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Who Produces the Peaks? Household Variation in Peak Energy Demand for Space Heating and Domestic Hot Water

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Abstract: Extensive research demonstrates the importance of user practices in understanding variations in residential heating demand. Whereas previous studies have investigated variations in aggregated data, e.g., yearly heating consumption, the recent deployment of smart heat meters enables the analysis of households' energy use with a higher temporal resolution. Such analysis might provide knowledge crucial for managing peak demand in district heating systems with decentralized production units and increased shares of intermittent energy sources, such as wind and solar. This study exploits smart meter heating consumption data from a district heating network combined with socio-economic information for 803 Danish households. To perform this study, a multiple regression analysis was employed to understand the correlations between heat consumption and socio-economical characteristics. Furthermore, this study analyzed the various households' daily profiles to quantify the differences between the groups. During an average day, the higher-income households consume more energy, especially during the evening peak (17:00–20:00). Blue-collar and unemployed households use less during the morning peak (5:00–9:00). Despite minor differences, household groups have similar temporal patterns that follow institutional rhythms, like working hours. We therefore suggest that attempts to control the timing of heating demand do not rely on individual households' ability to time-shift energy practices, but instead address the embeddedness in stable socio-temporal structures.

Keywords: peak energy usage; energy demand; energy flexibility; district heating; occupant behavior; energy practices; smart heat meters

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1. Introduction

The building sector is responsible for nearly 45% of global CO_2 emissions, and the energy used for domestic hot water (DHW) production and the heating of spaces constitutes the largest share of these emissions [1]. Individual heat pumps and collective heating systems, also known as district heating (DH) systems, are sustainable, cost- and energy-effective methods for supplying heat to buildings, especially in densely populated areas [2]. However, the foundation of the decarbonization process of electrical grids and DH systems is the growing use of intermittent renewable energy (RE), such as solar energy and wind [3,4]. Increasing the share of RE challenges the operation of energy systems and requires greater insight into fluctuations in production as well as demand. Where energy production previously tended to follow energy demand [5,6], for example, by activating fossil-fuel boilers during peak-load periods, the demand side now needs to offer more temporal flexibility to match the variability in RE production [7]. This new approach to controlling and operating energy systems calls for in-depth insight into the patterns and mechanisms of energy demand. Demand response tools such as price incentives [8] and energy scheduling [9,10] depend on an understanding of the energy practices of users in order to reduce uncertainties as well as align comfort expectations and demand patterns. Knowing how energy peaks are constituted, and which occupant practices contribute the most to creating peaks, becomes increasingly important for energy system operators seeking to balance energy supply and demand [11–13]. As the building envelope becomes more energy efficient (a result of stricter requirements in national building regulations), the share of DHW in total household energy demand is increasing [14–16]. Furthermore, the timing of DHW usage can cause significant peak demand at very specific periods, especially in the morning or in the evening when households use a significant quantity of hot water for baths and showers [17,18]. This may impair the stability and reliability of energy grids. The metered heat data reflect practices related to space heating, such as heating and comfort practices [19,20], as well as DHW usage, such as showering and personal hygiene [18], where the shower and kitchen taps are found to constitute around 90% of the total DHW usage [21]. Thus, the data result from a complex interaction between occupants, building physics, and heating systems, particularly the components responsible for the indoor temperature adjustment and the use of DHW (see Figure 1).

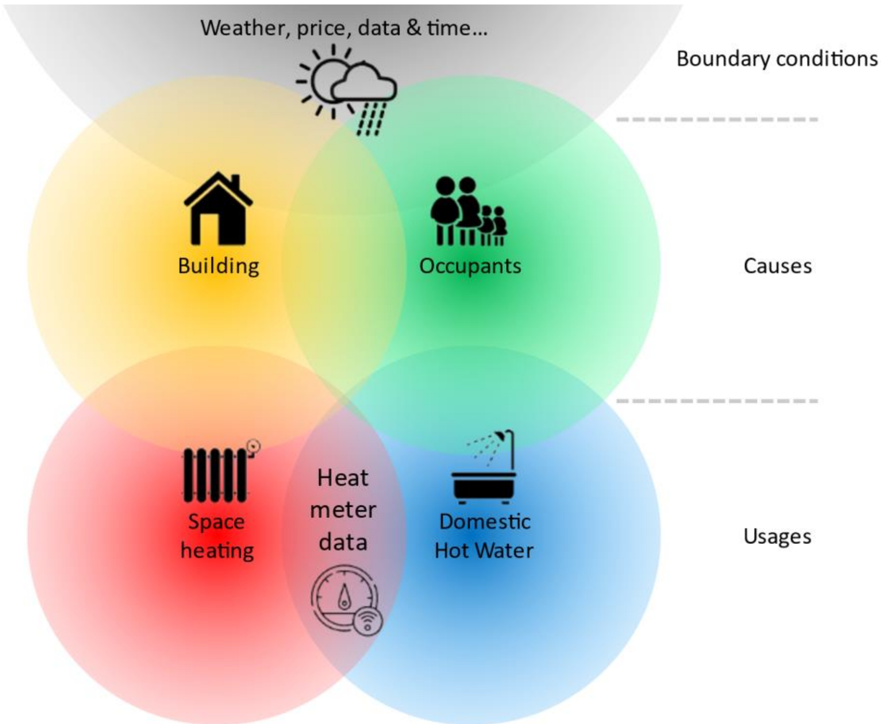

Figure 1. Conceptual representation of interactions between various factors influencing residential heat demand. One should note that the share of DHW and space heating in the total building heat demand varies significantly from buildings to buildings, depending on the occupants' habits and the energy performance of the building envelope [14,16,21].

Recent studies estimate that explanations for variation in residential heating demand can be found more or less equally in buildings and occupants [16,22]. Household characteristics, such as income, demographics, and family composition, are found to explain some of the energy use variations related to occupants [23–29]. The deployment of smart meters and the collection of hourly energy use data provide a unique opportunity to gain a deeper understanding of energy consumption dynamics during the day. Several studies have shown the potential of such high-temporal-resolution energy consumption data for better understanding temporal patterns in energy demand. For example, various clustering techniques have been applied to identify typical groups of load patterns [30–35] and to investigate heterogeneity regarding building and occupant characteristics in daily load patterns [17,36–39]. An effort was also made to make the smart heat data accessible to the research environment [40] and thereby foster an interest in this dynamic heat data, which from 2027 will be available for all buildings connected to DH networks

[41]. However, to the authors' knowledge, no previous studies have investigated daily residential heating consumption together with socio-economic characteristics. This paper taps into the potential of the hourly smart heat meter data correlated with the socio-economic data of the households, delivering an in-depth understanding of how heat consumption is shaped by household characteristics.

Novelty and Contribution of the Present Study

This paper contributes in the following three ways:

Development of the unique hourly-based dataset combining the household's dynamic energy use for heating (readings from smart heat meters) with data from administrative registers, including building characteristics and socio-economic characteristics of the household occupants, such as occupation (blue- and white-collar, pensioner, unemployed); age of the youngest child (no child, pre-school child (0 to 6 years), young child (7 to 12 years), teenager (13 to 19 years)); age of the oldest adult (18 to 40 years, 41 to 50 years, 51 to 60 years, 61 to 70 years, 71 years or older); household income (DKK <300,000, DKK 300,000 to 399,999, DKK 400,000 to DKK 499,999 500,000 to 599,999, DKK 600,000 to 699,999, DKK <700,000).

Application of a novel methodological approach to investigate the correlation of hourly and daily variations in residential heating use for space heating and DHW with the novel dataset (including smart heat meters readings and detailed information on household and building characteristics from administrative registers) for each month of the Danish heating season (i.e., from October to March).

Delivery of new knowledge on what contributes to domestic heating peaks and to what degree peaks can be explained by household characteristics, specifically the four features of occupation, household composition, age, and income.

This study builds on the assumption that household categories related to, for example, occupation and income, reflect variations in household energy practices. This assumption is supported by previous studies on the temporality of energy practices [42,43], which describe social-temporal rhythms of showering [18], space heating [44], and family practices [45].

The paper is structured as follows: Section 2 presents a review of relevant studies previously conducted on the topic. Section 3 continues with a description of the dataset and methodology used. Section 4 presents the results, with four subsections dedicated to the socio-economic parameters and a final subsection focusing on morning and evening peaks. Finally, the results are discussed and related to future policy and research.

2. Background

To what extent variations in residential heating are explained by building characteristics versus occupants' behavior is a well-established discussion in energy research [19,46]. A recent study replicating the method of a former study suggests that occupants and buildings are equally important [16,47]. Other studies support the importance of occupant behavior and practices in residential heating demand [22,25,27,48–50]. This is especially useful in attempts to explain the discrepancy between predicted and actual energy use [51–53]. Although the division between occupants and buildings appears simplified, it makes one point clear: *what* occupants do and *how* they interact with the built environment in everyday household practices are crucial for understanding household energy consumption patterns [25,46].

Numerous studies have sought to understand how occupant characteristics and their variations affect the amount of energy used for heating in residential buildings [54]. Several studies show how energy consumption relates to activities such as opening windows or regulating thermostats [55–58], and how residential heating consumption is correlated with socio-economic characteristics, such as income, education, and occupation [23,25,27–29,59], as well as with household characteristics, such as age, children, and gender [24,60]. The importance of household characteristics in combination with contextual factors, such as the impact of energy prices, price subsidies, and weather, is also well-established empirically [61–66]. Analysis of a national survey conducted among English homes also suggests variation in the timing of heating among households [67].

Where the studies mentioned above rely primarily on quantitative methods, there is a rich social science literature applying qualitative methods to describe how social conventions of thermal comfort shape heating practices in everyday life [19,20,67–73], or what could be referred to as home comfort [20,74]. It is also in line with these studies that the existing primary knowledge on the link between (temporality of) everyday practices and (timing of) energy consumption is found, for example, related to showering and DHW use [18,75], laundry routines, and energy use [76–79] or smart home control [69]. In addition, a range of studies directly addresses the relationship between everyday energy practices and peak demand [12], for example, by referring to 'family peak periods' [45] or flexibility of everyday activities [80,81]. Together, these studies suggest that temporal patterns of energy demand reflect what could be referred to as socio-temporal rhythms [42], which are closely linked to societal or institutional rhythms [11,82].

This paper builds on these qualitative studies' understanding of energy consumption as reflective of energy practices and combines this understanding with quantitative measures of timing and intensity of energy demand.

With smart meter data, it is possible to get closer to the actual actions of the occupants, for example, their daily energy patterns. Several studies have used such high temporal-resolution data, primarily for studying electricity demand [35,37,83,84] and even in combination with time-use data [85]. Recent studies also analyze hourly data on heating consumption using smart meter registrations [31,86,87]. One study uses smart meter data from district heating systems to investigate the correlation between temporal clusters and household characteristics (e.g., the presence of multiple adults, teenagers, and children) and indicates fairly constant load profiles across the different groups [38]. In combination, these studies underline the usefulness of exploiting high-resolution data to investigate temporal patterns in energy demand.

To gain further knowledge on which types of households contribute the most to heating demand peaks, we use detailed information on households to identify groups according to occupation, family composition, and income. Moreover, we focus directly on daily load profiles and peak demand.

3. Data and Methods

This paper consists of (1) descriptive analysis of hourly data, where average hourly heating consumption is used to create daily profiles for various household types, and (2) multivariable analysis of morning and evening peak heating consumption, where correlations in use during the two peak periods and household types were modeled using regression techniques. These two steps were intended to exploit the available data and communicate the patterns in the best way according to the aim of the study.

The energy monitoring data used in this study have been collected for previous research projects [30,31]. The data consisted of information on heat usage for 1665 buildings connected to the DH network in a small town in the northern region of Denmark. The data were provided by the DH utility company. All installed smart meters gathered the cumulative heat (combined space heating and domestic hot water) usage. Measurements were recorded at an hourly rate. The recording period was from 00:00—5 November 2018 to 00:00—7 October 2019. The months from 1 October 2018 to 1 March 2019, which constitute the Danish heating season, were selected for this study. To focus on everyday patterns in energy consumption, weekends and Danish holidays were removed from the data (see also Figure 3 in Section 4).

The smart heat data were combined with data on household characteristics from Danish administrative registers provided by Statistics Denmark (Description (https://www.dst.dk/en/TilSalg/Forskningsservice) and overview (https://econ.au.dk/the-national-centre-for-register-based-research/danish-registers)). Merging these datasets was possible using address codes, which were anonymized by Statistics Denmark on a secure server to which the authors have access. This enables statistical analysis of micro-level data on a range of personal and household information, for example, from the Civil Registration Register (CPR) [88] and the Building and Housing Register (BBR) [89], which are provided in an anonymized form under a range of restrictions for the researchers [90,91].

After merging the different datasets and selecting only households living in single-family dwellings, the final dataset comprised 803 units. Figure 2 is a flow chart illustrating the data structure and the analysis process with the different data resolution levels. The daily profiles (Sections 4.1–4.4) were based on data from 803 households (n) with 2497 time points (T) each, which resulted in a total of 2,005,091 observations (N). The models on peak energy demand (Section 4.5) were based on 803 households (n) with an average of 103.8 time points (T), which resulted in a total of 83,338 observations (N). Finally, the comparison of the sample of 803 households with the full Danish population of 1,140,419 households was based on information for the year 2019 (the full population used for comparison was restricted to single-family homes and townhouses and other minor corrections similar to the sample).

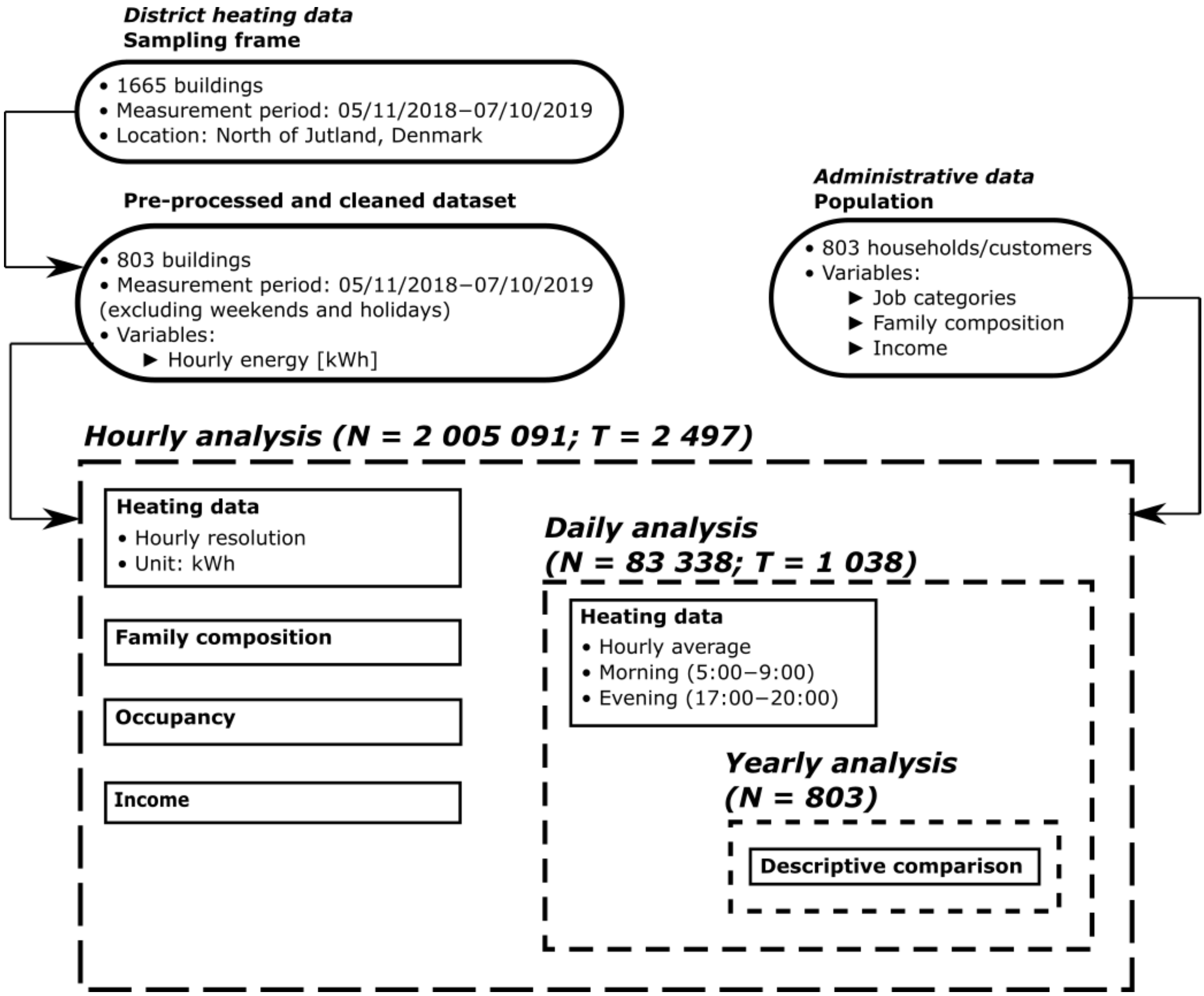

Figure 2. Overview of data structure and the applied analysis process.

The household variables were based on data from the Danish administrative registers, which contain rich information about household occupants, e.g., income, occupation, and family composition. The household variables were divided into three groups.

First, the households were categorized according to occupation. The variables are presented in Table 1. Based on the socio-economic classification in the Danish registers (SOCIO13) (https://www.dst.dk/en/Statistik/dokumentation/nomenklaturer/socio) and the classification of professions or jobs (DISCO-08 (https://www.dst.dk/en/Statistik/dokumentation/nomenklaturer/disco)), which refers to the International Standard Classification of Occupations (ISCO-08) [92], the occupation categories were intended to indicate household variations in morning and evening routines, for example by indicating showering practices and other practices related to space heating and DHW (see, for example, [18,75] on the temporality of DHW demand practices).

Table 1. Presentation and description of occupational variables with share (%) of the total sample. Each household can have several characteristics, so the percentages do not sum to 100%.

Variable Name	Description	Examples	Reference [1]	Sample (%)	Population (%)
Blue-collar (physical job)	At least one person in the household has a job requiring physical work or other sorts of manual or routine labor.	Working with machinery, maintenance, construction, crafts, transport, manufacturing, agriculture, or fishery.	DISCO major groups: 6, 7, 8, 9.	19.7%	24.3%
White-collar (*office* job)	At least one member of the household has a job in clerical or another type of office work.	Working with administrative tasks, specialized services, engineering, and technicians.	DISCO major groups: 1, 2, 3, 4.	66.6%	56.1%
Pensioner	At least one member of the household receives retirement benefits.	Includes senior pension and early retirement benefits.	Socio-Economic Classification (SOCIO13) [2]: 321, 322, 323.	32.3%	38.7%
Unemployed	At least one member of the household receives unemployment benefits.	Includes unemployed receiving sick pay or social security.	Socio-Economic Classification (SOCIO13): 210, 220, 330.	4.6%	7.2%
		Number of households		*803*	*1,140,419*

[1] See https://en.wikipedia.org/wiki/International_Standard_Classification_of_Occupations for an overview of ISCO major groups. [2] https://www.dst.dk/en/Statistik/dokumentation/nomenklaturer/socio.

Second, households were categorized according to family composition, i.e., age and presence of children in the household. The intention was to reflect variations in everyday practices and temporal rhythms related, e.g., related to 'family peaks' [45] and 'busy spots' during the day [42,43]. Therefore, the categories were rather detailed, with four types of households according to the presence of children, and five categories of age based on the oldest member of the household. Table 2 presents these categories with descriptions.

Table 2. Presentation and description of household composition variables with share (%) of the total sample. Each household can have several characteristics, so the percentages do not sum to 100%.

Variable Name	Description		Categories	Sample (%)	Population (%)
Child	Child in the household, based on age of the youngest child	1	No child (Ref.)	54.6	66.7
		2	Pre-school child (0 to 6 years)	20.9	10.9
		3	Young child (7 to 12 years)	14.1	10.6
		4	Teenager (13 to 19 years)	10.5	11.8
Age		1	18 to 40 years (Ref.)	20.4	13.0

Age of oldest adult in the household	2	41 to 50 years	23.4	19.6
	3	51 to 60 years	18.3	22.2
	4	61 to 70 years	15.3	19.4
	5	71 years or older	22.5	25.8
Number of households			*803*	*1,140,419*

Third, households were categorized according to income. The variable consists of six groups representing different degrees of household financial resources (see Table 3). It was constructed by summing the individual annual disposable incomes of each adult household member. Disposable income refers to income after taxes for each adult household member.

Table 3. Presentation and description of household composition variables with share (%) of the total sample. Each household can have several characteristics, so the percentages do not sum to 100%.

Variable Name	Description		Categories	Sample (%)	Population (%)
Income	Six groups categorized by total annual disposable household income (income after taxes).	1	Less than DKK 300,000 (app. EUR 40,000)	11.5	21.7
		2	DKK 300,000 to 399,999 (app. EUR 54,000)	15.1	14.6
		3	DKK 400,000 to 499,999 (app. EUR 67,000)	14.1	13.5
		4	DKK 500,000 to 599,999 (app. EUR 81,000)	19.3	13.3
		5	DKK 600,000 to 699,999 (app. EUR 94,000)	16.2	11.5
		6	DKK 700,000 or higher	23.9	25.4
Number of households				*803*	*1,140,419*

Finally, the physical attributes of houses, including construction year and house size, were used to control for the correlations with the household variables in the models in Section 4.5. The full list can be found in Appendix A. Previous studies have used similar control variables based on Danish registers [25,37,93].

The last part of the analysis (Section 4.5) aimed to model household variation in the morning (5:00–9:00) and evening (17:00–20:00) peak heating demand. The models were based on time-series data, where each household had multiple observations according to the number of hours. These multiple observations are assumed to cluster and correlate within households (units) over time, thereby being strongly interdependent and having serially correlated errors [94]. To account for this serial correlation, a panel regression model was applied, and as we were in the variation between households, we used the 'between estimator', which refers to an ordinary least square estimator applied to averaged estimates over time within households [95] (we used the Stata function *xtreg* with the specification of between effects (*be*)).

The data enforced some limitations on the analysis. For example, the sample included only households with district heating. Therefore, some bias related to the correlation between the type of primary energy source used for heating and socio-economic groups might exist. Around half of the Danish households living in single-family homes or townhouses are supplied with DH (Statistics Denmark, table BOL105), and compared with the full Danish population, Tables 1–3 show that the sample appears relatively representative according to occupation, household composition, and income.

4. Results

We start the analysis by looking at how heating load patterns vary according to various aspects of temporal rhythms. Figure 3 displays daily energy loads based on average values for each hour across different categories. Thus, it highlights important differences between weekends versus weekdays (Monday to Friday), working days versus holidays (Danish school holidays), and heating season (October to April) versus all-year data.

As seen in Figure 3, the morning peak occurs much later on the weekend than on workdays, and the same pattern is found for holidays. Moreover, the general heating load is lower outside the heating season.

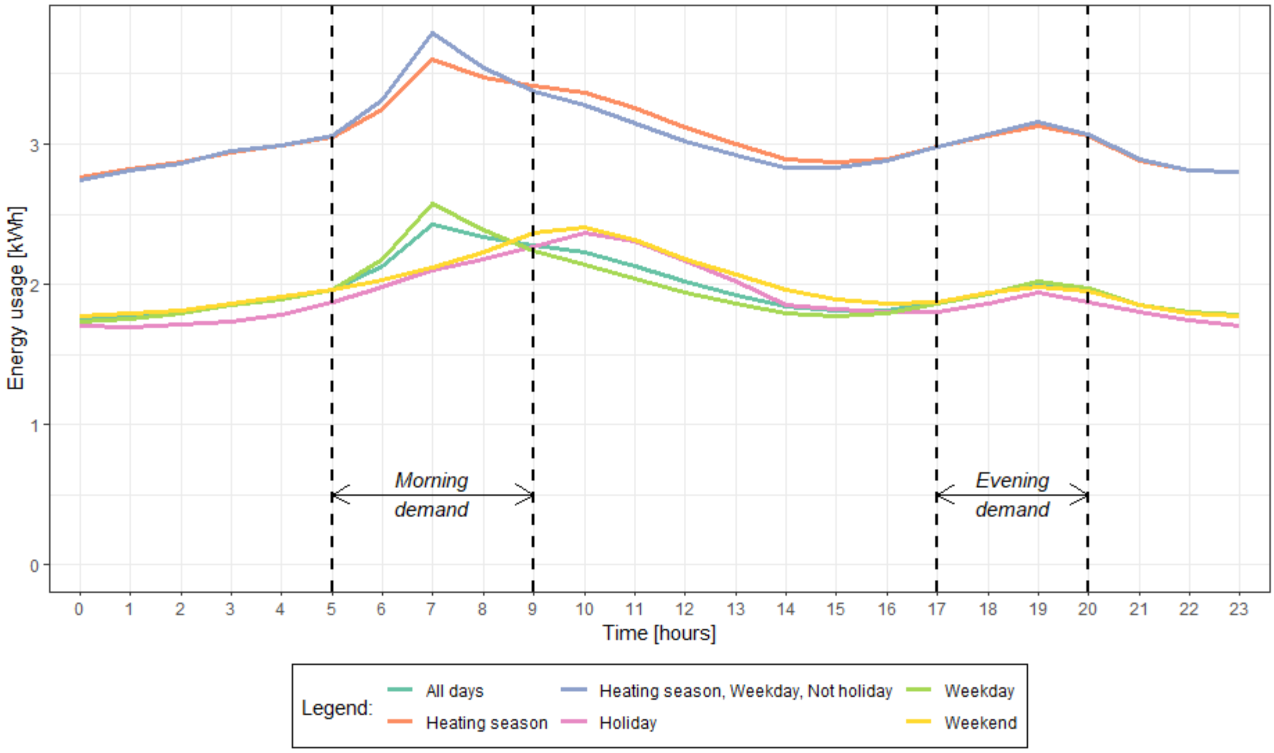

Figure 3. Daily heating load profiles for all week, weekdays, and weekends based on average hourly consumption. N = 6,475,392, n = 803.

We chose to focus on the most regular heating patterns. Therefore, we limited the rest of the analysis to the periods when it is expected that the household practices are the most regular, which we assume to be on working weekdays during the heating season. This means we choose to analyze weekdays (Monday to Friday) in the heating season (October to April) exclusive of Danish school holidays.

The rest of the result section is divided into five parts. Sections 4.1–4.4 use data on an hourly resolution to describe variations in daily heat profiles across various household groups. Tables with selected data used for the figures can be found in Appendix B. Section 4.5 presents the results of panel models on average hourly consumption during morning and evening peaks to estimate differences in heating use.

4.1. Occupation

The first household groups that we compare relate to occupation. Figure 4 shows that households with white-collar workers tend to have a higher morning peak, whereas households with pensioners have the latest morning peak and, in general, the flattest daily profile. Households with unemployment almost have the same morning peak as households with blue-collar workers, but the profile during the day is slightly higher. There seems to be a negligible difference during the evening peak.

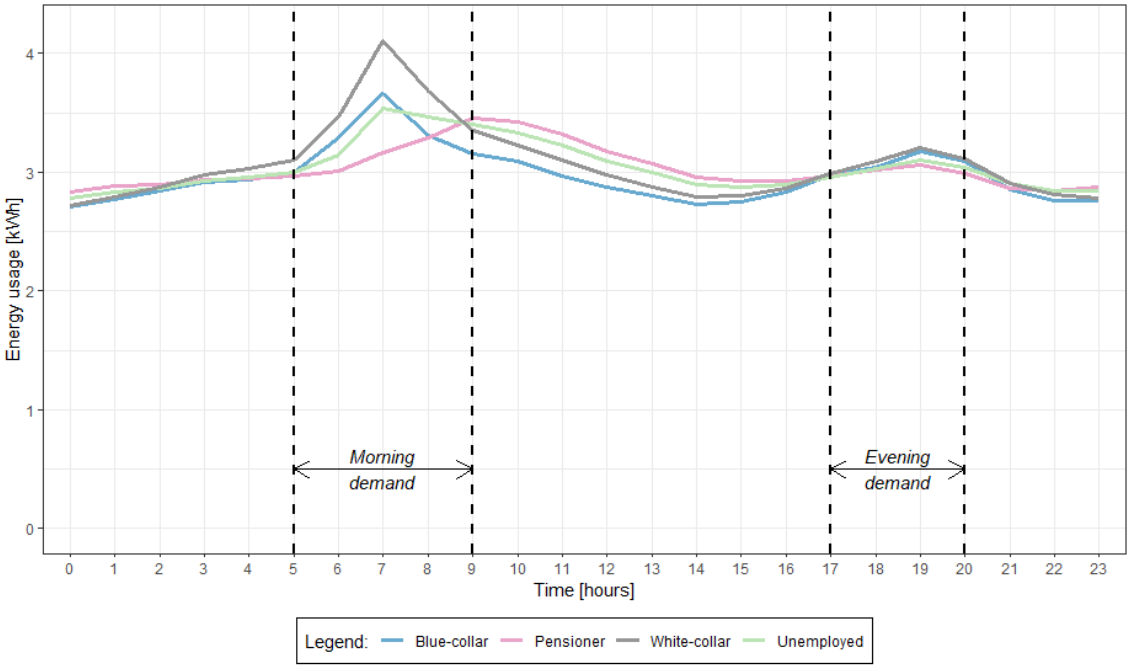

Figure 4. Heat usage profile for an average day for occupational groups based on average hourly consumption. N = 2,005,091; n = 803.

4.2. Age

The second household category we compare is based on the age of the household. In Figure 5, we compare the daily heat profiles according to the categorizations of the oldest occupant represented in the household. The comparison shows that the group aged 41 to 50 years has the most substantial morning peak with 4.5 kWh at 7 h. The younger group (aged 18 to 40) and the slightly older group (aged 51 to 60) follow with an average peak demand of just below 4 kWh. As with the pensioner group in Figure 4, the oldest group (aged 71 or older) has the latest morning peak and highest load during the day, whereas the group aged 61 to 70 has the flattest and generally lowest load profile.

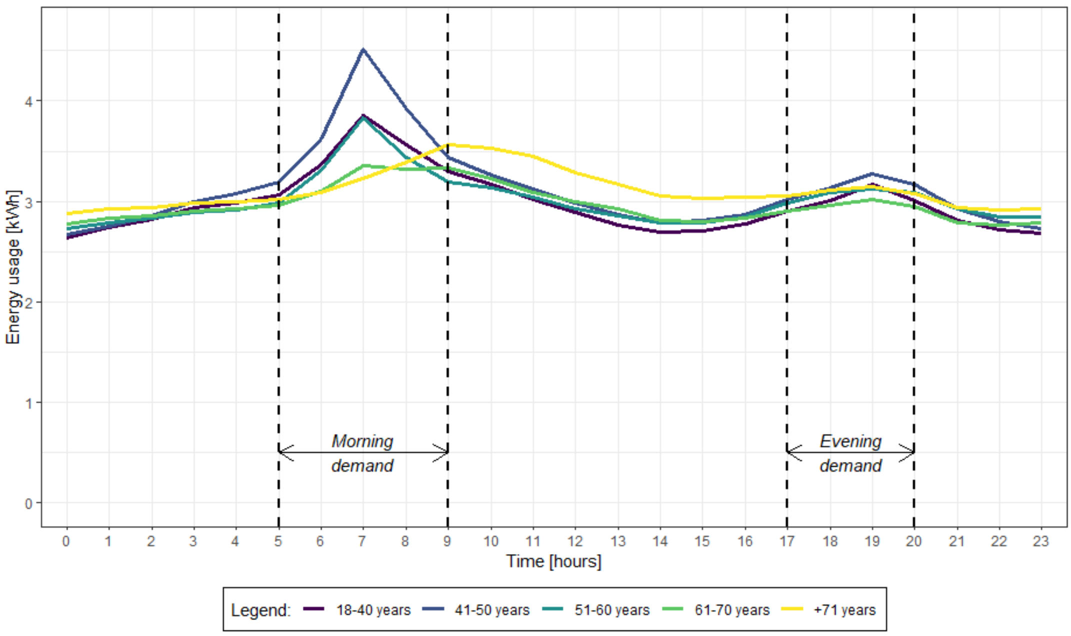

Figure 5. Heat usage profile for an average day for age groups based on the oldest occupant in the household based on average hourly consumption. N = 2,005,091; n = 803.

4.3. Children

The third occupant group we compare reflects the presence of children in the household. Here, we compare households based on the youngest child in the household. Figure 6 shows that households with no children seem to have a flatter daily profile than other households. In particular, the morning peak appears much lower, at 3.4, compared to a peak of 4.6 for the group with young children (aged 7 to 12). The morning peaks of households with teenagers (aged 13 to 19) and households with pre-school children (aged 0 to 6) as the youngest in the household are similar. However, the evening peak for households with teenagers appears slightly different, with a slightly lower peak at 3.1 kWh at 20 h, compared to 3.3 kWh at 19 h for households with younger children.

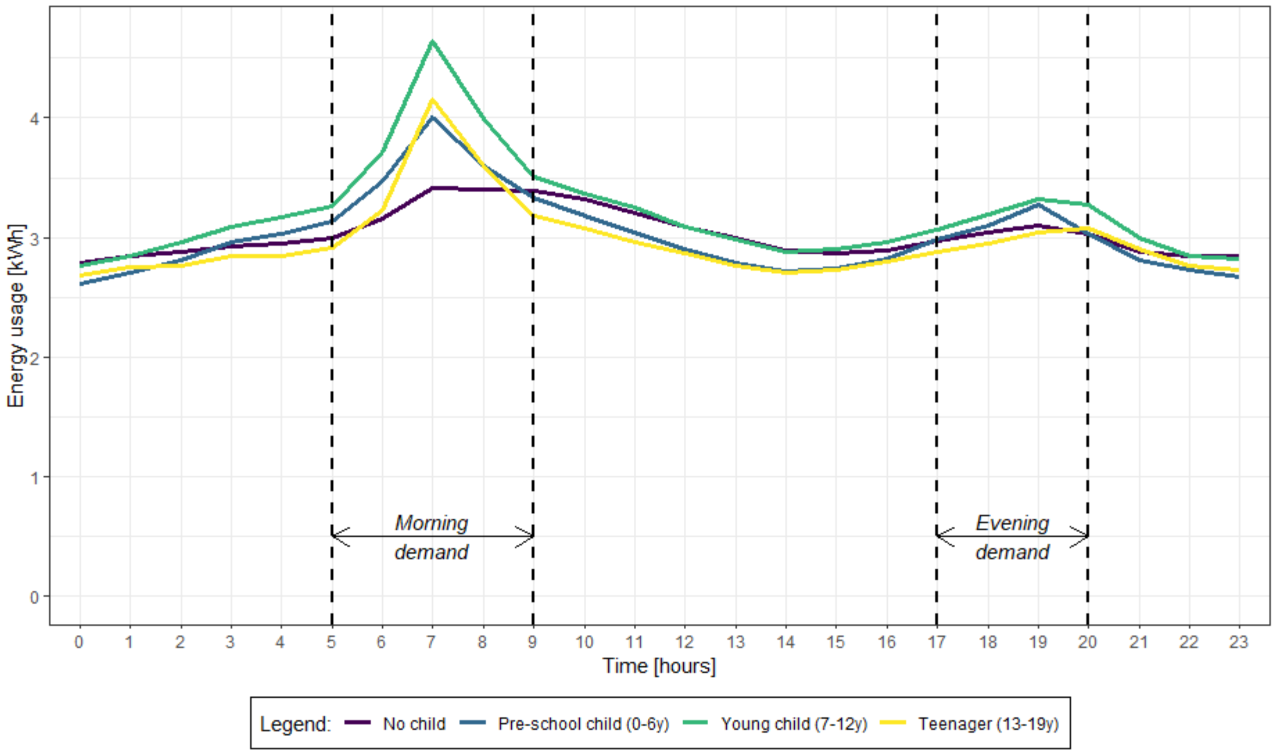

Figure 6. Heat usage profile for an average day for groups comparing the age of children based on the youngest child in households based on average hourly consumption. N = 2,005,091; n = 803.

4.4. Income

The fourth and final comparison uses five total household disposable income groups to identify differences in heating use profiles related to financial consumption capacity. Figure 7 clearly shows that the higher-income groups tend to consume more during the morning and evening peaks. The highest income groups (above DKK 500k) have morning peaks of around 4 kWh at 7 h and evening peaks of around 3.3 at 19 h. The lowest income groups (less than DKK 400k) tend to have flatter daily profiles with smaller and somewhat later morning peaks.

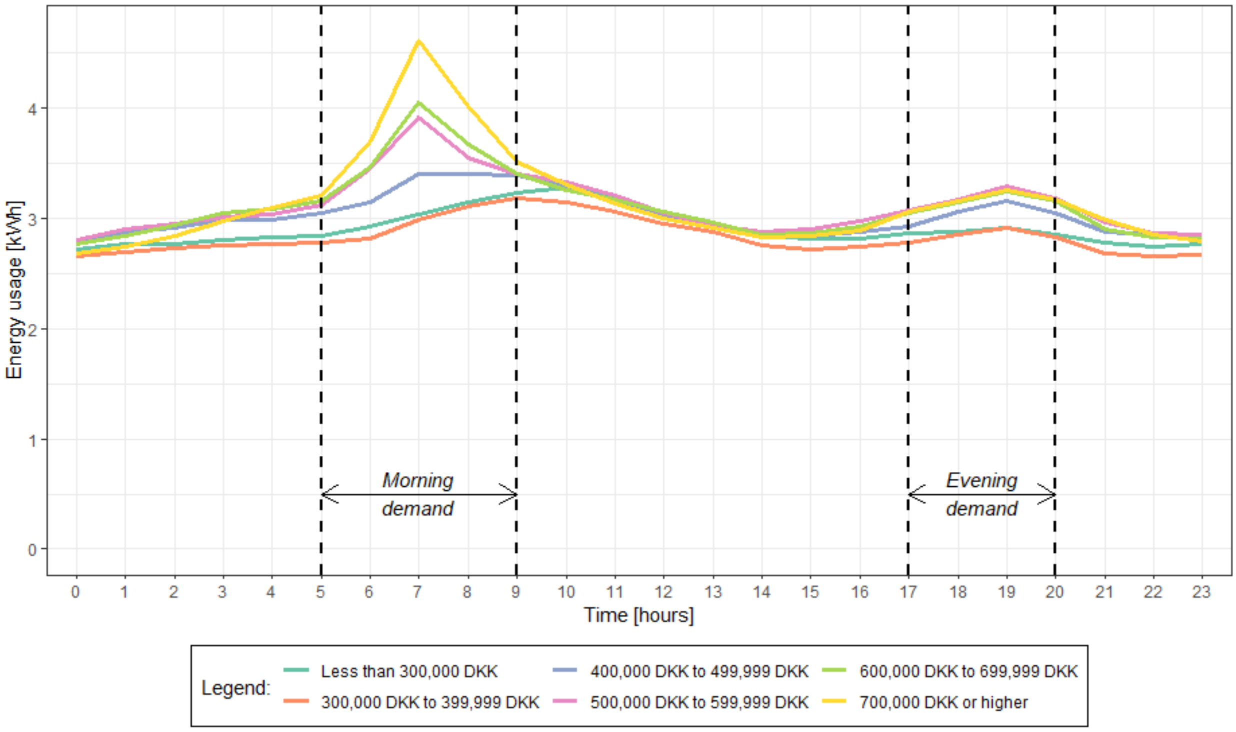

Figure 7. Heat usage profile for an average day for groups comparing income groups based on total annual household disposable income based on average hourly consumption. N = 2,005,091; n = 803.

4.5. Modeling Variation Morning and Evening Peak

In the presentation of the differences in load profiles in Sections 4.1–4.5, the comparison of one variable does not take a variation on another characteristic into account. In other words, the average load profiles do not control for other socio-economic or building variables. Therefore, profiles of lower-income households resemble those of unemployed and pensioners, which indicates that these categories contain some of the same households. To distinguish the importance of each of the characteristics, we employ a multiple regression analysis, which includes multiple variables at the same time and, in addition, controls for building characteristics.

Table 4 presents the estimates of the regression model. It shows that before controlling for building variables, blue-collar households tended to consume less during the morning peak (5:00–9:00), whereas households tended to consume more as their income was higher (*M1*). When controlling for building characteristics (*M2*), the blue-collar estimate was no longer significant, but the correlation with income persisted, although the impact became less significant. Instead, the unemployed households now seemed to consume less during the morning peak at a lower significance level.

Table 4. Between-effect panel regression model for morning peak (5:00–9:00). Complete table found in Appendix C. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; standard error in parentheses.

	M1		***M2***	
Blue-collar (1 = Yes)	**−0.191 ****	*(0.081)*	−0.092	*(0.064)*
White-collar (1 = Yes)	−0.075	*(0.111)*	0.020	*(0.088)*
Pensioner (1 = Yes)	−0.132	*(0.149)*	−0.081	*(0.119)*
Unemployed (1 = Yes)	−0.172	*(0.144)*	−0.204 *	*(0.116)*
Child (youngest)				
No child	Ref.		Ref.	
Pre-school child (0–6 years)	−0.036	*(0.124)*	−0.070	*(0.098)*
Young child (7–12 years)	0.096	*(0.120)*	−0.037	*(0.095)*
Teenager (13–19 years)	−0.161	*(0.118)*	−0.108	*(0.094)*

Age (oldest)				
18 to 40 years	Ref.		Ref.	
41 to 50 years	0.105	*(0.110)*	0.118	*(0.088)*
51 to 60 years	−0.050	*(0.130)*	−0.056	*(0.104)*
61 to 70 years	0.105	*(0.157)*	0.068	*(0.126)*
71 years or older	0.349 *	*(0.185)*	0.116	*(0.149)*
Total income				
Less than DKK 300,000	Ref.		Ref.	
DKK 300,000 to 399,999	−0.014	*(0.115)*	−0.036	*(0.093)*
DKK 400,000 to 499,999	0.339 ***	*(0.123)*	0.144	*(0.101)*
DKK 500,000 to 599,999	0.624 ***	*(0.134)*	0.347 ***	*(0.110)*
DKK 600,000 to 699,999	0.599 ***	*(0.142)*	0.274 **	*(0.118)*
DKK 700,000 or higher	0.741 ***	*(0.137)*	0.395 ***	*(0.117)*
Building control variables included			Yes	
Constant	2.924 ***	*(0.170)*	3.382 ***	*(0.186)*
R^2 (between variance)	0.10		0.45	
N (observations)	83,338		83,338	
n (households)	803		803	
T (avg. observations per household)	103.8		103.8	

Table 5 presents the correlations between household characteristics and heating consumption during the evening peak (17:00–20:00). Before controlling for building characteristics (E1), the oldest age group (71 years or older) seemed to consume more, and the higher-income households again also tended to consume more. When taking variation due to the building into account (E2), only the correlation with the highest income groups (above DKK 500,000) remained significant and positive.

Table 5. Between-effect panel regression model for evening peak (17:00–20:00). Complete table found in Appendix D. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; standard error in parentheses.

	E1		***E2***	
Blue-collar (1 = Yes)	**−0.063**	*(0.085)*	0.018	*(0.062)*
White-collar (1 = Yes)	−0.089	*(0.118)*	0.017	*(0.084)*
Pensioner (1 = Yes)	−0.119	*(0.158)*	−0.022	*(0.114)*
Unemployed (1 = Yes)	−0.153	*(0.153)*	−0.102	*(0.111)*
Child (youngest)				
No child	Ref.		Ref.	
Pre-school child (0–6 years)	0.049	*(0.131)*	0.020	*(0.094)*
Young child (7–12 years)	0.058	*(0.127)*	−0.084	*(0.092)*
Teenager (13–19 years)	−0.141	*(0.125)*	−0.095	*(0.090)*
Age (oldest)				
18 to 40 years	Ref.		Ref.	
41 to 50 years	0.106	*(0.116)*	0.157 *	*(0.084)*
51 to 60 years	0.155	*(0.138)*	0.094	*(0.100)*
61 to 70 years	0.235	*(0.167)*	0.094	*(0.121)*
71 years or older	0.499 **	*(0.196)*	0.185	*(0.143)*
Total income				
Less than DKK 300,000	Ref.		Ref.	
DKK 300,000 to 399,999	0.009	*(0.122)*	0.008	*(0.089)*
DKK 400,000 to 499,999	0.309 **	*(0.131)*	0.132	*(0.096)*
DKK 500,000 to 599,999	0.493 ***	*(0.142)*	0.242 **	*(0.106)*
DKK 600,000 to 699,999	0.455 ***	*(0.151)*	0.228 **	*(0.114)*
DKK 700,000 or higher	0.417 ***	*(0.145)*	0.235 **	*(0.113)*
Building control variables included			Yes	
Constant	2.600 ***	*(0.180)*	3.031* **	*(0.179)*

R^2 (between variance)	0.04	0.52
N (observations)	83,382	83,382
n (households)	803	803
T (avg. observations per household)	103.8	103.8

In both Tables 4 and 5, the building characteristics explained most of the variation in heating consumption. For the morning peak, the explained variation between households increased from 0.10 to 0.43 after adding building variables, and for the evening peak, the explained variation increased from 0.04 to 0.52. Because we chose to use detailed occupational categories in this analysis, we also had to accept a few cases of multicollinearity. This means that the variance inflation factor (VIF) was above five for white-collar and unemployed households, and the highest age group in both the morning and evening peak models, as well as the highest income group, were slightly higher than five in the morning peak model.

5. Discussion

This study investigated the types of households that contribute the most to morning and evening peaks of space heating and DHW usage. By combining smart meter data on hourly heat consumption for 803 households with household information from administrative registers, the analyses indicate that temporal variations in heating demand are stable across different types of households. This is in line with previous studies [38], and it underlines the importance of socio-temporal rhythms, for example, related to working hours and school hours [11,42,82], for structuring the timing of energy demand.

The results also indicate important variations among household groups. For example, white-collar (office jobs) households tend to have higher morning peaks (5:00–9:00) than blue-collar (physical labor) households and unemployed households, and pensioner households tend to have later morning peaks and flatter daily heating load profiles. These tendencies might be explained by variations in morning routines, where for example, the timing of showering routines relates to the type of work and the need for showering in the morning (before office jobs) or in the evening (after physically active jobs) [18].

Households with children have strong morning peaks, but households with young children (7–12 years) seem to have the highest morning peak, compared to households with teenagers (13–19 years) or pre-school children (0–6 years). This might be explained by strong institutional rhythms, especially for early-school children, and thereby reflecting socio-temporal rhythms [11,42,82] or what could be referred to as family peak periods [45].

However, when controlling for building characteristics, these correlations are insignificant, and only the positive correlation with higher income remains significant. Additionally, unemployed households now tend to consume less during morning peaks, although at a lower significance level. This suggests that although variations in daily rhythms across occupation and family composition exist, these seem less important than the factors of household income and building characteristics.

The analysis of evening peak demand for heating supports this. In general, the evening heating demand contained less variation than the morning (i.e., the timing and size of the peak are remarkably stable across the groups). It should be noted that for all household groups, the evening peak occurs at 19 o'clock. The evening meal, therefore, seems to occur around the same time in the 803 households analyzed. Still, higher-income groups seem to contribute the most to the evening peak, also when controlling for other household characteristics and building characteristics. Again, this relates to family peak periods [45].

Where previous studies suggest that socio-economic household variation related, for example, to occupation and family composition, correlates with the amount of energy used for heating [23,25,59], our results question whether mechanisms explaining levels of (aggregated) heating consumption also apply to the timing of (hourly) heating consumption, with the exception of the correlation with household income.

6. Conclusions, Policy, and Research Implications

As the percentage of RE in energy supply increases, energy systems, such as DH systems, require a greater understanding of household energy demand dynamics. In particular, the timing of household energy demand seems important, and this study used high-resolution consumption data to contribute to providing new evidence on the timing of energy demand across different household types.

The results of this study support well-described theories suggesting that the timing of household energy demand (i.e., at which time household activities are performed) reflects societal rhythms, for example, school hours, opening hours, and working hours. This study suggests a strong convergence between societal rhythms and daily load patterns of diverse types of households. For example, the different characteristics of households did not affect daily patterns of heat demand very much. Based on this, we suggest focusing on collective energy *practices* rather than individual *customers*. This means focusing on what people generally do in their homes (and when) rather than relying on specific assumptions about consumers and their behavior. The timing of energy demand practices seems largely determined by external factors that the household cannot change. These factors could also be referred to as collective norms of energy practices, for example, when morning and evening peaks fit regular school and work hours. In other words, there might be little room for occupants to change their daily rhythms deliberately and thereby time-shift heating demand.

New evidence on how peak heat demand reflects occupant practices might be valuable for utility companies' energy demand management. In this case, income level and job type reflect variations in user practices, which for example, influence energy demand patterns and choices made by the households.

A recent study comparing temporal aspects of everyday practices in several European countries during the COVID-19 lockdown suggests strong similarities across cultural contexts [96]. Like this study, we suggest that efforts to promote energy demand flexibility should focus on the intersection of everyday practices, institutional time structures, and societal temporal rhythms rather than individual behaviors and occupants' ability to change the timing of their everyday practices.

This study is based on one case in the northern part of Jutland in Denmark. This approach needs to be replicated in other contexts to collect better evidence on the relation between occupants (characteristics) and peak heat demand (timing). Furthermore, the effect of opening hours or office hours could be tested by comparing cases where these variables already differ. Further research is needed to better understand the mechanisms suggested in this study.

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Conflicts of Interest: The authors declare no conflict of interest.

Nomenclature

BBR	Building and Housing Register
CPR	Civil registration register

DHW	Domestic hot water
DH	District heating
RE	Renewable energy

Appendix A

Variable Name	Description		Categories	Sample (%)	Population (%)
Construction year	Five group categorization of year of construction, which partly reflect energy efficiency [93,97]	1	Built before 1961 (Ref.)	6.6	38.3
		2	Built 1961 to 1972	35.1	24.6
		3	Built 1973 to 1978	33.6	13.9
		4	Built 1979 to 2006	12.2	17.5
		5	Built after 2006	12.5	5.8
Area	Three groups of house sizes are based on the residential area (m^2).	1	Area less than 130 m^2	24.4	39.2
		2	Area 130 m^2 to 160 m^2 (Ref.)	44.0	30.7
		3	Area more than 160 m^2	31.6	30.1
Rooms	Categorization of the number of rooms.	1	Fewer than 5 rooms	38.4	45.9
		2	5 rooms (Ref.)	40.5	27.9
		3	More than 5 rooms	21.2	26.2
Townhouse	The building is a townhouse (1 = Yes), and not a single-family home			8.1	13.4
Multiple bathrooms	The building unit has more than one bathroom installed (1 = Yes)			34.3	31.6
Multiple toilets	The building unit has more than one toilet installed (1 = Yes)			68.5	55.9
Renovation	The house has a registered renovation or extension.	1	No registered renovation/extension (Ref.)	65.8	64.2
		2	Until 1978	10.5	12.5
		3	After 1978	23.8	23.3
Attic floor	The building unit has a registered attic floor area (1 = Yes).			11.8	36.5
Basement	The building unit has a registered basement area (1 = Yes).			9.2	28.3
	Number of households			*803*	*1,140,419*

Appendix B

		Blue-Collar	White-Collar	Pensioner	Unemployed
5–9	Peak (kW)	3.7	4.1	3.3	3.5
	Energy (kWh)	13.3	14.4	12.4	13.2
	% of daily use	*18.6*	*19.5*	*17.1*	*18.0*
17–20	Peak (kW)	3.2	3.2	3.1	3.1
	Energy (kWh)	9.2	9.3	9.1	9.1
	% of daily use	*12.9*	*12.6*	*12.4*	*12.5*

		18–40 y	41–50 y	51–60 y	61–70 y	71 y+
5–9	Peak (kW)	3.9	4.5	3.8	3.4	3.4
	Energy (kWh)	13.8	15.3	13.6	12.7	12.7
	% of daily use	*19.3*	*20.4*	*18.8*	*17.9*	*17.0*
17–20	Peak (kW)	3.2	3.3	3.1	3.1	3.2
	Energy (kWh)	9.1	9.4	9.2	8.9	9.3
	% of daily use	*12.7*	*12.6*	*12.7*	*12.5*	*12.5*

		No Child	Pre-School Child (0–6 y)	Young Child (7–12 y)	Teenager (13–19 y)
5–9	Peak (kW)	3.4	4.0	4.6	4.2
	Energy (kWh)	13.0	14.2	15.6	13.9
	% of daily use	*17.8*	*19.6*	*20.3*	*19.5*
17–20	Peak (kW)	3.1	3.3	3.1	3.1

Energy (kWh)	9.1	9.4	9.6	8.9
% of daily use	*12.5*	*12.9*	*12.5*	*12.5*

		Less than DKK 300K	DKK 300K to DKK 399.999	DKK 400K to DKK 499.999	DKK 500K to DKK 599.999	DKK 600K to DKK 699.999	DKK 700.000 or higher
5–9	Peak (kW)	3.1	3.1	3.4	4.6	4.0	4.6
	Energy (kWh)	12.0	11.7	13.0	14.0	11.2	15.5
	% of daily use	*17.1*	*17.2*	*17.9*	*18.8*	*15.0*	*20.5*
17–20	Peak (kW)	2.9	2.9	3.1	3.1	3.2	3.3
	Energy (kWh)	8.7	8.6	9.2	9.5	9.4	9.5
	% of daily use	*12.4*	*12.6*	*12.6*	*12.7*	*12.6*	*12.5*

Appendix C

	M1		***M2***	
Blue-collar (1 = Yes)	**−0.191 ****	*(0.081)*	−0.092	*(0.064)*
White-collar (1 = Yes)	−0.075	*(0.111)*	0.020	*(0.088)*
Pensioner (1 = Yes)	−0.132	*(0.149)*	−0.081	*(0.119)*
Unemployed (1 = Yes)	−0.172	*(0.144)*	−0.204 *	*(0.116)*
Child (youngest)				
No child	Ref.		Ref.	
Pre-school child (0–6 years)	−0.036	*(0.124)*	−0.070	*(0.098)*
Young child (7–12 years)	0.096	*(0.120)*	−0.037	*(0.095)*
Teenager (13–19 years)	−0.161	*(0.118)*	−0.108	*(0.094)*
Age (oldest)				
18 to 40 years	Ref.		Ref.	
41 to 50 years	0.105	*(0.110)*	0.118	*(0.088)*
51 to 60 years	−0.050	*(0.130)*	−0.056	*(0.104)*
61 to 70 years	0.105	*(0.157)*	0.068	*(0.126)*
71 years or older	0.349 *	*(0.185)*	0.116	*(0.149)*
Total income				
Less than DKK 300,000	Ref.		Ref.	
DKK 300,000 to 399,999	−0.014	*(0.115)*	−0.036	*(0.093)*
DKK 400,000 to 499,999	0.339 ***	*(0.123)*	0.144	*(0.101)*
DKK 500,000 to 599,999	0.624 ***	*(0.134)*	0.347 ***	*(0.110)*
DKK 600,000 to 699,999	0.599 ***	*(0.142)*	0.274 **	*(0.118)*
DKK 700,000 or higher	0.741 ***	*(0.137)*	0.395 ***	*(0.117)*
Construction year				
Before 1961			Ref.	
1961 to 1972			−0.223 *	*(0.117)*
1973 to 1978			−0.450 ***	*(0.120)*
1979 to 2006			−0.888 ***	*(0.132)*
After 2006			−1.096 ***	*(0.148)*
Area				
Less than 130 m²			−0.243 ***	*(0.069)*
130 m² to 160 m²			Ref.	
More than 160 m²			0.335 ***	*(0.062)*
Rooms				
Fewer **than 5**			0.020	*(0.060)*
5 (Ref.)			Ref.	
More than 5			0.216 ***	*(0.067)*

Townhouse (1 = Yes)			−0.508 ***	*(0.100)*
More bathrooms (1 = Yes)			0.065	*(0.063)*
More toilets (1 = Yes)			0.115 *	*(0.066)*
Renovation				
No registered renovation			Ref.	
Until 1978			0.207 **	*(0.087)*
After 1978			0.062	*(0.061)*
Attic floor (1 = Yes)			−0.199 **	*(0.091)*
Basement (1 = Yes)			0.463 ***	*(0.084)*
Constant	2.924 ***	*(0.170)*	3.382 ***	*(0.186)*
R^2 (between variance)	0.10		0.45	
N (observations)	83,338		83,338	
n (households)	803		803	
T (avg. observations per household)	103.8		103.8	

Note Between-effect panel regression model for morning peak (5 h to 9). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; standard error in parentheses.

Appendix D

	E1		***E2***	
Blue-collar (1 = Yes)	−0.063	*(0.085)*	0.018	*(0.062)*
White-collar (1 = Yes)	−0.089	*(0.118)*	0.017	*(0.084)*
Pensioner (1 = Yes)	−0.119	*(0.158)*	−0.022	*(0.114)*
Unemployed (1 = Yes)	−0.153	*(0.153)*	−0.102	*(0.111)*
Child (youngest)				
No child	Ref.		Ref.	
Pre-school child (0–6 years)	0.049	*(0.131)*	0.020	*(0.094)*
Young child (7–12 years)	0.058	*(0.127)*	−0.084	*(0.092)*
Teenager (13–19 years)	−0.141	*(0.125)*	−0.095	*(0.090)*
Age (oldest)				
18 to 40 years	Ref.		Ref.	
41 to 50 years	0.106	*(0.116)*	0.157 *	*(0.084)*
51 to 60 years	0.155	*(0.138)*	0.094	*(0.100)*
61 to 70 years	0.235	*(0.167)*	0.094	*(0.121)*
71 years or older	0.499 **	*(0.196)*	0.185	*(0.143)*
Total income				
Less than DKK 300,000	Ref.		Ref.	
DKK 300,000 to 399,999	0.009	*(0.122)*	0.008	*(0.089)*
DKK 400,000 to 499,999	0.309 **	*(0.131)*	0.132	*(0.096)*
DKK 500,000 to 599,999	0.493 ***	*(0.142)*	0.242 **	*(0.106)*
DKK 600,000 to 699,999	0.455 ***	*(0.151)*	0.228 **	*(0.114)*
DKK 700,000 or higher	0.417 ***	*(0.145)*	0.235 **	*(0.113)*
Construction year				
Before 1961			Ref.	
1961 to 1972			−0.153	*(0.112)*
1973 to 1978			−0.391 ***	*(0.115)*
1979 to 2006			−0.875 ***	*(0.126)*
After 2006			−1.609 ***	*(0.142)*
Area				
Less than 130 m^2			−0.220 ***	*(0.066)*
130 m^2 to 160 m^2			Ref.	
More than 160 m^2			0.340 ***	*(0.060)*
Rooms				
Fewer than 5			0.052	*(0.055)*
5 (Ref.)			Ref.	

More than 5			0.167 ***	*(0.065)*
Townhouse (1 = Yes)			−0.575 ***	*(0.095)*
More bathrooms (1 = Yes)			0.054	*(0.060)*
More toilets (1 = Yes)			0.085	*(0.064)*
Renovation				
No registered renovation			Ref.	
Until 1978			0.291 ***	*(0.083)*
After 1978			0.040	*(0.059)*
Attic floor (1 = Yes)			−0.135	*(0.087)*
Basement (1 = Yes)			0.482 ***	*(0.080)*
Constant	2.600 ***	*(0.180)*	3.031 ***	*(0.179)*
R^2 (between variance)	0.04		0.52	
N (observations)	83,382		83,382	
n (households)	803		803	
T (avg. observations per household)	103.8		103.8	

Note Between-effect panel regression model for evening peak (17:00–20:00). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; standard error in parentheses.

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