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Impact of Time-Use Behaviour on Residential Energy Consumption in the United Kingdom

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Abstract: In order to have the best possible chance of achieving 'decent work' and 'climate action' as laid forth in the UN Sustainable Development Goals, government and policy makers must pay close attention to current time-use patterns, as well as the way these might change in the near future. Here we contribute to the existing literature on time-use behaviour through a systematic exploration of the relationship between working patterns and energy consumption from the perspective of time-use. Our starting point is the premise that different work arrangements impact the timing of energy demand not only in workplaces, but also at home. Using the data from the 2014–2015 UK time-use survey, we were able to capture patterns of time-use behaviours and to assess their relationship with daily energy consumption. We propose a systematic time-use-based approach for estimating residential energy consumption with regards to activity timing, activity location, activity coordination, and appliance type. We use this method to discover patterns in residential activities and energy consumption, as well as the causal relationship between residential energy consumption and work patterns. In this study, we unpack the heterogeneity in the work–energy relationship, particularly when comparing full-time and part-time workers. Our results suggest that full-time employees have a higher potential to reduce their energy use compared to part-time employees. We also discover a non-linear change in total energy consumption for respondents with varying levels of work time. Energy consumption reductions associated with differences in work schedules are greatest during the first few hours of the workday, but then level off. Our findings suggests that time-use data can provide useful insights for evaluating and possibly designing energy and labour-market policies.

Keywords: time-use behaviour; work patterns; energy consumption

1. Introduction

In 2019, the residential sector was the largest end user of electricity in the United Kingdom, accounting for 30 percent of total annual consumption [1]. Peaks in residential electricity demand also account for up to 50% of national peak demand, which makes it the single largest contributor [2]. In many countries, meeting demand during peak periods entails making use of less efficient, more carbon-intensive generation plants, making electricity provision particularly costly—both in economic and environmental terms—during these times. Part of the intervention plans aimed at mitigating peaks in residential electricity demand focuses on investigating the impact of time-use tariffs (TOU) on people's energy consumption. For example, Torriti [3] investigated the effect of TOU tariffs on electricity demand and load shifting at the substation level in the Province of Trento in Northern Italy. Meter reading data was collected from two groups of households, one on flat rate tariffs and the other one on TOU tariffs. When the TOU group was compared to the flat rate one, the results indicated a relatively higher average electricity consumption of 13.69% but with reduced electricity spending of 2.21% due to morning peak shifts. Bartusch [4] conducted semi-structured interviews with Swedish consumers in order to

assess their perceptions and experiences with TOU tariffs. Overall electricity consumption decreased between 2005 and 2006 by 11.1–14.2%, and some loads were shifted to off-peak times. Using data from a randomized controlled smart metering trial in Ireland, Carroll [5] analysed demand reduction as a function of smart meter use and TOU tariffs. In the study, participation in smart metering programmes with TOU tariffs resulted in a 1.8% reduction in demand. More recently, Srivastava [6] examined the effect of consumers' behaviour and perceptions of smart appliances on demand flexibility using a quantile regression model based on survey data from 155 Belgian households. The findings indicated a variance of 44.2% in demand flexibility due to consumer behaviour. Furthermore, the findings appeared to provide evidence that consumer behaviour does, in fact, change as a result of awareness creation, thus providing additional support to the position that consumer literacy about the benefits of smart devices has a tendency to affect their energy consumption.

While it is clear that there has been widespread interest in investigating people's responses to interventions designed around financial incentives, the impact of their typical daily schedules—particularly when it comes to largely fixed commitments such as working arrangements—has received substantially less attention. A number of academic and policy studies have focused on gaining a better understanding of which everyday activities contribute to residential peak demand, in part to determine the degree of temporal flexibility that may exist when activities typically associated with electricity consumption are conducted (for a brief discussion see Table A2 in the Appendix A). These studies have shown how the timing of energy demand is dynamic, social, cultural, political, and historical, and is inextricably linked to society's evolving temporal rhythm. Their findings suggest that electricity demand is shaped by the synchronicity, sequencing, and interdependence of daily activities.

More attention has recently been paid to the effects of leisure time allocation and its environmental impact when work hours change [7–9]. The purpose of these studies is to examine time budgets, but they tend to look at average effects across populations. This approach does not consider the different effects of working time on leisure activities, which obscure the subgroups that should be targeted for energy demand reductions [9]. Another limitation of these studies is that they rely heavily on separate datasets such as time-use surveys and household expenditure surveys, which leads to errors in estimating energy intensities.

Furthermore, little consideration has been given to the impact of working hours on issues such as environmental sustainability, social equity, and increased life satisfaction [7-9]. Environmental activists have long argued for a reduction in working hours in order to protect the environment. Proponents of new working models advocate for a reduction in annual labour hours, whether through a four-day work week, increased leisure time, or other flexible work arrangements [10]. The underlying argument is that working fewer hours must always be accompanied with a smaller environmental footprint, as people may purchase fewer items while having more time available for time-consuming activities [7-8]. As a result, it is critical to determine to what extent a change in working hours is likely to cause a change in energy consumption patterns.

Here we contribute to the existing literature on time-use behaviour through a systematic exploration of the relationship between working patterns and energy consumption from the perspective of time use. Our starting point is the premise that different work arrangements impact the timing of energy-related activities—and thus, energy demand—not only in workplaces, but also at home. This is because the differences in work arrangements in terms of number of hours per week will result in different combinations and scheduling of energy-related activities in the home, which need to be analysed in terms of how activities are connected throughout the day, and which activities are central to everyday life. Therefore, if we want to understand what factors trigger the use of residential energy, we need to better understand (a) what residents do; (b) where they do it; (c) how long they do it for; and (d) what kind of appliance (if any) they are likely to use.

We established three research questions that guided our analysis:

(i). Which energy-relevant activities are undertaken more or less often when comparing regular and irregular work patterns?

(ii). How does the duration of energy-relevant activities change with regular and irregular work patterns?

(iii). How does the energy intensity of energy-relevant activities change in response to different work patterns?

To answer these questions, we estimated a number of econometric models relating work time and energy use using national-level data for the United Kingdom. The context of the analysis was regular and irregular working patterns, which revealed time-use behaviour before and after work and have a direct impact on individuals' energy consumption behaviour. For the decision maker, this analysis provides a theoretical basis to formulate energy-saving policies from the perspective of time-use behaviour. Our argument is that regular and irregular work patterns influence the timing and interconnection between activities that can change residential energy consumption and that policymakers should formulate customised time-use policies based on what different types of residential consumers do, where they do it, how long they do it for, and what kind of appliances they use.

The remainder of the paper is organised as follows: Section 2 offers an overview of the proposed conceptual framework. Data and methodology are explained in Section 3. Section 4 presents the results of our econometric analysis, which are discussed in Section 5, and Section 6 concludes.

2. Conceptual Framework

For the purposes of our study, we considered energy consumption to be the result of time-use behaviours that could be classified based on four key dimensions: namely, the location in which activities take place, the duration of said activities, the type of appliance(s) likely associated with them, and whether there is an incentive for activity coordination across members of a household. We thus proposed a framework which can assist in analysing different time-use behaviours based on such dimensions. The underlying assumption of the proposed framework (Figure 1) was that external factors, such as work schedules, influence time-use behaviour, which in turn influences activity energy intensity. The choice of the four dimensions considered in our framework was based on a comprehensive literature review which covered past studies that focused on aspects relevant to the analysis of time-use behaviour (See Appendix A). Our framework recognises that in order to understand activity energy intensities, we must first address the following questions: where are activities performed, how long are they performed for; what type of appliances/equipment are involved; and how are these activities coordinated with others during this time? Thus, achieving behaviour changes in residential energy consumption can be thought of as unlocking a series of time-use related locks; that is, all time-use related characteristics need to be in place. On this basis, a behaviour diagnosis may involve finding out what aspects of time–use behaviour (e.g., activity location, duration, coordination and appliance use) can usefully be targeted to achieve the desired behaviour change.
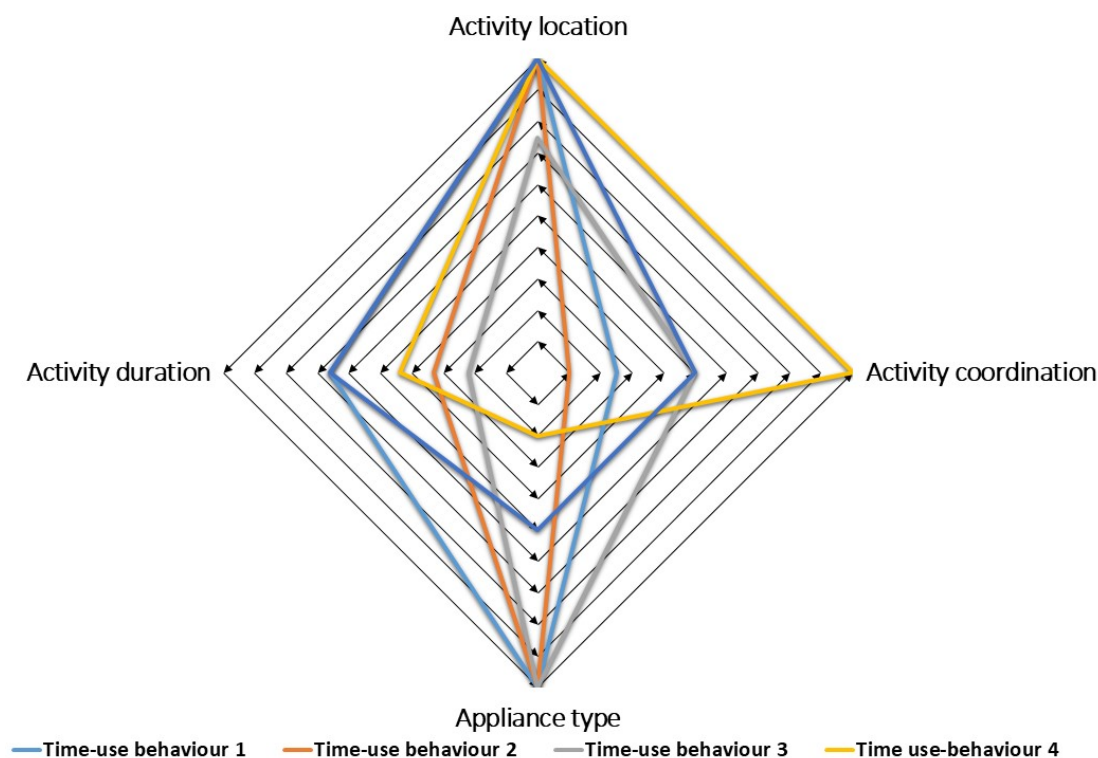
Figure 1. The four dimensions that characterise time-use behaviours. The different polygons are examples of the graphical representation of different time-use behaviours.

For example, the time-use behaviour related to TV watching observed amongst people in full-time employment (Figure 2) can be characterised in part by the resident's location, in part by the duration of the TV watching activity, in part by the importance of the activity within the consumer's daily life, and in part by the presence of any type of TV appliance. The four concepts and their interactions form the core of time-use behaviours that in turn influence energy consumption. Each aspect, be it the duration, location, or coordination (in order to be completed on time, some activities must be coordinated with others or timed with other activities) of an activity, along with any associated appliance type, is impacted in some way by wider influences. For example, TV-watching location will be affected by the availability of the technology or by having a TV license—in the UK, a TV licence is required in order to have access to live TV content; the duration of TV watching periods will be affected by level of education; the coordination of the TV watching activity could be affected by energy tariff plans and the choice of purchasing a TV is influenced by affluence levels and attitudes towards energy efficiency rating schemes.

Figure 2. Example of four different TV watching time-use behaviours (based on UKTUS 2014/15 data).
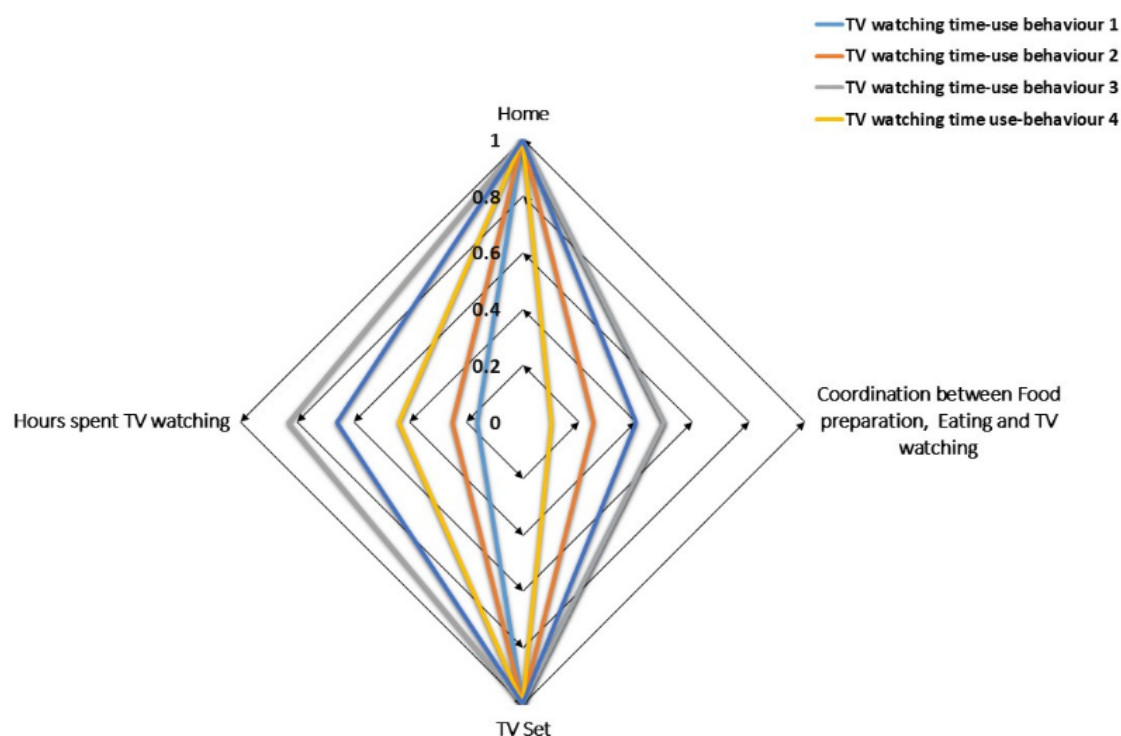
Having a clear idea of the factors underpinning behaviours provides the basis for identifying the types of intervention that are likely to be effective. Based on our extensive literature review (see Appendix A) we provide broad types of interventions that can be used (Table 1). Each of these target a mixture of time-use behaviour and some intervention types are better suited to certain time-use behaviour characteristics than others. These interventions are not intended to cover all possible scenarios, but rather to provide a starting point.

Table 1. Time-use behaviour intervention types.

Information framing	Information framing is extremely effective at utilising behavioural principles and heuristics that people already employ when making decisions. When presented with the option of paying more for a lower-efficiency model or paying less for a higher-efficiency alternative, loss aversion causes consumers to consider purchasing an energy-efficient appliance. To improve framing information, use useful time frames and metrics that are easy to understand.
Innovative product design and physical environments	Innovative product design and physical environments can influence customer's habits, as consumers frequently take habits for granted rather than thinking through energy-relevant decisions. Consider for example, attractive, informative smart energy meters located in obvious places and connected to smartphone or web applications, which would enable consumers to better understand their energy bills.
Changes to the default policy	Promotion of a sustainable transportation policy to replace long-distance commuting. This could include concerted efforts to replace biking with driving or to bridge the gap between workplace and home by promoting home or flexible working.

This particular framework was developed with a view to assisting in the development of policy, regulation, and market design initiatives aimed at increasing energy efficiency through a better understanding of how energy use is influenced by working arrangements. Having the ability to identify consumers with similar time-use behaviours can assist in developing more effective interventions and incentives to target specific energy consumption patterns. For example, this conceptual framework could assist energy companies in better tailoring their schemes and products by understanding the different time-use behaviours observed among their customers and how these relate to their energy consumption.

2.1. Types of Work Schedules

The types of work arrangements defined in this paper are based on the analysis of week-long work diaries collected as part of the UK Time-Use Survey[11]. In operationalising our definition, the variation between start and end times during workdays is used to distinguish between regular and irregular work patterns. As a result, a regular work pattern is characterised by less variation in the beginning and end times of the periods spent working. Both regular and irregular work patterns are further classified as full-time or part-time based on the number of days spent working per week. In this sense, a full-time worker is someone who worked five days, whereas a part-time worker is someone who worked at least two days but less than five days.

Similar approaches have been used in previous studies; Appendix A (Tables A1 and A2) summarises the various types of work schedules identified based on the same type of data (i.e., time-use survey diaries) used in our study.

A growing body of literature is investigating the marginal effects of reduced work hours on energy use and emissions. For instance, Nässén [7] and Buhl [8] estimated the average income elasticity of energy consumption for the Swedish and German populations, respectively, based on government statistics. Their findings show a positive relationship between energy consumption and income and a negative relationship between energy consumption and work time. Particularly interesting from our perspective is a study by Klein [9], which investigates how work time relates to leisure activity structures and associated energy use for different types of employees. Their results suggest that, in Finland, the effects of work time on energy use are rather homogeneous, whereas in France there appears to be more diversity between employee types. In both countries, adjustment of leisure-activity duration is sometimes strong initially but flattening for longer work hours. This relates to another finding, namely that the composition of leisure activities differs between people with distinct work hours.

2.2. Timing and Duration

Data from time diaries provide empirical evidence about how people spend their time. Sullivan [12] investigated whether there was an increase in the fragmentation of daily activities (measured by the number and duration of events per day) and the intensity of activities per unit of time between 2000 and 2015. Furthermore, they investigated whether any increases in fragmentation and intensity are related to survey respondents reporting a sense of being rushed and their perceived use of ICTs. They report no increase in the number of events per day and a decrease across all socioeconomic groups. Women's time is also more fragmented than men's (more events and more events of shorter duration), but the differences between the two years 2000 and 2015 are marginal. In both years, more women reported feeling rushed than men, but feeling rushed has decreased significantly in the professional and middle socioeconomic groups. ICT use has no statistically significant effect on event fragmentation, activity intensification per event, or reported feelings of being rushed. Sullivan [12] found no evidence to support a generalized speeding-up of lives across the UK, and that any variations in how rushed people feel are due to the amount of time they spend on 'constrained activities' of paid and unpaid work. A possible explanation is Gershuny's [13] claim that being busy at work has become a

"badge of honour" as it symbolizes occupational success and achievement. Furthermore, Gershuny [13] claims that those in managerial, professional, and technical occupations, which have the highest levels of intrinsic reward from work, have increased as a proportion of total time spent in work across the UK population, while those in manual occupations, which have the lowest level of intrinsic reward, have decreased.

In another study that looks more specifically at the influence of particular activities over the temporalities of others, Bittman [14] demonstrated that even though men and women in all OECD countries enjoy roughly equal amounts of leisure time, the experience of leisure time differs significantly. Taking into account secondary activities, men seem to enjoy consolidated periods of leisure, whereas childcare appears to be a prominent feature of women's "leisure". Sorrell [15] investigated the relationship between working time, energy consumption, and emissions. According to Sorrell [15], if people reduced their working hours, they would have more time for leisure and would be more concerned with saving money and, indirectly, energy. They demonstrate this concept through changes in spending patterns, such as cooking at home instead of buying ready meals or taking public transportation instead of a taxi. Those who investigated the potential for a non-linear relationship between working time and environmental impact contradict the preceding example, which suggests that after a certain income level, leisure time is used to fuel energy-intensive activities such as air travel. In conclusion, we argue that time-use diaries allow us to study how time is used and experienced by working individuals.

2.3. Location

In this paper, we were also interested in the likely energy intensity of energy-relevant activities carried out at home after work, based on the usage of the associated appliances. It is generally believed that working from home is likely to deliver energy savings, which may well be the result of increased hot-desking—hot-desking refers to the practice of allocating desks to workers on an as-needed basis, rather than providing each worker with their own—practices along with an overall reduction of office space requirements, resulting in office buildings not needing to be heated or cooled to the same degree. Williams [16] estimated that adoption of 4-day per week teleworking by Japan's specialist/technical workers (14% of the workforce) could reduce national energy consumption by 1% by eliminating the need for office heating and cooling on non-working days. Similarly, Matthews [17] estimated that the potential energy savings from less office space are comparable to those from less commuting. Energy savings from reduced office use may be smaller in countries such as Japan, where office space per worker is lower, than in the United States, where offices are larger. According to Kitou [18], the gains may be smaller in more temperate regions because less energy is required to heat and cool office buildings and they may also be offset in part by the embodied energy associated with duplicated equipment such as printers.

2.4. Sequential Order

In general, there is a lack of understanding of how the temporal variation of work hours affects the scheduling and sequencing of domestic activities and how these relate to the timing of energy demand. From our day-to-day experiences, we can appreciate that "normal" working hours contribute to the creation of peaks in the level of certain activities at particular times of day. For instance, we all have the notion of "rush hours". When the activities in question are energy-relevant—meaning that they have a significant impact on observed energy demand loads—this also gives rise to peaks in demand for energy. This explains the prevalence of the evening peak periods in the UK, which occur when people arrive home and start cooking, watching TV, eating, or socializing.

Studies which have focused on the impact of work schedules on commuting suggest that flexible work schedules have the potential to reduce peak demand by shifting the

time of or substituting these journeys. Burkinshaw [19], for example, interviewed 29 workers with the goal of investigating the potential use of home working and time shifting among workers from different professions (e.g., architects, academics) who were assumed to have different levels of access to flexible working arrangements. While the findings of said study showed no differences in flexible working arrangements between the professions studied, they identified several factors that constrain participants' working patterns. According to this study, the main reason for the low uptake of flexible working hours is the temporal sequencing of commuting to work with other activities such as household upkeep and/or caring responsibilities (e.g., children's school runs or dog walking). As a result, Burkinshaw [19] contended that flexible working policies aimed at changing patterns of commuting must be understood in relation to all of the other practices to which they are linked.

Durand-Daubin [20] compared French and British cooking and eating practices using over 20 years of time-use survey data, focusing on where, for how long, and when people engage in these practices. Their research discovered that the variation in eating location is influenced by the type of meal as well as the surrounding activities that shape evening meals. The employment rate was identified as a factor influencing the timing of cooking and eating practices. The authors propose a sequential analysis of the connections surrounding eating and cooking in order to understand where, when, and with whom energy is shared in doing these practices in a future study.

The (un)coordination and planning of daily activities among dual-earner couples has also been extensively investigated (see Table A2), and a number of studies have provided strong evidence to suggest that time balance within couples' activities, as well as how it changes throughout the day, is not random. Instead, they discovered that it is influenced by a variety of factors such as family, gender, employment, and socioeconomic status. These variables have an impact on the relevance and shape of behavioural patterns, and as the reviewed studies suggest, a holistic approach that considers both the sequence of activities and the time of day at which each activity is performed allows for a better understanding of time-use patterns [21].

According to Hellgren [21], the sequence of activities that an individual performs during the course of a day is influenced by social factors as well as three types of constraints: capacity, coupling, and authority constraints. Vagni [22] examined the work, leisure, and other activities of 23 countries and more than 50 years of time diaries in a recent study. People's daily activities were compared and classified using techniques such as optimal matching and related sequence analysis techniques, as well as classification methods such as cluster analysis. They discovered recurring patterns of activity despite geographic and cultural differences. These people were divided into five distinct patterns of paid work (two of which were shift work patterns), two unpaid work patterns, and a leisure pattern. The work of Cornwell [23] is relevant for this paper because it begins by explaining in detail how a sequence can be represented as a network, with activity states as nodes and connections between time-adjacent states as edges. He then demonstrated how a number of network concepts, such as network density, centralisation, and—crucially—the betweenness centrality, can be used to characterize individual sequences and compare multiple sequence structures. The method was demonstrated by analysing daily activities using data from the American Time Use Survey.

In this paper, we used the betweenness centrality metric to identify activities that play an important role in connecting other activities in everyday activity schedules. In the case of activities, having a high betweenness centrality means having a one-of-a-kind combination of sequence transitions that others do not have. This provided potential insight into differences in activity sequences across groups that more traditional analyses of aggregate time-use patterns do not provide.

2.5. Estimation of Energy Consumption Based on Activity Data

In general, an activity is deemed energy-relevant if it can be reasonably expected that such an activity might entail the use of energy-consuming appliances. The choice of particular activities for analysis varies from study to study, and for a number of reasons—many of which are related. These include: (1) analyses of time-dependent residential occupancy and energy-relevant activity patterns across different days and seasons; (2) research into the relationship between the use of household electrical appliances and energy-relevant activities and practices; (3) clustering activities in order to identify similarities in occupancy data; and (4) visualization and generation of activity sequences. Food-related activities, such as cooking, are found to be consistently classified as energy-intensive activities [24,25], whereas sleeping and resting are classified as non-energy-relevant activities [26,27]. Table A3 summarises findings from studies that used time-use data to model residential energy consumption of various activities.

The number of optimal activities varies and is frequently dependent on the probabilistic methods used. For example, Stankovic [28] used an 'activity ontology' to connect ten activities with various energy-consuming devices. The author divided activities into four broad categories to define activities that categorise daily routines (such as cooking, laundering, eating, washing, and sleeping), social life and entertainment, leisure and computing (such as watching TV, gaming, and using a computer), and hobbies. Yamaguchi [29] investigated activities that do not involve an appliance to quantify the demand for maintaining an indoor environment. Their model categorised activities into two groups: routine and non-routine behaviours. Sleeping, paid or schoolwork, commuting to and from school or work, eating meals (breakfast, lunch, and dinner), and bathing were the routine behaviours. They were referred to as 'routine' because these behaviours are assumed to be performed once a day in most households. Non-routine behaviours that do not involve interaction with other household members filled in the gaps between routine behaviours; watching TV, doing laundry, or caring for oneself are examples of non-routine behaviours.

3. Data and Variables

Our analysis was based on the UK Time Use Survey 2014–2015 [11], which is the most recent nationally representative time-use survey available in the UK. The study included 9388 people from 4238 households who completed 16,550 diaries and 3523 week-long work schedules. The time-use diaries provide information about what people do on one weekday and one weekend day. The amount of time spent on paid work was recorded in the weekly work diaries without lunch breaks or commutes of 15 min. The weekly work diaries provided day-level information about the start and end of work, as well as information about the duration of work (e.g., for how many consecutive days people work during the week).

3.1. Dependent Variables

In accordance with the literature, we defined an activity as energy-relevant if it could be linked to the usage of particular types of appliances. In this case, we aimed to identify primary activities from the UKTUS 2014/15 that had a high probability of causing increased electricity consumption in homes [30,31]. We restricted our analyses to the following dependent variables (activities): dishwashing, ironing, food preparation, house cleaning, laundry, and TV watching. TV watching includes live TV or other forms of entertainment that require a TV, such as watching a film on DVD.

Estimating Likely Energy Use

In order to investigate the impact of different work patterns on likely energy intensity of energy-relevant activities we calculated energy use according to the following formula:

$$E_i = \sum_{i=1}^{I} A_i \times EI_i$$

A_i, is the duration of activity i (in hours) and EI_i is the corresponding appliance electricity consumption of each activity as calculated by Widén [32]. The time-use activities and associated appliances from the UKTUS 2014/15 are shown in Table 2.

Table 2. UKTUS 2014/2015 time-use activities and associated appliances, including electrical load and proportion of dwellings with appliance.

Time-Use Activity	Employed Electricity Appliance	Average Electrical Load (kW)	Proportion of Dwellings with Appliance (%), Source: UKTUS 2014/2015			
			Regular		Irregular	
			Full-time	Part-time	Full-time	Part-time
Preparing food	Microwave	1.25	95.25%	93.58%	92.15%	94.00%
Washing clothes	Tumble dryer	2.50	64.39%	63.77%	64.24%	62.50%
	Washing machine	0.41	99.11%	98.30%	98.94%	99.25%
Watching TV	TV	0.08	98.07%	97.17%	96.95%	97.88%
	TV receiver box	0.03	74.93%	75.28%	68.00%	69.00%
Washing the dishes	Dish washer	1.13	56.23%	54.91%	60.02%	56.50%

Source: Based on Torriti [31]

According to the estimates calculated, the electricity load associated with food preparation is approximately 2 kW when using an electric appliance. While not every household owns all of the listed appliances, most of them are nearly virtually ubiquitous, as is the case with TVs, washing machines, and microwaves. There are numerous limitations to this approach, two of which are worth mentioning: First, some of the activities in Table 2 do not require active involvement with devices, as is the case for washing machines. Second, in our analysis the appliance characteristics are uniform in each building (but they could be variable based on socio-economic structure). In spite of this, the estimates calculated are good enough for the purposes of the analysis presented in this paper, as they clearly illustrate the varying levels of energy intensity associated with engagement in particular activities and the use of particular types of appliances.

3.2. Explanatory Variables

Instead of looking at the total amount of time spent working, we look at the specific times of day when people reported working in their corresponding work diaries. We limit our analyses to the following independent variables: (a) the work time, i.e., the hours individual j spent in paid work per day; (b) the work pattern (regular/irregular and full time/part time), i.e., the number of days a given individual spent in paid work and (c) the betweenness centrality of an activity based on the network representations of the daily activity schedules.

3.2.1. Work Time and Work Pattern Calculation

In our analysis, when people recorded paid work in their work diary, they were considered to be working. Figure 3 shows a variation in the start and end time of work across weekdays. It appears that people do tend to have a working pattern of 8 h, with a typical workday starting at 8:44 h and finishing at 16:37 h.
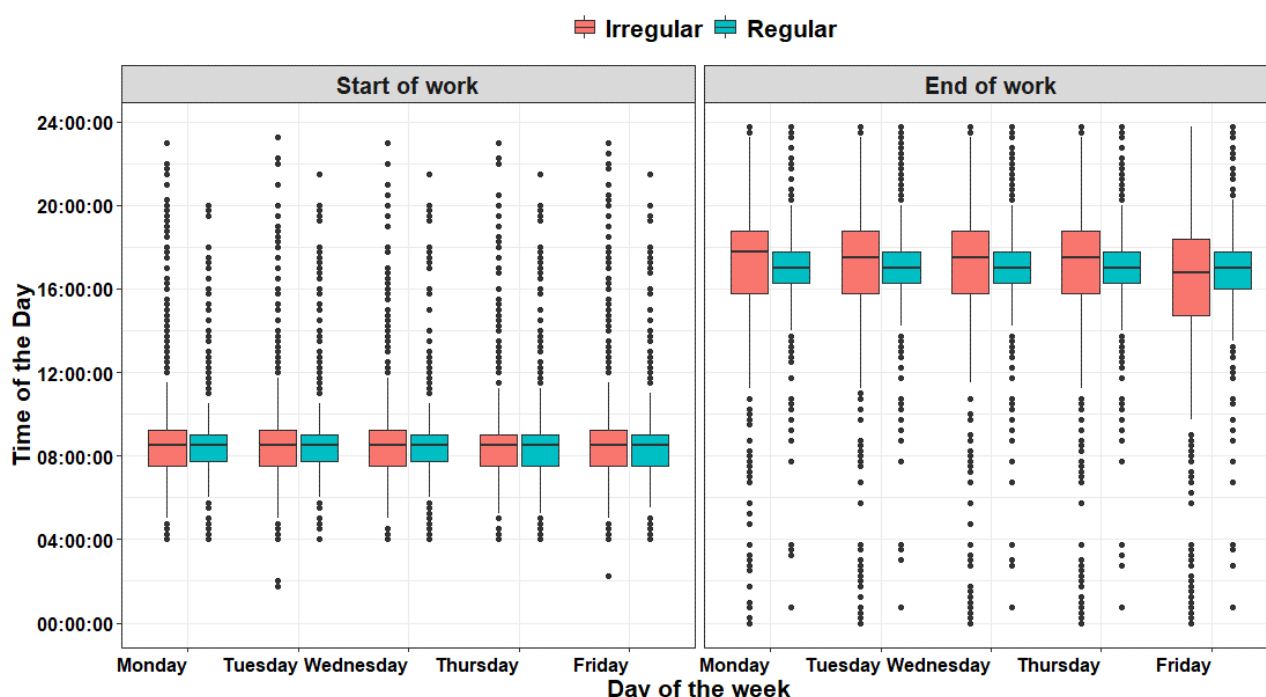
Figure 3. Distribution of work dairies relative to the start and end of work schedules.

As a way of determining whether weekly work schedules are regular or not, we calculated the standard deviation between the start and end of each week. Furthermore, work diaries were used to classify employees as full-time or part-time. A full-time employee is considered to have five daily work diaries, while an employee with at least two daily work diaries (and less than five work diary days) is considered a part-time employee. Using this information, we further divided the groups into regular full-time and part-time workers, as well as irregular full-time and part-time workers. Individuals with only one work diary were excluded from this analysis, and we restricted our study to Monday–Friday work patterns because Saturday–Sunday work patterns are mainly used to explore atypical work schedules in the literature on working time. We provide standard errors for all regression models to account for the fact that each individual has one time-use diary (on a weekday and on the weekend). In the final step, individuals' work diaries were matched with their corresponding time-use diaries to investigate the impact of regular or irregular work patterns on time-use behaviour.

3.2.2. Betweenness Centrality of Activities

The energy models in the reviewed literature do not take into account the causality between activities and make the simplifying assumption that the current performance of an activity is influenced by its past performance. We do not know what series of connections between activities causes time dependence. Data from time-use diaries implicitly captures the relationships between activities. The connection between activities can be illustrated using Markov-chain transitions, as shown in Figure 4.
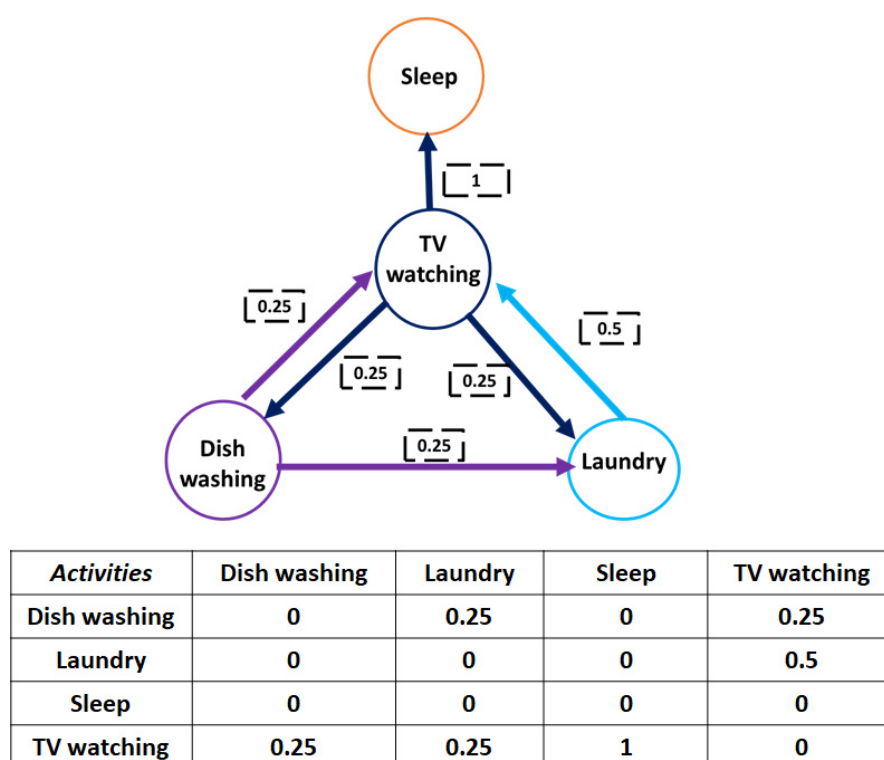
Activities	Dish washing	Laundry	Sleep	TV watching
Dish washing	0	0.25	0	0.25
Laundry	0	0	0	0.5
Sleep	0	0	0	0
TV watching	0.25	0.25	1	0

Figure 4. Graphical representation of transitions between activity states.

As an illustration, we will use four activities (dishwashing, laundry, sleeping, and watching TV). Every arrow represents a change from one activity to another, along with a probability indicating how likely the change is to occur. Because of time dependence or people's motivation to perform an activity in a specific order, there may be differences in transition probabilities between activities. The betweenness centrality metric is used to characterise the importance of the activity in the network. A high value of betweenness centrality for an activity indicates that it serves as an important intermediary or "gate-keeper".

We used Freeman's [33] formula to calculate the betweenness centrality of dishwashing, ironing, food preparation, house cleaning, laundry and TV/Video/DVD. For a given graph G = (V,E), the betweenness centrality of an activity v in a given network is defined as:

$$BC\ (v) = \sum_{u \neq v \neq w} \left(\frac{\sigma_{uw}(v)}{\sigma_{uv}} \right)$$

where σ_{uw} is the total number of shortest paths from activity u to w and $\sigma_{uw}(v)$ is the number of paths from u to w going through v. This way, we can determine how much of a given activity v is inbetween others. If the edges are weighted in the calculation of betweenness centrality, the shortest path with the lowest weighted value is taken into account. Based on our example, the TV watching (Figure 4) betweenness centrality equals 3, and there are three (with at least a weight of 1.25) shortest paths running through TV watching: (1) Laundry—TV watching—Dish washing; (2) Laundry—TV watching—Sleep; and (3) Dish washing—TV watching—Sleep. The longest weighted length is 1.75 for Dishwashing—Laundry—TV watching—Sleep.

3.2.3. Time-Dependence

Activities are time-dependent, so many of the same practices take place during the same period of time everyday [30,31]. We calculate the time-dependence of six activities using Torritti's [31] statistically derived time-dependence metrics, including dishwashing, ironing, food preparation, house cleaning, laundry and TV/Video/DVD.

Time-dependence is derived based on the following formula [31]:

$$T_{DEP} = \frac{MAX[(x_i - m(x))]}{m(x)}$$

where x_i is the duration of an activity at the time of the day I and $m(x)$ is the mean duration of activity x. The MAX Distance/Average captures the dependence of an activity on time throughout the day. In our analysis each activity is weighted by the T_{DEP} metric.

3.2.4. Regression Analysis

In order to address our research questions, we developed regression equations that included the following independent and dependent variables:

$$I_{i,j,d} = \beta_0 + \beta_1 WT_{j,d} + \beta_2 WT_{j,d}^2 + \beta_3 TP_j + \beta_4 WT_{j,d} * TP_j + \beta_5 BC_{i,j,d} + \beta_6 WT_{j,d} * BC_{i,j,d} + \beta_7 WT_{j,d}^2 * BC_{i,j,d} + \beta_n C_{n,j,d} + T_{DEPd} + \varepsilon_{i,j}$$

where $I_{i,j}$ is the time person j spends on energy-relevant activity i (i = 1,…,6) on a day d measured in minutes and β_0 is the fixed effect. $WT_{j,d}$ represents the work schedule time, i.e., the hours individual j spent in paid work during a day, while the $WT^2_{j,d}$ is the square of average work schedule time as we are interested in measuring the effect of longer work hours on energy-relevant activity allocation. TP_j measures the time j is facing and is approximated through two dummies reflecting an individual's employment status (full-time or part-time). $BC_{i,j}$ represents the importance of activity i for the person j and is measured using the betweenness centrality metric. We further included interaction terms between WT and TP as well between WT and BC as we expect the effect of an additional hour of work to be different depending on the individual baseline time poverty (TP_j). $C_{n,j,d}$ is a vector of n person-specific control variables including sex, age, household size, income and number of children. Table 3 summarizes the main exploratory variables. T_{DEPd} denotes the time dependents of the energy-relevant activity and $\varepsilon_{i,j}$ is the error term.

Table 3. Summary of the main explanatory variables.

	Irregular Work Patterns		Regular Work Patterns	
	Full-time **(n = 853)**	**Part-time** **(n = 800)**	**Full-time** **(n = 674)**	**Part-time** **(n = 530)**
Sample Day Work Hours				
Mean	8.23	6.10	5.79	6.16
SD	3.07	4.25	3.86	3.77
Median	8.50	7.00	7.50	7.66
Min–Max	0.00–23.25	0.00–19.5	0.00–24.00	0.00–24.00
Age				
Mean	43.03	41.81	42.64	41.69
SD	12.16	13.16	13.00	12.49
Median	44.00	43.00	44.00	42.00
Min–Max	16.00–75.00	16.00–81.00	16.00–73.00	16.00–74.00
Gender				
Mean	1.47	1.507	1.48	1.46
SD	0.49	0.50	0.40	0.49
Median	1.00	2.00	1.00	1.00
Min–Max	1.00–2.00	1.00–2.00	1.00–2.00	1.00–2.00
Household size				
Mean	2.95	2.93	3.03	2.96
SD	1.28	1.18	1.30	1.32
Median	3.00	3.00	3.00	3.00
Min–Max	1.00–8.00	1.00–7.00	1.00–8.00	1.00–8.00
Number of children				
Mean	0.66	0.607	0.61	0.65
SD	0.93	0.89	0.88	1.04

Median	0	0	0	0
Min–Max	0.00–4.00	0.00–4.00	0.00–5.00	0.00–5.00

We investigated multicollinearity because of the high correlation between employment status and hours worked on $WT_{j,d}$. The Pearson correlation coefficient for the two variables was low and significant: −0.133, with *p*-value < 0.001. The variance inflation factor (VIF) for employment status was equal to 1, below the conservative benchmark of 5 indicating that there is no multicollinearity between the variables used. Some energy-relevant activities may be underreported because they are not conducted on daily bases. This was reflected in the large number of zero values. While this did not result in biased OLS estimates, a higher proportion of zero-value observations resulted in higher standard errors and lower R^2 [34].

4. Results

In order to answer the first research question, we regressed the mean duration of each energy-relevant activity on average daily work hours, which allowed us to investigate how time is allocated for energy-relevant activities by individuals with varying levels and patterns of work. In this case, our relevant independent variable was work time ($WT_{j,d}$) as well as work time square, which measures the marginal effect of increasing work hours on the allocation of various energy-relevant activities.

4.1. Time-Use Results

Tables 4 and 5 show the marginal effect of spending time on six energy-related activities based on working hours and socioeconomic covariates. Working hours had a negative and highly significant effect on the time use of activities, which is consistent with findings for Germany in Buhl [8] and for France and Finland in Klein [9]. House cleaning, laundry, and television watching were three activities in the regular work schedules sample that had significant quadratic terms. In the case of laundry activity, the model showed significant positive coefficients for the square of average daily work time (WT^2), indicating relevant differences in the marginal effect of an hour worked on laundry allocation. Following a reduction in work hours, free time was reinvested in television viewing, followed by house cleaning and laundry. Figure 5 depicts the predicted duration of activities where the change in time allocated was proportional to work hours. For activities with a significant interaction between WT and employment status dummy at $p < 0.05$, we plotted the marginal effects for the average full-time and part-time employee.

Table 4. The marginal effect of regular work patterns on time usage.

Regular Work Patterns		Dish Wash	Food Preparation	House Clean	Ironing	Laundry	TV
WT	Estimates	−0.17	−2.26	−5.89 *	−0.77	−5.19 **	−11.57 **
	Standard error	0.98	1.72	2.40	2.22	1.63	4.26
WT²	Estimates	−0.02	−0.02	0.26	−0.01	0.37 *	0.46
	Standard error	0.09	0.16	0.24	0.22	0.17	0.40
Betweenness	Estimates	24.66.	−6.34	−14.03	−1.54	−59.57 **	−12.58
	Standard error	14.13	14.69	27.34	36.38	18.44	35.78
Full−time	Estimates	−2.07	−3.00	−9.05 **	−1.95	5.39 **	−12.16
	Standard error	1.81	4.05	3.37	1.83	1.76	11.76
Age	Estimates	0.17 ***	0.37 ***	0.18 *	0.11 **	0.07.	0.98 ***
	Standard error	0.04	0.09	0.07	0.04	0.04	0.22
Gender	Estimates	5.84 ***	18.24 ***	7.42 ***	4.56 ***	8.49 ***	−20.62 ***
	Standard error	0.98	2.18	1.80	0.99	0.97	5.47
HH size	Estimates	0.77	−1.81	−0.60	0.72	0.83.	−1.45
	Standard error	0.50	1.12	0.93	0.51	0.48	2.80
Numchild	Estimates	1.23 .	6.53 ***	2.52 *	0.34	0.74	−5.20

	Standard error	0.68	1.52	1.25	0.69	0.67	3.76
WT * Full−time	Estimates	0.32	−0.19	1.13 *	0.28	−0.59 *	2.80 *
	Standard error	0.25	0.57	0.47	0.26	0.25	1.42
WT * Betweenness	Estimates	−4.20	3.02	9.49	−2.46	26.01 **	14.33
	Standard error	5.70	4.66	12.49	15.53	9.61	16.09
WT² * Betweenness	Estimates	0.09	−0.16	−0.87	0.26	−2.06 *	−1.40
	Standard error	0.54	0.41	1.27	1.58	0.99	1.59
Intercept		−7.40 .	8.51	17.86 *	−4.39	−0.39	147.55 ***
N		1206	1206	1206	1206	1206	1206
R²		0.092	0.138	0.130	0.056	0.117	0.092
R² adjusted		0.083	0.130	0.122	0.047	0.109	0.084

Significance codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1.

Table 5. The marginal effect of irregular work patterns on time usage.

Irregular Work Patterns		Dish Wash	Food Preparation	House Clean	Ironing	Laundry	TV
WT	Estimates	−0.13	−0.70	−0.26	−6.50 ***	0.84	−0.8
	Standard error	0.72	1.60	1.64	1.57	1.05	4.27
WT²	Estimates	0.01	−0.04	0.01	0.45 ***	−0.06	−0.14
	Standard error	0.05	0.11	0.13	0.12	0.08	0.29
Betweenness	Estimates	−8.62	−35.58 *	20.34	−20.02	46.33 **	77.15 .
	Standard error	12.65	14.46	22.01	33.31	17.86	43.48
Full−time	Estimates	6.36 **	13.98 **	14.32 ***	2.94 .	2.56	30.03 *
	Standard error	2.12	5.02	3.48	1.57	2.23	14.28
Age	Estimates	0.18 ***	0.51 ***	0.16 **	0.09 ***	0.11 **	0.43 *
	Standard error	0.03	0.08	0.05	0.02	0.03	0.21
Gender	Estimates	3.41 ***	17.64 ***	8.33 ***	2.54 ***	3.99 ***	−26.15 ***
	Standard error	0.84	1.93	1.40	0.59	0.88	5.33
Household size	Estimates	−0.54	−1.66 .	−0.02	0.31	1.29 **	−9.34 ***
	Standard error	0.45	1.00	0.77	0.31	0.49	2.70
Number of children	Estimates	2.33 ***	6.12 ***	2.81 **	−0.12	0.03	−0.44
	Standard error	0.61	<0.001	1.03	0.42	0.66	3.77
WT * Full−time	Estimates	−0.01 *	−0.03 **	−0.02 **	−0.01 *	−0.00	−0.05 .
	Standard error	0.00	0.004	0.01	0.00	0.00	0.03
WT * Betweenness	Estimates	0.02	0.11	−0.01	0.74 ***	−0.15 .	−0.27
	Standard error	0.06	0.08	0.13	0.18	0.09	0.22
WT² * Betweenness	Estimates	−0.08	−0.27	−0.07	−3.03 ***	0.47	0.60
	Standard error	0.28	0.35	0.62	0.85	0.40	0.98
Intercept		−2.70	−5.30	−13.31 .	−3.49	−14.21 **	182.69 ***
N		1653	1653	1653	1653	1653	1653
R²		0.056	0.114	0.082	0.089	0.051	0.086
R² adjusted		0.050	0.108	0.076	0.082	0.045	0.080

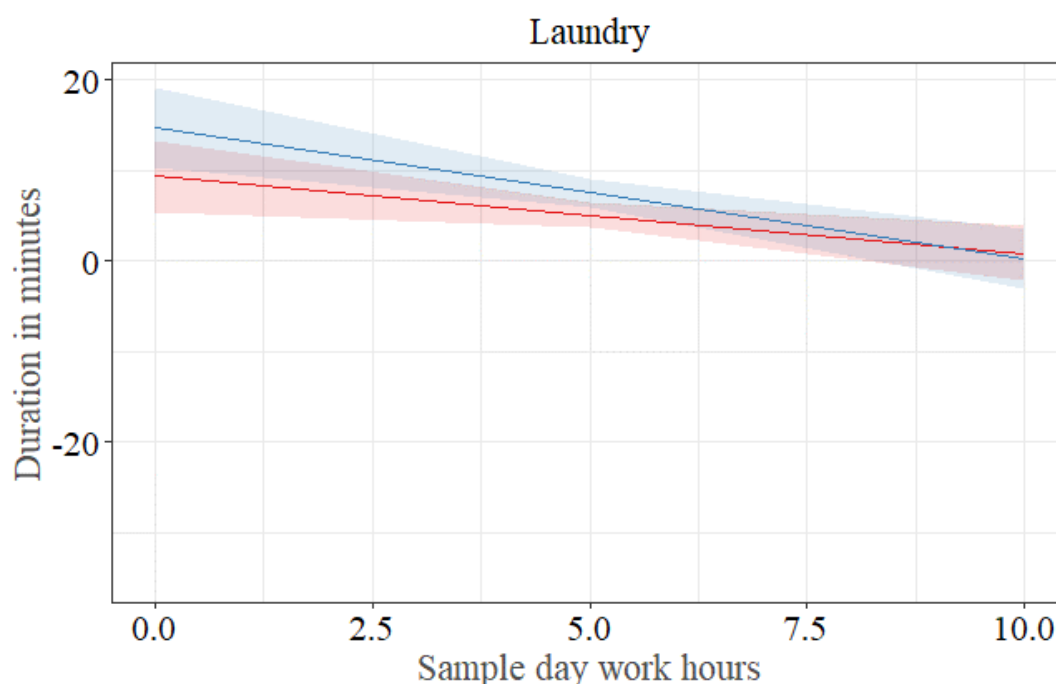Significance codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1.

Figure 5. Significant linear regression lines of regular work patterns (blue line part-time and red line full-time).

Laundry time tended to decrease linearly with work hours. Part-time employees had the longest baseline duration of house cleaning activity and the greatest marginal reduction. Full-time employment reduced the amount of time spent on house cleaning while increasing the amount of time spent on laundry. This finding is consistent with Anderson's [35] finding that weekday morning laundry was primarily reported by full-time paid workers. The amount of time spent watching television was inversely related to gender. This finding is consistent with the findings of Druckman [36], who reported significant differences in resource implications between men and women. The amount of time spent on food preparation and housekeeping increased as the number of children increases.

Apart from laundry activity, all models in the irregular sample showed that irregular work hours reduced the time spent on energy-related activities. Only ironing had a statistically significant coefficient for the squared term of *WT* and *WT²*, indicating significant differences in the marginal effect of an hour worked on ironing allocation. Working full-time increased the amount of time spent ironing. Gender and age had significant effects in all time-use categories, indicating that gender has a large influence on time-use patterns. Gender was associated with the amount of time spent watching television in the same way that it was associated with regular work patterns [36]. With an increase in household size, people spent less time cooking and watching television and more time doing laundry [8]. If children were still living in the home, parents devoted more time to food preparation, house cleaning, and dish washing.

4.2. Investigating the Position of Activities throughout Workdays

In the case of regular work patterns (Table 4), there was a negative significant difference in betweenness centrality for laundry. This would imply that as the duration of work increased, people placed less emphasis on laundry activities. Furthermore, the interaction between work time and betweenness suggested that the effect of an additional hour of work varies depending on how activities are ordered. This finding is consistent with Southeron [37], who contended that because individuals perceive modern life to be time-constrained, they actively attempt to coordinate their multiple personal and shared commitments, resulting in the emergence of "hot spots" of activity defined by the intensity of practises occurring in time-spaces and, in particular, the confluence of shared practises

such as family. When comparing the two employment groups (Figure 6), the betweenness centrality of the laundry activity was higher among full-time workers than among part-time workers. There was also a significant difference in dishwashing centrality betweenness. This would imply that as the duration of the work increased, people paid more attention to dishwashing activities and less attention to laundering activities. These activities must be viewed as having the potential to be implemented on a different timetable.
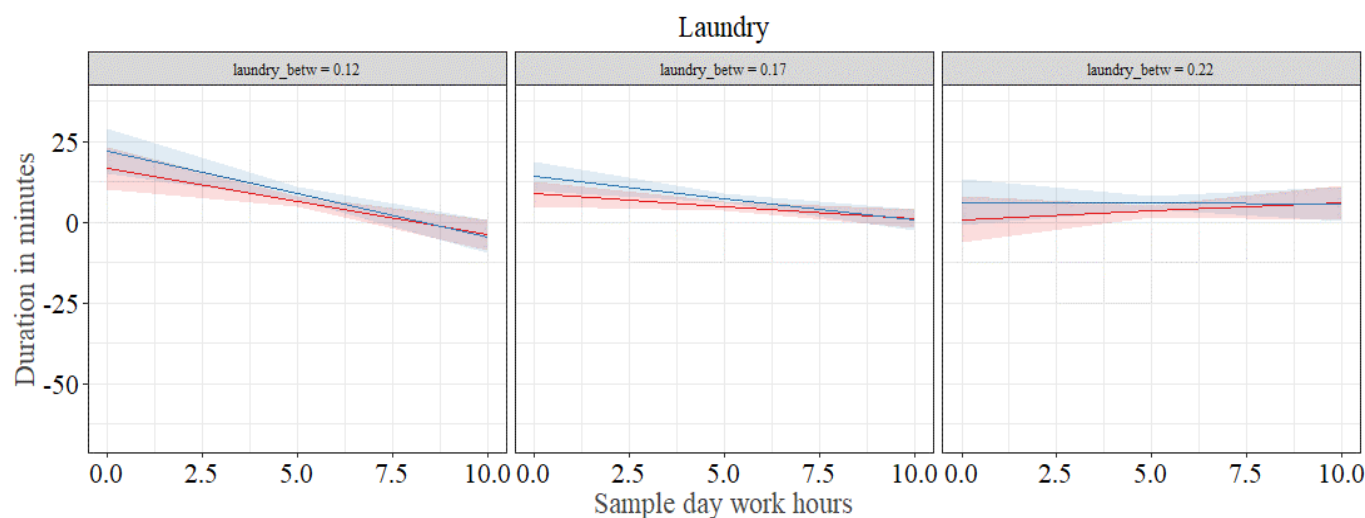

Figure 6. Linear regression lines with significant coefficients for the betweenness centrality metric of regular work patterns (blue line part-time and red line full-time).

In the case of irregular work patterns (Table 5), work hours significantly affected the amount of time spent on food preparation, laundry, and television viewing. None of the employment status estimates (e.g., full-time or part-time) were statistically significant. In the case of food preparation, as work hours increased, people placed less importance on food preparation at home. Food preparation, on the other hand, is a time-consuming task that requires cooking and clean-up. This could indicate that individuals do not prepare food on a daily basis. Laundry and television watching betweenness was statistically significant, indicating that they are ingrained in daily activities. This is consistent with Anderson [35], who discovered that the most frequent activities preceding laundry were meals or snacks (32%) and food preparation (12%), followed by watching TV (25%) and food preparation (12%).

4.3. Energy Intensity Results

Our final set of regressions calculated the relationship between work hours and the energy intensity of daily activities. The time-use data in Tables 6 and 7 provide context for interpreting the changes in energy consumption observed in this section as a result of the different work schedule. Due to the fact that energy consumption is proportional to the amount of time spent on a particular activity, we estimated appliance energy consumption (in kWh) as an outcome variable. It is critical to note that factors such as home energy efficiency, weather, and energy generation efficiency were not included in the energy intensity calculation. Importantly, even if the model is expanded to include the contributions of these additional factors, the magnitude of the time-use factor would remain unchanged.

To begin, the models developed showed that regular work hours significantly reduced the energy intensity of television viewing, tumble dryer use, and washing machine use (Table 6). This would imply that the energy intensity of activities is directly related to the occupants' daily work schedules. Second, in the tumble dryer and washing machine,

we found significant coefficients for the square of average daily work time (WT^2), indicating significant differences in the marginal effect of an hour worked on activity energy intensity. This would imply that the reduction in energy intensity of tumble drying, for example, was stronger at first but faded with longer work hours. Third, for regular work patterns, we found a significantly different effect of work time on tumble dryer and washing machine between the two employment groups (Figure 7). The energy intensity of activities, for example, decreased more sharply with work time among full-time employees than among part-time employees.

Table 6. Marginal effect of regular work time on energy intensity.

Regular Work Time		Dish Wash	Television	Tumble Dryer	Washing Machine
WT	Estimates	−0.00	−0.02 **	−0.22 **	−0.04 **
	Standard error	0.02	0.00	0.07	0.01
WT²	Estimates	−0.00	0.00	0.02 *	−0.00 ***
	Standard error	0.00	0.00	0.01	0.00
Betweenness	Estimates	0.46.	−0.02	−2.48 **	−0.41
	Standard error	0.27	0.05	0.77	0.13
Full−time	Estimates	0.02	−0.02	0.22 **	0.04 **
	Standard error	0.04	0.01	0.07	0.01
Age	Estimates	0.00 ***	0.00 ***	0.00.	0.00.
	Standard error	0.00	0.00	0.00	0.00
Gender	Estimates	0.11 ***	−0.03 ***	0.35 ***	0.06 ***
	Standard error	0.02	0.01	0.03	0.01
Household size	Estimates	0.01.	−0.00	0.02.	0.01 *
	Standard error	0.01	0.00	0.03	0.00
Number of children	Estimates	0.02.	−0.01	0.03.	0.01
	Standard error	0.01	0.00	0.03	0.00
WT *Full−time	Estimates	0.01	0.00 *	−0.02 *	−0.00
	Standard error	0.00	0.00	0.01	0.00
WT * Betweenness	Estimates	−0.08	0.02	1.08 **	0.18 ***
	Standard error	0.11	0.02	0.40	0.07
WT² * Betweenness	Estimates	0.00	−0.00	−0.09 *	−0.01 ***
	Standard error	0.01	0.00	0.04	0.01
Intercept		−0.14.	0.20 ***	−0.02	0.00
N		1206	1206	1206	1206
R²		0.092	0.092	0.114	0.117
R² adjusted		0.083	0.084	0.106	0.109

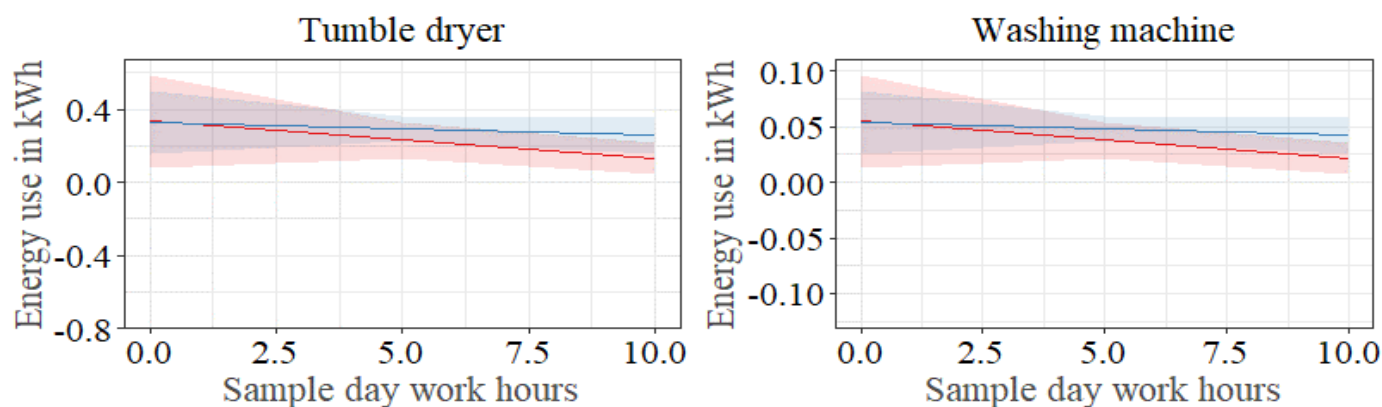Significance codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1.

Figure 7. Significant linear regression lines of regular work patterns. (Blue line part-time and red line full-time).

Fourth, the tumble dryer had a negative significant difference on betweenness centrality while the dishwasher had a positive significant difference on betweenness centrality. This would imply that the activities that occurred before and after dishwashing and tumble drying had an effect on energy intensity. Fifth, the significant coefficients of the interaction between work hours and betweenness centrality showed that dishwashing and tumble-drying initially acted as bridges for other activities, but that this decreased as work hours increased. Finally, it appeared that age and gender were important predictors of the energy intensity of activities on the sample day.

First, for irregular work patterns (Table 7), we discovered a significant positive correlation between working hours and tumble dryer and washing machine energy intensity. This means that the energy intensity of the tumble dryer and washing machine increased as the number of work hours increased. Second, in the case of tumble dryers, significant coefficients for the square of average daily work time (WT^2) were found, indicating relevant differences in the marginal effect of an hour worked on activity energy intensity. Third, there was no statistically significant difference in activity energy intensity between the two employment groups. Fourth, there was a negative significant difference in betweenness centrality between the dish washer and the tumble dryer and washing machine. This finding suggests that activities that occurred before and after dishwashing, tumble drying, and machine washing had an effect on energy intensity, just as they did in regular work patterns. Fifth, the significant coefficients of the interaction between work hours and betweenness centrality showed that as work hours increased, dishwashing and tumble-drying served as bridges in the work–life continuum. Age, gender, and household size appeared to be important predictors of energy intensity of activities on the sample day, as they were in the case of regular work patterns.

Table 7. Marginal effect of irregular work time on energy intensity.

Irregular Work Time		Dish Wash	Television	Tumble Dryer	Washing Machine
WT	Estimates	−0.02	−0.01	0.12 **	0.02 **
	Standard error	0.01	0.01	0.04	0.01
WT^2	Estimates	0.00	0.00	−0.01.	−0.00.
	Standard error	0.00	0.00	0.00	0.00
Betweenness	Estimates	−0.64 **	0.03	3.73 ***	0.61 ***
	Standard error	0.24	0.05	0.76	0.12
Full−time	Estimates	0.02	0.01	−0.01	−0.00
	Standard error	0.04	0.02	0.09	0.01
Age	Estimates	0.00 ***	0.03 .	0.00 ***	0.00 ***
	Standard error	0.00	0.05	0.00	0.00
Gender	Estimates	0.08 ***	−0.03 ***	0.19 ***	0.03 ***
	Standard error	0.02	0.01	0.04	0.01
Household size	Estimates	−0.01	−0.01 ***	−0.05 **	0.01 **
	Standard error	0.01	0.00	0.02	0.00
Number of children	Estimates	0.04 ***	−0.00	−0.00	−0.00
	Standard error	0.01	0.01	0.03	0.00
WT * Full−time	Estimates	0.00	0.00	−0.00	0.00
	Standard error	0.00	0.00	0.01	0.00
WT * Betweenness	Estimates	0.11	0.00.	0.01	−0.13
	Standard error	0.08	0.02	−0.80	0.04
WT^2 * Betweenness	Estimates	−0.00	−0.00	0.24 **	0.01 **
	Standard error	0.01	0.00	0.04	0.00
Intercept		0.04	0.26 ***	0.02.	−0.16.
N		1653	1653	1653	1653
R^2		0.059	0.047	0.052	0.054
R^2 adjusted		0.053	0.041	0.045	0.047

Significance codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1.

5. Discussion and Policy Implications

We set out to investigate the effect of different working patterns on time-use behaviour and its likely impact on domestic energy consumption. Our findings indicate that (1) working hours have a statistically significant influence on the amount of time spent on energy-related activities while at home, and (2) the marginal allocation of time differs between part-time and full-time workers. These group-specific patterns resulted in different energy consumption between regular and irregular work patterns. In our discussion, we address how our findings inform policy decisions (Figure 8).
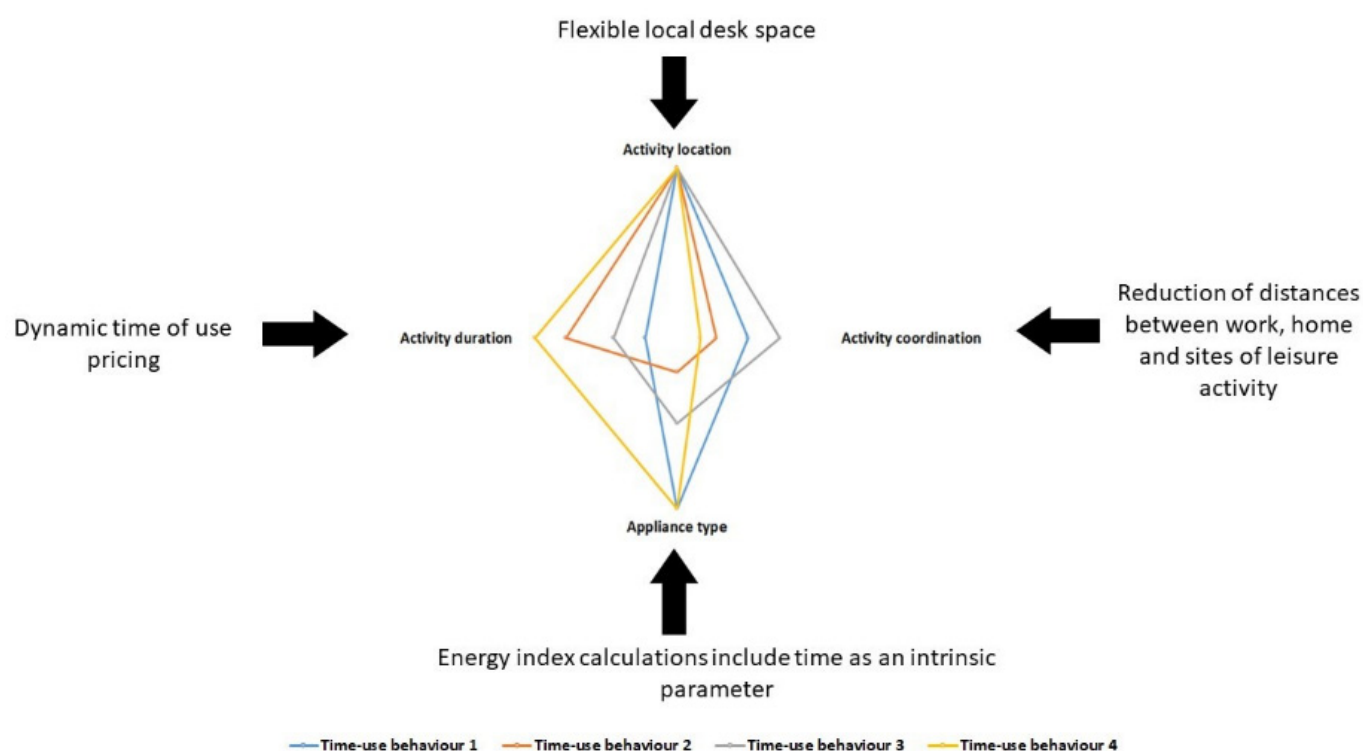

Figure 8. Examples of time-use policy measures aimed at decreasing residential energy consumption.

According to the findings derived from our first research question, namely, "Which energy-relevant activities are undertaken more or less often when comparing regular and irregular work patterns?", not all energy-related activities are simply scaled down linearly as work hours increase. Reductions in the amount of time spent doing laundry and ironing were greater in the first hours of work and flattened out for longer work hours (see Tables 6 and 7). This suggests that work time has a strong effect on specific activities, which spreads to a broader range of activity changes among respondents who work a lot. Because of these distinct marginal reductions, the ordering of energy-relevant activities changed under different amounts of work hours. In the case of regular work patterns, time was typically deducted from TV watching activities in favour of energy-relevant activities sustaining non-routine activities such as house cleaning and laundry. The time required for dishwashing and food preparation was largely unaffected by regular and irregular work schedules.

As these findings suggest, overly simplistic, ill-designed time-use policies that target in-home activities that are relevant for energy demand might adversely affect those people with regular working patterns. For instance, if a time-use tariff scheme intended for reducing the frequency and duration of energy-intensive activities during particular times does not provide suitable alternatives, workers in this group might receive no real benefit

from the time-use tariff scheme and end up paying more for electricity on an annual basis as a result [38]. That is, customers who are required to do energy-intensive activities during peak periods would be negatively affected, since their charges would be based on a more cost-reflective tariff plan. Shifting the timing of these activities to a different time of day or week might benefit those who have greater flexibility to adjust their schedules and slash their energy bill.

The results of our analysis make a clear case for the need to cater for different groups, with similar but clearly differentiated policies or measures aimed at reducing their energy consumption while at home. Among other resources, these might include replacing energy intensive appliances, promoting the usage of energy storage devices or the implementation of more cost-reflective tariffs, along with extensive consumer education programmes, that encourage customers to shift or reduce the time spent in energy-intensive activities in order to save energy (and money).

When it comes to the effect of a respondent's employment status on the moderation of effects of time, the findings derived from our second research question, namely, "How does the duration of the energy-relevant activities change with regular and irregular work patterns?", show that time allocation for purposes other than work differs between part-time and full-time employees, particularly in the case of people with irregular work patterns. This could be due to the effect of stricter work schedules on the timing of various energy-related activities, which more often than not result in peaks in demand that are costly—both in economic and environmental terms—and therefore undesirable. Previous studies have suggested that the best energy savings are realised when full-time employees work from home instead of juggling home and office schedules [39]. Even when working from home full-time, additional considerations for non-work-related travel are necessary. Time-use policies might do well in recognising that providing more flexibility in the scheduling of in-home, energy-relevant activities by means of encouraging work-from-home schemes might deliver substantial energy savings. It remains important, however, to advise consumers on how to use more energy-efficient equipment when at home or to perform activities in a specific order to save energy during this time. Peaks in travel activity (and thus traffic congestion) could be reduced using hybrid work schedules during peak travel times. For instance, studies have shown that working from home during peak hours may help to reduce peak travel by 20% [29].

Finally, as the findings derived from our third and final research question, namely, "How does the energy intensity of energy-relevant activities change in response to different work patterns?", show, the total energy intensity of activities decreases as the number of hours worked increases in a regular work pattern. This makes sense because it reflects a reduction in the time we account for appliance energy use. Interestingly, our findings show that the energy intensity of tumble dryers and washing machines increased as the total number of hours in the case of irregular work hours increased. One reason could be that laundry can be done at later hours. When compared to the significant impact of age, gender, and household size, the conclusion may be that, while work hours are important for total energy intensity of activities, age, gender, and household size effects dominate overall energy use.

In this case, an adequate policy response might entail providing individuals with relevant data when purchasing various appliances, such as energy labels, as well as energy-related feedback while using appliances. One problem when purchasing an appliance is the confusion that consumers have when looking at the energy labels. The new generation of energy labelling A (previously known as A+++) and B (previously known as A++) ratings have been shown to increase the likelihood of purchase, whereas some people believe that an A rating is sufficient [40]. Overall, the evidence shows that smart meters could be effective in promoting more energy-efficient attitudes as they work as constant reminders for users [5]. However, the effectiveness of this policy may change depending on the message (how and in what form it is provided) and the country [41]. According to

a recent study by Boyano [42], including an additional time parameter related to the duration of the programme in the energy efficient index would result in energy savings of up to 2.31 TWh/year in the EU by 2030. In this case, there is a significant amount of uncertainty since the development of market players could influence the results of the measure.

6. Limitations

This study has a number of limitations that we deem worth noting. Firstly, time-use data from 2014–2015 was relied on for our analysis. Thus, any causal inference or policy implications would have to be revisited whenever more appropriate datasets become available. Scientists and policymakers could benefit greatly from more frequent data collection, as this would allow for gaining a better understanding of the dynamics of different lifestyles and how they influence energy consumption.

Secondly, we relied on estimates of energy consumption from other studies. One issue is that the energy intensities for a specific household type are fixed and cannot be changed over time. Others have argued that the linkage between activities and their associated electricity demand cannot be explicitly measured as, they point out, the time-use diary codes were not intended to be used for investigating particular energy end uses, and consequently, they do not distinguish between high and low-energy activities [26,43]. Mealtime activities are used as an example because their associated energy consumption can range from none (preparing a cold meal), low (such as microwaving food) to high (such as cooking using an electric oven). Another key shortcoming is the fact that certain energy-intensive end uses, such as boiling the kettle, may last less than the time diary's 10 min. Therefore, it is not possible to fully capture the level of consumption associated with energy-relevant activities. Moreover, activities are not carried out in isolation, and modelling them separately misses the dynamics between them. For example, private activities such as personal care, watching TV, or doing laundry, are linked to the routines of other household members and are shaped by various factors that allow certain activities to take place at specific times and locations. Daily rhythms, according to social practice researchers, are the result of these arrangements, as well as the fact that some practices are prioritised over others [37]. Activity-based models ignore activity interdependence and make the simplifying assumption that an activity's current performance is influenced by its past performance. This level of modelling precision falls beyond the scope of this paper, as our goal is merely to estimate the relationship between work hours and likely energy intensity of activities on "a typical day" rather than to reconstruct daily demand loads.

Finally, as with any other year-specific surveys, the time-use data only provides a snapshot in time. At the time of this study, the world's zeitgeist was dominated by the COVID-19 pandemic, which threw most countries into strict lockdowns that completely shattered the notions of normality. Among the most obvious implications for our study is the fact that the data used for our analysis could not possibly capture how changes in location associated with wider changes in work arrangements affected the timing of activities during the pandemic. Recent research by Anable [44] and Mehlig [45] indicated that demand for gas and energy was significantly lowered during the UK's first COVID-19 national lockdown in the spring of 2020. The less severe restrictions in the second national lockdown in November 2020 reduced demand by half of that of the first. Daily patterns of power demand shifted, with weekday demand approaching that of a pre-lockdown "normal" weekend, mirroring cultural shifts that saw more people staying at home during the week. The findings of this study, as well as additional research on the pandemic, can help shape future policies aimed at incentivizing work from home. For obvious reasons, the possibility of organising large-scale surveys during this time were severely limited, so we may never get the opportunity to analyse the effects of the pandemic on the temporalities of everyday life in depth. However, the observed aggregate effects on energy demand patterns might provide enough indications of the potential benefits of a more flexible life.

7. Conclusions

Despite its inherent relevance on the timing and scheduling of other activities, the effect of working time (and working patterns) on time-use patterns and associated energy consumption has seldom been investigated. In this study, we conducted a systematic time-use analysis of the relationship between working time, scheduling of energy-relevant activities and the likely implications for energy consumption among the working population in the United Kingdom. Using time-diary data on six energy-relevant activities, we used an econometric approach to investigate how time is allocated among people with various employment statuses. We then estimated likely total energy use at home after work by linking activities to appliance ownership and usage data. Using this information, we were able to calculate the correlation between work hours and energy use. In this study, we saw heterogeneity in the work-energy relationship, especially in the comparison of full-time and part-time workers. In the case of regular work patterns energy use reductions were stronger among full-time relative to part-time employees. We also found a non-linear change in total energy use for respondents with varying levels of work time. Energy consumption reductions were strongest during the first hours of work but flattened out over time. More research is needed to understand the differences in employment groups. This could help bridge the gap between micro- and macro-estimates of the work–time–energy relationship explored in previous studies. As a result, policymakers must pay close attention to time-use patterns of different segments of the labour force. As the results of this study point out, taking time use into account could aid in the formulation of more targeted, and thus more effective, climate mitigation policies.

With this paper, we demonstrated to the research community that weekly work diaries are extremely useful when investigating work-hour arrangements. The combination of time-use diaries and weekly work diaries yields more information about the temporal organisation of paid work than aggregated working hour estimates, for example, from the Labour Force Survey. As a result, in line with Minnen [46] we believe that in order to produce more accurate results, national time-use surveys should include separate weekly work diaries, which provide less biased estimates of the time spent on various activities.

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Appendix A. Systematic Review of Previous Time-Use Behaviour Studies

Table A1. Types of work schedules on working days.

Author	Data	Weekly Work Patterns	Data Resolution	Sample Size
Lesnard [47]	UK Time Use Survey (2000)	Identified five types of workdays and seven types of workweeks and more varieties of part-time work in the UK.	15 min—Seven days	4944 individuals
Lesnard [48]	French Time-Use Survey 1985/86 1998/99	Used three indexes (conjugal parent–child and parent–child time) to measure off-scheduling and calculated work synchronicity percentages based on the ratio of the number of hours of simultaneous work to the number of hours at least one spouse works (the length of the family workday)	10 min—One day	17,832 individuals
Glorieux [49]	Belgian Time Use Survey (1966-1999)	Distinguished between four types of non-standard work times: (1) evening work, from 7:00 pm to 10:00 pm on any day of the week; (2) night work, from 10:00 pm to 6:00 am on any day of the week; (3) Saturday work, from 6:00 am to 7:00 pm on Saturdays; and (4) Sunday work, from 6:00 am to 7:00 pm on Sundays. Standard work times refer to weekdays between 6:00 am and 7:00 pm	10 min—One weekday and weekend	3211 individuals
Glorieux [50]	Flemish Time Use Survey (1994–2004)	Identified 12 different time-use patterns in terms of the amount of paid and unpaid work and the dominant leisure activity (i.e., watching TV or more active leisure activities)	15 min—Seven days	2285 individuals
Barnes [35]	UK Time Use Survey (2000)	Identified atypical work schedules based on weekly work grid diaries and performed a cross-sectional ordinary least squares (OLS) regression, which revealed that time spent with children, and time spent on particular activities involving children, is negatively associated with atypical working patterns (including weekend working) of both fathers and mothers.	15 min—Seven days	1028 individuals
Minnen [46]	Belgian Time Use Survey (1966–1999)	Used two dimensions of paid work to typify weekly work patterns. The first dimension is the number of hours worked, which indicates the continuum of part-time through full-time work (i.e., 40 h/week) to overwork (i.e., ex-	15 min—Seven days	6330 individuals

| | | tended workweek). The second dimension is the percentage of work performed on non-standard periods, which we define as weekend work (i.e., work performed on weekend days from 6 am to 7 pm), evening work (i.e., work performed all days from 7 pm to 10 pm) and night work (i.e., work performed on all days from 10 pm to 6 am the next day). The 'standard workweek pattern' has to meet the standard of both dimensions, that is, contain about 40 h of paid work and the least percentage of work performed on non-standard working periods. | | |
| Chenu [51] | French Time-Use Survey 1998/99 | Defined a dissimilarity index to quantify the gap between dual earners work schedules and to explore how married couples who have similar or different patterns of work hours engage in other activities. | 15 min—Seven days | 1488 individuals |

Table A2. Types of work schedules on working days.

Author	Data	Method	The Application of the Sequence Analysis Method
Glorieux [49]	Belgian Time-Use Surveys from 1966 and 1999	Optimal matching algorithm (Dynamic Hamming Distance)	Using a sequencing method, the authors were able to identify 12 types of work schedules.
Glorieux [50]	Belgian Time-Use Surveys from 1999 and 2004	Optimal matching algorithm	Using sequence and cluster analysis, the authors distinguished between 12 different time-use patterns and labelled them in terms of the amount of paid and unpaid work and the dominant leisure activity (i.e., watching TV or more active leisure activities).
Hellgren [21]	Swedish time-use survey conducted in 2010	Regression modelling compared with optimal matching algorithm	Using an approach that takes the sequence of activities into account allows to gain a better understanding of how people plan their day in the context of their daily activities
Lesnard [52]	Two French time-use surveys (1985, 1998)	Optimal matching analysis	Twelve configurations of family workdays of French families are uncovered
Lesnard [47]	Two French time-use surveys (1986, 1999)	Optimal matching algorithm (Dynamic Hamming Distance)	Off-scheduling is widespread and on the rise, according to this analysis of the empirical typology of couple's work schedules built using optimal matching.

Lesnard [53]	French time-use survey conducted in 1999	Optimal matching algorithm (Dynamic Hamming Distance)	A typology of nine workweek schedules was derived using two-stage optimal matching
Lesnard [47]	7-day diary data from the UK 2000–2001	Two-stage optimal matching	Using two-stage optimal matching the authors identified five types of workdays and seven types of workweeks and more varieties of part-time work in the UK.
Minnen [46]	Belgian time-use surveys of 1999 and 2005	Optimal matching algorithm (Dynamic Hamming Distance) and Ward's Hierarchical Clustering	Using optimal matching the authors identified 10 weekly work patterns.

Table A3. Studies that employed time-use survey data in occupant behaviour-related building energy analysis.

Study	Data	Activities	Data Resolution	Sample Size
Richardson [54]	UK Time Use Survey (2000)	Washing, Ironing, House cleaning, Laundry, Watching TV, Cooking, Other (at home)	10 min—one weekday and weekend	10,000 individuals
Chiou [55]	American Time-Use Survey (2008)	Sleeping, Computer use for leisure, TV and movies, Research and homework, Wating and drinking	10 min—one weekday and weekend	13,000 individuals
Widén [32]	Statistics Sweden (SCB) (1996)	Away, Sleeping, Cooking, Dishwashing, Washing, TV, Computer, Audio, Other	5 min—one weekday and weekend	463 individuals in 179 households
López-Rodríguez [56]	Spanish National Institute of Statistics (2010)	Personal care, Food preparation and conservation, Washing dishes, Clean house and garden, Doing laundry, Ironing, Watching TV, Watching DVD or video, Listening to radio, Listening to records, Using computer	10 min—one weekday and weekend	19,295 individuals from 9541 households
Wilke [57]	French Time-Use Survey	Other, Other leisure, Conversation,	10 min—one weekday and weekend	15,441 individuals from 7949 households

		Relax, Read, Study, Watch TV or video, Listen to music, Dances or parties, Religious/Civic activities, Sleep, Meals and snacks, Dress/personal care, Childcare, Gardening, Odd jobs, Housework, Cook, wash up, School, classes, Paid work		
Neu [58]	National Time-Use Survey of Ireland (2005)	Washing, Ironing, House cleaning, Laundry, Watching TV, Cooking, Other (at home)	15 min—one weekday and weekend	1089 individuals from 567 households
Aerts [59]	Belgian Time-Use Survey (TUS)	Away, At home but awake, Sleeping	10 min—one weekday and weekend	6400 individuals from 3455 households
Fischer [60]	German TUS (2002)	Entertainment, Laundry, Cooking, Dish washing, Other	10 min	14,000 individuals from 5200 households
Torriti [61]	UK Time Use Survey (2005)	Preparing food, Washing, Cleaning, Washing clothes, Watching TV, Computer	10 min—one weekday and weekend	3554 diaries
Anderson [30]	UK TUS 1985 and 2005	Laundry	10 min (2005) 1-diary day	4854 individuals

			15 min (1985)—each day of the selected week	
Palm [62]	Statistics Sweden (SCB) (2010/2011)	Cooking, Doing laundry, Watching TV	10 min—one weekday and weekend	6477 individuals
Barthelmes [24]	Danish Time Use Survey (2008/09)	Sleeping, Toilette, Eating, Cooking/washing dishes Cleaning/washing clothes, Practical work Family care/free time, Relaxing/TV/IT, Not at home, Others	10 min—one weekday and weekend	9640 individuals from 4679 households.
Liu [63]	Danish Time Use Survey (2008/09)	Sleeping, Cooking, Washing dishes, Laundry, Cleaning, Leisure, Away, Other	10 min—one weekday and weekend	9640 individuals from 4679 households
Ramírez-Mendiola [26]	UK Time Use Survey (2015)	Absence, Sleep, Generic active, occupancy TV watching, Food preparation, Laundering, Dish washing, ICT related	10 min—one weekday and weekend	10,208 individuals from 4733 households
Yamaguchi [64]	Japanese TUD (Statistics Bureau of Japan 2006)	Activities are classified as routine and non-routine activities.	15-min intervals—two sequential days	8,291 diaries collected from people aged 10 or older in 3866 households.

		Routine activities include: sleeping, work/school, having breakfast, lunch, dinner and bathing. Non-routine activities include: laundry and watching TV.		
Yilmaz [25]	French Time Use Data (2010)	Sleeping, Cleaning clothes, Cleaning dishes, Cooking, Eating in, Listening, Watching TV, Computer, Other (at home), Other (outside)	10 min—one weekday and weekend	27,903 individuals
Escobar [65]	Spanish National Institute of Statistics (2010)	Cleaning clothes, Cleaning dishes, Cooking, Eating in, Watching TV, Computer	10 min—one weekday and weekend	19,295 individuals from 9541 households
Buttitta [66]	UK Time Use Survey (2015)	Away, At home and active, Home asleep	10 min—one weekday and weekend	10,208 individuals from 4733 households
Torriti [67]	UK Time Use Survey (2014/15)	Preparing food, Washing, Cleaning, Washing clothes, Watching TV, Computer	10 min—one weekday and weekend	3554 diaries

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