Sustainable Cities and Society 81 (2022) 103817

Contents lists available at ScienceDirect

Sustainable Cities and Society

journal homepage: www.elsevier.com/locate/scs

Are fuel poverty metrics fit for purpose? An assessment using behavioural microsimulation

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ARTICLE INFO

JEL classification:
H23
Q18
H31

Keywords:
Household energy demand
Microsimulation
Energy taxes
Fuel poverty

ABSTRACT

This paper contributes to the literature on fuel poverty measurement by analysing the ability of different metrics to identify fuel poor households. We consider existing expenditure-based metrics and recently-developed metrics for multidimensional poverty, and compare three aspects: (a) Their ability to identify households at high risk of experiencing fuel poverty, (b) their ability to identify low income households with a large carbon tax burden, (c) their ability to measure changes in fuel poverty under carbon taxes and compensatory measures, including increases in fuel efficiency. We employ a fully flexible model to quantify demand responses to changes in fuel prices and energy expenditure for residential heating. We find that in general all analysed metrics perform well at identifying the household types frequently mentioned in the literature as fuel poor. Regarding the second aspect (b), we find that in general, the metrics performed badly at identifying vulnerable households with the largest tax burden. Finally, we show that using a multidimensional metric that includes energy efficiency can track changes in fuel poverty under the analysed scenarios, and it generally is a promising approach to measuring fuel poverty.

1. Introduction

Fuel poverty is defined by Pye et al. (2015) as "a situation where individuals or households are not able to adequately heat or provide other required energy services in their homes at affordable cost", and has attracted a lot of attention in the literature. The battery of existing metrics of energy affordability is defined on the basis of only two variables: disposable household income, and energy expenditure (see Charlier & Legendre, 2021). Several reviews of the question of fuel poverty from a policy perspective exist, see for example Bouzarovski (2017), Csiba (2016) and Council of Europe Development Bank (2019). The literature has identified the household types with a higher risk of being in fuel poverty. For instance, You and Kim (2019) found that inefficient dwellings such as old and detached houses are occupied by elderly owners who often lack both the financial capability and intention to properly maintain their dwellings. Healy and Clinch (2002) found that over half of elderly households endure inadequate ambient household temperatures during winter. O'Sullivan et al. (2015) concluded that households on prepayment metring experience greater levels of fuel poverty in New Zealand. The tenure of the dwelling, the level of income and the education of the head of the household are also identified as important drivers (see Lyra et al., 2022).

In spite of the growing literature on the topic, the appropriate measurement of fuel poverty is still at the core of the academic and policy debate. Faiella and Lavecchia (2021) argue that the first step to tackle fuel poverty is to measure it accurately. Legendre and Ricci (2015) use data from France to analyse the extent of fuel poverty. They question the suitability of defining fuel poverty as expenditure of 10% or more of net income on fuel, and instead examine households that are not considered poor when considering their income net of housing costs, but that become poor when fuel expenditure is considered. Burlinson et al. (2018) also question expenditure-based metrics of fuel poverty by considering housing costs in tandem with low income and with high fuel expenditure. They propose alternative metrics for fuel poverty and identify households at risk of fuel poverty. Existing fuel poverty metrics are not rooted in economic theory; to overcome this issue, researchers have used well-established metrics for income poverty to measure fuel poverty (see Ye & Koch, 2021). Furthermore, despite being a topic studied for the last 30 years, inconsistency of definitions and lack of multidisciplinary collaboration feature across all of these years (see Primc et al., 2021).

Rademaekers et al. (2016) recommend several measures of fuel poverty for use in EU policy-making. However, the incidence and extent of fuel poverty vary greatly depending on the metric chosen.

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https://doi.org/10.1016/j.scs.2022.103817
Received 15 June 2021; Received in revised form 2 March 2022; Accepted 2 March 2022
Available online 12 March 2022
2210-6707/

Quantifying the capability of existing metrics to identify the household types identified in the literature as fuel poor is a relatively simple exercise, and is an effective method of evaluating the quality of such metrics. Despite this, the procedure is relatively uncommon in the literature. This observation motivates the current study.

An important drawback of existing fuel poverty metrics is that they neglect the role of energy efficiency (or lack thereof) as a driver of energy bills. Research shows that improvements in energy efficiency alongside awareness of energy-saving attitudes can reduce energy consumption in Ireland by up to 19% (see Rau et al., 2020). Lack of adequate insulation levels can increase the likelihood of being in fuel poverty (see Best & Sinha, 2021). Péan et al. (2019) provide a literature review of several indicators and conclude that fuel poverty is the result of the combined effect of low energy efficiency, low income, and high energy expenditure. The drivers of fuel poverty are therefore (a) multidimensional and (b) most likely correlated with other forms of deprivation. Furthermore, dwelling retrofitting has been proposed and supported as a means of combating energy poverty at both EU (Pye et al., 2015) and national level in Ireland (Joint Committee on Climate Action, 2019). However, the evidence base for such a policy is limited to date. While engineering models indicate that retrofitting can improve a dwelling's rated energy efficiency, research from Ireland (Coyne et al., 2018) and elsewhere (Casquero-Modrego & Goñi-Modrego, 2019; Fowlie et al., 2018) suggests that this does not translate into a commensurate reduction in energy usage for low-income tenants. An examination of the ability of energy efficiency upgrades to address energy poverty is therefore apposite, with applications in climate policy, energy policy and civil engineering standards and regulations.

Another issue with existing metrics of fuel poverty is that they assume variables such as household energy expenditure and income do not change. This fails to account for the emergence of carbon taxation as a key policy tool for environmental protection. Energy price increases via carbon taxation can erode the (already relatively lower) income of vulnerable households in real terms, which can prevent households from meeting their energy bills and increase the number of households in fuel poverty. Furthermore, Klenert et al. (2018) analyse several revenue reallocation channels that are already used in some jurisdictions to compensate vulnerable households and improve public acceptance of carbon taxation. The impact of such schemes, if any, on energy poverty and affordability should be evaluated.

Péan et al. (2019) argue that the main purpose of measuring fuel poverty is to identify the most affected households, and to evaluate fuel poverty reduction policies. Correct identification can lead to better targeted policies that can reduce fuel poverty and income inequality in general (see Simshauser, 2021). However, badly designed policies could have opposite effects (see García Alvarez & Tol, 2021). Effective policy design, therefore requires an understanding of the demand response of vulnerable households to changes in energy prices. The inability to reduce energy consumption when facing higher energy prices can be linked to low energy efficiency levels, with Tovar Reaños (2021) finding that households at the bottom of the income distribution tend to live in dwellings with low energy efficiency levels. Income and other supports to increase energy efficiency levels have been suggested in the literature to reduce fuel poverty (see Scheier & Kittner, 2022). In addition, building regulations could decrease fuel poverty by increasing energy efficiency levels (see Mafalda Matos et al., 2022). Improving energy efficiency levels for vulnerable households may also have benefits that extend beyond monetary ones: Casquero-Modrego and Goñi-Modrego (2019) find improvements in mental and physical health after retrofitting. These observations demonstrate several gaps in the measurement of energy poverty that should be investigated, particularly when considering policies to protect vulnerable households.

This paper performs a behavioural microsimulation, parameterised by the estimation of a demand system, which we then use to estimate changes in energy demand and expenditure to examine fuel poverty. A demand system is a behavioural model that represents consumption decisions as a system of equations, and it depends on prices, consumption budgets, and observed as well as unobserved household characteristics. This model facilitates the quantification of own and cross prices elasticities as a measure of households' demand responses to higher energy prices. We employ the Exact Affine Stone Index (EASI) model (see Lewbel & Pendakur, 2009) to parameterise the demand curves. Unlike previous models, the EASI model does not impose a shape to the Engel curves, which describe how household expenditure on a particular commodity varies across different levels of household income. In particular, recent studies assume linear Engel curves (see Deaton & Muellbauer, 1980; Lewbel & Pendakur, 2009) or quadratic Engel curves (see Banks et al., 1997).

There is very little literature that employs a behavioural microsimulation approach to examine fuel poverty. Heindl and Schüssler (2015) use a "morning after" microsimulation model to examine the dynamic behaviour of various fuel poverty metrics. This model does not take demand elasticities into account, which as noted above are important for determining the impact of price changes via carbon taxation and/or revenue recycling policies on energy poverty. The use of these behavioural models is not exclusive to economic models: current engineering studies show the advantages of including behavioural responses when modelling demand-side flexibility and evaluating energy policies (see Alamaniotis et al., 2019; Romanchenko et al., 2021). Furthermore, in analysing fuel poverty, the importance of measuring demand responses to income and fuel prices has been highlighted (see Charlier & Kahouli, 2022).

In addition to considering the capabilities of fuel poverty metrics proposed by the EU Commission (described in Rademaekers et al. (2016)) to identify household types that are in fuel poverty, we go significantly beyond the extant fuel poverty literature by considering the multidimensional poverty framework proposed by Alkire and Foster (2011). We use the EASI model to determine the impacts not only of prices but also of the energy efficiency of dwellings on expenditure on energy and non-energy goods and services. We also estimate demand responses to energy prices measured by price elasticities for different household types. As a final novel contribution, we simulate the impact of carbon taxes and two proposed policy interventions to mitigate the increase in fuel poverty, namely an increase in the energy efficiency of dwellings via housing retrofits, and a policy that recycles the revenues from carbon taxation back to households. We evaluate to what extent the analysed metrics can measure the extensive and intensive margins of fuel poverty under these scenarios.

We quantify the carbon tax burden using a framework rooted in economic theory. We use statistical methods to identify the vulnerable households with the higher tax burden, and compare these findings against the results obtained from existing fuel poverty metrics under the analysed scenarios, thereby quantifying the capability of existing metrics to identify vulnerable households. In addition, Alkire and Foster (2011) propose a multidimensional poverty methodology that both counts the number of deprivations being experienced by each household and determines the depth of the deprivation in each case. We apply this methodology to explore an alternative method of determining the extent of fuel poverty in Ireland.

We find that expenditure-based metrics for fuel poverty identify a very small number of households with low income and high carbon tax burdens as vulnerable households. In addition, the minimum income standard low-income metric is found to be insensitive to changes in fuel prices and energy efficiency levels. The multidimensional poverty framework finds very small own price elasticities in absolute terms for the households classified as energy poor by this metric. Households in this group and with low energy inefficiency levels have the lowest per capita energy expenditure. This suggests that these households may be depriving themselves of energy services in the face of higher energy prices.

The remainder of this article is structured as follows. Section 2 describes the methodology for estimating the demand system. Section 3 describes the data used and the microsimulation scenarios chosen. Section 4 presents the results, and Section 5 discusses and concludes.

2. Methodology

2.1. EASI demand system estimation

We use the Exact Affine Stone Index (EASI) implicit Marshallian demand system to estimate the household expenditure function and derive a demand system developed by Lewbel and Pendakur (2009). It is the latest major advancement in the literature on household demand systems. It provides a first-order approximation of an arbitrary expenditure function from which a demand system can be derived. In order to estimate the EASI, only information on the expenditure for different goods and their prices is required. Unlike the Almost Ideal Demand System and its variations, the EASI demand system can represent the relationship between expenditure and income, the Engels curves, in a flexible manner. Recent applications of this methodology can be found in Lewbel and Pendakur (2009), Pothen and Tovar Reaños (2018). Tovar Reaños and Wölfing (2018) show that the utility function, y, can be expressed in the following way:

$$y = \frac{\log(X) - \sum_i w_i \log(p_i) + \frac{1}{2}\sum_i \sum_j a_{i,j} \log(p_i)\log(p_i)}{1 - \frac{1}{2}\sum_i \sum_j b_{i,j} \log(p_i)\log(p_j)}. \tag{1}$$

where X is total household expenditure. By applying Shephard's lemma to the cost function embedded in expression (1),[1] the following set of equations for the budget shares w_i is obtained[2]:

$$w_i = \sum_j a_{i,j} \log p_j + \sum_j b_{i,j} \log y + \sum_{r=0}^{R} b_{i,r}[\log y]^r + \sum_l g_{i,l} z_l + \sum_l d_{i,l} z_l \log y + \epsilon_i. \tag{2}$$

where p_i are commodity prices, y is the implicit household utility, and z_l are demographic characteristics. R is chosen by the modeller and determines the degree of the polynomial which allows for highly flexible Engel curves. $a_{i,j,l}$, $b_{i,j}$, $b_{i,r}$, $d_{i,l}$ and g_{il} are the parameters to be estimated. ϵ_i represents unobserved preference heterogeneity. The Almost Ideal Demand System (AI-DS) model proposed by Deaton and Muellbauer (1980) and the Quadratic Almost Ideal Demand System (QUAIDS) proposed by Banks et al. (1997) assume linear and quadratic Engel curves. Lewbel and Pendakur (2009) show that (2) can be estimated with an approximation of y or with (1), with very similar estimates. The authors approximate y by using $\log(X) - \sum_i \bar{w}_i \log(p_i)$ where $\bar{w}_i$ is the mean of the budget share. We use the first approach where approximating y reduces the computational burden of estimating the parameters of the system and standard errors using three-stage least squares (3SLS). We use information on intra-group variation of the aggregated consumption categories to obtain household-specific prices following Lewbel (1989) to further improve identification. Once the parameters in Eq. (2) are estimated, price elasticities and expenditure elasticities can be computed as follows (see appendix for details in the derivation):

$$EQiPj = \left\{ \frac{\partial w_i}{\partial \log(p_j)} \right\} \frac{1}{w_i} \text{ for } i \neq j$$

$$EQiPi = \left\{ \frac{\partial w_i}{\partial \log(p_i)} \right\} \frac{1}{w_i} - 1 \text{ for } i = j$$

$$EQiX = \left\{ \frac{\partial w_i}{\partial \log(X)} \right\} \frac{1}{w_i} + 1$$

where qi and pi are quantities and prices

Once the parameters from the system (2) are estimated, we can compute the cost function $C(p, U)$ embedded in the indirect utility function (see Eq. (1)). We can describe the impacts of changes in welfare by estimating Hicks' equivalent variation (HEV). $HEV = C(p^0, U^1) - C(p^0, U^0)$, where U is the level of household utility. This follows Creedy and Sleeman (2006a) and Tovar Reaños and Wölfing (2018). See the appendix for more details on this metric.

Table 1
Expenditure-based fuel poverty metrics considered. The values correspond to the years 2015–2016.

MISLI	Minimum Income Standard Low-Income: A household is considered to be experiencing fuel poverty if equivilised disposable income after energy and housing costs is below the Minimum Income Standard.
LIHC	Low Income High cost: A household is considered to be experiencing fuel poverty if equivilised disposable income after energy costs is below 60% of the income poverty line and its equivilised expenditure level is higher than the median
Multidimensional	A household is considered to be experiencing fuel poverty if equivilised disposable income after energy costs is below 60% of the income poverty line and the equivilised expenditure level is higher than its median or energy requirement (BER) is higher than its median

Table 2
Poverty lines.

Minimum standard (Weekly Euro)	290.71
Median equivilised energy expenditure (Weekly Euro)	22.29
Median equivilised disposable income net of energy cost (Weekly Euro)	490.43
Median energy requirement (kWh/m^2/year)	234.36

2.2. Fuel poverty metrics

We consider three expenditure-based fuel poverty metrics analysed by the European Commission and described in Rademaekers et al. (2016)[3] and we also propose using a multidimensional metric as described in Table 1. The MISLI metric is defined as the median equivalised overall income net of energy and housing costs for the two bottom quintiles of the income distribution.[4] In our case, this minimum standard is computed as €290.71 (see Table 2). As for the low income high cost (LIHC) metric, the weekly equivilised median of expenditure for energy for residential consumers is estimated to be €22.29. In addition, the median equivilised disposable income net of energy costs is €490. The years 2015 and 2016 from the HBS are used to compute these values. Equivalised quantities are estimated by dividing the quantities by the square root of the household size (see Madden, 2015).

The three initial metrics described in Table 1 are head count ratios. Regarding the LIHC proposed by Hills (2012),[5] the author extended his analysis by including a metric for the intensity of fuel poverty experienced by households. This gap is simply the difference between the energy expenditure and the threshold for those households classified as fuel poor by the LIHC. The intensity of fuel poverty measured by

[1] Note that $\log(x) = \log[C(\boldsymbol{p}, y)]$.

[2] The implicit expenditure function must have all the properties that hold for a theoretical expenditure function (Varian, 1992). The following restrictions ensure the theoretical consistency of the estimated expenditure function: $a_{i,j,l} = a_{j,i,l}$, $\sum_i a_{i,j,l} = 0\ \forall\ l$, $b_{i,j} = b_{j,i}$ $\sum_i b_{i,j} = 0$, $\sum_i d_{i,l} = \sum_i g_{i,l} = 0\ \forall\ l$, $\sum_i b_{i,r} = 0$ for $r \neq 0$, $\sum_i b_{i,r} = 1$ for $r = 0$.

[3] see pag. 36 in Rademaekers et al. (2016).

[4] Note that Rademaekers et al. (2016) used overall consumption instead of income. We used income in all the analysed metrics.

[5] Note that in the original LIHC proposed by Hills, required energy costs were used instead of actual energy costs. We use actual expenditure data in all the analysed metrics to be in line with the metrics analysed by Rademaekers et al. (2016).

the LIHC is not directly comparable with the multidimensional metric. While the LIHC gap is measured as the average value in € for those classified as fuel poor, the comparable multidimensional metric is the M_1 index described in the following subsection. Note that the LIHC, MISLI and multidimensional metrics impose an income threshold. This avoids identifying as energy-poor those households in the top income brackets. Even if they were to be considered energy-poor by their energy expenditure, this would call for a completely different policy response than a policy designed to protect vulnerable households. Consequently, we concentrate on low income households.

Regarding the multidimensional poverty metric proposed by Alkire and Foster (2011), the deprivation dimensions chosen are: (i) income, (ii) equivalised energy expenditure and (iii) energy requirement. The associated thresholds we choose are (i) equivalent disposable income net of energy costs of less than 60% of the median, (ii) equivilised energy expenditure less than the median and (iii) a dwelling energy requirement in kWh per m^2 greater than the median, respectively. The methodology requires us to set the thresholds for the deprivation dimensions and weights for each of the dimensions to reflect their policy importance. The methodology also requires us to set a threshold for the sum of weights. We have chosen the following weight for the deprivation dimensions: 50%, 25% and 25%, respectively. The chosen threshold for the sum of weights is 70%. This implies that households with total weights larger than 70% are considered fuel poor. Consequently, only households with equivalised disposable income below the income threshold and with either higher expenditure or high energy requirements are classified as fuel poor.[6] Note that this choice of policy is our own design and it is not a policy that is already implemented. The results presented in this article regarding the multidimensional metric correspond to this design.

The multidimensional methodology computes a *multidimensional headcount ratio*, H, which measures the incidence of simultaneous deprivation in the population. This ratio is adjusted by the specified weights. The index A then computes the *breadth* of these simultaneous deprivations. The index $M_0 = H \cdot A$ is the adjusted head count. The index M_1 considers the intensity of poverty by including the poverty gap across the deprived dimensions G.

The index H is given by

$$H = \frac{\sum_{i=1}^{N} \rho_k(y_i^*, z)}{N} = \frac{q}{N} \tag{3}$$

where y^* is a vector of deprivation indicators, z is a vector of threshold levels below which deprivation is indicated for each element of y^*, k is the number of deprivations that a household must experience in order to be considered to be experiencing multidimensional poverty, N is the total number of households and ρ is a binary function that is equal to one if a household experiences k or more deprivations, and is equal to zero otherwise. A is computed by first computing the *deprivation matrix* $g^0_{i,j}$, whose elements are $weights_{i,j}$ if $y^*_{i,j} < z_{i,j}$ and zero otherwise, for all households i and deprivation indicators j. The vector $weights_j$ is a vector of weights assigned to each deprivation. $\mid g^0_k \mid$ is defined as the sum of all elements in the matrix g^0_k, and from this A is derived:

$$A = \frac{\mid g^0_k \mid}{q} \tag{4}$$

The adjusted head count is defined as: $M_0 = H * A$. In addition, the intensity of poverty is defined as: $M_1 = M_0 * G$, where : $G = \frac{|g^1(k)|}{N}$ and $g^1(k)$ is the sum of the poverty gaps of poor individuals and G is the average poverty gap across all possible deprivations.

[6] We compute these metrics using the `mpi` command in Stata (Pacifico & Poege, 2017).

3. Data and scenarios

3.1. Household, housing, commodity and pricing data

The dataset employed in this work is the Household Budget Survey (HBS), conducted by the Central Statistical Office (CSO) every five years. The purpose of the survey is to determine a detailed pattern of household expenditure, which in turn is used to update the weighting basis of the Consumer Price Index.[7] We use the cross section for the following available years: 1994, 1999, 2004, 2009 and 2015–2016. The sample size used for the demand system estimation is 18,030 units and varies across years. In this work, a pooled cross-sectional dataset is constructed. We have included dummy variables for each year of the survey, interacting with parameters related to the price and expenditure in the demand system. We also use indices for commodity prices for the same years provided by the CSO. For the simulation exercise and the fuel poverty measurement we used the most recent available micro data, which is the years 2015–2016. For the purposes of this study, the consumption goods were grouped into several categories: foods, housing, lighting and heating, transportation, education and leisure, and other goods and services. This aggregation is similar to that used in Böhringer et al. (2017) and Tovar Reaños and Wölfing (2018) and largely follows the Classification of Individual Consumption According to Purpose (COICOP). As in Baker et al. (1989), we do not include the purchase of vehicles and white goods appliances. Instead, dummy variables for ownership of these goods are included in the analysis. The rationale for this is that purchase of durables is an investment, and modelling changes in household investment would require a different approach from the one used in this study. Lighting and heating expenditure, which we shall also denote as "energy" expenditure throughout the paper, comprises expenditure on electricity, natural gas, liquid fuels and solid fuels for residential heating. Transportation expenditure comprises petrol, diesel, maintenance, insurance and public transport. Pricing data was obtained from the price index from the CSO. Given that this is a price index, we do not have actual prices in monetary values. However, the precise evolution of prices for the goods categories observed in the expenditure data is sufficient to identify the EASI demand system. Summary statistics for expenditure and price data are shown in Table 3.

In addition, dummy variables are included for whether a dwelling is in a rural area (according to the CSO classification of same), the age of the dwelling, whether the dwelling has a washing machine or dishwasher, vehicle ownership and dwelling tenure. Summary statistics for these variables are shown in Table 3. We also include dummy variables in our econometric specification for the quarter in which the data were collected. Interaction of expenditure levels and variables for family types are introduced in the econometric specification. Family categories are shown in Table A.13 in Appendix A. The category "Rest other Households" is comprised of persons that share the dwelling with a composition that ranges from 2 to 4 adults and without dependent children.

Carbon taxes in the non-ETS sector affect the prices of heating fuels, and so we can estimate the changes in the expenditure distribution as a result of the carbon tax's effect on both groups. Pricing data was obtained from the price index from the CSO. Given that this is a price index, we do not have actual prices in monetary values. However, the precise evolution of prices for the goods categories observed in the expenditure data is sufficient to identify the EASI demand system.

Regarding energy efficiency, we follow Curtis et al. (2015) and use the data from the Sustainable Energy Authority of Ireland (SEAI). The SEAI maintains a public register of completed Energy Performance

[7] See https://www.cso.ie/en/methods/housingandhouseholds/householdbudgetsurvey/.

Table 3
Summary statistics.

Variable	Mean	Std. Dev.
Expenditure shares:		
Food	0.230	0.110
Housing	0.145	0.113
Energy	0.047	0.032
Transport	0.151	0.107
Education	0.127	0.106
Services	0.299	0.137
Prices (logs):		
Food	4.222	0.267
Housing	3.283	0.498
Energy	3.79	0.389
Transport	3.456	0.535
Education	3.567	0.875
Services	2.851	0.891
Total expenditure	1124.795	1528.493
Energy requirement (kWh/m^2)	261.656	94.536
Rural	0.347	0.476
Washing_machine	0.982	0.134
Dishwasher	0.623	0.485
Tenant	0.202	0.402
Owning a car	0.919	0.273
N	18 030	

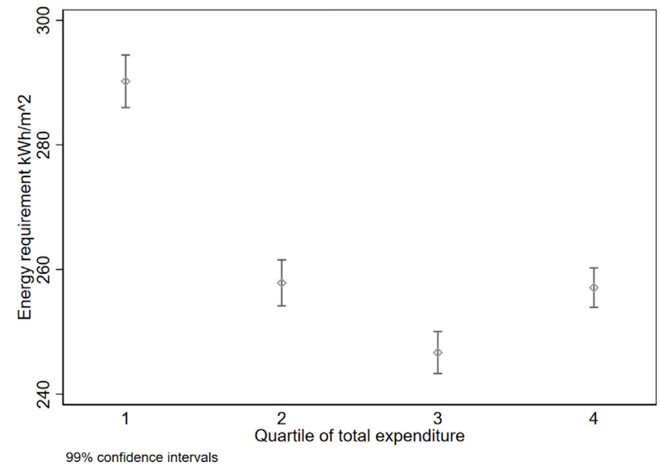

Fig. 1. Energy requirement.

Table 4
Scenario overview.

Scenario	Description	Income change	Price change
NoTax	No carbon tax	NO	NO
Tax	Carbon tax	NO	YES
TaxRev	Tax and lump-sum	YES	YES
Tax efficiency	Tax and energy efficiency increase	NO	YES

Certificates (EPCs), termed Building Energy Ratings (BERs) in Ireland.[8] This dataset provides information on dwelling characteristics and energy requirements of 872,056 dwellings, expressed as kWh/m^3. We re-run the regression from Curtis et al. (2015) on an updated version of the SEAI data. Using the coefficients of the regression, we later predict BERs for households in the household budget survey (HBS).[9] The estimates are displayed in Table A.14 in Appendix A. The parameters from the regression are in line with the estimates provided by Curtis et al. (2015).

In general, newer dwellings, dwellings with a gas fired central heating system and semi-detached and terraced dwellings have higher levels of energy efficiency. The HBS dataset includes data on the age of dwellings, the type of heating system and fuel of the dwelling and the dwelling type (detached house, semi-detached house, apartment, etc.), and so we use these parameters to impute the energy requirement of each dwelling in the HBS. The descriptive values for this variable are displayed in Table 3. Energy efficiency is also allocated unequally across income levels, with poorer households more likely to live in poorer quality housing, which has lower energy efficiency. Fig. 1 shows the average energy requirement of dwellings by expenditure quartile, which decreases as incomes increases, indicating that more affluent households live in more energy efficient properties. The equivalised energy demand in kWh is also shown, which increases across expenditure quartiles.

3.2. Microsimulation scenarios

According to Klenert et al. (2018) a maximum value of \$100 per tonne of carbon (around €80 per tonne of carbon) is required in order to reach the goals in the Paris agreement by 2030. A carbon tax was introduced in 2010 in Ireland which applies to non-ETS emissions. The latest available data on energy expenditure covers the period 2015–2016 where the tax stood at €26 per tonne.[10] We determine the impact on fuel poverty of several potential scenarios via microsimulation. We simulate the impact of increasing carbon taxation by €70 per tonne. Consequently, the total carbon tax that we simulate is €96 per tonne which is expected to be reached in Ireland by 2030. We apply the tax increase to the price of natural gas, liquid fuels and solid fuels for residential heating. We model the impacts of this scenario combined with an increase in energy efficiency, by decreasing the energy requirement of each dwelling by 10 kWh/m^2.[11] Finally we model the impact when combined with a revenue recycling scheme, where the revenue from carbon taxation is distributed totally via a lump sum payment to each household, colloquially known as a "green cheque". Table 4 summarises these scenarios. Note that in the scenario where there is an improvement in energy efficiency, there is no compensatory policy as the revenue recycling policy.

In order to compute the carbon tax, we compute the direct carbon embedded in the consumption of energy and transportation. We translate expenditures reported in € in the HBS into emissions using energy prices (in € per kWh) and emissions factors (in CO_2 g per kWh) provided by the SEAI (see Curtis et al., 2020). We then compute the ratio of emissions per kWh of consumption. With this information and the simulated price for carbon, we compute the carbon tax as the proportion to be increased in relation to initial energy prices. Under a carbon tax of €70 per tonne, we estimate an average increase in the price of heating of 9%.

4. Results

4.1. Assessment of fuel poverty metrics to identify vulnerable households

The literature suggests that households in low income levels, households in retirement age, households with low energy efficiency levels, and single adults with dependent children are normally identified as more likely to experience fuel poverty (see Healy & Clinch, 2002; Tovar Reaños, 2021). Table 5 shows the output of a logistic regression where the dependent variable is an indicator of fuel poverty as described in

[8] The database of BERs is available to download at: http://www.seai.ie/Your Building/BER/National BER Research Tool.

[9] We thank Dr. John Curtis for providing the estimation routine used in their paper.

[10] In 2021 the tax was set to €34 per tonne.

[11] Using the estimated demand system, we estimate that this reduces equivalised energy expenditure by 0.5% with respect to the level under the tax scenario.

Table 5
Logistic regression for the probability of experiencing fuel poverty.

Regressor:	Dependent variable: Facing fuel poverty		
	LIHC	Mult.	MISLI
Head count ratio	9.08%	16.50%	14.99%
Base: Other households			
Adult aged 14–64 years	0.311	0.073	−0.086
	(0.190)	(0.163)	(0.158)
1 adult aged 65 or over	0.899***	0.456***	0.482***
	(0.192)	(0.171)	(0.170)
Single adult with children	0.787***	0.929***	0.999***
	(0.227)	(0.196)	(0.184)
Married couple with children	−0.097	0.288**	0.207
	(0.178)	(0.146)	(0.137)
Married couple only	0.467***	0.244*	−0.112
	(0.147)	(0.127)	(0.131)
Rural	0.254*	0.312**	0.06
	(0.145)	(0.131)	(0.129)
Base: Quarter4			
Quarter1	0.211	0.064	−0.133
	(0.141)	(0.123)	(0.121)
Quarter2	0.192	0.015	−0.195
	(0.143)	(0.125)	(0.124)
Quarter3	−0.358**	−0.337***	−0.299**
	(0.154)	(0.130)	(0.125)
Base: Built after 2000			
Building 1918–1960	0.228	1.120***	0.005
	(0.155)	(0.139)	(0.130)
Building 1961–1980	0.004	0.851***	−0.17
	(0.158)	(0.142)	(0.133)
Building 1981–2000	0.03	0.359**	−0.042
	(0.154)	(0.143)	(0.125)
Using gas	−0.169	−0.103	−0.214**
	(0.133)	(0.112)	(0.109)
Base: Detached			
Semi-detached	−0.21	−0.179	−0.277**
	(0.147)	(0.130)	(0.127)
Apartment	−1.187***	−0.484**	−0.473**
	(0.318)	(0.228)	(0.201)
HH male	−0.093	−0.109	0.004
	(0.106)	(0.092)	(0.092)
Studies up to secondary	0.333***	0.465***	0.312***
	(0.115)	(0.099)	(0.101)
HH ill	0.889***	1.095***	1.235***
	(0.189)	(0.174)	(0.176)
Log (Total Expenditure)	−0.943***	−1.626***	−1.982***
	(0.110)	(0.101)	(0.104)
Tenants	0.186	0.458***	0.685***
	(0.138)	(0.116)	(0.109)
Constant	3.485***	7.841***	11.170***
	(0.795)	(0.713)	(0.727)
N	4745	4745	4745

Significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 4. In general, the different metrics show that there is a seasonal component to fuel poverty. Living in an apartment or using mainly gas for heating reduces the likelihood of fuel poverty. Having an ill member of the family or a low educational level increases the probability of experiencing fuel poverty. Regarding the household type, the metrics show that when the head of the household is a single parent with children or is of retirement age, the probability of experiencing fuel poverty increases. Regarding the head count ratio, one can see that the multidimensional metric has the largest group classified as fuel poor, followed by the MISLI metric. Note that while the identification is acceptable in the analysed metrics, it fails to identify the dwelling age as a factor for fuel poverty. Old buildings are more likely to have lower energy efficiency levels and therefore result in a higher likelihood of experiencing fuel poverty.

4.2. Energy demand elasticities

The estimated parameters of the EASI demand system estimation are displayed in Table A.15 in the appendix. We find statistically significant and greater than zero parameters for the polynomials of up to degree four. This confirms the nonlinearity of the Engel curves and justifies the EASI demand system approach used. Note the coefficient related to energy requirement is positive in the equation related to energy expenditure, showing that increases in the kWh/m^2 will increase energy expenditure. Including this variable of the energy requirement of the dwelling, measured in kWh/m^2, is a novel contribution and so is difficult to evaluate in the absence of data from other countries.

Table 6
Uncompensated Own- and cross-price elasticities for expenditure quartiles.

	Food $\Delta\%Q_1$	Housing $\Delta\%Q_2$	Energy $\Delta\%Q_3$	Transport $\Delta\%Q_4$	Education $\Delta\%Q_5$	Services $\Delta\%Q_6$
$\Delta\%P_3$	0.133	−0.005	−0.465	−0.009	−0.033	0.006
	(0.015)	(0.011)	(0.015)	(0.011)	(0.007)	(0.008)
$\Delta\%P_3$	0.159	0.030	−0.425	−0.003	−0.036	0.022
	(0.013)	(0.009)	(0.013)	(0.011)	(0.006)	(0.007)
$\Delta\%P_3$	0.183	0.033	−0.383	0.009	−0.049	0.025
	(0.014)	(0.009)	(0.015)	(0.013)	(0.007)	(0.007)
$\Delta\%P_3$	0.222	−0.013	−0.514	0.076	−0.049	−0.017
	(0.031)	(0.026)	(0.035)	(0.024)	(0.016)	(0.012)

Table 7
Expenditure elasticities for expenditure quartile.

	Food $\Delta\%Q_1$	Housing $\Delta\%Q_2$	Energy $\Delta\%Q_3$	Transport $\Delta\%Q_4$	Education $\Delta\%Q_5$	Services $\Delta\%Q_6$
1st quartile	0.722	1.317	0.373	0.759	1.178	1.441
	(0.013)	(0.026)	(0.014)	(0.022)	(0.032)	(0.020)
2nd quartile	0.642	1.117	0.253	0.969	1.391	1.281
	(0.008)	(0.015)	(0.013)	(0.016)	(0.020)	(0.012)
3rd quartile	0.624	0.977	0.182	1.061	1.456	1.191
	(0.009)	(0.013)	(0.017)	(0.014)	(0.014)	(0.009)
4th quartile	0.644	0.685	0.295	1.166	1.358	1.088
	(0.018)	(0.021)	(0.025)	(0.020)	(0.024)	(0.010)

Regarding the elasticities, Table 6 shows the price elasticities for energy in the four expenditure quartiles. Each cell in the table quantifies the change in demand of the commodity specified in each column in response to the change in energy prices. This is estimated for each quartile of the total household expenditure, shown in each row. For instance, the row P_{31} refers to the change in the price of the third commodity (i.e. energy) for the first quartile of total expenditure. Following West and Williams (2007) standard errors are estimated using non-parametric bootstrapping.[12] Our estimated own price elasticities for lighting and heating are similar in magnitude to the one estimated by Pothen and Tovar Reaños (2018) and higher than the one estimated by Savage (2016). While the latter author used Irish data, he includes energy used for private transportation in the energy group and a quadratic demand system.[13] Consequently, direct comparison is not possible.

Table 7 displays our estimated expenditure elasticities. Salotti et al. (2015) show that estimates for different European countries are in the range of 0.12 and 0.47; our estimates for energy are at the lower bound of this range. One can see that expenditure elasticities for food, energy and transport are inelastic, and thus these commodities are necessary goods. Increases in the price of these commodities will have regressive effects. Creedy and Sleeman (2006b) show that when the value of the expenditure elasticities are less than one, indirect taxes will be regressive.[14]

[12] 300 replications are carried out using Monte Carlo simulations as described in Horowitz (2001).

[13] Full matrix of elasticities is provided in the appendix in Table A.16.

[14] Note that apart from expenditure in rent, and mortgage, our category housing also includes insurance, water consumption and dwelling maintenance. Hence, the elasticities measure changes in the demand of these commodities with respect to changes in income.

Table 8
Uncompensated Own- and cross-price elasticities for expenditure quartiles.

	Food $\Delta\%Q_1$	Housing $\Delta\%Q_2$	Energy $\Delta\%Q_3$	Transport $\Delta\%Q_4$	Education $\Delta\%Q_5$	Services $\Delta\%Q_6$
$\Delta\%P_3$	0.120	0.005	−0.441	−0.017	−0.017	0.143
	(0.021)	(0.014)	(0.019)	(0.017)	(0.008)	(0.017)
$\Delta\%P_3$	0.125	0.036	−0.435	−0.019	−0.010	0.181
	(0.016)	(0.012)	(0.015)	(0.014)	(0.008)	(0.017)
$\Delta\%P_3$	0.137	0.032	−0.438	−0.015	−0.018	0.229
	(0.016)	(0.011)	(0.017)	(0.014)	(0.009)	(0.020)
$\Delta\%P_3$	0.148	−0.040	−0.665	0.043	−0.007	0.260
	(0.034)	(0.029)	(0.039)	(0.029)	(0.020)	(0.055)

In order to investigate the sensibility of our estimated price elasticities to the household specific prices used in the estimation, Table 8 also displays price elasticities, but this time we use mean commodity prices for different household types as described in Table A.13. One can see that the estimates are very similar to the ones displayed in Table 6. Note that own price elasticities for energy are slightly larger but they also show that vulnerable households are less price responsive than more affluent households.

Table 9 shows own price elasticities for energy for different household types in the first and second quartiles of total household expenditure. Increasing energy prices will reduce energy demand through two channels. In the face of higher prices, economic theory predicts a reduction in demand for the product. The purchasing power of vulnerable households will be affected too, yielding a further reduction in demand for the product. These two effects are summarised by the uncompensated elasticities displayed in Table 9.[15] We see that own price elasticities for these groups are in line with the estimates displayed in Table 8 for the first quartile. Note that the own price elasticity for tenants has the smallest absolute value. Higher energy prices and low demand responses will expose vulnerable households to higher energy expenditure. This group already spends a higher proportion of their income on energy expenditure relative to more affluent households.

Table 10 shows the price elasticities for households in each of the four groups identified as fuel poor in the previous sections. It shows that households classified as fuel poor by the multidimensional and the MISLI metrics have the lowest demand response. This implies that in the face of higher energy prices, households in these groups will face the largest burden given (a) their inability to reduce energy consumption and (b) the fact that they already spend a disproportionate share of their income on this commodity.

4.3. Microsimulation results

4.4. Comparing high tax burden on vulnerable households and fuel poverty measurement

Fig. 2 shows the Hicks equivalent variation relative to total household expenditure for households at the bottom 40% of the total household expenditure distribution. The figure shows two panels where households are classified as not fuel poor and fuel poor by different metrics. One can see that the panel for fuel poverty for the minimum income standard low-income (MISLI) and the multidimensionally metrics are more densely populated than the low income high cost metric (LIHC). Unlike the LIHC, they also cover households across the entire expenditure distribution. However, in general there is still room for improvement in all the fuel poverty metrics because Fig. 2 shows that a considerable number of households in low income levels and with high incidence are not classified as fuel poor under each metric.

[15] Given the small sample of these groups, expenditure elasticities are not statistically significant for single adults and tenants.

An important issue is energy deprivation, which is difficult to measure. Fig. 3 shows equivilised energy expenditure for households classified by the multidimensional metric as energy poor, displayed for each quintile of the energy requirement of the dwelling. One can see that households in the highest quintile (i.e. more energy inefficient dwellings) have the lowest expenditure levels. Consequently, further increases in energy prices could potentially put this group into an energy deprived situation.

4.5. Assessment of capabilities to measure changes in fuel poverty under carbon taxation, revenue recycling and improvements in energy efficiency

Table 11 shows the HEV as a proportion of total expenditure for households in the first five deciles of the total expenditure distribution. In line with existing literature, we find that carbon taxes are regressive. In addition, the lump-sum transfer is progressive. While a generalised improvement in energy requirement (BER) reduces the tax burden, it does not counteract the regressive effect of carbon taxes. Under this logic, one can expect an increase in fuel poverty under a carbon tax scenario and a reduction under the two other scenarios modelled.

Table 12 shows the changes in the head count ratio and in the intensity of fuel poverty across the simulated scenarios. One can see that increases in carbon taxes increase the number of households in fuel poverty, with the LIHC reporting the highest change. Under the compensatory scenarios, only the LIHC and the multidimensional metrics follow the trend in the HEV metric. The simulated decrease of the energy requirement by 10 kWh/m2 reduces energy expenditure by 0.5% with respect to the expenditure under the carbon tax. This change is too small to be detected by the head count MISLI. As to the intensity, Table 12 displays the average weekly fuel poverty gap for the LIHC metric and the $M1$ index for the multidimensional metric. We can see similar patterns to the changes in the head count ratio.

In the energy efficiency scenario, there are important issues to be considered. The literature does not provide an average estimate for the relationship between grants and improvements in energy efficiency levels. Consequently, the outcome of simulating this policy and the outcome from the revenue recycling scenario are not directly comparable in terms of their cost. However, this is not the main aim of this article: here, we compare the capabilities of different metrics to quantify changes in fuel poverty under different scenarios. In addition, in reality, there are important implementation issues, such as different incentives for landlords vs tenants, credit constraints, limited-foresight, the exact cost of improving energy efficiency levels for each dwelling, etc. Here it is assumed a full take-up rate of energy efficiency improvements, but this assumption is probably unrealistic. Thus, the actual incidence of a policy that would aim to improve the energy efficiency of dwellings would likely differ from that modelled here.

5. Discussion and conclusion

Fuel poverty is recognised as a distinct societal and policy challenge around the world. However, the appropriate measurement of the same is still an open question. Faiella and Lavecchia (2021) point out the lack of a homogeneous metric of fuel poverty among EU Member States as an important impediment for a more regional diagnosis of the problem. The development of a theory rooted-metric that considers several dimensions of fuel poverty is one such potential homogeneous metric. This paper contributes to the literature on fuel poverty measurement by analysing the capabilities of existing metrics in three aspects: (a) Their ability to identify the households that the literature has defined as being at risk of experiencing fuel poverty, (b) their ability to identify low income households with a large carbon tax burden, (c) their ability to measure changes in fuel poverty under carbon taxes and compensatory measures, including increases in energy efficiency. Current literature shows that it is important to quantify demand responses to changes in energy prices and income changes when analysing fuel poverty (see

Table 9
Heterogeneity in uncompensated price elasticities.

	Food $\Delta\%Q_1$	Housing $\Delta\%Q_2$	Energy $\Delta\%Q_3$	Transportation $\Delta\%Q_4$	Education $\Delta\%Q_5$	Services $\Delta\%Q_6$
$\Delta\%P_{3Singleadult}$	0.204	0.048	−0.453	0.014	−0.003	0.106
	(0.020)	(0.014)	(0.009)	(0.014)	(0.009)	(0.017)
$\Delta\%P_{3Ill}$	0.214	0.018	−0.456	0.004	−0.025	0.033
	(0.017)	(0.015)	(0.007)	(0.013)	(0.007)	(0.009)
$\Delta\%P_{3Tenant}$	0.188	0.105	−0.400	−0.008	−0.048	−0.015
	(0.016)	(0.015)	(0.007)	(0.013)	(0.007)	(0.010)

Table 10
Heterogeneity in uncompensated own-price elasticities.

	Food $\Delta\%Q_1$	Housing $\Delta\%Q_2$	Energy $\Delta\%Q_3$	Transportation $\Delta\%Q_4$	Education $\Delta\%Q_5$	Services $\Delta\%Q_6$
$\Delta\%P_{3LIHC}$	0.066	0.015	−0.515	0.082	0.008	0.008
	(0.015)	(0.014)	(0.007)	(0.015)	(0.007)	(0.009)
$\Delta\%P_{3MISLI}$	0.106	0.055	−0.157	0.111	0.009	−0.048
	(0.031)	(0.029)	(0.013)	(0.027)	(0.013)	(0.018)
$\Delta\%P_{3Mult.}$	0.092	0.012	−0.157	0.120	0.008	−0.038
	(0.030)	(0.029)	(0.016)	(0.028)	(0.016)	(0.018)

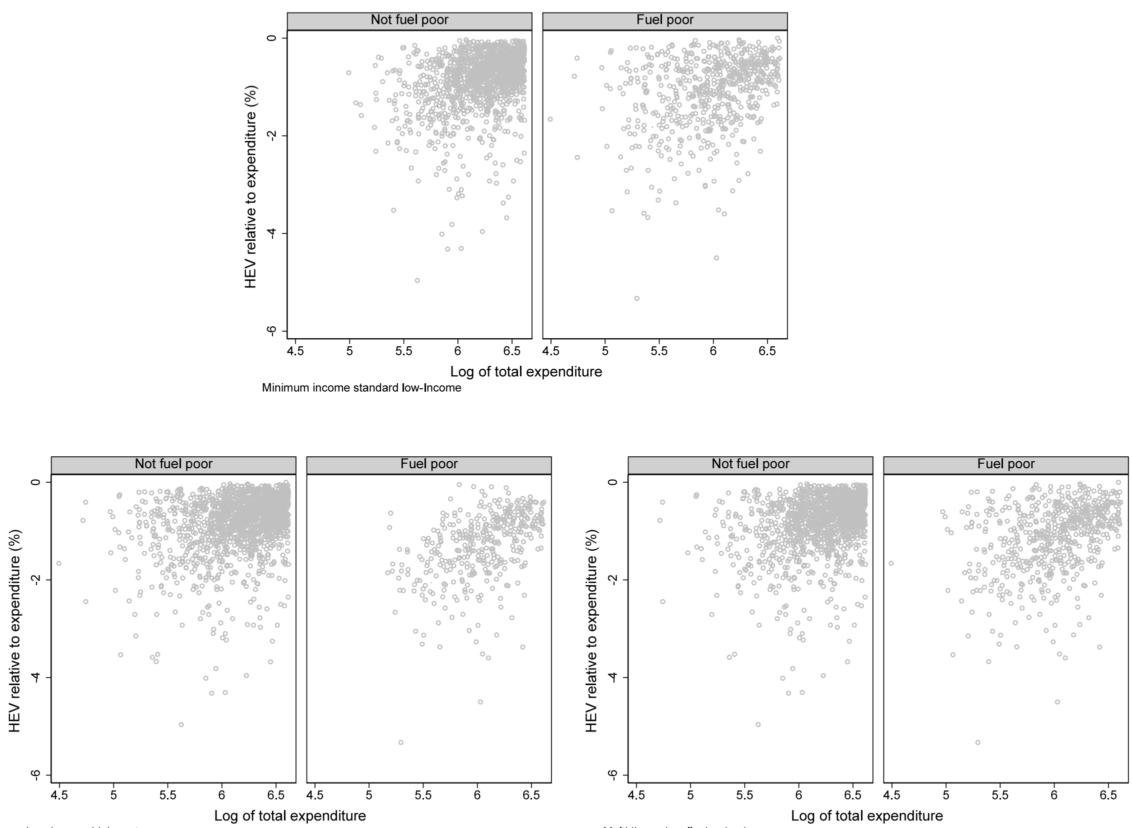

Fig. 2. HEV and fuel poverty incidence.

Table 11
HEV in % of total household expenditure.

	Tax	TaxRev	TaxEfficiency
1st decile	−0.964	1.325	−0.788
2nd decile	−0.952	0.460	−0.762
3rd decile	−0.817	0.195	−0.624
4th decile	−0.697	0.095	−0.510
5th decile	−0.569	0.065	−0.403

Charlier & Kahouli, 2022). We use a fully flexible model rooted in economic theory to estimate these metrics for low income households. Furthermore, the use of well-established methods to measure poverty in general are being used to measure fuel poverty (see Ye & Koch, 2021). We extend this literature by using state of the art multidimensional methods that are widely used to measure income poverty.

There is emerging literature on identifying those experiencing fuel poverty and simulating the effects of policies designed to target these households (see Simshauser, 2021). We contribute to this literature by using our model to measure changes in the extensive and intensive margins of fuel poverty under different scenarios to compensate vulnerable households in the face of increases in carbon taxes via energy prices.

Regarding the first dimension, we find that in general all three metrics considered perform well at identifying the household types

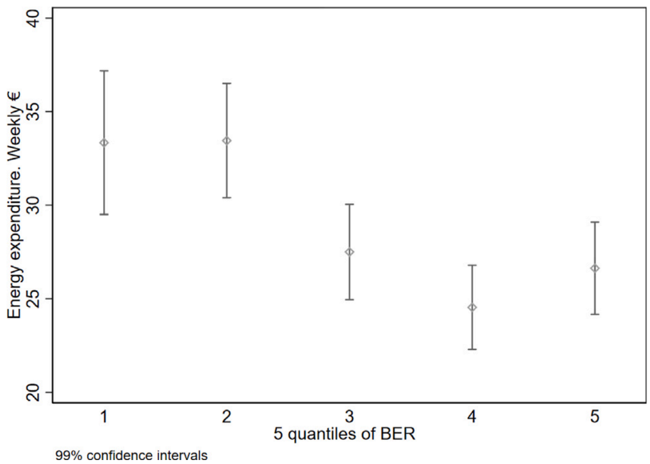

Fig. 3. Energy expenditure across quintiles of energy requirements for energy poor households.

Table 12
Simulated changes in the fuel poverty metrics.

	LIHC	MISLI	Mult.
	Head count ratio(%)		
Base scenario	9.087	16.502	14.932
	Δ w.r.t. the base scenario (%)		
Tax	11.098	0.594	3.978
	Δ w.r.t. the tax scenario (%)		
TaxRev	−0.524	0.000	−0.309
Efficiency	−0.366	0.000	−2.968
	Fuel poverty intensity		
Base scenario	12.334 (€)		0.045 (M1)
	Δ w.r.t. the base scenario (%)		
Tax	2.358		6.790
	Δ w.r.t. the tax scenario (%)		
TaxRev	−0.404		−0.435
Efficiency	−0.687		−3.930

frequently mentioned in the literature as fuel poor. However, the MISLI metric cannot identify the dwelling age as a driver of fuel poverty. We found that while living in an apartment reduces the likelihood of fuel poverty and the tax incidence, having an ill member of the family, having a low educational level, being a single parent with children or being of retirement age increases the probability of being in the most vulnerable groups. In designing policies to protect households in fuel poverty, it is important to implement policies that do not only target households in income poverty as frequently is the case (see Kyprianou et al., 2019), but include some elements of energy efficiency or dwelling quality to be able to reach those in fuel poverty. We also find that rural households tend to experience fuel poverty. This can be linked to not having access to cheaper and more cost-effective fuels such as natural gas (see Curtis et al., 2020).

Regarding the second dimension, we find that there is still room for improvement. Specifically, expenditure-based fuel poverty metrics, in general, performed badly at identifying vulnerable households with the largest tax burden, as measured by our estimated welfare losses after carbon taxes. Finally, the LIHC and the multidimensional metrics both perform well on the third dimension, namely tracking changes in fuel poverty in response to various environmental policies and compensation packages. Both metrics follow the trend indicated by the estimated tax burden quite well. Given that only the multidimensional poverty metric performs well across all three dimensions, we argue that this metric is most reliable for measuring both the extensive and intensive margins of the simulated policy reforms.

Table A.13
Household types.

	Sample size	Frequency
Adult aged 14–64 years	1690	9.37
1 adult aged 65 or over	880	4.88
Single adult with dependent children	837	4.64
Married with dependent children	5330	29.56
Married only	3584	19.88
Rest other households	5709	31.66

Table A.14
Dependent variable log(energy requirement). Using ordinary least squares.

Pre 1919	Ref.
1919–1945	−0.042***
1946–1960	−0.110***
1961–1970	−0.219***
1971–1980	−0.306***
1981–1990	−0.398***
1991–2000	−0.476***
2001–2010	−0.666***
2011	−1.848***
Detached house	Ref.
Semi-detached house and Terrace	−0.005****
Apartments	0.007***
Other	−0.001
No central heating	Ref.
Electricity	0.416***
Gas	0.095***
Oil	0.177***
Solid fuels	0.671***
Other	0.728***
constant	5.673***
N	872 056
R-squared	0.664

Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A general issue with the existing metrics is the lack of theoretical consistency, which is rarely mentioned in the literature. This necessitates research on the development of microeconomic foundations that allow transparency, homogeneity and replicability of these metrics. The multidimensional poverty metric also fills this gap, and therefore is a strong contender for adoption by policy-makers as the metric of choice.

Regarding our estimated price elasticities, we find that low income households identified as fuel poor by the multidimensional metric have the smallest own price elasticities in absolute terms. Consequently, increases in fuel prices (via carbon taxation or otherwise) will increase the burden to these households. In addition, we also find that tenants in low income deciles have smaller elasticities in absolute terms than other vulnerable groups.

We found that fuel poor households with low energy efficiency have the lowest energy expenditure levels. This, combined with low demand response, will increase the number of households in fuel poverty. Increases in fuel prices could push these households into energy deprivation. This aspect of fuel poverty is not frequently mentioned, and furthermore expenditure-based metrics can fail to identify households that have low energy expenditure due to under-consumption. Identifying vulnerable households using more accurate metrics can help to implement cost-effective measures that could increase public acceptability of environmental taxes by ensuring these vulnerable households are protected.

Based on our simulation results, we found that increases in energy efficiency and lump-sum transfers can reduce fuel poverty in both the extensive and intensive margins. This lends support to policies that promote increased energy efficiency as a means of simultaneously combating climate change and energy poverty. This has commensurate implications for building standards and regulations, as well as retrofitting policy. In our research, we do not consider the cost and other issues regarding the implementation of the adoption of energy

Table A.15
Results of the EASI demand system estimation. Iterated 3SLS, full sample.

	Food	Housing	Energy	Transport	Education	Other
Polynomial coefficient:						
br_{1i}	0.242***	−0.024	0.012	−0.272***	−0.145***	0.188***
	(0.055)	(0.056)	(0.017)	(0.071)	(0.085)	(0.078)
br_{2i}	−0.123***	0.056**	−0.029***	0.067***	0.037	−0.008
	(0.023)	(0.023)	(0.007)	(0.030)	(0.037)	(0.033)
br_{3i}	0.020***	−0.017***	0.007***	−0.005	0.002	−0.006
	(0.004)	(0.004)	(0.001)	(0.005)	(0.007)	(0.006)
br_{4i}	−0.001***	0.001***	0.000	0.000	−0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Interaction term:						
Zy_{1i}	0.008***	0.002	0.001	0.019***	−0.004	−0.027***
	(0.003)	(0.003)	(0.001)	(0.005)	(0.004)	(0.006)
Zy_{2i}	0.01**	−0.02***	0.004**	0.025***	0	−0.019**
	(0.004)	(0.006)	(0.002)	(0.006)	(0.007)	(0.008)
Zy_{3i}	0.002	0.002	0.001	0.009	−0.006	−0.007
	(0.004)	(0.005)	(0.001)	(0.007)	(0.005)	(0.007)
Zy_{5i}	−0.003	0.008***	0	0.008***	−0.005	−0.009**
	(0.002)	(0.002)	(0.001)	(0.003)	(0.003)	(0.004)
Zy_{6i}	0	0.007***	0	0.024***	−0.013***	−0.017***
	(0.002)	(0.002)	0.000	(0.003)	(0.003)	(0.003)
Interaction between price and expenditure ($b_{i,j}$):						
b_{1j}	−0.041***	−0.003	0.001	0.014***	0.026***	0.004***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.003)	(0.001)
b_{2j}	−0.003	0	0.001	0.002	−0.003	0.003
	(0.002)	(0.002)	(0.001)	(0.002)	(0.004)	(0.002)
b_{3j}	0.001	0.001	−0.008***	0.001	0.003***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	0.000
b_{4j}	0.014***	0.002	0.001	−0.062***	0.022***	0.023***
	(0.002)	(0.002)	(0.001)	(0.004)	(0.003)	(0.003)
b_{5j}	0.026***	−0.003	0.003***	0.022***	−0.073***	0.025***
	(0.003)	(0.004)	(0.001)	(0.003)	(0.009)	(0.004)
b_{6j}	0.004***	0.003	0.002***	0.023***	0.025***	−0.056***
	(0.001)	(0.002)	0.000	(0.003)	(0.004)	(0.005)
Price parameter ($a_{i,j}$)						
a_{1j}	0.158***	−0.023***	−0.004	−0.046***	−0.057***	−0.028***
	(0.008)	(0.006)	(0.003)	(0.006)	(0.009)	(0.006)
a_{2j}	−0.023***	0.038***	−0.01***	0.001	0.003	−0.009
	(0.006)	(0.010)	(0.004)	(0.009)	(0.011)	(0.007)
a_{3j}	−0.004	−0.01***	0.044***	−0.007**	−0.012***	−0.012***
	(0.003)	(0.004)	(0.005)	(0.003)	(0.003)	(0.002)
a_{4j}	−0.046***	0.001	−0.007**	0.16***	−0.05***	−0.058***
	(0.006)	(0.009)	(0.003)	(0.015)	(0.010)	(0.009)
a_{5j}	−0.057***	0.003	−0.012***	−0.05***	0.165***	−0.05***
	(0.009)	(0.011)	(0.003)	(0.010)	(0.022)	(0.010)
a_{6j}	−0.028***	−0.009	−0.012***	−0.058***	−0.05***	0.156***
	(0.006)	(0.007)	(0.002)	(0.009)	(0.010)	(0.017)
Energy requirement						
$log(BER_i)$	0.021***	−0.043***	0.003***	0.002	0.011***	1.007***
	(0.002)	(0.002)	(0.000)	(0.002)	(0.001)	(0.002)
N	18 030					

Significance: * p < 0.10, ** p < 0.05, *** p < 0.01.

efficiency measures, leaving these for further research. Furthermore, given the lower elasticities observed in households experiencing fuel poverty, it may be that energy efficiency upgrades that are targeted towards energy poor households can reduce energy poverty by more than the improvement in energy efficiency across the board, which is simulated here. We leave the consideration of this for future work.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

Tovar Reaños and Lynch acknowledge funding from the ESRI's Energy Policy Research Centre, Ireland.

Appendix A

See Tables A.13–A.15.

A.1. Complete matrix of elasticities

See Table A.16.

A.2. Hicks Equivalent Variation metric (HEV)

The following cost function $C(p, y)$ can be estimated after estimating $a_{i,j,l}$, $b_{i,j}$, $b_{i,r}$, $d_{i,l}$ and g_{il} from the demand system.

$$\begin{aligned}\log\left[C(\boldsymbol{p},y)\right] = y &+ \sum_{i=1}^{I} m_i(y,\boldsymbol{z})\log(p_i)\\ &+ \frac{1}{2}\sum_{i=1}^{I}\sum_{j=1}^{I} a_{ij}\log(p_i)\log(p_j)\\ &+ \frac{1}{2}\sum_{i=1}^{I}\sum_{j=1}^{I} b_{ij}\log(p_i)y\\ &+ \sum_{i=1}^{I}\varepsilon_i\log(p_i)\end{aligned} \tag{A.1}$$

Table A.16
Own- and cross-price elasticities for the lowest expenditure quartile. Full sample.

	Food	Housing	Energy	Transportation	Education	Services
First quartile						
$\Delta\% P_1$	−0.747	−0.035	0.007	−0.006	0.031	0.028
	(0.012)	(0.006)	(0.004)	(0.010)	(0.005)	(0.005)
$\Delta\% P_2$	−0.255	−0.804	−0.075	−0.124	−0.071	0.011
	(0.016)	(0.018)	(0.006)	(0.015)	(0.009)	(0.011)
$\Delta\% P_3$	0.133	−0.005	−0.465	−0.009	−0.033	0.006
	(0.015)	(0.011)	(0.015)	(0.011)	(0.007)	(0.008)
$\Delta\% P_4$	−0.023	−0.034	−0.034	−0.527	−0.056	−0.085
	(0.019)	(0.012)	(0.006)	(0.020)	(0.008)	(0.009)
$\Delta\% P_5$	−0.034	−0.085	−0.090	−0.157	−0.824	0.012
	(0.020)	(0.014)	(0.006)	(0.014)	(0.015)	(0.012)
$\Delta\% P_5$	−0.180	−0.011	−0.080	−0.156	−0.020	−0.994
	(0.010)	(0.006)	(0.003)	(0.007)	(0.005)	(0.009)
Second quartile						
$\Delta\% P_1$	−0.779	0.000	0.014	0.027	0.039	0.058
	(0.010)	(0.005)	(0.003)	(0.007)	(0.004)	(0.004)
$\Delta\% P_2$	−0.121	−0.823	−0.038	−0.099	−0.061	0.024
	(0.009)	(0.010)	(0.003)	(0.009)	(0.005)	(0.008)
$\Delta\% P_3$	0.159	0.030	−0.425	−0.003	−0.036	0.022
	(0.013)	(0.009)	(0.013)	(0.011)	(0.006)	(0.007)
$\Delta\% P_4$	−0.037	−0.084	−0.042	−0.663	−0.057	−0.086
	(0.013)	(0.009)	(0.004)	(0.014)	(0.006)	(0.007)
$\Delta\% P_5$	−0.096	−0.137	−0.084	−0.143	−0.937	0.006
	(0.011)	(0.009)	(0.003)	(0.008)	(0.007)	(0.008)
$\Delta\% P_5$	−0.107	−0.012	−0.054	−0.093	0.014	−1.028
	(0.005)	(0.005)	(0.002)	(0.004)	(0.003)	(0.006)
Third quartile						
$\Delta\% P_1$	−0.818	0.011	0.016	0.059	0.036	0.072
	(0.011)	(0.007)	(0.003)	(0.008)	(0.005)	(0.005)
$\Delta\% P_2$	−0.064	−0.792	−0.025	−0.080	−0.052	0.035
	(0.009)	(0.010)	(0.002)	(0.009)	(0.005)	(0.006)
$\Delta\% P_3$	0.183	0.033	−0.383	0.009	−0.049	0.025
	(0.014)	(0.009)	(0.015)	(0.013)	(0.007)	(0.007)
$\Delta\% P_4$	−0.011	−0.100	−0.034	−0.799	−0.051	−0.065
	(0.011)	(0.009)	(0.004)	(0.014)	(0.006)	(0.006)
$\Delta\% P_5$	−0.118	−0.151	−0.070	−0.126	−0.993	0.001
	(0.010)	(0.009)	(0.003)	(0.008)	(0.008)	(0.006)
$\Delta\% P_5$	−0.073	−0.016	−0.038	−0.052	0.032	−1.043
	(0.003)	(0.004)	(0.001)	(0.004)	(0.003)	(0.005)
Fourth quartile						
$\Delta\% P_1$	−0.959	−0.021	0.025	0.164	0.073	0.072
	(0.019)	(0.013)	(0.005)	(0.015)	(0.012)	(0.007)
$\Delta\% P_2$	−0.032	−0.680	−0.012	−0.021	−0.023	0.083
	(0.016)	(0.020)	(0.005)	(0.018)	(0.012)	(0.009)
$\Delta\% P_3$	0.222	−0.013	−0.514	0.076	−0.049	−0.017
	(0.031)	(0.026)	(0.035)	(0.024)	(0.016)	(0.012)
$\Delta\% P_4$	0.075	−0.081	−0.010	−1.176	0.000	0.026
	(0.014)	(0.014)	(0.003)	(0.020)	(0.011)	(0.009)
$\Delta\% P_5$	−0.045	−0.108	−0.034	−0.032	−1.193	0.054
	(0.014)	(0.011)	(0.003)	(0.012)	(0.016)	(0.009)
$\Delta\% P_5$	−0.038	−0.021	−0.021	0.026	0.071	−1.104
	(0.003)	(0.004)	(0.001)	(0.005)	(0.004)	(0.006)

where p_i are commodity prices, y is the implicit household utility, $m_i = \sum_{r=0}^{R} b_r \log(y)^r + \sum_l d_{il} z_l \log(y) + \sum_l g_{il} z_l$, and z_l are demographic characteristics. R is the degree of the polynomial and ϵ_i represents unobserved preference heterogeneity. We can describe the impacts of changes in welfare by estimating Hicks' equivalent variation (HEV). $HEV = C(p^0, U^1) - C(p^0, U^0)$, where U is the level of household utility. The indices 0 and 1 represent the initial and post-tax periods.

$$\begin{aligned} HEV = exp &\left\{ \sum_i \log p_i{}^0 w_i(y, p_i{}^0) - \kappa * [\sum_i \log p_i{}^1 w_i(y, p_i{}^1)] \right. \\ &- [\frac{1}{2} \sum_{l=0}^{L} \sum_{i,j} a_{i,j,l} \log p_i{}^0 \log p_j{}^0 z_l \\ &\left. -\kappa * \frac{1}{2} \sum_{l=0}^{L} \sum_{i,j} a_{i,j,l} \log p_i^1 \log p_j^1 z_l] + \kappa * \log pX^1 \right\} \\ &- X^0, \end{aligned} \tag{A.2}$$

where

$$\kappa = \frac{[1 - \frac{1}{2} \sum_{i,j} b_{i,j} \log p_i{}^0 \log p_j{}^0]}{[1 - \frac{1}{2} \sum_{i,j} b_{i,j} \log p_i^1 \log p_j^1]} \tag{A.3}$$

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