How work patterns affect leisure activities and energy consumption: A time-use analysis for Finland and France

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Abstract

Studies on socio-economic impacts of climate and energy policies tend to focus on income and expenditure effects. For analyses that go beyond monetary dimensions, time-diary data have proven to be useful. Here we investigate how work time relates to leisure activity structures and associated energy use for different types of employees. To this end, an analysis of time-use data is undertaken for Finland and France. Novel elements are (1) a differentiation between part-time and full-time employees, (2) the use of distinct energy intensities of different activities by household type instead of average energy intensities, and (3) allowing for non-linear relationships between work time and the allocation of other activities. Our results suggest that the effects of work time on energy use are rather homogeneous in Finland, whereas we find more differences between employee types in France. 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. Our study suggests that analysis of disaggregated time-use data can add relevant insights for evaluation, and possibly design, of energy, climate and labour-market policies.

Keywords: Employment status, energy demand, energy intensity, time-use analysis, work time.

Highlights:

- Activity allocation associated with work time is more heterogeneous in France than in Finland
- The relation between work duration and certain leisure activities is non-linear
- Employment status can moderate the link between work time and energy use
- Disaggregated time-use data can support design of energy, climate and labour-market policies.

1. Introduction

Existing policies in the context of the climate crisis often aim at reducing greenhouse gas (GHG) emissions, while fostering or redistributing employment. Examples include work time reduction [1,2] or environmental tax reforms with revenue recycling through labour taxes [3]. Researchers frequently refer to multiple dividends of these policies, such as the 'double dividend' of environmental and economic (efficiency) goals of tax reforms, or the 'triple dividends' of work time reduction: "enhanced ecological sustainability, social equity and life satisfaction" [4].

Such comprehensive policies affect multiple aspects of human life and behaviour, including work and consumption decisions, work-life balance and societal arrangements, such as labour organisation. Yet quantitative approaches to assess policies for sustainability have often been limited to monetary effects [5]. Lately, more attention has been paid to the impacts of leisure time allocation and its environmental impact when work hours change [see e.g. 4,6]. These studies include time budgets into their analysis, but they tend to focus on average effects across populations. Doing so neglects potentially different impacts of work time on leisure activities and thus conceals which sub-groups should be targeted by policy interventions to effectively reduce energy demand.

In this study we perform an activity-based time-use analysis of the impact of work time on leisure activities and energy use for Finland and France. Our focus is on the heterogeneity of activity patterns and their impact on energy use, especially with respect to individuals' general availability of leisure time, which we measure through a respondent's employment status (part-time or full-time). Four research questions (RQs) are guiding our analysis:

(i) Which activities are undertaken more or less when comparing different levels of work time?
(ii) How do people change duration of their leisure activities in response to changing work time?
(iii) Does a person's employment status moderate the allocation of leisure time?
(iv) How does the energy use of leisure activities change in response to different work hours?

To answer these questions, we estimate a number of econometric models relating work time, leisure activities and energy use, using national-level data for Finland and France. The context of the analysis is thus one of two wealthy European societies with relatively high rankings in energy use per capita. Total primary energy use per person for instance was 6924.7 and 3692.0 kg of oil equivalent in 2015 in Finland and France, respectively [7]. There are however important cultural, geographic and socio-economic differences between the two countries. The sub-arctic Finnish climate explains higher energy consumption, typical for the Nordic countries, compared to the French temperate climate. There are also some important differences with respect to work patterns. According to its Fifth European Working Conditions Survey [8], dual-earner households are very common in both countries, but the share of households with a male 'breadwinner' is more dominant in France and the share of female 'breadwinners' is higher in Finland. Part-time contracts are much more usual among French women compared to men, whereas the gender shares are rather balanced in Finland [8]. From the fourth survey wave we also know that autonomy over working time is higher in Finland than in France [9]. While our empirical analysis does not include societal or labour market institutions, results should be interpreted against this geographical, cultural and institutional backdrop.

The remainder of the paper is organised as follows. Section 2 offers an overview of the relevant literature and places our study therein. Data and methodology are explained in

Section 3. Section 4 presents the results of our econometric analysis, which are discussed in Section 5. Section 6 concludes.

2. Literature review

Time use has played an increasing role in recent undertakings to comprehend the environmental impact of household behaviour. The fact that both human well-being and emissions are not the sole and instantaneous result of the act of purchasing, but also arise from the use of goods and services over time, has led to the evaluation of environmental impacts of different activities per unit of time. Such studies typically combine national time-use diaries with the respective household expenditure surveys to calculate energy use or emissions per hour of an activity [10–16]. The recent studies in particular highlight the importance of differentiating between various household types, because energy intensities of one activity can vary widely with context (think, for instance, about different modes of transportation).

The relationship between work patterns and environmental impacts has been addressed especially in the context of work time reduction scenarios (see [17] for a systematic literature review). A number of empirical studies have been carried out with a macroeconomic focus, comparing average work time and environmental impact [1], energy use [18] or carbon footprints [19] across countries. These studies typically find that an increase in average work time by 1% leads to an increase in energy use or emissions by more than 1%. This effect is mostly attributed to income effects.

A scenario analysis of five potential work time reduction policies focusing on full-time employees in the United Kingdom (UK) finds a large variation in mitigation potential [20]. Employee time use is one of many elements included in this analysis, alongside income effects and changes in business activities. It is assumed that additional leisure time is utilised consistent with current time-use patterns.

Recently, a strand of literature has emerged that uses a microeconomic framing to analyse the marginal effects of a work time reduction on energy use and emissions [6] or on the triple dividend mentioned above [4]. Nässén and Larsson [6] calculate the average income elasticity of energy use for the Swedish population. The study connects expenditure and time-use data to distinguish between income and time effects. The results indicate a positive relationship between energy use and income and a negative relationship between energy use and work time. As the time effect (shift in activities) is weaker than the income effect, a 1% reduction in work time leads to a drop in energy use by 0.7%. Households with one or more unemployed or retired adult members are excluded from this sample. An open question remains why the reduction in emissions the study finds is lower than the estimates of most macroeconomic studies.

Buhl and Acosta [4] apply a similar framework of marginal effects to German data. They look at the causal effects of work time reduction on activities using two waves from the German Socio-Economic Panel survey. Their mixed methods approach also includes interviews with people who have reduced their work hours. Analysing the triple dividend of work time reduction, they also disregard unemployed individuals when drawing conclusions about social equity impacts of work time reduction. While the study indicates potential quadratic relationships between work time and undertaking particular activities, these results are not pursued any further.

So far household heterogeneity in terms of employment patterns as well as energy intensity per time unit of an activity remains neglected in these studies, especially given that other authors have highlighted the need for assessing differences across household groups. The environmental impact of particular activities can vary widely depending on factors such as income, age, household size, urban form or employment status [14,21–23]. Particularly interesting from our perspective is a study by Gough et al. [21], which investigates drivers of GHG emissions in the United Kingdom based on the UK Expenditure and Food survey. While income is identified as the main driver, employment status alone explains 7% of variation in per capita emissions in their model. Although their findings indicate no significant difference between full-time employees and either part-time employees or retirees, unemployed individuals or self-employed people have significantly lower or higher emissions than full-time workers, respectively. Moreover, the study investigates differences in work time and occupation, without applying any time-use data which may help to explain how differences in emissions come about.

Finally, the change in marginal duration of different activities is interesting. By analogy with the better known 'marginal propensity to consume', Buhl and Acosta [4] call this change 'marginal propensity to time use'. Intuitively, it makes sense that the reaction in time use given an additional work hour is different for someone with a 40-hour work week, compared to someone with a 20-hour work week. The impacts of a change in working time at the margin are highly relevant to policy design: a non-linear 'marginal propensity to time use' would imply varying effectiveness for energy use reduction depending on the target group of a policy.

Our study builds on microeconomic approaches to analysing energy use through activities as in [4,6]. Our contribution involves a focus on heterogeneity of individuals in terms of (a) differentiating between effects on occupational groups with varying degrees of available non-work time (i.e. part-time versus full-time employees), (b) using different energy intensities for different household types, and (c) allowing for non-linear relationships between work and other activities. Finally, we extend the investigation of the relationship between work hours and non-work activities from Sweden and Germany in previous studies to Finland and France, motivated by data availability. Using harmonised activity data for two countries allows us to compare discrepancies in time allocation in different contexts.

3. Data and method

Conceptual framework

In order to address the four research questions posed previously, three sets of regression models are estimated (Figure 1). Model 1 (M1) involves regressing the duration of each non-work activity on average daily work hours, which allows us to investigate how leisure time is allocated by respondents with various levels of work. This can be thought of as a form of time budgeting: an increase (decrease) in work time will necessarily lead to a decrease (increase) in other activities. Model 2 (M2) investigates how the relative share of time in various activities changes with work time. These two steps address research questions (i) through (iii), which all concern the relationship between duration of paid work and other activities[1]. The relevant independent variables are work time (RQ i), squared work time (RQ ii), and an interaction term between work time and the employment status of a person. The latter allows to assess differences in effects between full-time and part-time employees (RQ iii). The categorisation is taken directly from the time use data base. Students and people who are retired, seeking work, or looking after family, but who work at least some hours, are also coded as working part-time. Regression Model 3 (M3) estimates the relationship

[1] Note that there is not one model per research question, but rather certain model coefficients relate to specific questions.

between energy use during leisure time and working hours (RQ iv). Energy use is calculated based on the leisure activities performed by each household type. We use a consumption-based approach to calculate total energy use and energy-intensity (per hour) during leisure time. The term 'energy intensity' appears throughout this paper to refer to energy use per unit of time, for one specific or all non-work activities. To obtain energy use, we multiply energy intensity factors per hour of each activity with the time spent on these activities. This means no energy use is allocated to time spent at work, which is in line with previous studies (as mentioned in Section 2).

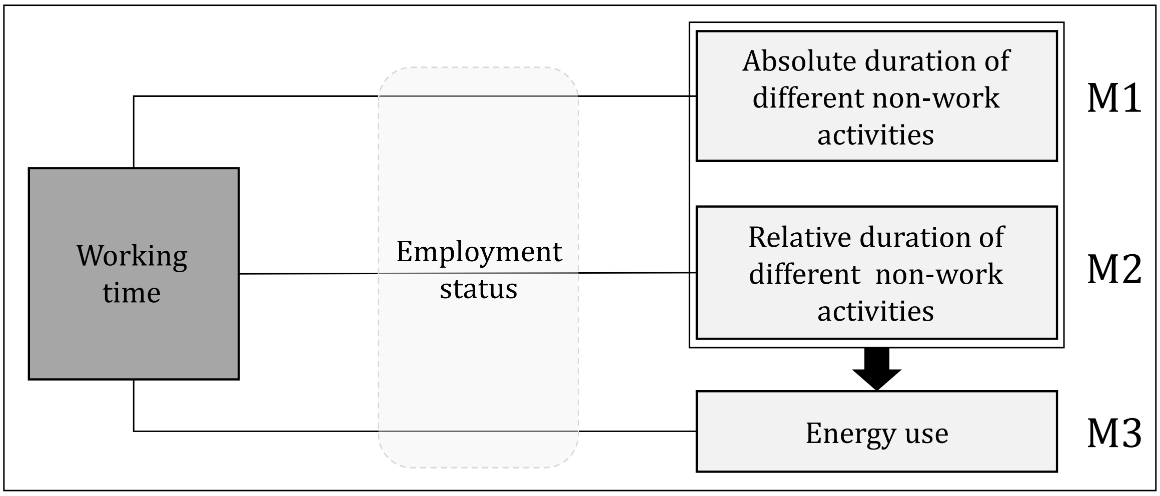

Figure 1. **Conceptual framework**

Note: Dark grey left box indicates the main independent variable and the light grey boxes on the right dependent variables of models M1-M3. The employment status is expected to moderate the relationship between work and leisure.

Data sources

Our main data source is the Multinational Time Use Survey (MTUS) [24]. It collects and harmonises time diary data from various countries. The analysis is performed using the most recent available time-use data sets, which are from 2009 for both countries. This data is originally collected in a diary format, where participants fill in information on their activities in 10-minute-intervals during up to two sample days, mostly one weekday and one weekend day. Reported activities are then coded and provided in 24 different categories. In each regression model we use observation weights provided by the MTUS data base ('PROPWT'), in order to ensure a representative sample in terms of days, gender and age (weekend days are over-represented, for instance)[2].

To link activity patterns to energy use, we are building on the energy-intensities of different activities estimated by Jalas and Juntunen [14] for Finland and de Lauretis et al. [22] for France. We assign 23 of the 24 activity categories (excluding paid work) from the MTUS data set to the categories used in those studies. Table A.1 in the Appendix offers an overview of the activity categories and the classifications used by [14] and [22] for calculating hourly energy intensities. Both papers group households according to age, civil and family status, i.e. whether someone lives with a partner and whether they have

[2] For details on the construction of the weights, we refer the interested reader to the description section of the PROPWT variable on the MTUS website: https://www.mtusdata.org/.

children[3]. This household typology implicitly covers some other important factors, such as disposable income (typically lower for older people) or scale effects (reflected in household size).

While the time-use categories are identical for both countries, an important difference that prohibits the two countries' energy use to be directly comparable, is that the Finnish data includes embodied energy (used during the production of goods), whereas the data for France is limited to direct energy use (fuel, electricity, etc.). Both studies calculate energy use by combining expenditure survey data with time-use data. De Lauretis et al. [22] additionally use housing, appliance and mobility surveys. For Finland, monetary values are converted into energy demand using environmentally-extended input-output tables with a four-digit COICOP classification of goods. For France, energy expenses are converted using energy prices specific to energy form and household type. Table A.6.a in the Appendix indicates the average energy intensity for each activity group from the two reference studies. We refer the interested reader to the two original studies [14,22] for further details on energy intensity calculations. Keeping these differences in mind, our results on energy use should be seen as outcomes pertaining to different contexts, rather than as a direct country comparison.

Data preparation

The time-use data is provided through two data bases which contain different variables from the same survey (MTUS and MTUS-X). Thus, we first have to merge these data sets based on observations' unique identifiers. As we are mainly interested in the workforce, we then discard observations of minors below the age of 16 years and unemployed people, as well as observations which were neither categorised as full-time employed or part-time employed and who had not indicated any work on the sample day or during the week preceding the sample day. Lastly, we delete observations which lack information on weekly work hours, control variables or activities throughout the day or which cannot be assigned to any of the household types used in the underlying energy use studies. The remaining sample size is 3,291 observations for Finland and 10,983 for France. The observations represent person-days and the sample covers 1,756 individuals (1,223 households) for Finland and 6,976 individuals (5,218 households) for France.

We test whether the data preparation leads to a biased sample by performing a Kolmogorov-Smirnov test (with the null hypothesis that the two samples are drawn from the same distribution) and a Wilcox rank sum test (equivalent to the Mann-Whitney test, with the null hypothesis that the two distributions differ in terms of a location shift, see Table A.3 in the Appendix). The results for Finland show that household size, age, education level and employment status of missing observations differ from the overall sample, with differences in means between the final sample and eliminated values being equal to 6.78% (household size), 3,76% (age), 1.4% (education) and 3.53% (employment status). People in the remaining sample tend to live in slightly larger households, are less educated, older and more often full-time employed. For the French sample, the observations we delete are also slightly older and from larger households. The deleted observations include more educated, female, full-time and higher-income respondents. These differences in means are all within 5%, except for employment status (13.01%). Table 1 offers an overview of the main variables in the final data set.

Econometric analysis

[3] The categories for both countries are 'Single < 65', 'Couple, reference person < 65', 'Single parent', 'Couple with children', 'Couple, reference person > 65', and for France in addition 'Other'.

We estimate three regression equations with the following specification:

$$Y_{i,j,d} = \beta_0 + \beta_1 WT_j + \beta_2 WT_j^2 + \beta_3 WT_j * PT_j + \beta_4 PT_j + \beta_n C_{n,j,d} + \mu_d + u_{i,j}$$

In the first set of regressions (M1) $Y_{i,j,d}$ is the time person *j* spends on activity *i* (*i*=1,…, 23) on day *d* (measured in minutes). The second set of models (M2) is estimated using the share of non-work time for each activity as an outcome ($Y_{i,j,d}$) to investigate relative changes in pastimes. In the third set (M3), energy use during leisure acts as the dependent variable, $Y_{i,j,d}$, so we can get an idea of potential environmental impacts. WT_j , represents the work time, i.e. the hours individual *j* spent in paid work on per day during the preceding week. PT_j indicates person *j*'s employment status (1 for part-time employees). More time poverty implies less leisure time to reschedule certain activities to a different time slot. We further integrate interaction terms between *WT* and *PT*, as we expect the effect of an additional hour of work to be different depending on a respondent's employment status (reflecting the long-term level of work time). This reduces potential variation in work time across weeks, as the variable for weekly work hours is based on information about one week only. Additionally, being a part-time worker can capture other unobserved characteristics regarding a respondent's life stage or non-work duties, for instance, related to parenthood or education.

$C_{n,j,d}$ is a vector of *n* person-specific control variables including age, gender, household size, education level, income group and a work day dummy (1 if respondent worked at least 30 minutes on the diary day). μ_d is a vector of time-specific fixed effects for month and day of the week, accounting for the idea that many social practices differ between days or month [25,26]. $u_{i,j}$ is the error term.[4]

[4]We also considered the sector of employment (public versus private), self-reported stress levels and work time of other household members. The employment sector and stress levels show a significant coefficient for few activities, but are only available for Finland. The work time of other household members proves to be significant only for certain activities among the French sample, while cutting the sample size approximately by half in both countries. We thus discarded these potential control variables. The results are available from the authors upon request.

***Table 1*. Summary of main variables by country and occupational status**

	Finland			France		
	Full-time (N=2957)	**Part-time (N=334)**	**Overall (N=3291)**	**Full-time (N=9146)**	**Part-time (N=1837)**	**Overall (N=10983)**
Average daily work time (WT)*						
Mean (SD)	5.75 (1.02)	2.42 (1.02)	5.41 (1.43)	5.33 (1.32)	3.10 (1.20)	4.96 (1.55)
Median [Min, Max]	5.43 [4.29, 13.9]	2.86 [0.143, 4.14]	5.43 [0.143, 13.9]	5.29 [0.429, 14.1]	3.29 [0.143, 5.29]	5.00 [0.143, 14.1]
Household size						
Mean (SD)	2.95 (1.35)	2.80 (1.58)	2.93 (1.38)	2.75 (1.31)	2.96 (1.34)	2.78 (1.32)
Median [Min, Max]	3.00 [1.00, 10.0]	2.00 [1.00, 9.00]	3.00 [1.00, 10.0]	3.00 [1.00, 11.0]	3.00 [1.00, 11.0]	3.00 [1.00, 11.0]
Age						
Mean (SD)	43.3 (11.2)	42.6 (17.8)	43.3 (12.1)	42.2 (10.5)	42.9 (11.3)	42.3 (10.6)
Median [Min, Max]	45.0 [16.0, 71.0]	46.0 [16.0, 78.0]	45.0 [16.0, 78.0]	42.0 [16.0, 69.0]	43.0 [18.0, 68.0]	42.0 [16.0, 69.0]
Gender						
Mean (SD)	1.52 (0.500)	1.74 (0.441)	1.54 (0.498)	1.45 (0.498)	1.83 (0.378)	1.52 (0.500)
Median [Min, Max]	2.00 [1.00, 2.00]	2.00 [1.00, 2.00]	2.00 [1.00, 2.00]	1.00 [1.00, 2.00]	2.00 [1.00, 2.00]	2.00 [1.00, 2.00]
Education						
Below Secondary	1509 (51.0%)	180 (53.9%)	1689 (51.3%)	1378 (15.1%)	442 (24.1%)	1820 (16.6%)
Completed Secondary	1448 (49.0%)	154 (46.1%)	1602 (48.7%)	4928 (53.9%)	998 (54.3%)	5926 (54.0%)
Above Secondary	-	-	-	2840 (31.1%)	397 (21.6%)	3237 (29.5%)
Income						
Lowest quartile	371 (12.5%)	93 (27.8%)	464 (14.1%)	1311 (14.3%)	465 (25.3%)	1776 (16.2%)
Medium quartiles	1613 (54.5%)	157 (47.0%)	1770 (53.8%)	4092 (44.7%)	835 (45.5%)	4927 (44.9%)
Highest quartile	973 (32.9%)	84 (25.1%)	1057 (32.1%)	3743 (40.9%)	537 (29.2%)	4280 (39.0%)
Work day						
Mean (SD)	0.474 (0.499)	0.389 (0.488)	0.466 (0.499)	0.558 (0.497)	0.484 (0.500)	0.546 (0.498)
Median [Min, Max]	0 [0, 1.00]	0 [0, 1.00]	0 [0, 1.00]	1.00 [0, 1.00]	0 [0, 1.00]	1.00 [0, 1.00]

Note: * Main explanatory variable. Figure A.2 in the Appendix contains histograms of work time by group.

As the correlation between employment status and work time (WT_j) is potentially high, we need to check for multicollinearity. The Pearson correlation coefficient for the two variables is -0.537 in France and -0.701 in Finland (both p-values < 2.2e-16). As the generalised variance inflation factor (GVIF) for employment status and the interaction term are very high (41.24 and 18.15 for Finland; 16.07 and 11.80 for France), we add the covariates one by one, as recommended by Murray et al. [27] for regression models with dummy variables. When we leave out the quadratic term (WT^2), the GVIFs remain below the popular benchmark of 10 for both countries, indicating that there is no multicollinearity between the variables used.

Time-use data fluctuates a lot on a day-to-day basis. As some activities are not performed daily, their duration may be underreported. This is reflected in the high number of zero values for basically all activities. Another unique feature of time diary data is that it is usually based on only two sample days per person, whereas other household surveys often cover a whole week. Using person-day specific activities as an independent variable typically does not allow to distinguish intra-personal from inter-personal variation [28]. We thus use person-specific weekly work time, rather than the work reported on each sample day. While the particularities of time diary data do not lead to biased OLS estimates, a higher fraction of zero-value observations leads to higher standard errors and lower R^2 [29]. To account for the fact that we normally have two observations per individual (on a weekday and on a weekend), we report clustered standard errors for all regression models.

4. Results

4.1. Time-use results

Absolute and relative time allocation

We first regress the absolute and relative duration of all 23 non-work activities on average daily working time. To show absolute and relative changes combined, Figure 2 represents the marginal effects of a change in *WT* for both countries in Cartesian coordinate systems[5]. Each point represents one activity, its x-coordinate being the marginal relative change in the activity's share of leisure time associated with a one-hour increase of paid work per day, and its y-coordinate reflecting the marginal absolute change in minutes associated with an additional hour at work. Using this visualisation, we can separate how different types of activities relate to changes in times of paid work, both in absolute and relative terms. For example, the time spent on sleeping is lower among respondents with higher work hours (negative y-coordinate), while the share of leisure time spent on sleeping increases (positive x-coordinate).

Activities in the upper right quadrant play a complementary role to work. For respondents with longer work hours, these activities increase in absolute and relative terms. For Finland none of the activities in this quadrant is significant. For the French sample, commuting and personal care show positive significant coefficients in both regression models, meaning that respondents with higher average work hours engage longer in these activities.

The lower left quadrant of Figure 2 includes all activities whose duration decreases in absolute and relative terms. There appears to be some sort of substitution between these activities and paid work. Examples are sports, reading or media use. All these activities are performed significantly less among people with longer work hours. In Finland child care 1

[5] Note that we show the marginal effects for an average worker, i.e. calculating the effects using the mean of work time (*WT*) for each sample.

(playing, talking, etc.) is also significantly lower among people who work more. In France many household tasks and chores, such as shopping, gardening, maintenance and food preparation also fall in this category.

The lower right quadrant shows what we call 'weak substitutes for work'. While these activities are reduced in absolute terms, they gain a larger share of leisure time when work hours increase. These are mostly activities which can only be reduced to some extent because they are essential for a healthy lifestyle, in particular sleep. Time is reallocated away from activities in the lower left quadrant towards those in the lower right quadrant for respondents with longer work hours. Expectedly no activities fall in the upper left quadrant (increase in absolute duration while falling as a share of leisure).

It is apparent that only a modest number of activities are affected significantly according to our pre-defined confidence levels. Religious activities, voluntary work and medical child care seem to be linked least to paid work, compared to other activities (small and mostly insignificant estimates). We find the largest relative effects for sleep in both countries. The French sample shows a higher number of significantly affected activities. This suggests a more diverse re-allocation of leisure when people face different work time. The detailed results in traditional table form can be found in Tables A.4 and A.5 in the Appendix.

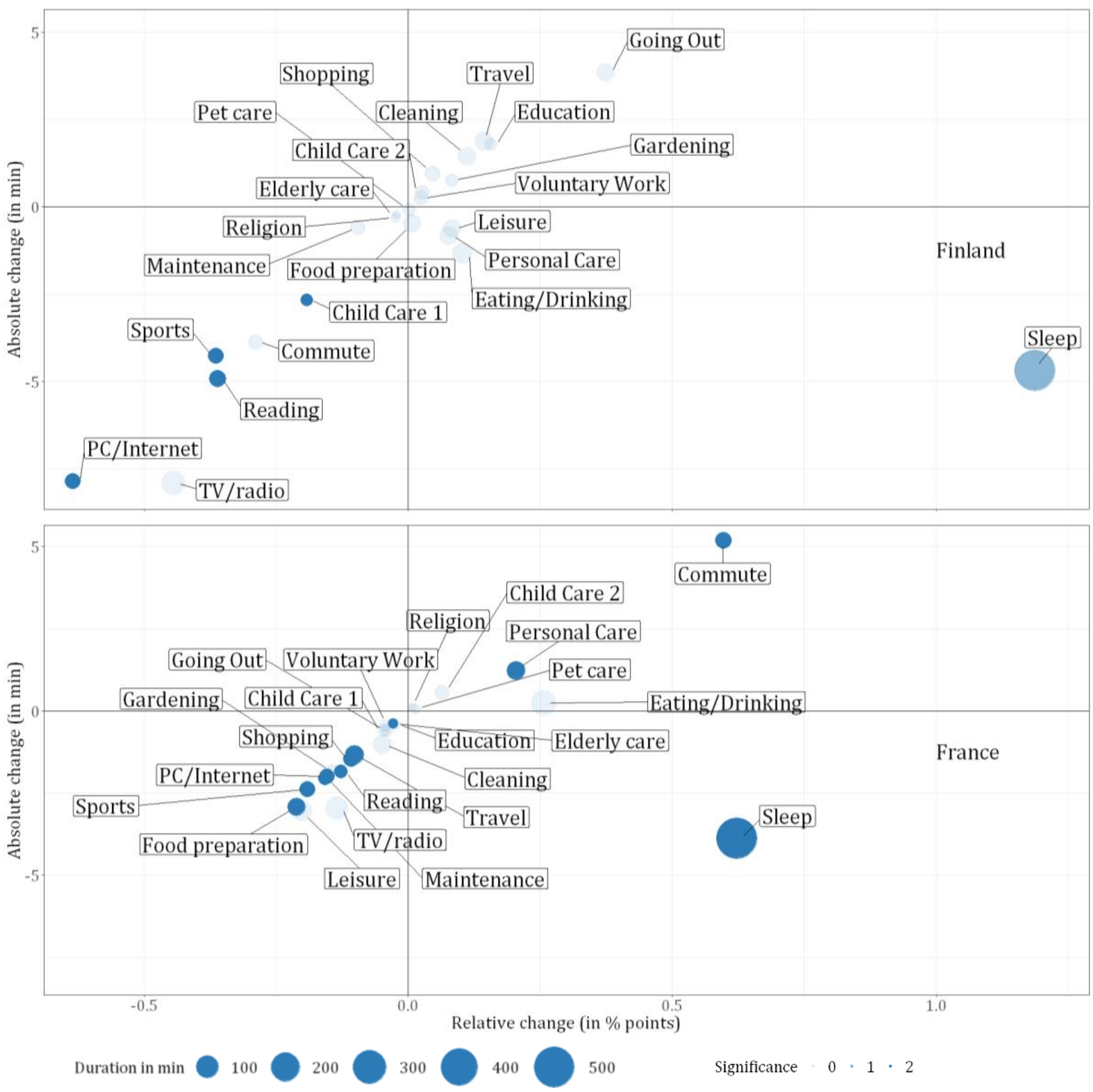

***Figure 2*. Relative and absolute changes in activity duration associated with a one-hour increase of work**

Note: Finland (upper plot) and France (lower plot). Coordinates reflect the total marginal effect of a change in work time (including interaction term and squared term). Transparency of the points indicates whether the respective β_1 coefficients in the two models, M1 and M2, are at least statistically significant at the 5% level.

Non-linear effects

Our second research question was *how* activity allocation changes, particularly whether changes in activity duration are linear, an implicit assumption in previous studies. Indeed, this does not seem to be the case for all activities. Several regression models show significant coefficients for the square of average daily work time (WT^2), indicating relevant differences in the marginal effect of an hour worked on activity allocation. Figure 3 displays the predicted duration of activities where the change in time allotted is non-linearly related to work hours (with $p<0.05$) for an average person. For activities with significant interaction between WT and the part-time dummy (PT), we plot the marginal effects for the average full-time employee and part-time employee, respectively.

In the Finnish sample three activities show significant ($p < 0.05$) quadratic terms: sports, PC/Internet use and child care 1. PC/Internet use and child care show significant group differences.[6] In line with the β_1 coefficients (M1), these activities all decrease with work hours, mostly in a convex manner, i.e. flattening with a rise in WT. An exception is child care among part-time employees, which is positively related with work time.

In the French sample nine activities show significant coefficients for the quadratic term: sports, commuting, food preparation, personal care, maintenance, sleep, reading, shopping and elderly care. Many of them also show significant group differences between the two employment types[7]. Commuting time and personal care increase with decreasing marginal effects. All other activities fall concavely when work time increases. Comparing the two employment groups, almost all activities change stronger among full-time workers than part-time workers, potentially indicating a more targeted adjustment by full-time workers, or put the other way around, more variation in the activity patterns of part-time workers. An exception is child care in Finland, where we see opposite effects between the two groups.

The insights are also interesting from an energy/environmental point of view. Energy-intensive commuting time increases in France, while the Finnish coefficient is negative (albeit not statistically significant). Furthermore, commuting in France increases more strongly with work time among full-time than part-time employees, for example. The reduction of maintenance time with rising work hours might point towards a 'throw-away' behaviour, rather than prolonging the lifetime of consumption goods.

[6] The relationship between work hours and reading and education also differs significantly between employment groups. These are not displayed here because their squared term was non-significant (see Table A.4.a).

[7] For France, PC/Internet use and education are also affected differently (with significant coefficients) for full-time and part-time workers (see Table A.4.b).

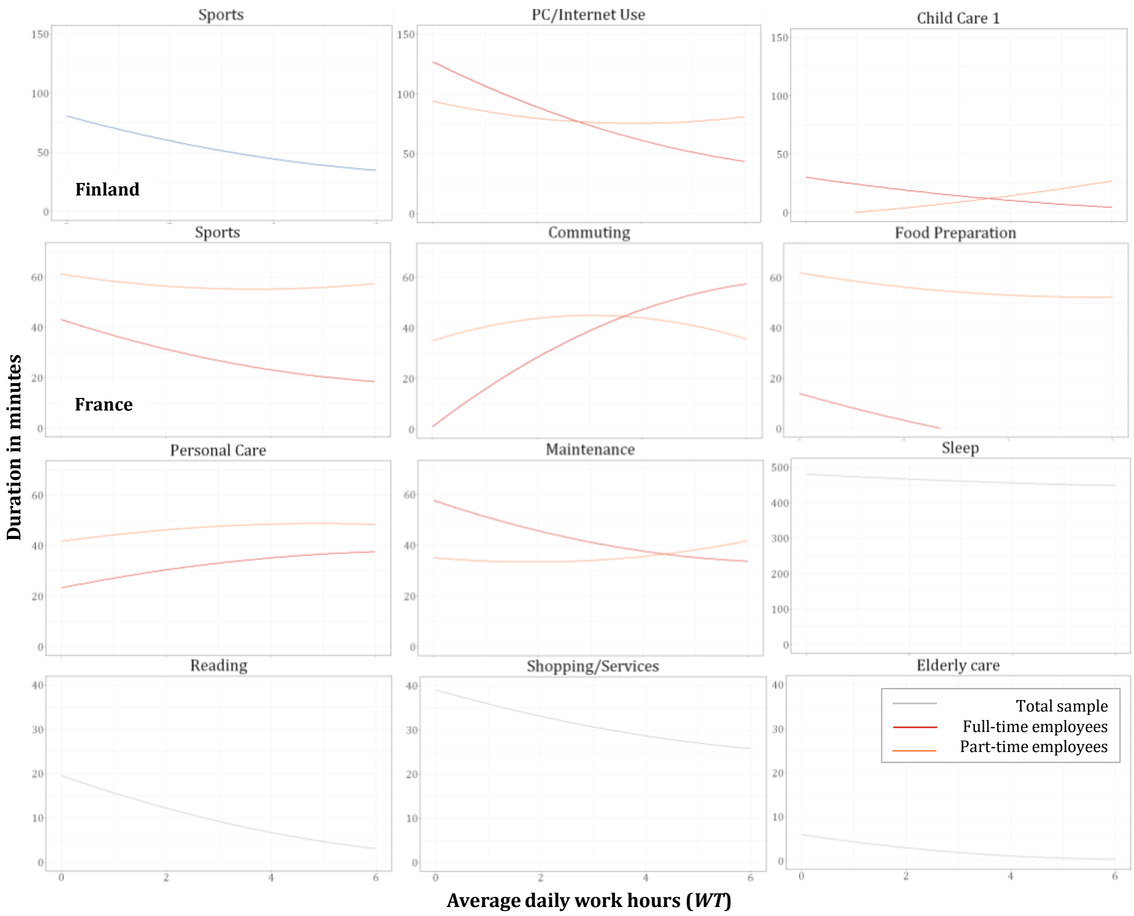

Figure 3. Significant non-linear regression lines

Note: Finland (upper row) and France (lower three rows). Coloured activities have a significantly different relationship for different employment groups.

4.2 Energy use results

In order to investigate the impact of different work and activity patterns on energy use (RQ iv), we calculated the total energy use per sample day according to the following formula:

$$EU_{total} = \sum_{d=1}^{D}\sum_{i=1}^{I}\sum_{h=1}^{H} A_{i,h,d} * EI_{i,h}$$

$A_{i,h,d}$ is the duration of activity i (in hours) on day d of a household of type h. $EI_{i,h}$ is the corresponding energy intensity of each activity for the particular household type as calculated by Jalas and Juntunen [14] and de Lauretis et al. [22]. They both provide average energy intensities per activity for six different household types distinct in terms of age, civil status and the number of children. It is not possible to compare energy use directly between the two countries for two reasons. First, they categorise activities differently. Secondly, they do not use the same indicator, namely direct energy use in France versus total energy use in Finland.

Our last set of regressions (M3) then estimates the relationship between average daily work time (WT) and individuals' energy use during leisure time. The time-use results from Section 4.1 serve as a guide for interpreting the changes in energy use we observe in this section. An overview of the contribution of the different activities to total energy use is provided in Figure A.6.b in the Appendix.

As energy use during leisure depends on the total leisure time available, we estimated both, total energy use (in kWh) and the energy-intensity of leisure (in kWh/h) as outcome variables. Table 2 presents the results of these regressions. Total energy use during leisure is significantly related to the time spent in paid work only in France. However, for Finland the estimate similarly points to an inverse relation, although it is not significant at our pre-defined level. As higher work time implies less leisure time by definition and thus less potential for energy use, the negative coefficients for total energy use are in line with what we expected. For France we find a significantly different effect of work time on energy use (or the slope of the curve) between the two employment groups.

Regarding the energy intensity of non-work time, we cannot confirm that this variable changes with hours in paid work for Finland. None of the coefficients related to work time is significant. More important determinants for energy-intensity seem to be household size and gender. Age plays a significant role in France, whereas the coefficients for income groups are only significant for Finland. Note, however, that the energy reduction associated with less leisure is irrespective of the respondent's income group. Figure 4 illustrates the relationship between energy use and time in paid work for both countries.

***Table 2*. Effect of work time on total energy use and energy intensity of leisure**

	Finland		*France*	
	Total energy use	Energy intensity	Total energy use	Energy intensity
WT	-8.255	-0.387	-1.701***	-0.021
	(5.824)	(0.277)	(0.242)	(0.011)
WT^2	0.325	0.016	0.089***	0.001
	(0.376)	(0.018)	(0.02)	(0.001)
Part-time	-14.709	-1.189	-1.376	0.015
	(21.359)	(1.017)	(0.827)	(0.037)
WT*Part-time	4.308	0.28	0.588**	0.005
	(5.292)	(0.252)	(0.210)	(0.009)
Age	-0.031	-0.007	0.103***	0.006***
	(0.086)	(0.004)	(0.008)	(0.0003)
Gender	4.833*	0.254*	4.620***	0.222***
	(2.103)	(0.100)	(0.163)	(0.007)
Completed 2ary Education	-4.031	-0.250*	-0.472*	-0.007
	(2.082)	(0.099)	(0.223)	(0.01)
Above 2ary education			-1.037***	-0.036**
			(0.267)	(0.012)
HH size	-14.861***	-0.743***	0.416***	0.018***
	(0.792)	(0.038)	(0.066)	(0.003)
Medium Income	10.942***	0.628***	-0.168	-0.01
	(3.117)	(0.148)	(0.245)	(0.011)
High Income	17.298***	0.941***	-0.267	-0.007
	(3.511)	(0.167)	(0.279)	(0.013)
WD	-35.185***	0.034	-12.506***	-0.161***
	(2.436)	(0.116)	(0.190)	(0.009)
Intercept	174.407***	7.995***	26.703***	0.877***
	(22.657)	(1.079)	(1.044)	(0.047)
Time FE	Yes	Yes	Yes	Yes
N	3,290	3,290	12,295	12,295
R^2	0.221	0.142	0.441	0.186
Adjusted R^2	0.214	0.135	0.439	0.184

Note: *$p<0.05$; **$p<0.01$; ***$p<0.001$

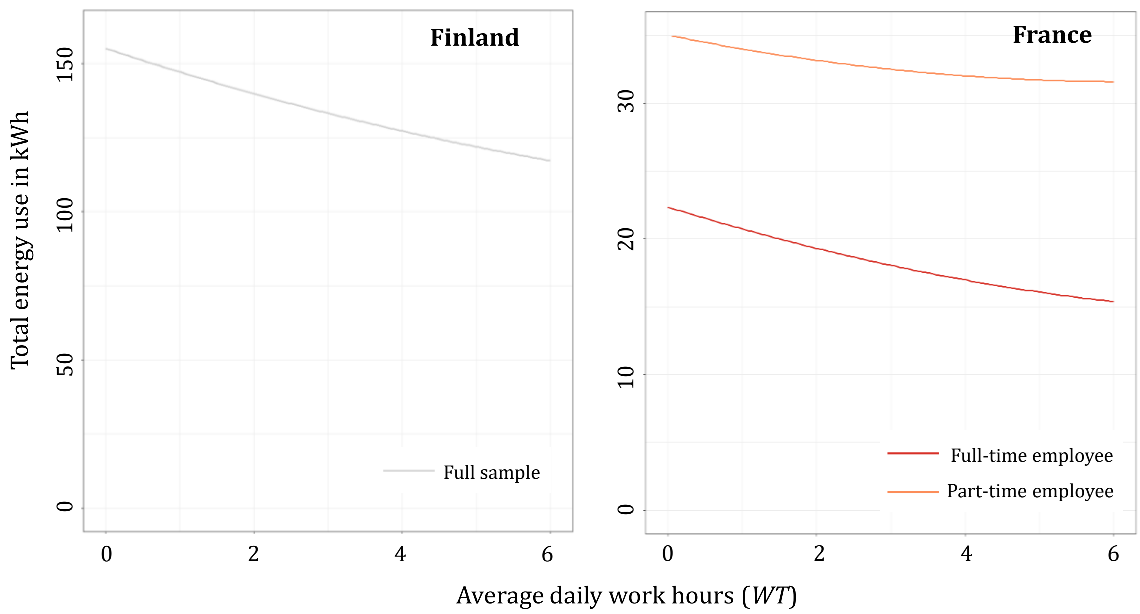

***Figure 4*. Regression line for energy use for different average daily work time.**

5. Discussion

We set out to investigate heterogeneity in work-leisure patterns and the resulting energy use. Our findings suggest that (1) certain activities have a non-linear relationship with working time, (2) marginal allocation of time differs between part-time and full-time workers, and (3) inter-country differences exist in the allocation of leisure[8]. These non-linear and group-specific patterns also translate into differentiated energy use in France, but not in Finland.

Our first research question aimed to identify the reallocation patterns of non-work time given different levels of paid work. We find that many, but not all activities are reduced when work hours increase. Among activities with the strongest reductions are sports, reading and PC/Internet use. Personal care and commuting seem to have a significant complementary role to work in France. Sleep falls in absolute duration, but increases in relation to other activities. As people work more, time is shifted away from care, sports, reading and PC/Internet use towards sleep in both countries. While we observe some similarities, there are also important differences in the reallocation of time between Finland and France.

Most notably, the correlation between commuting and work time is positive in France, but negative in Finland. There may be several explanations for this. For instance that telecommuting may be more common in Finland – the country has a very high share of 'e-nomads' [8], or that the distance to the workplace is shorter. Differences in transportation modes or traffic can play a role as well. The bottom line is that it is important to understand these context-specific effects when one aims to implement policies related to work and energy use. The higher number of significantly affected activities in France indicates a more diverse re-allocation of time. This may be due to a more heterogeneous structure of the population (for example due to migration backgrounds), or due to distinct work culture and institutions. Household chores, such as shopping, cleaning or food preparation showed

[8] The inter-country difference in the effect of work time on activity duration (M1) is statistically significant ($p<0.05$) for commuting, food preparation, personal care, reading, cleaning, PC use, going out, maintenance, education and child care. Results are available from the authors on request.

positive coefficients for Finland and negative ones for France. This is in line with the common dual-earner classification for Finland, versus a homemaker-breadwinner distinction between household members in France. While we did not study such cultural implications and explanations here, it is important to acknowledge that these differences between countries exist.

Regarding research question (ii) our results suggest that not all activities are simply scaled down linearly when work hours increase. Reductions in some activities are stronger for the first hours of work and flattening for longer work hours and vice versa (see Figure 3). Due to these distinct marginal reductions, the composition of leisure time in relative terms changes under distinct amounts of work hours. Typically, time is deducted from certain leisure activities and household chores, in favour of activities sustaining a person physically (e.g. sleep or personal care). The time for voluntary work and religious activities is hardly affected in both countries. Among activities with a significant quadratic term, changes are typically stronger at first and flattening for longer hours. This indicates that there is a strong effect of work time on particular activities, which diffuses to a wider range of activity changes among respondents who work a lot.

Research question (iii) concerned the moderation of effects by a respondent's employment status. We find that allocation of non-work time differs between part-time and full-time employees, especially in France. This is a potential reflection of stricter separation of tasks within households. The direction of change for most activities is similar when considering the average person (see Figure 2), and changes seem to be stronger for the full-time employees. One could interpret this as a more consistent re-allocation of time within this group, whereas time is reallocated to more activities among part-time employees. One very interesting result is the positive effect of work time on child care for part-time employees in Finland. One possible explanation is related to life stages. In the group of part-time employees with shorter work hours (<15) the share of students is more than twice as high as among part-time workers with 15 or more hours per week. The former also have 13% less children on average. Generally, we see that the allocation of leisure time is more diverse in France than in Finland. This is possibly due to cultural diversity compared to a more homogeneous population in Finland.

Regarding our last research question, total energy use during leisure falls with rising hours at work for France. This makes sense, because it reflects an overall reduction in time during which we account for energy use. Interestingly, we cannot confirm this result for Finland. One reason could be a shift towards more energy-intensive leisure activities among respondents who work more. However, we do not see changes in the energy-intensity of leisure either. Hence, another explanation is more likely. Embodied energy, which is measured for Finland, includes energy use throughout the production process of goods and can be expected to vary less with time spent using these goods, whereas direct energy use used for France is typically directly linked to the use of goods or services (e.g. transport fuels for driving your car). Comparing this with the significant impact of income group affiliation in Finland, a tentative conclusion may be that while work hours are a more relevant for direct energy use, income effects dominate overall energy use (including embodied energy). The non-linear relationship with different slopes for part-time and full-time workers in the French sample reflects the results of the time-reallocation (Figure 3). As mentioned before, there is no significant effect of work time on the energy intensity of leisure in either of the countries. We can conclude that there is no time-effect on energy intensity.

Similar to the findings in Buhl and Acosta [4], we see relatively large time-use effects for certain hobbies, in particular sports and reading. On the other hand, we see less significant changes in household work and the largest effects for sleep. The latter findings are conflicting with previous evidence [4]. One reason could be that – contrary to Buhl and

Acosta [4] – we are not using sample day work as an independent variable, but weekly work hours. Thus, the coefficients from our study can be clearly interpreted as the extent to which time spent on an activity differs for people who engage on average one more hour per day in paid work and do not include intra-personal variation between sample days. Our energy use results are comparable to results of Nässén and Larsson [6]. We find that for a typical full time employee, a work time reduction by 1% corresponds to an increase in energy use by approximately 0.22% in Finland and 0.25% in France (0.05% for part-time employees), compared to 0.23% in Nässén and Larsson's study for Sweden [6].[9]

Contrary to Gough et al. [21], who find that the effect of hours worked on GHG emissions in the UK is statistically insignificant when combined with employment status, we see that for France the WT coefficient remains significant. For the same country, the effect of an additional work hour on total energy use differs significantly between the two groups, with reductions in energy use associated with an extra hour of work being significantly weaker for part-time employees compared to full-time employees ($p < 0.01$).

Limitations

This study faces several limitations that we would like to mention. First, we had to rely on cross-sectional data from 2009 for our analysis. Due to the nature of the data we abstain from any causal inference or policy scenarios. Scientists and policy makers could greatly benefit from more frequent data collection in a time series manner to understand dynamics of different lifestyles and how they drive energy use.

Second, we relied on other studies for the energy use estimates, which were not overlapping entirely. This complicates the inter-country comparison regarding energy use, although it should not affect our main results. As recently highlighted also by [17] it is generally a challenging task to match activity data with material footprints, as expenditure surveys and time diaries are collected separately. Collecting these data together could improve estimations of energy (or material) intensity of different activities greatly. One problem is, for instance, that the energy intensities for a given household type are fixed and cannot change over time.

Third, household income has been discussed widely as one of the main drivers for energy use or GHG emissions more generally [14,18,25,26]. While we control for income quantiles in all regression models and our household typology reflects income to a certain extent, a lack of detailed income data prevents us from clearly separating time and income effects. We cannot control for any effects of income adjustments following an actual work time reduction on energy use or differences within a household's income group. Additionally, better income data would be desirable to discuss the role of income in time budgeting, given differences in employment status.

6. Conclusions

Few studies have undertaken time-use analyses in the context of labour markets, leisure activities and energy use. Here we performed a time-use analysis of the relationship between work time, leisure and energy use of individuals in Finland and France. Using time-diary data on 23 activities, we applied an econometric approach to study how time is allocated among individuals with distinct levels of work time and different employment status. Using energy intensity factors per time unit of each activity for six different household types, we calculated total energy use during leisure as well as energy intensity

[9] Note that our estimates are not a pure time effect, as we cannot perfectly control for all income effects.

(per hour of leisure). From this we estimated the relationship between work hours and energy use.

We find heterogeneity in this work-energy relationship, especially within the French sample, where total energy use is affected differently between part-time and full-time workers. In France, energy use reductions are stronger among full-time than part-time employees. We also find a non-linear change in total energy use for respondents with distinct levels of work time. Energy use reductions are stronger during the first hours of work, but flattening for longer hours. The differences in patterns between the two countries may be due to the measure of energy use applied. In particular, direct energy use, as measured for France, is likely to vary much more with activity time than indirect energy use (occurring during production) as captured by the Finnish energy data. To study this further, internationally comparable energy use estimates of activities are needed. However, one should generally avoid simply transferring results for one country to another.

The changes in absolute duration of activities that go along with varying work hours, as well as shifts in respective relative shares of leisure activities were only somewhat similar for both countries. Higher working hours lead to time being shifted away from exercising, reading and PC use to self-sustaining activities, such as personal care or sleeping, and in the case of France to commuting. Variation in these activities across employment groups in France leads to the distinct marginal effects on energy intensity between the two worker types.

More research is needed to clarify the variation between employment groups. This could help overcome the gap in micro- and macro-estimates of the work-time-energy relationship other studies have found. The variation in marginal effects of work hours on energy use also implies that changing work hours among distinct employment groups can lead to different environmental outcomes. Hence, paying close attention to time-use patterns of different segments of the labour force is crucial for policy makers when combing the aims of 'decent work' and 'climate action', as formulated in the United Nations' Sustainable Development Goals [32]. Relatedly, carbon taxation is frequently linked to cuts in labour-related taxes, such as in Canada [33] or Finland [34], which may affect energy use and emissions through work time and activity patterns. In view of this, taking time-use into account could help to formulate better targeted and thus more effective climate policies.

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Declaration of Interest

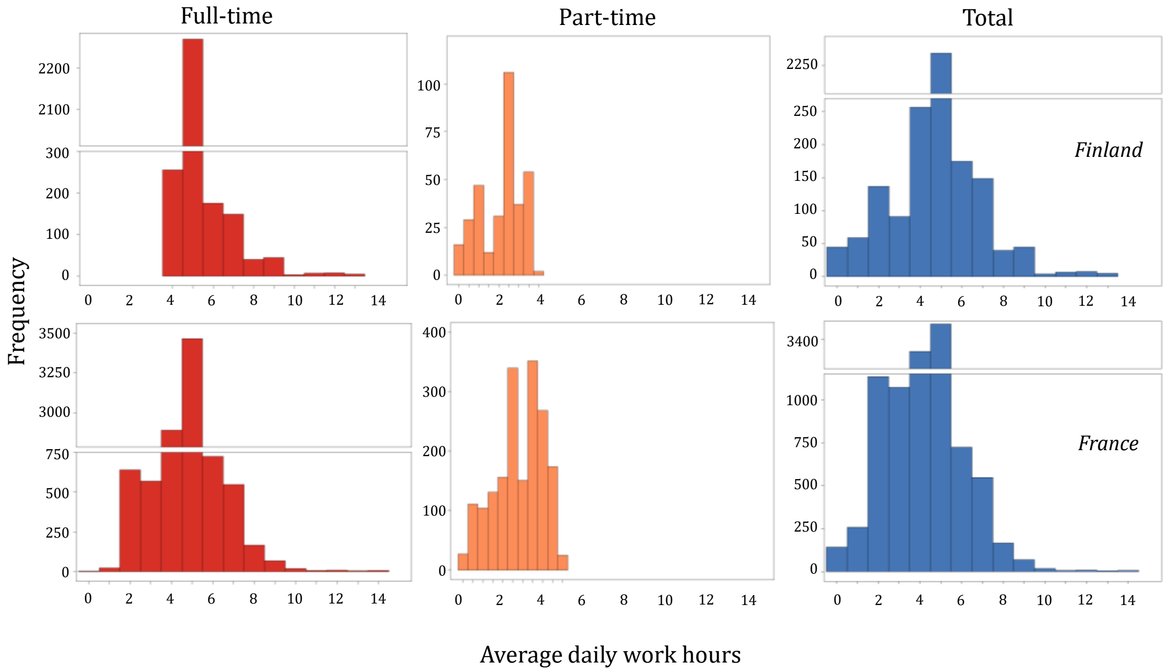
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

A.1 Original activities and categorisations used by other authors

TUS activities	Description of activities according to MTUS	Jalas & Juntunen (2015)	De Lauretis et al. (2017)
Sleep	Sleep and naps	-	Sleep
Eating & Drinking	Meals or snacks, also at work, school or elsewhere	Eating	Eating at home
Personal care	Wash, dress, care for yourself	Personal hygiene, dressing	Personal time
Education	Regular schooling, , homework, other education	Studies	Work & study
Food preparation	Food preparation, cooking, setting table, washing dishes	Eating	Housework: meals
Cleaning, etc.	Cleaning, laundry, ironing, repair clothing, other domestic work	Housework	Housework: home, Housework: clothes
Maintenance	Home/vehicle maintenance or improvement, collecting fuel	Maintenance work	Housework: home
Shopping & Services	Purchasing goods, consuming personal care services/other services	Shopping, personal services, public administration and related trips	Shopping & administration
Gardening	Gardening, foraging, hunting, fishing	Maintenance work	Housework: home
Pet care	Walking dog, etc.	-	Care
Adult care	Caring for adult person, e.g. elderly	-	Care
Medical child care (Child care 2)	Physical or medical child care, supervision	-	Care
Child care (Child care 1)	Teach skills, help with homework, read, talk play with children	-	Care
Religion	Worship and religious activity	-	-
Voluntary work	Voluntary work, civic or organisational activity	-	-
Commuting	Travel to/from work, education related travel	Trips to work and study	Commuting (ancillary)
Traveling	Travel for voluntary/ civic/ religious activity, care-related travel, travel for shopping, etc.	Free time trips	Other travel time (ancillary)
Sports exercise	General sports or exercise, walking, cycling	Sports and recreation	Non energy-intensive leisure Sports & outings
TV & radio	Listen to music, radio, watching TV/DVD or streaming content	Television	Energy-intensive leisure
Reading	Reading	Reading	Non energy-intensive leisure
PC/ Internet use	Play computer games, email, surfing the Internet, programming, computing	Phone conversations	Energy-intensive leisure
Going out	Out-of-home leisure, attending sports or public event, cinema, theatre, opera, concert, restaurant, café, bar, pub, party, reception, social event, gambling and other	Eating Cultural events Hobbies	Eating out Sports & outings
Leisure	Receive or visit friends, conversation, games, general indoor leisure, artistic or musical activity, written correspondence, knit, craft or hobbies, relaxing, thinking	Phone conversations Hobbies	Non energy-intensive leisure
Paid work	All types of jobs, looking for work	-	Work & study

A.2 Histogram of the average work time per day (*WT*).



Note: Please note the axis breaks. Values plotted here are not weighted.

A.3 Results of the Kolmogorov-Smirnov (K-S) and Wilcoxon rank sum tests

	Variable	N	Mean of missing observations	Mean of all data	p-value (K-S test)	p-value (Wilcoxon test)
Finland	Household size	312	3.154	2.954	0.323	0.009
	Age	312	45.051	43.419	0.109	0.042
	Gender	312	1.513	1.541	0.977	0.339
	Education	312	1.670	1.646	0.647	0.083
	Income group	312	2.196	2.182	0.937	0.621
	Employment status	312	1.144	1.105	0.774	0.033
France	Household size	1485	2.908	2.797	0.137	0.004
	Age	1485	42.993	42.363	0.003	0.090
	Gender	1485	1.576	1.524	0.001	0.000
	Education	1485	41.642	40.004	0.000	0.000
	Income group	1485	2.313	2.238	0.004	0.000
	Employment status	1485	1.343	1.188	0.000	0.000

Note: A p-value > 0.1 for the K-S test means that one cannot reject the hypothesis that the two samples come from the same distribution. For the Wilcox rank sum test (equivalent to Mann-Whitney test) a p-value < 0.1 means that one cannot reject the hypothesis that one of the distributions generally has larger values. N: number of missing observations tested.

A.4.a Regression results for M1 ($Y_{i,j,d}$ equals absolute activity duration, in minutes), Finland

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)
Intercept	31.439**	42.111	−26.963	39.347**	66.739***	698.962***	−52.336*	50.437**	−65.127**	209.686***	84.013***	49.390	−11.724	−11.880	17.269	64.310**	11.170	5.585	16.536	282.026***	−1.619	2.127	41.474***
	(12.204)	(29.944)	(15.974)	(13.065)	(15.977)	(38.717)	(25.116)	(18.782)	(22.897)	(20.189)	(19.985)	(31.227)	(15.946)	(14.596)	(12.546)	(21.728)	(18.019)	(4.432)	(21.963)	(36.830)	(4.770)	(19.341)	(9.629)
WT	−3.576	9.741	3.976	−2.998	−5.848	−6.763	−6.189	−10.488*	8.718	−21.405***	−11.877*	12.338	3.575	3.092	−1.963	−7.486	4.702	−0.905	0.239	−13.269	−0.107	3.298	−6.318*
	(3.137)	(7.697)	(4.106)	(3.358)	(4.107)	(9.952)	(6.456)	(4.828)	(5.885)	(5.189)	(5.137)	(8.027)	(4.099)	(3.752)	(3.225)	(5.585)	(4.632)	(1.139)	(5.645)	(9.467)	(1.226)	(4.971)	(2.475)
WT^2	−0.027	−0.728	−0.411	0.200	0.417	0.192	0.514	0.515	−0.672	1.252***	0.703*	−0.785	−0.243	−0.216	0.174	0.636	−0.270	0.056	0.0004	0.496	−0.010	−0.266	0.337*
	(0.202)	(0.496)	(0.265)	(0.217)	(0.265)	(0.642)	(0.416)	(0.311)	(0.380)	(0.335)	(0.331)	(0.518)	(0.264)	(0.242)	(0.208)	(0.360)	(0.299)	(0.073)	(0.364)	(0.611)	(0.079)	(0.321)	(0.160)
PT	−17.408	14.681	−16.143	−3.430	1.210	−42.675	6.379	−33.341	4.973	−51.653**	−32.098	44.604	2.860	7.205	−15.773	−21.687	114.368***	−2.555	10.935	−23.748	−2.716	−11.651	−37.451***
	(11.505)	(28.229)	(15.059)	(12.317)	(15.062)	(36.499)	(23.677)	(17.706)	(21.586)	(19.033)	(18.840)	(29.438)	(15.033)	(13.760)	(11.828)	(20.483)	(16.987)	(4.178)	(20.705)	(34.721)	(4.497)	(18.234)	(9.077)
WT*PT	2.127	0.912	5.777	0.984	−2.406	10.505	−1.424	8.773*	1.033	11.744*	5.330	−7.173	2.613	−0.360	5.600	4.841	−28.808***	0.477	−3.981	−0.449	1.029	2.379	9.339***
	(2.850)	(6.993)	(3.731)	(3.051)	(3.731)	(9.042)	(5.866)	(4.387)	(5.348)	(4.715)	(4.667)	(7.293)	(3.724)	(3.409)	(2.930)	(5.074)	(4.208)	(1.035)	(5.129)	(8.602)	(1.114)	(4.517)	(2.249)
Age	−0.285***	−0.088	0.634***	0.011	0.527***	−0.908***	0.023	0.912***	0.706***	−1.022***	0.108	−0.594***	0.134*	0.238***	−0.106*	0.267**	−0.624***	0.030	0.175*	0.573***	0.028	−0.581***	−0.251***
	(0.047)	(0.114)	(0.061)	(0.050)	(0.061)	(0.148)	(0.096)	(0.072)	(0.087)	(0.077)	(0.076)	(0.119)	(0.061)	(0.056)	(0.048)	(0.083)	(0.069)	(0.017)	(0.084)	(0.140)	(0.018)	(0.074)	(0.037)
Female	1.278	−2.352	25.456***	12.135***	−0.699	−0.567	9.823***	2.630	27.804***	−20.323***	−1.549	−5.106	5.744***	−1.488	4.177***	−22.488***	6.042***	−0.417	−1.484	−36.463***	0.624	5.945***	0.041
	(1.133)	(2.780)	(1.483)	(1.213)	(1.483)	(3.594)	(2.332)	(1.744)	(2.126)	(1.874)	(1.855)	(2.899)	(1.480)	(1.355)	(1.165)	(2.017)	(1.673)	(0.411)	(2.039)	(3.419)	(0.443)	(1.796)	(0.894)
2ary Edu	−1.508	−0.729	−0.407	0.229	3.325*	−0.272	2.188	11.762***	1.138	2.603	3.971*	−4.045	0.701	−1.405	−2.465*	−1.120	−1.100	0.255	−1.330	−12.765***	−0.654	8.947***	3.306***
	(1.122)	(2.752)	(1.468)	(1.201)	(1.468)	(3.558)	(2.308)	(1.726)	(2.104)	(1.855)	(1.837)	(2.870)	(1.465)	(1.341)	(1.153)	(1.997)	(1.656)	(0.407)	(2.018)	(3.385)	(0.438)	(1.777)	(0.885)
HH size	−1.312**	−1.260	3.731***	−1.698***	1.903***	−1.868	−0.210	−1.410*	5.295***	−2.823***	−2.969***	−4.334***	0.463	0.460	−1.406**	1.245	−0.159	0.114	−0.477	−7.606***	0.139	9.305***	3.735***
	(0.427)	(1.047)	(0.558)	(0.457)	(0.559)	(1.354)	(0.878)	(0.657)	(0.801)	(0.706)	(0.699)	(1.092)	(0.558)	(0.510)	(0.439)	(0.760)	(0.630)	(0.155)	(0.768)	(1.288)	(0.167)	(0.676)	(0.337)
Med Inc	6.127***	1.293	−1.136	1.016	1.325	−15.001**	1.865	−4.950	3.153	−3.105	1.341	−3.627	−3.633	1.314	4.545**	9.214**	1.001	0.187	−3.064	−4.276	0.907	3.980	0.440
	(1.679)	(4.120)	(2.198)	(1.798)	(2.198)	(5.327)	(3.456)	(2.584)	(3.150)	(2.778)	(2.750)	(4.297)	(2.194)	(2.008)	(1.726)	(2.990)	(2.479)	(0.610)	(3.022)	(5.068)	(0.656)	(2.661)	(1.325)
High Inc	8.851***	3.085	−2.548	3.168	5.529*	−22.583***	1.303	−4.064	7.601*	−0.561	6.876*	2.844	−5.826*	0.412	4.408*	2.227	3.498	0.522	−1.792	0.106	0.193	−5.167	−1.960
	(1.891)	(4.640)	(2.475)	(2.024)	(2.476)	(5.999)	(3.891)	(2.910)	(3.548)	(3.128)	(3.097)	(4.838)	(2.471)	(2.262)	(1.944)	(3.367)	(2.792)	(0.687)	(3.403)	(5.707)	(0.739)	(2.997)	(1.492)
WD	37.285***	−45.180***	−23.117***	−4.710***	−14.149***	−81.166***	−29.269***	−13.680***	−33.890***	−16.523***	−17.066***	−33.718***	−18.337***	−7.571***	−2.297	−20.309***	−13.764***	−1.448**	−12.340***	−45.750***	0.656	−18.524***	−5.775***
	(1.312)	(3.220)	(1.718)	(1.405)	(1.718)	(4.163)	(2.701)	(2.020)	(2.462)	(2.171)	(2.149)	(3.358)	(1.715)	(1.570)	(1.349)	(2.336)	(1.938)	(0.477)	(2.362)	(3.960)	(0.513)	(2.080)	(1.035)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3,291	3,291	3,291	3,291	3,291	3,291	3,291	3,291	3,291	3,291	3,291	3,291	3,291	3,291	3,291	3,291	3,291	3,291	3,291	3,291	3,291	3,291	3,291
R^2	0.323	0.101	0.224	0.080	0.087	0.256	0.086	0.099	0.177	0.129	0.057	0.103	0.073	0.073	0.030	0.092	0.148	0.017	0.021	0.146	0.015	0.137	0.105
Adj R^2	0.318	0.094	0.217	0.072	0.079	0.250	0.079	0.092	0.170	0.122	0.049	0.095	0.065	0.065	0.022	0.084	0.140	0.009	0.013	0.139	0.006	0.130	0.097

Note: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Activity code: Commute (1), Travel (2) Food preparation (3) Personal care (4), Eating/Drinking (5), Sleep (6), Leisure (7), Reading (8), Cleaning (9), PC/Internet (10), Sport (11), Going out (12), Shopping/Services (13), Gardening (14), Pet care (15), Maintenance (16), Education (17), Religion (18), Voluntary work (19), TV/Radio (20), Elderly care (21), Child care 2 (22), Child care 1 (23).

A.4.b Regression results for M1 ($Y_{i,j,d}$ equals absolute activity duration, in minutes), France

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)
Intercept	−45.864***	77.293***	14.938**	26.625***	145.912***	617.791***	173.676***	4.549	−16.265	102.359***	86.401***	23.624***	6.384	18.814***	5.780*	60.649***	31.663***	−0.401	2.682	221.890***	6.599	6.863	10.451***
	(6.049)	(8.738)	(5.768)	(4.293)	(9.086)	(11.964)	(10.953)	(4.662)	(8.701)	(6.296)	(6.953)	(5.029)	(5.831)	(5.357)	(2.332)	(6.514)	(4.878)	(1.870)	(4.512)	(12.173)	(3.404)	(6.309)	(3.126)
WT	14.916***	−2.529	−4.574***	5.135***	−0.991	−7.741**	−3.711	−3.577***	−1.356	−3.204**	−5.965***	−1.459	−3.337**	−3.151**	−0.007	−5.231***	−0.998	0.309	−0.775	−1.530	−1.335*	0.713	−0.721
	(1.279)	(1.728)	(1.131)	(0.853)	(1.793)	(2.368)	(2.155)	(0.918)	(1.694)	(1.210)	(1.350)	(0.975)	(1.131)	(1.060)	(0.454)	(1.280)	(0.927)	(0.400)	(0.890)	(2.375)	(0.670)	(1.211)	(0.611)
WT^2	−1.099***	0.132	0.195*	−0.413***	0.182	0.442*	0.156	0.200**	0.048	0.095	0.363***	0.108	0.169*	0.144	−0.005	0.322***	0.074	−0.018	0.037	−0.252	0.105*	−0.043	0.024
	(0.094)	(0.128)	(0.084)	(0.063)	(0.133)	(0.175)	(0.159)	(0.068)	(0.125)	(0.089)	(0.100)	(0.072)	(0.084)	(0.078)	(0.034)	(0.095)	(0.068)	(0.030)	(0.066)	(0.176)	(0.049)	(0.090)	(0.045)
PT	36.980***	−4.982	−6.830	9.816**	5.726	−16.343	−7.434	−7.393*	3.860	−17.652***	−18.173***	−4.205	−10.233*	−12.058***	1.191	−16.325***	14.001***	0.994	0.547	−15.305	−2.259	5.355	−2.492
	(4.711)	(6.369)	(4.168)	(3.143)	(6.609)	(8.725)	(7.941)	(3.383)	(6.243)	(4.458)	(4.976)	(3.591)	(4.166)	(3.904)	(1.673)	(4.718)	(3.416)	(1.475)	(3.279)	(8.752)	(2.468)	(4.464)	(2.253)
WT*PT	−9.300***	2.075	2.489*	−1.753*	−0.169	4.448	2.681	0.693	0.187	4.135**	3.483*	1.395	1.935	2.064	−0.721	3.727**	−2.808**	−0.544	0.211	1.454	0.715	0.292	1.089
	(1.215)	(1.755)	(1.158)	(0.862)	(1.824)	(2.402)	(2.200)	(0.936)	(1.747)	(1.264)	(1.396)	(1.010)	(1.171)	(1.076)	(0.468)	(1.308)	(0.979)	(0.375)	(0.906)	(2.444)	(0.683)	(1.267)	(0.628)
Age	−0.056	0.022	0.563***	0.038	0.294***	−0.700***	−0.414***	0.457***	0.703***	−0.498***	−0.033	−0.067	0.214***	0.421***	0.061***	0.148**	−0.448***	0.031*	0.139***	0.224*	0.105***	−0.759***	−0.170***
	(0.045)	(0.065)	(0.043)	(0.032)	(0.068)	(0.089)	(0.081)	(0.035)	(0.065)	(0.047)	(0.052)	(0.037)	(0.043)	(0.040)	(0.017)	(0.048)	(0.036)	(0.014)	(0.034)	(0.090)	(0.025)	(0.047)	(0.023)
Female	−4.806***	1.095	27.141***	9.896***	−5.863***	8.419***	−1.224	2.680***	37.866***	−14.798***	−5.882***	−0.415	7.377***	−10.597***	0.071	−19.005***	−0.985	0.569	−2.249**	−25.373***	−1.593**	13.370***	1.619***
	(0.944)	(1.364)	(0.900)	(0.670)	(1.418)	(1.868)	(1.710)	(0.728)	(1.358)	(0.983)	(1.086)	(0.785)	(0.910)	(0.836)	(0.364)	(1.017)	(0.761)	(0.292)	(0.704)	(1.900)	(0.531)	(0.985)	(0.488)
2ary Edu	1.052	3.989*	−4.492***	−0.913	3.876*	−0.559	−8.793***	4.511***	0.162	1.341	2.732	−0.183	2.572*	−0.945	−1.290**	−2.679	2.458*	0.267	2.580**	−15.920***	0.255	2.786*	0.039
	(1.294)	(1.870)	(1.234)	(0.918)	(1.944)	(2.560)	(2.344)	(0.998)	(1.862)	(1.347)	(1.488)	(1.076)	(1.248)	(1.146)	(0.499)	(1.394)	(1.044)	(0.400)	(0.965)	(2.605)	(0.728)	(1.350)	(0.669)
>2ary	0.371	11.136***	−6.608***	−2.942***	4.807*	−5.637	−9.654***	14.763***	−1.505	4.748**	7.390***	3.009*	3.460*	−4.950***	−3.117***	−7.169***	4.296***	0.563	6.174***	−36.032***	0.221	11.322***	2.855***
	(1.544)	(2.231)	(1.472)	(1.096)	(2.319)	(3.054)	(2.796)	(1.190)	(2.221)	(1.607)	(1.775)	(1.284)	(1.489)	(1.368)	(0.595)	(1.663)	(1.245)	(0.477)	(1.152)	(3.108)	(0.869)	(1.611)	(0.798)
HH size	−0.184	1.734**	2.319***	−1.890***	−0.692	−0.437	−4.590***	−1.201***	2.288***	−2.514***	−1.140**	−1.055***	−0.772*	0.559	−0.908***	2.030***	−1.455***	0.524***	−0.152	−2.961***	−0.228	10.031***	3.919***
	(0.384)	(0.555)	(0.366)	(0.272)	(0.577)	(0.759)	(0.695)	(0.296)	(0.552)	(0.400)	(0.441)	(0.319)	(0.370)	(0.340)	(0.148)	(0.413)	(0.310)	(0.119)	(0.286)	(0.773)	(0.216)	(0.400)	(0.198)
Med Inc	−2.326	−5.554**	−0.564	−0.270	9.242***	−2.958	−3.020	2.468*	2.945	−1.394	−3.918*	1.265	3.071*	1.709	0.827	1.499	−5.766***	−1.706***	0.270	−6.131*	0.014	1.609	0.198
	(1.417)	(2.047)	(1.351)	(1.005)	(2.128)	(2.803)	(2.566)	(1.092)	(2.038)	(1.475)	(1.629)	(1.178)	(1.366)	(1.255)	(0.546)	(1.526)	(1.143)	(0.438)	(1.057)	(2.852)	(0.797)	(1.478)	(0.732)
High Inc	−0.305	−2.079	−2.490	−0.300	13.348***	−2.556	−8.185***	3.181*	2.060	−1.285	−0.935	4.578***	3.097*	2.323	0.736	1.800	−5.303***	−2.054***	1.301	−13.722***	−1.647	−1.571	−1.091
	(1.615)	(2.334)	(1.540)	(1.146)	(2.427)	(3.195)	(2.925)	(1.245)	(2.324)	(1.681)	(1.857)	(1.343)	(1.557)	(1.431)	(0.623)	(1.740)	(1.303)	(0.499)	(1.205)	(3.251)	(0.909)	(1.685)	(0.835)
WD	47.287***	−50.748***	−21.714***	−2.291**	−29.708***	−69.058***	−44.359***	−8.031***	−41.473***	−13.389***	−21.464***	−6.665***	−25.174***	−12.356***	−3.025***	−18.937***	−9.961***	−1.426***	−3.965***	−39.124***	−4.620***	−14.942***	−3.912***
	(1.103)	(1.594)	(1.052)	(0.783)	(1.657)	(2.182)	(1.998)	(0.850)	(1.587)	(1.148)	(1.268)	(0.917)	(1.063)	(0.977)	(0.425)	(1.188)	(0.890)	(0.341)	(0.823)	(2.220)	(0.621)	(1.151)	(0.570)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	10,983	10,983	10,983	10,983	10,983	10,983	10,983	10,983	10,983	10,983	10,983	10,983	10,983	10,983	10,983	10,983	10,983	10,983	10,983	10,983	10,983	10,983	10,983
R^2	0.270	0.137	0.186	0.036	0.097	0.178	0.130	0.063	0.177	0.057	0.092	0.030	0.115	0.066	0.017	0.068	0.046	0.010	0.013	0.092	0.013	0.140	0.066
Adj R^2	0.268	0.134	0.184	0.033	0.094	0.176	0.128	0.060	0.175	0.054	0.090	0.028	0.112	0.064	0.015	0.066	0.043	0.007	0.011	0.089	0.010	0.137	0.064

Note: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Activity code: Commute (1), Travel (2) Food preparation (3) Personal care (4), Eating/Drinking (5), Sleep (6), Leisure (7), Reading (8), Cleaning (9), PC/Internet (10), Sport (11), Going out (12), Shopping/Services (13), Gardening (14), Pet care (15), Maintenance (16), Education (17), Religion (18), Voluntary work (19), TV/Radio (20), Elderly care (21), Child care 2 (22), Child care 1 (23).

A.5.a Regression results for M2 ($Y_{i,j,d}$ equals relative activity duration, in percent), Finland

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)
Intercept	2.311	2.544	−3.181*	1.349	3.568*	39.474***	2.352	3.247*	−5.838**	16.494**	6.675***	2.721	−0.831	−1.276	1.255	5.298**	0.361	0.421	0.818	19.279***	−0.154	0.115	2.999***
	(1.259)	(2.280)	(1.259)	(1.135)	(1.403)	(3.511)	(2.033)	(1.492)	(1.807)	(1.628)	(1.611)	(2.452)	(1.298)	(1.101)	(1.063)	(1.695)	(1.341)	(0.314)	(1.738)	(3.056)	(0.439)	(1.454)	(0.742)
WT	−0.146	0.766	0.419	0.069	−0.302	1.797*	−0.192	−0.768*	0.657	−1.679***	−1.049*	1.072	0.185	0.314	−0.165	−0.612	0.424	−0.070	0.080	−0.555	−0.011	0.218	−0.453*
	(0.324)	(0.586)	(0.324)	(0.292)	(0.361)	(0.902)	(0.523)	(0.384)	(0.464)	(0.418)	(0.414)	(0.630)	(0.334)	(0.283)	(0.273)	(0.436)	(0.345)	(0.081)	(0.447)	(0.786)	(0.113)	(0.374)	(0.191)
WT^2	−0.013	−0.057	−0.038	0.001	0.037	−0.056	0.025	0.038	−0.050	0.096***	0.063*	−0.064	−0.013	−0.021	0.015	0.048	−0.025	0.004	−0.005	0.010	−0.001	−0.018	0.024*
	(0.021)	(0.038)	(0.021)	(0.019)	(0.023)	(0.058)	(0.034)	(0.025)	(0.030)	(0.027)	(0.027)	(0.041)	(0.022)	(0.018)	(0.018)	(0.028)	(0.022)	(0.005)	(0.029)	(0.051)	(0.007)	(0.024)	(0.012)
PT	−1.418	1.115	−0.950	0.508	0.386	3.525	1.110	−2.526	0.128	−4.429**	−3.069*	3.888	−0.263	0.822	−1.356	−1.976	8.523***	−0.202	0.866	−0.513	−0.229	−1.112	−2.827***
	(1.187)	(2.149)	(1.187)	(1.070)	(1.322)	(3.310)	(1.916)	(1.407)	(1.703)	(1.535)	(1.519)	(2.311)	(1.223)	(1.038)	(1.002)	(1.598)	(1.264)	(0.296)	(1.639)	(2.881)	(0.414)	(1.371)	(0.699)
WT*PT	0.122	0.069	0.348	−0.124	−0.229	−0.885	−0.208	0.655	0.130	1.006**	0.538	−0.641	0.276	−0.089	0.464	0.421	−2.134***	0.038	−0.318	−0.477	0.079	0.243	0.715***
	(0.294)	(0.532)	(0.294)	(0.265)	(0.328)	(0.820)	(0.475)	(0.349)	(0.422)	(0.380)	(0.376)	(0.573)	(0.303)	(0.257)	(0.248)	(0.396)	(0.313)	(0.073)	(0.406)	(0.714)	(0.103)	(0.340)	(0.173)
Age	−0.026***	−0.008	0.050***	0.002	0.046***	−0.072***	0.001	0.076***	0.055***	−0.084***	0.008	−0.046***	0.010*	0.017***	−0.009*	0.018**	−0.045***	0.002	0.015*	0.052***	0.003	−0.046***	−0.020***
	(0.005)	(0.009)	(0.005)	(0.004)	(0.005)	(0.013)	(0.008)	(0.006)	(0.007)	(0.006)	(0.006)	(0.009)	(0.005)	(0.004)	(0.004)	(0.006)	(0.005)	(0.001)	(0.007)	(0.012)	(0.002)	(0.006)	(0.003)
Female	0.043	−0.207	2.090***	1.022***	−0.205	−0.586	0.801***	0.212	2.305***	−1.674***	−0.122	−0.374	0.512***	−0.095	0.355***	−1.808***	0.488***	−0.031	−0.100	−3.062***	0.049	0.400**	−0.012
	(0.117)	(0.212)	(0.117)	(0.105)	(0.130)	(0.326)	(0.189)	(0.139)	(0.168)	(0.151)	(0.150)	(0.228)	(0.120)	(0.102)	(0.099)	(0.157)	(0.124)	(0.029)	(0.161)	(0.284)	(0.041)	(0.135)	(0.069)
2ary Edu	−0.195	−0.060	−0.063	0.044	0.133	−0.263	0.123	0.918***	0.038	0.169	0.334*	−0.280	0.010	−0.142	−0.218*	−0.147	−0.051	0.019	−0.101	−1.149***	−0.057	0.689***	0.252***
	(0.116)	(0.210)	(0.116)	(0.104)	(0.129)	(0.323)	(0.187)	(0.137)	(0.166)	(0.150)	(0.148)	(0.225)	(0.119)	(0.101)	(0.098)	(0.156)	(0.123)	(0.029)	(0.160)	(0.281)	(0.040)	(0.134)	(0.068)
HH size	−0.128**	−0.075	0.316***	−0.141***	0.190***	−0.100	0.022	−0.137**	0.428***	−0.242***	−0.260***	−0.355***	0.058	0.040	−0.114**	0.094	−0.017	0.008	−0.015	−0.650***	0.012	0.754***	0.312***
	(0.044)	(0.080)	(0.044)	(0.040)	(0.049)	(0.123)	(0.071)	(0.052)	(0.063)	(0.057)	(0.056)	(0.086)	(0.045)	(0.038)	(0.037)	(0.059)	(0.047)	(0.011)	(0.061)	(0.107)	(0.015)	(0.051)	(0.026)
Med Inc	0.648***	0.171	−0.139	0.101	0.00001	−1.256***	0.362	−0.387	0.276	−0.203	0.126	−0.244	−0.361*	0.088	0.357*	0.680**	0.107	0.014	−0.287	−0.429	0.082	0.269	0.025
	(0.173)	(0.314)	(0.173)	(0.156)	(0.193)	(0.483)	(0.280)	(0.205)	(0.249)	(0.224)	(0.222)	(0.337)	(0.179)	(0.151)	(0.146)	(0.233)	(0.184)	(0.043)	(0.239)	(0.420)	(0.060)	(0.200)	(0.102)
High Inc	0.908***	0.312	−0.278	0.253	0.407	−2.264***	0.140	−0.357	0.623*	0.025	0.584*	0.244	−0.494*	0.002	0.368*	0.103	0.262	0.036	−0.205	−0.045	0.023	−0.451*	−0.196
	(0.195)	(0.353)	(0.195)	(0.176)	(0.217)	(0.544)	(0.315)	(0.231)	(0.280)	(0.252)	(0.250)	(0.380)	(0.201)	(0.171)	(0.165)	(0.263)	(0.208)	(0.049)	(0.269)	(0.474)	(0.068)	(0.225)	(0.115)
WD	3.919***	−2.338***	−0.819***	1.059***	1.072***	8.391***	−1.195***	−0.204	−1.550***	−0.558**	−0.731***	−1.724***	−0.762***	−0.383**	0.112	−1.065***	−0.873***	−0.096**	−0.513**	−0.511	0.090	−1.043***	−0.277***
	(0.135)	(0.245)	(0.135)	(0.122)	(0.151)	(0.378)	(0.219)	(0.160)	(0.194)	(0.175)	(0.173)	(0.264)	(0.140)	(0.118)	(0.114)	(0.182)	(0.144)	(0.034)	(0.187)	(0.329)	(0.047)	(0.156)	(0.080)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3,291	3,291	3,291	3,291	3,291	3,291	3,291	3,291	3,291	3,291	3,291	3,291	3,291	3,291	3,291	3,291	3,291	3,291	3,291	3,291	3,291	3,291	3,291
R^2	0.329	0.057	0.174	0.079	0.073	0.238	0.042	0.085	0.136	0.115	0.036	0.070	0.051	0.069	0.029	0.079	0.139	0.016	0.013	0.090	0.016	0.139	0.106
Adj R^2	0.324	0.049	0.167	0.071	0.065	0.232	0.033	0.077	0.129	0.107	0.027	0.062	0.042	0.061	0.021	0.071	0.132	0.008	0.005	0.082	0.007	0.132	0.098

Note: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Activity code: Commute (1), Travel (2) Food preparation (3) Personal care (4), Eating/Drinking (5), Sleep (6), Leisure (7), Reading (8), Cleaning (9), PC/Internet (10), Sport (11), Going out (12), Shopping/Services (13), Gardening (14), Pet care (15), Maintenance (16), Education (17), Religion (18), Voluntary work (19), TV/Radio (20), Elderly care (21), Child care 2 (22), Child care 1 (23).

A.5.b Regression results for M2 ($Y_{i,j,d}$ equals elative activity duration, in percent), France

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)
Intercept	−5.058***	5.382***	0.337	0.708	8.374***	37.756***	12.845***	0.049	−2.239***	8.099***	6.533***	1.745***	0.344	1.274**	0.387*	4.412***	2.209***	−0.062	0.212	15.335***	0.528*	0.186	0.645*
	(0.569)	(0.674)	(0.460)	(0.376)	(0.753)	(1.104)	(0.873)	(0.381)	(0.671)	(0.520)	(0.530)	(0.391)	(0.452)	(0.402)	(0.192)	(0.489)	(0.357)	(0.138)	(0.356)	(1.022)	(0.253)	(0.493)	(0.252)
WT	1.644***	−0.359*	−0.390***	0.561***	0.156	0.911***	−0.250	−0.302***	−0.022	−0.261*	−0.526***	−0.167	−0.239*	−0.173	0.016	−0.484***	−0.100	0.031	−0.036	0.146	−0.156**	0.095	−0.093
	(0.132)	(0.156)	(0.106)	(0.087)	(0.174)	(0.255)	(0.202)	(0.088)	(0.155)	(0.120)	(0.123)	(0.091)	(0.105)	(0.093)	(0.045)	(0.113)	(0.083)	(0.032)	(0.082)	(0.236)	(0.058)	(0.114)	(0.058)
WT^2	−0.106***	0.026*	0.018*	−0.036***	0.010	−0.029	0.005	0.018*	−0.003	0.011	0.034***	0.013	0.013	0.003	−0.0003	0.033***	0.008	−0.002	−0.001	−0.028	0.013**	−0.003	0.005
	(0.011)	(0.013)	(0.009)	(0.007)	(0.014)	(0.021)	(0.016)	(0.007)	(0.013)	(0.010)	(0.010)	(0.007)	(0.008)	(0.008)	(0.004)	(0.009)	(0.007)	(0.003)	(0.007)	(0.019)	(0.005)	(0.009)	(0.005)
PT	4.220***	−1.060*	−0.567	1.046***	0.880	1.407	−0.590	−0.547	0.497	−1.182**	−1.506***	−0.486	−0.762*	−0.922***	0.175	−1.340***	1.018***	0.124	−0.088	−0.390	−0.306	0.605	−0.225
	(0.450)	(0.534)	(0.364)	(0.298)	(0.596)	(0.874)	(0.691)	(0.301)	(0.531)	(0.411)	(0.420)	(0.310)	(0.358)	(0.318)	(0.152)	(0.387)	(0.283)	(0.109)	(0.282)	(0.809)	(0.200)	(0.390)	(0.200)
WT*PT	−0.986***	0.183	0.193*	−0.252***	−0.238	−0.436*	0.220	0.060	0.055	0.300**	0.282**	0.111	0.150	0.167*	−0.047	0.266**	−0.204**	−0.039	0.039	0.008	0.069	0.016	0.085
	(0.114)	(0.135)	(0.092)	(0.076)	(0.151)	(0.222)	(0.175)	(0.076)	(0.135)	(0.104)	(0.106)	(0.079)	(0.091)	(0.081)	(0.039)	(0.098)	(0.072)	(0.028)	(0.071)	(0.205)	(0.051)	(0.099)	(0.051)
Age	−0.005	−0.001	0.044***	0.002	0.024***	−0.068***	−0.036***	0.037***	0.055***	−0.042***	−0.005	−0.006*	0.018***	0.033***	0.005***	0.012**	−0.032***	0.003*	0.011***	0.020**	0.008***	−0.063***	−0.014***
	(0.004)	(0.005)	(0.003)	(0.003)	(0.006)	(0.008)	(0.006)	(0.003)	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.001)	(0.004)	(0.003)	(0.001)	(0.003)	(0.008)	(0.002)	(0.004)	(0.002)
Female	−0.539***	0.111	2.210***	0.795***	−0.740***	0.033	−0.173	0.194**	3.038***	−1.295***	−0.478***	−0.029	0.574***	−0.833***	0.003	−1.484***	−0.072	0.044*	−0.189***	−2.238***	−0.111***	1.059***	0.120**
	(0.089)	(0.105)	(0.072)	(0.059)	(0.117)	(0.172)	(0.136)	(0.059)	(0.105)	(0.081)	(0.083)	(0.061)	(0.071)	(0.063)	(0.030)	(0.076)	(0.056)	(0.021)	(0.056)	(0.160)	(0.039)	(0.077)	(0.039)
2ary Edu	0.185	0.309*	−0.332***	−0.057	0.383*	0.285	−0.755***	0.347***	0.013	0.117	0.200	−0.043	0.202*	−0.071	−0.100*	−0.214*	0.181*	0.018	0.224**	−1.141***	0.013	0.226*	0.009
	(0.122)	(0.144)	(0.098)	(0.080)	(0.161)	(0.236)	(0.187)	(0.081)	(0.144)	(0.111)	(0.113)	(0.084)	(0.097)	(0.086)	(0.041)	(0.105)	(0.076)	(0.029)	(0.076)	(0.219)	(0.054)	(0.106)	(0.054)
>2ary	0.181	0.861***	−0.536***	−0.249***	0.438*	−0.099	−0.861***	1.224***	−0.165	0.374**	0.523***	0.210*	0.249*	−0.416***	−0.259***	−0.607***	0.329***	0.049	0.516***	−2.910***	−0.009	0.914***	0.241***
	(0.145)	(0.172)	(0.117)	(0.096)	(0.192)	(0.282)	(0.223)	(0.097)	(0.171)	(0.133)	(0.135)	(0.100)	(0.115)	(0.103)	(0.049)	(0.125)	(0.091)	(0.035)	(0.091)	(0.261)	(0.064)	(0.126)	(0.064)
HH size	−0.022	0.145***	0.163***	−0.182***	−0.088	−0.139*	−0.382***	−0.114***	0.167***	−0.207***	−0.106**	−0.093***	−0.073*	0.040	−0.082***	0.157***	−0.111***	0.042***	−0.013	−0.252***	−0.016	0.836***	0.328***
	(0.036)	(0.043)	(0.029)	(0.024)	(0.048)	(0.070)	(0.055)	(0.024)	(0.043)	(0.033)	(0.034)	(0.025)	(0.029)	(0.026)	(0.012)	(0.031)	(0.023)	(0.009)	(0.023)	(0.065)	(0.016)	(0.031)	(0.016)
Med Inc	−0.107	−0.465**	−0.026	−0.014	0.894***	0.040	−0.190	0.215*	0.261	−0.134	−0.294*	0.118	0.190	0.154	0.073	0.134	−0.408***	−0.137***	0.019	−0.449	−0.009	0.124	0.010
	(0.133)	(0.158)	(0.108)	(0.088)	(0.176)	(0.259)	(0.204)	(0.089)	(0.157)	(0.122)	(0.124)	(0.092)	(0.106)	(0.094)	(0.045)	(0.115)	(0.084)	(0.032)	(0.083)	(0.239)	(0.059)	(0.116)	(0.059)
High Inc	0.130	−0.190	−0.183	−0.010	1.244***	0.277	−0.708***	0.281**	0.211	−0.138	−0.058	0.420***	0.182	0.210	0.061	0.126	−0.377***	−0.170***	0.128	−1.080***	−0.124	−0.138	−0.093
	(0.152)	(0.180)	(0.123)	(0.100)	(0.201)	(0.295)	(0.233)	(0.102)	(0.179)	(0.139)	(0.142)	(0.104)	(0.121)	(0.107)	(0.051)	(0.131)	(0.095)	(0.037)	(0.095)	(0.273)	(0.067)	(0.132)	(0.067)
WD	4.992***	−2.831***	−0.701***	1.239***	1.175***	8.301***	−1.886***	−0.296***	−2.061***	−0.514***	−1.218***	−0.365***	−1.402***	−0.724***	−0.117***	−1.151***	−0.662***	−0.083***	−0.161*	−0.463*	−0.289***	−0.662***	−0.122**
	(0.104)	(0.123)	(0.084)	(0.069)	(0.137)	(0.201)	(0.159)	(0.069)	(0.122)	(0.095)	(0.097)	(0.071)	(0.082)	(0.073)	(0.035)	(0.089)	(0.065)	(0.025)	(0.065)	(0.186)	(0.046)	(0.090)	(0.046)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	10,983	10,983	10,983	10,983	10,983	10,983	10,983	10,983	10,983	10,983	10,983	10,983	10,983	10,983	10,983	10,983	10,983	10,983	10,983	10,983	10,983	10,983	10,983
R^2	0.317	0.082	0.142	0.071	0.033	0.222	0.072	0.055	0.141	0.049	0.069	0.024	0.085	0.064	0.014	0.063	0.043	0.009	0.012	0.054	0.011	0.144	0.064
Adj R^2	0.315	0.080	0.140	0.068	0.030	0.220	0.070	0.053	0.138	0.046	0.066	0.022	0.082	0.062	0.011	0.060	0.041	0.006	0.010	0.052	0.009	0.141	0.061

Note: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Activity code: Commute (1), Travel (2) Food preparation (3) Personal care (4), Eating/Drinking (5), Sleep (6), Leisure (7), Reading (8), Cleaning (9), PC/Internet (10), Sport (11), Going out (12), Shopping/Services (13), Gardening (14), Pet care (15), Maintenance (16), Education (17), Religion (18), Voluntary work (19), TV/Radio (20), Elderly care (21), Child care 2 (22), Child care 1 (23).

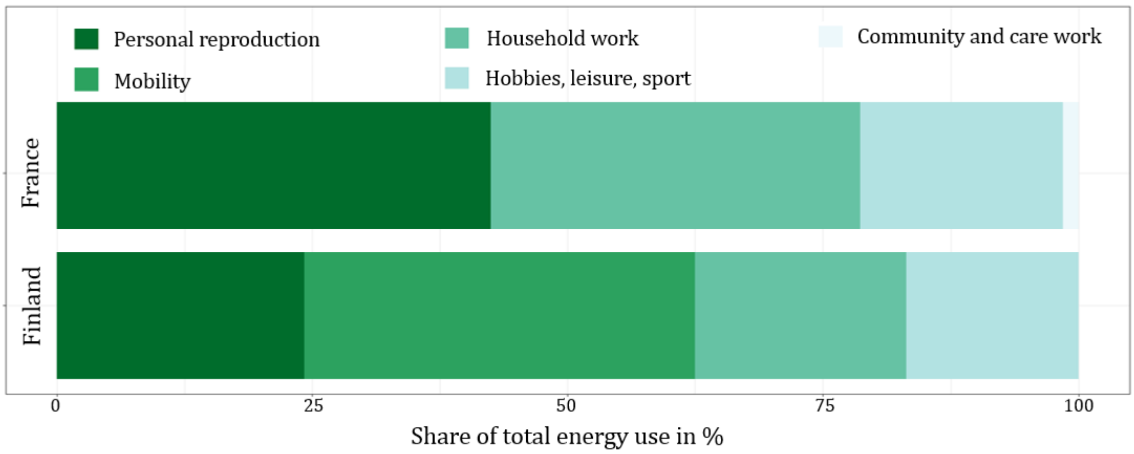
A.6 Activities and their energy use

A.6.a Energy use intensities of different activities for France and Finland

Activities Finland	kWh/h	Activities France	kWh/h
Free time trips	35.69	Housework: meals	7.21
Trips to work and study	32.64	Sport and outings	5.73
Eating	15.04	Personal time	5.65
Shopping, Services, Public administration and related	12.27	Shopping and administration	5.09
Phone conversations	10.26	Housework: clothes	3.28
Personal hygiene and dressing	7.66	Housework: home	1.51
Housework	5.61	Work and study	1.47
Maintenance, gardening, pets	5.23	Leisure (energy-int.)	1.39
Culture events	4.59	Eating at home	0.92
Reading	1.41	Leisure (non-energy-int.)	0.91
Hobbies	1.35	Eating out	0.80
Studying	1.02	Care (for others)	0.79
Television	0.94	Sleep	0.77
Sports and recreation	0.82		

Note: Energy use for France corresponds to direct energy, numbers for Finland include direct and indirect (embodied) energy use. Source: Jalas & Juntunen (2015) and de Lauretis et al. (2017).

A.6.b Sources of energy use by activity



Note: Care work is not included for Finland, as no energy use values were available. Mobility is treated as an ancillary activity in France and already allocated to all out of home activities.

References

[1] J.B. Schor, Sustainable consumption and worktime reduction, J. Ind. Ecol. 9 (2005) 37–50. https://doi.org/10.1162/1088198054084581.

[2] T. Jackson, P. Victor, Productivity and work in the 'green economy': some theoretical reflections and empirical tests, Environ. Innov. Soc. Transitions. 1 (2011) 101–108.

[3] A.L. Bovenberg, Green tax reforms and the double dividend: an updated reader's guide, Int. Tax Public Financ. 6 (1999) 421–443.

[4] J. Buhl, J. Acosta, Work less, do less?, Sustain. Sci. 11 (2016) 261–276. https://doi.org/10.1007/s11625-015-0322-8.

[5] J.C. Minx, G. Baiocchi, Time use and sustainability: An input-output approach in mixed units, in: Handb. Input-Output Econ. Ind. Ecol., Springer, 2009: pp. 819–846.

[6] J. Nässén, J. Larsson, Would shorter working time reduce greenhouse gas emissions? An analysis of time use and consumption in Swedish households, Environ. Plan. C Gov. Policy. 33 (2015) 726–745. https://doi.org/10.1068/c12239.

[7] World Bank, World Development Indicators, (2015). https://databank.worldbank.org/reports.aspx?source=world-development-indicators# (accessed February 1, 2021).

[8] Eurofound 2012, Fifth European Working Conditions Survey. Publications Office of the European Union, Luxembourg, n.d. https://doi.org/10.2806/34660.

[9] A. Parent-Thirion, Fourth European working conditions survey, (2007).

[10] L. Schipper, S. Bartlett, D. Hawk, E. Vine, Linking life-styles and energy use: a matter of time?, Annu. Rev. Energy. 14 (1989) 273–320.

[11] M. Jalas, A time use perspective on the materials intensity of consumption, Ecol. Econ. 41 (2002) 109–123. https://doi.org/10.1016/S0921-8009(02)00018-6.

[12] M. Jalas, The everyday life context of increasing energy demands: Time use survey data in a decomposition analysis, J. Ind. Ecol. 9 (2005) 129–145. https://doi.org/10.1162/1088198054084644.

[13] A. Druckman, I. Buck, B. Hayward, T. Jackson, Time, gender and carbon: a study of the carbon implications of British adults' use of time, Ecol. Econ. 84 (2012) 153–163. https://doi.org/https://doi.org/10.1016/j.ecolecon.2012.09.008.

[14] M. Jalas, J.K. Juntunen, Energy intensive lifestyles: Time use, the activity patterns of consumers, and related energy demands in Finland, Ecol. Econ. 113 (2015) 51–59. https://doi.org/10.1016/j.ecolecon.2015.02.016.

[15] B. Smetschka, D. Wiedenhofer, C. Egger, E. Haselsteiner, D. Moran, V. Gaube, Time Matters: The Carbon Footprint of Everyday Activities in Austria, Ecol. Econ. 164 (2019) 106357. https://doi.org/https://doi.org/10.1016/j.ecolecon.2019.106357.

[16] B. Yu, J. Zhang, Y.-M. Wei, Time use and carbon dioxide emissions accounting: An empirical analysis from China, J. Clean. Prod. 215 (2019) 582–599. https://doi.org/10.1016/j.jclepro.2019.01.047.

[17] M. Antal, B. Plank, J. Mokos, D. Wiedenhofer, Is working less really good for the environment? A systematic review of the empirical evidence for resource use, greenhouse gas emissions and the ecological footprint, Environ. Res. Lett. (2020).

https://doi.org/10.1088/1748-9326/abceec.

[18] D. Rosnick, M. Weisbrot, Are shorter work hours good for the environment? A comparison of US and European energy consumption, Int. J. Heal. Serv. 37 (2007) 405–417. https://doi.org/10.2190/D842-1505-1K86-9882.

[19] K.W. Knight, E.A. Rosa, J.B. Schor, Could working less reduce pressures on the environment? A cross-national panel analysis of OECD countries, 1970–2007, Glob. Environ. Chang. 23 (2013) 691–700. https://doi.org/10.1016/j.gloenvcha.2013.02.017.

[20] L.C. King, J.C.J.M. van den Bergh, Worktime reduction as a solution to climate change: Five scenarios compared for the UK, Ecol. Econ. 132 (2017) 124–134.

[21] I. Gough, S. Abdallah, V. Johnson, J. Ryan-Collins, C. Smith, The distribution of total greenhouse gas emissions by households in the UK, and some implications for social policy, (2011).

[22] S. De Lauretis, F. Ghersi, J.-M. Cayla, Energy consumption and activity patterns: an analysis extended to total time and energy use for French households, Appl. Energy. 206 (2017) 634–648. https://doi.org/10.1016/j.apenergy.2017.08.180.

[23] D. Wiedenhofer, B. Smetschka, L. Akenji, M. Jalas, H. Haberl, Household time use, carbon footprints, and urban form: a review of the potential contributions of everyday living to the 1.5 C climate target, Curr. Opin. Environ. Sustain. 30 (2018) 7–17. https://doi.org/10.1016/j.cosust.2018.02.007.

[24] J. Gershuny, K. Fisher, Multinational Time Use Study, Centre for Time Use Research, University of Oxford, 2013.

[25] B. Anderson, Laundry, energy and time: Insights from 20 years of time-use diary data in the United Kingdom, Energy Res. Soc. Sci. 22 (2016) 125–136. https://doi.org/10.1016/j.erss.2016.09.004.

[26] J. Torriti, Understanding the timing of energy demand through time use data: Time of the day dependence of social practices, Energy Res. Soc. Sci. 25 (2017) 37–47. https://doi.org/10.1016/j.erss.2016.12.004.

[27] L. Murray, H. Nguyen, Y.-F. Lee, M.D. Remmenga, D.W. Smith, Variance inflation factors in regression models with dummy variables, (2012). https://doi.org/https://doi.org/10.4148/2475-7772.1034.

[28] H. Frazis, J. Stewart, How to think about time-use data: What inferences can we make about long-and short-run time use from time diaries?, Ann. Econ. Stat. d'économie Stat. (2012) 231–245. https://doi.org/10.2307/23646463.

[29] J. Stewart, Getting Started with Time-Use Data, J. Time Use Res. Art. 2. (2018).

[30] M. Büchs, S. V Schnepf, Who emits most? Associations between socio-economic factors and UK households' home energy, transport, indirect and total CO2 emissions, Ecol. Econ. 90 (2013) 114–123. https://doi.org/10.1016/j.ecolecon.2013.03.007.

[31] A. Druckman, T. Jackson, Understanding households as drivers of carbon emissions, in: Tak. Stock Ind. Ecol., Springer, Cham, 2016: pp. 181–203.

[32] UN General Assembly, Transforming our world : the 2030 Agenda for Sustainable Development, 2015.

[33] M. Beck, N. Rivers, R. Wigle, H. Yonezawa, Carbon tax and revenue recycling:

Impacts on households in British Columbia, Resour. Energy Econ. 41 (2015) 40–69. https://doi.org/10.1016/j.reseneeco.2015.04.005.

[34] J. Sumner, L. Bird, H. Dobos, Carbon taxes: a review of experience and policy design considerations, Clim. Policy. 11 (2011) 922–943. https://doi.org/https://doi.org/10.3763/cpol.2010.0093.