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Key factors determining the energy rating of existing English houses

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Key factors determining the energy rating of existing English houses

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In the UK, the Standard Assessment Procedure (SAP) is used to rate the energy performance of existing dwellings whenever they are let or sold. This study investigates which of the inputs to SAP account for the most variance in energy rating across existing gas central heated houses in England. Data from the English Housing Survey (EHS) 2009 are used to generate a representative set of dwellings and variance-based global sensitivity analysis is then applied to assess each input's contribution to the variance in the calculated ratings. It is demonstrated that heating system efficiency, external wall *U*-value and dwelling geometry account for 75% of the variance of the energy rating of gas central heated houses in England. This suggests that improving heating system efficiencies and wall *U*-values of the worst performing dwellings will go a long way towards improving their energy rating and potentially reducing their energy consumption. It is also demonstrated that dwelling geometry has a much bigger influence on the calculated carbon emissions (accounting for 80% of the variance) than it does on the SAP energy rating (accounting for 30%), meaning that significant improvements in energy rating might not be accompanied by significant reductions in carbon emissions.

Keywords: building stock, energy rating, global sensitivity analysis, household energy, housing stock, modelling, Standard Assessment Procedure (SAP)

Introduction

All existing dwellings in the UK must be given an Energy Performance Certificate (EPC) whenever they are sold or let. The EPC includes two indicators of the dwelling's energy performance: the Energy Efficiency Rating (EER), which is a non-dimensionalized indicator of the financial cost of the dwelling's energy use; and the Environmental Impact Rating (EIR), which is a non-dimensionalized indicator of the carbon emissions associated with the dwelling's energy use. These ratings are produced using a calculation procedure known as the Standard Assessment Procedure (SAP).

SAP is also used to assess whether new dwellings comply with energy efficiency-related building regulations (Part L1A) and is the calculation methodology used in other UK government energy efficiency programmes. For example, EPCs calculated using SAP form part of the assessment process for the Green Deal scheme (the Green Deal assessment also includes an Occupancy Assessment that use a dwelling's measured energy consumption to estimate the benefits of upgrade measures). SAP is therefore one of the key tools in use by the UK government to evaluate the energy performance of dwellings.

A recent study (Fuerst, McAllister, Nanda, & Wyatt, 2013) found evidence of a positive correlation between higher EPC ratings and higher dwelling price per m^2, finding that dwellings with the highest energy ratings sold for 14% more per m^2 than dwellings with the lowest rating. This provides evidence that the EPC rating system is helping to price energy efficiency into the housing market and that there is a real cost to dwelling owners of having a low EPC rating.

In the context of existing dwellings, SAP is effectively being used as a tool to incentivise dwelling owners to improve the dwelling's energy efficiency (as dwellings with low ratings may be perceived as undesirable when let or sold), as well as a tool for assessing the appropriateness of various upgrades (*e.g.* in the

Green Deal scheme). The goal of this paper is to understand which inputs into the SAP calculation procedure are the biggest cause of the observed variation in energy ratings across UK dwellings, and thereby gain insight into which interventions might be the most effective in improving a building's energy rating and also which interventions the SAP methodology is indirectly promoting. An understanding of the most important factors in determining the energy rating may also give some guidance on which inputs should be determined the most accurately when performing an energy rating assessment.

No attempt is made in this paper to assess SAP's suitability as a legislative tool; this has been discussed recently, *e.g.*, by Kelly, Crawford-Brown, and Pollitt (2012). Nor is any attempt made in this paper to assess how well the energy ratings calculated using the SAP methodology correlate with real-world energy use (*e.g.*, see Kelly, 2011, for a discussion of this; and de Wilde, 2014, for a more general discussion of the gap between predicted and measured energy performance).

This study investigates which of the inputs to the SAP calculation process explain the variance in energy rating across the existing gas central-heated English houses, which account for approximately 68% of the English dwelling stock (81% of UK dwellings are houses, 90% of UK dwellings have central heating, 93% of UK dwellings are gas heated; DECC, 2012). In this paper the word *house* is used to describe a dwelling with a complete heat loss ground floor and a completely exposed roof, consistent with the definition used in SAP. The variation in energy rating is quantified by applying variance-based global sensitivity analysis (Saltelli, Tarantola, Campolongo, & Ratto, 2004). Data from the English Housing Survey (EHS) 2009 are used to develop probability distributions for each input based on existing houses; a Monte Carlo technique is then used to quantify the effect of the input distributions on the model output.

The next section gives a brief overview of SAP. Previous studies that address its sensitivity are then reviewed. Next the sensitivity indices used in this study are introduced, as well as the scheme developed to produce Monte Carlo samples representative of English houses (where it is demonstrated that correlations between some of the variables have an important influence on the distribution of the model output). The sensitivity indices for each input are then produced and the implications discussed.

Overview of SAP

SAP is a simplified physics-based calculation of a dwelling's energy performance under standardized conditions of occupancy and climate. It does not incorporate any use of measured energy data. Different versions of SAP can vary significantly in terms of core algorithms, *e.g.* SAP 2005 was an annual calculation based around degree-days as compared with SAP 2009 which uses a monthly calculation with an explicit thermal capacity. This study uses SAP 2009 version 9.90, which is described fully in BRE (2010). A bespoke implementation of SAP 2009 coded in the Python language (http://www.python.org) has been used in this study.

SAP is derived from BREDEM (Building Research Establishment Domestic Energy Model), a well-known model used to calculate the energy use of individual UK dwellings (Anderson et al., 2002). SAP is designed as an energy rating tool, whereas BREDEM is a general-purpose dwelling energy model. The main differences between SAP and BREDEM are that SAP uses standardized occupant behaviour assumptions (such as heating demand temperatures and heating periods), and standardized climatic inputs representative of average UK values, instead of values specific to the region in which the dwelling is located. A consequence of this is that these fixed parameters, which have been found to have a high sensitivity in previous studies of BREDEM-like models, are not assessed in this study.

The core thermal dynamics calculation of SAP 2009 is based on ISO (13790:2008) and is a two-zone, quasi-steady-state, one-node lumped capacitance building model. The dwelling's thermal mass is characterized by the *thermal mass parameter* (with units of kJ/m^2 K). Monthly mean internal temperatures are calculated from mean external temperature, internal and solar heat gains, heat gain utilization factor, heat losses through the fabric, the heating system hours of operation, the heating system characteristics and the dwelling's thermal mass.

Coupled with the thermal response model are a set of empirical algorithms for calculating the performance of a range of heating systems. Heating systems are characterized by *responsiveness*, *control type* and a *temperature adjustment factor*:

- *Responsiveness* is a measure of how quickly the heating system brings the dwelling to the set-point temperature when it is switched on, *e.g.* hot water radiators will tend heat a space faster than an under-floor heating system. In SAP 2009, buildings with a more responsive heating system will also cool down faster than buildings with a less responsive system (physically this is because after being switched off under-floor heating will tend to stay warm for longer than radiators, and so slow the cooling of the dwelling). In SAP, the times between which the temperature set-point is maintained are fixed, so a slower heating system must be activated earlier to achieve the temperature set-point by the specified time. The effect of the shorter ramping up and ramping down period of more responsive systems is a lower average internal temperature and consequently a lower dwelling heat loss.

- *Control type* determines the temperature difference between the two thermal zones. It characterizes how well controlled the temperature is in areas other than the living space. For example, in dwellings with one thermostat, which is common in the UK, the temperature of other areas in the dwelling is not directly controlled by the heating system.
- The *temperature adjustment factor* is applied to the calculated mean internal temperature and therefore increases or decreases the heat loss depending on the type of heating system (*e.g.* boiler-based systems without thermostatic temperature controls are assumed to result in 0.6°C warmer temperature than systems with thermostatic control).

SAP also specifies a set of equations for calculating the number of occupants and various sources of internal heat gain based on the dwelling floor area. It provides standard factors for converting fuel consumption to CO_2 emissions. So although the core of SAP is relatively simple and physics based, SAP and BREDEM are a complex combination of a physics-based calculation, empirical-based relationships plus expert judgements that have been developed and refined over a period of three decades.

SAP calculates two different energy ratings for existing dwellings: the EER, which is related to the dwelling's annual energy cost; and the EIR, which is related to the dwelling's annual emissions. EER is scaled such that a rating of 100 corresponds to zero net annual energy cost, with higher values representing lower annual costs; EIR is scaled such that a rating of 100 corresponds to zero net annual CO_2 emission, with higher values representing lower annual CO_2 emission. These ratings are then converted into a letter grade from A to G, with A being the most energy efficiency and G the least (Table 1).

As well as the official EER and EIR, SAP calculates the dwelling's carbon emissions (in tonnes of CO_2 per year), energy cost (£/year) and primary energy consumption (kWh/year). These may be evaluated in absolute terms or relative to the dwelling floor area. The carbon emissions, energy cost and primary energy consumption are all closely related to each other – all are calculated by multiplying the dwelling's fuel consumption by appropriate factors (*e.g.* in SAP natural gas is assumed to have a cost of 3.1 p/kWh, a primary energy factor of 1.02 and emissions of 0.198 kg CO_2/kWh). As all the dwellings in this study use the same heating system fuel, the emissions, cost and primary energy consumption will be heavily correlated with each other (there will be some differences due to the split between gas and electricity consumption). This study therefore presents results for the EER and EIR and for the gross and per floor area carbon emissions.

Table 1 Standard Assessment Procedure (SAP) rating bands

Rating	Band
1–20	G
21–38	F
39–54	E
55–68	D
69–80	C
81–91	B
92 or more	A

Previous sensitivity analyses of SAP

Sensitivity studies of building energy models are often approached from the point of view of building design uncertainty: given a proposed design, what is the effect of uncertainty in the design parameters (*e.g.* due to tolerances in material properties, or climatic variables)? Or alternatively from a design optimization/robustness perspective: given a proposed design, which variable is the performance most sensitive to and how might those parameters be manipulated either to improve the predicted performance or to reduce the risk of underperformance?

These studies are typically performed with detailed dynamic building thermal simulation programmes (as they are usually interested in the detailed behaviour of a proposed design or sometimes existing building). Lomas and Eppel (1992) present a detailed comparison of three sensitivity techniques applied to a detailed thermal model of a simple single-zone example building, which using the terminology of Lomas and Eppel are as follows:

- *Differential sensitivity analysis (DSA)*, where the input variables are varied a small amount one at a time in order to calculate the local partial derivative of the model output with respect to each input. The limitations of this approach, which is called One-At-a-Time (OAT) using another paper's terminology (Saltelli & Annoni, 2010), are discussed below.

- *Monte Carlo analysis (MCA)*, in which a series of model runs are performed, and for each run each model input is set to a value selected at random from a specified probability distribution. The result of this is the distribution of model outputs expected due to the assumed input distributions. In the way in which MCA is applied by Lomas and Eppel (1992) it is not possible to rank the inputs in terms of their contribution to the output distribution: the result of the analysis is simply the total sensitivity of the model output. This paper uses a similar analysis technique, except that the approach used here takes the analysis a step further and relates the variance of the model output back to individual model inputs, so that inputs can be ranked in order of importance.

- *Stochastic sensitivity analysis (SSA)*, in which inputs are varied at each time step of the dynamic thermal model solution. As the model under consideration in this paper is quasi-steady-state, this approach is not applicable.

The comparison in Lomas and Eppel (1992) notes that DSA produces individual sensitivities for each input and the total sensitivity of the output, at the expense of assuming that the system must be linear and additive, whereas MCA produces only total sensitivity information but without imposing additional assumptions (a linear system is one in which changes in the output are directly proportional to the changes made to the inputs; an additive system is one in which the sum of effects of changing individual inputs one at a time from a base value is the same as changing all the inputs simultaneously, *i.e.* there are no interactions between variables). As will be explained below, the technique used in this paper is based on MCA and produces both individual and total sensitivities without making assumptions of the underlying model.

This study takes a slightly different approach to many previous studies as it addresses the sensitivity of the SAP model output across an entire stock of existing dwellings (*i.e.* gas central-heated English houses). The target of the study is the model itself rather than a specific dwelling design, however the same basic principles apply.

The factors affecting the SAP energy rating of individual houses have not previously been explicitly assessed, however three recent papers have explored the sensitivity of BREDEM-based housing stock models. It seems reasonable to expect broadly similar sensitivity results for individual dwellings as for a full housing stock as many of the input variables are monotonic with the output, and stock models are linear superpositions of individual building models. For example, increasing boiler efficiency will always decrease emissions calculated by the model, all else being equal. Some variables, however, are not monotonic (such as glazing area – increased glazing area both increases solar heat gains and dwelling heat loss, so that depending on other dwelling properties there may be an optimum value for this input), and the relative effect of the variables on individual dwellings versus the entire stock may be different.

Firth, Lomas, and Wright (2010) present a model of the UK residential stock, the Community Domestic Energy Model (CDEM), which is based on modelling 47 dwelling archetypes, designed to be representative of the entire stock. A DSA is conducted on the 27 model inputs, from which it is determined that the model is most sensitive to heating demand temperature, heating period, dwelling size, gas boiler efficiency and wall *U*-values. For example, the normalized sensitivity coefficient of heating demand temperature is determined as 1.55, meaning that at 1% increase in heating demand temperature (in °C) across the stock would result in a 1.55% increase in emissions. Simple tests were conducted to show that the model was roughly linear with respect to the input variables (over the range of inputs considered) and that for small changes in the input variables (1% changes) the model was additive. It is noteworthy that temperatures were measured in degrees Celsius for this analysis as opposed to degrees Kelvin. If the average external temperature were, hypothetically, 0°C, then a 1% change would be zero, and the misleading conclusion could be reached that the model is insensitive to changes in external temperature.

Cheng and Steemers (2011) present a similar study using a different BREDEM-based UK housing stock model, the Domestic Energy and Carbon Model (DECM). DECM uses models of the 16 194 dwellings surveyed in the English Housing Condition Survey 2007 data. Their results largely match the results of Firth et al. (2010), with the most important variables being mean internal temperature of the living area, total floor area, external air temperature, gas boiler efficiency, and wall and window *U*-values. They find evidence that DECM is linear over approximately a $\pm 10\%$ range of the input variables, and develop curves for predicting the effects of larger changes in the input variables; however they find that the model is in general not additive for changes in inputs larger than 1%.

Hughes, Palmer, Chang, and Shipworth (2013) present a sensitivity analysis of the Cambridge Housing Model (CHM), which is largely similar to the model of Cheng and Steemers (2011), except that it uses SAP 2009 as its building model (compared with SAP 2005 in Cheng & Steemers, 2011; Firth et al., 2010). As well as calculating the normalized sensitivity coefficient, their study performs an MCA to assess the combined effect of the input variable uncertainty on the model output; however the relative effects of the individual variables are not assessed in the Monte Carlo section of their study.

All three studies suggest that the mean internal temperature, dwelling size, heating efficiency and *U*-values are important factors in determining the output from BREDEM. The mean internal temperature is not an input that can be directly manipulated in SAP, however it is expected that the other variables will be important in determining the output from SAP.

Local versus global sensitivity

The studies of Firth et al. (2010), Cheng and Steemers (2011), and Hughes et al. (2013) are a form of *local sensitivity analysis* (apart from the MCA performed in Hughes et al.): they assess the sensitivity of the model to deviations in the model inputs in the region of a predefined point, the base case. As is usual in a local sensitivity analysis, both studies use a 'best guess' of the correct value of each input and examine the effects of departures away from this point. This provides useful information about the sensitivity of the model in the region of the base case. However, except in the case of linear, additive models, the local sensitivity of each model input will change depending on the assumed base case. As shown in Cheng and Steemers (2011) and Hughes et al. (2013), their BREDEM stock model is non-linear and non-additive (except for very small changes in the inputs). Even though the local sensitivity was evaluated over a large range for each input variable, the DSA method used in these studies only changes one variable at a time away from the base case, and this can be shown to explore a surprisingly small region of the input space.

The DSA method has also been called the One-At-a-Time (OAT) method (Saltelli & Annoni, 2010). Saltelli and Annoni (2010) develop an upper bound for how much of the solution space the DSA method can explore, even if each input variable is varied over its maximum possible range. Their approach shows that in the case of a model with two inputs, at most 78.5% of the solution space can be explored, but that this rapidly drops as more variables are added. For three dimensions, at most 52.4% of the solution space can be explored by varying a base case model one input at a time. For 12 dimensions no more than 0.0326% of the solution space can be explored using the OAT approach.

If the model's sensitivity to its inputs varies significantly across the input space (where the input space is defined by the maximum possible ranges that have been assigned to each input), then the result of a 12-dimensional, one-at-a-time local sensitivity analysis becomes heavily influenced by the values that were chosen as the base case around which the variation is conducted and the results of the analysis are anchored to the original choice of the base case.

Global sensitivity analysis assesses the sensitivity of the model output to variation of the model inputs independently from any assumed base case value (Saltelli et al., 2004). A simple but inefficient way of doing this would be to repeat the one-at-a-time local sensitivity analysis for many different base cases, in effect performing an MCA of the sensitivity measures. The resulting sensitivity measures would then depend only on the distributions assumed for each input, not on any individual base case selected. The next section describes the variance-based global sensitivity indices that are used in this study.

Variance-based sensitivity measures

This study uses variance-based global sensitivity indices to evaluate the relative importance of the SAP model inputs (in the context of modelling gas central-heated English houses). The sensitivity indices used in this study are not new and are well documented in several previous publications: the method used in this study closely follows that of Saltelli et al. (2010). The overall approach is illustrated in Figure 1.

Each model input is assigned a probability distribution based on the occurrence of that input in the stock of gas central-heated English houses. As a result, the model output also has an associated probability distribution. The aim of variance-based global sensitivity analysis is to determine how the model inputs contribute to the variance of this output distribution. If the output of interest is the EER, for example, then the probability distribution of the model output will be the same as the distribution of the EER across the stock, and the goal of the sensitivity analysis is to determine how the model inputs contribute to the variance in the EER.

If an input variable is fixed to a known value instead of being assigned a probability distribution, then the variance of the output distribution will be reduced. In the extreme case where all the model inputs are fixed, the model output has zero variance, *i.e.* it is a single fixed value. Generally the magnitude of the reduction in variance due to fixing a particular model input will depend on the value that the input is fixed to, so the *expected variance* is defined, which is the remaining variance in the output averaged over all the values to which the input could be fixed (taking into account the probability of each input value occurring).

Let the model be represented as $Y = f(X)$, where Y is the model output and $X = (X_0, X_1, \ldots, X_k)$ is a

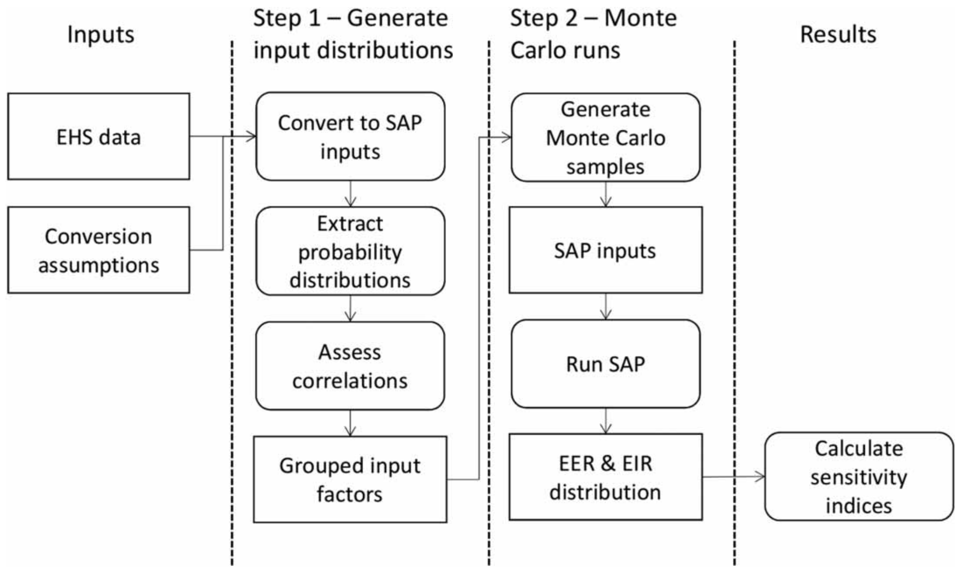

Figure 1 Overall calculation approach

vector of k random variables representing the model inputs. The variance of the model output is denoted $V(Y)$.

The *sensitivity index* of Y to X_i is then defined as (Saltelli et al., 2004):

$$S_i = \frac{V(Y) - E(V(Y|X_i))}{V(Y)}$$

where $V(Y|X_i)$ is the remaining variance of Y after variable X_i has been fixed to a certain value; and $E(V(Y|X_i))$ is the expected value of this variance across all possible values of X_i. So S_i is the expected reduction in the variance of the model output if input i is fixed. S_i will always be scaled from 0 to 1, and the larger S_i, the more that input contributes to the variance of the output. Hence, this is a good measure for determining which of the input variables would most reduce variance in the model output if they were fixed to their correct value (Saltelli et al., 2004). Other names for this measure include the *importance factor*, *correlation ratio* and *first order effect*.

The S_i's will sum to less than or equal to 1 in the case of uncorrelated model inputs. If the model is purely additive, *i.e.* there are no interaction effects between the variables, then the S_i's will sum to exactly 1.

The second sensitivity index used in this study is the *total sensitivity index*, which is defined as (Saltelli et al., 2004):

$$S_{T,i} = 1 - \frac{V(E(Y|X_{-i}))}{V(Y)}$$

The notation $E(Y|X_{-i})$ means the expected value of Y given that all inputs apart from X_i have been fixed. The $V(E(Y|X_{-i}))$ term is therefore the variance expected to remain if all inputs other than X_i were fixed (sometimes referred to as the *bottom marginal variance*). $S_{T,i}$ is therefore 1 minus the proportion of $V(Y)$ that would be left if all variables apart from X_i had been fixed (Saltelli et al., 2004). This sensitivity index therefore includes the effects of interactions between variable X_i and other variables. In additive models with uncorrelated inputs, $S_{T,i}$ will equal S_i. If the model is non-additive, $S_{T,i}$ will be larger than S_i. $S_{T,i}$ is a good measure to use when deciding which (if any) of the model inputs can be set to fixed values without significantly changing the output of the model, *i.e.* for removing unimportant inputs from the model (Saltelli et al., 2004). If $S_{T,i}$ is close to 0, then the variable is not influential.

These sensitivity indices are *model free* as they make no assumptions about the underlying model: the model does not need to be additive and there is no assumption of linearity or assumption that the model output is monotonic to model inputs.

In the case of uncorrelated inputs, these sensitivity indices can be calculated efficiently using Monte Carlo-based estimators (Saltelli et al., 2010). As will be discussed in the next section, care has been taken to select a set of factors that can be treated as if they

Table 2 Standard Assessment Procedure (SAP) inputs varied in the sensitivity analysis, the factors into which they are grouped, the range of possible values (excluding the highest and lowest 2.5%), and the median value

ID	SAP input	Sensitivity study factor	Percentile		Median	Unit
			2.5th	97.5th		
0	Total floor area	*geometry*	44.2	243.6	90.1	m^2
1	Number of storeys	*geometry*	1	4	2	–
2	Storey height	*geometry*	2.2	2.9	2.5	m
3	Roof heat loss area	*geometry*	27.4	125.0	48.2	m^2
4	External wall area	*geometry*	27.4	198.8	84.7	m^2
5	Ground floor heat loss area	*geometry*	27.4	125.0	48.2	m^2
6	Party wall area	*geometry*	0.0	149.9	30.2	m^2
7	Glazing area (for each orientation)	*geometry*	8.3	64.0	23.2	m^2
8	Living area fraction	*geometry*	0.1	0.3	0.2	–
9	Roof *U*-value	*Uroof*	0.1	2.3	0.4	W/m^2 K
10	External wall *U*-value	*Uextwall*	0.4	2.5	1.6	W/m^2 K
11	Ground floor *U*-value	*Ugndfloor*	0.0	0.9	0.7	W/m^2 K
12	Glazing *U*-value	*glazing_type*	Single glazing (13%); double glazing (87%)			
13	Percentage of windows draught stripped	*glazing_type*				
14	Glazing *g*-value	*glazing_type*				
15	Glazing light transmittance	*glazing_type*				
16	Thermal mass parameter	*thermal_mass_parameter*	103.2	509.5	232.9	kJ/m^2 K
17	Fraction of low energy bulbs	*low_energy_bulb_ratio*	0.0	1.0	0.2	–
18	Number of open flues	*Nflues*	0	2	0	–
19	Number of intermittent fans and passive vents	*Nfansandpassivevents*	0 (67%); 1 (18%); 2(4%); 3(6%); 4(5%)			
20	Number of flueless gas fires	*Nfluelessgasfires*	0	1	0	–
21	Floor infiltration	*floor_infiltration*	0.1	0.2	0.2	ach
22	Window frame factor	*frame_factor*	0.7	0.8	0.7	–
23	Main heating system efficiency	*main_sys_effy*	50.0	91.3	65.0	%
24	Main heating system control type	*heating_control_type*	1 (51%); 2(48%); 3(1%)			
25	Main heating system temperature adjustment	*temperature_adjustment*	−0.15	0.60	0.00	C
26	DHW cylinder volume	*hw_cylinder_volume*	None (51%); 110 L (27%); 140 L (17%); 210 L (3%); 245 L (1%)			
27	Cylinder insulation type	*hw_cylinder_insulation_type*	Jacket (26%); factory applied (71%); none (3%)			
28	Cylinder insulation thickness	*hw_cylinder_insulation*	0	150	25	mm
29	Cylinderstat	*has_cylinderstat*	Yes (75%); no (25%)			

Notes: For category variables the probability for each category has instead been listed.
Cylinderstat = thermostat for domestic hot water cylinder.
DHW = domestic hot water.

are uncorrelated, so that these efficient estimators can be used. The exact estimators used are presented below.

Generating the input distributions

The probability distribution assigned to each input is the probability distribution of that input across the gas central heated subset of the English housing stock. The EHS is the main data source in this study. The EHS includes a physical survey of approximately 16 600 dwellings, of which approximately 12 500 are houses, and is published annually (in this work data from the 2009 survey have been used). The data recorded in the EHS do not correspond exactly to the

Table 3 Standard Assessment Procedure (SAP) inputs set to fixed values in the study

SAP input	Fixed value
External door area	2*1.89 m^2
Party floor area	0
Party ceiling area	0
Party wall *U*-value	0.2 W/m^2 K
External door *U*-value	3 W/m^2 K
Thermal bridging *y*-value	0.15 W/m^2 K
Ventilation system	Naturally ventilated
Number of chimneys	0 (it is assumed that most chimneys qualify as flues)
Structural infiltration	Masonry wall – 0.35
Draught lobby exists?	Yes
Number of sheltered sides	2
Window over-shading	Average over-shading
Glazing orientation	East/west
Main heating system type	Gas boiler
Main heating system emitter type	Radiators, responsiveness = 1
DHW system	Main heating boiler
Water heating efficiency	Same as main system efficiency
Is primary pipework insulated?	No
Secondary heating system type	None

Note: DHW = domestic hot water.

inputs required for an SAP calculation (*e.g.*, the survey does not measure *U*-values; they must instead be assumed based on dwelling age, which is recorded in the survey). In this study the methodology described in CAR & UCL (2012) is used to generate the required inputs. Table 2 lists the SAP inputs generated, and indicates the ranges of values extracted from the EHS dataset. Table 3 lists the inputs that are set to fixed values throughout this study, in most cases because the study is restricted to gas-heated houses, but in some cases due to a lack of available data (*e.g.* in the absence of better information, it is assumed that all houses have two external doors).

Each dwelling in the EHS dataset represents several hundred dwellings in the UK, however the distribution of surveyed dwelling types does not exactly match the distribution of dwelling types in the English housing stock, as certain types are over-sampled in order to achieve adequate sample sizes. The survey therefore includes a weighting factor for each of the surveyed dwellings which must be used to reproduce correctly stock-wide distributions. These weightings are included in the generated probability distributions so that an extra weighting step is not required during the sampling process.

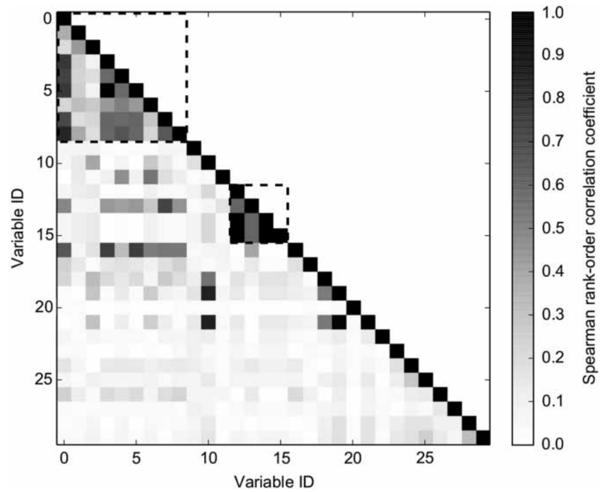

Figure 2 Plot of the absolute value of the Spearman rank correlation coefficient between each of the input variables. *x*- and *y*-axes' values refer to the variable identifications shown in Table 2. The inputs corresponding to the glazing type and geometry factors are highlighted by the dashed squares

Some of the inputs in Table 2 are strongly correlated with each other, *e.g.* floor area and external wall area. Neglecting these correlations has the potential to skew the results of the MCA. For example, consider the case of floor area and external wall area. Houses with a large floor area tend to have a large wall area, hence these variables are correlated with each other. In general, a UK house with a larger floor area is likely to have a higher energy use than a house with a smaller area; and a house with a larger external wall area is likely to have higher energy use than a house with a smaller wall area. The effect of these two variables being correlated across the housing stock therefore is to produce more extreme values in the output, increasing the output variance. If this correlation were ignored and a stock were generated with the correct distributions of floor area and wall area except that they were uncorrelated with each other, then the spread in the model output would be reduced and the variance in the model output would be reduced.

It is possible to calculate the sensitivity indices described previously in the presence of this type of correlation by using a Monte Carlo sampling scheme that preserves the correlations, *e.g.* using replicated Latin hypercubes (McKay, 1995), but this significantly increases the complexity of the procedure and also complicates the interpretation of the resulting indices (since in the presence of correlations between the variables, fixing one variable to a known value will affect the sensitivity of the output to the correlated variables). It is therefore simpler to choose the inputs such that there are no correlations.

Figure 2 shows the Spearman rank-order correlation coefficient between each pair of variables, where the *x*- and *y*-axes' values show the variable identification (ID) from Table 2, and the colour scale shows the absolute value of the correlation coefficient. The two groups of correlated variables highlighted on the plot are the glazing type variables and the building geometry variables.

The glazing *g*-value, light transmittance, *U*-value, and presence or absence of draught stripping are all correlated. This is unsurprising as these inputs are all generated according to the window type specified in the EHS data. This makes physical sense as these properties are all more or less determined by the number of panes of glazing present (though coatings and different thicknesses of the layers can cause variations). A new input is therefore defined called *glazing_type* which can take the value 'single' or 'double', according to the relative frequency of occurrence of single- and double-glazing in the EHS stock. The glazing properties are then all set according to the randomly selected value of the *glazing_type*.

The variables describing building geometry are also unsurprisingly correlated with each other. It is possible to devise a set of geometry inputs that are less correlated with each other (*e.g.* glazing ratio is less correlated with floor area than is glazing area), but no set of inputs that were adequately uncorrelated could be found in this study. Instead the geometry from each of the houses in the EHS dataset is taken as a whole. A new integer variable called *geometry* is defined and used to select between the EHS geometries. For example, if *geometry* is assigned the value 100, then the geometry of the 100th house in the EHS dataset will be used for the generated house. Table 2 shows which SAP inputs are driven by the *geometry* variable. The variable is weighted so that different geometries occur with the same relative frequency as they do in the EHS dataset. In this way the correlations between the geometric inputs are preserved at the expense of being unable to ascertain the relative importance of the individual geometric variables.

A few other variables are quite strongly correlated, *e.g.* wall *U*-value, number of passive vents and floor infiltration (variable IDs 10, 19 and 21). This is because these variables are derived in whole or in part from the age of the dwelling indicated by the EHS data. Also the thermal mass parameter (variable 16) is correlated with some of the geometric inputs. This is because the thermal mass parameter is calculated in part from the internal exposed areas. These inputs are treated as uncorrelated for the purpose of this study, which, as will be shown in the next section, does not significantly affect the calculated distribution of emissions.

To avoid confusion, the term *factor* is used to refer to the parameters varied in the sensitivity analysis, versus *input* which refers to the input values required to perform an SAP calculation. The final model inputs are derived from the assigned values of the factors, and in the case of the *geometry* and *glazing_type* factors several model inputs are determined based on the factor's assigned value.

The next section verifies that the sampling scheme described above adequately replicates the distribution of energy ratings that arises from running the EHS dataset directly through the SAP model.

Comparing the Monte Carlo samples with EHS data

As this study analyzes the variance of the output of the SAP calculation procedure, it is important that the generated samples produce the same output distribution as would be obtained by using the EHS dataset directly, *i.e.* that the Monte Carlo samples adequately represent the characteristics of the surveyed gas central heated houses.

Figure 3 shows the cumulative probability distribution of the CO_2 emissions of the gas central heated houses in the EHS stock compared with a Monte Carlo-generated stock where all the SAP inputs were allowed to vary independently, and with a Monte Carlo stock where the sensitivity analysis factors were varied independently (so that the model inputs related to the *geometry* factor, for example, will be correlated as they are in the EHS stock). The Monte Carlo stocks consist of 1000 houses each, as this is sufficient to detail accurately the overall output distribution. Visually the uncorrelated factors case is much closer to the original

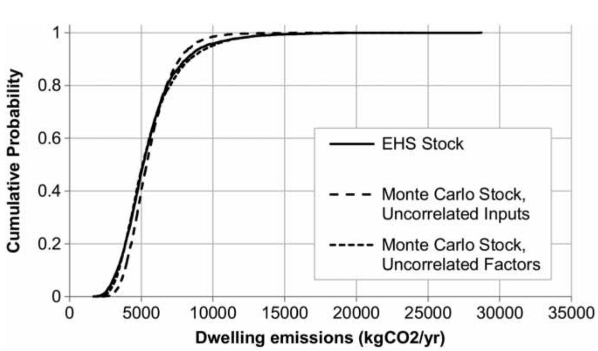

Figure 3 Distribution of dwelling CO_2 emissions for the English Housing Survey (EHS) stock and the Monte Carlo-generated stock with (a) uncorrelated model inputs and (b) using the geometry and glazing-type factors to produce correlated inputs

EHS distribution than the uncorrelated inputs case. The uncorrelated inputs distribution shows fewer extreme values (the slope of the curve around the steepest part is steeper for the uncorrelated case), as expected.

The Kuiper test (Press, Teukolsky, Vettering, & Flannery, 1992) is a standard statistical test for assessing/testing whether two datasets are likely to be drawn from the same underlying distribution. Testing the null hypothesis that the distribution of CO_2 emissions produced by the generated input samples is the same as that produced by the EHS data, a Kuiper test statistic of 0.0514 is obtained, and there is a 0.17 probability of a statistic this large arising from a sample of size $N = 1000$ drawn from the EHS data (larger values of the test statistic indicate bigger differences between the two distributions). The null hypothesis is therefore accepted. In other words, the chosen parameterization of the model inputs has not significantly affected the calculated distribution of CO_2 emissions.

The 19 grouped factors are therefore used in the Monte Carlo calculation of the sensitivity indices, rather than treating all 29 SAP inputs individually.

Calculating the sensitivity indices

As discussed previously, in order to calculate the sensitivity indices S_i and $S_{T,i}$, the two terms $E(V(Y|X_i))$ and $V(E(Y|X_{-i}))$ must be determined. Saltelli et al. (2010) present an efficient method for estimating these quantities. Two sets of N dwellings are generated using the Monte Carlo approach outlined above. The larger N, the more accurate the end result will be, but the more model evaluations will be required. The two sets of dwellings are denoted A and B; these can be thought of as matrices with one row for each of N dwellings and one column for each input. Another set of dwellings is generated for each model input, $A_{B,i}$, which is the same as A, except that the ith column has been replaced with values from column i of B. The notation $f(A_j)$ means the result of the SAP calculation for the jth dwelling in A. Saltelli et al. then give estimators for each of the terms required:

$$E(V(Y|X_i)) = V(Y) - \frac{1}{N}\sum_{j=1}^{N} f(B_j)(f(A_{B,ij}) - f(A_j))$$

$$V(E(Y|X_{-i})) = V(Y) - \frac{1}{2N}\sum_{j=1}^{N} (f(A_{B,ij}) - f(A_j))^2$$

Bespoke Python code was implemented to perform these calculations.

The calculated sensitivity indices are themselves uncertain due to the limited numerical accuracy of Monte Carlo methods. It was found that using $N = 30\,000$ gave a reasonable balance between accuracy and calculation time, so that the total number of SAP calculations was 60 000 plus an extra 30 000 for each model input.

Sensitivity results

Tables 4 and 5 show the calculated S_i's and S_T's for the EER, EIR, modelled emissions and modelled emissions per unit floor area. The same three variables, geometry, heating system efficiency and external wall U-value, are identified as the most important for all four outputs. The Fuerst et al. (2013) study of the impact of EPC rating on dwelling house price also found evidence that older dwellings tend to have lower EPC ratings. This is consistent with the results presented here as older dwellings will tend to have a lower heating system efficiency and worse external wall U-values.

In all cases, the S_i's for these three variables sum to more than 0.75, indicating that over 75% of the variance in the model output can be attributed to these variables. This means that over 75% of the variance in EER and EIR rating for existing gas central-heated English houses is explained by geometry, wall U-value and heating system efficiency.

To illustrate this, the model estimate of the median EER for the stock included in this study is 62.8 with 90% of houses falling in the range 48.1–73.5. The equivalent median and range for EIR are 52.6 and 38.9–64.7, respectively (Table 6). If the heating system efficiency and external wall U-value are fixed to their median values of 68% and 1.6 W/m^2 K, and the dwelling geometry is fixed to match a house with a floor area matching the median stock floor area of 88.3 m^2, then the resulting median EER is 59.4 with 90% of houses being in the range 52.3–63.2, and the median EIR is 48.5 with 90% in the range 42.0–52.7. A grading band in SAP is on average 14.3 points wide (ranging from 20 points for grade G to 8 points for grade A), so the range of 10.9 points from 52.3 to 63.2 is less than a typical grade (though in this case the range 52.3–63.2 sits across the boundary between grades D and E).

Similarly for carbon emissions, the model estimate of the median carbon emissions for the stock included in this study is 5094 kg CO_2/year, with 90% of houses falling in the range 3090–9945 kg CO_2/year. Fixing the heating system efficiency, external wall U-value and geometry as above results in median dwelling emissions of 5208 kg CO_2/year and 90% of houses fall in the range 4788–5797 kg CO_2/year, or

Table 4 First-order and total sensitivity coefficients for Energy Efficiency Rating (EER) and Environmental Impact Rating (EIR)

Factor	EER		EIR	
	S_i	S_t	S_i	S_t
main system efficiency	0.3157	0.3236	0.3308	0.3326
U-value external wall	0.2305	0.2548	0.2394	0.2571
geometry	0.2199	0.2641	0.2195	0.2508
U-value roof	0.0768	0.0979	0.0745	0.0883
thermal_mass_parameter	0.0184	0.0214	0.0170	0.0186
U-value ground floor	0.0158	0.0183	0.0176	0.0196
hw_cylinder_insulation	0.0145	0.0131	0.0135	0.0128
glazing type	0.0109	0.0138	0.0109	0.0136
heating_control_type	0.0096	0.0133	0.0115	0.0137
temperature_adjustment	0.0074	0.0078	0.0065	0.0070
low_energy_bulb_ratio	0.0055	0.0055	0.0024	0.0026
has_cylinderstat	0.0040	0.0059	0.0044	0.0060
hw_cylinder_insulation_type	0.0038	0.0052	0.0039	0.0054
Nfansandpassivevents	0.0022	0.0015	0.0022	0.0016
Nflues	0.0022	0.0027	0.0019	0.0029
floor_infiltration	0.0011	0.0011	0.0016	0.0012
hw_cylinder_volume	0.0009	0.0023	0.0011	0.0022
frame_factor	0.0002	0.0002	0.0002	0.0002
Nfluelessgasfires	0.0001	0.0001	0.0001	0.0001
Total	0.9394	1.0524	0.9590	1.0363

−8.1% to 11.3% of the median value. Note that geometry is relatively much more important for total carbon emissions than for EER and EIR, because EER and EIR are both normalized to the dwelling floor area, which tends to reduce the importance of the geometry inputs.

Fixing the next four variables to their median values, roof *U*-value (median = 0.395 W/m^2 K), thermal mass parameter (median = 238 kJ/m^2 K), ground floor *U*-value (median = 0.707 W/m^2 K) and hot water cylinder insulation thickness (median = 25 mm) further reduces the range, with the median EER now being 59.5 and 90% of houses in the range 55.6–62.4 and the median EIR being 48.8 with 90% in the range 44.8–51.6.

This means that 90% of houses with the specified geometry, heating system efficiency, external wall *U*-value, roof *U*-value, ground floor *U*-value, thermal mass parameter and hot water cylinder insulation thickness will have an EER and EIR grade of D. The other model inputs are therefore unimportant in determining the grade for these houses. The exact range of EER and EIR remaining is specific to the values at which the seven factors are fixed, but it illustrates how a relatively small number of factors account for the majority of the variance in the rating.

The sum of the first-order sensitivity coefficients compared with the total sensitivity coefficients gives some indication of the additivity of the model. The sums of the first-order sensitivity coefficients for the outputs are in the range 0.94 and 0.98 and total sensitivity is in the range 1.03–1.05. This indicates that there are some interactions between the variables within the model, but not so large as to dominate the results. This matches the previous findings of Cheng and Steemers (2011) that their BREDEM-based stock model was additive for small changes in the input variables.

Note how the sensitivity indices account for the expected distribution of the model inputs. For example, external wall *U*-value and roof *U*-value both act on the model in the same way: as a term in the fabric heat loss. It might therefore be expected that the sensitivity of the model to these two inputs would be similar. However, according to the stock generated from the EHS data,

Table 5 First-order and total sensitivity coefficients for gross CO_2 emissions (kg/year) and emissions per square metre (kg/m^2/year)

Factor	Gross emissions (kg/year)		Emission per square metre (kg/m^2/year)	
	S_0	S_t	S_0	S_t
geometry	0.8107	0.8405	0.3583	0.3940
main system efficiency	0.0817	0.0930	0.2835	0.2894
U-value external wall	0.0598	0.0740	0.2153	0.2421
U-value roof	0.0081	0.0101	0.0281	0.0329
glazing type	0.0049	0.0053	0.0124	0.0132
heating_control_type	0.0036	0.0047	0.0115	0.0125
thermal_mass_parameter	0.0028	0.0043	0.0078	0.0088
hw_cylinder_insulation_type	0.0013	0.0009	0.0052	0.0053
temperature_adjustment	0.0012	0.0022	0.0050	0.0066
U-value ground floor	0.0011	0.0010	0.0025	0.0032
hw_cylinder_insulation	0.0010	0.0010	0.0055	0.0054
has_cylinderstat	0.0007	0.0010	0.0052	0.0056
Nfansandpassivevents	0.0005	0.0003	0.0015	0.0016
Nflues	0.0004	0.0005	0.0041	0.0027
floor_infiltration	0.0003	0.0004	0.0012	0.0010
low_energy_bulb_ratio	0.0003	0.0005	0.0017	0.0018
hw_cylinder_volume	0.0003	0.0002	0.0013	0.0013
Nfluelessgasfires	0.0001	0.0000	−0.0001	0.0001
frame_factor	0.0000	0.0000	0.0003	0.0002
Total	0.9788	1.0397	0.9503	1.0279

Note: The small negative value is not physically possible and is caused by the numerical error in the Monte Carlo integration.

Table 6 Effect on the median and range of the Energy Efficiency Rating (EER) and Environmental Impact Rating (EIR) of setting the most important model factors to fixed values

	EER			EIR		
	Median	5th percentile	95th percentile	Median	5th percentile	95th percentile
No factors fixed	62.8	48.1	73.5	52.6	38.9	64.7
Top three factors fixed	59.4	52.3	63.2	48.5	42.0	52.7
Top seven factors fixed	59.5	55.6	62.4	48.8	44.8	51.6

roof *U*-values are on average lower than external wall *U*-values (median = 0.4 versus 1.6 W/m^2 K) and roof heat loss areas are smaller than external wall heat loss areas (median = 48.2 versus 84.7 m^2). The sensitivity indices for external wall *U*-values are therefore significantly higher than for roof *U*-values.

The sensitivity to the low energy lighting input is larger for EER than for EIR (the total sensitivities are 0.0055 and 0.0026, respectively). This is because in SAP electricity is 3.7 times more expensive than gas and has associated emissions of 2.6 times that of gas, so for gas-heated dwellings the electricity consumption accounts for a larger portion of the EER, which is cost based, than the EIR, which is emissions based (and therefore inputs that directly affect electricity consumption will tend to be more important for the EER than the EIR).

Conclusions

The results of the previous section demonstrate that the factors with the largest contribution to the observed variance in energy rating are geometry, heating system efficiency and external wall *U*-value. Together these account for just over 75% of the variance in energy rating. However the remaining variance represents a fairly large range in energy rating. Fixing the next four most important factors, roof *U*-value, ground floor *U*-value, thermal mass parameter and hot water cylinder insulation thickness, was shown to reduce the expected remaining variance to around 10% of the total observed variance, to a point where most houses that share common values for those seven parameters are likely to share the same EER and EIR grades (fixing the seven most important factors is equivalent to fixing 15 out of 30 of the SAP input variables considered in this study).

The sensitivity of a particular input is a measure of how much the observed variation in that input across the stock affects the model output. A high sensitivity therefore indicates either that the model is very sensitive to that input or that there is a wide range in observed values of that input across the stock (or a combination of these). Conversely, a small sensitivity coefficient indicates either that the model is not sensitive to the value, or that there is little variation in the input across the stock.

To the extent to which SAP is an accurate description of energy use in UK houses, these results are useful when thinking about energy upgrades to existing houses. If the goal is to reduce carbon emissions, then according to the results presented in this study the areas with the largest scope for improvement in the existing housing stock are heating system efficiency and external wall *U*-value (though this study looks only at gas-heated houses: alternative fuel heating systems may be of interest in an energy upgrade project). This matches well with what is already known: improving boilers and insulating external walls are effective strategies; however these results indicate that there may still be considerable scope for improvement in the existing stock (though it will not be technically possible or financially viable to upgrade all existing houses). This study therefore confirms that to the extent that an energy rating influences dwelling owner behaviour, the SAP energy rating methodology does encourage the upgrade of wall insulation and improved efficiency of heating systems.

Interestingly the glazing type (single- versus double-glazing) appears relatively far down the list of important factors. This is likely to be because of the prevalence of double-glazing across the housing stock (90% of UK dwellings have some level of double-glazing; DECC, 2012). Since a large number of dwellings will therefore have the same value for this model input, it becomes unimportant in determining the variation of the energy rating across the stock. This indicates that there is now much less scope for improving the performance of the existing stock by upgrading windows.

The results also show that dwelling geometry is a very important factor, with over 80% of the variance in annual CO_2 emissions being caused by geometric inputs. This is not something that can easily be changed for existing dwellings, but is something that could be looked at closely for new dwellings. This result might also have implications for adding extensions to existing dwellings. Of interest is the difference in importance of the dwelling geometry between gross CO_2 emissions, where it accounts for over 80% of the variance, and EER and EIR, where it accounts for around 20% of the variance. EER and EIR are both normalized by dwelling floor area, so as to avoid penalizing large dwellings; however this does mean that energy ratings have a different sensitivity to the key variables than the output that we really want to control, which is carbon emissions (or perhaps total energy cost, which will be closely correlated with carbon emissions). Designing dwellings to achieve a better EER and EIR by improving heating system efficiency and wall *U*-value therefore might not result in dwellings with significantly lower CO_2 emissions if the dwelling geometry remains unchanged. It is not very practical to suggest controlling dwelling floor area, which is controlled by market forces and expectations other than energy consumption, but a closer study of the variables encapsulated by this factor might provide useful guidelines. The approach used in this paper combined all the geometry-related variables in order to avoid the complications arising from having correlated inputs in the MCA. A logical next step would be to repeat this analysis using an approach such as replicated Latin hypercube sampling (McKay, 1995) in order to understand which of the geometry variables have the largest impact.

This study has shown the importance of correlations between the SAP input variables. Any future Monte Carlo study of SAP (and it seems reasonable to extend this result to BREDEM) risks underestimating the extremes of dwelling emissions if these correlations are not accounted for.

As the input distributions used in this study were derived from a stock of existing dwellings, the sensitivity results presented are only valid in that context. The probability distribution of many of the inputs for new-build dwellings will be significantly constrained compared with the stock as a whole, as modern building regulations place strict limits on many aspects of new buildings. It would be interesting to repeat this study using input distributions more appropriate to new dwellings in order to understand which design parameters are most critical in meeting or exceeding building regulations.

The EHS dataset, in combination with assumptions from sources, has been used as the basis for determining the distribution of dwelling properties across the stock. Like any survey, the EHS has uncertainties arising from sampling errors, weighting errors and instrument errors which introduce variable levels of inaccuracy and imprecision across the variables measured. The effect of this will be to cause the input distributions drawn from the survey to differ from the real distributions. This has not been accounted for in this study. In general the effects of random measurement errors should cancel out when the input probability distributions are derived, but any systematic measuring error will obviously affect the estimate distribution and may therefore affect the sensitivity results. In particular, the age bands used in the EHS survey group all post-1990 dwellings into the same category, so that new-build dwellings, which will likely have much improved energy performance, are not well represented in the EHS stock.

This analysis has not included the effect of renewable energy systems attached to the dwelling. Primarily this is because the EHS dataset from 2009 predates the UK's Feed-in Tariff scheme and so renewable energy systems were relatively rare in the stock (and hence contributed little to the variance in energy rating across the stock). With the recent growth in photovoltaic systems in the UK, it would be interesting to repeat this analysis when a more recent dataset becomes available to assess what impact that has had on improving the energy rating of existing dwellings.

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