People use the services energy provides – but buildings and technologies determine how much is used

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Abstract
Most people in the field of energy research are familiar with the phrase "Buildings don't use energy: people do" (Janda, 2006). Whilst this is undoubtedly true, it is also true that the same people would use very different amounts of energy in different buildings. This paper addresses the question which class of variables (building factors, socio-demographics, attitudes and self-reported behaviours) contribute most to explaining energy use in buildings. Knowing the contribution of different classes of predictors would indicate what kind of variables need measuring to understand domestic energy consumption. Knowing the relative importance of different predictors can help shape the most effective policy interventions. The paper also discusses the need to collect more relevant people-related variables to give a 'fair representation' of the impact of behaviour. We analysed a sample of 991 households approximately representative of the English population. Using regression analysis, we estimated that building factors accounted for about 40 % of the variability in energy consumption. Whilst socio-demographics alone also accounted for a substantial part of the variability (~25 %), the joint regression explained only about 43 % of the variability, a modest increase in comparison to the building-factors-only model. Attitudes on climate change and self-reported behaviours on energy added an even smaller amount of explanatory power. This finding, together with the relatively greater temporal constancy of building factors, suggests focusing on building factors to understand domestic energy consumption on a stock level. However, potential important variables such as heating temperatures and heating durations were not collected or only collected via self-report. Measuring the right variables correctly might shift the balance of explanatory power of different variables groups. The results also highlight that more than half of the variability in energy consumption cannot be explained, even not when using such a breadth of predictors.

Introduction
Energy use in buildings is one of the largest contributors to global and local energy consumption. In the UK, domestic buildings are responsible for 26 % of total carbon emissions with 60 % of those thought to be due to space heating (Palmer & Cooper, 2012). The UK Government established the goal of reducing emissions from homes by 29 % by 2020 (DECC, 2009). Energy efficiency improvements in UK homes form a central part of the decarbonisation plans, with millions of retrofits of domestic homes planned over the next decades (UK CCC, 2010). However, in the field of research of energy in buildings, the phrase "Buildings don't use energy, people do" (Janda, 2011) has become a maxim for those emphasising the importance of occupant practices. Whilst this is undoubtedly true, it is a separate question from what determines how many units of energy are consumed. For example, many heating systems and controls, once set, do not require further human interaction, thus making this maxim tenuous.

Previous research has shown that building factors alone explain at least 40 % of the variability in energy use, as summarized below. However, not all of the building predictors commonly examined can be impacted on by measures that seek to improve energy efficiency, therefore non-building factors are likely to be of crucial importance as well. Furthermore, from a practical perspective, we might ask which variables do we need to measure to understand domestic energy consumption? Building variables are seen as being easier to assess and more temporally stable, and potentially cheaper to measure than attitudes and behaviours. However, if non-building factors played a significant role as well in understand domestic energy consumption, they would need to be measured as well.

The aim of this research is to show in a sample that is representative of the English housing stock how much of the variability of domestic energy consumption can be explained by different categories of predictors, contrasting the explanatory power of building variables, socio-demographics, self-reported heating behaviour, and attitudes towards energy. The results are discussed in terms of their practical relevance for reducing domestic energy consumption and necessary data collection.

IMPACT OF BUILDING CHARACTERISTICS ON ENERGY USE

A large number of studies have looked at the impact of building variables on energy use (for an excellent summary and overview, see Guerra Santin, Itard, & Visscher; 2009). Building factors were found to explain about 42 and 54 %, respectively, of the variability in energy use (Guerra Santin et al., 2009; Sonderegger, 1978). Building size was one of the strongest predictors (Kelly, 2001; Theodoridou et al., 2011, Santin et al., 2009). Dwelling type is likewise an important predictor (e.g. Guerra Santin et al., 2009). Without providing a combined score for the total predictive power of building factors, Steemers and Young Yun (2009) also found that those were more important than occupant characteristics in explaining space heating demand. Location of the building is another highly important factor (Steemers & Young Yun, 2009), because of local differences in climate and building characteristics. Generally, predictors that could not be easily changed through energy-efficiency interventions, such as floor area (e.g. Theodoridou et al., 2011, Guerra Santin et al., 2009; Yohanis et al., 2008), dwelling type (Santin et al., 2009; Yohanis et al., 2008) and climate (Steemers & Young, 2009) were most important in predicting energy demand. The role of dwelling age has been shown to have a linear negative relationship with energy consumption in some studies (e.g. Guerra Santin et al.) but not all (Theodoridou et al., 2011). Although a loose proxy for energy performance, the differences in the effect of dwelling age in different countries may be due to changes in building regulation, or building technologies or retrofitting programs occurred at different times in different countries. Presence of basement, shed, and garage were all associated with greater energy use (Santin Guerra et al., 2009), which may also reflect building size. Whilst those could be regulated to some extent, e.g. limiting their presence in new construction, it is not an attribute usually targeted by regulation. Although, in the UK, adding glass conservatories to houses was shown to be a significant factor in increasing heating energy use because they effectively extended the living space throughout the year, which led to their energy performance being regulated.

Of those variables that could be targeted by energy-efficiency intervention, double glazing, insulation levels of walls, floors, and windows are associated with energy consumption (for findings and a review, see Santin et al, 2009, also Theodoridou et al, 2011; Steemers & Young Yun, 2009). Whilst those studies do not cite the joint amount of variability explained by those factors, their respective impact weight (i.e. beta value) is generally lower than those of the more fixed factors of dwelling type and size (Guerra Santin et al., 2009).

IMPACT OF OCCUPANTS ON ENERGY USE

When reviewing studies on the impact of any occupant characteristics, the composition of the sample needs to be considered: If occupants live in very similar building types in the same location, i.e. there is hardly any variation in building factors, one would expect that the remaining variability is mainly due to non-building factors, e.g. occupant characteristics. Indeed, a number of studies have shown that in similar buildings, energy consumption can vary tremendously due to occupant characteristics (e.g. Gill, Tierny, Pegg et al., 2010; Gram-Hanssen, 2010). However, those studies do not address the relative impact of building versus human factors, which is the main aim of this paper, given that building factors are already accounted for by choosing very similar buildings. Hence, here, we focus on studies that have not artificially restricted the sample to very similar buildings.

Guerra Santin et al. (2009) found that when controlling for building characteristics, occupant characteristics explained an additional 4.2 % of the variability in domestic energy consumption. For space heating occupant characteristics account for 20 % of the variability in energy use (Steemers & Young Yun, 2009). This estimation is considerable; however, the authors do not discuss the issue of multicollinearity of predictors which, if present, makes interpretation of the role of an individual predictor difficult. Sonderegger (1978) concluded that 18 % of the variability in gas consumption was due to occupant behaviour; however, this was estimated from changes observed when houses changed occupants which could have also brought other significant changes.

One indicator of the importance of occupant behaviour comes from intervention studies aimed at reducing energy consumption (for an overview, see Abrahamse et al., 2005). Of those studies that focused on gas consumption or total energy consumption, savings through behaviour change interventions resulted in savings between 0 and 12 % (e.g. Hirst & Grady, 1982/83; Hutton et al., 1996; McMakin, Malone, & Lundgren, 2002; Van Houwelingen & Van Raaij, 1989). Without discussing the studies in detail, as they do not allow disentangling which characteristics of occupants were related to the savings, it is noteworthy that they indicate that behaviour is related to energy use through showing that behavioural interventions can lead to changes in energy use.

In the following section, the impact of different predictors is discussed in more detail, first regarding household characteristics, and then for psychological factors.

Household characteristics

Two of the most well-documented household characteristics with known impacts on energy use are income and household size. Generally speaking energy consumption increases with higher income (e.g. Abrahamse & Steg, 2009; Brandon & Lewis, 1999; Druckman & Jackson, 2008). Household size has been shown to be positively correlated with total energy usage (e.g. Brandon & Lewis, 1999; Druckmann & Jackson, 2008). The role of household age is less clear, with some studies finding a negative relationship between age and energy consumption (e.g. Gatersleben, Steg, & Vlek, 2002) some finding no significant relationship (Abrahamse and Steg, 2009), while others find a positive relationship between age and energy consumption (e.g. Liao & Chang, 2002; Guerra Santin et al., 2009). Tenure is related to energy consumption. However, it is also likely confounded with building characteristics, e.g. socially rented dwellings tend to be better insulated and privately rented dwelling fare the worst (Palmer & Cooper, 2012).

Psychological constructs

Values are generally defined as desirable trans-situational goal varying in importance, which serves as a guiding principle in the life of a person (Schwartz, 1992, p. 21). While a range of studies have looked at the relationship between values and specific environmentally significant behaviours (see Nordlund & Garvill, 2002 for an overview), little research has been carried out on the relationship between values and overall domestic energy consumption. Vringer and Blok (2007) found no relationship between domestic energy requirements and values/problem perception of climate change. Only the motivation to save energy was associated with a small difference in total energy requirement between the least motivated and the average motivated group. Abrahamse and Steg (2009) found that psychological variables such as attitudes and perceived behavioural control were not related to energy consumption but only to energy savings in an intervention program, similarly Brandon and Lewis (1999) found that environmental attitudes did not predict historic energy consumption but were related to energy savings in a subsequent intervention program.

Much of human behaviour consists of habits which are described as learned sequences of acts that have become automatic responses to specific cues (Verplanken & Aarts, 1999). Many energy consumption behaviours, such as switching off lights, are assumed to carried out habitually (Maréchal, 2010). Huebner, Cooper, and Jones (2013a) showed that self-reported habit strength was significantly related to self-reported energy consuming behaviours and to actual energy consumption, when controlling for several building factors. However, the sample was restricted to social housing tenants only, and the overall impact of habits relatively small.

Hence, previous research found no or little impact of psychological variables on domestic energy consumption.

Heating behaviour

In the models of domestic energy consumption that are most commonly used in the UK (BREDEM models, for an overview see Kavgic et al, 2010), occupant influence can be modelled using the heating demand temperature and heating pattern, even though generally standard assumptions are used for those parameters. A sensitivity analysis on the BREDEM-informed model, CDEM, found that heating demand temperature was the most important input variable, followed by heating pattern (Firth, Lomas, & Wright, 2010). Hence, these two variables might be important predictors of domestic energy consumption and are of a type that could be changed through an intervention.

Empirical studies have confirmed the link between indoor temperature and space heating demand (Haas, Auer, and Biermayr (1998) and total energy consumption (Palmborg, 1986) between heating set point and space heating demand (Steemers & Young Yun, 2009), and between day, night, and evening temperature and energy consumption (Guerra Santin et al., 2009). The proportion of heated rooms (Steemers & Young, 2009) and bed rooms (Guerra Santin et al., 2009) was also positively related to energy consumption. However, it needs to be considered that an average daily temperature is related to building characteristics, i.e. heat loss impacts energy consumption; only the heating set point can be considered a true indicator of an occupant driven heating behaviour. Using a thermostat as a temperature control was associated with higher energy use (Santin Guerra, et al., 2009) as well as more frequent heating (Kelly, 2011).

OUR STUDY

The main aim of our study is to calculate and compare the explanatory power of different types of variables on domestic energy consumption. First, the explanotory power of building variables alone, socio-demographic variables alone, heating behaviour variables, and a mixed category of other "people" variables is calculated. In order to arrive at coefficients for individual predictors that can be interpreted, reduced models are defined that have no issue of multicollinearity. Then, the combined explanatory power of the individual models is calculated and discussed to show much other variables classes to the basic model using building factors.

Methods

DATA SET

The data analysed for this paper formed part of the Energy Follow-Up Survey (EFUS), commissioned by the Department of Energy and Climate Change (DECC). The EFUS encompassed three parts. A self-completed survey asking about details of their dwelling and their heating practices. Gas and electricity meter readings were obtained in a subsample of homes, and were used to estimate a yearly consumption. All participating households had also been part of the English Housing Survey (EHS) which collects detailed information about the English building stock. The sample size for EFUS was N = 2,616; meter readings were available for N = 1,345 households. Of those 1,345 households, another 345 were excluded further based on four criteria: (1) positive reply to the question if physical changes to the dwelling had been carried out since the last EHS, (2) positive reply to the question if the household composition had been changed since the last EHS, (3) annual energy consumption considered an outlier (±3 SD from the mean), and (4) usage of a heating fuel that was not gas or electricity. The last criterion was included to avoid too small subsamples, e.g. only 12 households had a solid-fuel system and only 9 a communal or other system, which would not allow meaningful analysis.

VARIABLES USED IN SUBSEQUENT ANALYSIS

Predictors were broadly categorized into building characteristics, i.e. factors that are pertinent to the building, socio-demographics, and a wider range of human factor variables, such as attitudes toward climate change, energy-saving actions, self-reported heating practices. The variables were chosen based on previous research (see introduction), and limited by what was available in the data set.

Building variables

Table 1 summarizes the building variables. Loft insulation is a difficult predictor because the category ”not applicable” is hard to interpret and highly related to dwelling type: ”not applicable” predominantly indicates flat with no direct roof above, and hence is highly correlated to dwelling type.

Note that boiler type is not included as it is highly correlated with fuel type: All properties with electric as their main heating fuel do not have boiler. Similarly, type of heating system is not included as it is largely identical to fuel type: Those using electric as their main fuel had storage heaters and those using gas had a central heating system, with only nine households using a fixed room heating (3 of an electric type).

Socio-demographic variables

Table 2 summarizes the variables used for the socio-demographic set of predictors. Household size was used as continuous predictor. Income was coded as equivalized income, meaning that household incomes were adjusted for household composition and size such that those incomes can reasonably be directly compared with each other. This means increasing the incomes of small households and decreasing the incomes of large households and the extent of these increases and decreases is determined by an internationally agreed set of scales. Age of the household reference person (HRP) was coded as a categorically variable, with another variable indicating if anyone over 75 years was present in the household.

Heating behaviour variables

Participants had been asked about their heating behaviour. Table 3 summarizes the variables used. When asking about the usage of a timer, the no-category represented not having a timer or not using it.

Whilst EFUS asked a variety of questions on pro-environmental behaviour, energy use, and climate change, only a subset were used in the following analysis. The questions were selected on several grounds. Firstly, availability of data played a role. If for more than 10 % of responses, the chosen option was “not applicable”, the item was excluded. This was the case for items such as such as composting or setting the dishwasher in certain ways (only possible to those who have such options), and also when asking about the likelihood of investing in new loft insulation (not applicable to those in rented accommodation and those living in flats). For behavioural items, only those items were selected that were related to domestic energy consumption, such as turning off lights. Finally, items were included that had been impactful in previous research, e.g. habit (Huebner et al., 2013) and perceived behavioural control (Abrahamse & Steg, 2009). Those (few) households that had answered with “don’t know” or “not applicable” to the selected items were excluded, resulting in a remaining sample size of N = 924. The Likert-Scale variables were treated as continuous variables.

Note that individual items are used as predictors as factor analysis and reliability analysis did not provide evidence for scales underlying the items. The correlations between items

Table 1. Overview of building variables and their frequencies.

Variable (abbreviation)	Categories (N)
Floor area (FloorArea)	n/a (continuous: M = 91.12 m^2, SD = 43.07)
Dwelling type (DwType)	Converted & purpose built flat (151), detached (234), end terrace (119), mid-terrace (119), semi-detached (305)
Number of storeys (NoStorey)	n/a (continuous: M = 2.11; SD = 0.85)
Government Office Region (GOR)	East (108), East Midlands (68), London (106), North East (73), North-West (176), South East (134), South-West (96), West Midlands (97), Yorkshire and the Humber (133)
Dwelling age (DwAge)	pre 1919 (142), 1919–44 (171), 1945–64 (229), 1965–80 (233), 1981–90 (77), post 1990 (139),
Wall type (WallType)	9-inch solid wall (139), cavity uninsulated (302), cavity with insulation(489), other (63)
Double glazing (DblgGlaz)	entire house (786), more than half (117), less than half (38), no double glazing (35)
Loft insulation (LoftIns)	150 mm or more (457), 100 up to 150 mm (257), none – up to 100 mm (172), not applicable – no roof directly above (105)
Attic (Attic)	Yes (106), no (885)
Conservatory (Conservatory)	Yes (195), no (796)
Fuel type (Fuel)	electrical system (46), gas system (945)
SAP rating (SAP)	C (134), D (552), E(256), F&G (49)

Table 2. Socio-demographic variables and their frequencies.

Variable (abbreviation)	Categories (N)
Household size (HHSize)	n/a (continuous: M = 2.37, SD = 1.24)
Age of youngest dependent children (DepChild)	No dependent children (680), 0–4 years (130), 5–10 years (88), 11–15 years (63), older than 16 (30)
AHC (After-Housing-Costs) equivalised income quintiles (Income)	1st quintile – lowest (145), 2nd quintile (218), 3rd quintile (209), 4th quintile (209), 5th quintile – highest (210)
Tenure (Tenure)	Local authority (117), owner occupied (633), private rented (101), Registered Social Landlord RSL (140)
Sex of Household Reference Person (SexHRP)	Female (391), male (600)
Age of HRP (AgeHRP)	16–29 years (49), 30–44 (238), 45–64 (404), 65 or over (300)
Employment status of household (EmployHH)	1 or more work full time (482), 1 or more work part time (86), none working and none retired (97), none working, one or more retired (326)
Someone in household sick or disabled? (sick/disabled)	No (647), yes (344)
Someone in household over 75 years?	No (868), yes (123)
Length residency (LengthRes)	2 years or less (168), 3–4 years (116), 5–9 years (195), 10–19 years (216), 20–29 years (134), 30+ years (162)

Table 3. Variables measuring heating behaviour.

Variable (abbreviation)	Categories (N)
Timer used (Timer)	No (391), Yes (600)
Proportion of rooms heated by supplementary heating (SupplHeating)	More than 20 % (446), 20 %–50 % (50), none (495)
Proportion of rooms not heated (PropNotHeated)	None (371), up to 10 % (115), 10–20 % (225), 20–50 % (209), Over 50 % (41)
Length heating season (HeatingSeason)	not applicable (45), 1–3 months (65), 4 months (141), 5 months (246), 6 months (268), 7 months (141), 8 months (52), 9–12 months (33)
Heating duration hrs/day (HeatingDuration)	na (264), <4 hrs (486), 4–10 hrs (97), 11–16 hrs (97), >17 hrs (47)

were generally low, e.g. the mean correlation between the four items asking about energy-saving actions in the household was $r = .112$, ranging from $r = .036$ to $r = .181$.

One item was used as a categorical predictor, asking participants to indicate “Which of these statements best reflects how you currently feel?”. The answer options and number of participants who chose it are summarized below; bold shows the abbreviation used later in the paper.

- Climate change is caused by energy use and I'm beginning to think that I **should do something** (N = 102).
- Climate change is caused by energy use and I'm **doing a few small things** to help reduce my energy use and emissions (N = 407).
- Climate change is caused by energy use and I'm **doing lots of things** to help reduce my energy use and emissions (N = 49).
- Climate change is caused by energy use and I'm **doing quite a number** of things to help reduce my energy use and emissions (N = 220).
- **Don't know** (50).
- I **don't believe** there are climate change problems caused by energy use and I'm **not willing or able to change my behaviour** (N = 54).
- Whether there are climate change issues or not, I'm **not willing or able to change** my behaviour with regards to energy use (N = 68).

Table 4. Overview of the variables measuring attitudes and values.

	Variable (abbreviation)	*M (SD)*
Answer scale	Do you agree that …	
1 = Agree strongly 2 = Tend to agree 3 = Neither agree nor disagree 4 = Tend to disagree 5 = Disagree strongly	The Government is taking sufficient action to tackle climate change? (*Government*)	3.19 (1.03)
	It would embarrass me if my friends thought my lifestyle was purposefully environmentally friendly? (*Embarrass*)	3.06 (1.07)
	Being green is an alternative lifestyle, i's not for the majority? (*BeingGreen*)	3.05 (1.22)
	I find it hard to change my habits to be more environmentally-friendly? (*Habit*)	3.32 (1.20)
	It's not worth me doing things to help the environment if others don't do the same? (*NotWorth*)	3.64 (1.27)
Answer scale	How often, if at all, do you personally …	
1 = Always 2 = Very often 3 = Quite often 4 = Occasionally 5 = Never	Switch off lights when you are not in the room? (*LightsOff*)	1.64 (0.98)
	Boil the kettle with more water than you are going to use? (*BoilKettle*)	3.73 (1.31)
	Leave your TV or PC on standby for long periods of time? (*TVStandby*)	357 (1.62)
	Wash clothes at 30 degrees or lower? (*Wash30*)	3.35 (1.59)

DEPENDENT VARIABLE: ANNUALIZED COMBINED ENERGY CONSUMPTION

The dependent variable used was the annualized energy consumption in kWh. This value either reflected the sum of both gas and electricity data, or just electricity consumption for households that were not connected to the gas grid. The dependent variable was log-transformed (natural log) to achieve greater symmetry of the distribution. Values three standard deviations above or below the mean value were excluded from analysis, i.e. 9 cases, which left a total sample size of $N = 991$ households. The mean log-transformed energy consumption was $M = 9.77$ with a standard deviation of $SD = 0.57$.

STATISTICAL ANALYSIS

Linear regression analyses were used to test the predictive power of different categories of variables in explaining domestic energy consumption. Four separate regression models were built, a "building factors", a "socio-demographic", a "heating pattern", and a "attitudes and behaviours" model, and their respective explanatory power compared. Then the models were combined to arrive at a joint building and socio-demographic model and a model encompassing all predictors.

A potentially problematic issue in analysis of these kinds of data is that different predictors are correlated, e.g. dwelling type is related to floor area as in that detached houses tend to be larger and floor area is related to household size, i.e. more people liver in bigger dwellings. Whilst collinearity does not bias the overall explanatory power of a model, it can create unstable and unreliable coefficients for the predictors. This paper focuses more on overall explanotory power of models, but checks for collinearity by inspecting variance inflation factors (VIF) and presents models with a reduced predictor set to allow interpretation of coefficients.

Results

IMPORTANCE OF BUILDING CHARACTERISTICS

All building factors together explained 41% of the variability in domestic energy consumption (adjusted $R^2 = 39$ %). Inspection of the variance inflation factor (VIF) showed one value of 8, a generally unacceptable value, and two values of about 3. Hence, we re-ran the analysis after discarding the variable loft insulation because it was strongly related to dwelling type. In addition, number of storeys was deleted due to its relationship to floor size. In the reduced model, all VIF were smaller than 3.0. R^2 was still 40 % [$F(7, 963) = 23.79$; adj. $R^2 = 38$ %]. Figure 1 shows the standardized regression coefficients (filled bar indicating a significant effect).

By far the largest predictor was the type of dwelling, with flats and mid-terraced houses using significantly less energy than the reference category of detached housing. The presence of an attic was also associated with greater energy use, as was fuel type with electricity being linked to significantly lower energy use. Wall type and double glazing also showed some significant comparisons. However, for wall type, only the comparison between cavity insulated walls and other wall types (i.e. not cavity unfilled and not 9-inch solid), was significant. For double-glazing, only more than half was associated with greater consumption than full double glazing; the other comparisons were not significant. Hence, those variables that can be targeted through energy efficiency measures, both showed a significant effect but of smaller magnitude than dwelling type, floor size, and fuel type.

IMPORTANCE OF SOCIO-DEMOGRAPHICS VARIABLES

The overall model of socio-demographic variables explained 25.4 % of the variability in the log-transformed annual energy consumption, with an adjusted R^2 of 23.4 %, $F(23, 967) = 14.26$,

$p < .001$. However, three variance inflation factors were greater than 3, for the presence of dependent children, the age group of the household reference person, and the employment status of the household reference person. Hence, we ran a reduced model omitting the variable on dependent children, and age of the HRP. The adjusted R^2 was largely unchanged (adj. $R^2 = 23.1$ %), and all VIF were smaller than 2.4. Figure 2 shows the standardized coefficients.

Household size and income are both significant factors, in line with previous research. Tenure likewise plays a role; however, given that dwelling type and quality is not controlled for, the effect is likely inflated. Those variables rarely tested systematically before, i.e. employment status and presence of a sick or disabled person played no role, neither did the presence of a person over 75 years. Length of residency played a role with longer periods linked to greater energy use.

IMPORTANCE OF SELF-REPORTED HEATING BEHAVIOUR

The overall model of self-reported heating behaviour explained 11 % of the variability in annual energy consumption (adj. R_2), $F(18, 972) = 8.02$, $p < .001$. All VIF were lower than 2.5, indicating no or little colinearity. Figure 3 shows the standardized coefficients of the different predictors.

The strongest predictor by far is the use of a heating system timer with those using a timer using significantly more energy than those who don't use a timer ($\beta = .245$). However, this variable is likely confounded with fuel type, and the "no-category" encompasses both households not using and not having a timer. Those using supplementary heating use significantly more energy than those who don't, and the duration of the heating season is also of importance with those having a heating season less than heating' 9–12 months', using less energy. These variables, albeit being behavioural ones, are potentially impacted by other factors, such as geographic location and hence climate and the efficiency of building and heating technology. It is noteworthy that self-reported heating duration does not impact significantly on energy usage in this model, despite have a strong influence in building stock models.

IMPORTANCE OF ATTITUDINAL AND BEHAVIOURAL VARIABLES

The final individual model consisted of testing the explanatory power of other "human" variables (Figure 4).

The overall model was significant, $F(15, 908) = 3.02$, $p < .001$, with an adjusted $R^2 = 3.20$. Collinearity was not an issue with all VIF smaller than 1.4. The sample size was 924 households due to exclusions of respondents either stating "not applicable" or "don't know" for any item.

For the item asking about belief of climate change and corresponding behaviour, the reference category was "doing lots of things because of climate change". All other categories but one were associated with using more energy. For self-reported behaviours, only the one asking about leaving TV on standby was significant with those reporting doing this to a lesser extent using less energy. Three other items were significant. For the

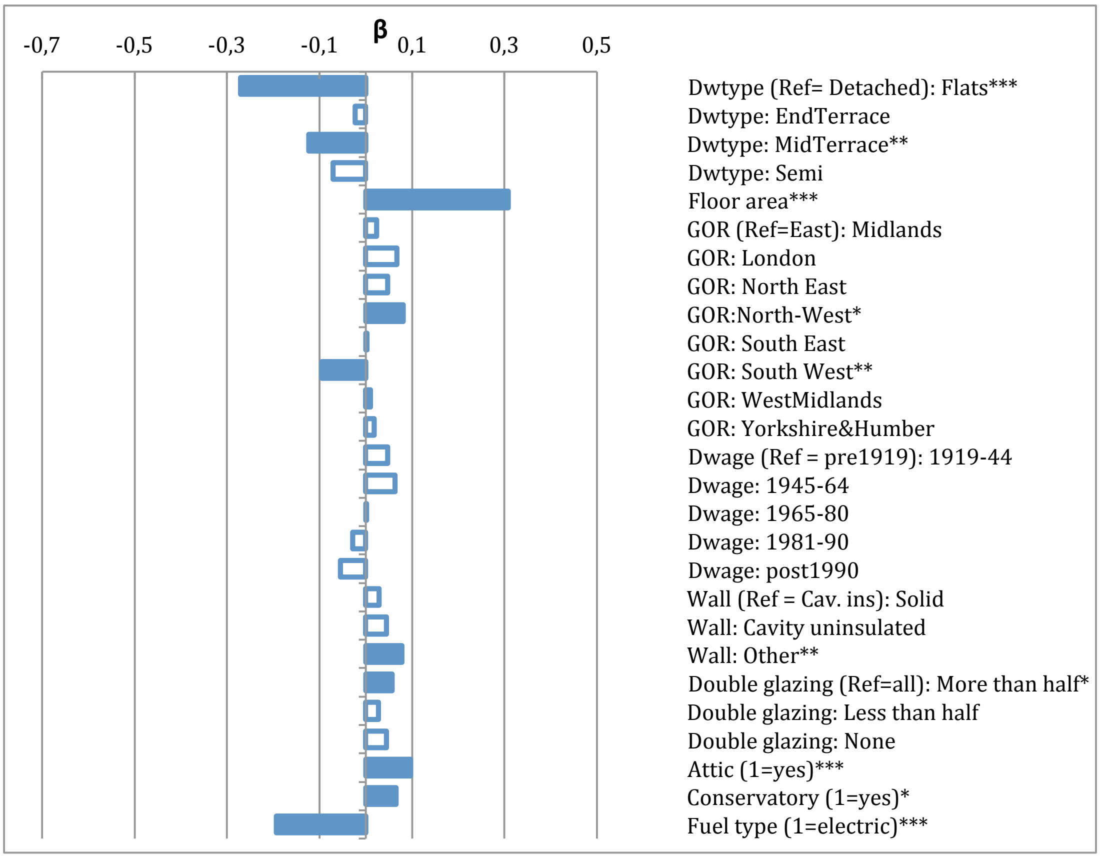

Figure 1. Standardized coefficients for building variables. The stars indicate significance at the different levels: .001 (***), .01 (**), and .05 (*). The reference category is only shown for the first category of a variable.

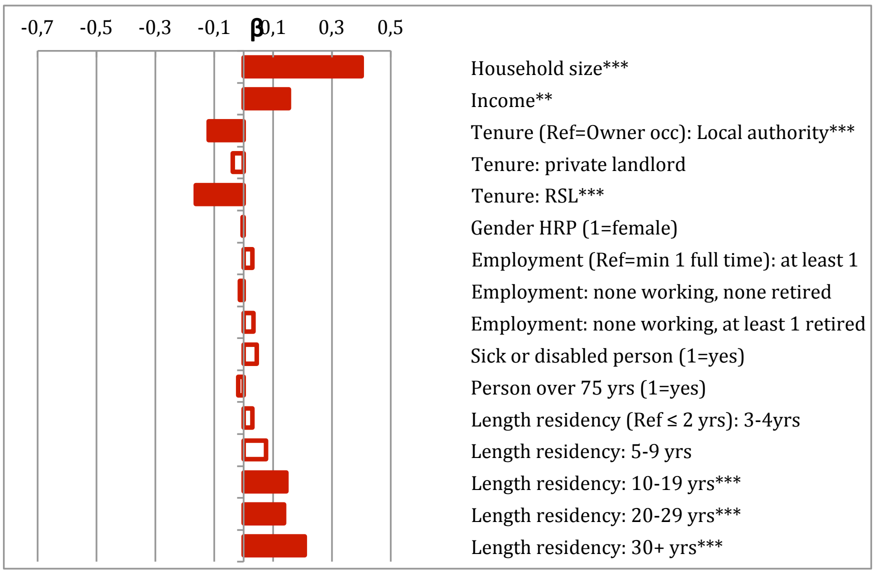

Figure 2. Standardized coefficients for socio-demographic variables.

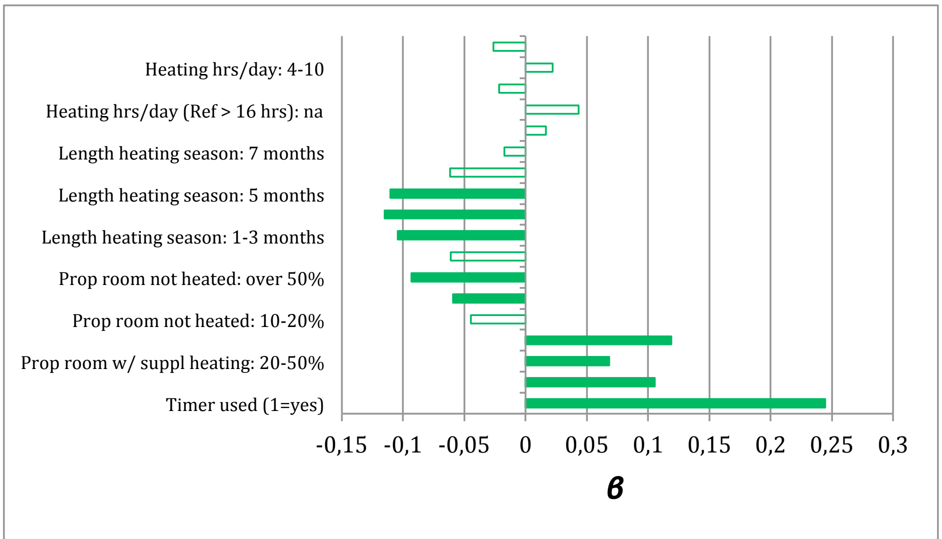

Figure 3. Standardized coefficients for variables assessing self-reported heating behaviour.

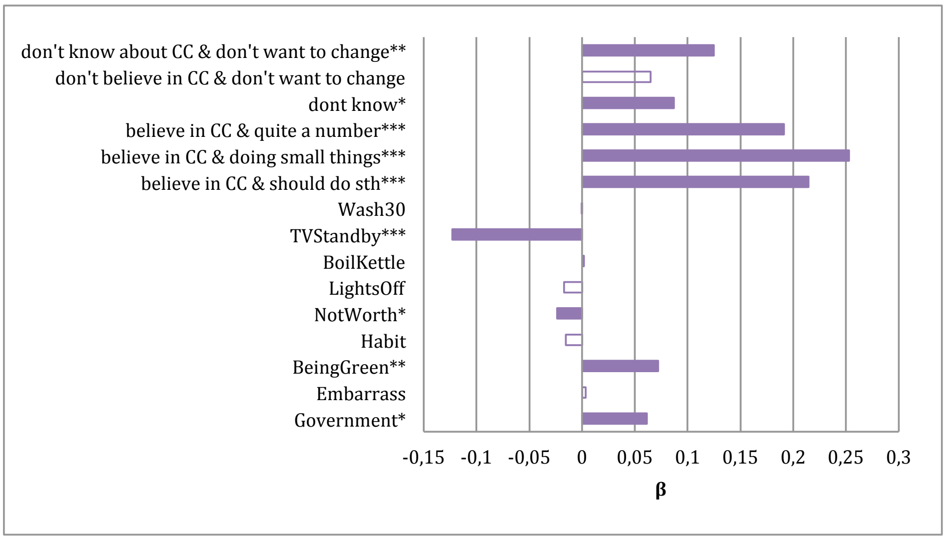

Figure 4. Standardized coefficients for variables assessing self-reported heating behaviour.

item "It's not worth me doing things to help the environment if others don't do the same?" the direction of the coefficient was as expected, i.e. negative, indicating that those disagreeing used less energy. However, for the other two items, the coefficient was not as expected, disagreeing more strongly with the statement that "being green is not for the majority" and that "the Government is not doing enough" was associated with using greater energy. This might reflect confound with income and associated greater energy use.

INTERIM SUMMARY

The individual regression analyses have shown that building factors explain the largest share of domestic energy consumption, followed by a purely socio-demographic model. To a lesser extent, self-reported information about the heating system and "attitudes and behaviours" can explain some of the variability. However, for the latter two classes of variables, confound with building and socio-demographic variables is likely, pointing to the necessity of controlling for those variables, and the danger of for example, studying the impact of "people variables" without controlling for building variables.

In particular for building variables and socio-demographic variables, correlation between variables can be an issue, leading to regression coefficients that can only be interpreted with care. In this paper, the approach was to exclude one variable at a time based on theory and then to compare model fit for the resulting models omitting the variable. More sophisticated – statistical – methods are available and discussed in the final discussion.

In the following part, the different regression models are combined to see how much a model adds to the core building model in explanatory power.

COMBINATIONS OF MODELS

To combine the models, only the subset of those 924 households with complete data was used, i.e. those that had complete attitudinal and behavioural data. The three individual models on building, socio-demographics and heating behaviour were re-run using this data set, with very similar results to the models done on the full data set of 991 households. Figure 5a shows the adjusted R^2 for the models on 924 households. Note that for the building and the socio-demographic models, the reduced versions were used to circumvent the issue of colinearity.

Then, in a first step, the socio-demographic model was added to the building model, and the combined explanatory power compared to the building only model. The building model explained on its own 38.9 % of the variability, with an adjusted R^2 of 37.1 %, $F(27, 896) = 21.15$, $p < .001$). The combined model (*build_and_socio*) explained 42.7 % of the variability, with the adjusted R^2 being 40.2 %, $F(43, 880) = 15.29$, $p < .001$. An ANOVA showed that this numeric difference corresponded to a significant difference ($p < .001$), hence, adding socio-demographic variables increases the explanatory power of the model, if only by 3 %.

Then, the heating behaviour variables were added to the combined building and heating model. This model, referred to as 'build_socio_heating' explained 44.7 % of the variability in energy consumption, with an adjusted R^2 of 40.8 % [$F(61, 862) = 11.44$, $p < .001$]. This increase, albeit small, was significant, as indicated by an ANOVA ($p = .032$).

In the final model, the attitudes and self-reported behaviours were added to the build_socio_heating model to arrive at the 'build_socio_heating_attitudes' model. This model explained 46.7 % of the variability (adjusted $R^2 = 41.9$ %), $F(76, 847) = 9.76$, $p < .001$. This increase was significant ($p = .009$). Figure 5b shows the adjusted R^2 for the combined models.

It is clear that building variables contribute by far the most to explaining energy consumption. This is demonstrated both by the overall much larger R^2 for the building model as compared to all other individual models (Figure 5a), and by the relative small increases in adjusted R^2 through adding more variables to the building model (Figure 5b).

The remaining question then is which of the variables play the greatest roles in explaining energy consumption. This analysis is again hindered through the fact that variables of the different categories are not necessarily independent, e.g. heating season duration likely related to geographic location, household size to house size, and timer usage to fuel type. The VIF of the final model were all smaller than 3.7, a relatively high value already considered inacceptable by some but acceptable by others. For this paper, the standardized coefficients are calculated and presented nonetheless, however, interpretation should be

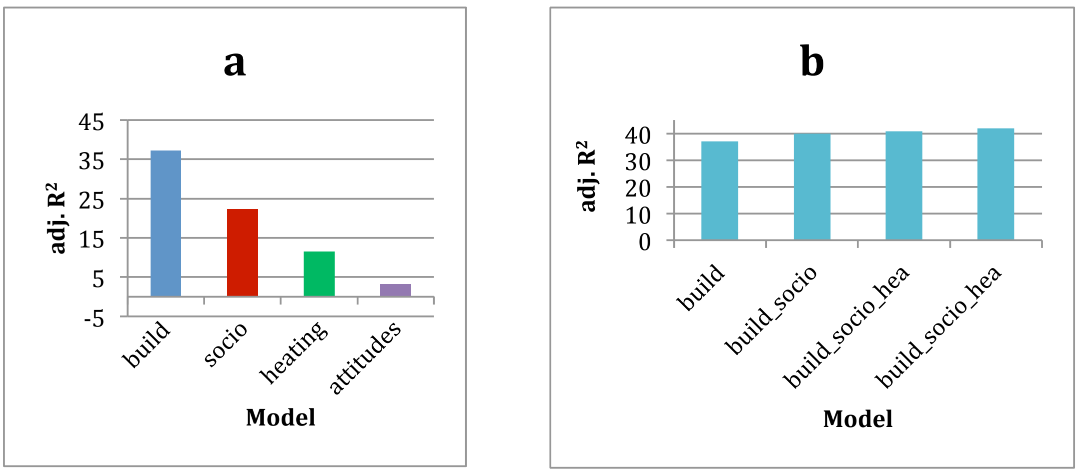

Figure 5. Adjusted R^2 for the four models (5a) and for the combined models (5b).

done with care only. Figure 6 shows the standardized coefficients for all variables, or comparisons, which were significant.

Dwelling type, floor area, and household size were the most important predictors: Flats, mid-terraced, and semi-detached houses used less energy than detached houses, and a larger floor area was associated with greater energy consumption. Larger households used significantly more energy. Electrically heated homes used less energy than gas-heated homes. Both wall type and double glazing were related to energy consumption, indicated the importance of retrofitting homes to ensure cavity-filled walls and full double-glazing.

Even when controlling for geographic location and hence climate, the self-reported length of the heating season was significant, with homes heated for fewer months using less energy than those heated year round. For heating hours per day, shorter durations were associated with lower energy use; however, this effect was not significant for all categories. Also when controlling for fuel type those not using a timer used less energy than those using a timer. From the attitudinal and self-reported behaviour items, three were significant in this analysis, all showing effects as can be expected from a theoretical approach.

Discussion

One central conclusion is that we are limited in how much of the variability in domestic energy consumption we can explain. Even using all variables measuring a variety of predictor types, we can only explain just under half of the variability in domestic energy consumption. Hence, there is a huge limit in our understanding of energy consumption, indicating the need for more and better data, and for including error terms when modelling energy consumption. While it is tempting to postulate explanations for the remaining variability, it is important to note that any such explanations must be treated as hypotheses and empirically tested before any conclusions can be drawn. For example, a finding that building factors explain 40 % of the variability does not indicate that the remaining 60 % are down to people.

The other central conclusion is the dominance of building variables in explaining domestic energy consumption over socio-demographic, self-reported heating behaviour, and attitudes and values. This holds true both when looking at the overall explanatory power of models with predictors from different classes of variables, and when looking at the incremental explanatory power when adding more variables to building stock models. Hence, whilst people use energy, it is indeed buildings that determine to a much larger extent the amount of energy used. However, this statement needs to be restricted insofar as that people also impact on building variables, e.g. they choose the building they live in and might do so considering energy effects of their choice. But if the aim was to calculate energy demand of the building stock, measuring building variables will be of much greater use than measuring any other type of variable, and the added effect through measuring lots of other variables is negligible except for household size.

In particular building size and type dominate energy consumption strongly, in line with previous research (Kelly, 2001; Theodoridou et al., 2011, Guerra Santin et al., 2009). Those measures that can be impacted on through energy-efficiency

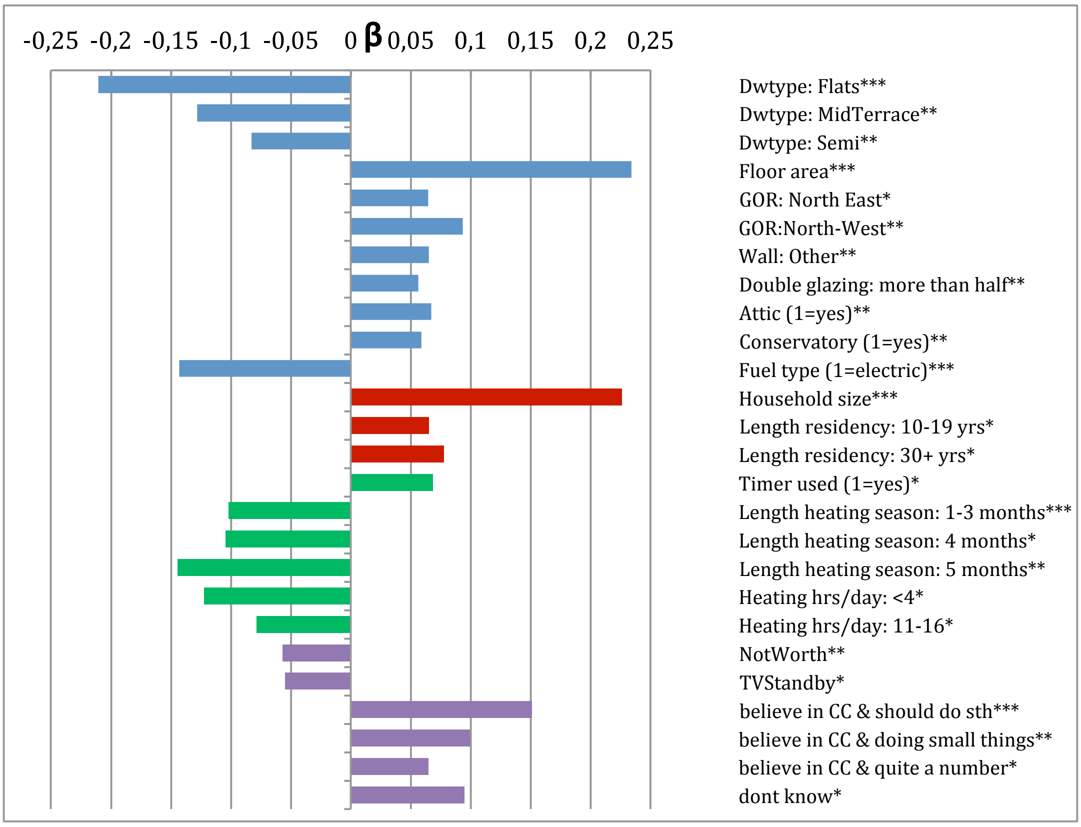

Figure 6. Standardized coefficients for variables assessing self-reported heating behaviour.

improvements (double-glazing, wall insulation) also played a role, albeit a much smaller one. In terms of energy policy, this would indicate that in addition to deep-retrofitting, focus could be on promoting downsizing, i.e. choosing a building size that is appropriate for the number of occupants and their needs. The previously little tested variables of presence of attic and conservatory were associated with greater energy use.

Of the socio-demographic variables, household size and income were the strongest predictors, in line with previous data (e.g. Brandon & Lewis, 1999; Druckmann & Jackson, 2008). Employment status was not a significant predictor, neither was presence of a sick or disabled person, despite this seeming like a likely effect.

Interestingly, from the heating behaviour data, both usage of a timer and the length of the heating system, were significant predictors, even when controlling for other variables such as fuel type and location. These variables can be impacted through retrofitting and behaviour change, and are hence potentially important variables for further research and intervention.

The dominance of building data can be challenged on other grounds: Some potentially crucial variables in other categories of predictors have been poorly measured or not measured at all.

THE NEED FOR BETTER DATA

A sensitivity analysis on a BREDEM-informed model showed that heating demand temperature was the most important input variable followed by heating pattern (Firth, Lomas, & Wright, 2010). Heating pattern was to some extent included in the present data analysis, i.e. self-reported heating hours per day; however, heating temperature did not feature. Plus, self-report is not necessarily accurate, e.g. Shipworth et al. (2010) showed that there was no correlation between self-reported and actual thermostat settings. Also, asking about a typical value for heating temperatures and hours ignores the large variability observed within a house (Huebner et al., 2013). The EFUS data set measured internal temperatures for a subset of homes in bedroom, living room, and hallway. From these temperature measurements estimates of heating demand temperature and hours could be derived (e.g. as done by Huebner et al., 2013). However, given that actual heating system usage can only be inferred from those temperatures measurements, more direct measurement of heating system use would be needed, e.g. by measuring directly at the boiler and at the thermostat. Temperature measurements within a room are subject to vertical stratification, air movement, and distance to heat and light sources, and hence will likely exhibit some sort of bias. Correctly measured heating duration and temperatures might give much larger importance to those variables in explaining energy consumption, and hence show the impact of people on energy use and also show potential pathways for interventions.

The need for more, or rather better, data is also paramount in variables measuring sustainability related behaviour, attitudes, and worldviews. As stated in the Methods section, factor and reliability analysis showed no underlying scale for presumably related items. In our study the very small effect of those variables could reflect inadequate measurement of the variables and casts doubt on their validity in measuring an underlying construct. Also, the amount of missing data made it necessary to discard a range of variables. An item with a large part of missing data in a nationally representative survey is clearly not a good item to represent society. Hence, a survey of such scale should aim at including only items applicable to most members of the population, unless the explicit aim was to understand the applicability of the item.

THE NEED FOR BETTER ANALYSIS

As mentioned throughout the paper, a major issue in analysing the data was the presence of colinearity where an item was strongly related to another item. This leads to regression coefficients that are unstable and cannot be reliably interpreted. What is worth noting, is that of all the papers reviewed in the Introduction, only one paper reported having checked for this issue (Guerra Santin et al., 2009) but it can be expected to play a role in a large share of papers addressing domestic energy consumption. Hence, it should become the norm to report having checked for this issue when analysing correlated predictors, and to develop adequate ways of dealing with multicolinearity. In this paper, a very simple approach was taken by identifying variables with high variance inflation factors, and then re-running models excluding one or several of the variables in question, and comparing model fit. Under consideration of interpretability, it was decided which model to keep. However, this is a rather crude way of performing variable selection. An often used approach is to use stepwise regression; however, stepwise regression has been critiqued repeatedly. Newer – and more sophisticated ways – are Lasso or Ridge regression that basically perform variable selection (e.g. Tibshirani, 1996).

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