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Residential electricity consumption and household characteristics: An econometric analysis of Danish smart-meter data

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A B S T R A C T

Households are heterogeneous customers that consume different amounts of electricity for different purposes at different hours of the day. Understanding how the level and timing of electricity consumption is related to household characteristics is important in planning production and grid capacities and in designing policies.

Linking Danish smart-meter data for 2017 to detailed household characteristics derived from administrative registers, we analyse how the level and profile of hourly electricity consumption is related to these characteristics. In addition, we examine to what extent having a flat rate for electricity implies cross-subsidies between residential customers in Denmark.

We find that both the level and timing of consumption vary significantly with household characteristics, mainly the type of dwelling, its heating technology, its use of electric vehicles, and the number and age of the adults and children who live there, all of which affect the level and timing of consumption. Assuming hourly pricing with constant consumption rates, the average price per kWh paid by different categories of household varies only marginally. That is, the flat rate presently seen by Danish households implies limited cross-subsidies between groups of residential customers. Consequently, introducing real-time pricing for Danish residential customers should not pose serious redistribution concerns and would improve economic efficiency.

1. Introduction

Households are heterogeneous electricity customers that consume different amounts of electricity for different purposes at different hours of the day. McLoughlin (2013) and Yohanis et al. (2008) show that both the level and the hourly profile of electricity consumption vary considerably between categories of residential customers. Understanding how the level and timing of consumption are related to household characteristics is important in planning electricity production and grid expansion, as well as in designing policy. By linking Danish smart-meter data for 2017 to detailed household attributes derived from administrative registers, we analyse the links between household attributes and electricity consumption. The dataset covers approximately 667,000 households (approximately 25% of all Danish households) with an hourly meter. The Danish Transmission System Operator (TSO) Energinet collects data from all hourly meters, which it delivers to Statistics Denmark. Unique to Denmark, Statistics Denmark anonymizes meters and links them to a comprehensive list of register data containing detailed information on household and dwelling characteristics. That is, unlike previous studies that rely on field trails and surveys or questionaires from a limited number of households, we apply high-frequency data from a large number of individual household meters linked to administrative registers giving reliable information on household and dwelling characteristics. First, we analyse the annual electricity consumption of individual households by linking consumption to socioeconomic characteristics, showing how annual consumption rates vary with these characteristics. Next, we group households according to their characteristics and analyse the average hourly consumption profiles for the different categories. This shows how the timing of consumption varies between different household categories. Finally, combining hourly consumption profiles and wholesale prices, and assuming constant consumption rates, we calculate the average price per kWh individual households would have paid with hourly pricing. This shows the size of residential cross-subsidies in a system in which residential customers are charged a flat rate regardless of the time of use.

Analyses of electricity consumption and socioeconomic characteristics may be grouped into studies looking at either 1) individual households, by linking household characteristics and electricity consumption

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over a longer period, e.g. applying annual observations; or 2) the daily or seasonal timing of consumption for different categories of customers by applying high-frequency data with an hourly resolution or finer.

Including both types of study, by applying smart-meter data from an experiment with approximately 5000 Irish households for the second half of 2009, supplemented by a survey of the households' socioeconomic and dwelling characteristics, McLoughlin et al. (2012) and McLoughlin (2013) analyse how both the levels of consumption and the daily consumption profiles vary with these characteristics. They conclude that the type of dwelling, the number and age of the adults and children who live there, and the heating and cooking technologies used are the main factors affecting consumption levels and daily peaks. Using half-hourly electricity consumption data from 27 representative dwellings in Northern Ireland over nearly two years, Yohanis et al. (2008) also analyse how dwelling and household characteristics affect both the levels and hourly profiles of electricity consumption. They show large differences in both levels and daily consumption profiles between types of dwellings, the number and age of occupants, and household incomes.

The literature linking electricity consumption and household characteristics is quite comprehensive, as it analyses the effects of many different household attributes obtained from field trials and surveys or questionaires of different sizes covering different geographical areas. Applying annual electricity consumption data and using anonymised microdata from the Irish Household Budget Survey for 2010, which covers 5891 households, Chesser et al. (2019) analyse how socioeconomic characteristics affect electricity consumption and conclude that the number of people living in a house, the household's disposable income and the number of bedrooms significantly affect the level of consumption. Applying U.S. household data for approximately 12,000 households, Burnett and Burnett and Madariaga (2018) analyse how dwelling and socioeconomic characteristics affect the energy efficiency of different categories of household, while Dalen and Larsen (2015) use repeated Norwegian cross-sectional data for 1990, 2001 and 2006 to evaluate how appliance ownership affects annual electricity consumption. In an earlier paper, Larsen and Nesbakken (2004) analyse annual electricity consumption in 1453 Norwegian households and conclude that dwelling size and the heating system considerably affect annual consumption. Gouveia et al. (2015) investigate Portuguese electricity consumption data from 230 households and a door-to-door survey of dwelling and household characteristics to conclude that it is mainly the dwelling's physical characteristics, its electrical heating or cooling equipment, its number of occupants and their incomes that affect electricity consumption. Analysing annual electricity consumption data from 8573 Danish households living in detached houses, Gram-Hanssen (2011) concludes that the number of inhabitants, their incomes and the size of the dwelling are the main factors affecting consumption. Combining dwelling and household characteristics with appliance ownership, Baker and Rylatt (2008) analyse 148 dwellings in Leicester and Sheffield (UK) and conclude that it is especially the floor area, whether occupants work at home and appliance ownership that are the most important factors affecting electricity consumption. As already mentioned, compared to these references, which rely on field trials and self-reported data from surveys and questionnaires of relatively few dwellings and households, this paper contributes to these debates by analysing all Danish households that had a smart meter in 2017 (approximately 667,000 valid household meters). In addition, the background variables are obtained from comprehensive administrative registers giving detailed and reliable information on household and dwelling characteristics, thus allowing quite detailed and reliable analyses and evaluations of the links between household characteristics and electricity consumption.

In regard to the timing of consumption for categories of customers, the literature is more limited, though it shows consumption profiles for categories of customers with quite different charactericties by using smart-meter data for a limited number of households. Using hourly data for different categories of customers, an early study by Pratt et al. (1993) investigated 288 homes in the Pacific Northwest USA by developing hourly profiles for heating and cooling and different household appliances. Investigating hourly data for 181 households from New York, Blaney et al. (1996) estimated consumption profiles for large and small homes and the effects of temperature on profiles for electric space-heating. Analysing 204 residences in central Florida, Parker (2003) develops consumption profiles for several household characteristics and types of appliance ownership, e.g. space heating and cooling, water-heating, swimming pools and different appliances. Looking at Norwegian data from 3930 household meters, Ericson and Halvorsen (2008) calculate an average household consumption profile that distinguishes between weekdays, weekends and months. They also develop similar profiles for aggregated categories of sectors. Applying data from 22 households in Lisbon and taking into account the social class of their occupants, Pombeiro et al. (2012) develop average profiles for three social classes. Applying Danish data for 4500 representative customers covering all categories of customers (incl. sectors) from 2012 and focusing on households, Andersen et al. (2017) analyse how categories of appliances contribute to the average household consumption profile (distinguishing weekdays, weekends and months). Also with reference to aggregated categories of appliances, Csoknyai et al. (2019) investigated data from 150 homes in France and Spain for 2017 and 2018 and generate profiles for heating, domestic hot water and other appliances. Examining data for 2007–2010, Andersen et al. (2013) develop an average consumption profile for categories of Danish customers, including a profile for households, and test whether these profiles vary significantly between workdays, weekends, days in the week and months. Looking at data from 608 detached households in Norway, Kipping and Trømborg (2015) estimate how the number of adults, children, age, heating system, heating degree days and number of appliances (e.g. an electric water-heater) affect hourly electricity consumption. Expanding on this, by grouping households into types of dwellings, e.g. apartments, terraced houses, detached houses and semi-detached houses, Kipping and Trømborg (2016) use Norwegian data for 470 households in the city of Hønefoss to investigate hourly electricity consumption for types of dwellings. Using data for two hundred Swedish households, Vesterberg and Krishnamurthy (2016) estimate end-use profiles and summarize the potential for load shifting. Finally, analysing UK data for 3488 households, Anderson et al. (2016) go in the opposite direction of deriving household characteristics from their temporal load profiles. In relation to hourly consumption profiles, the novelty of the present paper is that we present and compare profiles for quite detailed categories of households with attributes like age and number of adults, children, the type of dwelling, the heating system and possible ownership of an electric vehicle, testing whether profiles with different characteristics differ significantly. In particular, we show that electric heating and electric vehicles have quite distinct hourly consumption profiles.

Finally, combining hourly consumption and prices, in looking at cross-subsidies, Horowitz and Lave (2014) use data for 1260 Commonwealth Edison residential customers and show that, if customers do not respond to hourly prices going from a flat rate to hourly real-time pricing, 35% of residential customers will save money, while the remaining 65% will lose money. Using smart-meter data for 160,000 residential customers in Australia, Simshauser and Downer (2016) show that it is mainly poor households and pensioners who benefit from accepting hourly pricing. Looking at data for 2000 Danish customers covering all categories of customers, Andersen et al. (2014) show that for Denmark, it is typically industry, private services and households that stand to lose from hourly pricing, while agriculture and public services stand to gain. Concerning cross-subsidies under flat-rate pricing, our contribution in this paper is to investigate relations between cross-subsidies and household characteristics, in particular, who loses and who gains from hourly pricing. We find that a flat rate implies cross-subsidies between households with different characteristics, but, contrary to the American and Australian studies mentioned, for Denmark the cross-subsidies between households are minor.

Section 2 presents the data and analyses the links between annual electricity consumption and household attributes. Section 3 presents hourly consumption profiles for categories of households, while Section 4 combines hourly consumption profiles and wholesale prices, estimating cross-subsidies under flat-rate pricing. Finally, Section 5 presents the main conclusions and some policy implications.

2. The data and links between annual electricity consumption and household attributes

For 2017, after cleaning the dataset for outliers,[1] we analyse hourly electricity consumption data from 667,373 Danish households having a smart meter. Each meter is linked to several administrative registers containing data on a comprehensive list of household attributes. For annual electricity consumption, the literature review showed that the attributes that significantly affected household consumption are the type of dwelling, the heating technology, the number and ages of the occupants, and the presence or absence of children. Aggregating households into categories with different attributes, average annual consumption per household is presented in Table 1 by distinguishing apartments from one- and two-family houses, households with and without electric heating, households with one adult from households with two or more adults, three age categories for the oldest adult in the household (between 18 and 24 years, between 25 and 64 years, and 65 years or older), and households with and without children. Finally, we distinguish households possessing an electric vehicle (EV).[2]

The main observations from Table 1 are that average annual electricity consumption varies by a factor of ten between categories of households. The technological parameters especially (type of dwelling, heating technology, electrical vehicles) imply large differences in consumption, but the number and ages of adults and whether there are children or not also affect the household's annual consumption.

Inspired by the literature review and observations from Table 1, for respective households living in apartments and one- and two-family houses, we specify a long-term demand equation as eq. (1). In addition to the categories in Table 1, household income is included as an explanatory variable.[3] We have chosen the linear additive specification over a log-linear multiplicative specification,[4] as we include several technical attributes that are better described by adding an amount of kWh to household consumption than by adding a percentage to the consumption in a household without the attribute: e.g. the kWh an electric vehicle adds to household consumption depends on its drive pattern, which is not directly related to the electricity consumption of households without an electric vehicle. That is, the equation we estimate is specified as:

$$
\begin{aligned}
e^i = {} & \left[\alpha_{0,nh} + \alpha_{y,nh}\cdot y^i/y^* + \alpha_{ad,nh}\cdot D^i_{ad} + \alpha_{ch,nh}\cdot D^i_{ch} + \sum\nolimits_{age=2}^{age=3} a_{age,nh}\cdot D^i_{age}\right]\cdot D^i_{nh} \\
& + \left[\alpha_{0,wh} + \alpha_{y,wh}\cdot y^i/y^* + \alpha_{ad,wh}\cdot D^i_{ad} + \alpha_{ch,wh}\cdot D^i_{ch} + \sum\nolimits_{age=2}^{age=3} a_{age,wh}\cdot D^i_{age}\right]\cdot D^{i.}_{wh} \\
& + \alpha_{ev}\cdot D^i_{ev} + \varepsilon^i
\end{aligned}
\tag{1}
$$

where e^i is annual electricity consumption in kWh by household i living in either an apartment or a one- or two-family house. The first bracket relates to households without electric heating, the second bracket models households with electric heating, y^i is household income, and y^* is the average income for the default household in the type of dwelling. D^i_{ad} is a binary variable with the value of one for households with two or more than two adults and zero for households with one adult. D^i_{ch} is a binary variable for households with children, and D^i_{age} are two binary variables for households where the oldest inhabitant is respectively between 18 and 24 years or 65 years or older. D^i_{wh} and D^i_{nh} are binary variables for households with and without electric heating. Finally D^i_{ev} is a binary variable for electric vehicles, and ε^i is a stochastic error term.

Therefore the category used for comparison (the default category of households) is households with one adult in the age range of 25–64 years, without children, and without an electric vehicle. $\alpha_{0,\ wh}$ and $\alpha_{0,\ nh}$ are constant terms, and the effect of income on electricity consumption in households without and with electric heating is given by the coefficients $\alpha_{y,\ nh}$ and $\alpha_{y,\ wh}$ respectively. Furthermore, the coefficients to the dummy variable show the marginal effect of the chosen category relative to the category used for comparison: e.g. $\alpha_{ch,\ nh}$ shows that a household with children but without electric heating on average consumes $\alpha_{ch,nh}$ kWh more than a similar household without children. Summary statistics of the variables used in the regression are shown in Table 2, and estimation results for households living in the different types of dwellings (apartments and one- and two-family houses) are given in Table 3.[5]

By examining Table 2, we can see that the variation in electricity consumption both between and within categories is quite large. The maximum/minimum consumption is almost the same for all categories (close to the criteria for excluding meters), and the standard deviation is approximately 0.6 times the average consumption in this category. Still, the average consumption varies by a factor of five between the categories. Incomes also vary considerably. The standard deviation within the categories is approximately 75% of the average income. The average

[1] The original dataset includes all 824,261 smart meters that were installed in Danish households in 2017. 83,042 m with an annual consumption below 100 kWh or above 35,000 kWh were deleted as outliers on the basis of their being non-normal households. An additional 74 m in households with more than ten adults were also deleted. A further 1646 households with annual incomes below 5000 DKK or above 10 million DKK were deleted as outliers, while a further 72,126 m that had not been recorded for more than 500 h were deleted as being incomplete, e.g. they were installed during the year. Ultimately, therefore, we analysed 667,373 valid meters. Finally, for included meters with missing observations of a few hours, total consumption was corrected using average hourly consumption at that meter.

[2] As the number of EVs is limited, for EVs Table 1 only reports data for households in one- and two-family houses, without electric heating, and with two or more adults in the middle age-group. (427 households with children have EVs, and 178 without children. The total sample includes 1064 households with an electric vehicle.) In addition, a few cells in Table 1 are given as 'N/A', as these cells include very few households. Finally, a few statistics on aggregated categories of customers are given in Table 2.

[3] Normally a demand equation would also include the price of electricity. However, as residential customers are exposed to a flat rate, individual prices are not available and estimating a price effect is not possible.

[4] In many studies the demand equation is specified as log-linear in the variables, implying that coefficients are interpreted as elasticities and effects are expressed as percentage changes.

[5] The Breusch-Pagan LM test for heteroscedasticity (Wooldridge, 2013, p. 227) shows quite significant heteroscedasticity: in particular, the estimated variance is larger for households with electric heating than for households without electric heating. However, the estimated variance also increases with household income and ownership of an electric vehicle. That is, types of households that are expected to have large electricity consumption are also expected to show large variations between individual households.The test-statistic $-2\cdot[\ln L_R - \ln L_U] \approx \chi^2_\upsilon$. That is, twice the change in the log-likelihood of the restricted and unrestricted estimates is χ^2 distributed with degrees of freedom (υ) equal to the number of restrictions imposed. See Greene (1997) or Madsen (2007).From Harnett (1975) we have for large values of υ that $\chi^2_\upsilon = \frac{1}{2}\left[z_\alpha + \sqrt[2]{(2\upsilon - 1)}\right]^2$ where z_α is the critical value from the normal distribution and υ is the degrees of freedom equal to the number of parameter restrictions imposed on the equation. For the significance level $\alpha = 2.5\%$: $z_\alpha = 1.96$, and for $\alpha = 0.5\%$: $z_\alpha = 2.58$.

Table 1
Average annual electricity consumption per household in kWh in 2017.

	Without electric heating						With electric heating					
Average consumption in kWh. 2017	1 adult			2 or more adults			1 adult			2 or more adults		
Apartments in multifamily houses	18–24 years	25–64 years	65+ years	18–24 years	25–64 years	65+ years	18–24 years	25–64 years	65+ years	18–24 years	25–64 years	65+ years
No children	1032	1363	1267	1559	1962	2175	4057	4461	5071	4621	6145	6576
Children	1633	2052	2258	2228	2801	3048	N/A	5522	N/A	N/A	7669	N/A
One- and two family houses												
No children	1941	2420	2036	2960	3829	3359	5195	6182	7116	7162	8931	9031
Children	2584	3078	3401	3633	4654	5180	6990	7495	7379	7474	10,058	12,266
No children and EV					6815							
Children and EV					8391							

Table 2
Summary statistics of variables.

Apartments	Without electric heating: no 181,939				With electric heating: no 2636			
	Mean	Stdv	Max	Min	Mean	Stdv	Max	Min
Elecricity[1] (kWh)	1641	1042	34,569	102	5199	3099	24,533	114
Income[1] (y/y*)	1.2	0.9	32.5	0.0	1.2	0.8	7.5	0.0
Adults[1]	1.4	0.6	10.0	1.0	1.3	0.5	5.0	1.0
Children[1]	0.3	0.7	8.0	0.0	0.2	0.6	4.0	0.0
Age of adults	50.3	20.3	108.0	18.0	53.6	18.9	100.0	18.0
	No.	Stdv	Max	Min	No.	Stdv	Max	Min
Electric vehicles	86.0	0.02	1.0	0.0	1.0	0.0	1.0	0.0
Households with:	1 adult		2 or more adults		1 adult		2 or more adults	
Share	0.64		0.36		0.70		0.30	
Households:	Without children		With children		Without children		With children	
Share	0.82		0.18		0.84		0.16	
Age categories	18–24	25–64	65+		18–24	25–64	65+	
Share	0.10	0.61	0.29		0.07	0.61	0.32	

One- and two family houses	**Without electric heating: no 445,307**				**With electric heating: no 37,491**			
	Mean	**Stdv**	**Max**	**Min**	**Mean**	**Stdv**	**Max**	**Min**
Elecricity[1] (kWh)	3363	2079	34,948	102	8241	4425	34,985	122
Income[1] (y/y*)	1.6	1.2	5.8	0.0	1.5	1.0	19.8	0.0
Adults[1]	1.7	0.6	10.0	1.0	1.7	0.6	10.0	1.0
Children[1]	0.6	1.0	8.0	0.0	0.5	0.9	7.0	0.0
Age of adults	57.2	15.8	106.0	18.0	58.1	14.9	103.0	18.0
	No.	Stdv	Max	Min	No.	Stdv	Max	Min
Electric vehicles	868.0	0.04	1.0	0.0	109.0	0.1	1.0	0.0
Households with:	1 adult		2 or more adults		1 adult		2 or more adults	
Share	0.32		0.68		0.34		0.66	
Households:	Without children		With children		Without children		With children	
Share	0.65		0.35		0.71		0.29	
Age categories	18–24	25–64	65+		18–24	25–64	65+	
Share	0.01	0.63	0.36		0.01	0.61	0.38	

[1] Per household.

Table 3
Estimation results for annual electricity consumption by type of dwelling in kWh per household (robust standard error in brackets).

kWh/household		Constant	Income	More than one adult	Children	Age 18–24	Age 65+	Electric vehicle	R^2
Apartments (184,575 households)	without electric heating	1141.1 (6.99)	158.6 (6.06)	565.5 (6.24)	686.2 (7.40)	−280.0 (6.91)	22.7 (4.88)	1249.6 (391.61)	0.32
	with electric heating	3923.0 (160.43)	448.0 (146.68)	1211.7 (180.12)	1205.6 (199.97)	−445.0 (210.51)	715.4 (132.1)		
One- and two family houses (482,798 households)	without electric heating	2048.1 (8.30)	269.2 (5.44)	1088.4 (7.05)	650.7 (7.94)	−452.4 (33.49)	−252.4 (7.34)	2756.7 (145.39)	0.37
	with electric heating	5218.5 (57.42)	985.6 (40.66)	1404.0 (55.09)	853.2 (58.55)	−853.2 (198.38)	928.7 (54.25)		

income is larger in houses than in apartments, but it does not differ between households with and without electric heating.[6] The lower income in apartments is partly due to a larger share of households with only one adult and partly due to a larger share of young adults than in one- and two-family houses. Furthermore, the share of households without children is larger in apartments than in houses. Looking at technologies, today most Danish houses are heated by natural gas or district heating, and almost all vehicles run on fossil fuels. As can be seen from the Table, very few houses have electric heating,[7] and the number of electric vehicles is very small. However, to reduce CO_2 emissions, comprehensive electrification of the heating and transport sectors by introducing individual heat pumps and electric vehicles is planned. This is expected to more than double household electricity consumption before 2040 and will pose considerable challenges for both the production and distribution systems. However, it also opens up important opportunities for demand-side flexibility assisting the transformation to a renewable energy system in which both the size and timing of consumption are important.

As can be seen from the estimation results in Table 3, adding the constant term and the coefficient to income gives the annual consumption in kWh of the average default household living in this particular type of dwelling.[8] Comparing households in apartments with one- and two-family houses, for the default household without electric heating, the annual consumption of one- and two-family houses is approximately 1000 kWh, or approximately 75% higher than in apartments. In addition, the coefficient to income is larger in one- and two-family houses than in apartments. However, the marginal effect of additional income, given the effect of other explanatory variables, is quite limited. Doubling the annual household income in apartments and one- and two-family houses respectively increases the figure for annual electricity consumption by approximately 12% or 159 kWh in apartments and 269 kWh in one- and two-family houses.[9]

Adding an adult increases annual electricity consumption by approximately 45% or 500 kWh in an apartment and 1000 kWh in a one- and two-family house without electric heating. Adding a child increases consumption by approximately 650 kWh in both apartments and one- and two-family houses.

Looking at age-categories, young households consume somewhat less than the middle age-group, as do households aged 65+ in one- and two-family houses.

Electric heating adds considerably to household consumption. Not only is the constant term considerably larger in households with electric heating, but also the effects of income, the number of adults and children, and the ages of the occupants are considerably larger in households with electric heating. All these effects have the same direction in households with and without electric heating except for the effect of household members aged 65+ in one- and two-family houses. In this category electric heating increases consumption, while in households without electric heating consumption in this age category is lower than consumption in the age category 25–64 years. This result is consistent with a hypothesis that elderly households generally consume less electricity than other households, but also demand higher indoor temperatures or live in houses that are larger, older, badly insulated and/or equipped with less efficient heating systems.

In comparing households with and without electric heating, another observation is that the standard error of the estimated coefficients is considerably larger in households with electric heating. This mirrors two effects: 1) the number of households with electric heating is much smaller than the number of households without electric heating; and 2) the variation in consumption between individual households is much larger in households with electric heating than in households without electric heating.[10]

As specified in Eq. (1), consumption by electric vehicles is considered to be independent of whether a household has electric heating or not. Theoretically, there is little argument for a link between heating and consumption by electric vehicles. Besides, given the relatively few households with electric heating that have electric vehicles, estimating coefficients becomes very uncertain. The estimation shows that for households living in apartments the estimated coefficient to owning an electric vehicle is approximately half of the coefficient for households living in one- and two-family houses. This is not necessarily due to vehicles owned by households living in apartments being driven less and consuming less electricity than vehicles owned by households living in one- and two-family houses. The difference rather suggests that most electric vehicles owned by households in one- and two-family houses are charged via the household meter, while in many apartments the meter does not have a charging device for the vehicle. That is, many vehicles owned by households living in an apartment are charged at a public charging station, consumption that is not registered by the household meter. The addition of 2757 kWh for electric vehicles in one- and two-family houses is consistent with a vehicle driving around 14,000 km per year with an efficiency of approximately 0.2 kWh/km.

[6] The income variable is larger than 1 for all categories, as it is measured relative to the income in the default household with only one adult (the average Danish household includes more than 1 adult participating in the labour force and earning an income).

[7] In this paper, electric heating includes both direct electric heating and individual heat pumps. Today most electric heating is direct heating, but in the future electric heating is expected to consist mainly of individual heat pumps providing both heating and hot water in the household.

[8] The average income y^* of the default household living in apartments is 41,246 Euro/year, while the average income of default households living in a one- and two family house is 51,504 Euro/year.

[9] The total effect of additional income is somewhat larger, as other explanatory variables are correlated with income: e.g. both the number and age of adults is positively correlated the household income, and on average households with an electric vehicle have relatively high incomes. Estimating the total income-elasticity by specifying a log-linear equation with only income as an explanatory variable, the estimated income-elasticity is 0.34 for apartments and 0.40 for one- and two family houses.

[10] See Table 2.

Finally, given the explanatory power of the equations, the R^2 value shows that the equation explains only about a third of the variation in household electricity consumption. That is, electricity consumption by individual households is only partly explained by the characteristics included in the equation: other differences, like ownership and the efficiency of electric appliances, as well as habits and attitudes towards energy savings, are equally important in determining their electricity consumption.

Summing up this section, we have seen that annual electricity consumption by households varies considerably with household attributes. Knowledge of this variation is important for policy design and analyses of the distributional effects of, for example, tariffs and taxes. It is also important for grid-planning, as households with similar attributes and types of dwelling are often concentrated in specific geographical areas. In particular, the technical attributes of electric heating and ownership of an electric vehicle considerably increase the electricity consumption of a household, and the expected electrification of the heating and transport sectors will considerably affect the distribution of taxes, the future need for production, and distribution capacity. For mid-term planning purposes, first movers are especially important. Further research into linking first movers to household characteristics may give additional valuable information.

3. Hourly consumption profiles for different categories of households

In addition to annual electricity consumption, the timing of consumption also varies with household characteristics. Aggregating individual households into categories, this section compares average hourly consumption profiles for households with different attributes. For each hour of the day, we calculate the average consumption over the month and type of day. E.g. for a workday in January at 6 p.m., we calculate the average of consumption on all workdays in January at 6 p.m.. In many applications, including grid planning, the maximum and minimum consumption is equally interesting. Therefore, for a few categories of households, Appendix 1 shows the the maximum, average and minimum consumption profiles. That is, instead of taking the average over months and days, the appendix also shows the maximum and minimum consumption at specific hours on types of days and months.[11] Comparing the curves for respectively the maximum and minimum consumption, a general observation from the appendix is that the maximum-minimum variation is large especially for individual heat pumps and electric vehicles, while for households in one- and two family houses mainly the maximum consumption in December differs considerably from the average consumption. However, to illustrate how consumption profiles vary with household attributes, in this section we focus on average consumption profiles.

Looking first at types of dwellings, for similar households living respectively in apartments and one- and two-family houses, Fig. 1 shows average hourly consumption rates for months, workdays and non-workdays. Besides the level of consumption, the main difference in profiles is that the morning peak is more pronounced in one- and two-family houses than in apartments.

For age categories, Fig. 2 shows the hourly profile for one- and two-family houses with one adult, no children and the age categories 18–24 years, 25–64 years, and 65+.

The consumption profiles for young and middle-aged households are quite similar, peaking at 7 p.m. on workdays, and with a small morning peak. However, day-time consumption is lower in young households and on non-workdays, and young households start consuming slightly later than households in the middle age category. The consumption profile for the oldest age category is quite distinct: workdays and non-workdays are similar, and evening consumption peaks one hour earlier than for other age categories. In addition, the morning and day-time consumption rates are earlier and larger than for other age categories. A future higher share of older people may thus shift consumption in the direction of day-time consumption, which would coincide with the system's usual high-load hours.

Comparing the profiles for households with and without children, Fig. 3 gives profiles for two cases: young households in apartments, and the middle age category living in one- and two-family houses.

Looking at the middle age category in one- and two-family houses, the main difference between having and not having children is a morning peak and the fact that the evening peak becomes steeper. In addition, consumption in July becomes relatively lower, indicating a greater tendency to have holidays in July (school holidays). Looking at young households with one adult in an apartment, the effect of having children is a steeper evening peak one hour earlier than in households without children.

Looking at how the number of adults in households changes electricity consumption, Fig. 4 shows that the level of consumption varies, but the hourly consumption profile is almost the same.

Comparing households with and without electric heating, Fig. 5 shows that profiles are quite different and that heating implies a considerable seasonal variation in consumption.[12] In winter, heating considerably increases consumption both in the day and at night, and in all months there are slight peaks in the morning and evening, mainly caused by the consumption of hot water.

Finally, comparing households with and without electric vehicles, Fig. 6 shows that owning an electric vehicle considerably changes both the level and the hourly profile of consumption. On average, on a workday, charging of electric vehicles starts after work, when occupants come home from work, lasts for several hours, and contributes considerably to increased consumption during the night. Charging peaks from 7 p.m. to 11 p.m., then decreases gradually until the morning. There is considerable seasonal variation, as the efficiency of vehicles decreases during the cold months, implying an increase in charging. Charging in July is considerably lower than in other months. This may be due to the summer holidays, probably implying both reduced consumption and increased charging at public stations. Finally, charging on non-workdays is lower and later than on workdays.

Mathematically, the profiles shown in Figs. 1–6 can be described with:

$$c_t^i = \left(\sum_d a_d^i \cdot D_{d,t}\right) \cdot \left(\sum_m a_{d,m}^i \cdot D_{m,t}\right) \cdot \left(\sum_h a_{d,m,h}^i \cdot D_{h,t}\right) + \varepsilon_t^i \tag{2}$$

where t is time with an hourly resolution (8760 h per year), i is a category of customers, c_t^i is hourly electricity consumption, and $D_{d,\ t}$, $D_{m,\ t}$, $D_{h,\ t}$ are different binary variables (i.e. with zero/one values). $D_{d,\ t}$ includes two binary variables that represent different types of days (d) (workdays and non-workdays), $D_{m,\ t}$ represents 12 variables each representing a month (m), and $D_{h,\ t}$ 24 binary variables, each being 1 for one hour of the day (h) and zero for the other hours of the day. a_d^i, $a_{d,\ m}^i$ and $a_{d,\ m,\ h}^i$ are coefficients that describe the level and shape of the individual curves in the figures, and ε_t^i is a stochastic error term assumed distributed $i.\ i.\ d.\ N(0, \sigma^2)$.

The coefficients $a_{d,\ m,\ h}^i$ describe the shape of the daily consumption curve for one month (one of the monthly curves in Figs. 1–6). The coefficients $a_{d,\ m}^i$ describe the relative position of the monthly curve, and the coefficients a_d^i describe the average level of consumption in kWh on the type of day (workdays and non-workdays).

For a given hour t of the year, specifying the type of day (d), the month (m) and the hour (h) of the day, consumption is determined

[11] By applying data in the uploaded datafile 'hourly electricity consumption data', similar profiles may be calculated for all the analysed categories of households.

[12] Denmark is a Nordic country with cold winters and temperate summers.

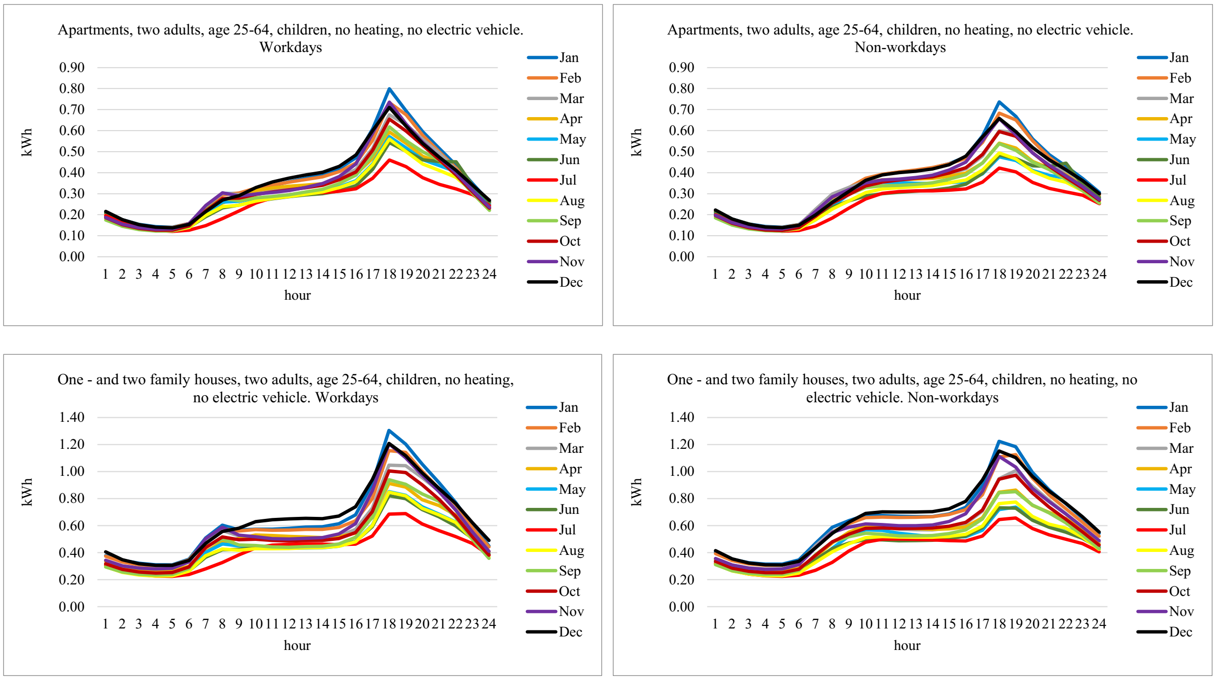

Fig. 1. Hourly consumption profiles for types of dwelling (average over days per month, 2017).

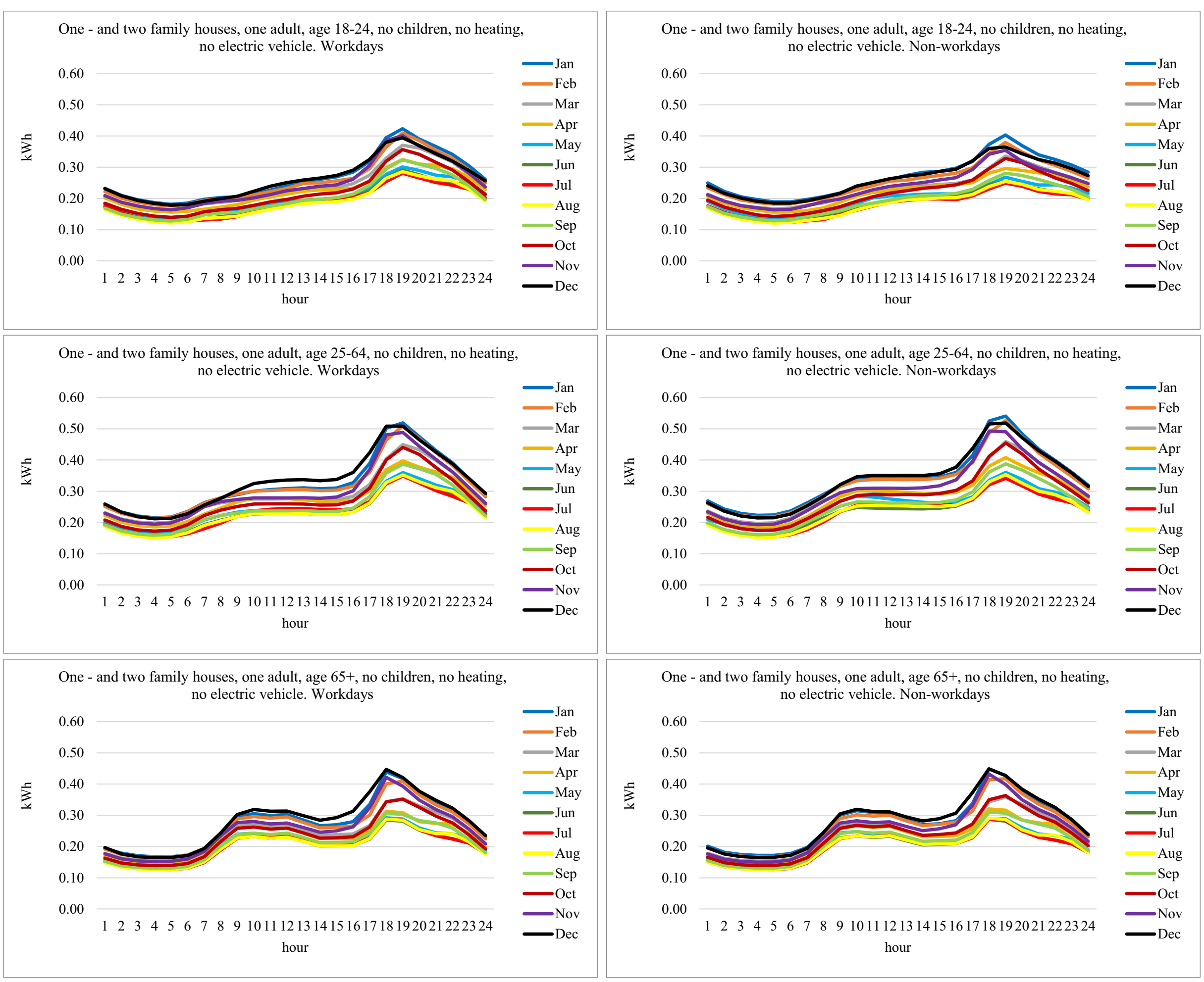

Fig. 2. Hourly consumption profiles for age categories (average over days per month, 2017).

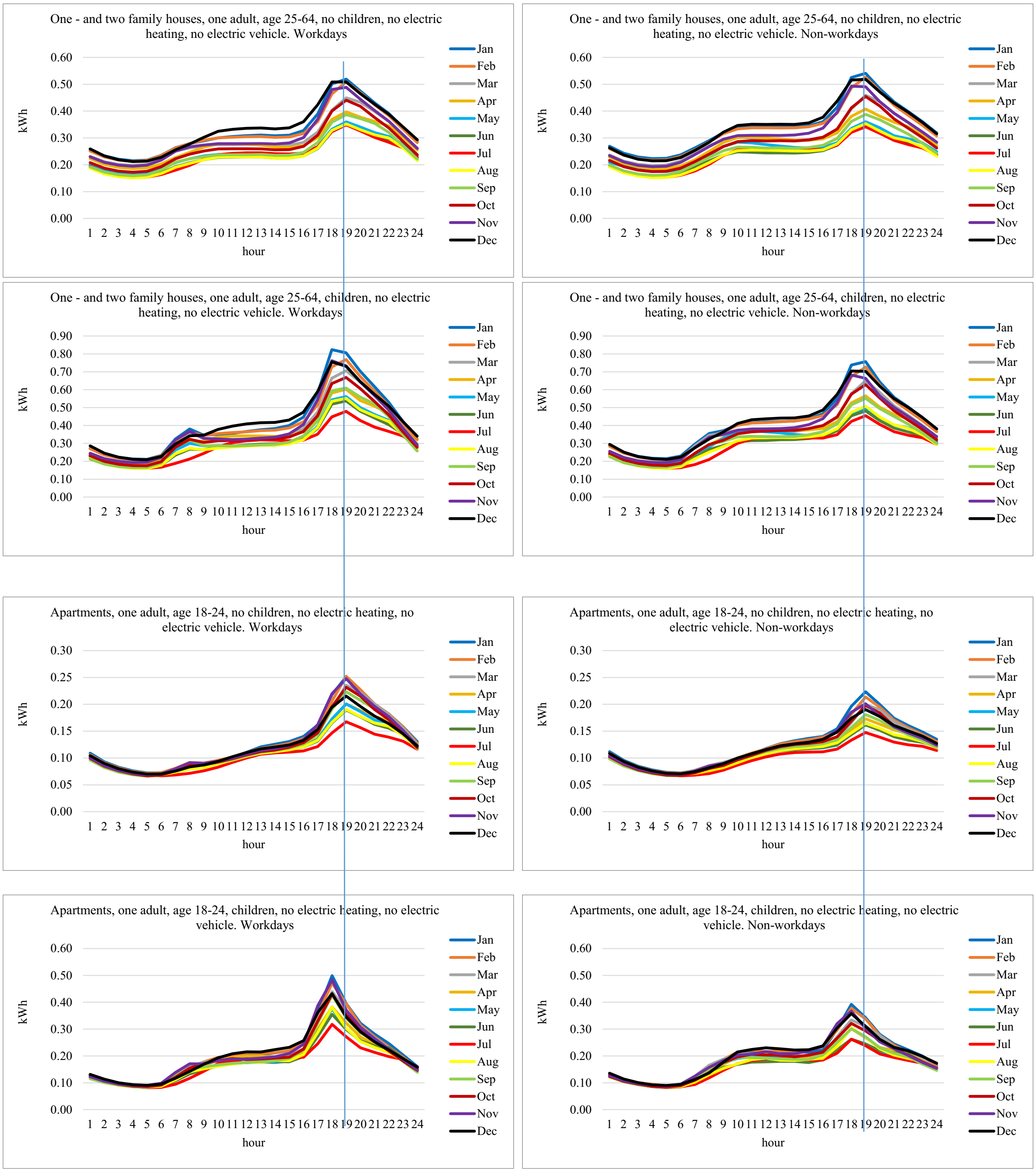

Fig. 3. Hourly consumption profiles for households with and without children (average over days per month, 2017).

using:

$$c_t^i = a_d^i \cdot a_{d,m}^i \cdot a_{d,m,h}^i \tag{3}$$

Finally, the coefficients of eq. (2) are normalised by imposing the restrictions:

for all types of days (d): $\sum_{m=1}^{12} a_{d,m}^i = 12$ and

for all types of days and months: $\sum_{h=1}^{24} a_{d,m,h}^i = 24$

which implies that for these coefficients the average is 1.0.

If for a given hour (h) and month (m) $a_{d,\ m,\ h}^i = 1.1$, for this hour consumption is 10% larger than the average consumption for the month; and if $a_{d,\ m}^i = 1.4$, consumption for that month (m) is 40% larger than the average annual consumption for the type of day. When combined, the consumption for that hour (h) and month (m) is 54% (1.1*1.4 = 1.54) larger than the average hourly consumption for the type of day (d). Finally, multiplying by a_d^i (the average hourly consumption for the type of day), we arrive at the average consumption in kWh for the specified hour: e.g. the average consumption on a workday in July at 7 p.m. or exactly one point on the curves in the figure for the specific category of customers (one point on a curve in one of Figs. 1–6).

To test whether the profiles compared in Figs. 1–6 are statistically different, eq. (2) is estimated for the two profiles simultaneously. Comparing, for example, profiles for categories of dwellings, equations for apartments and one- and two-family houses are each specified as eq. (2), and the two equations are estimated simultaneously. In the

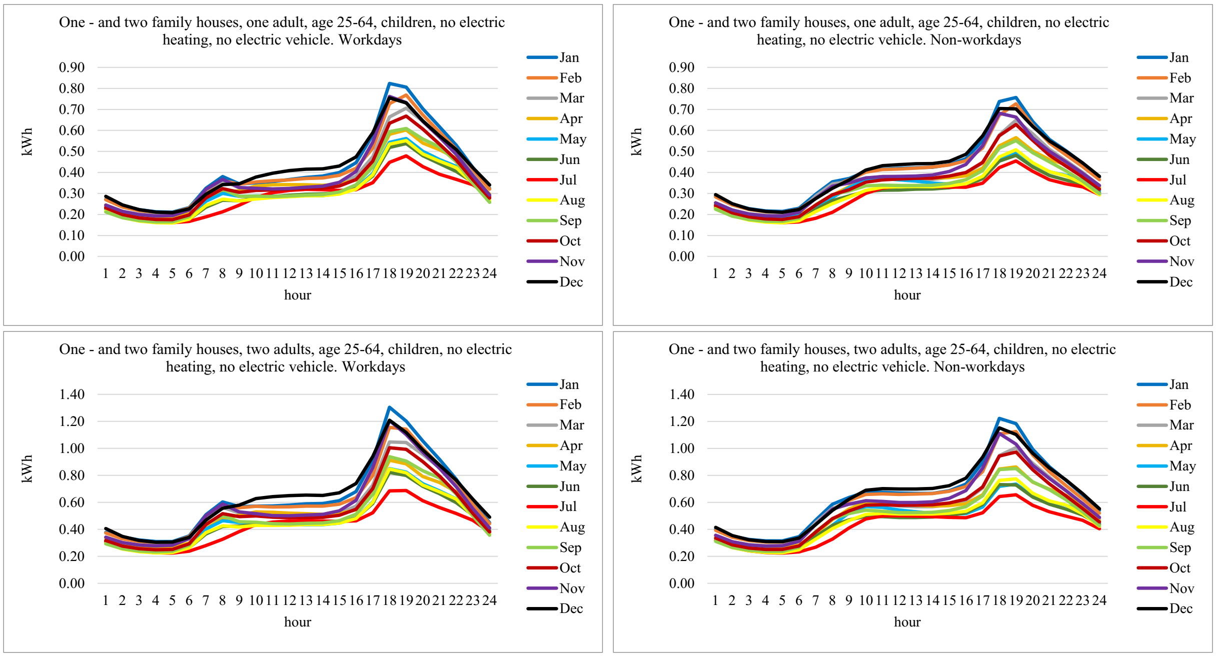

Fig. 4. Hourly consumption profiles for households with one or more adults (average over days per month, 2017).

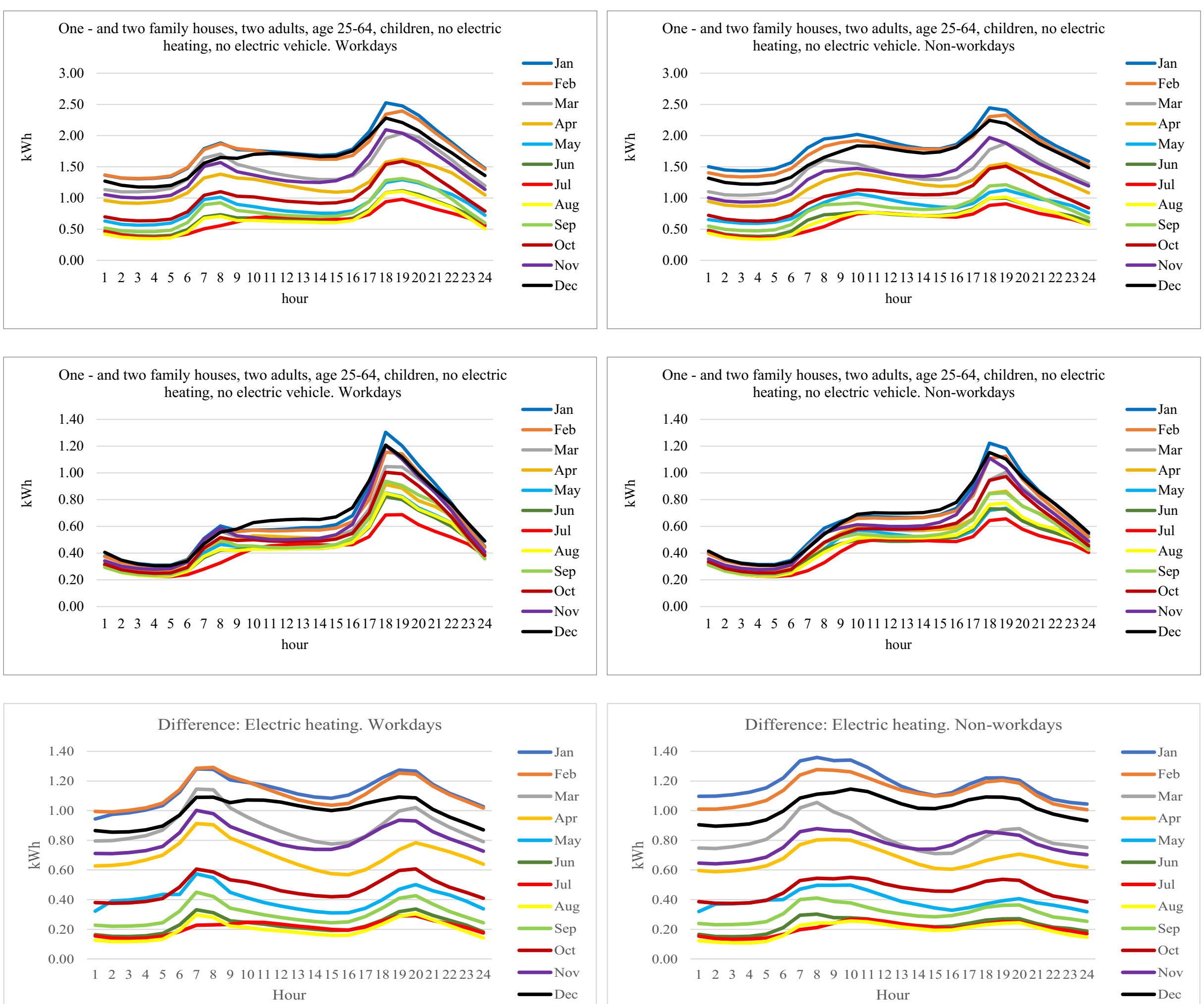

Fig. 5. Hourly consumption profile for households with and without electric heating (average over days per month, 2017).

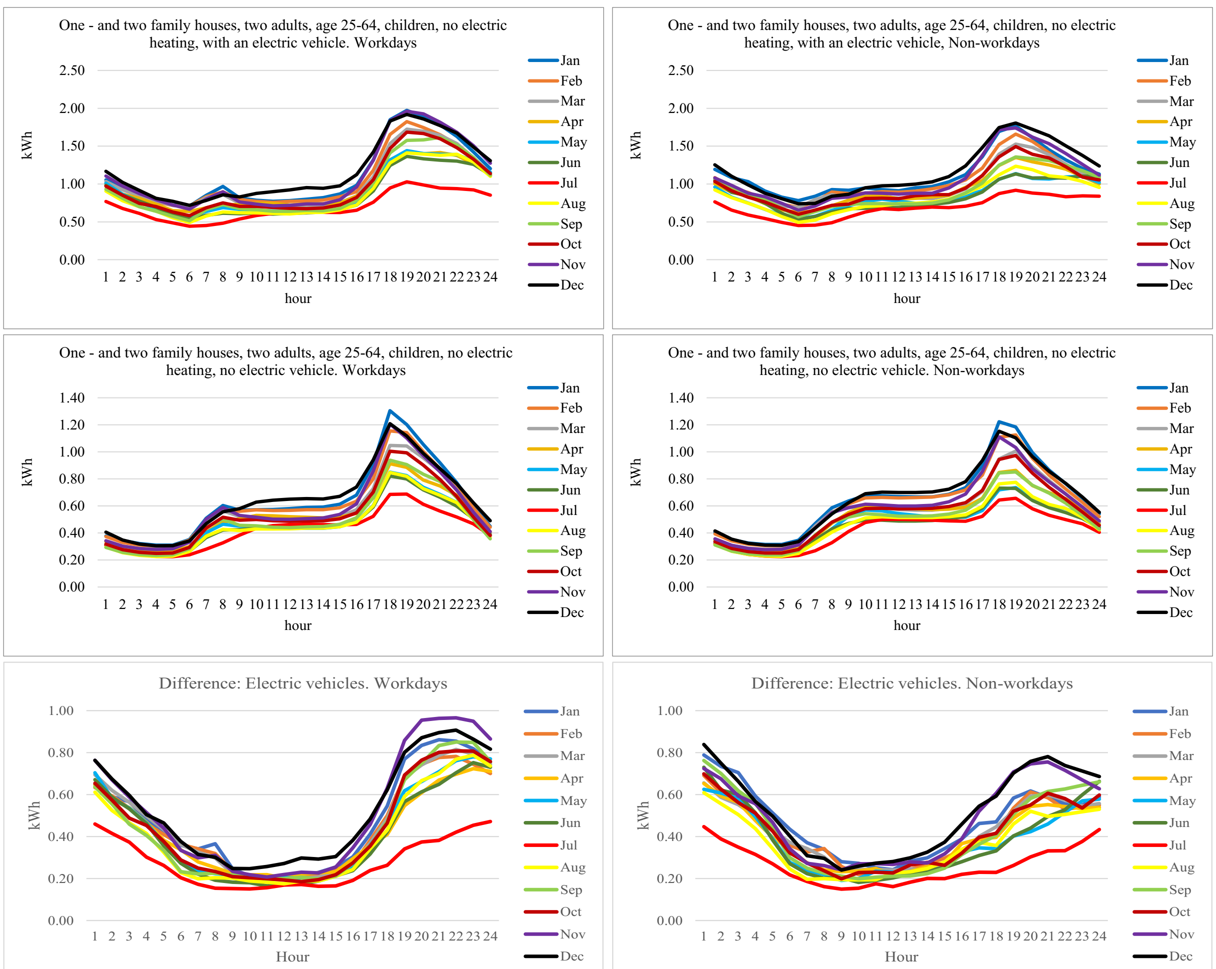

Fig. 6. Hourly consumption profiles for households with and without an electric vehicle (average over days per month, 2017).

Table 4
Tests for identical daily consumption profiles, allowing monthly levels to differ.

	Log-likelihood unrestricted model	Log-likelihood restricted model	Change in log-likelihood	χ^2_υ-value
No of parameters estimated/degrees of freedom (υ)	*1152*	*600*		*552*
Type of dwellings	38,595	30,914	−7681	15,362
No. of adults	40,928	35,589	−5339	10,678
Age 18–24 versus 25–64 years	47,763	43,279	−4484	8968
Age 25–64 versus 65+	50,806	46,645	−4161	8322
Children	35,657	30,535	−5122	10,244
Electric heating	17,940	10,932	−7008	14,016
Electric vehicles	18,723	10,951	−7772	15,544
Critical value 0.5%/0.1%				640/659

The text and figures in italic is the number of parameters estimated, the other figures in the table are log-likelihood and test values that depend on the number of parameters estimated.

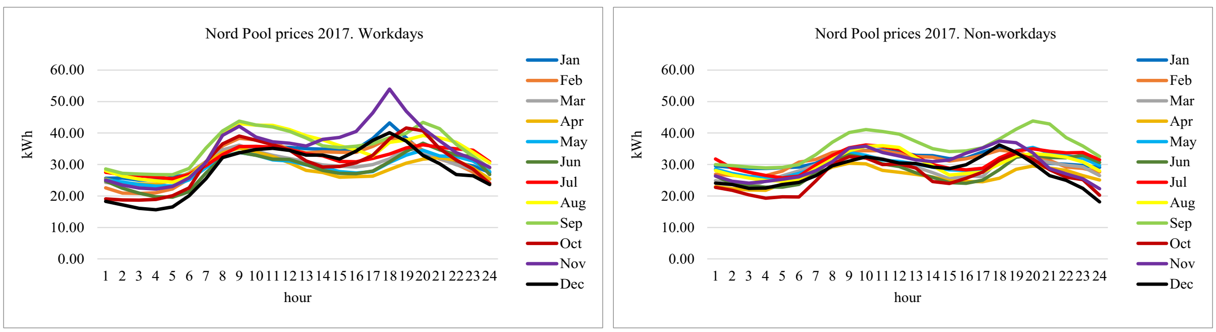

Fig. 7. Average hourly Nord Pool prices in Euro/MWh for workdays and non-workdays in Denmark, 2017.

estimates, the daily coefficients are either restricted to being identical in the two equations (the restricted model), or else the daily coefficients are allowed to differ in the two equations (the unrestricted model). That is, in the restricted model (for categories i1 and i2), the hourly coefficients in the two equations are restricted to be identical ($a^{i1}_{d,\,m,\,h} = a_{d,\,m,\,h}{}^{i2}$), but the coefficients for the level of days and months (a^i_d and $a^i_{d,\,m}$) are allowed to differ. That is, the level and seasonal variation are allowed to differ between the categories, and we only test whether the daily profiles are identical.

For the investigated profiles, the log-likelihood value for the simultaneous estimation of the two equations with and without restrictions is shown in Table 4. Using a χ^2 test, twice the absolute change in the log-likelihood is χ^2_υ, distributed with degrees of freedom (υ) equal to the number of imposed restrictions.[13] Table 4 also gives the χ^2 statistics for the estimated comparisons, the number of restrictions imposed and the critical value. The conclusion from Table 4 is that for all comparisons the daily coefficients are significantly different. Consequently, we conclude from the analysis that statistically the type of dwelling, the age and number of adults and children, the heating system, and ownership of an electric vehicle all affect the daily consumption profile of a household significantly.

As a result, in designing policy or developing a distribution grid, considering both the level and profile of electricity consumption by categories of customers may significantly improve the quality of such plans and policies. Considering grid-planning, individual grid-operators with their own portfolios of customers may weight the average consumption level and profile for detailed categories of customers to evaluate future loads in specific parts of their grid. The figures and the test in Table 4 show that households with electric heating and electric vehicles in particular have quite distinct hourly consumption profiles. Looking at these profiles and considering the planned electrification of the heating and transport sectors, the aggregated consumption profile is expected to change considerably, and in particular, consumption during the winter, the evenings and at night is expected to increase. For grid-planning purposes, consumption during peak hours is especially important. For example, the charging of electric vehicles will contribute moderately to the peak consumption period of 5–6 p.m. However, simultaneously most electric vehicles are charged later in the evening, so that the charging profile peaks at 7–11 p.m. and declines gradually till the morning. For policies targeting demand flexibility, the importace of the charging profile for electric vehicles is that charging may be postponed for a couple of hours but still produce fully charged vehicles the next morning.

4. Cross-subsidies between residential customers

Almost all residential customers in Denmark are charged a flat rate for their electricity consumption, regardless of the time of use. Theoretically this is inefficient because the price does not reflect the marginal cost of producing electricity, and for optimal resource allocation, real-time pricing is more efficient. Furthermore, as the hourly consumption profile varies significantly between customers and the price/marginal cost of electricity varies hour by hour, flat-rate pricing implies cross-subsidies from residential customers consuming mainly in cheap hours to customers consuming mainly in expensive hours. In addition, large cross-subsidies may imply considerable resistance to switching to hourly pricing, as some customers will lose the cross-subsidy they have under flat-rate pricing. To analyse the size of cross-subsidies between Danish residential customers, in this section we apply the individual consumption profiles and calculate the average price per kWh residential customers would have paid had they been exposed to hourly market

[13] The test-statistic $-2 \cdot [\ln L_R - \ln L_U] \approx \chi^2_\upsilon$. That is, twice the change in the log-likelihood of the restricted and unrestricted estimates is χ^2 distributed with degrees of freedom (υ) equal to the number of restrictions imposed. See Greene (1997) or Madsen (2007).From Harnett (1975) we have for large values of υ that $\chi^2_\upsilon = \frac{1}{2}\left[z_\alpha + \sqrt[2]{(2\upsilon - 1)}\right]^2$ where z_α is the critical value from the normal distribution and υ is the degrees of freedom equal to the number of parameter restrictions imposed on the equation. For the significance level $\alpha = 2.5\%$: $z_\alpha = 1.96$, and for $\alpha = 0.5\%$: $z_\alpha = 2.58$.

Table 5
The average Nord Pool price for categories of Danish customers in 2017.

	Without electric heating						With electric heating					
Euro/MWh	1 adult			2 or more adults			1 adults			2 or more adults		
Apartments in multifamily houses	18–24 years	25–64 years	65+ years	18–24 years	25–64 years	65+ years	18–24 years	25–64 years	65+ years	18–24 years	25–64 years	65+ years
No childern	31.78	31.67	32.10	32.29	32.08	32.32	31.27	31.36	31.53	31.55	31.62	31.86
Children	32.29	32.16	31.87	32.38	32.22	32.08	na	31.62	na	na	31.76	na
One- and two family houses												
No childern	31.49	31.52	31.90	31.89	31.82	32.12	31.19	31.29	31.42	31.44	31.50	31.65
Children	32.13	31.92	31.72	32.07	31.99	31.93	31.86	31.53	31.63	31.74	31.62	31.57
No children and EV					31.24							
Children and EV					31.32							

Table 6
Estimation results for the average Nord Pool electricity price paid by households in types of dwellings in Euro per MWh (robust standard error in brackets).

Price per kWh (euro/MWh)		Constant	Income	More than one adult	Children	Age 18–24	Age 65+	Electric vehicle	R^2
Apartments (184,575 husholds)	without electric heating	32.000 (0.004)	−0.034 (0.003)	0.349 (0.004)	0.336 (0.005)	0.200 (0.006)	0.374 (0.004)	−0.478 (0.135)	0.10
	with electric heating	31.677 (0.030)	−0.043 (0.026)	0.300 (0.036)	0.259 (0.039)	−0.073 (0.057)	0.228 (0.031)		
One- and two family houses (482,798 households)	without electric heating	31.942 (0.003)	−0.109 (0.002)	0.276 (0.002)	0.250 (0.002)	0.036 (0.012)	0.325 (0.003)	−0.418 (0.038)	0.07
	with electric heating	31.669 (0.008)	−0.123 (0.007)	0.260 (0.007)	0.190 (0.007)	−0.080 (0.036)	0.130 (0.007)		

prices in 2017. Furthermore, we look at the characteristics of customers who would become better or worse off by switching to hourly pricing.

Fig. 7 shows the hourly Nord Pool market prices for Denmark in 2017, averaged monthly for each hour of the day. General observations from the figure are that prices are low during the night, have slight peaks in the morning and evening, and are generally slightly higher on workdays than on non-workdays. In addition, there is a slight seasonal variation, with higher prices during winter 2017. That is, households that consume relatively large shares of their electricity consumption during the night, on non-workdays and in the summer will gain from hourly pricing, whereas households with relatively large consumption during the afternoon and early evening peak on workdays will lose from hourly pricing. Under flat-rate pricing, however, they will benefit from an implicit cross-subsidy covered by other residential customers.

Combining consumption profiles and the Nord Pool hourly prices, under hourly pricing the average wholesale price per kWh $\overline{p}^i$ is calculated using:

$$\overline{p}^i = \left(\sum_{t=1}^{t=8760} p_t \cdot c_t^i\right) \Big/ \sum_{t=1}^{t=8760} c_t^i \tag{4}$$

where p_t is the Nord Pool electricity price at hour t, and c_t^i is the hourly consumption by category i.

For different categories of customers, Table 5 shows the resulting average price in Euros per MWh.

The overall observations from Table 5 are:

- Households with children have a more expensive consumption profile than households without children. In particular, young households with children have an expensive consumption profile.
- Households living in apartments have a slightly more expensive profile than households living in one- and two-family houses.
- Households with electric heating have a less expensive consumption profile.
- In particular, households with an electric vehicle have a less expensive consumption profile.
- The main observation is that, given the hourly prices for 2017, the variation in the average price paid by categories of customers with different consumption profiles is quite limited.

Applying eq. (4) to individual households, under hourly pricing, the equation calculates the average kWh price that an individual household would have paid for its specific consumption profile in 2017. Looking at the variation between households, except for a few extreme profiles (typically with low consumption), 98% of households pay an average price per kWh ±6%.

Analysing the links between household attributes and the average price, an equation similar to eq. (1), but with the average kWh price paid by individual households as the dependent variable, is formulated using:

$$\overline{p}^i = \left[\alpha_{0,nh} + \alpha_{y,nh} \cdot y^i / y^{avg} + \alpha_{ad,nh} \cdot D_{ad}^i + \alpha_{ch,nh} \cdot D_{ch}^i + \sum_{age=2}^{age=3} a_{age,nh} \cdot D_{age}^i\right] \cdot D_{nh}^i$$
$$+ \left[\alpha_{0,wh} + \alpha_{y,wh} \cdot y^i / y^{avg} + \alpha_{ad,wh} \cdot D_{ad}^i + \alpha_{ch,wh} \cdot D_{ch}^i + \sum_{age=2}^{age=3} a_{age,wh} \cdot D_{age}^i\right] \cdot D_{wh}^i$$
$$+ \alpha_{ev} \cdot D_{ev}^i + \varepsilon^i \tag{5}$$

where $\overline{p}^i$ is the average price in Euro/MWh household i would have paid for its consumption profile in 2017 under hourly pricing. That is, under hourly pricing eq. (5) describes the links between household attributes and characteristics, and the average kWh price paid by individual households, or which household characteristics are related to receiving or paying a cross-subsidy under flat-rate pricing.

Estimation results for eq. (5) for households living in apartments and one- and two-family houses respectively are reported in Table 6.

The estimates show a small negative coefficient for income, implying that a high income means a slightly lower average electricity price. That is, on average, households with large incomes have consumption profiles with a relatively large share of consumption in cheap hours, while households with low incomes have consumption profiles with a relatively large share of consumption in expensive peak hours. Similarly, households with more than one adult and children have relatively expensive consumption profiles, and both young and old households without electric heating have more expensive consumption profiles than households in the middle age group.

Comparing households with and without electric heating, and looking at the constant term, we find that households with electric heating have less expensive consumption profiles. Although the difference between the constant terms is statistically significant, the difference is minor. However, the effects of all variables imply a less expensive profile for households with electric heating, e.g. the coefficient for income is more negative if households have electric heating, and the coefficients for children, additional adults and the age dummies are all smaller if the household has electric heating. Finally, as already observed above, an electric vehicle implies a less expensive consumption profile. That is, under flat-rate pricing households with low incomes, children and both young and elderly occupants without electric heating and an electric vehicle in general benefit from an implicit cross-subsidy covered by high-income, middle-aged households without children and with electric heating and an electric vehicle.

In conclusion, as shown in Tables 5 and 6, the average price per kWh does vary between categories of customers, and for individual residential customers the variation is somewhat larger. Consequently, a flat rate does generate cross-subsidies between residential customers, but for 98% of households the size of the cross-subsidy is quite marginal.[14] Therefore, for residential customers in Denmark, switching from a flat rate to hourly pricing should create minimal resistance. That is, given the implementation of hourly metering, hourly pricing could be introduced to improve system efficiency. Flexible customers and the system will benefit from hourly pricing (reducing the costs of and need for generation and distribution capacities), while non-flexible customers will be affected only marginally.

5. Conclusions

Households are heterogeneous customers that consume different amounts of electricity for different purposes and at different hours of the day. For purposes of planning and policy design, it is important to understand how the level and timing of consumption are related to household attributes and how they may change in the future.

Analysing smart-meter data from 667,000 Danish households by linking electricity consumption to household attributes, we show that annual consumption varies considerably with the type of dwelling, the number of adults and children in the household, the heating system, and ownership or not of an electric vehicle. Also, household income and the age of the adults in the household affect electricity consumption, but the size of these effects is limited. Overall, for aggregated categories of households, annual electricity consumption in Denmark varies by a factor of ten from 1032 kWh to 12,266 kWh. Therefore, information on household attributes is quite important in grid-planning, e.g. evaluating the need for grid enforcements in areas where new dwellings are being developed. In particular, electric vehicles and individual heat pumps are expected to increase future household consumption, thus affecting the need for production and distribution capacities.

Analysing the timing of consumption, the type of heating system and ownership of an electric vehicle particularly affect the timing of consumption, but the age of adults and children also affects the consumption profile. Electrification of the heating and transport sectors is therefore expected to change aggregated consumption profiles considerably, and will become of great concern for future grid-planning. As shown by Figs. 5 and 6, the load will increase especially during the winter evenings and at night. However, the two technologies affect the aggregated load profile quite differently and therefore also the need for generation and distribution capacities. Consumption in peak hours is still expected to increase considerably, but the flexibility of individual heat pumps and the charging of electric vehicles may assist in reducing the need for additional production and distribution capacities.

As individual consumption profiles differ significantly and hourly market prices vary, flat-rate pricing implies cross-subsidies between customers. Economically, real-time pricing that gives flexible customers an incentive to react to the varying production costs of electricity is more efficient. However, switching from a flat rate to hourly pricing implies some customers losing a cross-subsidy, which they may resist. For Danish households, assuming hourly pricing and unchanged timing of consumption, we estimate the impact of hourly pricing on the average kWh price to be only marginal. For aggregated categories of households, the difference in the average price is less than 4%, while for 98% of individual households the variation is less than $\pm 6\,\%$. As a consequence, switching Danish residential customers from a flat rate to hourly pricing would not greatly affect their electricity bills. Assuming smart meters are installed, policy-makers may therefore make use of hourly pricing to provide incentives for flexible customers and improve economic efficiency without having to be strongly concerned about the distributional impacts.

Credit author statement

F.M. Andersen made most of the writing, modelling/estimation of equations and calculations.

P.A. Gunkel contributed significantly to the writing and developing the idea of the paper and especially to handling of the large amount of data analysed.

H.K. Jacobsen and L. Kitzing contributed considerably to the writing and developing the idea of the paper, the policy analysis and some of the calculations.

Acknowledgement

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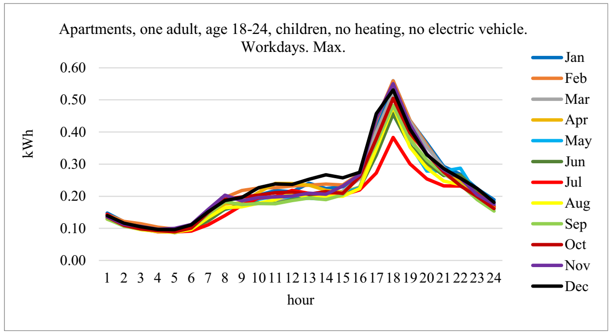
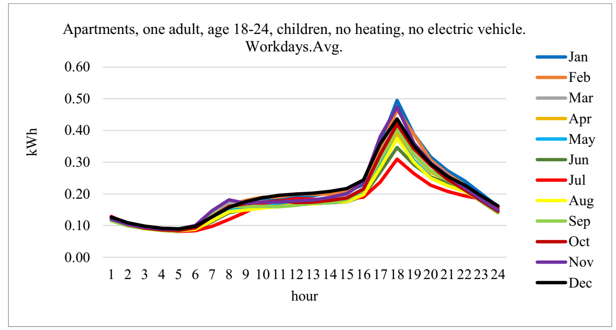
Appendix A. Appendix 1. Consumption profiles for categories of customers. Maximum, average and minimum consumption over hours for months and types of days

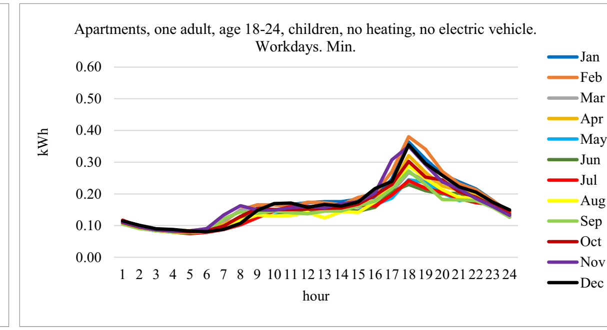
[14] Less than ±6% of the wholesale market price, which for residential customers in Denmark is less than a third of the price they pay for electricity.

Maximum	Average	Minimum

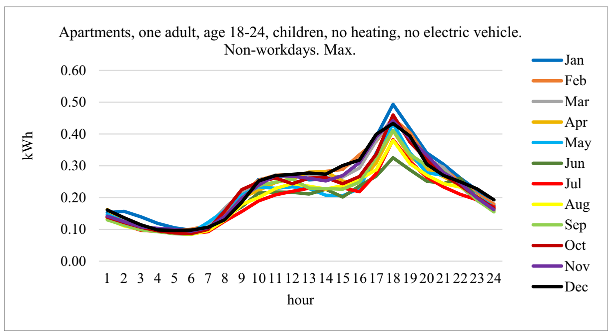
Apartments, one adult, age 18–24, children, no heating, no electric vehicle. Workdays

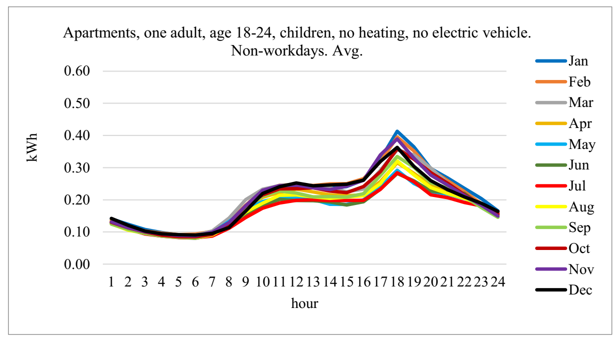


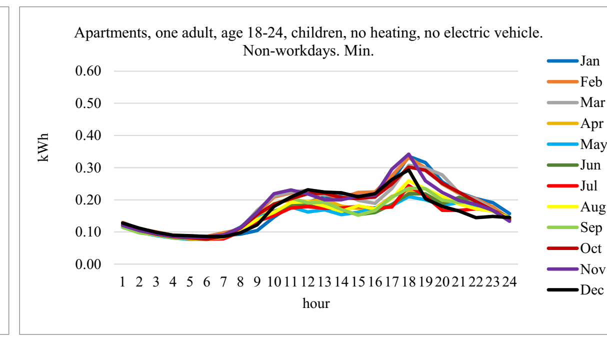




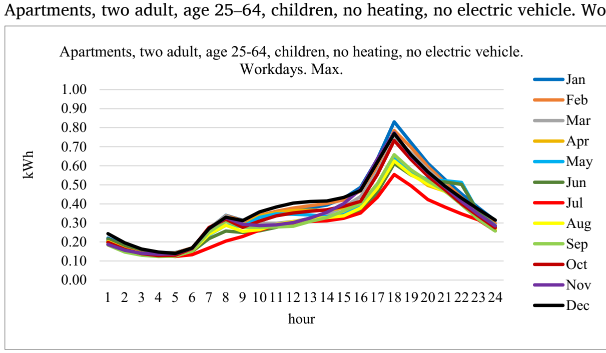
Apartments, one adult, age 18–24, children, no heating, no electric vehicle. Non-workdays

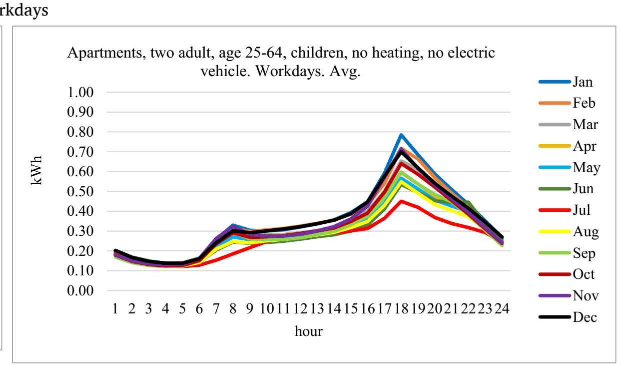


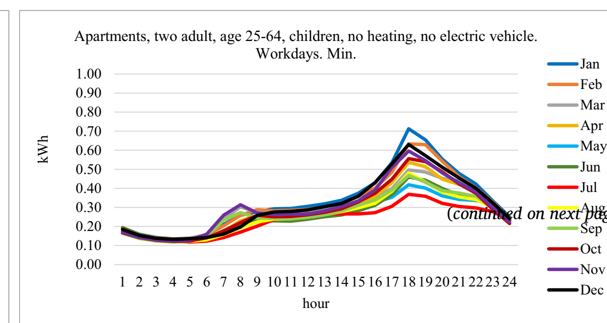




Apartments, two adult, age 25–64, children, no heating, no electric vehicle. Workdays







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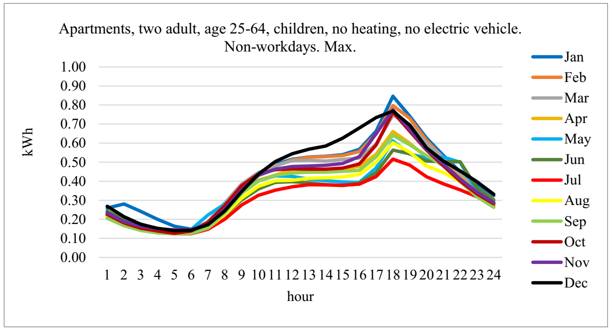
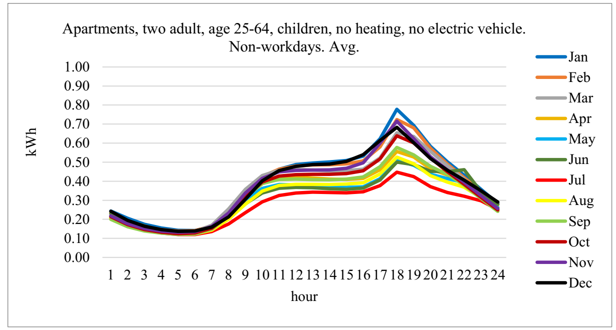
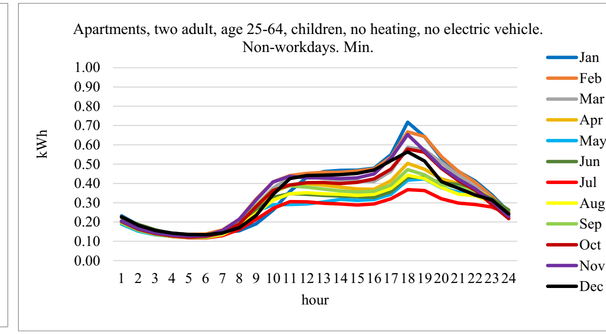
Maximum	Average	Minimum

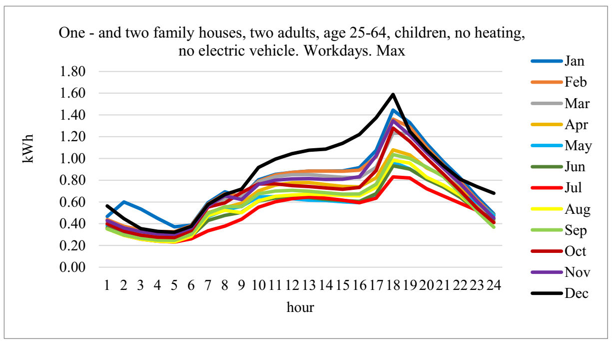
Apartments, two adult, age 25–64, children, no heating, no electric vehicle. Non-workdays

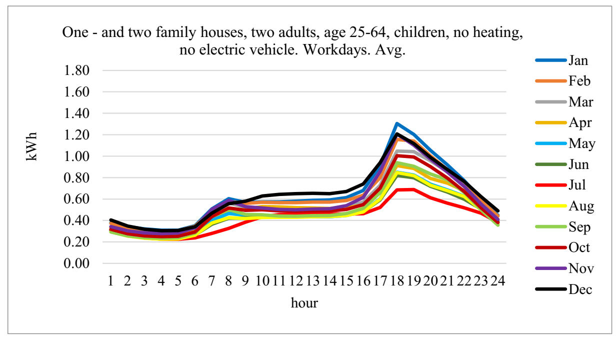


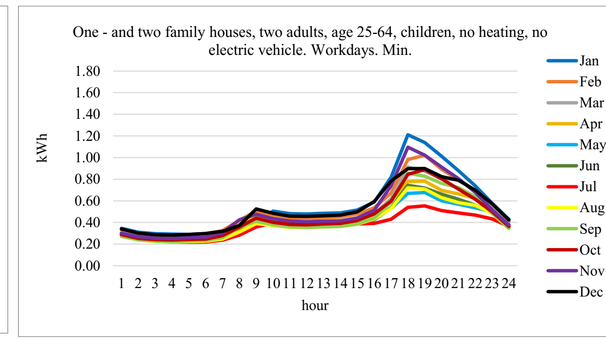




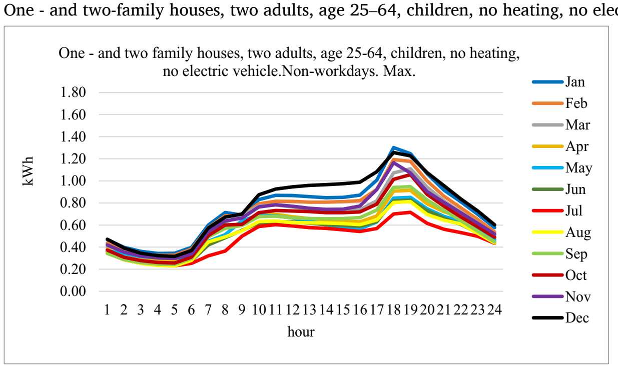
One - and two-family houses, two adults, age 25–64, children, no heating, no electric vehicle. Workdays

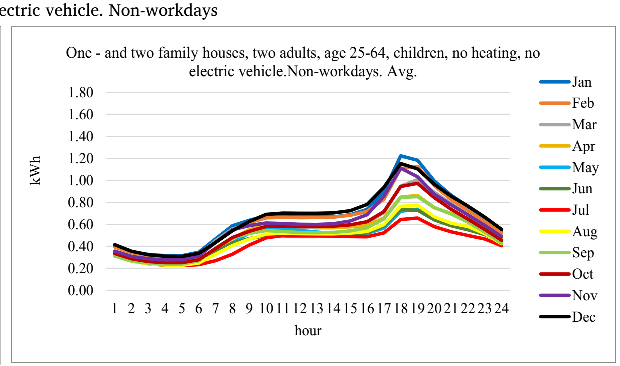


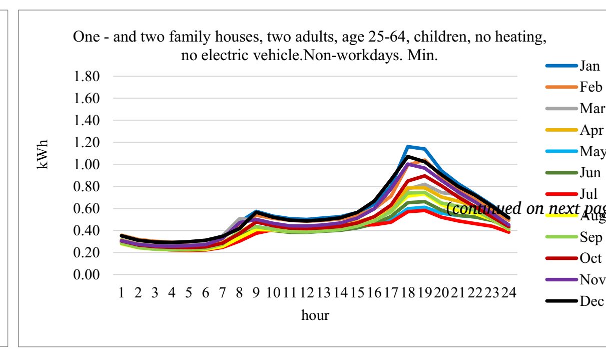




One - and two-family houses, two adults, age 25–64, children, no heating, no electric vehicle. Non-workdays







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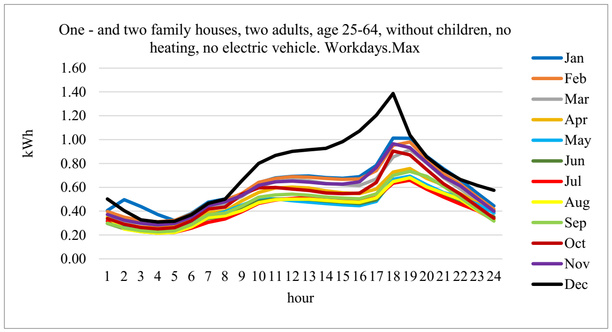
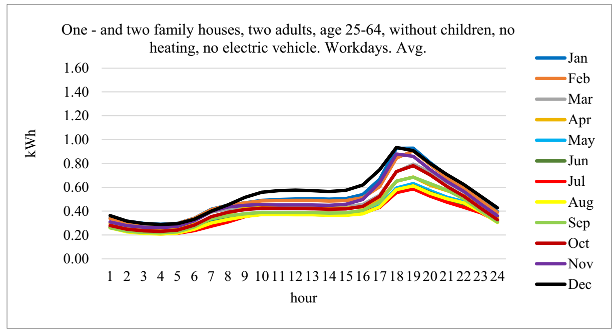
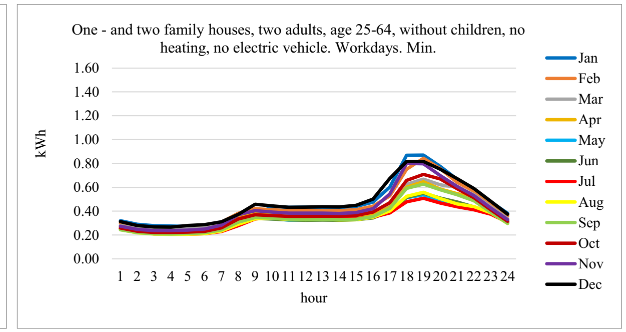
Maximum	Average	Minimum

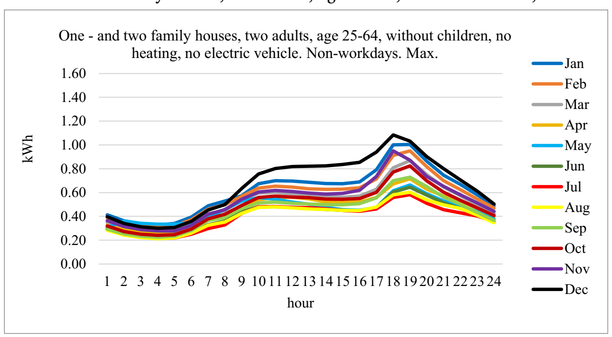
One - and two-family houses, two adults, age 25–64, without children, no heating, no electric vehicle. Workdays

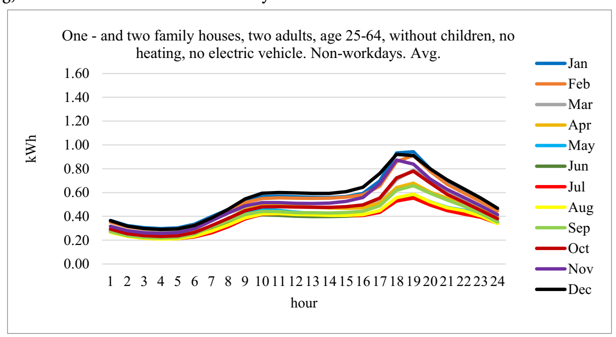


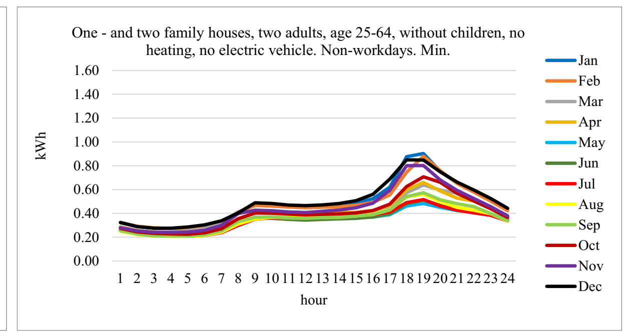




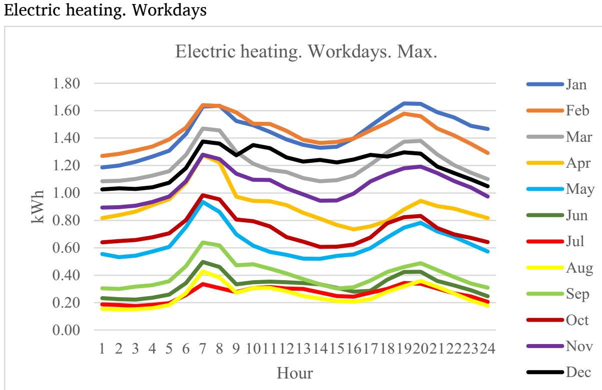
One - and two-family houses, two adults, age 25–64, without children, no heating, no electric vehicle. Non-workdays

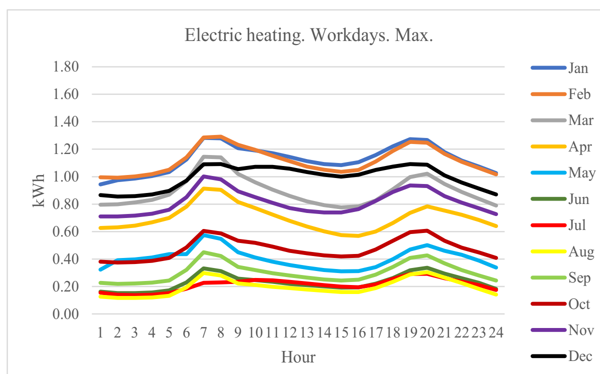


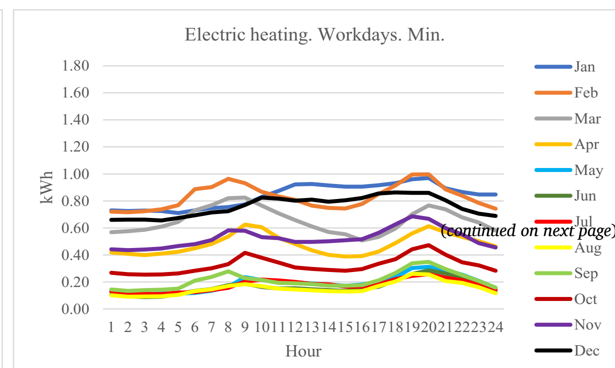




Electric heating. Workdays







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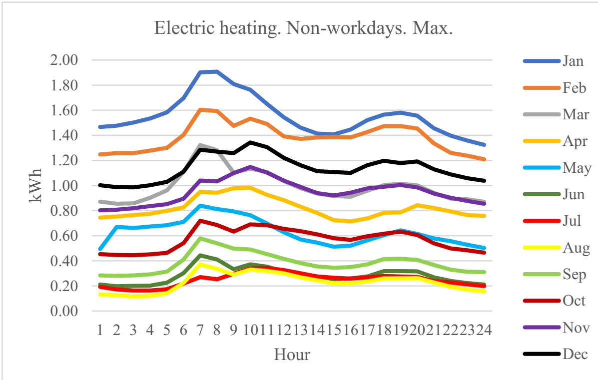
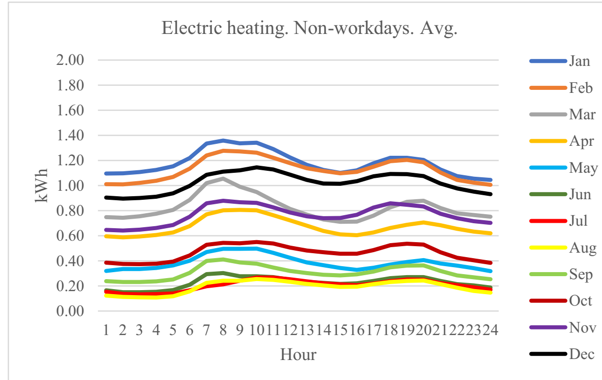
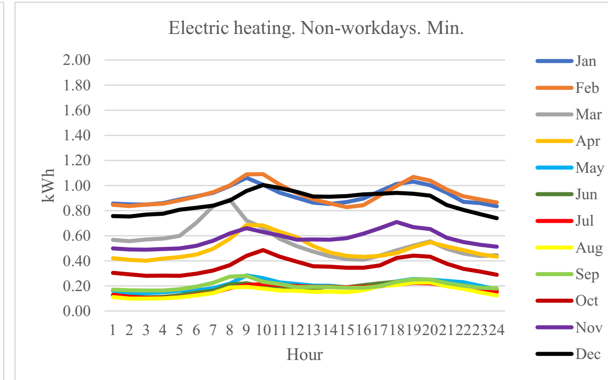
(*continued*)

Maximum	Average	Minimum

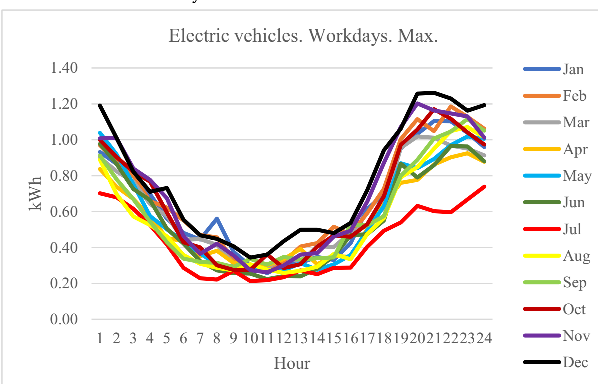
Electric heating. Non-workdays

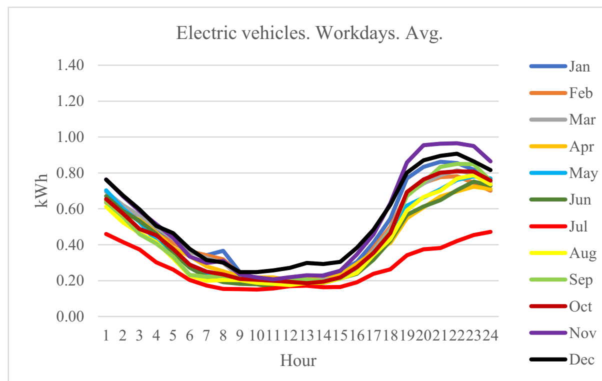


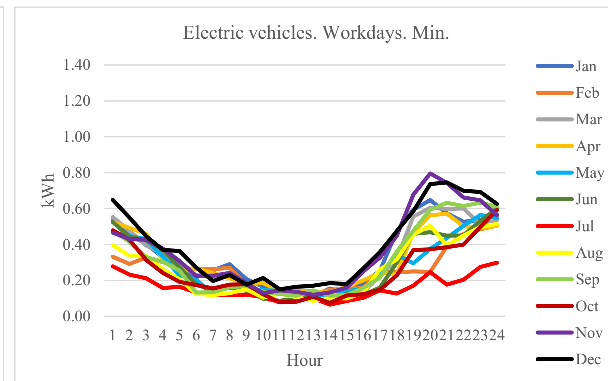




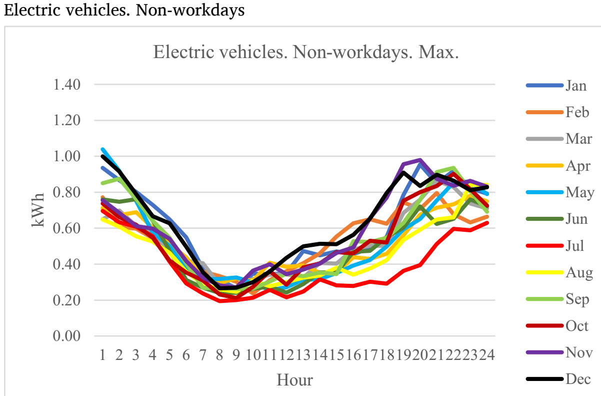
Electric vehicles. Workdays

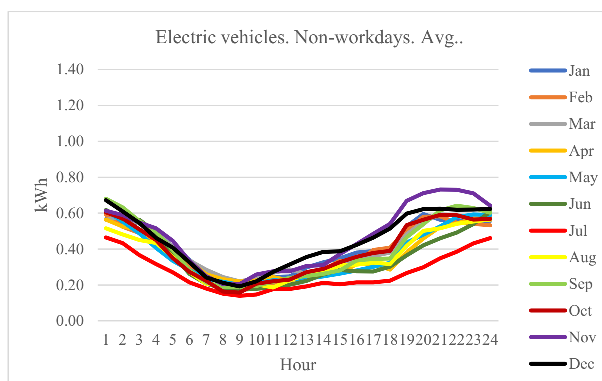


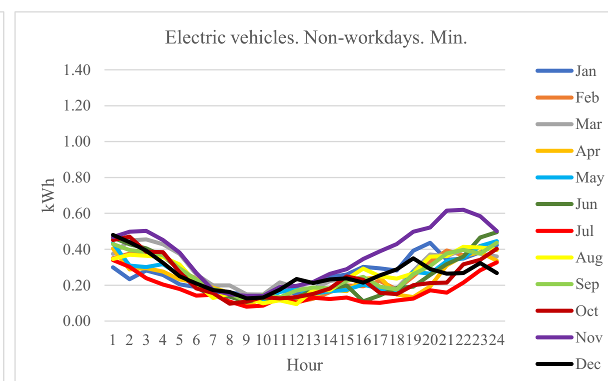




Electric vehicles. Non-workdays







Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2021.105341.

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