.

3. We are not aware of any other smart metering project of a comparable sample size or observation period, where data is publicly available.

Methods

DATA

Our empirical analysis relies on the load records from a smart metering trial project conducted by the Commission for Energy Regulation Ireland (CER), the Sustainable Energy Authority of Ireland (SEAI) and the Department of Communications, Energy and Natural Resources (DCENR) for customers of the largest Irish utility "Electric Ireland". The data set is publicly available on the web[4] and has been previously been used in a few studies[5]. Households were selected to obtain a representative sample for Ireland in terms of geographical location, social class, building type and family status. The project aimed at a better understanding of the benefits of smart meter data and their influence on electricity usage patterns. In addition, the insights gained were used to assess the costs and benefits of a nationwide smart meter rollout. In more than 5,000 households the existing mechanical meters were replaced by smart meters. These households were metered for 536 days (14 July 2009 until 31 December 2010).[6,7,8] The electricity consumption of each household (in kWh) was measured in intervals of 30 minutes (ISSDA 2014). In total, more than 100 million load values were measured. To allow for meaningful analyses, we corrected the data for clock changes. The average household in the sample consumed 4,300 kWh in 2010[9]. The mean maximum load was 6.5 kW.

In addition, an extensive survey was conducted to gather information about the socio-economic characteristics of the household, the appliance stock and the building. Thus, the data collected includes, amongst others, the number of occupants (adults and children) living in the household, the respondent's attitude towards environmental issues, the type and age of the building, building insulation, and number of end-uses (for 16 different types). A large share of the households did not respond to all the questions. For example, about 60 % of the survey households failed to report income, and 50 % did not provide information about the size of the dwelling (floor area).

ECONOMETRIC MODEL

In the first step, ordinary least squares regression methods are employed to estimate reduced form household electricity consumption equations using cross-sectional data. We distinguish three seasons (summer, winter, and transition period): the winter period from November 1 to March 20, the summer period from May 15 to September 14, and the transition period covers the times between the summer and the winter periods. For each season, we consider three days of the week, i.e. weekday, Saturday and Sunday/public holiday. Thus, we estimate demand functions for nine typical days.

The *dependent variable* is the mean half-hourly electricity consumption for a typical day. We therefore run 48 regressions for each of the nine typical days, i.e. a total of 432 regressions. As is standard in the literature, we use the natural logarithm of electricity consumption in the actual model specification, since log-transformed variables tend to better meet the assumptions required for parametric tests. The *explanatory variables* are grouped in seven categories (see Table 2). Socio-demographic variables include the number of household members by age group. Note that our specification allows for non-linearity in the number of household members per age group on electricity use. Thus, we do not presume the marginal effect on electricity consumption of each household member (per age group) to be the same. To prevent singularity of the regressor matrix, the lowest category (i.e. number of adults = 1 and number of children = 0) is not included in the regression. A dummy variable captures the stated household electricity-saving efforts. *Save* takes on the value of one if respondents strongly agreed or agreed with the following statement: "I/we have already done a lot to reduce the amount of electricity I/we use". Building characteristics comprise the type and age of the building. In addition, for households, where electricity is the main heating fuel, information about building insulation is also taken into account. More specifically, we interact the variables for wall insulation, the share of double glazed windows, attic insulation and any alternative heating system with the electric heating system (i.e. electric central heating/storage heating or plug-in heaters). For all households with electricity as the main or auxiliary heating fuel, information about the type and number of space and water heating installations is available (i.e. immersion heater, *immers_heater,* vs. instantaneous shower water heater, *shower_1 and shower_2*). The share of energy-saving bulbs compared to the overall number of lighting points (*lights*) is also included as an explanatory variable. Last but not least, fairly detailed information is available on the type and number of white goods and ICT equipment in a household. Similar to the number of household members, we allow non-linear effects for most end-uses. For example, the average TV use in a household with one TV may differ from the average TV use in a household with two TVs, all other things being equal. Because of limited data availability, household floor area and household income are not included as explanatory variables. Arguably, income effects are, at least to some extent, captured by building type and appliance stock.

GENERATING LOAD PROFILES

In the second step, load profiles are generated for each of the nine typical days using the parameter estimates from the regression analysis. First, all the coefficients are transformed

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4. The data is provided by ISSDA (2014).

5. This data has also been used in other publications: McLoughlin et al. (2012) run multivariate regressions to assess the impact of dwelling and occupant variables as well as electrical end-uses (in a separate regression) on (1) half-hourly household electricity demand, (2) daily load factor, (3) daily maximum demand and (4) maximum time-of-use parameter. In contrast, our analysis performs a multivariate regression for each half-hour period of selected typical days. McLoughlin et al. (2013) forecast system demand employing times series analyses. Duffy et al. (2010) generate domestic electricity load profiles using Markov Chain modelling, but do not look at individual end-use activities. Di Cosmo et al. (2014) explore the effects of introducing time-of-use pricing.

6. The data may be accessed via the Irish Social Science Data Archive – www.ucd.ie/issda.

7. The metering campaign also included approximately 500 small and medium-sized enterprises. Data from these enterprises is not included in our analysis.

8. The initial target of the survey was to assess the impact of TOU tariffs and information stimuli to household consumption behavior. After a pre-trial period of 6 months, all households, except a control group of 1,000 households, received a specific TOU tariff and an information stimuli. The TOU tariff provided graded prices for day, night (11.00 pm to 8.00 am) and peak hours (5.00 pm to 7.00 pm) (CER, 2011). Given that the households were subject to different stimuli would make it necessary to restrict the CDA to the control group. However, Di Cosmo et al. (2014) found out that the only significant impact of the stimuli can be observed with respect to the TOU tariff in peak hours. In addition, the results of the CDA showed that using the entire sample of households delivers more robust and significant results than limiting the sample to the households of the control group. Thus, the CDA was applied to the load records of all households.

9. The average electricity consumption of an Irish household in 2010 was equal to 5,300 kWh (SEAI 2013).

from logarithmic to linear and coefficients with $p > 0.1$ are set to zero. The 48 coefficients of an end-use type for a specific typical day then represent the respective half-hourly load profile. We conduct plausibility checks for end-use types where a substantial share of the coefficients is zero. For example, insignificant coefficients would make sense during daytime hours for lighting but not during evening hours.

APPLYING THE LOAD PROFILES TO THE ELECTRICITY DEMAND OF IRELAND

To assess the potential of end-use-specific energy efficiency improvements and load shifting for managing the electricity system load of Ireland, we relate our estimated load profiles to the Irish electricity demand. To do so, we rely on two types of existing data for Ireland. First, for the year 2011 (but not for 2010 or 2009), the Sustainable Energy Authority of Ireland, SEAI (2013), provides estimates of residential annual electricity demand by end uses. These figures are calculated based on standard values for ownership rates, end-use consumption and data on average appliance usage. We use these annual figures to calibrate our parameter estimates for 2009/2010. The end-use-specific annual demand is spread over the individual load profiles of the nine typical days in proportion to their frequency in 2011. The resulting load curves of residential end-uses allow a partial decomposition of the Irish system load curve in 2011 into different end-uses. Second, to construct the system load curve, we use hourly load records from the European Network of Transmission System Operators for Electricity, ENTSO-E (2013). We scale these load records according to the annual Irish electricity demand in 2011 (SEAI 2012) so that the hourly load matches the final electricity demand after netting out the grid losses which were originally included in the ENTSO-E data.

Results

ECONOMETRIC ANALYSIS

Results from estimating the household electricity consumption are displayed in Table 3 for twelve half-hour periods of a weekday in winter.[10,11] Table 3 shows the coefficients after they were transformed from logarithmic to linear, i.e. they may be interpreted as the marginal effects on the level of electricity use in a particular half-hour period. Overall, the values for the coefficient of determination i.e. the (adjusted) R^2 range between about 25 % and 50 %. Thus, the models appear to fit the data quite well, since they explain a fairly large share of the variation in half-hourly household electricity consumption. The predictive power tends to be higher for half-hour periods in the evening than in the morning.

For all half-hour periods, including also those not shown in Table 3 to save space, electricity consumption is positively and (statistically) significantly related to the number of adult household members, with larger households using more electricity. As expected, the effects of the number of adults vary significantly over the course of the day and are particularly low at night and during early morning hours. For all half-hour periods, the coefficient of adults is larger than the coefficient of children. Electricity use tends to be lower in households claiming to have made electricity-saving efforts, but the difference is statistically significant only for a few hours (in the morning and in the evening).

For almost all half-hour periods, bungalows and detached houses are associated with significantly higher electricity consumption than terraced houses (i.e. the base category), and semi-detached exhibit the same electricity use as terraced houses. In comparison, households with apartments are correlated with lower consumption for a considerable number of half-hour periods. Older houses are associated with higher electricity use[12]. The coefficients for *age 30+* are significantly higher for most half-hour periods.

The findings for the interaction terms associated with *insulation* suggest that when electricity is the main heating fuel, better insulation tends to be associated with lower electricity use, in particular during the night and early morning hours. For a few night-time hours we find, somewhat unexpectedly, that *attic insulation* in households using electricity for heating purposes is associated with higher electricity consumption.

Households with permanently installed electric heating devices (*electric_heat*) are associated with statistically significantly higher electricity use from 8.30 am until about 0.30 am. The same holds for plug-in heaters, but with the bulk of electricity use taking place during daytime hours. As *electric_heat* includes central heating and night storage heaters, the relatively high electricity use in the late evening and night-time hours is likely due to the night storage heaters. Thus, the related night-time electricity consumption may, to some extent, also explain the reduced electricity demand through *insulation* during the night.

Night storage heaters, which are often also used for sanitary hot water generation, may also help to explain the statistically significant negative coefficient of instantaneous shower water heaters (*shower_1* and *shower_2)* during night-time hours. The latter produce hot water during actual water withdrawal so that electricity consumption coincides with shower usage. In contrast, the electricity consumption of a shower that is linked to a night storage heater is temporally decoupled from the actual shower usage. Thus, instantaneous shower water heaters are characterised by negative electricity consumption during the night as opposed to those showers relying on night storage heaters.

Unlike for the other typical days, but similar to the findings by McLoughlin et al. (2012), the coefficient for showers during daytime hours is not statistically significant for the typical weekday in winter (Table 3).

Immersion heaters are characterised by two periods of statistically significant usage on weekdays, from 6.00 am until 11.30 am and again from 5.00 pm until 10.30 pm. On Saturdays, coefficients are also significant for midday hours, and on Sunday for the entire period ranging from 7.30 am to 10.00 pm.

10. Outliers were removed from the sample based on Cook's distance. Depending on the daytime this leads to a loss of 3 % to 5 % of the observations.

11. Due to limited space, the results for all half-hourly consumption regressions and for the other eight typical days cannot be presented here. They are available upon request from the authors.

12. Results from F-Tests suggest that the coefficient associated with age 30+ is higher than the coefficient associated with age 10–30 in 36 of the 48 half-hour periods (at $p < 0.05$), in particular during the daytime.

Table 2. Overview of explanatory variables (acronyms).

Category	Variable	Definition	Unit	Mean	Std. dev.	Min.	Max.
Socio-demographics	Number of adults living in the household (# of adults)	*1*	0/1	0.229	0.420	0	1
		2	0/1	0.493	0.500	0	1
		3	0/1	0.151	0.358	0	1
		4 and more	0/1	0.126	0.289	0	1
	Number of children living in the household (# of child.)	*0*	0/1	0.710	0.454	0	1
		1	0/1	0.118	0.323	0	1
		2	0/1	0.107	0.309	0	1
		3 and more	0/1	0.065	0.215	0	1
	Electricity saving efforts (*save*)	No/Yes	0/1	0.655	0.576	0	1
Building	Building type (build_type)	Terraced house	0/1	0.017	0.129	0	1
		Bungalow (*bungalow*)	0/1	0.252	0.434	0	1
		Detached house (*detached*)	0/1	0.265	0.466	0	1
		Semi-detached house (*semi_det*)	0/1	0.320	0.441	0	1
		Apartment (*apt*)	0/1	0.145	0.352	0	1
	Building age	Less than 10 years old	0/1	0.199	0.267	0	1
		10–30 years old (*age 10–30*)	0/1	0.292	0.455	0	1
		more than 30 years (*age 30+)*	0/1	0.509	0.502	0	1
Insulation (for buildings with electric heating only)	Wall insulation *(wall_insulation)*	No/Yes	0/1	0.627	0.484	0	1
	Share of double glazed windows (*double-glazed*)	Share categories	0, 0.25, 0.5, 0.75, 1	3.342	1.350	1	4
	Attic insulation *(attic_insulated)*	No/Yes	0/1	0.899	0.301	0	1
	Additional non-electric heating *(additional_heat)*	No/Yes	0/1	0.935	0.246	0	1
Heating	Electric central/storage heating *(electric_heat)*	No/Yes	0/1	0.043	0.202	0	1
	Plug-in heater	0	0/1	0.699	0.459	0	1
		1 (*plugin_1*)	0/1	0.233	0.423	0	1
		2 or more (*plugin_2*)	0/1	0.068	0.221	0	1
	Electric immersion heater *(immers_heater)*	No/Yes	0/1	0.769	0.423	0	1
	Electric shower	0	0/1	0.306	0.461	0	1
		1 (*shower_1*)	0/1	0.638	0.480	0	1
		2 or more (*shower_2*)	0/1	0.056	0.219	0	1
Lighting	Share of energy-saving bulbs (*light*)	Share categories	0, 0.25, 0.5, 0.75, 1	1.834	1.425	0	4
White goods	Electric stove *(stove)*	No/Yes	0/1	0.773	0.421	0	1
	Washing machine *(washing)*	No/Yes	0/1	0.983	0.148	0	1
	Dryer *(dryer)*	No/Yes	0/1	0.683	0.466	0	1
	Dishwasher *(dish_washer)*	No/Yes	0/1	0.672	0.470	0	1
	Stand alone freezer *(freezer)*	No/Yes	0/1	0.496	0.500	0	1
	Water pumping system *(water_pump)*	No/Yes	0/1	0.195	0.393	0	1
ICT	Router/broadband modem *(router)*	No/Yes	0/1	0.697	0.460	0	1
	Desktop PC *(desk_PC)*	No/Yes	0/1	0.472	0.498	0	1
	Number of laptop PCs	0	0/1	0.472	0.499	0	1
		1 (*laptop_1)*	0/1	0.428	0.495	0	1
		2 or more *(laptop_2*)	0/1	0.113	0.279	0	1
	Number of game consoles	0	0/1	0.660	0.474	0	1
		1 *(console_1)*	0/1	0.226	0.418	0	1
		2 or more *(console_2)*	0/1	0.114	0.280	0	1
	Number of TVs smaller than 21"	0	0/1	0.346	0.476	0	1
		1 *(TV<21"_1)*	0/1	0.396	0.489	0	1
		2 or more *(TV<21"_2*)	0/1	0.258	0.392	0	1
	Number of TVs larger than 21"	0	0/1	0.157	0.364	0	1
		1 (*TV≥21"_1*)	0/1	0.510	0.500	0	1
		2 or more (*TV≥21"_2*)	0/1	0.333	0.441		1

Table 3. Regression results for a typical weekday during winter.

		1 (12.00 to 12.30 am)	9 (4.00 to 4.30 am)	17(8.00 to 8.30 am)	25 (12.00 to 12.30 pm)	33 (4.00 to 4.30 pm)	41 (8.00 to 8.30 pm)
#adults	2	0.066***	0.017***	0.176***	0.236***	0.320***	0.302***
	3	0.161***	0.025***	0.218***	0.346***	0.520***	0.43***
	4	0.201***	0.031***	0.428***	0.413***	0.675***	0.637***
#child.	1	-0.009	-0.002	0.194***	0.043**	0.112***	0.161***
	2	-0.003	0.017**	0.385***	0.097***	0.288***	0.315***
	3	0.072***	0.016*	0.518***	0.207***	0.460***	0.398***
	save	-0.01	-0.004	-0.037**	0.017	0.007	-0.044***
build_type	bungalow	0.071***	0.045***	0.093***	0.047**	0.014	0.098***
	detached	0.066***	0.04***	0.09***	0.067***	0.042*	0.109***
	semi_det	0.013	0.007	0.014	0.01	0.001	0.012
	appt	-0.088**	-0.014	-0.035	-0.046	-0.152**	-0.191***
age	age 10–30	0.048***	0.006	0.072***	0.081***	0.109***	0.02
	age 30+	0.066***	0.014**	0.102***	0.178***	0.196***	0.024
insulation	wall_insulation	-0.022	0.001	-0.02	-0.027	0.013	0.004
	double-glazed	-0.016**	-0.005*	0.006	-0.015*	-0.007	-0.019*
	attic_insulated	0.029	0.029**	0.06	-0.025	-0.072*	-0.01
	additional_heat	0.001	-0.026*	-0.079	-0.057	-0.111*	-0.007
heating	electric_heat	0.062*	0.009	0.038	0.127***	0.122**	0.07
	plugin_1	0.064	0.019	0.044	0.213***	0.296***	0.111
	plugin_2	0.115*	0.043*	0.077	0.342***	0.4***	0.159*
	immers_heater	-0.007	-0.003	0.021	0.005	0.012	0.031*
	shower_1	-0.027***	-0.008*	0.031*	-0.015	-0.01	0.009
	shower_2	-0.004	-0.001	0.094***	0.014	0.035	0.052
	light	0.009***	0.001	0.006	0.004	0.005	0.038***
white goods	stove	0.021*	0.004	0.047***	0.095***	0.137***	0.089***
	washing	0.005	0.001	0.044	0.067	0.026	-0.025
	dryer	0.051***	0.015***	0.106***	0.138***	0.149***	0.131***
	dish_washer	0.1***	0.031***	0.117***	0.033**	0.06***	0.225***
	freezer	0.043***	0.038***	0.03*	0.058***	0.074***	0.034**
	water_pump	0.029**	0.029***	0.043**	0.029*	0.027	0.047**
ICT	router	0.057***	0.014**	0.047**	0.039*	0.086***	0.129***
	desk_PC	0.041***	0.031***	0.043**	0.022	0.03*	0.045**
	laptop_1	0.019	0.012**	0.026	-0.052***	-0.074***	-0.005
	laptop_2	0.078***	0.031***	0.098***	-0.016	-0.048*	0.048
	console_1	0.057***	0.017***	0.054**	0.021	0.058***	0.063***
	console_2	0.084***	0.03***	0.073**	0.008	0.117***	0.095***
	TV<21"_1	0.01	0.006	-0.007	0.017	0.049***	0.048**
	TV<21"_2	-0.01	0.005	0.026	0.035*	0.077***	0.052**
	TV≥21"_1	0.031*	-0.001	0.006	0.015	0.051**	0.081***
	TV≥21"_2	0.068***	0.015**	0.023	0.078***	0.124***	0.142***
	const.	0.117***	0.069***	0.127***	0.118***	0.153***	0.345***
	Adj. R^2	**0.302**	**0.304**	**0.383**	**0.32**	**0.43**	**0.5**
	N	3,837	3,803	3,795	3,810	3,806	3,825

*Note: *** indicates significance at $p < 0.01$, ** indicates significance at $p < 0.05$ and * indicates significance at $p < 0.1$ in an individual two-tailed t-test based on robust standard errors.*

As expected, higher shares of energy-efficient light bulbs imply lower electricity consumption, especially during the morning and evening periods, i.e. at times where household lighting needs are highest.

The coefficient of electric stoves is positive and significant for all half-hour periods apart from the periods between midnight and 7.30 am. As expected, the coefficients tend to be highest around lunch and dinner time. The parameter estimate associated with a washing machine is not statistically significant at any of the half-time periods. This finding is counterintuitive, but may be partially explained by the fact that almost all households own a washing-machine, leaving little variation to be exploited by the regression analysis[13]. The coefficients of dishwashers and dryers are statistically significant for all half-hour periods of a day. Arguably, some households may program these end-uses so they run during times of low human activity i.e. at night. However, note that the coefficients of dryers are highest during daytime and those of dishwashers during the early morning and evening hours, reflecting the times of most intensive usage. For freezers and water pumps, we also find statistically significant results over the course of all typical days.

The parameter estimates associated with a router and a desktop PC exhibit the expected positive sign and are statistically significant for almost all half-hour periods. The coefficients for game console variables are positive and significant for almost all half-hour periods, apart from late morning hours. As expected, the coefficients for console_2 are larger than for console_1 for most half-hour periods[14]. At first, the findings for laptops are somewhat surprising, suggesting (statistically) significant higher use during the evening and night-time hours, but lower use during the daytime. The latter may be explained by a likely negative correlation of laptops and presence at home: people with laptops are more likely to be at work during daytime hours. For smaller TVs (<21" screen) and single large TVs (≥21" screen) the coefficients are found to be significant for periods between 3.00 pm and midnight, peaking around 4.30 pm but remaining on a relatively high level during the evening hours. Results for households with two large TVs are significant for nearly the entire day (except from 5.00 am to 9.00 am). The associated coefficients imply electricity use of TVs throughout the entire day. This may be explained by more or less constant use of at least one TV or by stand-by consumption. About two thirds of the electricity consumption of TVs occurs between 3.30 pm and midnight, with a consumption peak at 5.30 pm.

Finally, the intercept term, which also captures the effect of those end-uses not included as explanatory variables (e.g. refrigerators), is positive and statistically significant for all half-hour periods.

In general, the findings of our regression results are quite intuitive. Apart from the findings for showers, the estimated coefficients exhibit the expected positive sign. Similarly, the coefficients' level of significance and their magnitudes over the course of a day reflect expected use patterns.

The findings for the other typical days are generally quite similar to those presented for the winter weekday in Table 3. We observe seasonal variation for heating technologies, lighting, washing machines, dryers, as well as the categories #of adults≥4 and #of child≥3, all of which exhibit, as expected, larger coefficients during the winter. In terms of variations across the different days of the week, the main differences are found in electric stoves, dishwashers, and TVs. Unlike for weekdays, where coefficients of these variables peaked during evening hours, they tend to exhibit a more elevated level during daytime of weekend days.

In sum, estimating reduced-form household electricity equations relying on consumption data with high temporal resolution appears to work particularly well in our data set for electricity-intensive end-uses, for lighting and for end-uses with well-mixed ownership patterns, such as dryers, dishwashers, electric stoves and electric heating. Similar to Aigner et al. (1984), Brodsky et al. (1988), Blaney et al. (1994), or Aydinalp et al. (2008), we find less robust results for end-uses with a low rated power, for those owned by a few households only, or by almost all households. The impact of end-uses with a low rated power on total metered electricity use is difficult to isolate. For end-uses which tend to be owned by only a few or by almost all households, there is little variation in the explanatory variable. In this case, regression techniques are bound to fail because the regressor matrix is almost singular, and the standard errors are very large. None of the reviewed studies is able to generate a lighting profile of high temporal resolution distinguished by season and weekday. Given that every household has lighting installed, the electricity use of lighting is typically captured via the intercept (e.g. in Brodsky et al. (1988), Blaney et al. (1994)). Our findings suggest that reasonable lighting profiles may be obtained using the share of installed energy-saving bulbs.

LOAD PROFILES

In Figure 1 to Figure 6 we depict exemplary load profiles that are generated from the end-use-specific regression coefficients. The load profile of an electric stove in Figure 1 differs distinctively between weekdays, Saturdays and Sundays. The electricity consumption at lunch time is three times higher on Sundays than on weekdays, while the electricity consumption during supper time is higher on weekdays than on Sundays. The consumption levels on a Saturday range between the levels on a weekday and a Sunday. The load profile of a stand-alone freezer in Figure 2 reflects the expected higher cooling demand in summer. With respect to the daily load distribution, the profile is characterised by a continuous increase over the course of the day and three usage peaks that coincide with those of the load profile from the electric stove. The load profile of a dishwasher in Figure 3 shows a small peak in the morning on weekdays, but not on weekend days. Further, the shape of the load profile is quite similar for Saturdays and Sundays, but the level is slightly higher on Sundays. For weekdays and weekend days, major electricity consumption takes place during evening hours between 6:00 pm and 11:00 pm. The load profile for a dryer in Figure 4 is significantly higher during winter days than during summer days, probably because laundry frequently tends to be dried outdoors during the summer.

Figure 5 depicts the lighting profile for weekdays in the three different seasons. The lighting profile is based on the energy savings per 25 % share of energy saving lights. The absolute values of the determined regression coefficients represent the

13. For summer days and for morning hours of days in the transition period, the coefficients for washing machines tend to be statistically significant.

14. Results from F-Tests suggest that the coefficient for console_2 is higher than the coefficient for console_2 in 32 of the 48 half-hour periods (at $p < 0.05$).

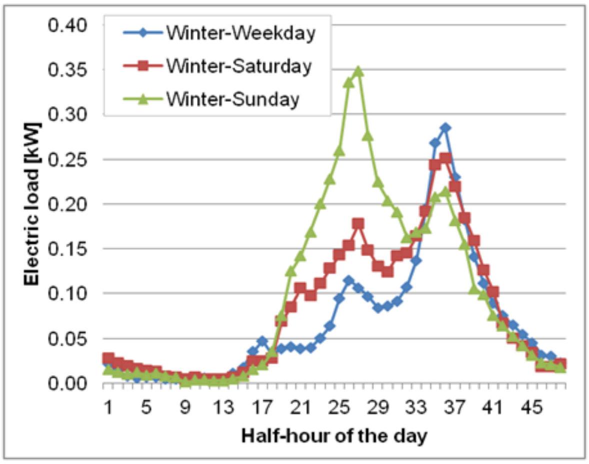

Figure 1. Load profile for an electric stove.

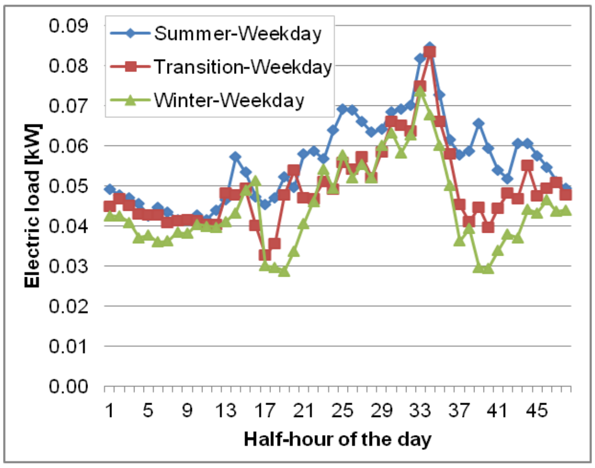

Figure 2. Load profile for a stand-alone freezer.

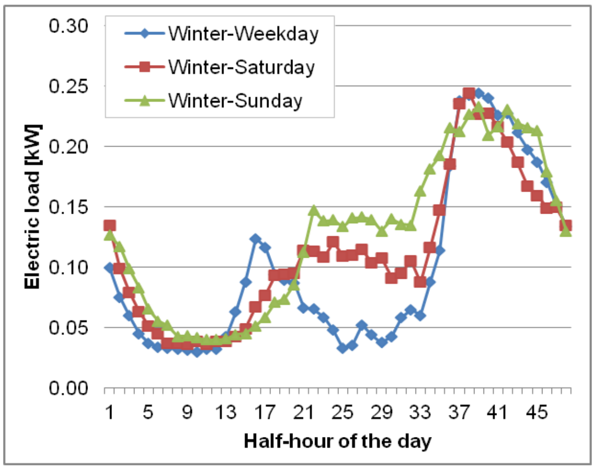

Figure 3. Load profile for a dishwasher.

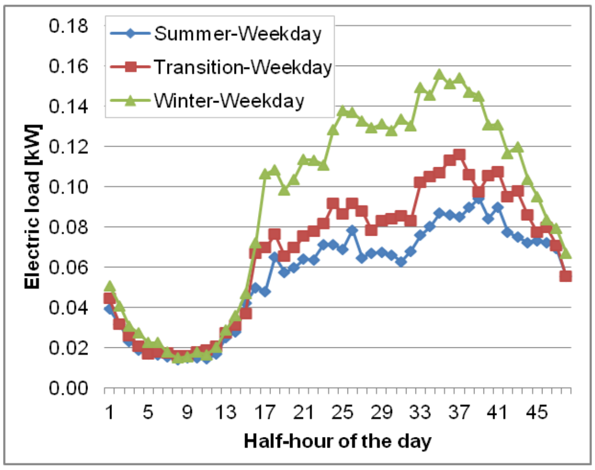

Figure 4. Load profile for a dryer.

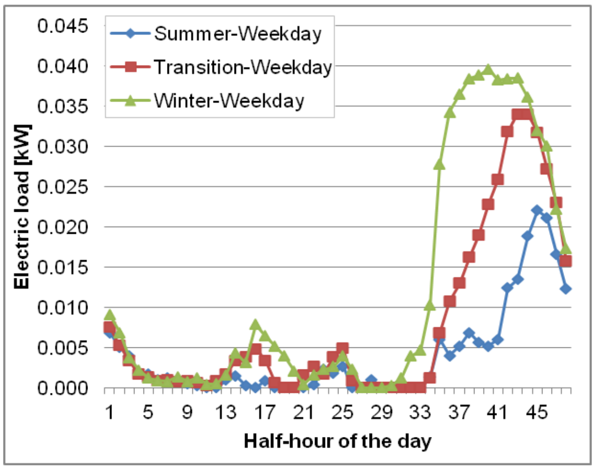

Figure 5. Load profile for lighting (energy savings per 25 % share of energy saving lights).

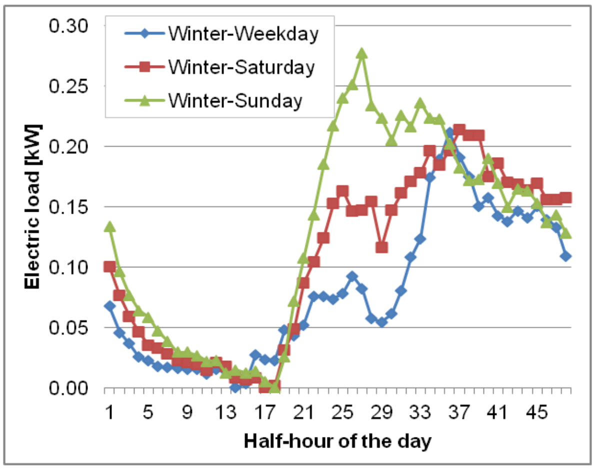

Figure 6. Load profile for two TVs (≥21”).

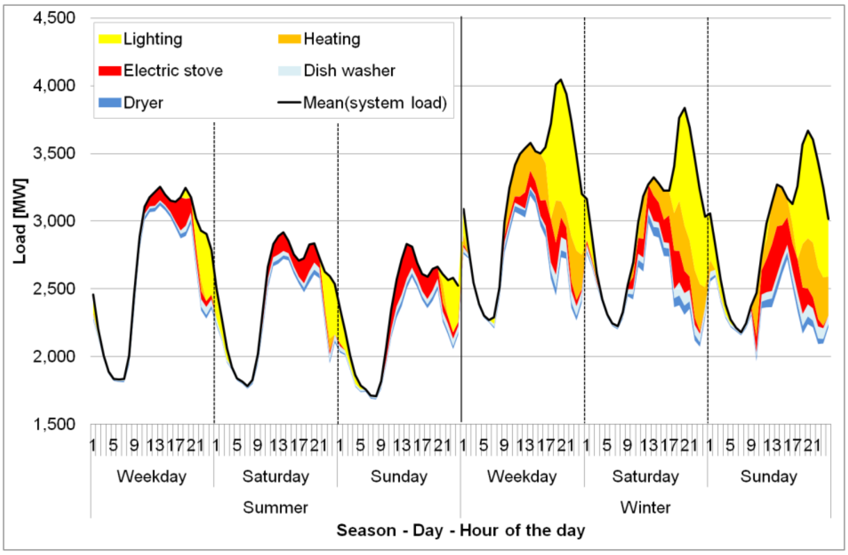

Figure 7. Daily load profile of system load and end-uses in Ireland in 2011. Source: own calculation based on data from ENTSO-E (2013) *and SEAI* (2012; 2013).

saving in a half-hour period, i.e. a negative profile. However, in absolute terms, the distribution profile of savings may be interpreted as an indicator for the lighting profile since absolute savings are higher for higher loads. As can be seen in Figure 5, electricity consumption is highest during the winter and starts earlier in the evening than during the transition period or the summer because the sun sets earlier during winter days. Figure 6 shows the load profile if households own two TVs with screens larger than 21 inches. The after-lunch peak in TV use on Sundays may be explained by the Irish TV programme. From 1.30 pm on, "The Sunday game" broadcasts live popular sports events like hurling and soccer, with average audience shares of over 40 % (RTE 2014). For weekdays and Saturdays, the load peak is at about 6.30 pm.

APPLICATION OF LOAD PROFILES TO THE ELECTRICITY DEMAND OF IRELAND

Final electricity demand of Ireland in 2011 equalled 24,881 GWh (SEAI, 2012). The corresponding system load curve is shown in Figure 7 in terms of the mean load at each hour for six of the nine typical days. A typical weekday or weekend day in winter is associated with an early afternoon local load peak of 3.6 and 3.3 GW, respectively, and an evening global load peak of 4.0 and 3.7 GW, respectively, (around 8.00 pm). The summer profile is more balanced at a level of 3.2 GW during the daytime and a load of 1.8 GW during the night. The load peak in 2011 for Ireland equalled 4.45 GW. Figure 7 illustrates the decomposition of the system load curve into the individual end-use components lighting, heating, electric stoves, dishwashers and dryers as explained in Section 2.5. Our findings illustrate that electricity demand for lighting is characterized by low variation across different days of the week, but high variation across seasons. Specifically, the winter period accounts for nearly 60 % of annual demand. During this period, the load for lighting is concentrated on morning and evening hours, and ranges between 0.7 and 0.9 GW. In contrast, during the summer period, the load for lighting drops to between 0.2 and 0.5 GW. On winter Sundays at 10.00 pm, lighting accounts for up to 24 % of the mean system load. As expected, electric heating shows even stronger seasonal variations than lighting. More than 80 % of all electricity for space heating purposes is consumed during the winter period. The load for electric heating is located primarily between 9.00 am in the morning and 1.00 am at night, reaching up to 0.4 GW (i.e. up to 10 % of the mean system load) during the late evening across all days of the week. Electricity demand for dryers varies substantially by season and by days of the week. During the winter period, the daily electricity demand for dryers is nearly twice as high as during the summer period. On weekdays and Saturdays, the load for dryers is highest in the evening (up to 0.05 and 0.07 GW, respectively), whereas on Sundays, it is highest around midday (0.04 and 0.06 GW respectively). However, the load for dryers is relatively low and never exceeds 2.2 % of the system load. The electricity demand by electric stoves varies mainly across different weekdays, peaking on weekdays at around 6.00 pm (at 0.25 GW during the winter and 0.32 GW during the summer period) and on Sundays around midday (at 0.25 GW during the winter period and 0.36 GW during the summer period). On winter Sundays at lunch time, electric stoves account for 11.0 % of the system load. The load distribution of dishwashers is similar to that of electric stoves, just shifted slightly towards later hours during the day. The load of dishwashers ranges between 0.01 GW (during night-time hours) and 0.06 GW in peak periods and never exceeds 2.6 % of the system load.

Discussion

In sum, our estimated load profiles help explain the pattern of the load curve of Ireland and to better understand differences in load across seasons and different days of the week. The regression-based load profiles for five end-uses facilitate the decomposition of a substantial part of the system load (up to 40 %), in particular for winter days. The evening load peak on winter days is mostly related to the use of lighting and electric heating, accounting for 22 % and 11 % of the overall load, respectively. The lower midday load peak is partially caused by electric stoves (approx. 11 %) (see also Leahy & Lyons 2010). In comparison, dishwashers and dryers only have a marginal impact on the total load. The remaining gap, which is not explicitly explained by the load profiles, is related to other residential end-use activities (such as cooling devices, washing machines, information and communication technologies, hot water provision) as well as to electricity demand in the sectors industry, commercial, tertiary, agriculture and rail.

To reduce peak demand related to lighting and heating services during winter days, improving energy efficiency is a more sensible strategy than trying to shift loads to off-peak periods, unless electric heat storage systems are in place. Thus, incentivizing energy efficiency (e.g. CFLs, LEDs, electric heat pumps, insulation measures) seems most promising (see also Chiodi et al. 2013). To quantify the savings potential based on our load curves for lighting and heating, we assume that energy efficiency for lighting improves by one third (by using CFLs and LEDs rather than incandescent and halogen bulbs, e.g. Wall & Crosbie 2009) and that energy efficiency of electric heating improves by 67 % (by shifting all electric heating to heat pumps, e.g. Connolly et al. 2014). Neglecting potential rebound effects,[15] these measures lower the evening peak load during a winter day by about 0.4 GW, which corresponds to a reduction of about 10 %, whereof about 8 percentage points are related to lighting[16]. In this case, the system load curve during the winter and the summer periods show similar levels of peak loads, which suggest a significantly lower need for peak load and back-up capacity. While less pronounced than the evening peak, the midday peak could also be shaved, e.g. by switching from electric ovens to microwaves or gas stoves. As pointed out by Borg & Kelly (2011), the trend towards microwaveable ready-cooked meals lowers electricity demand by approx. 30 %, which – according to our estimates – translates into a midday peak load reduction by nearly 0.2 GW or 6 %.

Moreover, peak loads can be reduced by shifting electricity use from peak hours to off-peak periods. According to (Gottwalt et al. 2011), the most suitable end-uses for load shifting are heating and cooling, as well as washing machines, dishwashers and dryers. Our findings for Ireland suggest that electric heating has the largest potential for shifting in terms of winter peak load reduction, provided that heating systems are equipped with a heating storage unit. Assuming a shift of the entire heating capacity by a few hours would reduce peak load by about 7 % or 0.25 GW. Of course, the potential to shift loads shrinks as conventional heating systems become more efficient, or are replaced by heat pumps or non-electric heating technologies.

In comparison, the potential to shift loads related to dishwashers and dryers is rather small: 2.4 % or 0.1 GW peak load reduction for dishwashers and 1.4 % or 0.06 GW for dryers.

These findings are derived from a large sample, involving data from more than 4,000 households. Compared to other studies, our data also allowed for a fairly long observation period of 18 months, high temporal resolution of half-hourly load data, and a rich set of explanatory variables. In general, with increasing availability of smart meter data, similar analyses could easily be carried out for other countries or regions. Future studies could integrate weather and geographic data (e.g. temperature, heat degree days, solar radiation, and location), more technical details for end-uses (e.g. energy class, rated power) and additional information on household characteristics (e.g. education, income, employment status)[17]. We find that constructing load curves based on econometric analysis works particularly well for electricity-intensive end-uses, for lighting and for end-uses with varied ownership patterns, such as dryers, dishwashers, electric stoves and electric heating. In contrast, the impact of end-uses with a low rated power may be difficult to detect via econometric analysis. Similarly, for end-uses with little variation in ownership, the regressor matrix is almost singular and standard errors are large. Thus, the presented approach may not be suitable for identifying the load profiles of end-uses with very high or very low penetration rates (such as washing machines). Electricity use of these end-uses could be metered directly (at relatively low cost), in particular if they are designed as "smart appliances" that allow direct communication with the utility.

Conclusion and policy implications

Based on data from a large representative smart meter project in Ireland we employ econometric analyses to derive half-hourly load profiles for major end-uses. Distinguishing between weekdays and weekend days proves essential, in particular for electric stoves, dishwashers and TVs. Likewise, the load profiles for lighting and electric heating differ substantially between summer, winter and the transition season. Validity checks relying on data from time use surveys and on load data from the UK corroborate our findings.

The derived load profiles allow for a better understanding and quantification of the factors driving observed loads in the electricity system. For example, calibrating our estimated load profiles for five household appliances to the actual load curve of Ireland in 2011, we are able to explain up to 40 % of the total system load. Our findings further suggest that electricity for lighting services accounts between 20 % and 25 % of the peak system load on winter weekday evenings. For electric heating, this share reaches up to 10 %.

In particular, end-use specific load profiles provide valuable information for designing effective energy efficiency and load management programs, which help integrating fluctuating renewables into the power grid, lowering total capacity needs in the system, and saving costs for building and running generation and transmission infrastructure (e.g. Faruqui et al. 2010; Joskow 2012). For the Irish power system, this means lowering the winter peak, which determines capacity requirements on the supply side. End-use specific load profiles also allow quantifying the likely contribution of these policy programs towards cutting peak demand. To reduce lighting-related peak demand during winter days, promoting the diffusion of energy efficient light bulbs and tubes will be particularly effective, potentially

15. For lighting services, the direct rebound effect is likely to be small, i.e. well below 10 % (e.g. (Schleich et al. 2014)), but may be larger for heating services (e.g. (Sorrell et al. 2009)).

16. Part of the efficiency improvement in lighting may already have been realized since 2010 due to the ban on incandescent light bulbs in the EU.

17. For our analysis, however, heterogeneity in whether conditions across our cross-sectional observations is unlikely to distort our estimates since weather conditions do not vary much for a particular point in time within the geographic region where the sample was drawn.

reducing the evening peak by up to 8 %. Peak time demand for electric heating could be lowered by policies incentivizing thermal insulation, fuel switching (e.g. to gas-fired, solar thermal or geo-thermal heating systems) or the adoption of heat pumps. Based on estimates from the literature, we find that energy efficient lighting and shifting all electric heating to heat pumps lead to an overall reduction in the winter evening peak load by 10 %.

Dynamic pricing provides financial incentives to shift demand from peak to off-peak hours (Faruqui & Sergici 2010; Di Cosmo et al. 2014). While the EU Energy Services Directive 2006/32/EC requires utilities to offer electricity tariffs which vary by load or by time of use, in practice, incentives to switch loads have often been low because the difference between peak- and off-peak tariff is too small. However, our findings suggest that electric heating exhibits the largest potential to shift loads away from the peak loads in the Irish residential sector, e.g. via heat storage systems. Thus, as an alterative to dynamic pricing, direct load control systems for electric heating could be introduced (Ericson 2009). We also find that the potential of other end-uses suitable for load shifting such as dishwashers or dryers is small compared to electric heating. Thus, policies promoting load shift in the residential sector in Ireland should focus on electric heating before targeting other end uses, which require a direct interaction of the consumer and hence a specific tariff design.

Our findings also allow assessing the impact of social or demographic developments. For example, the trend towards microwaveable ready-cooked meals lowers electricity demand for electric stoves, implying a reduction of midday peak load by about 6 %.

Finally, deriving load curves with a high temporal resolution provides valuable information for demand side management to better facilitate the integration electricity generated by fluctuating renewable energy sources or to manage emerging smart grid solutions at the community level.

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