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Sick and stuck at home – how poor health increases electricity consumption and reduces opportunities for environmentally-friendly travel in the United Kingdom

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ABSTRACT

Research on the determinants of direct and indirect energy use has identified a range of relevant socio-economic factors. However, we still know little about possible influences of people's health on their energy use. Do people in poor health use less energy because they are on lower incomes, or do they have additional domestic energy needs as they spend more time at home? Does poor health reduce mobility for all or just some (environmentally-friendly) modes of travel? This paper examines these questions through analysis of the representative UK Understanding Society survey. We find that poor health is generally linked to lower home energy use and lower engagement in all forms of travel. However, once we control for income and other socio-demographic factors, poor health is related to higher electricity consumption. These findings have important policy implications as it means that people in poor health would be additionally burdened by higher cost of electricity but, due to their low mobility, less so by higher cost of energy-intensive forms of travel. While promoting good health could support environmentally-friendly travel, additional measures would be required to prevent a rise of energy-intensive modes of travel.

1. Introduction

From a policy perspective, it is important to understand the ways in which socio-economic factors influence people's energy use because it shows which groups are likely to be especially affected by higher energy prices or taxes which may arise from energy reduction or climate change mitigation policies. If high energy use relates to individual or household characteristics that are difficult or impossible to change, people with these characteristics are at a disadvantage because they will struggle to adopt more environmentally-friendly behaviours to adjust to higher energy prices. Additional policies may be needed to protect these groups from unfair burdens and to make energy reduction policies more acceptable to them.

There is already a lot of research on the socio-economic factors for direct and indirect energy use (or related emissions). Income, household size, age, education and rural/urban location have been identified as especially important in this context [1–5]. However, health status has been largely overlooked in this research. We argue that health is a policy-relevant factor for energy use which deserves further attention.

First, if poor health was linked to high energy use, this could indicate a case of 'necessity': health conditions are not only arising from behavioural factors, but are also influenced by factors that are largely out of people's control such as age, gender, genetic disposition, and various environmental and contextual factors [6]. Here, policies may be necessary to help people save energy at low cost, or to compensate them for financial burdens of energy reduction policies that affect them. At the same time, promoting good health could be a relevant strategy for decreasing energy use in the population.

Second, if good health was related to high energy use, additional policies would be necessary to encourage (healthy) people to save energy. Which one of these scenarios is correct remains unclear; something that our paper will therefore examine.

Before we review the literature on the relationship between health and energy use, it is important to acknowledge that there is a two-way relationship between them. While health status has not yet played an important role in research on the *determinants* of householders' energy

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use or carbon emissions, there is some research on health *implications* of energy consumption, production, and reduction. For instance, several studies examine the health implications of home insulation and find largely positive effects from warmer homes, especially if increased mould or poorer air quality are avoided through appropriate ventilation [7–15]. Several studies have also shown overall positive health effects of 'active' and environmentally-friendly forms of travel such as walking or cycling which outweigh health risks associated with poor air quality or injury [16–19]. However, health benefits can vary by gender, age, and other characteristics [20].

At the macro-level, several studies focus on the health implications of different energy or electricity generation systems, for instance through their impacts on air pollution, occupational health hazards or risk of radiation (from nuclear technologies) [21–26]. In developing country contexts, several studies have examined the health implications of different indoor cooking technologies [22,25,27]. Furthermore, several studies seek to determine whether it is possible to achieve high levels of health and wellbeing at low levels of energy use. They show that while there are some countries, mostly in South America, in which life expectancy is high despite comparatively low levels of energy use (the so-called "Goldemberg corner") [28,29], energy use and good health usually increase in tandem [29–33]. However, these macro-level studies often say little about the 'direction of influence' – which likely goes both ways: high energy use might promote good health as it is generally associated with higher levels of comfort and higher living standards, while good health could also lead to higher energy use if people are more mobile and active and thus travel, work, earn and consume more.

Also lacking are studies that compare the relationships between health and energy use across behavioural domains such as heating and electricity use in the home, or different forms of travel. We think this is important because the relationship between health status and energy consumption might vary across these domains, requiring a more differentiated policy approach. Another complication is that, as pointed out above, energy use is associated with a range of other socio-demographic characteristics, some of which are also tightly linked with health. Instead of just studying bivariate relationships between energy use and health, one needs to control for these socio-demographic characteristics to establish whether health status makes an additional difference to people's energy use, holding all other factors constant. To carry out this type of investigation, we use micro-level household and individual data from the representative United Kingdom (UK) survey Understanding Society [34], examining different types of energy use separately and controlling for various socio-demographic characteristics.

The paper proceeds as follows. Section 2 develops two competing hypotheses regarding the relationships between health status and energy use for different types of behaviours. Section 3 describes the Understanding Society study, the variables included in this paper, and methods of analysis. Section 4 reports the results and section 5 discusses them and concludes.

2. Theory: competing lines of reasoning

While there is so far no comprehensive theory on the ways in which health status influences energy use in different domains of everyday life, we can draw on related bodies of literature to formulate alternative hypotheses. Generally speaking, two opposing lines of reasoning have some initial plausibility. The first focusses on the role of income and suggests that poor health might be linked to lower energy use, both in the home and related to more expensive modes of travelling. The second focusses on mobility and suggests that poor health might increase energy use in the home and decrease most forms of travel apart from perhaps car travel.

The first line of reasoning, the 'income hypothesis', assumes that poor health is, on average, associated with low income [35]. This relationship can be bi-directional as people on low incomes may be less able to afford healthier lifestyles (fresh, healthy food; gym memberships, sport club fees, etc.) and more likely to smoke or consume alcohol due to higher levels of stress. On the other hand, poor health can also contribute to low incomes as people's capacity to participate in the labour market is likely to be restricted. At the same time it is well-known from previous research that low income is one of the most important correlates of lower energy use, both in the home and whilst travelling [1,3,4,36]. If poor health and low income are related, people in poor health may have fewer resources to spend on energy consumption in the home and (relatively) expensive modes of travel such as vehicle fuels, air travel and trains while they might have to satisfy some of their mobility needs using less expensive means of travel. Expressed in CO_2 emissions, car and air travel are more energy-intensive per passenger kilometre than train or bus travel (or walking or cycling which are emission-free when performed) (see Table 1). This means that, according to the 'income hypothesis', people in poor health are predicted to consume less energy from more polluting modes of travel, but are also at a disadvantage when it comes to using more energy-friendly train travel as this is often more expensive than car travel in the UK [37].

Table 1
CO_2 emissions per passenger kilometre in the UK.

Travel mode	kg CO_2/km
Average car	0.19
UK flight	0.34
EU flight	0.19
Overseas flight	0.22
Train	0.06
Bus	0.11
Coach	0.03

Note: Data are taken from DEFRA/DECC [38]. The figures for flights relate to "average passengers", averaging out different flight classes. The figure for buses refers to average local buses.

The second 'mobility hypothesis' focuses on what determines people's mobility. More mobile and active people are likely to spend less time at home, thus consuming less energy there, and more time travelling for both high and low carbon modes of travel. Previous studies found that good health supports, and ill-health prevents, higher engagement in cycling, walking, or other physical activity [39–42]. Conversely, previous research has shown that the relationship between travel and age is inversely u-shaped, which means that while travel tends to increase with age, it drops again with old age, especially for people aged over 80 [e.g. 5]. This drop is likely to be linked to decreased mobility. However, since old age and poor health are related (Table 2 below), it would again be important to control for age in multivariate analysis.

For home energy, several other studies have shown that old age is associated with higher electricity and gas consumption [5,43] which could be explained by larger amounts of time spent at home due to limited mobility. In addition, older people might 'feel the cold' more easily in winter as they are generally less physically active, and hence require higher indoor temperatures to feel comfortable. Similar mechanisms might apply to people in poor health but it will again be crucial to control for age to determine whether poor health is linked to higher home energy use *in addition* to old age.

In summary, the 'income hypothesis' states that people in poor health use less energy in the home and for relatively more expensive modes of travel, based on the assumption that their financial circumstances are more limited than those of healthier people. The 'mobility hypothesis' expects that people in poor health use more energy at home but engage less in both high and low carbon forms of travel, based on the assumption that illness reduces people's mobility. An open question

Table 2
Health status and socio-demographic characteristics – individuals.
Source: Understanding Society Wave 4 (2012/3). Standard errors in parentheses.

Health status	N Individuals	Percent	Mean individual age	Mean proportion of higher education	Mean proportion 'at home'
1–Very good	23,751	50.39	43.71 (0.18)	0.30 (0.00)	0.26 (0.00)
2 – Good	13,533	28.71	49.41 (0.23)	0.21 (0.01)	0.39 (0.01)
3 – Fair	6672	14.16	56.49 (0.35)	0.14 (0.01)	0.61 (0.01)
4 – Poor	3174	6.73	59.32 (0.46)	0.09 (0.01)	0.82 (0.01)
Total/mean	*47,130*	*100.00*	*48.18 (0.15)*	*0.24 (0.00)*	*0.38 (0.00)*

is whether poor health creates additional mobility needs, e.g. to attend medical appointments. If, at the same time, people with impaired health are less able to use low energy forms of travel such as walking, cycling or public transport (due to difficulties accessing bus stops and train stations), this might increase car use.

This paper will investigate these contrasting hypotheses by employing multivariate analysis which controls for income, age, and other factors, and by directly comparing home energy and various modes of travel.

3. Material and methods

3.1. Data

This paper uses data from *Understanding Society* (USoc), a representative longitudinal survey in the UK which started in 2009, continuing and expanding the *British Household Panel Survey* initiated in 1991. For this analysis, we utilise data from wave 4, collected in 2012 and 2013, because this is the most recent wave that covers questions on the number of flights, public transport use, and environmental attitudes. For the analysis, we match responses at the household level with those at the individual level. The merged file has a sample size of 47,157 individuals in 25,831 households.

3.2. Variables

While USoc does not contain any variables on people's actual energy use, other variables in this dataset can serve as proxies. Variables on home energy expenditure and car mileage are used to estimate energy consumption in kWh. To do this for electricity and gas consumption, we utilise data on average annual consumption in kWh and spending on electricity and gas from the UK government statistic *Quarterly Energy Prices* (QEP, Tables 2.2.1 and 2.3.1) to calculate kWh per £ expenditure. Since poorer households often pay for electricity and gas in advance, e.g. through card or token meters, which is more expensive than paying by direct debit or standing order, one would overestimate poorer households' consumption if payment method is not taken into account in this procedure. This would be especially problematic for our analysis if poor health is also related to low income. To deal with this issue, we utilise the payment method variables in USoc, distinguishing between prepayment and direct debit payments, and QEP price information for these different payment methods, to estimate home energy consumption in kWh. The variables for electricity and gas consumption in kWh are log transformed before analysis to deal with skewed distribution.

USoc also asks each individual how many miles they have driven in cars owned by the household in the last year, annual number of flights, and frequency of other travel behaviours. USoc does not include variables on the use of taxis or lifts which therefore cannot be included in the analysis. To estimate kWh related to car travel, we use data from the Department for Transport on total fuel consumption for petrol and diesel car travel in the UK in 2012 in million tonnes (Table ENV0101), and the Department for Business, Energy & Industrial Strategy's *Digest of UK Energy Statistics* on calorific values (Table A3) which provides Giga Joules per tonne of diesel and petrol ("motor spirit"), which can then be easily converted into kWh to calculate total kWh consumed from petrol and diesel travel in the UK in 2012. To get kWh per mile travelled, we need to estimate total miles travelled by car in the UK in 2012. To do this we take mean annual personal miles from USoc, multiplied by the UK adult population provided by the Census 2011, by which we then divide the total kWh from road travel in 2012. The variable kWh for car travel is also log transformed for regression analysis to address skewed distribution.

USoc contains three variables on flights, differentiating between domestic, EU, and outside-EU flights in the past 12 months for each individual. These three variables are summed up to get the total number of flights per person. Since several household members are likely to go on flights together, e.g. for a holiday, we use the mean number of annual flights per person per household in the regression analysis.

USoc also includes questions on the frequency with which people walk (or cycle) for short journeys (as this question is in the environmental behaviours section it is implied here that this is done instead of using the car), or travel by bicycle, train or bus on scales from 1 to 6 (walking) or 1 to 8 (cycling, trains, buses). Treating these dependent variables as continuous would not be appropriate because these models would not fulfil common linear regression assumptions such as normally distributed residuals. One alternative would be to treat them as ordinal dependent variables, however, due to the relatively high number of answer categories, this would generate difficult-to-interpret regression results. Instead, we created dummy variables on which we can perform logistic regressions. In all four logistic travel models, 1 represents engagement, and 0 very infrequent or no engagement. For the walking for short journeys model, the three highest scores, 'always', 'very often' and 'quite often' are coded 1, the other three 0. For the bike and bus frequency models, the top four scores, the lowest of which includes 'more than twice a month', are coded 1, everything less frequent 0. For the train usage model, we include the next lower category, 'once or twice a month' in the coding for 1 because trains are used less frequently than buses (for instance, 40% of participants travel by bus once or twice a month, compared to only 22% who travel that often by train).

A range of independent variables are included in multivariate analysis, some of which are provided at the household and some at the individual level. Independent individual level variables such as health status, education level, etc. are aggregated to or averaged at the household level for models that use electricity, gas and flight data at the household level as dependent variables. The alternative would be to use independent variable scores from just one individual in the household to predict household level energy use. This approach would be problematic because it is not clear which individual one should choose to represent household characteristics. Selecting the nominated household representative could be a pragmatic choice, but there is no reason to assume that their characteristics (or those of another 'default' person) have more influence on household energy use than those of other household members. We therefore design household level independent variable scores utilising information from all household members because we think this is a better predictor of *household* energy use and mean number of flights.

The main independent variable represents individuals' self-assessed health status on a scale from 1 to 4 where 1 is 'excellent/very good' and 4 'poor'. To aggregate health status to the household level, we take the mean of health status ratings from each household member and then recode the variable back to a scale from 1 to 4, rounding 'in-between' scores up (for scores > = x.5) or down (for scores < x.5) to the next higher or lower level respectively, to facilitate interpretation of coefficients.

Individuals' age and age squared divided by 100 (to account for the inverse u-shaped relationship between age and energy use) are included in all models. For 'household models', the age of the oldest person in the household is used (based on the assumption that the age of the oldest person is more relevant for decisions on home energy use or travel than, for instance, mean household age). Net household income, household size, and the presence of children (a dummy variable, coded 1 if one or more children are present, 0 if not) are included as control variables in all models. We have chosen household rather than individual income for 'individual level models' based on the assumption that income is often shared within households and that therefore household income will have greater explanatory value than individual income for decisions on travel by car or public transport. The variable 'at home' is derived from a variable on economic activity, coded 1 for unemployed, retired, on maternity leave, family care and sick/disabled, and 0 otherwise. For 'household models', this variable counts the number of people who are 'at home'.

The dummy variable 'higher education' is derived from a variable on the highest educational qualification achieved (which has 17 categories and is hence not very useful for this type of analysis in its original form). It is re-coded 1 for respondents who completed an undergraduate university degree or above, and 0 for everyone else. For 'household models', the variable counts the number of people who gained a higher education qualification. 'Gender' is coded 0 for male and 1 for female at the individual level. For 'household models', this variable counts how many more women than men there are per household. 'Rural' is coded 0 for urban and 1 for rural location, where 'urban' relates to places with a population of > = 10,000 inhabitants. Finally, 'environmental attitudes' is based on a question that asks the respondent to rate their agreement with the statement 'If things continue on their current course, we will soon experience a major environmental disaster' on a scale from 1 'strongly agree' to 5 'strongly disagree'. For the household level variable, we take the household mean and then recode the variable back to a scale from 1 to 5, rounding 'in-between' scores up or down to the next higher or lower level respectively to facilitate interpretation.

3.3. Methods of analysis

The USoc survey uses a stratified sample with primary sampling units. Data analysis for means and regressions takes complex survey design into account by declaring the variables that identify the primary sampling units and strata in Stata. Weights which account for response bias and non-response at the household (electricity, gas and flight models) or individual level (all other models), are also applied.

In the results section, we first present a descriptive overview of the distribution of health status in the sample population and its relationship to various socio-economic characteristics (4.1), followed by a bivariate analysis of the relationships between health status and different types of energy use (4.2). Since, as demonstrated in Section 4.2, health status is associated with a variety of other socio-economic characteristics, it is important to conduct multivariate analysis which holds these other characteristics constant to 'separate out' the influence of health status (4.3). Linear ordinary least squares regression is used for the models with continuous variables such as log kWh for electricity, gas, and car miles, and mean number of person flights per household. Logistic regression is used to estimate the probability of not having had a flight in the last year, not having a car, as well as the probability of engagement in walking for short journeys or travelling by bicycle, bus or train, using dummy variables as explained in the section above. We also conducted multicollinearity tests for correlations between independent variables. As expected, age and age squared have factors far above the recommended threshold of 10, but it is accepted practice to include both variables despite this issue because it often generates a better model fit. All other independent variables have factors below that threshold in all models.

Table 3
Health status and socio-demographic characteristics – households.
Source: Understanding Society Wave 4 (2012/3). Standard errors in parentheses.

Health status	N Households	Percent	Mean monthly hh income, GBP
1–Excellent/very good	9079	36.91	£2945.19 (26.66)
2 – Good	9788	39.80	£2695.51 (23.48)
3 – Fair	4271	17.36	£2046.53 (29.37)
4 – Poor	1458	5.93	£1613.48 (39.80)
Total/mean	*24,596*	*100.00*	*£2597.91 (15.14)*

4. Results

4.1. Health status

Tables 2 and 3 show the distribution of health status scores in the sample population. The majority of individual participants rate their health as 'very good' or 'good' (scores 1 and 2, 79%), only 7% rate it as 'poor' (Table 2). The mean health score is 1.79 (standard error 0.01). The distribution of average household-level scores is similar, as 77% of households have health scores of 'very good' or 'good' (scores 1 and 2), and only 6% 'poor' (Table 3). The mean score at the household level is 1.95 (standard error 0.01).

Health status is correlated with a range of other socio-demographic characteristics, for instance age, income, economic activity and education. As one would expect, people with better health tend to be younger than people in poor health. People in the group with health score 1 ('very good') have a mean age of 44. Age increases to a mean of 59 for people in the group with health score 4 ('poor') (Table 2). The differences of mean age are significant between neighbouring health score groups at the 1% level ($p < 0.01$).

Healthier households also tend to be richer households. For households with a mean health score of 1 ('very good'), mean monthly household net income is £2945, while it is only £1614 for households with a mean health score of 4 ('poor') (Table 3). Income differences between neighbouring health score groups are significant at the 1% level ($p < 0.01$). In addition, health is strongly related to education status and economic activity. In the group of respondents with 'very good' health, an average of 30% achieved a higher education qualification. This drops to an average of 9% in the group of respondents with 'poor' health. In contrast, in the group of respondents with 'very good' health, only an average of 26% is 'at home'. This increases to 82% for the group of respondents with 'poor' health (Table 2). These differences for education and economic activity are significant at the 1% level between neighbouring health status groups. Women are also significantly more likely than men to rate their health as only 'fair' or 'poor', with 22 versus 20% respectively ($p < 0.01$).

4.2. Health status and energy use – bivariate distribution

First, we examine the relationship between mean kWh or frequency of engaging in different travel behaviours and people's self-reported health status. Generally speaking, results suggest that, on average, people in poor health use less energy than people in good health. This would confirm the 'income hypothesis' discussed in Section 2 (Fig. 1).

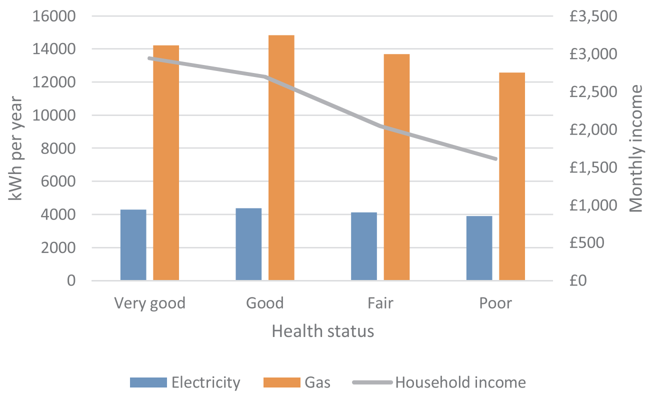

Fig. 1. Annual kWh for electricity & gas and monthly household income over health status.

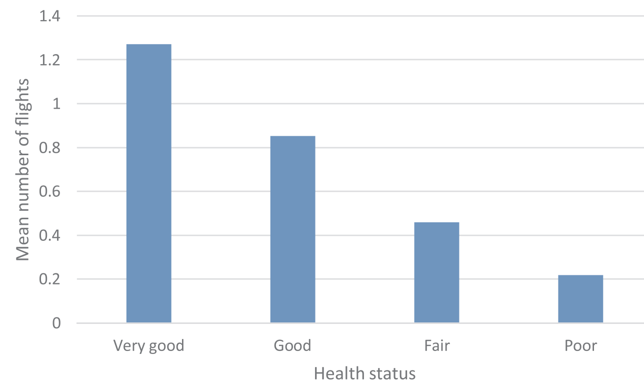

Fig. 2. Mean number of flights per person in each household over health status.

For both electricity and gas, consumption is distributed in an inverse u-shaped curve over the different health status groups; the group of households with the second best health status score 'good' used most kWh: 4394.50 kWh for electricity, and 14853.09 kWh for gas per year. Most of the differences of gas and electricity consumption between health status groups are not statistically significant (see Fig. 1 and Table 4). However, a bivariate regression using log-transformed variables, returns a significant, and negative coefficient for both electricity and gas (models 1 and 5 in Table A1 in Appendix A).

The pattern of declining consumption over health status groups is clearer for most travel behaviours. For instance, the average number of person flights per household consistently increases with rising health status, from 0.2 flights for households in 'poor' health to 1.3 flights for households in 'very good' health. Conversely, the probability for the whole household not to have had a flight during the past year consistently increases with falling health scores: 86% of those with 'poor' health did not have a flight, compared to only 43% of those with 'very good' health. The differences between neighbouring health status groups are significant at the 1% level (see Fig. 2 and Table 4). Participation in walking, cycling and train travel also increases significantly ($p < 0.01$) with rising health status across groups, here measured by the dummy variables as described in Section 3. For instance, 64% of respondents with 'very good' health state they walk for short journeys, compared to only 26% of respondents in 'poor health' (Table 5). In contrast, participation in bus travel is more evenly distributed across health groups. The likelihood not to have driven increases significantly with falling health status – 53% of respondents with 'poor' health did not drive, compared to only 26% of those with 'very good' health (Table 4). While there are no significant differences in kWh associated with car travel between health status groups, a bivariate regression returns a significant, negative coefficient (model 9 in Table A2 in Appendix A).

Table 5
Participation in different travel behaviours over health status.
Source: Understanding Society Wave 4 (2012/3). Standard errors of proportions in parentheses. 'ind' = individuals. The proportions are based on dummy variables, coded as described in Section 3.

Health status	Walking for short journeys	Cycling	Train use	Bus use
Very good	0.64 (0.00)	0.16 (0.00)	0.27 (0.00)	0.29 (0.00)
Good	0.57 (0.01)	0.11 (0.00)	0.20 (0.01)	0.33 (0.01)
Fair	0.43 (0.01)	0.07 (0.00)	0.15 (0.01)	0.34 (0.01)
Poor	0.26 (0.01)	0.03 (0.00)	0.08 (0.01)	0.27 (0.01)
N	*47,049 ind*	*47,051 ind*	*47,052 ind*	*47,052 ind*

However, since health status is related to a range of other socio-economic characteristics as discussed in the previous section, bivariate analysis can be misleading in trying to determine whether, and if so how, health status makes a difference to direct and indirect energy use. The next section uses multivariate analysis to control for factors such as age, income, etc.

4.3. Health status and energy use – multivariate analysis

Results from multiple regression analysis show that health status is a significant factor for electricity consumption and all travel modes. However, an interesting contrast emerged between home energy and travel. As we have seen earlier, while poor health tends to be linked to *lower* electricity and gas consumption as well as less travel in bivariate analysis, this picture reverses for electricity use once we control for age, income and other factors. In these multivariate models, poor health is linked to *higher* electricity use, while poor health still significantly reduces travel or increases the likelihood of non-travel.

Table 4
Energy use and travel behaviours over health status.
Source: Understanding Society Wave 4 (2012/3). Standard errors in parentheses. 'hh' = households, 'ind' = individuals, 'pp' = per person. The figures for gas, electricity, car travel, and number of flights represent averages per year.

Health status	MWh Electricity	MWh Gas	Mean flights pp per hh	Proportion zero flights	MWh car travel	Proportion zero miles
Very good	4.32 (0.05)	14.23 (0.18)	1.3 (0.0)	0.43 (0.01)	5.69 (0.24)	0.26 (0.01)
Good	4.39 (0.04)	14.85 (0.16)	0.9 (0.0)	0.54 (0.01)	5.11 (0.09)	0.33 (0.01)
Fair	4.13 (0.07)	13.69 (0.20)	0.5 (0.0)	0.73 (0.01)	4.42 (0.19)	0.44 (0.01)
Poor	3.92 (0.11)	12.58 (0.30)	0.2 (0.0)	0.86 (0.01)	4.61 (1.10)	0.53 (0.01)
N	*14,549 hh*	*11,412 hh*	*24,546 hh*	*24,546 hh*	*35,878 ind*	*46,532 ind*

Table 6
Health status, energy use and travel – regression models.
Source: Understanding Society Wave 4 (2012/3). Standard errors in parentheses.

VARIABLES	(1) Electricity kWh (log) OLS	(2) Gas kWh (log) OLS	(3) Number of flights OLS	(4) No flight Logit	(5) Car travel kWh (log) OLS	(6) No car travel Logit	(7) Walking short distances Logit	(8) Bicycle use Logit	(9) Train travel Logit	(10) Bus travel Logit
Health status	0.02**	−0.00	−0.24**	0.43**	−0.06**	0.42**	−0.43**	−0.63**	−0.21**	−0.05*
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.04)	(0.02)	(0.02)
Age	0.01**	0.01**	0.02**	−0.05**	0.06**	−0.24**	0.01	0.10**	−0.06**	−0.11**
	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)
Age2/100	−0.01**	−0.01*	−0.03**	0.06**	−0.07**	0.20**	−0.03**	−0.14**	0.04**	0.09**
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)
Household size	0.15**	0.10**	−0.22**	−0.26**	−0.08**	0.15**	−0.05**	−0.07**	−0.11**	−0.02
	(0.01)	(0.01)	(0.02)	(0.03)	(0.01)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)
Children present	−0.05**	0.06**	−0.54**	0.62**	0.14**	−0.60**	−0.05	0.14	−0.22**	−0.29**
	(0.02)	(0.02)	(0.04)	(0.04)	(0.03)	(0.06)	(0.05)	(0.07)	(0.05)	(0.06)
"At home"	−0.00	0.02	−0.05*	0.25**	−0.37**	1.08**	0.36**	0.01	−0.25**	0.67**
	(0.01)	(0.01)	(0.02)	(0.03)	(0.02)	(0.05)	(0.04)	(0.08)	(0.05)	(0.04)
Household income	0.04**	0.04**	0.20**	−0.25**	0.03**	−0.34**	−0.03**	0.06**	0.14**	−0.06**
	(0.00)	(0.01)	(0.01)	(0.02)	(0.00)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Higher education	0.01	0.06**	0.35**	−0.42**	0.03	−0.86**	0.21**	0.42**	0.84**	0.03
	(0.01)	(0.01)	(0.03)	(0.03)	(0.02)	(0.06)	(0.04)	(0.06)	(0.04)	(0.04)
Female	−0.00	0.04**	−0.02	−0.05*	−0.51**	0.84**	−0.27**	−2.10**	−0.18**	0.23**
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.04)	(0.03)	(0.06)	(0.03)	(0.03)
Environmental attitudes	0.01	0.00	0.10**	−0.13**	0.06**	−0.20**	−0.13**	−0.18**	−0.12**	−0.15**
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.03)	(0.02)	(0.02)
Rural location	0.14**	−0.09**	−0.05	0.13**	0.29**	−0.93**	−0.39**	0.32**	−0.92**	−1.00**
	(0.01)	(0.02)	(0.03)	(0.04)	(0.02)	(0.05)	(0.04)	(0.06)	(0.05)	(0.05)
Constant	7.31**	8.66**	0.76**	1.61**	7.24**	5.05**	2.85**	0.05	2.38**	3.12**
	(0.07)	(0.08)	(0.19)	(0.20)	(0.09)	(0.17)	(0.13)	(0.24)	(0.16)	(0.14)
Observations	12,229	9182	22,911	22,911	21,644	31,387	32,331	31,372	32,024	32,217
R-squared	0.19	0.11	0.11		0.17					

* $p < 0.05$.
** $p < 0.01$.

In more detail (Table 6), a decrease of the health score from one level to the next increases electricity consumption in kWh by 2% (exp(0.02)), but it decreases the number of annual person flights per household by 21% (exp(−0.24)) and increases the odds of not having had a flight by a factor of 1.53 (exp(0.43)). It also decreases kWh associated with car travel by 6% (exp(−0.06)) and increases the odds of not having driven a car by a factor of 1.52 (exp(0.42)). A decrease of health score from one level to the next also decreases the odds of walking for short journeys (instead of using the car) by a factor of 0.65 (exp(−0.43)), the odds of using a bicycle by a factor of 0.53 (exp(−0.63)), the odds of engaging in train travel by a factor of 0.81 (exp(−0.21)), and the odds of engaging in bus travel by a factor of 0.95 (exp(−0.05)). All this indicates that good health is generally linked to greater mobility, which implies less time spent at home and energy use there, and more time spent travelling, both for high-energy (flights and car travel) and environmentally-friendly (walking, cycling, public transport) modes of travel. This largely confirms the second hypothesis discussed in Section 2 which focusses on the role of mobility/time spent at home for energy use and travel. Even though health status is not significant in the full model on gas consumption, it is significant with a positive sign in a model which excludes variables that are also likely to influence the amount of time spent at home such as age, presence of children, and being economically 'inactive' (and hence more likely 'at home') while still controlling for income and other factors (model 6 in Table A1 in Appendix A). Overall, the results therefore fit with the 'limited mobility' hypothesis.

Health status is a significant factor despite controlling for age and age squared, both of which are significant in all models (apart from age for walking and age squared for gas). The fact that age squared always takes on the opposite sign to age suggests that age and home energy use or travel activity are related to each other in a non-linear, inverse u-shaped or u-shaped pattern, confirming previous studies. It means, for instance, that electricity and gas consumption, car travel, as well as the number of flights, are all increasing with age, but only up to a point beyond which they decrease again. Correspondingly, the opposite applies to the probability of not having had a flight or not driving a car. For travel behaviours we see an interesting pattern in that car use, flying and cycling increase with age and decrease again when people become older, while the frequency of train and bus travel first decreases with age but increases again beyond a certain age. This might reflect a switch from car use to public transport for older people, as they might feel less confident to drive safely and to whom concessions on public transport tickets are provided.

In addition to age, we control for other factors that are likely to influence the time people spend 'at home', including the status of economic activity (e.g. studying, employed, retired, on sick leave, etc.) and the presence of children. Spending more time 'at home' remains to be a significant variable in most travel models. People or households with higher numbers of people 'at home' (economically inactive) have a greater likelihood than those who study or are in employment not to have had a flight or driven a car. Individuals who are 'at home' are also significantly more likely to walk for short distances and use buses than those who work or study, perhaps because they have more time on their hands and are on more limited budgets. The presence of children is also significant in most models. The electricity and gas consumption models which only include age, 'at home' and presence of children but exclude health status, show very high positive coefficients for the presence of children which increases electricity use by 32% (exp(0.28)) and gas use by 34% (exp(0.29)) (models 3 and 7, Table A1 in Appendix A). In relation to travel, the presence of children significantly decreases the number of flights, and participation in bus and train travel, but increases car travel, probably due to the greater flexibility and convenience that travelling by car offers to families with children.

In Section 4.2 we have seen that health status is closely related to household income. Our results show that household income remains to be a significant variable in all multivariate models. Higher income generally means higher energy use or mobility. For instance, an increase of monthly net household income by £1000 increases electricity and gas consumption by 4% (exp(0.04)) and car related energy use by 3%. The mean number of annual person flights per household increases by about 22% (exp(0.20)). There are two exceptions for this pattern as people with higher household incomes are significantly less likely to walk for short journeys or to travel by bus than people with lower incomes (while they remain to be more likely to participate in train travel).

Gender is significantly related to gas use (but not electricity) and travel. With each additional woman in a household compared to the number of men, gas consumption increases by 4% (exp(0.04)), and the likelihood of the household to fly significantly increases. At the individual level, women consume around 40% (exp(−0.51)) less kWh related to driving a car than men, while they are nearly 2.3 times more likely not to drive (exp(0.84)) and 1.26 times more likely to use buses (exp(0.23)). At the same time, women are also significantly less likely to walk for short distances rather than travel by car, or to use bicycles or trains than men.

5. Discussion and conclusion

This paper investigates the role of health status for energy use. Does poor health limit mobility and thus generate additional needs for energy consumption in the home and for more flexible forms of travel such as the car? Or is it so closely linked to low income (possibly bidirectionally) that it is related to lower energy consumption both in the home and whilst travelling? Especially if the former was the case, poor health could be a factor that creates an ‘unfair’ disadvantage when it comes to the question of who is bearing the cost burden for energy reduction and climate change mitigation policies: people in poor health would be affected by higher energy prices or taxes even though their poor health is at least partly beyond their control. However, since poor health is closely related to factors such as old age, low income, economic inactivity, and low education, we needed to establish whether health is a factor that independently influences energy use at home and whilst travelling, or whether these activities remain primarily driven by people’s socio-demographic characteristics and economic circumstances.

Results presented in this paper show a complex picture. Generally speaking, if one does not control for other factors, energy use in the home and all types of travel tend to increase with good health and decrease with poor health. This would support the ‘income hypothesis’ which states that energy use in all behavioural domains remains to be driven by financial resources. However, this result also indicates that mobility generally decreases with poor health, which of course includes environmentally-friendly modes of travel such as walking, cycling and public transport use (including buses, even though they are a cheaper means of travel than cars).

However, this picture changes for home energy once we control for factors that are closely related to health. Once income, as well as household size, education, gender, attitudes, and rural location, are controlled for, while leaving out other factors that are likely to reflect time spent at home such as status of economic activity, presence of children and age, poor health becomes *positively* associated with electricity and gas consumption, reflecting higher energy requirements in the home (see models 2 and 6 in Table A1 in Appendix A). Even after controlling for other factors that influence time spent at home, poor health remains to be significant and positively associated with electricity use, but it becomes insignificant for gas use.

While further research is required to explain this difference between electricity and gas consumption, possible reasons could be that people with limited financial resources who are in poor health might find it easier to cut down on heating, e.g. by wearing more layers, compared to reducing (non-heating related) electricity consumption: once one is at home, one needs to switch on the light if it is dark, and many people will use appliances such as TVs, computers, etc. to entertain themselves. Another possibility is that people in poor health are more likely to have electric rather than gas central heating so that the variable on gas expenditure does not sufficiently reflect higher heating needs. Since there is no variable in USoc on the type of heating, unfortunately we cannot examine this idea using this survey. However, using the Living Costs and Food Survey 2013, we can check the relationship between low income (which is linked to poor health as discussed above) and type of heating. This confirms that households in the lowest income quartile are more likely to have electric heating and less likely to have gas central heating than households in the top income quartile: 8.5% of households in the lowest income quartile have electric heating, but only 4.6% of the highest income quartile. Conversely, 81.9% of the top income quartile have gas central heating, but only 78.9% of the lowest income quartile. A chi squared test shows that these differences are significant with $p < 0.001$. The significant coefficient for electricity might therefore also reflect higher heating requirements of households in ‘poor health’.

The multivariate models also show that mobility generally decreases with poor health, both for environmentally-friendly and high energy forms of travel such as driving and flying. Overall, the results from multivariate analysis support the ‘mobility hypothesis’ discussed in Section 2.

There are several limitations of this study that need to be mentioned. We used the USoc survey because it provides the rare opportunity of examining health status and energy use across a range of different behaviours which is not offered by other surveys. However, since USoc does not provide variables on actual energy use, this study relies on proxies such as expenditure on electricity and gas, car miles, number of flights, and frequency of use of other travel modes. Inevitably, this is a source of inaccuracy. For instance, since the survey asks for electricity and gas payments and miles driven for the last year, and as it is unclear to what extent the responses are based on actual energy bills or mileage readings, it is possible that some respondents provide rounded estimates. Furthermore, while USoc contains a variable on dual fuel bill expenditures, it is not included in this study because there is no way of estimating the split of expenditure between electricity and gas for individual households (applying a global factor would introduce additional errors). The USoc survey also does not contain variables on the type of property the respondents live in, their insulation level or type of heating, which would be important factors to control for in the home energy models. USoc does not collect data on travel behaviour through a travel diary, rather, the travel behaviour variables present the frequency of engagement in different modes of travel. This might explain why we find that women are less likely than men to state that they walk for short journeys (instead of using the car), whilst several other studies have shown that women often walk more than men, especially if other socio-demographic factors are not controlled for [44]. Furthermore, health status is self-reported, and hence a subjective measure. It is fair to assume that it will be related to people’s objective health status, but it would be interesting to conduct further research with data on people’s actual health conditions. Having said this, subjective assessments of one's health might play an important factor for the kinds of decisions that this study is interested in, such as how much light and heating people desire, or whether they are 'in the mood' or feel confident enough to travel and if so how. Finally, since this study is based on a UK survey, the question arises to what extent the results may be valid for other countries, too. Generally speaking, many of the socio-demographic factors that influence households' home and travel-related energy use are consistent across countries of similar economic development, especially income, household size, age, and rural/urban location (see references in Section 1). We find it plausible that our general findings regarding the role of health status are likely to hold for other wealthy countries, too, because health status influences the amount of time people spend at home or how much they travel. However, some cross-country variation regarding the *strength* of the role of health status might occur related to varying cost of home energy (as a proportion of household spending), the cost and availability of different modes of travel, as well as climatic conditions which might influence mobility and heating/cooling requirements. Further research would be required to examine these assumptions.

Our results have important policy implications. Poor health significantly increases people's electricity use at given income and education levels. This applies even after controlling for age, presence of children and economic inactivity which, like health status, tend to influence the time people spend at home. Poor health also increases people's gas use at given income levels, but it does not seem to increase it over and above other factors that influence time spent at home. Since poor health is, at least partly, outside people's direct control, this puts them at a potentially unfair disadvantage compared to people in good health, as they will be relatively more affected by rising energy prices or taxes which aim at energy reduction or climate change mitigation. Poor health also significantly decreases people's travel. This includes environmentally-friendly forms of travel such as train and bus use, possibly due to accessibility issues, as well as walking and cycling. People in poor health are therefore at a disadvantage when it comes to switching to more active and low carbon modes of travel, and they might have mobility needs that they find difficult to satisfy due to financial and mobility constraints. Making the public transport system more accessible and affordable would be important to address this.

At the same time, it means that people in poor health will tend to be relatively less affected by eco-taxes on motor fuels or flights than healthy people because they generally travel less than those in good health. According to our results, promoting health could increase engagement in low carbon modes of travel, but it is also likely to increase environmentally damaging modes such as car and air travel. This means that additional measures remain important to dis-incentivise these forms of travel and cut energy use and emissions associated with them.

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Appendix A

Table A1
Electricity and gas models – stepwise.
Source: Understanding Society Wave 4 (2012/3). Standard errors in parentheses.

VARIABLES	(1) Electricity kWh (log) OLS	(2) Electricity kWh (log) OLS	(3) Electricity kWh (log) OLS	(4) Electricity kWh (log) OLS	(5) Gas kWh (log) OLS	(6) Gas kWh (log) OLS	(7) Gas kWh (log) OLS	(8) Gas kWh (log) OLS
Health status	−0.03**	0.03**		0.02**	−0.02**	0.02*		−0.00
	(0.01)	(0.01)		(0.01)	(0.01)	(0.01)		(0.01)
Age			0.03**	0.01**			0.02**	0.01**
			(0.00)	(0.00)			(0.00)	(0.00)
Age2/100			−0.02**	−0.01**			−0.02**	−0.01*
			(0.00)	(0.00)			(0.00)	(0.00)
Children present			0.28**	−0.05**			0.29**	0.06**
			(0.02)	(0.02)			(0.02)	(0.02)
"At home"			0.03**	−0.00			0.03*	0.02
			(0.01)	(0.01)			(0.01)	(0.01)
Household size		0.14**		0.15**		0.09**		0.10**
		(0.00)		(0.01)		(0.01)		(0.01)
Household income		0.04**		0.04**		0.05**		0.04**
		(0.00)		(0.00)		(0.01)		(0.01)
Higher education		0.01		0.01		0.04**		0.06**
		(0.01)		(0.01)		(0.01)		(0.01)
Female		−0.00		−0.00		0.04**		0.04**
		(0.01)		(0.01)		(0.01)		(0.01)
Environmental attitudes		0.01		0.01		0.00		0.00
		(0.01)		(0.01)		(0.01)		(0.01)
Rural location		0.15**		0.14**		−0.07**		−0.09**
		(0.01)		(0.01)		(0.02)		(0.02)
Constant	8.29**	7.56**	7.47**	7.31**	9.48**	9.12**	8.60**	8.66**
	(0.01)	(0.03)	(0.06)	(0.07)	(0.02)	(0.04)	(0.08)	(0.08)
Observations	12,229	12,229	12,229	12,229	9182	9182	9182	9182
R-squared	0.00	0.18	0.06	0.19	0.00	0.09	0.04	0.11

* $p < 0.05$.
** $p < 0.01$.

Table A2
Flights and car travel models – stepwise.
Source: Understanding Society Wave 4 (2012/3). Standard errors in parentheses.

VARIABLES	(1) Number of flights OLS	(2) No flight (logit)	(3) Number of flights OLS	(4) No flight (logit)	(5) Number of flights OLS	(6) No flight (logit)	(7) Number of flights OLS	(8) No flight (logit)	(9) Car travel kWh (log) OLS	(10) Car travel kWh (log) OLS	(11) Car travel kWh (log) OLS	(12) Car travel kWh (log) OLS
Health status	−0.37**	0.62**	−0.28**	0.48**			−0.24**	0.43**	−0.13**	−0.11**		−0.06**
	(0.02)	(0.02)	(0.02)	(0.02)			(0.02)	(0.02)	(0.01)	(0.01)		(0.01)
Age					0.03**	−0.09**	0.02**	−0.07**			0.06**	0.06**
					(0.01)	(0.01)	(0.01)	(0.01)			(0.00)	(0.00)
Age2/100					−0.03**	0.09**	−0.03**	0.07**			−0.06**	−0.07**
					(0.00)	(0.01)	(0.00)	(0.01)			(0.00)	(0.00)
Children present					−0.45**	0.29**	−0.22**	0.66**			0.02	0.14**
					(0.05)	(0.04)	(0.05)	(0.06)			(0.02)	(0.03)
"At home"					−0.29**	0.42**	−0.05*	0.18**			−0.50**	−0.37**
					(0.02)	(0.03)	(0.02)	(0.03)			(0.02)	(0.02)
Household size			−0.20**	0.09**			−0.19**	−0.05		0.01		−0.08**
			(0.01)	(0.02)			(0.02)	(0.02)		(0.01)		(0.01)
Household income			0.21**	−0.35**			0.20**	−0.29**		0.04**		0.03**
			(0.01)	(0.02)			(0.01)	(0.02)		(0.00)		(0.00)
Higher education			0.36**	−0.44**			0.33**	−0.43**		0.09**		0.03
			(0.03)	(0.03)			(0.03)	(0.03)		(0.02)		(0.02)
Female			−0.03	0.01			−0.01	−0.03		−0.50**		−0.51**
			(0.02)	(0.02)			(0.02)	(0.02)		(0.02)		(0.02)
Environmental attitudes			0.10**	−0.09**			0.11**	−0.11**		0.05**		0.06**
			(0.02)	(0.02)			(0.02)	(0.02)		(0.01)		(0.01)
Rural location			−0.09**	0.16**			−0.06	0.13**		0.25**		0.29**
			(0.03)	(0.04)			(0.03)	(0.04)		(0.02)		(0.02)
Constant	1.63**	−0.98**	1.08**	0.19*	0.83**	1.80**	0.80**	1.65**	8.30**	8.35**	6.93**	7.24**
	(0.04)	(0.04)	(0.09)	(0.09)	(0.18)	(0.18)	(0.19)	(0.21)	(0.02)	(0.05)	(0.08)	(0.09)
Observations	22,911	22,911	22,911	22,911	22,911	22,911	22,911	22,911	21,644	21,644	21,644	21,644
R-squared	0.03		0.10		0.03		0.11		0.01	0.09	0.09	0.17

* $p < 0.05$.
** $p < 0.01$.

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