Metrics for Cold Homes: The Performance of Policy-Relevant Indicators of Energy Poverty in the UK

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Abstract

Energy poverty most commonly refers to the situation where individuals are not able to adequately heat (or provide necessary energy services for) their homes at affordable cost (Pye et al 2015). Unfortunately, the definition and measurement of energy poverty are a complicated undertaking due to the number of factors influencing this phenomenon, the way in which energy poverty can be defined and the many different ways in which it can be measured. Defining energy poverty in terms of adequate level of energy services require the quantification of the energy consumption required to achieve either a minimum heating regime to safeguard health or to provide a standard level of thermal comfort. Defining energy poverty in terms of observed level of spending is likely to understate the extent of the problem, as those households who constrain energy expenditure because they cannot afford it might not be incorporated among the energy poor.

Based on the fact that the health impacts of energy poverty are largely due to inadequate level of thermal comfort, it becomes important to assess the extent of the overlap between different metrics of energy poverty on one side and whether homes are heated to an adequate temperature on the other. Our work assesses the extent to which a number of energy poverty metrics can identify cold homes, where cold homes are defined as those with an average wintertime daily temperature lower than 18°C. We use data on temperature from the English House Surveys (EHS) follow-up to identify cold homes. Energy poverty metrics considered in this paper include the Low Income – High Cost (LIHC) definition, a simple 10% ratio between observed energy cost / income rule, with and without a range of benefits, and the qualifying criteria for the WHD scheme criteria, a policy introduced in the UK to tackle energy poverty. We also introduce two new models, one based on Random Forests, the other based on a logistic regression, in order to identify the characteristics that are normally associated with cold homes.

1 Introduction

Energy poverty most commonly refers to the situation where individuals are not able to adequately heat (or provide necessary energy services for) their homes at affordable cost (Pye et al 2015). The definition and measurement of energy poverty is a complicated undertaking due to the number of factors influencing energy poverty, the way in which energy poverty can be defined and the many different ways in which it can be measured. Our work assesses the extent to which a number of energy poverty metrics can identify cold homes, where cold homes are defined as those with an average wintertime daily temperature lower than 18°C.

Our paper is structured as follows. Section 2 briefly discusses the complexity related to the concept of energy poverty, i.e. a complexity related to the number of factors influencing the experience of being energy poor but also to the way in which energy poverty is defined – in terms of adequate or observed level of energy services. Measurement of energy poverty and in particular the data one can use in building a certain metric adds to this complexity. Section 3 discusses the rationale for assessing the extent to which existing energy poverty metrics overlap with experiencing cold homes. This is a very policy-relevant endeavor as different choices in relation to the way energy poverty metrics are built have an implication on the extent of and incidence of energy poverty across a certain population, the selection of policy instruments to address energy poverty and the effectiveness of policy interventions. In Section 4 we briefly put forward a methodology to identify the characteristics that are most commonly related to cold homes in the UK. We conduct our analysis on a recently published dataset – discussed in Section 5 - and present our results in Section 6. Section 7 concludes.

2 Complexities related to the Concept Energy Poverty

The definition of energy poverty has to deal with several complications, as discussed below, which are reflected in the way energy poverty is measured. Preston et al (2014) identifies five factors influencing the risk of energy poverty, including i) the rate of energy price rises versus income growth; ii) ability to access cheaper energy prices; iii) household energy needs; iv) efficiency of energy use; and v) policy interventions.

2.1 Problems related to the definitions of energy poverty

Energy poverty has become recognized as a distinct form of inequality, i.e. a basic right and entitlement to a sufficient and healthful everyday life (Walker and Day, 2012). Energy poverty most commonly refers to the situation where individuals are not able to adequately heat (or provide necessary energy services for) their homes at affordable cost (Pye et al 2015). A fundamental question, which immediately arises, when defining energy poverty is related to which energy services should be considered in its definition, i.e. those related to an adequate level of warmth or more simply to the household's past consumption. Unfortunately, the difference between observed and adequate demand for energy services can be substantial especially for households affected by energy poverty. A last resort strategy to cope with energy poverty is, in fact, to reduce energy consumption in order to allocate a limited amount of income to other more pressing, objectively or perceivably, necessities.

Defining energy poverty in terms of adequate level of energy services implies quantifying the energy consumption required to achieve either a minimum heating regime to safeguard health or to provide a standard level of thermal comfort. In either case one needs to add adequate lighting, cooking and typical appliance use (Moore 2012). Defining energy poverty in terms of "needs to spend", i.e. the expenditure required to provide adequate level of energy services, has the obvious advantage of enabling statistics to incorporate among the energy poor also those households which constrain energy expenditure simply because they cannot afford it. Although defining energy poverty in terms of "needs to spend" seems preferable to actual expenditure, the former is affected by shortcomings related to the way weather is factored in. i.e. reflecting long-term (sometimes called seasonal normal) weather conditions (DECC and ONS 2015) rather than the actual weather experienced by the households. From the perspective of those being affected, energy poverty is particularly severe in cold winters, i.e. when budgetary constraints bite harder due to the increase in energy bills, even though this is not reflected in the modeled definition of the concept. In other words, using required energy services to define energy poverty is likely to understate statistics when energy poverty is likely to have the strongest impact on the thermal comfort and health conditions of those directly affected.

2.2 Problems related to the measurement of Energy Poverty

Much discussion has focused as to whether energy poverty should be measured by using an absolute or a relative threshold. In the case of the former, households are considered energy poor if their energy expenditure as proportion of their income is above a predetermined threshold, e.g. the popular 10% threshold introduced by Boardman (1991). In the case of a relative threshold, households are considered energy poor if their energy expenditure as proportion of their income is above a certain multiple of a statistic supposed to convey information about the distribution of energy expenditure as proportion of income in the whole population, e.g. twice the median value. The drawback of an absolute threshold is that any fixed value seems arbitrary or might quickly become dated while the advantage of a relative threshold is that it can adjust to changes in the factors determining energy poverty. Unfortunately, a relative definition of energy poverty, e.g. as implemented in the LIHC metric discussed below, seems right in principle but problematic in practice, as argued by Moore (2012). In the case of increasing energy prices, which have been observed throughout Europe in the last decade, an absolute metric would show energy poverty increasing across time while a relative metrics would remain largely constant if the rise in energy expenditure as a percentage of income is observed throughout the distribution. Hills (2012) shows that this applies to the LIHC metric in the UK over the period 2003-2009. One can see how a stable relative metrics occurring when the whole population is affected by increasing energy prices or decreasing income fails to draw attention to the increasing number of households having genuine difficulties in meeting their energy costs.

Another set of problems in the measurement of energy poverty is related to whether income needs to be adjusted. First of all, income needs to be reflective of the household composition, i.e. "equivalised", to reflect the fact that larger households need higher income than smaller households to achieve a comparable standard of living. Secondly, one needs to decide which benefits should be included as part of disposable income. Finally, one needs to consider how to treat housing costs, i.e. whether income used in the metrics is measured before (BHC) or after housing costs are deducted (AHC). The rationale for not considering housing costs as part of income that can be spent on energy seems obvious (housing costs cannot be avoided and therefore logically preceded any other costs sustained by the households) and in fact the AHC version of income is used to produce the official UK statistics on energy poverty.

Additional complications in the measurement of energy poverty relate to the computation of energy expenditure. As average fuel prices are normally used by national agencies, measures of energy poverty are very likely to significantly under-estimate the extent of the problem, due to the fact that those at risk of or affected by energy poverty tend to be on higher than average tariffs (Moore 2012). The frequency of energy poverty measurement produces some additional complications. Energy poverty metrics are normally based on annual income and expenditure but, unfortunately, energy costs are largely seasonal with relatively high expenditure in the winter and a relative small amount of money in the summer.

A final set of problems related to measuring energy poverty is related to the fact that the ratio between energy expenditure and income may hide information about the actual affordability of energy services. This implies that households that are not energy poor might become so if increases in the income are less than proportional than the increase in energy expenditure even though disposable income after energy cost actually increases[1]. This problem has been dealt with by the new official UK metrics of energy poverty, the so-called "low income, high costs" (LIHC) where income and energy expenditure are considered separately rather than as a ratio, i.e. households are considered energy poor only if they are affected by low income and high-energy costs. Detailed explanation on how this metric is computed can

[1] Moore (2012) discusses the example of a household with income equal to £10,500 and energy expenditure of £1,000. As this household is not considered energy poor based on the 10% threshold one could conclude that it can afford adequate energy services. However, if the following year its income increases by £1000 and energy cost by £200 the household is considered energy poor despite the increase in income more than compensate the increase in energy expenditure, as testified by the fact that income after energy cost is £9,500 in the first year and £10,300 in the second year.

be found for example in Preston et al (2014). The LIHC metric can be considered a double-relative metrics, in the sense that two relative thresholds are used to define 'reasonable' energy costs and 'low income', i.e. the median in the case of energy costs and 60% of the national median in the case of income

A completely different approach in measuring energy poverty takes as a starting point the fact that issues related to the objective measurement of this phenomenon cannot be easily dealt with, maybe due to limited data availability. The solution in these cases is to resort to survey-based data so that one can build so-called consensual metrics measuring the households' subjective assessments of their ability to maintain an adequately warm home. Reflecting the availability of EU-SILC[2], a consistent pan-European dataset, the majority of analyses of energy poverty at the European level have been undertaken using consensual indicators, e.g. BPIE (2014), Thomson and Snell (2013) and Tirado Herrero and Bouzarovski (2014). Strengths associated with the consensual approach are related to its simplicity in term of data collection and to the possibility of assessing wider elements related to perceived impacts of being energy poor. Weaknesses of this approach are related to the implicit assumption that participants in a survey consider 'adequacy of warmth' in a similar way, and to the potential for self-exclusion, i.e. households not identifying themselves as fuel poor, even though they are defined under objective measures. Thomson (2013) notes that the reverse is also true.

3 Energy Poverty Metrics or Cold Homes?

The existence of different ways to measure energy poverty implies different conclusions about the extent and severity of this social phenomenon and the identification of demographic, socio-economic and technological characteristics that are frequently observed in households at risk or affected by energy poverty. These characteristics are important from a policy perspective, even if they do not cause being energy poor, as they can provide guidance on effectively targeting energy poverty. As different policy implications and targeting of resources can be drawn from alternative distributions of energy poverty across social groups, the lack of agreement on the definition of energy poverty – at least at the EU level – and on the way it should be measured is a potential concern from a policy perspective. Moore (2012) explores how distribution of energy poverty in the UK varies across tenure types, household composition, age groups and regions when income is computed based on the before/after housing costs and on the with/without equalization approaches; a similar analysis is found in King Baduoin Foundation (2016) for Belgium. Preston et al (2014) compare the prevalence of energy poverty under the LIHC described above and the 10% threshold for the ratio between observed energy expenditure and income. Substantial differences can be seen between the two metrics, e.g. 30% of the households composed by one person over the age of 60 were considered energy poor based on the 10% definition while only 15% would be so under the LIHC definition; about 12% of couples with no children under the age of 60 were considered energy poor under the LIHC definition while only 5% would be considered so under the 10% definition.

Concerns have also been raised about the reliability of self-reported indicators and their limited overlap with objective metrics, a finding discussed in Waddams and Deller (2015), King Baduoin Foundation (2016) and Price et al. (2012). Price et al. (2012) discuss how subjective metrics give very different results from the expenditure-based 10% metric in the case of the UK. While 28% of households spent more than 10% expenditure on energy, only 16% of the sample felt unable to sufficiently heat their homes. In addition, only less than half

[2] Some weaknesses of EU-SILC, such as sampling procedure and the inclusion of all utilities together, are discussed in Thomson and Snell (2013)

of this group was fuel poor based on the expenditure-based indicator, although this could be due to households not sufficiently heating their homes, and therefore not crossing the 10% threshold. Price et al. (2012) argues for self-reported measures as a valuable indicator, in addition to expenditure-based metrics. Similar results on the limited overlap between expenditure-based and consensual metrics and similar conclusions on the utility of consensual metrics have been discussed for Belgium in King Baduoin Foundation (2016).

Health consequences of energy poverty and evidence linking energy poverty to poor physical and mental health have been recently thoroughly discussed in Marmot (2010). Exposure to wintertime indoor temperatures is an important determinant of health, both physical and mental. Being in energy poverty is associated with living in low indoor wintertime temperatures (Gilbertson et al., 2012; Healy and Clinch, 2002), related diseases and illness (Thomson et al., 2013), and being exposed to excessive heat in the summer. The UK has a particular large burden of excess winter mortality (EWM), i.e. number of deaths during winter periods (i.e. December to March) compared to the mean of non-winter period, with approximately 18,200 additional deaths in 2013/14 (and 31,280 in 2012/13) (ONS, 2013). Consequently, assessing the extent to which energy poverty metrics are a proxy for being exposed to low temperature is an important endeavor. Identifying the characteristics associated with the exposure conditions of low income household helps in improving existing policies to effectively target energy poverty and exposure to low indoor wintertime temperatures.

Based on the fact that the health impacts of energy poverty are largely due to inadequate level of thermal comfort, it becomes important to assess the extent of the overlap between different metrics of energy poverty on one side and whether homes are heated to an adequate temperature on the other. As low room temperature is largely responsible for the health costs of energy poverty, one could argue that statistics should focus on observed temperature rather than on the complex metrics discussed above. One might also argue for metrics based on observed temperature to determine the introduction of interventions to tackle energy poverty, but issues related to strategic behavior might make this approach unworkable[3]. Moore (2012) notice that data on actual fuel consumption, expenditure, tariffs and home temperatures collected in the 1991 and 1996 English House Condition Surveys (EHCS) enabled an exact computation of the extent to which each household under-spent and under-heated. Under-spending and temperature measurements provide powerful metrics of fuel poverty, i.e. a direct and straightforward measure, in contrast to the complex modeling and adjustment required to compute the metrics above (Moore 2012).

4 Methodology

Our work assesses the extent to which a number of energy poverty metrics can identify cold homes, where cold homes are defined as those with an average wintertime daily temperature lower than 18°C. We use data on temperature from the English House Surveys (EHS) follow-up to identify cold homes. Energy poverty metrics considered in this paper include:

1) **LIHC**: the Low Income – High Cost (LIHC) definition – currently the official measure of energy poverty in England and Wales

[3] This would be due to the fact an household wanting to be offered an intervention to increase energy efficiency in the home could for example keep temperature artificially low during the limited observation period and then revert to their normal room temperature. It is worth mentioning that similar strategic behavior could also be used if measured energy consumption or energy bills were used, e.g. households could use less energy for the observation period.

2) **Fuel Poverty Full**: a version of the previous official measures of energy poverty in the UK, i.e. the 10% observed energy cost / income rule, with income including Housing Benefit, Income Support for Mortgage Interest Relief, and Council Tax Benefit in addition to household income

3) **Fuel Poverty Basic**: i.e. a simpler version of the 10% rule above where the definition of income does not include any of the benefits mentioned in point 2)

4) **WHD Scheme**, i.e the qualifying criteria for the WHD scheme criteria (those who qualify for the Guarantee Credit portion of the Pension Credit), i.e. one of the policies introduced to tackle energy poverty in the UK

We also introduce two new models, one based on Random Forests, the other based on a logistic regression, in order to identify the characteristics that are normally associated with cold homes. Our methodology therefore comprises two different approaches, one simply computing the energy metrics mentioned above, the other building models to identify the variable that are related to cold homes. The first approach is not being discussed here as it simply implies the algebraic computation of a specific energy poverty metric, as we have access to all relevant data from the dataset discussed in Section 5. As building models to identify variables related to experiencing cold homes is more involved, this section will discuss how one can allocate observations, i.e. the households, which we have data for, to a number of mutually exclusive classes, i.e. namely i) living in a cold home, and ii) not living in a cold home, based on the information contained in a number of variables comprised in the dataset described in Section 5.

In this study we employ random forests, i.e. an ensemble learning methods comprising several sub-models estimated on the same dataset, the results of which are combined into the final model. Random forests, introduced by Breiman (2001), comprise several decision trees to classify observations across mutually exclusive classes[4]. One problem with decision trees is that they tend to overfit to data (i.e. fit patterns in the data which are the outcome of chance rather than being reflective of the underlying data generation process) that leads to poor generalisations when the data used in the estimation is not representative of the wider population (Hastie et al. 2009). Random forests overcome this problem, at the cost of a small increase in bias and poorer interpretability, through the estimation of several classification trees on a subset of the data and the available variables; these trees are combined into a forest through 'tree bagging', a kind of bootstrap aggregating process[5]. The fact that each decision tree within a random forest is estimated on a subset of the data and the available variables avoids the problem of a few very strong features dominating the classification procedure and allow analysts to rank variables in terms of their importance. This was very attractive to us as ultimately we use random forests to identify the variables which are most closely related to – although not necessarily causing – the experience of living in cold homes.

The importance of variables in random forests can be determined in two ways, i.e. according to prediction strength and based on the Gini impurity index. In order to assess the prediction strength of each variable we predicted "out of bag" (OOB) sample for each tree, i.e. the observations not included in the bagging process, and this process repeated across all trees with random permutations in a given variable. The average decrease in prediction accuracy caused by permuting that variable measures its importance in the random forest, expressed as

[4] In their simplest form, decision trees take a number of predictors and split them along 'branches' until they reach the 'leaves', which are the points at which all data are in one class or another or there are no further variables on which to split.

[5] Bagging involves estimating several trees (usually hundreds or thousands) on a random sample with replacement of the data set. Random forests take a random subset of the variables (also called features) at each split in the estimation process, a method sometimes referred to as 'feature bagging'.

percentage of the maximum. The other method of determining variable importance is based on the Gini impurity criterion that is used in the classification of splits during estimation. At each split in each tree, the improvement in the split-criterion is the importance measure attributed to the splitting variable. This improvement is accumulated over all the trees in the forest separately for each variable (Hastie et al 2009). The Gini impurity index is calculated as $G = \sum_{i=1}^{n_c} p_i(1 - p_i)$ where n_c is the number of classes in the dependent variable (in this case whether or not the home is cold) and p_i is the ratio of this class in the split.

Variable importance is then defined as $I = G_{parent} - G_{split1} - G_{split2}$ which is then averaged over all trees in which the feature is present. The advantage of the Gini impurity index is that it can assess the importance of 'groups' of features, or rather the discrete number of values in a categorical variable. For example, if a continuous variable is split into quintiles, the random forest algorithm treats each quintile as a separate feature and uses a dummy variable for each feature. To determine the overall importance of the continuous variable the average of the mean Gini decrease (I) across each feature's values is taken. For income, that is the mean of the I for each quintile.

We included the most important variables identifying whether households are at risk of living in cold homes in a logistic regression, in part for interpretability and in part because logistic regression allows for more complicated functional forms such as interaction between the variables. As an example, the effect of energy efficient appliances may depend on income, i.e. with higher income homes being less sensitive to appliances with poor energy efficiency. This can be expressed in a logistic regression through an interaction term, while it is difficult to include it in random forests because there is no ceteris paribus assumption (holding all other things equal). Our final logistic model includes 1) e-values[6]; 2) length of residency, 3) household type; 4) dwelling age; 5) presence of a boiler; 6) age of the household reference person; 7) number of people in the home; 8) household income; 9) number of bedrooms, and 10) whether the household reference person is employed. Income and e-value were interacted.

5 Dataset

In our study we used information from the *Energy Follow Up Survey, 2011* (DECC and BRE 2016). This dataset aims to provide detailed information on patterns of household and dwelling energy use as well as information about energy use appliance and the buildings where energy is consumed[7]. EFUS (2011) is a follow up interview survey of a subset of households, first visited as part of the *English Housing Survey, 2010-2011: Household Data* (EHS). A total of 2,616 interviews were completed, drawn from a sample of addresses provided from the first three quarters of the 2010/11 English Housing Survey (EHS). These data were then weighted to account for survey non-response and to allow estimates at the national level to be produced. For a sub-sample of these households - 823 homes - the EFUS involved collection of temperature data through the placement of up to three temperature monitors in three rooms of the home, which would record room temperatures every twenty minutes for around one year. For another sub-sample - 1,345 homes – meter readings were collected to provide information on how much electricity and gas was actually being used. These raw meter readings providing data on annual gas and electricity consumption were added to the data in the survey in November 2014. The EFUS data have been scaled up to represent

[6] E-values describe a building's annual consumption of purchased energy based on the heated net interior area (kWh/m^2a) and based on the standard use of the building.

[7] As an example, respondents are asked questions about the type and usage patterns of the main and secondary heating systems in their homes, the water heating system and usage, dwelling insulation, lighting indoor temperatures and the use of appliances

the national population (and to correct for nonresponse) using weighting factors (BRE 2013).

6 Results

The methodology was implemented over the 647 homes which contained observations for all variable of interest out of the 823 above. Our sample included 204 cold and 443 normal homes where cold homes were defined as homes with an average wintertime daily temperature lower than 18°C. Table 1 shows confusion matrices for each of the energy poverty metrics used in this study and the models we implemented. For each metric and model in Table 1 we show the match between predicted and actual observations and related diagnostics. The figures in the cells where the class of predicted observations, i.e. "Cold Homes" and Normal Homes" in the columns, matches the class of actual observations in the rows, show the number of correct predictions[8]. The other two cells are incorrect predictions (Normal Home, Cold Home) and (Cold Home, Normal Home). In order to assess the performance of energy poverty metrics and our model we present the *error rates*, i.e. the percentage of incorrect predictions for either class of actual observations, and the false rates, i.e. the percentage of incorrect predictions for either class of predicted observations.

In terms of results, it is interesting to notice that the WHD scheme criteria (i.e. low income pensioners who qualify for the Guarantee Credit portion of the Pension Credit) performed worst at predicting cold homes, finding only 9 of the 204 cold homes, leading to a false positive rate of 96%, i.e. (204-9)/204. Another interesting result is that the Low Income – High Cost (LIHC) definition performed considerably worse than the old and much simpler fuel poverty definition based on the 10% income rule in terms of identifying cold homes- see higher false positive rate of the LIHC criterion. This applies to both the case of the 'full income' definition, which includes Housing Benefit, Income Support for Mortgage Interest Relief, and Council Tax Benefit in addition to household income, and the 'basic income' definition that does not include any of the benefits above. In case of the LIHC, only 25 of the cold homes, i.e. about 12% of the 204 cold homes, were identified against an average 50 of the two versions of the fuel poverty criteria.

[8] For the avoidance of doubt this corresponds to the cells (Normal Homes, Normal Homes) and (Cold Homes, Cold Homes).

		Normal Homes	Cold Homes	False Positive Rates	False Negative Rates
WHD SCHEME	**Normal Homes**	413	30		7%
	Cold Homes	195	9	96%	
LIHC	**Normal Homes**	397	46		10%
	Cold Homes	179	25	88%	
FUEL POVERTY BASIC	**Normal Homes**	372	71		16%
	Cold Homes	149	55	73%	
FUEL POVERTY FULL	**Normal Homes**	383	60		14%
	Cold Homes	159	45	78%	
RANDOM FOREST	**Normal Homes**	399	44		10%
	Cold Homes	147	57	72%	
LOGIT	**Normal Homes**	409	34		8%
	Cold Homes	144	60	71%	

Table 1. Confusion matrices for cold home prediction criteria

Our methodology was able to identify a model that predicts cold homes more consistently than both fuel poverty criteria. As shown in Table 1, the Logit model outperformed both fuel poverty criteria as it was able to identify 60 of the cold homes against 45 and 55 for the fuel poverty, i.e. 29%, 22% and 27% of the 204 cold homes. Full and Basic criteria, respectively. A similar improvement in performance is displayed by the Logit model in identifying normal homes, as it is able to identify 409 against 383 and 372 identified by the fuel poverty Full and Basic criteria, respectively. This implies a considerable decrease in the false negative rate, i.e. incorrectly attributing 'cold' status to normal households. This occurs in 34 of the normal homes when using the Logit model, compared to 60 and 71 cases wrongly classified by the fuel poverty Full and Basic criteria, respectively. This implies a false negative rate of 8% for the Logit against an average 15% of the versions of the Fuel poverty criteria.

7 Conclusions

Households that are at risk of living in cold homes, i.e. average wintertime daily temperature lower than 18°C, are among the most vulnerable of those households living in fuel poverty. Health consequences of energy poverty and evidence linking energy poverty to poor physical and mental health are well established (Marmot 2010). Being in energy poverty and general poverty is associated with living in low indoor wintertime temperatures (Gilbertson et al., 2012; Healy and Clinch, 2002), related diseases and illness (Thomson et al., 2013), and be exposed to excessive heat in the summer. As the definition and measurement energy poverty is however problematic, this study tested the extent to which low indoor temperatures during wintertime conditions can be identified by four metrics of energy poverty, i.e the official metric used in England and Wales, two versions of the previous official UK metric, and finally the qualifying criteria for the Warm Home Discount (WHD) Scheme, one of the policies introduced to tackle energy poverty in the UK. We also estimated two models, one based on Random Forests, the other based on a logistic regression, to identify the characteristics that are normally associated with cold homes.

It was found that the use of the qualifying criteria for WHD scheme are not necessarily a strong indicator that households in receipt of the payment would be living in cold homes. This reflects the predominant type of home that those households occupy, i.e. socially rented mid-century flats built to a higher energy performance standard. The official energy poverty metric, the LIHC, adopted by the UK government for England and Wales performs only slightly better. Interestingly, the LIHC metrics performed considerably worse than the old and much simpler fuel poverty definition based on the 10% ratio between observed energy costs and income. This applies to both the case of the 'full income' version, which includes a number of benefits and the 'basic income' version that does not include any of the benefits above.

The models we implemented in this study enabled us to identify the characteristics that are normally associated with cold homes, which included a measure of the dwelling energy performance, i.e. the energy performance value (e-value), and other measures of household and dwelling age. Using a measure of energy performance (which would also reflect dwelling age) and some form of length of residence within the LIHC definition of energy poverty could make it a more appropriate proxy to better target households vulnerable to living in cold homes.

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