Energy Research & Social Science 123 (2025) 104032

Contents lists available at ScienceDirect

Energy Research & Social Science

journal homepage: www.elsevier.com/locate/erss

Original research article

In the rhythm of the home: How does increased home occupancy affect residential electricity consumption?

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ARTICLE INFO

Keywords:
Covid-19 pandemic
Electricity consumption
Demand-side flexibility
Demand response
Working from home
Home presence

ABSTRACT

Working from home and increased presence at home have the potential to affect households' ability to use electricity flexibly, by expanding the time window during which devices and appliances are used. The COVID-19 pandemic has led to increased home presence, potentially influencing this flexibility. As flexibility in electricity consumption is key focus in demand-side management, understanding how changes in home presence impact electricity consumption patterns and potential flexibility is important.

Using survey and electricity meter data, this study examined whether changes in Swedish households' electricity consumption during the pandemic differed between those who spent more time at home during the pandemic and those who did not, focusing on two measures capturing electricity consumption patterns: volume and variability.

All households showed an increase in average electricity consumption, with more pronounced increases during daytime hours among those who reported being home more. Increased presence at home also reduced variability, suggesting that those at home more often had a more regular electricity consumption pattern. These results are discussed in the light of practical implications for demand-side management.

1. Introduction

Being home and working from home can affect households' ability to be flexible with electricity use [1,2]. At the same time, occupants' presence at home and working from home can increase residential electricity consumption, as the COVID-19 pandemic has shown [3–8]. But does an increase in occupants' presence at home in and of itself lead to more flexible consumers, without incentives? This study investigated how changes in individuals' time spent at home, due to the pandemic, has affected electricity consumption patterns, in Sweden.[1] While this study was conducted in a Swedish suburb, changes in home presence and working-from-home activities are global phenomena, and understanding how electricity consumption patterns are affected by these is relevant across different countries and regions.

The following section provides a brief introduction to demand side flexibility and how time spent at home could affect both consumption and flexibility, followed by changes in home presence due to the pandemic, closed by a detailed research aim and questions.

1.1. Demand flexibility and time spent at home

Demand side flexibility (DSF) refers to “the ability of a customer (Prosumer) to deviate from its normal electricity consumption (production) profile, in response to price signals or market incentives” [9], p. 11, where prosumers are consumers who also engage in co-creation of products, in this case the generation of energy [10,11]. In its ideal form, DSF can support uptake of intermittent renewable energy [12], affect carbon emissions [13], reduce grid congestion during peak periods,

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[1] The Swedish context is different from many other Western countries in that the Swedish government refrained from enforcing strict lockdown measures, instead relying on public compliance to voluntary recommendations. It might be for this reason that in the study by van Zoest et al. [7] an increase in total consumption was observed: due to mild restrictions, few sectors could effectively reduce their electricity consumption, since there was usually someone available to work at workplaces. The few big industries that did have a drop in consumption did not weigh up to the increase of all households together.

https://doi.org/10.1016/j.erss.2025.104032
Received 14 June 2024; Received in revised form 5 February 2025; Accepted 12 March 2025
Available online 20 March 2025

reduce necessity for costly expansion of electricity infrastructure [14] and help balance transmission and distribution grids [15]. In a nutshell, DSF can play a key role in the development of a cost-reflective, resilient and sustainable future energy system, if users are willing and able to provide this flexibility.

Users can be flexible in multiple ways, for example by shifting consumption in time, reducing consumption or accumulating energy in batteries or accumulating heat. Moreover, users can be flexible for different reasons. For example, to support the uptake of renewables, households can show flexibility in line with the supply of wind and solar power, lowering the need for supplementary non-renewable power generation. Alternatively, households can be flexible in reducing their consumption during times when the electricity grid is congested, thus reducing the risk for costly investments in infrastructure. Capturing different kinds of flexibility can be difficult and no common quantification procedure exists [16]. Ettorre and colleagues [17] suggest that flexibility is captured "as the difference between the actual (measured) consumption and the baseline consumption (estimated), which would have been used in the absence of a flexibility event" (p. 8). This approach requires the presence of a flexibility event, such as a tariff or alternative incentive structure, as a baseline. Alternatively, Duarte et al. [18] look at variability in electricity consumption as an indicator of flexibility potential, assuming that users showing high variability during a certain period of the day have potentially less strict routines during that time, and thus higher potential to be flexible. This measure captures regularity of electricity consumption above a household's baseline consumption, in other words the consumption caused by stochastic use of devices. A benefit is that it captures variability that may be indicative of flexibility potential, even in the absence of a flexibility event. A downside is that it does not incorporate some important potential sources of flexibility such as automating heating systems.

As an example, say a hypothetical household has a strict routine at 9.00 on weekdays (see Fig. 1 – left panel, grey striped bars) using the same devices regularly, and thus exhibiting low variability across days during this hour.[2] This household might be less inclined to deviate from their pattern and has low flexibility potential, whereas a household that has a more versatile usage at 9.00 (orange bars: sometimes running the dishwasher, other times the toaster or oven) may have higher variability across days during this hour and may be more willing to perform shifts. The opposite is true at 12.00 (right panel), where the striped household has a few activities going on. Whomever is running these appliances may have the possibility to shift one or more activities to an earlier or later time, if needed. The orange household on the other hand, does not have much variation at noon, maybe because its household members are at work. For them, it might be harder to shift electricity consumption (to or from) this point during the day.

Regardless of how it is measured, DSF concerns changes made by electricity users in response to tariff-driven price signals [19]. Given the potential benefits of DSF, an important question is whether people are willing and able to be flexible with their electricity use. A review by Parrish et al. suggests that consumer participation to voluntary demand response programs may be lower than expected [20]. Moreover, households' technical capacity to be flexible may not be homogenously distributed among the population [21], so that not everyone has the same capacity to participate. Previous research has moreover put question-marks over people's ability to comprehend demand-based tariffs [22,23]. Additionally, the design of certain kinds of demand-based tariffs and the potential interference between multiple electricity price-signals may complicate people's ability to perform the 'correct' flexible behaviour that benefits the system [24,25]. In terms of facilitating factors, energy literacy is suggested to affect users' willingness to adopt demand response programs [26]. Non-monetary motivations, too, can play a role in uptake and engagement with demand response programs; Bartusch et al. [27], for example, show that motivations related to climate change were important drivers for intention to shift electricity. In sum, there are various barriers and facilitators to demand flexibility among consumers (for systematic reviews of drivers and barriers to DR, see [28,29]).

Besides these cognitive motivators, presence at home has also been suggested to affect households' response to demand-response tariffs [1,2]. There are various electricity-demanding tasks that most households want done during a day for its members to experience an acceptable level of comfort (e.g., using the stove, laundry machine, TV, or coffee maker). Though it is possible for some devices to be put on a timer, distance-controlled or automated, it is evident that it is more difficult to perform all tasks flexibly throughout the day when one is only home during a limited number of hours. Particularly wet appliances, such as laundry and dishwashers, are devices that are easier to shift in time when there is a person home to actively perform and monitor them [30,31]. This applies even to timer-steered washers, since they need to be emptied once done and either air-dried or tumble-dried, as laundry machines with integrated dryer are not common to have. In short, presence of an (adult) individual at home becomes an important enabling condition of households' ability to respond manually to demand-response programs. That said, while being at home has a clear facilitating effect on flexibly using appliances, time spent away from home may have implications for the 'flexible' space in which automated systems can operate – when people are away from home, homes need to be heated/cooled less than when people are home, and temperature might be allowed to fluctuate with larger deviations from set comfort levels, if no one is home.

Working from home obviously contributes to household members' time spent at home. While working from home can lead to an increase in the energy consumption for households (for a review, see [32]), it can also facilitate shifts in use of electricity. For example, in a sample of Canadian residents two months into the COVID-19 pandemic, a majority reported cooking and running laundries during daytime, between 9.00 and 17.00, activities that normally would have to wait until one comes home from work [33]. Similarly, a study in California found that, during a period of restrictions in the pandemic, people reported increased home occupancy during mid-day, and used a series of electric appliances more often, particularly households with minors [34].

In a nutshell, electricity consumption patterns are potentially affected by increased occupants' presence at home, and by occupants working from home. This brings us to the COVID-pandemic, which affected these routines dramatically.

1.2. The pandemic and staying/working from home

Apart from direct epidemiological effects, the COVID-19 pandemic has impacted people's daily routines, habits and behaviours, many of which involving the use of electricity [35]. Although energy demand fell by 4 % in 2020 [36], residential electricity consumption went in the opposite direction. For example, van Zoest et al. [7] showed that in the wake of the pandemic, electricity consumption in a Swedish residential sector increased, while consumption in the industrial, public and commercial sectors showed less dramatic changes or changes in the opposite direction. Studies elsewhere have found similar increases in residential electricity consumption, often combined with reduced electricity consumption in other sectors (e.g., [3,4,6], frequently, but not always, resulting in a reduction of overall electricity consumption for some period ([3,5,8], but not in [7]).

One of the causes for these dramatic changes in electricity consumption lies in changes in residents' home presence, due to sickness or as health safety precautions. Many activities were shifted to the online realm, while already digital or online activities increased in frequency,

[2] For sake of simplicity, this visualisation does not include baseline electricity consumption due to for example heating or refrigeration. The illustration oversimplifies: the illustrated households do not use heating flexibly and this is homogenously consuming across days, regardless of temperature.

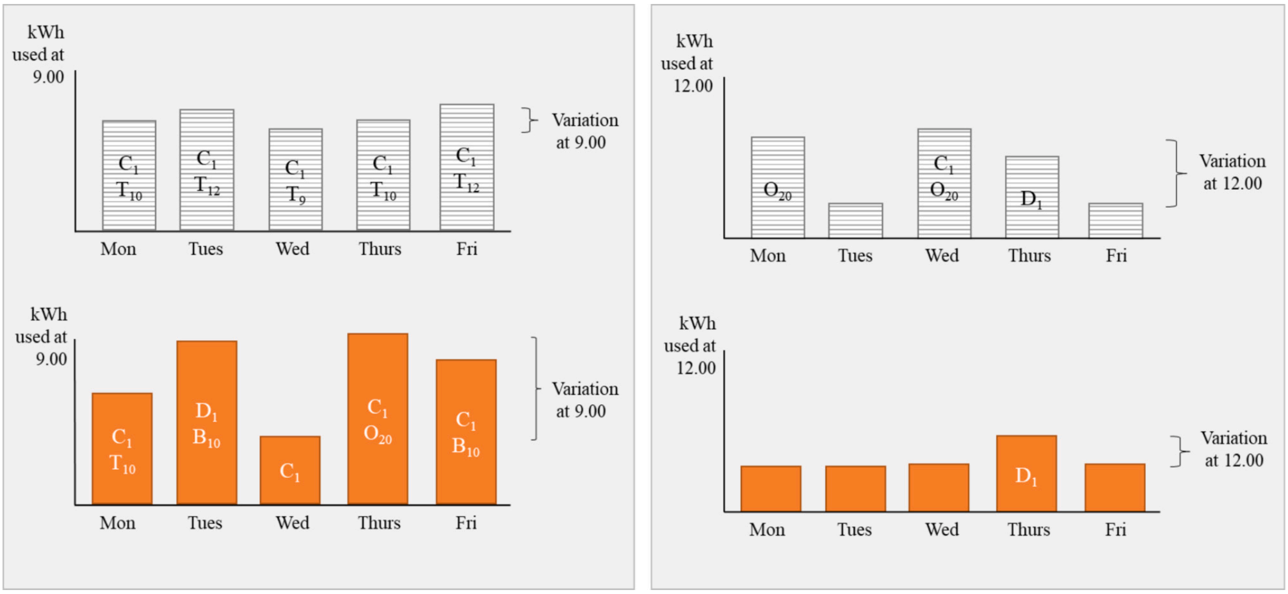

Fig. 1. Example of two hypothetical households with dissimilar levels of variability in their electricity consumption at 9.00 (left panel) and 12.00 (right panel) across several weekdays. The grey striped bars represent a household with strict routines and low variability between days at 9.00 (left panel), but more variation at 12.00 (right panel), whereas the orange bars represent a household with more variability in their use of appliances at 9.00, and less variation at 12.00. C = coffee machine, T = toaster, D = dishwasher, O = oven, B = blender, $_{10}$ = minutes or device runs. The aim of these graphs is to illustrate variability in consumption used by households with inhabitants present, above and beyond households' baseline consumption, such as refrigerators, heating, etc., to which end only use of some transient devices are presented.

such as personal communication [37,38] and entertainment [39]. Moreover, many people made the switch to (partly or fully) work from home during the pandemic. Bick et al., [40] concluded that, in the US, the amount of teleworking individuals increased from 14.4 % to 39.6 % from before the pandemic to during the first year of the pandemic, and remained high into the second year of the pandemic, at a rate of approximately 28.5 %. Overall, there were more people at home during more hours of the day, using electric appliances during a wider range of hours.

In the wake of the pandemic, energy prices went up due to the energy crisis that hit Europe,[3] while many workers desired to keep working from home to higher extents than before the pandemic [41–44], and while lifestyles have undergone, possibly lasting, changes [45]. This combination makes for an added layer of potential benefits or downsides of time spent at home. On the one hand, increased home presence can lead to higher consumption of electricity, and with higher electricity prices, this might imply a sharp increase in electricity costs. At the same time, being home might facilitate flexibility, and allow households to 'flatten their electricity curve', thus reaping the benefits from demand-based electricity tariffs.

1.3. Problem statement and research questions

Previous studies have investigated the role of spending time at home in consumers' adoption of, and response to demand response programs [28], but less is known about what effect presence at home has on electricity consumption without the pressure of financial incentives or specific demand programs added to the mix. This study aims to generate insights into how energy consumption and flexibility potential can change as a result of changes in home presence. In particular, we focus on two aspects of consumption: 1) how the volume of consumption changes when people are home more, and 2) how variability changes when people are home more.

In line with previous studies, we expected electricity to increase during the pandemic. Moreover, by comparing those who were home more to those who were not, we investigated two aspects more specifically, both of which are relevant for demand flexibility. First, by comparing changes in consumption per hour for those who were home more to those who were not, we investigated whether patterns during the day changed, i.e., whether being home more attenuated peak hour consumption, and increased daytime consumption. If increased presence at home indeed has this effect, then encouraging people to work from home might lead to reduced stress on the local distribution grid.

Second, by comparing changes in the variability of consumption per hour, we investigated whether increased presence at home led to a more regular or more variable consumption pattern (as in Fig. 1). Being home more could lead to an increase in variability during daytime hours, since more home presence means household members are able to run larger appliances at various moments during the day. Alternatively, being home more often could lead to a more even spread of appliance usage — instead of running all appliances during the one day one works from home, one can spread these evenly across the week. We had no expectations about the direction of this change, but expected differences in changed variability to be observable distinctly during daytime hours.

In sum, the following two research questions are inspected: 1) Is the *change in energy consumption* during the pandemic different for those who reported increased time spent at home during the pandemic, compared to those reporting the same or reduced time spent at home? And 2) Is the *change in variability* before compared to during the pandemic different for those who reported increased time spent at home during the pandemic, compared to those reporting the same or reduced time spent at home?

2. Methods

2.1. Study design

During the pandemic, most households in Sweden were paying

[3] On the 5th of May 2023, the WHO declared the global Public Health Emergency for Covid-19 to be over. From mid-2021 to late 2022, Europe experienced an energy crisis, with extremely high prices on gas, coal and electricity.

distribution and retail of electricity separately with volumetric tariffs (costs linearly increase per used kWh). Thus, an increase in electricity consumption cost more, but changes in flexibility did not. Demand-based tariffs were not yet implemented, and the study was conducted before the energy crisis, so that, to our knowledge, the only large-scale shock to the system was the pandemic and the subsequent change in home presence patterns. This set-up allowed us to observe what would happen to consumers' consumption patterns in terms of volume and variability in electricity use after an increase in home presence, but without any additional financial incentives (beyond 'regular' electricity costs).

Using self-report data, we identified which respondents' homes were more occupied during specific hours of the day during the pandemic, compared to before (more details in Section 2.3). For each hour, we could thus compare households where presence of occupants increased, to those where it did not increase during that hour. Using electricity meter data from before and during the pandemic, we compared these groups in terms of average electricity consumption and variation in their electricity consumption. In essence, the analysis followed a difference-in-difference logic, where the pre-pandemic data was used as the baseline measurement, and the during-pandemic data as the second measurement, grouping households into those who increased home presence or not. Fig. 2 illustrates this with a simplified schematic: in this example, there is an increase in electricity consumption at 9.00 during the pandemic for both households with increased home presence, and those without. Moreover, the increase in electricity consumption is greater for households with increased home presence than those without. The difference in these groups' differences from one timepoint to the next can be considered an indicator of the effect of home presence. The difference-in-difference approach allows us to see differences between categories even if general trends in electricity consumption exist; that is, even if general electricity consumption changes (e.g., due to electrification, weather, high energy prices), this approach will still allow us to investigate whether categories were differently affected, on top of this general trend.

2.2. Sample

Two linked sets of data were used: self-reported (stated) data and electricity meter data. Self-reported data was gathered via a survey conducted in the spring of 2023, among residents of a neighbourhood in Stockholm, Sweden.[4] The selection of this area was made in consultation with the local distribution system operator. This decision was motivated by the presence of a new generation of smart electricity meters in all households, enabling the collection of hourly electricity consumption data. Additionally, the population in this region is considered socio-demographically representative of a broader population in terms of family composition, household size, income and educational level, age and gender balance. Swedish households primarily consume energy for heating, hot water, and household electricity. Space heating accounts for the largest share of energy use, while household appliances and lighting represent a smaller but significant portion of electricity consumption [46]. Most electricity is used in the evening hours, with a smaller peak in the morning hours [46]. The Swedish electricity system is predominantly based on hydro and nuclear power, which together accounted for approximately 70–80 % of total electricity production in 2023 [47].

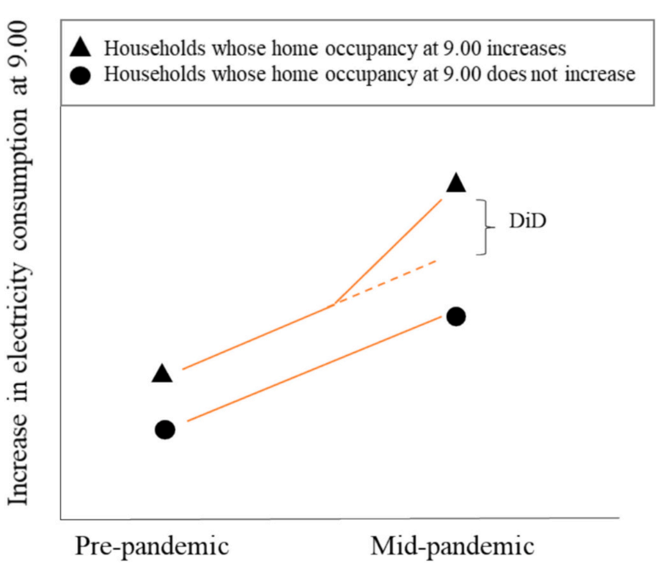

Fig. 2. Schematic depiction of the difference-in-difference (DiD) approach in the study.

A total of 7011 surveys were sent out, and 1153 households responded (response date = 16.4 %). Incomplete surveys were omitted (n = 282), and further data cleaning (see Section 2.2.2) resulted in a sample of 842 households (12.2 %). Demographics of this sample are presented in Table 1.

2.3. Measures and categories of flexibility opportunities

2.3.1. Home presence

Home presence was measured with a matrix-question that measured, for each hour of the day (e.g., 8.00 to 9.00) whether someone in the household would usually be home at that time, before, during and after the pandemic. Night-time hours (from 22.00 to 6.00 in the morning) were covered as a single item, as were weekend/holiday days. Respondents were asked to tick boxes for each hour where someone in their household usually was home, before, during and after the pandemic separately. Fig. 3 gives a fictive example of what a respondent's results could look like (though respondents did not see both pre and during pandemic columns at the same time).

For every hour during weekdays between 6.00 and 22.00 and the night-slot, we noted whether respondents reported at least one household member to be home during that hour, during the pandemic, but not before the pandemic. This constitutes an increase in home presence at that given hour. For example, the fictive respondent in Fig. 3 had an increased home presence at 9, 10 and 15 o'clock.

2.3.2. Electricity meter data

Access was granted to electricity meter data with hourly granularity from the same neighbourhood where the survey was distributed, by the local collaborating partner, a distribution system operator (sample details in Section 2.2). The complete dataset, described in detail in van Zoest et al. [7], contained data from over 14,000 unique electricity meters from the period of July 2019 to December 2021. Two periods were extracted from this data, one pre-pandemic dataset (from 11 July 2019 to 28 February 2020) and one during-pandemic dataset (from 11 July 2020 to 28 February 2021). These periods were selected based on data availability as well as to ensure the same months were used in the pre-pandemic dataset and in the during-pandemic dataset. For the purpose of this study, only meter data corresponding to the 855 survey respondents was used. In terms of overall average electricity usage, the sample had a slightly elevated consumption pattern compared to the area's residential population mean (reported in [7]).

[4] According to the Declaration of Helsinki, studies involving sensitive data, interventions, or vulnerable groups should apply to formal ethical approval. Our survey did not meet these criteria: no sensitive data was gathered, participant were anonymous, and participated voluntarily. Respondents were informed about their rights, including anonymity, data use for research purposes only, and the option to withdraw at any time.

Table 1
Descriptive statistics on demographic profile of the sample.

Variable	Level	Total sample (N = 842) M (SD)/count (%) in sample	(Semi-)detached homes[1] (N = 396) M (SD)/count (%) in sample	Apartments (N = 446) M (SD)/count (%) in sample
Number of household members		2.4 (1.20)	2.9 (1.18)	2.0 (1.05)
Gender	Female	347 (41 %)	122 (31 %)	225 (50 %)
	Male	488 (58 %)	272 (69 %)	216 (48 %)
	Other	7 (1 %)	2 (1 %)	5 (1 %)
Families without young children		668 (79 %)	297 (75 %)	371 (83 %)
Families without teenaged children		675 (80 %)	289 (73 %)	386 (87 %)
Families with children (under 18)		289 (34 %)	172 (43 %)	117 (26 %)
Occupation	Full time work	444 (53 %)	241 (61 %)	203 (46 %)
	Part time work	37 (4 %)	14 (4 %)	23 (5 %)
	Pension	319 (38 %)	130 (33 %)	189 (42 %)
	Other	42 (5 %)	11 (3 %)	29 (7 %)
Heating system	District heating	326 (39 %)	17 (4 %)	309 (69 %)
	Heat pump	364 (43 %)	327 (83 %)	37 (8 %)
	Electric boiler	32 (4 %)	27 (7 %)	5 (1 %)
	Biomass boiler	13 (2 %)	13 (3 %)	0 (0 %)
	Electric space heaters	30 (4 %)	11 (3 %)	19 (4 %)
	Other	77 (9 %)	1 (0 %)	76 (17 %)
Average household income before taxes		82,038 (167,377)	96,411 (178,779)	69,320 (155,698)

[1] There were separate categories for detached and semi-attached houses in the survey but since the latter category was relatively small (N = 38) and comparable in electricity consumption to detached homes, these two were combined.

		Before the pandemic	*During the pandemic*
	22:00 – 06:00	X	X
	06:00 – 07:00	X	X
	07:00 – 08:00	X	X
	08:00 – 09:00	X	X
	09:00 – 10:00		X
	10:00 – 11:00		X
	11:00 – 12:00		
	12:00 – 13:00		
Weekdays	13:00 – 14:00		
	14:00 – 15:00		
	15:00 – 16:00		X
	16:00 – 17:00	X	X
	17:00 – 18:00	X	X
	18:00 – 19:00	X	X
	19:00 – 20:00	X	X
	20:00 – 21:00	X	X
	21:00 – 22:00	X	X
Weekends and holidays	all day	X	X

Fig. 3. Example of a potential response to the question about home presence. Participants indicated during which hours of the day they usually were home, before and during the pandemic.

The indicators of electricity consumption and variation in this consumption described below are based on the assumption that electricity meters captured consumption by the hour. Thirteen households were omitted entirely from the analyses because there was zero within-day variation for all days within at least one of the two periods (pre or during pandemic), suggesting that the meters were not measuring hourly consumption. Moreover, several meters captured data with zero within-day variation on some but not all days, ranging from one to 187 days, while other meters only reported consumption for <3 h/day. Data from days where within-day variation was zero or close to zero (SD < 0.05), and on days where <3 h of meter data were reported, were removed.[5] Moreover, the analyses focus on reported changes in home presence during weekdays, which is in line with previous research that has shown that the pandemic had most impact on residential consumers' weekday consumption [7,48]. Accordingly, only electricity consumption during weekdays was used in analyses.

Two metrics were subsequently extracted from the meter data: 1) average hourly energy consumption across the two periods (before and during the pandemic), and 2) the coefficient of variation (CV) per hour, which indicates, for each hour of the day within a certain period, the variation in use.

For average hourly electricity consumption, we calculated, per respondent $i \in \{1\ldots n_i\}$ and per hour of the day $h \in \{1\ldots n_h\}$, the average hourly consumption $C_{i,h}$ across days $k \in \{1\ldots n_k\}$, separately for before and during pandemic data (respectively $\overline{C_{i,h,pre}}$ and $\overline{C_{i,h,mid}}$). This resulted in $n_h = 24$ observations of average hourly electricity consumption for $n_i = 842$ respondents, per period:

$$\overline{C_{i,h}} = \frac{\sum_k C_{i,h,k}}{n_k} \tag{1}$$

To calculate the coefficient of variation (CV) per hour, we calculated per respondent i and per hour of the day h, the standard deviation of electricity consumption $s_{i,h}$, based on the available data, and divided this by the mean of that hour's consumption $\overline{C_{i,h}}$, separately for before and during the pandemic. This resulted in in $n_h = 24$ observations of hourly CV for $n_i = 842$ respondents, per period:

$$CV_{i,h} = \frac{s_{i,h}}{\overline{C_{i,h}}} \tag{2}$$

Subsequently a 'first difference' estimator was calculated from average hourly electricity consumption respectively CV per hour, $\Delta\overline{C_{i,h}}$ denoting the *change in electricity consumption* and $\Delta CV_{i,h}$ denoting the *change in CV* from before to during the pandemic, for respondent i during hour h. This was done by subtracting the hourly average electricity consumption before the pandemic from the hourly average electricity

[5] At the level of data per day per household, respectively 23 % and 11 % of the data were omitted due to not fulfilling these criteria. These missing days were evenly spread out across months and weekdays, and not seasonally dependent, eliminating the possibility that the loss of data is caused by meters not working during cold days or specific sample-wide events.

consumption during the pandemic, so that positive values denote an increase over time, as follows:

$$\Delta\overline{C_{i,h}} = \overline{C_{i,h,mid}} - \overline{C_{i,h,pre}} \tag{3}$$

and similarly for the coefficient of variation:

$$\Delta CV_{i,h} = CV_{i,h,pre} - CV_{i,h,mid} \tag{4}$$

2.4. Analyses

In the results, we present analyses of average hourly electricity consumption first, and CV per hour thereafter, following the same procedure for both. First, descriptive plots visualise the average hourly electricity consumption (alternatively CV per hour) for those living in (semi-)detached homes vs. those living in apartments, comparing data from before to during the pandemic. These plots and subsequent analyses are split up per housing type because electricity consumption patterns are known to differ strongly between housing types. One of the main reasons for this difference lies in the different heating systems that are commonly used in detached houses compared to apartments. In this sample, as is shown in Table 1, over 80 % of the sample uses either district heating or heat pumps, with the former being used predominantly in apartments (69 %) and the latter predominantly in detached homes (83 %). Besides this difference, family size and income differed between apartments and detached homes. Separating the data instead according to heating type (i.e., comparing the largest groups: heat pumps and district heating) did not yield any different conclusions, as can be seen in the auxiliary analyses in the Supplementary Tables 4 and 6, and neither did the inclusion of predictors covering size of home, number of those living in the home and specific heating type (see Supplementary Tables 7–8).

After a visual inspection, a multilevel null model (unconditional means model) is used to identify whether the mean of change in electricity consumption is significantly different from zero ($\alpha = 0.05$). A random intercept u_i per household is included in the model, because the hourly observations are nested by household and cannot be considered independent. The estimated global intercepts from these models indicate the global mean of the change metrics, showing if, across households and hours of the day, there was an average positive or negative change for electricity consumption or CV.

$$\Delta\overline{C_{i,h}} = \beta_0 + u_i + \varepsilon_{i,h} \tag{5}$$

$$\Delta CV_{i,h} = \beta_0 + u_i + \varepsilon_{i,h} \tag{6}$$

where β_0 denotes the global intercept, u_i the household-level random intercepts and $\varepsilon_{i,h}$ the residual error term, assumed to be normally distributed with a mean of zero and a constant variance, but not required to be independent and identically distributed (i.i.d.) due to the hierarchical structure of the data. The use of restricted maximum likelihood (REML) for parameter estimation in our multilevel model accounts for this structure and provides robust estimates of the variance components. Subsequently, multilevel models were used to inspect whether changes in hourly electricity consumption (alternatively CV per hour) were conditional on the hour of the day as well as on whether, during specific hours, data came from households who increased home presence or not. That is, changes in hourly electricity consumption were predicted with hour of the day, and the interaction between hour and home presence status, as follows:

$$\Delta\overline{C_{i,h}} = \beta_0 + \sum\nolimits_h (\beta_h x_h) + \sum\nolimits_h \sum\nolimits_{HO} (\beta_{h,HO} x_h x_{HO,i,h}) + u_i + \varepsilon_{i,h} \tag{7}$$

where x_h is a dummy variable for hour $h \in \{1\dots24\}$ with coefficients β_h and x_{HO} is a binary dummy variable indicating increased home presence. Similarly, a multilevel model was built for changes in CV per hour:

$$\Delta CV_{i,h} = \beta_0 + \sum\nolimits_h (\beta_h x_h) + \sum\nolimits_h \sum\nolimits_{HO} (\beta_{h,HO} x_h x_{HO,i,h}) + u_i + \varepsilon_{i,h} \tag{8}$$

Interaction effects $\beta_{h,HO}$ between hour and home presence status indicate whether, for any given hour, there is a difference in estimated changes dependent on home presence status. If the coefficients of these interaction effects are significantly different from zero, we reject the assumption that home presence status had no effect on consumption or variability changes during that hour.

3. Results

3.1. Electricity consumption

Inspecting first the average electricity consumption per hour before and during the pandemic, descriptive plots in Fig. 4 show different patterns in electricity consumption for those living in (semi-)detached homes, compared to those living in apartments. Those living in detached homes exhibited two clear clusters of hours where electricity consumption tended to be higher; between 6 and 10 o'clock, and between 16 and 22 o'clock. For apartments, there was only one pronounced cluster of hours with higher electricity consumption, occurring between 16 and 22. Fig. 4 moreover gives the impression of an increase in electricity consumption during the pandemic, and furthermore that this increase

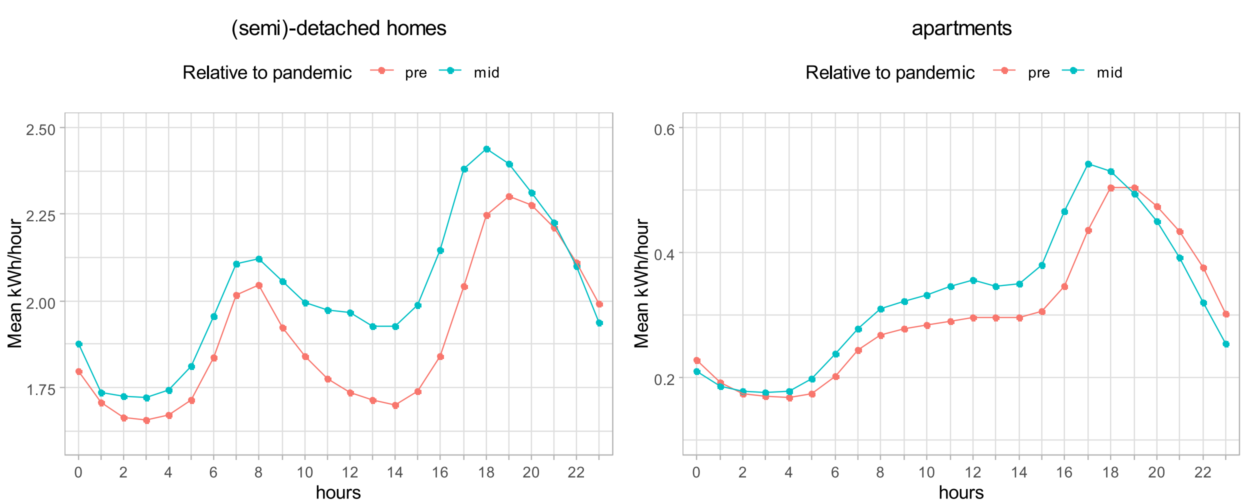

Fig. 4. Descriptive plots of average hourly electricity consumption before (red) and during (blue) the pandemic, plotted per hour (x-axis) and separated by housing type (left panel for (semi-)detached homes and right panel for apartments). Note there is a difference in y-axes, to optimally visualise consumption levels of (semi-)detached homes and apartments. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

occurred mostly during daytime hours. This begs the question, was this increase part of a normal trend, or due to occupants' increased presence at home?

Fig. 5 illustrates the distribution of changes in average hourly electricity consumption from before to during the pandemic, with positive values on the y-axis denoting an increase in consumption. Multilevel unconditional means models (Table 2) show that across all data, the changes in average hourly electricity consumption were above zero ($\beta_0 = 0.12$ respectively 0.03), indicating that there was an overall increase in electricity consumption. This was the case for both detached homes and apartments.

Multilevel models predicting this change in electricity consumption with hour of the day conditional on whether people were home or not, confirm that during several hours of the day, the increase in electricity consumption was larger for those who reported being home more during the day (see asterisks in Fig. 5, and Supplementary Table 1). More specifically, the increase in energy consumption during the pandemic was larger for those who reported being home more around 10 to 15 (for those in detached homes) and 9 to 16 (for those living in apartments). On two occasions, the reverse was true, with those who did not increase home presence having a stronger growth in consumption than those who increased presence at home: for those living in detached homes at 7 o'clock and for those living in apartments at 21 o'clock.

In conclusion, the data replicates earlier findings of increased electricity consumption during the pandemic. Moreover, the analyses show that the increase was stronger when people were home, suggesting that at least part of the increase can be attributed to increased home presence.

3.2. Average CV

Subsequently looking at CV per hour of the day, before and during the pandemic, the descriptive plots in Fig. 6 show different patterns for those living in (semi-)detached homes and those living in apartments. The difference between lowest and highest CV during the day is larger for those living in apartments, compared to those living in detached homes, and this does not change during the pandemic. Fig. 6 also suggests that there are larger increases in CV in detached homes during the morning hours, while there are larger decreases in apartments during the afternoon hours.

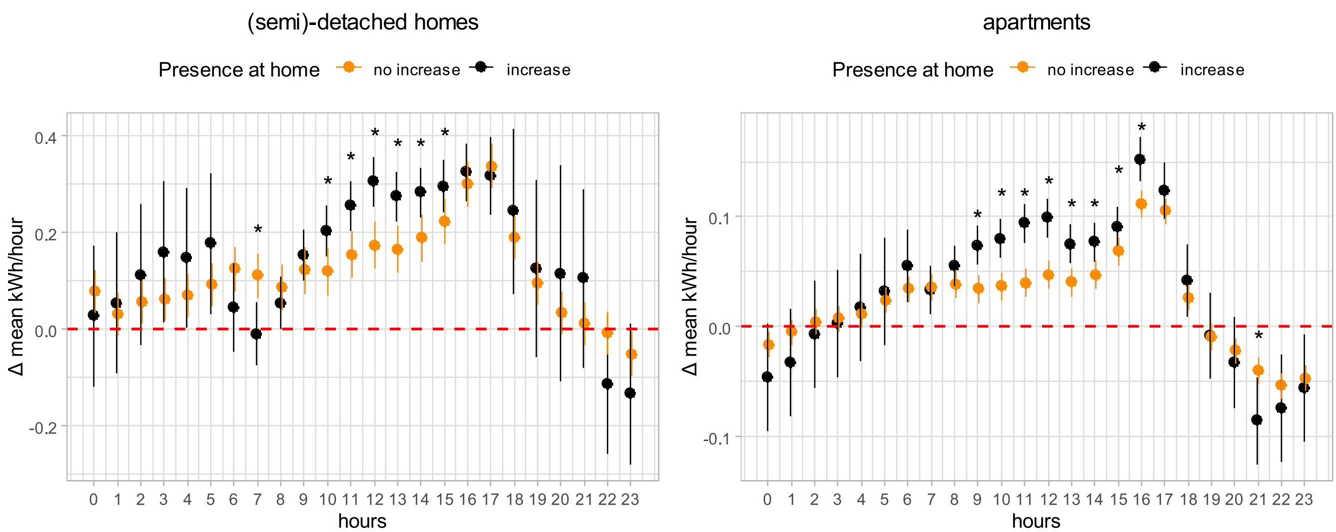

Fig. 5. Marginal effects of changes in households' average hourly electricity consumption from before to during the pandemic (y-axis), per hour of the day (x-axis) and by housing type (left panel for (semi-)detached homes and right panel for apartments). Positive values denote an increase in consumption. Colours denote whether data comes from households that indicated their home presence increased during that hour of the day. Red dashed line highlights the point where there was no difference in average hourly consumption from before to during the pandemic. Asterisks indicate significant differences in mean hourly consumption for specific hours between those who increased home presence compared to those that did not. Note there is a difference in y-axes between panels, to optimally visualise consumption levels of (semi-)detached homes and apartments. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 2
Unconditional means models predicting the change in hourly electricity consumption during the pandemic with a random intercept per household only, separated by housing type.

Predictors	(Semi-)detached homes			Apartments		
	Estimates	*CI*	*p*	*Estimates*	*CI*	*p*
Intercept (β_0)	0.12	0.08–0.16	**<0.001**	0.03	0.02–0.03	**<0.001**
Random effects						
σ^2	0.06			0.01		
τ_{00}	0.15_{ID}			0.01_{ID}		
ICC	0.73			0.47		
N (observations)	395 (9480)			444 (10656)		
Marginal R^2/conditional R^2	0.000/0.725			0.000/0.468		

Bold font indicates statistical significance at $p < 0.05$.

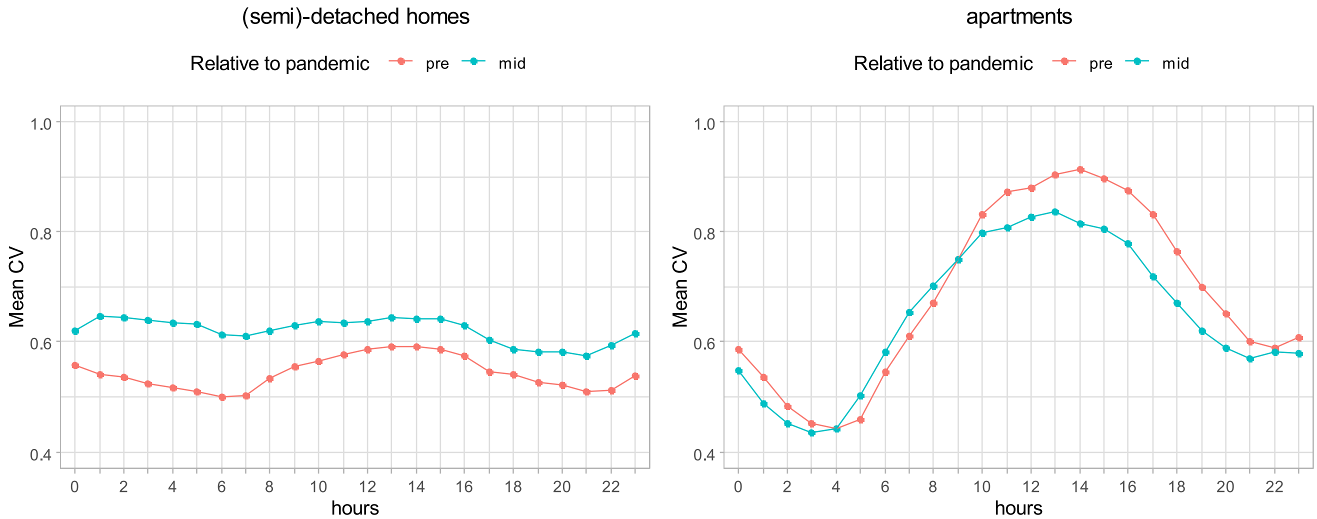

Fig. 6. Descriptive plots of average hourly CV before (red) and during (blue) the pandemic, plotted per hour (x-axis) and separated by housing type (left two panels for (semi-)detached homes and right two panels for apartments). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

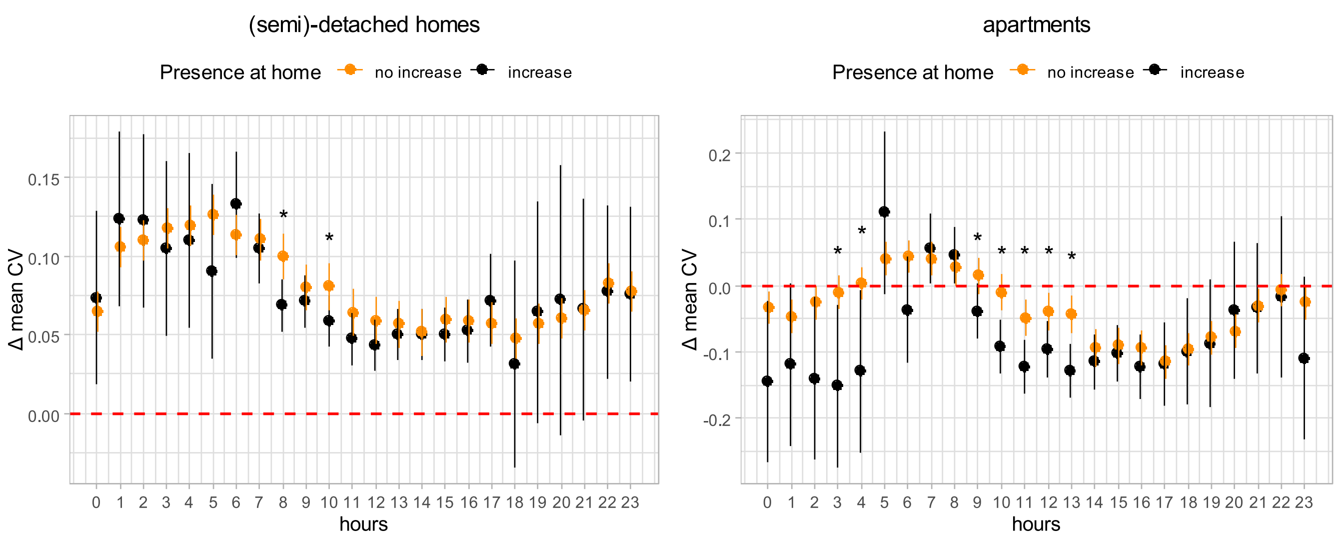

Fig. 7. Marginal effects of changes in households' average hourly CV from before to during the pandemic (y-axis), per hour of the day (x-axis) and by housing type (left panel for (semi-)detached homes and right panel for apartments). Positive values denote an increase in consumption. Colours denote whether data comes from households that indicated their home presence increased during that hour of the day. Red dashed line highlights the point where there was no difference in average hourly consumption from before to during the pandemic. Asterisks indicate significant differences in mean CV for specific hours between those who increased home presence compared to those that did not. Note there is a difference in y-axes, to optimally visualise consumption levels of (semi-)detached homes and apartments. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Fig. 7 illustrates the distribution of changes in average hourly CV from before to during the pandemic, with positive values denoting an increase in CV. Multilevel unconditional means models (Table 3) show that the changes in average hourly CV were above zero for those living in detached homes, indicating an overall increase in variability per hour during the pandemic. There was a decrease in CV for those living in apartments, indicating instead a reduction in variability per hour during the pandemic: consumption patterns became more regular.

These changes in CV over time should be interpreted with care, since the CV measure can be affected by changes in the average consumption of electricity. Two households who use exactly the same set of appliances at the same times, causing the same pattern of variation, but with different baseload energy use, can differ in CV, since CV equals the variation divided by the mean; thus, a household with a higher baseload and similar variation will have lower CV. A change in CV between pre and mid pandemic might thus be due to differences other than a change in variation, such as differences in temperatures.[6]

Multilevel models predicting pre-to during pandemic changes in CV with hour of the day and whether people were home or not suggest that for those living in apartments, during several hours during daytime (9 to 13 o'clock), and 2 h at night (3 and 4 o'clock) the decrease in CV is larger in those who reported being home more than those who were not (see asterisks in Fig. 7, and Supplementary Table 2). For those living in

[6] The average temperatures and deviations in the region were $M_{pre} = 8.22$, $SD_{pre} = 6.73$, $M_{mid} = 7.80$, $SD_{mid} = 8.06$, according to data from the Swedish Meteorological and Hydrological Institute [49].

Table 3
Unconditional means models predicting the changes in households' average hourly CV during the pandemic with a random intercept per household only, separated by housing type.

Predictors	(Semi-)detached homes			Apartments		
	Estimates	*CI*	*p*	*Estimates*	*CI*	*p*
Intercept	0.08	0.07–0.09	**<0.001**	−0.04	−0.05 to −0.02	**<0.001**
Random effects						
σ^2	0.01			0.05		
τ_{00}	0.01_{ID}			0.02_{ID}		
ICC	0.54			0.30		
N (observations)	395 (9480)			443 (10,632)		
Marginal R^2/conditional R^2	0.000/0.543			0.000/0.301		

Bold font indicates statistical significance at $p < 0.05$.

detached homes, CV increased less for those who were home more, compared to those who were not, for two day-time hours (8 and 10 o'clock).

In summary, three interesting observations can be made from the analysis of changes in CV per hour during the pandemic. First, though this should be interpreted with care as to what caused it, there is an increase in CV for those who live in detached homes, while there seems to be a decrease in CV for those living in apartments. Second, in detached homes, at least for some daytime hours, the variation in electricity consumption increased more for those who were not home more. Third, in apartments, at least for some daytime hours, the variation decreased less for those who were not home more. If the data from those who were not home more is taken as representative of the baseline changes in CV over time, then it seems that home presence has a decreasing effect on CV on top of that trend, during daytime.

3.3. Overview of findings

The findings are summarised as follows (see also Table 4): for those living in detached homes, average hourly electricity consumption seems to have increased during, compared to before the pandemic, and those who increased their home presence during daytime hours have a larger increase in electricity consumption than those who did not increase home presence during daytime hours. The same applied for those living in apartments.

Regarding CV in electricity consumption, there was a general increase in CV for those living in detached homes during, compared to before the pandemic, though during some daytime hours, this increase was lower for those who increased home presence. In other words, being home more dampened the increase in variation. There was a general decrease in CV for those living in apartments during, compared to before the pandemic, and during some daytime hours, this decrease was larger for those who increased home presence. In other words, here being home more exacerbated the decreased variation.

Table 4
Summary of main findings from analyses in the study, comparing changes in average hourly consumption and coefficient of variation over time, between those whose home presence increased compared to those whose home presence did not increase during the pandemic.

Housing type	Average hourly consumption	Coefficient of variation
(Semi-) detached homes	Larger increase in hourly consumption for those who increased home presence during daytime hours	Increase in CV is attenuated by increased home presence during daytime hours
Apartments	Larger increase in hourly consumption for those who increased home presence during daytime hours	Decrease in CV is exacerbated by increased home presence during daytime hours

4. Discussion

This study investigated whether there are differences in households' a) energy consumption pattern and b) variability, depending on changes in households' time spent at home. A difference-in-difference approach was used to compare trends over time *between* two groups: those who were home more vs. those who were not. The results showed that during the pandemic, households with increased home presence used more electricity, particularly during the expected workday hours, compared to those who were homeless. Among households living in detached homes, we moreover detected that those who were home more had a weaker increase in consumption during the morning, compared to households who were not home more. This might be because people who spent more time at home skipped activities they would typically do in the morning when leaving for work. A similar effect arose among apartment owners in the evening hours, where there was a stronger reduction in energy consumption during the pandemic among those who were home more; possibly since a set of household activities that typically were performed in the evening were moved to daytime. These observations suggest that being home may affect households' load shape in that electricity from morning or evening times is shifted towards daytime. In sum, besides an overall increase in consumption, being home more also seems to affect the pattern of energy consumption over the day, with a shift towards more daytime use, and potentially reduced use during the morning or evening hours.

Concerning variability, the results show that in both detached homes and apartments, households with increased home presence had a lower CV compared to households that did not increase home presence. This effect is predominantly occurring in the first half of the day. In other words, per hour variability was lower when people were home more; they were more regular. If high variability indicates flexibility potential, then being home more does not contribute to it. However, when CV is considered alongside the increased consumption for those who are home more, a different interpretation can be given. While variability decreased, consumption increased during the first half of the day, for those with increased home presence, which suggests that a) they used more electricity than those did not increase home presence and b) they were doing so more consistently. In sum, the lower variability in those who were home more is suggestive of changed routines.

4.1. Implications

This study adds to previous literature in highlighting that being home is a factor influencing households' response to demand-response programs [1,2]. It shows that, even without demand-response programs, the mere increase of home presence can affect energy consumption patterns, in ways that at least to some extent may be beneficial to the electricity system (i.e., by potentially shifting electricity consumption to daytime hours). On the other hand, depending on when peaks in the grid occur, an increase in afternoon consumption (16–17 o'clock) for those at home might exacerbate a system's peak capacity problems. While there is a trend towards working from home to higher extents than before the pandemic [41–44], this study has indicated that changes in time spent at home can have an impact on electricity consumption patterns. The teleworking trend is unlikely to revert back to pre-pandemic levels. What, then, are implications of changes in people's time spent at home, for demand response?

Recognizing the impact of consumers' presence at home on their electricity consumption patterns helps utilities and policymakers in tailoring demand-response strategies to consumer segments, to account for diverse consumer needs and preferences. For instance, the finding that higher and more regular electricity consumption was associated with being home more can be combined with other insights concerning consumer characteristics. An engaged 'resource man' [50] who is at home might be able to engage in different strategies compared to a similar household where members are often away from home during daytime, or to a household where members are at home, but whose desire to engage in electricity consumption patterns is minimal. For engaged consumers who are at home, communication and tariff incentive structures could emphasize shifting consumption, using time-of-use or real-time pricing schemes or real-time energy consumption feedback. For households with low time spent at home, or little desire to engage in their consumption patterns, automated solutions that prioritise convenience might be more suitable.

In this sense, the findings from this study are a small piece of a larger puzzle where the diversity of consumer preferences and lifestyles is recognized. Utilities can, rather than applying one-size-fits-all solutions, design flexible demand-response programs that accommodate different levels of engagement and participation. This approach allows consumers to engage with demand flexibility initiatives in a way that aligns with their needs and preferences.

4.2. Limitations and future research

A limit to this study is reliance on respondents' ability to remember their and household members' presence at home before, during and after the pandemic. Respondents might over- or underestimate their presence at home, but that in itself is not a threat to the study, since the main variable of interest was difference in presence. The study is sensitive to whether respondents had a biased memory of home presence conditional on the question concerning time before or during the pandemic. One source of confounding in this study therefore is if the group of respondents who had more (or less) of a bias in home presence differences before and during the pandemic, also had stronger changes in their consumption patterns, for other reasons. If this is the case, then the results might be due to these other reasons, and not changes in home presence. We do not see any obvious candidate suggestions for this, but it remains a limit of the study that we relied on self-reported home presence and could therefore not control for this potential influence of confounders.

A second limitation is the geographically limited scope of the study. The data originates from a suburb in Stockholm, and the response rate to the survey was low, which impacts the generalizability of the findings to other neighbourhoods, regions or countries. The socio-demographic data (Table 1) did not reveal a socio-demographic stratum that was notably underrepresented, but it remains a question how well the findings might be extrapolated beyond the Swedish context. Working from home is a trend that is found across many countries [42,51], and increased time spent at home might have similar effects on load curves in many European countries as it has in Sweden, though this should be confirmed with further studies.

A third limit is in the assumption that there are parallel trends in the groups of respondents with increased home presence and those without, which underlies the difference-in-difference approach used here. It is possible that there are differences in these groups that would have caused the groups to develop differently, even in the absence of changes in time spent at home. Future studies might consider different study designs to overcome this possible limitation, for example by designing experiments in living-lab settings (e.g., as in [52]).

This study looked at presence at home as a potential cause of changes in energy consumption. It is evident that mere presence is not sufficient to affect consumption: it is the activities that accompany such presence that matter. Given that this study was done during the pandemic, the results found here might be an attribute of pandemic-specific behaviours or more general behaviours that one undertakes when one is home. Future research should therefore focus on the mechanisms behind consumption pattern changes as a result of increased home presence. What are the activities that potentially lead to increased or decreased variability and increases in daytime consumption, with increased home presence?

5. Conclusion

This paper started with the question of whether increased time spent at home, without any other incentives to drive consumers, could lead to changes in electricity consumption patterns. In conclusion, the data suggest that consumption patterns changed during the pandemic, and these changes depended on whether people spent more time at home or not. Increased home presence was associated to increased energy consumption during the day, and in some cases, a reduced consumption during morning or evening hours, while it also resulted in a somewhat more regular energy consumption pattern during the morning hours.

It should be noted that, while people working from home during the pandemic may have had a changed potential for flexibly using energy, they were not actively encouraged to do so. This study looked at the changes in volume and variability in electricity consumption which naturally occur when people change home presence/time spent at home. Demand response programs and policy makers can utilise this by tailoring approaches to different consumer segments, which may have dissimilar kinds of flexibility that they can exhibit, and different abilities in responding flexibly.

CRediT authorship contribution statement

Britt Stikvoort: Writing – review & editing, Writing – original draft, Visualization, Investigation, Formal analysis, Data curation, Conceptualization. **Anders Nilsson:** Writing – review & editing, Writing – original draft, Investigation, Conceptualization. **Cajsa Bartusch:** Writing – review & editing, Funding acquisition, Conceptualization. **Vera van Zoest:** Writing – review & editing, Project administration, Methodology, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

We thank Fouad El Gohary and Karl Lindberg for their efforts in preprocessing the electricity meter data. We also thank Karl Lindberg and Emanuel Larsson for their help in constructing the survey. This work was supported by the Swedish Energy Agency (grant numbers 51340-1 and P2021-00187).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.erss.2025.104032.

Data availability

The authors do not have permission to share data.

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