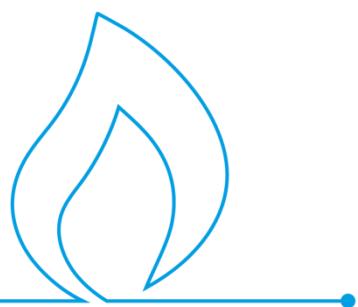




Department
of Energy &
Climate Change

ANNEX C

Predicting gas consumption



June 2016

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Introduction

This report details some novel analysis carried out by DECC into factors that can predict domestic gas consumption. This work builds upon previously published work that has used NEED variables to model gas consumption¹, with the considerable advantage of pulling together data from the main NEED model with household information from the English Housing Survey (EHS)² and from DECC's Fuel Poverty analysis³.

There is increasing interest in identifying factors that can predict residential energy consumption and much research has been carried out looking at both socio-demographic and psychological factors⁴. DECC is in a unique position to contribute to this debate as it has access to administrative data from a wide range of sources that are linked up through NEED.

The socio-demographic factors can be split into those relating to the people in the household versus those relating to the building itself. The sample size and accurate data held by DECC gives us a powerful starting point and, in order to use some indicator of behaviour, we can use previous gas consumption as a crude proxy to indicate the influence of some of the psychological contributors.

Summary of results

The modelling presented here indicates that building and demographic characteristics accounted for 44 per cent of the variance in domestic gas consumption. A hierarchical extension of the model, adding previous consumption as a proxy measure for previous behaviour, caused a large increase in model fit (to 80.8 per cent). This suggests that the behaviour of householders explains a significant proportion of the overall variation in the demand for gas.

Floor area was found to be the most important building characteristic for determining demand, and the presence of children the most important demographic characteristic. The latter may reflect a preference of those with young families to heat their home to a higher temperature, and also a tendency for the home to be

¹ NEED Report 2012 Annex E and Annex F

<https://www.gov.uk/government/statistics/national-energy-efficiency-data-need-report-summary-of-analysis>

² <https://www.gov.uk/government/collections/english-housing-survey>

³ <https://www.gov.uk/government/collections/fuel-poverty-statistics>

⁴ See Frederiks, Stenner & Hobman (2015) for a recent review. *Energies* **2015**, 8, 573-609; doi:10.3390/en8010573

Introduction

occupied (and heated) a greater proportion of the time. The age of the oldest resident was also found to be significant, with over the 60s being associated with higher demand. Again this is likely due to retired individuals spending more time in the home.

Sample selection

The NEED full dataset contains approximately 26 million records across England, Wales and Scotland, while the EHS sample contains approximately 6,200 records per year (combined to give ~12,000 across each two year period) where interviews and physical surveys were carried out⁵. The EHS dataset for any given year contains data from two combined financial years to boost the same size of those with a physical survey. We aimed to include all households that were present in both NEED and the EHS, where the address could be matched with a high degree of certainty. Note that not all addresses within the EHS sample consent for their data to be used in this way. We only included addresses with a valid gas consumption figure for 2012 and 2013 (i.e., between 2,500 and 50,000 kWh), which were not identical for both years and were based on actual rather than estimated meter readings. This gave a sample of 6,870 records.

⁵ <https://www.gov.uk/government/publications/english-housing-survey-2012-to-2013-technical-report>

Limitations

The households included in the analysis here were selected based on having a full set of EHS data, including physical survey. The EHS does not sample representatively across housing stock; it over-samples from the private rented sector to ensure sufficient data is collected for analysis⁶. The rented sector has a disproportionate number of flats and this means that they are over-represented in the sample.

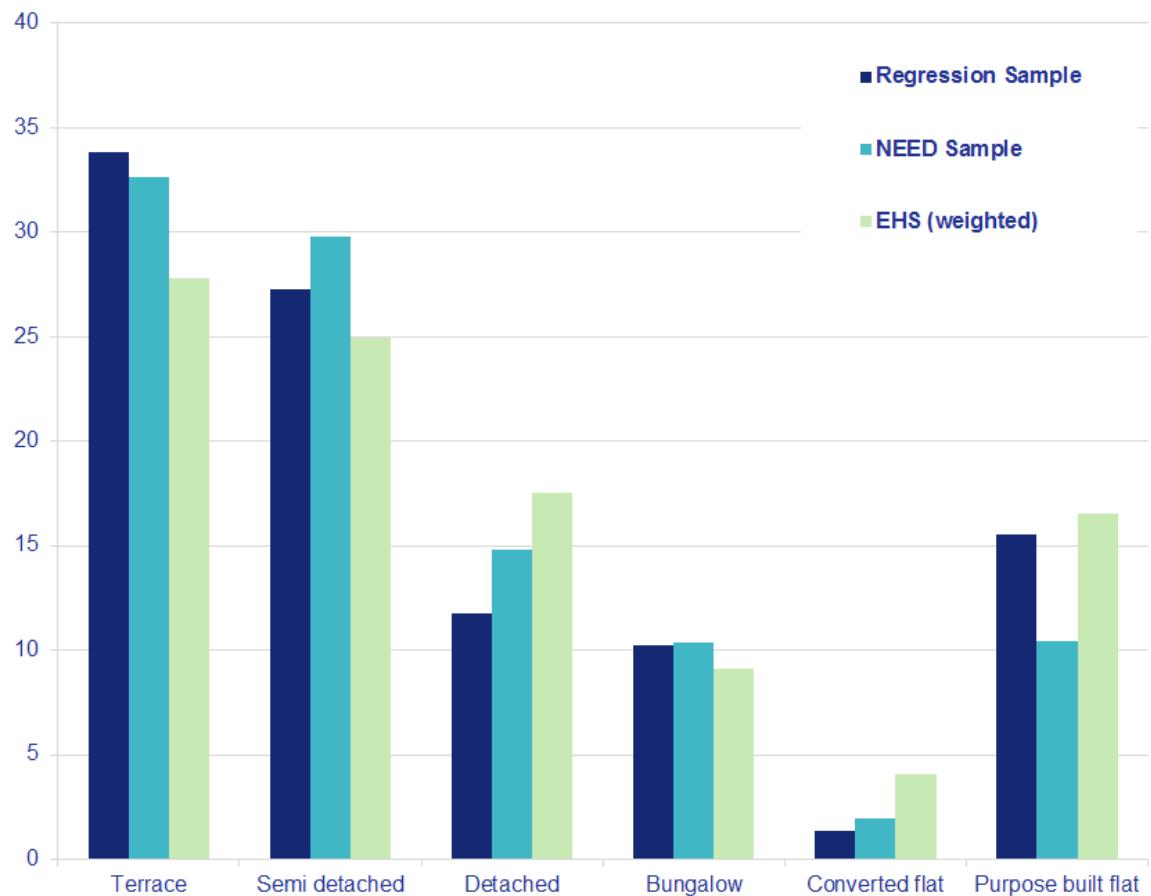
The EHS produces a weighting factor for each property⁷, which can be used to weight each household's data in order to make the sample representative of the whole housing stock. When we compared the results of our final sample here against what we would expect from a whole GB sample, we found that, as expected, flats were slightly over-represented compared to the NEED sample. Chart 1 shows the breakdown of counts by dwelling type comparing the regression sample here against the NEED sample and the full weighted EHS sample. The sample used here is, therefore, not completely representative of the full GB housing stock, but does not appear from the chart to be unduly biased towards flats.

⁶ See English housing survey 2012 to 2013: technical report (Chapter 1: Sampling)
<https://www.gov.uk/government/publications/english-housing-survey-2012-to-2013-technical-report>

⁷ See English housing survey 2012 to 2013: technical report (Chapter 6: Weighting)
<https://www.gov.uk/government/publications/english-housing-survey-2012-to-2013-technical-report>

Limitations

Figure C1: Percentage of properties by property type: Comparisons between data sources, 2014



Predictor variable selection

Using a combination of EHS and NEED variables gives a very large number of possible predictors to use in a regression model. The list of possible predictors we selected to be included in our analysis is shown in Table 1, with a summary of what the code names stand for and the data values in the sample. For full details of the EHS variables, see the EHS data dictionary⁸ and for further information on DECC's fuel poverty variables, see the methodology and user manual⁹. Some variables showed a high proportion of missing data, which mainly reflect questions in the EHS that are only applicable to home owners or to tenants, such as equity in home or weekly rent. These variables were not included in any of the analysis to avoid any need to impute mean values where they would not be appropriate.

This wealth of data, based on objective rather than self-report measures, is a significant advance of doing this analysis through NEED, but also represents a challenge; there will be high inter-correlations between many of the variables. We chose to carry out a Principal Components Analysis (PCA) in order to adopt a data-driven approach to predictor selection. We included all of the scale variables in the dataset, as well as any nominal variables with five or more levels. This gave us 45 variables to include, where identifying the underlying factors could allow us to select the most appropriate predictors for the later regression model to predict gas consumption.

For the PCA, we wanted to include the different demographic and household characteristic variables in the data to see how they clustered together. We did not include any variables relating to energy use at this stage in order to keep the two steps of the analysis (PCA to select variables then regression to predict gas consumption) independent. This included variables relating to energy costs from the Fuel Poverty dataset.

⁸http://doc.ukdataservice.ac.uk/doc/6923/mrdoc/pdf/6923dictionary_of_derived_variables_2012_14.pdf

⁹<https://www.gov.uk/government/publications/fuel-poverty-methodology-handbook-2013>

Predictor variable selection

Table 1: Variables in the sample

Variable name	Variable description	Source	Data Type	Mean	Min	Max	Missing	Included in PCA?
adults	Number of adults in HH	Experian	Scale	2.01	0.00	9.00	0%	Yes
ageoldx	Age of oldest resident	EHS	Scale	52.93	17.00	98.00	0%	Yes
agepartx	Age of partner	EHS	Scale	48.99	18.00	93.00	46%	No
AHCIncomeEQ	Equivalised after housing costs annual income (£)	EHS	Scale	21,120.58	-24,367.73	377,724.00	0%	Yes
arnatx	Type of area (city to rural scale - 6 categories)	EHS	Ordinal	2.94	1.00	6.00	0%	Yes
attic	Attic present?	EHS	Binary	1.92	1.00	2.00	0%	Yes
basement	Basement present?	EHS	Binary	1.99	1.00	2.00	0%	Yes
bedrqx	Number of bedrooms required (modelled)	EHS	Scale	1.71	1.00	7.00	0%	Yes
BEDS	Number of bedrooms (1 to 5+)	Experian	Ordinal	2.70	1.00	5.00	0%	Yes
boiler	Type of boiler	EHS	Nominal	n/a	n/a	n/a	1%	No
boiler_flag	Has boiler insulation been fitted?	NEED	Binary	0.26	0.00	1.00	0%	Yes
cookcost	Cooking cost	FP	Scale	41.26	25.27	96.93	0%	Yes
cstactbx	Basic repair costs (actual)	EHS	Scale	1,278.82	0.00	49,958.52	0%	Yes
cstactcx	Comprehensive repair costs (actual)	EHS	Scale	3,575.16	0.00	75,273.03	0%	Yes
cstactux	Urgent repair costs (actual)	EHS	Scale	820.34	0.00	45,085.22	0%	Yes
cststdbx	Basic repair costs standardised per square metre	EHS	Scale	12.56	0.00	455.29	0%	Yes
cststdcx	Comprehensive repair costs standardised per square metre	EHS	Scale	38.85	0.00	732.01	0%	Yes
cststdux	Urgent repair costs standardised per square metre	EHS	Scale	8.00	0.00	400.00	0%	Yes
cwi_flag	Has cavity wall insulation been fitted?	NEED	Binary	0.25	0.00	1.00	0%	Yes
draughtproof_flag	Has draughtproofing been fitted?	NEED	Binary	0.01	0.00	1.00	0%	Yes
dwage9x	Date of dwelling construction - 9 categories	EHS	Ordinal	5.40	1.00	9.00	0%	Yes
dwtypenx	Dwelling type - 8 categories	EHS	Nominal	n/a	n/a	n/a	0%	No
EHS_adults	Number of adults in property	EHS (derived)	Scale	1.81	0.00	8.00	0%	Yes
emphrp3x	Employment status of HH reference person - 3 categories	EHS	Nominal	n/a	n/a	n/a	0%	No
EPceir12e	Environmental impact rating	EHS	Scale	58.13	4.10	95.81	0%	Yes
famnumx	Number of family units in household	EHS	Scale	1.09	1.00	7.00	0%	Yes
fit_flag	Has a solar PV system under FITs been installed?	NEED	Binary	0.03	0.00	1.00	0%	Yes
floorx	Usable floor area	EHS	Scale	82.53	21.04	519.40	0%	Yes

Predictor variable selection

Variable name	Variable description	Source	Data Type	Mean	Min	Max	Missing	Included in PCA?
FPEER Band	Fuel Poverty Energy Efficiency Ratings	FP	Ordinal	3.90	1.00	7.00	0%	Yes
fpvuln	Fuel poverty vulnerable marker (elderly, disabled, children)	FP	Binary	0.80	0.00	1.00	0%	Yes
Fuel cost (equiv)	Equivalised fuel costs	FP	Scale	1,226.88	491.35	4,039.36	0%	Yes
fuelexpn	Total fuel expenditure	FP	Scale	1,259.78	402.91	5,331.96	0%	Yes
GCons2012	Gas consumption in 2012	NEED	Scale	13,091.01	2,522.00	47,739.00	0%	No
GCons2013	Gas consumption in 2013	NEED	Scale	12,644.90	2,504.00	49,647.00	0%	No
glazing_flag	Has double glazing been installed?	NEED	Binary	0.16	0.00	1.00	0%	No
heat4x	Main heating system - 4 categories	EHS	Nominal	n/a	n/a	n/a	0%	No
heat7x	Main heating system - 7 categories	EHS	Nominal	n/a	n/a	n/a	0%	No
hhbensx	HH on means tested benefits/tax credits with income below threshold?	EHS	Binary	1.63	1.00	2.00	0%	Yes
hhcompx	HH composition - 7 categories	EHS	Nominal	n/a	n/a	n/a	0%	No
hhltick	Anyone in HH have illness/disability?	EHS	Binary	1.62	1.00	2.00	0%	Yes
hholdincome	HH income (categories)	Experian	Ordinal	2.52	0.00	9.00	0%	Yes
hhsizex	Number of people in HH	EHS	Scale	2.48	1.00	11.00	0%	Yes
hhvulx	HH vulnerable? (On certain means tested or disability benefits)	EHS	Binary	1.60	1.00	2.00	0%	Yes
HousingCosts	Any rent or mortgage repayments	FP	Scale	4,761.06	0.00	68,400.00	0%	Yes
hpregdis	HH reference person or partner registered disabled?	EHS	Binary	1.89	1.00	2.00	1%	Yes
imd1010	IMD 2010 decile ranking of areas (deprivation declines)	EHS	Ordinal	4.82	1.00	10.00	0%	Yes
lenres2	Modelled length of residence (based on 2011 lenres)	EHS	Scale	13.16	0.00	41.32	0%	Yes
litecost	Lighting cost	FP	Scale	450.39	-268.50	1,535.69	0%	Yes
loft_flag	Has loft insulation been installed?	NEED	Binary	0.26	0.00	1.00	0%	Yes
loftinsx	Loft insulation thickness	EHS	Scale	166.52	0.00	325.00	10%	Yes
loncoupX	Single HHer or with partner?	EHS	Binary	0.54	0.00	1.00	0%	Yes
NBedsX	Total number of bedrooms	EHS	Scale	2.68	1.00	7.00	0%	Yes
ndepchild	Number of dependent children in HH	EHS	Scale	0.67	0.00	8.00	0%	Yes
olderx	Number of people (HRP plus partner) who are aged above 60	EHS	Scale	0.50	0.00	2.00	0%	No
othfamlp	Type of additional families in HH	EHS	Nominal	n/a	n/a	n/a	0%	No
propage	Property age banded - 6 categories	Experian	Ordinal	4.25	1.00	6.00	0%	Yes
pyngx	Age of youngest person in HH	EHS	Scale	36.20	0.00	95.00	0%	Yes

Predictor variable selection

Variable name	Variable description	Source	Data Type	Mean	Min	Max	Missing	Included in PCA?
reslength	Residency length in years (11 categories)	Experian	Ordinal	7.87	0.00	11.00	0%	Yes
rumorph	Rurality - 8 categories	EHS	Nominal	n/a	n/a	n/a	0%	No
sap12	Energy efficiency (SAP12) rating	EHS	Scale	62.31	1.00	93.47	0%	Yes
spahcost	Space heating costs	FP	Scale	615.67	124.28	3,328.28	0%	Yes
swi_flag	Has solid wall insulation been installed?	NEED	Binary	0.01	0.00	1.00	0%	Yes
tenure4x	Tenure - owner occupied/privated rented/local authority/RSL	EHS	Nominal	n/a	n/a	n/a	0%	No
Unoc	Is the property under-occupied?	FP	Binary	0.24	0.00	1.00	0%	Yes
wallinsy	Type of wall and insulation	EHS	Nominal	n/a	n/a	n/a	0%	No
watersys	Water heating system - 5 categories	EHS	Nominal	n/a	n/a	n/a	0%	No
wathcost	Water cost	FP	Scale	152.46	48.58	834.64	0%	Yes

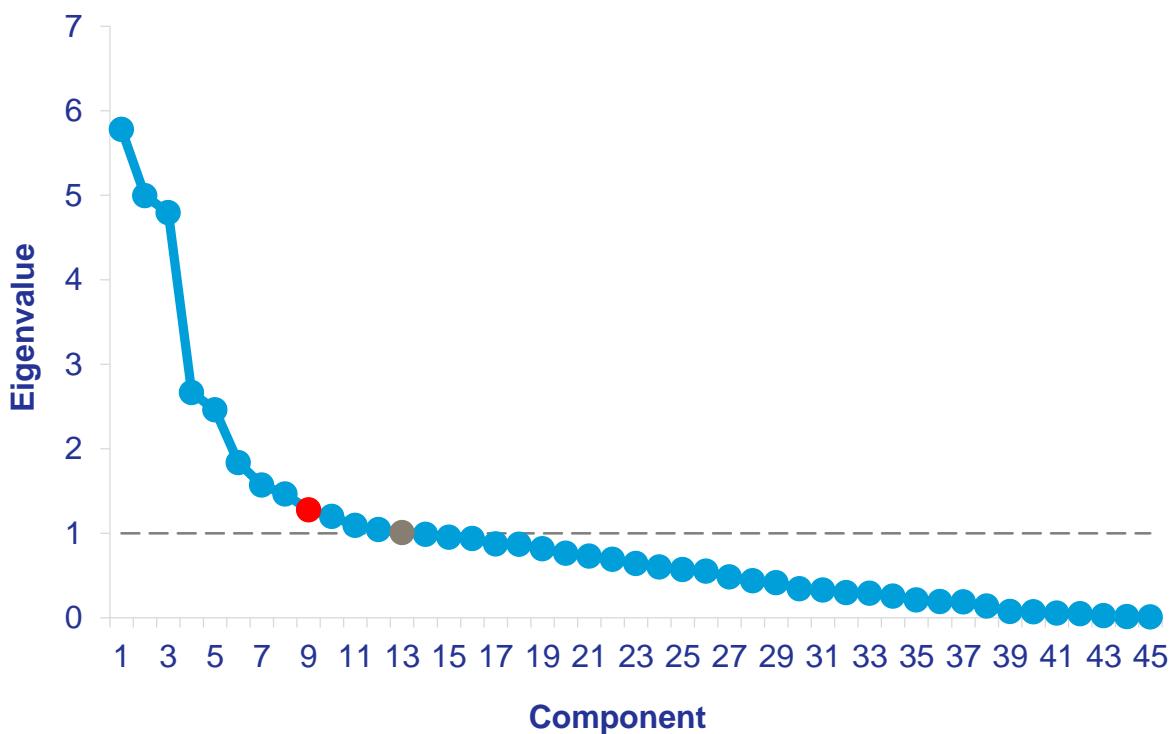
Key: CWI = Cavity wall insulation, EHS = English Housing Survey, FITs = Feed-in Tariffs, FP = Fuel Poverty, HH = Household, HRP = Household reference person, IMD = Index of multiple deprivation, NEED = National Energy Efficiency Data-framework, PV = Photovoltaic, RSL = Registered social landlord, SAP = Standard Assessment Procedure, SWI = Solid wall insulation.

Principal Components Analysis

The PCA was conducted on the 45 items identified in Table 1, using a non-orthogonal rotation (Promax with Kaiser Normalization). Due to some missing data, the sample size for the analysis was 6110. Sampling adequacy was verified using the Kaiser-Meyer-Olkin measure, where KMO = 0.72, indicating that this is a suitable sample for PCA¹⁰. All individual KMO values were above 0.5 (lowest value 0.585 for cststdbx). Correlations between items were significantly large to justify the use of PCA, as indicated by Barlett's test of sphericity, $\chi^2 = 208,272$, $p < 0.001$. The average communality was 0.693.

When the analysis was run to identify the components in the data, 13 components had eigenvalues greater than 1 and in combination, they could explain 69 per cent of the variance. The scree plot did not show one single clear inflection point, but arguably indicated that nine factors should be included, see Chart 2. Nine components could account for 60 per cent of the variance in the data. The red point on the chart indicates a possible inflection point at component 9 while the orange point indicates component 13, which is the final component with an eigenvalue greater than 1. Given our large sample size, all 13 components were kept.

Figure C2: Scree plot for PCA



¹⁰ Hutcheson, G & Sofroniou, N (1999) *The multivariate social scientist: Introductory statistics using generalized linear model*. Thousand Oaks, CA, USA: Sage Publications.

Table 2 shows the factor loadings after rotation in the pattern matrix, as well as suggested names for each component based on which variables clustered together. The structure matrix was highly consistent with the pattern matrix, with some subtle differences noted for factors 6. The full structure matrix is presented in the appendix for comparison. Note that for both factor loadings tables, loadings of less than 0.5 have been suppressed for clarity.

Based on the factor loadings in the pattern and structure matrices, the components appear to represent:

1. Immediate repair costs (required within five years)
2. Household composition
3. Energy efficiency
4. Property size
5. Length of residence
6. Number of adults
7. Marker of vulnerability
8. Urbanity
9. Comprehensive repair costs
10. Number of families
11. Loft insulation
12. Non-lived on floors
13. Presence of solid wall insulation or draught proofing

Predictor variable selection

Table 2: Pattern matrix for PCA

Component	1 Imm. Repairs	2 HH composition	3 Energy Efficiency	4 Property Size	5 Length of residence	6 # of adults	7 Vulnerable	8 Urbanity	9 Comp. repairs	10 # of families	11 Loft insulation	12 Non- lived on floors	13 Insulation installed
cststdux	0.967												
cstactux	0.963												
cststdbx	0.872												
cstactbx	0.857												
ndepchild		0.936											
hhsizex		0.839											
bedrqx		0.811											
pyngx		-0.702											
sap12			1.006										
FPEER Band				-.972									
EPceir12e					0.954								
dwage9x					0.503								
NBedsX				0.842									
floorx					0.828								
beds					0.828								
Unoc					0.639								
lenres2					0.849								
reslength						0.833							
HousingCosts						-0.683							
ageoldx						0.613							
loncoupX						0.931							
EHS_adults							0.757						
adults							0.598						
hpregdis							0.825						
hhltick							0.796						
hhvulx							0.683						
hhbensx							0.572						
arnatx							0.736						
imd1010							0.618						
cststdcx								0.935					
cstactcx								0.896					
famnumx									0.919				
loft_flag										0.850			
loftinsx										0.726			
basement											0.730		
attic											0.631		
swi_flag												0.662	
draughtproof_flag												0.622	

Key: Comp = comprehensive, HH = household, Imm = immediate. Dashed line indicates inflection point of scree plot.

Variables selected for regression

Based on the components from the PCA, we selected variables to use in the regression. Although we could have used factor scores from the PCA, this would not have allowed us to include some of the nominal variables also in the dataset. In addition, using ‘raw’ predictor variables has the advantage of being directly related to real world measures and therefore being easier to interpret for policy decisions.

Where possible, we prioritised data from EHS over modelled data from Experian. Where there were scale and ordinal variables contributing to a component, we prioritised scale variables or ordinal scales with as many levels as possible. We also selected some nominal variables not included in the PCA where they looked likely to fit well within some components and where there has been evidence in the literature that they are linked to energy consumption. We also selected variables where there was sufficient variability in the data; e.g., the addition of heating system type was considered as 99 per cent of the sample used a boiler system with radiators, this left very few cases to cover the other possible categories. The selected variables are listed below;

1. Urgent repair costs – cstactux (actual repair costs)
2. Household composition – hhcompx and ndepchild
3. Energy efficiency – sap12 (Rating band of dwelling)
4. Property size – floorx (useable floor area)¹¹
5. Length of residence – lenres2
6. Age – ageoldx and pyngx (Age of oldest and youngest resident)
7. Number of adults – EHS_adults
8. Vulnerability marker – hpregdis (Household reference person or partner registered disabled)
9. Urbanity – arnatx
10. Comprehensive repair costs – cststdcx (standardised repair costs)
11. Number of family units in household – famnumx
12. Non lived on floors – attic and basement
13. Loft insulation thickness - loftinsx
14. Energy efficiency measures fitted –swi_flag, draughtproof_flag
15. Dwelling type – dwtypenx¹²

¹¹ Previous work modelling gas consumption using NEED has only included floor areas ranging between 2 and 500 meters squared, based on advice from the VOA (<https://www.gov.uk/government/statistics/national-energy-efficiency-data-need-report-summary-of-analysis>). As shown in Table 1, our data in the regression sample ranged from 21 to 519 meters squared for floor area (floorx). Only one property had a useable floor area above 500 meters squared and no data was excluded.

These variables can broadly be split into household versus building characteristics;

- Building characteristics
 - Property size
 - Repair costs (urgent and comprehensive)
 - Energy efficiency (SAP plus measures fitted)
 - Dwelling type
 - Non-lived on floors
 - Urbanity
- Household demographics
 - Length of residence
 - Household composition (number of adults/family units and age of youngest/oldest resident, plus nominal composition variable)
 - Vulnerability

¹² This variable has eight categories but some were combined to match those most commonly presented within NEED. Low and high rise purpose built flats were considered as a single category of 'purpose built' while end and mid terrace were combined to a single category of 'terraced houses'.

Regression analysis

We carried out a hierarchical linear regression with three levels. These levels attempted to group potential predictor variables into three categories:

1. Building characteristics
2. Household demographic characteristics
3. Household behaviour (previous gas consumption)

The variables included at each step are summarised in the previous section, with the exception of gas consumption in 2012, which was added in stage three. This approach means that we could separately identify what proportion of the variance in gas consumption in 2013 could be explained by the characteristics of the building first, then see if adding in household demographic information would improve the model fit. Finally, we could add in a measure of energy use behaviour to see how much additional variance could be accounted for.

For the nominal variables included in the regression model (dwtypenx and hhcompx), dummy variables were created. For dwelling type, purpose built flats were used as the reference group since the main NEED analysis indicated that this property type had the lowest gas consumption. For household composition, we used the category of ‘one person under 60’ as the reference group, since this group showed the lowest mean gas consumption compared to the other six categories. An initial analysis indicated a concern of multicollinearity with the age of youngest person in household variable ($VIF^{13}=14.0$) and therefore this predictor was excluded from the final analysis. The choice of predictor variables meant that our sample size slightly increased to 6130, due to less missing data being present. Data at each stage of the regression used the forced entry method. We avoided more exploratory methods so that the results can hopefully be extrapolated from more easily and the model can be compared/used with different samples.

The results from the regression are shown in full in Table 3. The highest VIF was 6.22 and the lowest tolerance was 0.16. The Durbin-Watson statistic was 2.02. The model was significant at stage one, $F(15,6115) = 286.07$, $p<0.001$, where the building characteristics accounted for 41 per cent of the variance in the data. Adding in demographic characteristics significantly improved the model fit ($\Delta R^2 = 0.028$, $F(12,6103)=25.79$, $p<0.001$), so that it now accounted for 43 per cent of the variance in gas consumption. Notably, adding in a measure of previous behaviour in stage

¹³ Variance inflation factor (VIF)

Regression analysis

three caused a large increase in model fit ($\Delta R^2 = 0.369$, $F(1,6102)=11,793.28$, $p<0.001$). The final model accounted for 81 per cent of the variance in gas consumption.

Looking to individual coefficients in the final model (stage three), only a limited number of building characteristics were significant predictors. These variables were urgent repair costs (cstactux), energy efficiency rating (sap12), property size (floorx), urbanity (arnatx), the presence of an attic (attic) and having solid wall insulation fitted (swi_flag). Notably, none of the housing type categories were significant. The direction of the coefficients was mostly as expected, for example having a larger floor area led to higher consumption as does the presence of an attic (note that in the EHS, attic is coded '1' for yes and '2' for no, so a negative coefficient here is expected). A higher energy efficiency rating lead to lower gas consumption, as did the installation of solid wall insulation.

Half of the household demographic characteristics were significant predictors: being a couple (over or under 60, with or without children) or being a lone parent or multi person household. The age of the oldest resident was also significant. All types of household apart from single residents over 60 showed increased gas consumption relative to our reference group of single under 60 households.

One perhaps surprising result is that having higher urgent repair costs led to lower gas consumption. This is presumably because having urgent repairs that are not completed is an indicator of financial strain, meaning less energy is consumed over concern over paying bills.

Notably, we found an association between the age of the eldest householder and energy usage, such that as this age increased, so did gas consumption. Age is not always found to be a significant predictor of energy consumption, although the measure used is often age of household head rather than age of eldest resident¹⁴.

The size of the standardised coefficients highlights that previous gas use is by far the biggest predictor of current gas use. The largest contributor from the building characteristics is useable floor space and the largest contributor from the demographic characteristics is being a couple with children.

¹⁴ See Frederiks, Stenner & Hobman (2015). *Energies* **2015**, 8, 573-609; doi:10.3390/en8010573

Regression analysis

Table 3: Regression Results

Model	Unstandardised Coefficients B	SE B	Standardised Beta	t	Significance
Step 1	Constant	19593.082	1406.295	13.932	< 0.001
	cstactux	-0.063	0.039	-0.018	-1.603 0.109
	sap12	-151.960	7.808	-0.208	-19.461 < 0.001
	floorx	86.299	2.271	0.483	37.997 < 0.001
	arnatx	94.176	100.524	0.010	0.937 0.349
	cstdcx	2.830	1.255	0.025	2.255 0.024
	attic	-1441.155	249.757	-0.060	-5.770 < 0.001
	basement	-1654.303	594.924	-0.028	-2.781 0.005
	loftinsx	-1.403	0.821	-0.018	-1.709 0.087
	swi_flag	-1163.833	624.356	-0.018	-1.864 0.062
	draughtproof_flag	295.071	535.285	0.005	0.551 0.581
	terrace	695.834	277.595	0.051	2.507 0.012
	semi_detached	1903.774	289.343	0.132	6.580 < 0.001
	detached	2854.807	358.081	0.144	7.973 < 0.001
Step 2	bungalow	1807.782	325.928	0.086	5.547 < 0.001
	converted_flat	998.911	866.768	0.012	1.152 0.249
	Constant	16657.628	1510.469	11.028	< 0.001
	cstactux	-0.077	0.038	-0.021	-1.999 0.046
	sap12	-153.198	7.690	-0.210	-19.921 < 0.001
	floorx	78.553	2.280	0.440	34.460 < 0.001
	arnatx	102.065	98.544	0.010	1.036 0.300
	cstdcx	3.393	1.227	0.030	2.765 0.006
	attic	-1465.039	244.760	-0.061	-5.986 < 0.001
	basement	-1856.559	581.540	-0.032	-3.192 0.001
	loftinsx	-1.513	0.809	-0.019	-1.869 0.062
	swi_flag	-1404.041	611.255	-0.022	-2.297 0.022
	draughtproof_flag	279.043	523.804	0.005	0.533 0.594
	terrace	76.990	275.724	0.006	0.279 0.780
Step 3	semi_detached	1097.300	288.018	0.076	3.810 < 0.001
	detached	2126.003	352.977	0.108	6.023 < 0.001
	bungalow	1181.994	334.913	0.056	3.529 < 0.001
	converted_flat	947.611	847.604	0.011	1.118 0.264
	couple_under_60	1645.235	328.395	0.089	5.010 < 0.001
	couple_over_60	1454.538	335.162	0.082	4.340 < 0.001
	couple_children	2504.952	374.401	0.159	6.691 < 0.001
	lone_parent	2125.985	350.926	0.104	6.058 < 0.001
	multi_person	1541.453	382.004	0.064	4.035 < 0.001
	single_over_60	68.874	323.730	0.004	0.213 0.832
	lenres2	18.907	6.465	0.039	2.924 0.003
	ageoldx	47.643	7.232	0.121	6.588 < 0.001
	EHS_adults	412.694	136.232	0.050	3.029 0.002
	hpregdis	-325.098	217.173	-0.015	-1.497 0.134
	famnumx	150.366	227.418	0.009	0.661 0.509
	ndepchild	242.749	107.439	0.039	2.259 0.024
Step 4	Constant	2600.495	891.540	2.917	0.004
	cstactux	-0.053	0.022	-0.015	-2.360 0.018
	sap12	-23.982	4.646	-0.033	-5.162 < 0.001
	floorx	12.332	1.464	0.069	8.422 < 0.001
	arnatx	136.363	57.549	0.014	2.370 0.018
	cstdcx	0.502	0.717	0.004	0.700 0.484
	attic	-362.293	143.297	-0.015	-2.528 0.011
	basement	-638.305	339.796	-0.011	-1.878 0.060
	loftinsx	-0.358	0.473	-0.005	-0.758 0.448
	swi_flag	-906.545	356.994	-0.014	-2.539 0.011
	draughtproof_flag	150.819	305.897	0.003	0.493 0.622
	terrace	-9.904	161.021	-0.001	-0.062 0.951
	semi_detached	105.529	168.446	0.007	0.626 0.531
	detached	321.412	206.802	0.016	1.554 0.120
Step 5	bungalow	96.098	195.840	0.005	0.491 0.624
	converted_flat	-94.595	495.082	-0.001	-0.191 0.848
	couple_under_60	871.016	191.911	0.047	4.539 < 0.001
	couple_over_60	823.046	195.816	0.047	4.203 < 0.001
	couple_children	1041.067	219.060	0.066	4.752 < 0.001
	lone_parent	637.138	205.394	0.031	3.102 0.002
	multi_person	641.222	223.239	0.027	2.872 0.004
	single_over_60	200.321	189.058	0.011	1.060 0.289
	lenres2	-0.093	3.780	0.000	-0.025 0.980
	ageoldx	10.959	4.237	0.028	2.587 0.010
	EHS_adults	-97.994	79.697	-0.012	-1.230 0.219
	hpregdis	60.355	126.876	0.003	0.476 0.634
	famnumx	257.809	132.813	0.015	1.941 0.052
	ndepchild	14.958	62.778	0.002	0.238 0.812
	GCons2012	0.810	0.007	0.818	108.597 < 0.001

Key: See Table 1 for variable definitions. SE = standard error

Summary and next steps

By combining data from NEED with that of the EHS, we have managed to create a model of domestic gas consumption for 2013 data that can account for approximately 80 per cent of the variance in our dataset. We have used a data driven method to select predictor variables, selecting building and demographic characteristics to include based on results from a principal components analysis. Just using these socio-demographic predictors allowed us to produce a model more successful than previous attempts using NEED (44 per cent of variance accounted for here, compared to 37 per cent in 2008).

Most notably, a third step in our hierarchical regression added in gas consumption in 2012 as a proxy for previous behaviour. We do not have any measures in NEED that can directly address the psychological factors that contribute to household energy consumption, which will be varied and complex, covering personality, motivation, sense of responsibility etc. Using a previous measure of behaviour in this way, in a hierarchical analysis, demonstrates that once household and building characteristics are accounted for, previous behaviour can significantly increase model fit over and above what you would expect based on the socio-demographic characteristics. More information on attitudes and other psychological influences would be of great interest to break down the reasons behind behaviour, particularly with respect to targeting policy interventions surrounding energy consumption.

Summary and next steps

Appendix Table 1: Structure matrix from PCA

Component	1 Imm. Repairs	2 HH composition	3 Energy Efficiency	4 Property Size	5 Length of residence	6 # of adults	7 Vulnerable	8 Urbanity	9 Comp. repairs	10 # of families	11 Loft insulation	12 Non-lived on floors	13 Insulation installed
cststdux	0.936												
cstactux	0.935												
cststdbx	0.920												
cstactbx	0.910												0.508
bedrqx		0.870											
hhsizex		0.869											
ndepchild		0.868											
pyngx		-0.789					0.620						
sap12			0.944										
EPceir12e			0.941										
FPEER Band			-0.900										
dwage9x			0.652										
PROPAGE			0.538										
floorx				0.846									
NBedsX				0.845									
BEDS				0.824									
Unoc		-0.509		0.538									
lenres2					0.806								
ageoldx		-0.507				0.769							
Reslength						0.711							
HousingCosts						-0.661							
loncoupx							0.811						
EHS_adults							0.794						.592
adults							0.609						
hholdincome			0.500				0.557						
hhvulx					0.538		0.815						
hhbensx					0.566		0.742						
hhltsick							0.695						
hpregdis							0.645						
fpvuln							-0.520						
imd1010								0.657					
arnatx								0.602					
cstactcx	0.535								0.862				
cststdcx	0.501								0.852				
famnumx										0.851			
loft_flag											0.808		
loftinsx											0.697		
attic												0.567	
swi_flag													0.549
draughtproof_flag													0.535

Key: Comp = comprehensive, HH = household, Imm = immediate

