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

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Abstract: We assess the existing battery of metrics for measuring energy affordability. We analyse expenditure-based metrics and recently-developed metrics for multidimensional poverty under simulated scenarios which allow for the introduction of carbon taxation, increased housing costs, revenue re-allocation and increases in energy efficiency. We deploy the Exact Affine Stone Index (EASI) implicit Marshallian demand system to parameterise a microsimulation model. Expenditure-based metrics used by official bodies in Europe perform very poorly in capturing the impacts of both carbon taxation and policy responses. Multidimensional poverty metrics provide more intuitive results. Evidence from these metrics show that revenue recycling can mitigate the impacts of increased energy and housing costs in the extensive and intensive margins of energy poverty, while energy efficiency can exacerbate the intensity of those already classified as "energy poor".

Keyword(s): Household energy demand, energy taxes, microsimulation, Energy poverty

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1. Introduction

Energy poverty is defined by Pye et al. in [1] 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 are defined on the basis of only two variables, disposable household income and energy expenditure [see 2]. In addition, these metrics assume that these variables do not change, raising the question of how changes in energy expenditure, disposable income and energy efficiency affect the measurement of deprivation of energy consumption. In a context where carbon taxation has emerged as a key policy tool for environmental protection, lack of knowledge on how to appropriately measure energy poverty leaves an important gap that needs to be investigated, particularly when considering policies to protect vulnerable households. In this regard [3] analyse several channels that are already used in some jurisdictions to re-allocate additional revenues to compensate vulnerable households and improve public acceptance of carbon taxation. This raises the question of how metrics for energy affordability behave under changes in energy prices and household incomes due to increases in carbon taxes and re-allocation of additional revenues.

Increases in energy efficiency are seen as a key policy instrument to overcome energy poverty. However, [4] found that increases in energy efficiency might not yield reductions in energy consumption for the poorest households. In addition, the property value after retrofitting does not increase for these household types. Consequently, grants for energy efficiency need to be carefully designed. To the best of our knowledge this study is the first one that analyses how measures of energy affordability respond to changes in energy prices, energy efficiency and household expenditure using a behavioral microsimulation model. In this study, we also quantify energy affordability using a multidimensional approach for the first time. Under this approach, different dimensions of deprivation can be simultaneously considered when measuring energy affordability. In addition, multidimensional metrics can capture the extension of energy poverty and its intensity experienced by the individuals that are already in this condition.

Several reviews of the question of energy poverty from a policy perspective exist, see for example [5], [6] and [7]. Both the measurement and alleviation of energy poverty surface as important considerations. [8] recommends several different measures of energy poverty for use in EU policy-making. However, the incidence and extent of energy poverty varies greatly depending on the metric chosen. These works point out that there are several drivers of energy poverty, including energy prices themselves, low income, energy inefficient dwellings and energy inefficient appliances. The drivers of energy poverty are therefore (a) multidimensional, and (b) most likely correlated with other forms of deprivation. Furthermore, of particular relevance to policy makers is the impact of new policies, such as environmental taxes and/or energy efficiency retrofits, on energy poverty and on deprivation in general. We therefore examine these issues by means of a microsimulation model to evaluate existing energy poverty metrics and potential policy responses. The interaction between various indicators of deprivation when determining the extent of energy poverty has been considered at various points in the literature, giving rise to the concept of *multidimensional poverty*. [9] propose a methodology both for counting the number of deprivations being experienced by each household and for determining the depth of the deprivation in each case. We apply this methodology to determine the extent of energy poverty in Ireland.

The literature on energy poverty is broad and we focus on those articles that are most relevant to our study, either from a geographic or methodological point of view. The question of energy poverty in an Irish context has been addressed in two papers. The first, [10], estimates the extent of fuel poverty in Ireland using expenditure on fuel as a proportion of total income, and using a subjective self-reported metric. The work also identifies characteristics of households most likely to experience fuel poverty and discusses potential policy implications. [11] uses factor analysis and a multinomial regression to determine that fuel poverty is not a distinct type of deprivation in Ireland, and therefore does not warrant a policy response separate to that of addressing poverty in general.

Outside of Ireland, the suitability of the energy poverty metrics used by policy makers has received attention in the literature. [12] uses data from France to analyse the extent of fuel poverty. They question the suitability of defining fuel poverty as expenditure on fuel of 10% or more of net income, 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. [13] also questions expenditure-based metrics of fuel poverty by considering housing costs in tandem with low income with high fuel expenditure. They propose alternative metrics for fuel poverty and identify households at risk of fuel poverty. [14] uses German data to review the choice of fuel poverty line and the measurement of fuel poverty. The number of households determined to be experiencing fuel poverty is found to be highly sensitive to the fuel poverty line chosen. [15] use French data to examine the interaction between fuel poverty and self-assessed health, finding a causal relationship, by means of instrumental variables. [16] uses Armenian data to examine the impacts of a reform to the country's natural gas tariffs on poverty (as opposed to fuel poverty). They find that increased gas tariffs led to a switch away from gas and also to an increase in the number of households falling below the poverty line.

There is very little literature that employs a behavioural microsimulation approach to examine energy poverty. [17] uses a 'morning after' microsimulation model to examine the dynamic behaviour of various energy poverty metrics, and finds that some measures, including metrics recommended and used by the European Commission, described in [8], exhibit odd dynamic behaviour. However, this microsimulation exercise does not capture behavioural responses to changes in prices and income.

In contrast, this paper performs a behavioural microsimulation, paramaterised through the estimation of a demand system, which we then use to examine energy poverty. A demand system is a behavioural model that represents consumption decisions as a system of equations which depend on prices, consumption budgets, and observed as well as unobserved household characteristics. Demand systems have been used to study households' energy use and carbon emissions [see 18, 19, 20, 21, 22]. A significant limitation of the existing literature is the assumed shape of 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 (i.e. the Almost Ideal Demand System (AI-DS) model proposed by [23]) or quadratic Engel curves (i.e. Quadratic Almost Ideal Demand System (QUAIDS) proposed by [24]).

Relevant literature that employs demand systems to examine energy poverty include [25]. They use experimental data from India to construct a demand system for solar PV and for grid electricity. [26] uses the QUAIDS model to determine the impact of environmental taxes on both emissions and household welfare in Mexico. [27] also uses QUAIDS to determine the impact of energy price changes in Indonesia, and finds that energy pricing policies can reduce both emissions and welfare, and so should be accompanied by compensation measures. [28] uses a demand system to examine the distributional impacts of carbon taxes, and finds they depend on the underlying demand structure. Here we use a more flexible approach where Engel curves are allowed to have any shape. We followed [29] and employ the Exact Affine Stone Index (EASI) implicit Marshallian demand system.

In this paper, we use our 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 consider three different energy poverty metrics proposed by the EU Commission, described in [8]. We then go significantly beyond the extant microsimulation literature on energy poverty by considering the multidimensional poverty framework proposed by [9]. Furthermore, we also consider the impacts of increased housing costs, which [13] proposes are the "elephant in the room" when it comes to energy poverty. As a final novel contribution, we simulate the impact of two oft-proposed policy interventions to mitigate the increase in energy poverty, namely an increase in energy efficiency of dwellings via housing retrofits and a policy that recycles the revenues from carbon taxation back to households.

In line with [17] we find that expenditure-based metrics for energy poverty have two important drawbacks. First, they can only capture the extensive margin of energy poverty (i.e. the relative number of households experiencing energy poverty). Second, they have a counterintuitive behaviour, in that metrics based on setting the threshold above the median of expenditure find the largest proportion of energy poor in high income levels, while metrics based on minimum standard of living find increases of energy poverty when there is a lump-sum transfer. Recent proposals for multidimensional poverty open a promising door to designing more efficient policies to protect vulnerable households and so form the final part of our analysis.

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 [29]. 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 are 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 [30] and [31].

The generalized method of moments (GMM) estimator or an iterated linear approximation can be used to estimate the demand system. [29] propose the following expenditure function:

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

where

$$
m_i = \sum_{r=0}^{R} b_r \log(y)^r + \sum_{l} d_{il} z_l \log(y) + \sum_{l} g_{il} z_l \tag{2}
$$

and 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 m_i. This specification allows for highly flexible Engel curves while still keeping the functional form quite comprehensible. $a_{i,j,l}$, $b_{i,j}$, $b_{i,r}$, $d_{i,l}$ 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 [23] and the Quadratic Almost Ideal Demand System (QUAIDS) proposed by [24] assume linear and quadratic Engel curves. [29] has shown that the EASI demand system can approximate these models by setting r in the polynomial of m_i either linear or quadratic.

[29] show that the implicit utility, y, can be expressed in the following way:

$$y = \frac{\log(x) - \sum_i w_i \log(p_i) + \frac{1}{2}\sum_i \sum_j a_{i,j} \log(p_i) \log(p_i)}{1 - \frac{1}{2}\sum_i \sum_j b_{i,j} \log(p_i) \log(p_j)} \tag{3}$$

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:

$$\begin{aligned} w_i = & \sum_j a_{i,j} \log p_j + \sum_j b_{i,j} \log y \\ & + \sum_{r=0}^{R} b_{i,r} [\log y]^r + \sum_l g_{i,l} z_l + \sum_l d_{i,l} z_l \log y + \epsilon_i. \end{aligned} \tag{4}$$

[29] shows that (4) can be estimated with an approximation of y or with (3), with very similar estimates[2]. 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).

The estimated expenditure function must have all the properties that hold for a theoretical expenditure function [32]. The following restrictions ensure the theoretical consistency of the estimated expenditure function:

$$\begin{aligned} a_{i,j,l} = a_{j,i,l} \quad \text{and} \quad & \sum_i a_{i,j,l} = 0 \ \forall \ l, \\ b_{i,j} = b_{j,i} \quad \text{and} \quad & \sum_i b_{i,j} = 0, \\ \sum_i d_{i,l} = & \sum_i g_{i,l} = 0 \ \forall \ l, \\ \sum_i b_{i,r} = & \ 0 \text{ for } r \neq 0, \\ \sum_i b_{i,r} = & \ 1 \text{ for } r = 0, \end{aligned} \tag{5}$$

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

[2] 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.

DispInc	A household is determined to be experiencing energy poverty if their expenditure on energy is greater than 10% of their disposable household income
AboveMed	Above the median: A household is determined to be experiencing energy poverty if their expenditure on energy is more than the national median energy expenditure
MISLI	Minimum Income Standard Low-Income: A household is considered to be experiencing energy poverty if disposable income after energy costs is below the median income of the poorest 40 % after housing and energy costs

Table 1: Expenditure-based energy poverty metrics considered

We use information on intra-group variation of the aggregated consumption categories to obtain household-specific prices following [33] to further improve identification. Once the parameters in equation 4 are estimated, own-price elasticities (OPE) and expenditure elasticities (EE) can be computed as follows:

$$OPE = \left\{ \frac{\partial w_i}{\partial \log(p_i)} \right\} \frac{1}{w_i} - 1 \tag{6}$$

$$EE = \left\{ \frac{\partial w_i}{\partial \log(X)} \right\} \frac{1}{w_i} + 1 \tag{7}$$

2.2. Calculation of energy poverty metrics

Once the demand system above has been estimated, we use microsimulation to determine the impact of increasing fuel and housing costs on energy poverty, and to evaluate two potential policy responses. We first consider three expenditure-based energy poverty metrics recommended by the European Commission and described in [8]. The metrics we examine are described in Table 1.

In addition to these metrics, we calculate the proportion of households experiencing multidimensional poverty, as proposed in [9]. The methodology requires computing a *multidimensional headcount ratio*, H, which measures the incidence of simultaneous deprivation in the population. The index A then computes the *breadth* of simultaneous deprivation. The index $M_0 = H \cdot A$ computes the proportion of households experiencing multidimensional poverty, while the index M_1 considers the incidence of poverty H, the breadth of deprivation (A) and the average depth of deprivation across the deprived dimensions G. Finally the metric S can be computed, which is the average severity of deprivations.

The index H is given by

$$H = \frac{\sum_{i=1}^{N} \rho_k(y_i, z)}{N} = \frac{q}{N} \tag{8}$$

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 $w_{i,j}$ if $y_{i,j} < z_{i,j}$ and zero otherwise, for all households i and deprivation indicators j. The vector w_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:

$$A = \frac{\mid g^0_k \mid}{q} \tag{9}$$

M_0 is then computed as the product of H and A.

M_1 is computed by

$$M_1 = M_0 \cdot G = \frac{\mid g^1(k) \mid}{N} \tag{10}$$

,

where $g^1(k)$ is the sum of the poverty gaps of poor individuals and G is the average poverty gap across all possible deprivations,

$$G = \frac{\mid g^1(k) \mid}{\mid g^0(k) \mid} \tag{11}$$

Finally S is given by

$$S = \frac{\mid g^2(k) \mid}{\mid g^0(k) \mid} \tag{12}$$

where $g^2 = g^0 * \frac{z-y_0}{z}^2$ is an indicator of the rate in which a poor household becomes poorer[3].

The deprivation metrics y we consider are threefold: (i) income, (ii) equivalised energy consumption and (iii) energy requirement. The associated thresholds z we choose are (i) disposable income net of housing costs of less than 60% of the median, (ii) energy usage per person in kWh of less than the median and (iii) a dwelling energy requirement in kWh per m^2 greater than the median, respectively. We choose $k = 2$, and so ρ is equal to one if a household is below the threshold for at least two of these three deprivation metrics.

We perform two analyses, an unweighted analysis where the three deprivations considered are equally weighted ($w_j = \frac{1}{3} \; \forall \; j$) and a weighted analysis where the weighting on income is 45%, on energy requirement is 35% and on the quantity of energy used is 20%.

We compute these metrics using the mpi command in Stata [34].

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[4]. We use the waves from 1994, 1999, 2004, 2009 and 2015-2016 in this work, in a pooled cross-sectional manner. We also use indices for commodity prices for the same years provided by the CSO.

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 [30] and [35]. This grouping largely follows the Classification of Individual Consumption According to Purpose (COICOP). As in [18], we

[3] The expression generalises to $g^\alpha = g^0 * \frac{z-y_0}{z}^\alpha$

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

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 consumption of durables is an investment and in order to model changes in household investment would require a different approach from the one used in this study. Summary statistics for expenditure and price data are shown in Table 2.

Variable	Mean	Std. Dev.
Expenditure shares:		
Food	0.243	0.112
Housing	0.15	0.117
Energy	0.05	0.034
Transport	0.094	0.054
Education	0.145	0.134
Services	0.319	0.144
Prices (logs):		
Food	4.218	0.271
Housing	3.272	0.499
Energy	3.756	0.41
Transport	3.584	0.524
Education	3.525	0.883
Services	2.846	0.89
Total expenditure	996.004	1251.262
Income	10385.469	27988.161
Energy requirement (kWh/m^3)	263.912	94.116
Rural	0.339	0.473
Washing_machine	0.973	0.162
Dishwasher	0.597	0.490
Fridge	0.339	0.473
Owning a car	0.878	0.328
N	18504	

Table 2: Summary statistics

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, a dishwasher and a fridge, and finally whether the household owns a car. Summary statistics for these variables are also shown in Table 2. We also include dummy variables in our econometric specification for the quarter in which the data were collected.

Regarding energy efficiency, we follow [36] and use the data from The Sustainable Energy Authority of Ireland (SEAI). SEAI maintains a public register of completed Energy Performance Certificates (EPCs), termed Building Energy Ratings (BERs) in Ireland[5]. BERs are determined as the inverse of the energy requirement of the dwelling, expressed as kWh/m^3. In order to determine the energy requirement of each dwelling in our sample, we rerun the regression as in [36] with updated data and an adjusted specification to suit the data available in the household budget survey (HBS) [6]. The estimates are displayed in Table 3. The parameters are in line with the estimates provided by [36]. In general, one can see that 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 2.

Interaction of expenditure levels and variables for family types are introduced in the econometric specification. Family categories are shown in Table 4.

Heating and lighting expenditure, which we shall also denote as "energy" expenditure throughout the paper, comprises expenditure on electricity, natural gas, liquid fuels and solid fuels. Transportation expenditure comprises petrol, diesel, maintenance, insurance and public transport. Carbon taxes in the non-ETS sector affect the prices of heating fuels and of fuels for private transportation, 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.

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

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

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	872056
R-squared	0.664

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

Table 3: Dependent variable log(energy requirment). Using ordinary least squares

	Sample size	Frequency
Adult aged 14-64 years	1,633	8.83
1 adult aged 65 or over	1,408	7.61
Single adult with children	862	4.66
Married couple with children	5,457	29.49
Married couple only	3,517	19.01
Rest other households	5,627	30.41

Table 4: Household types

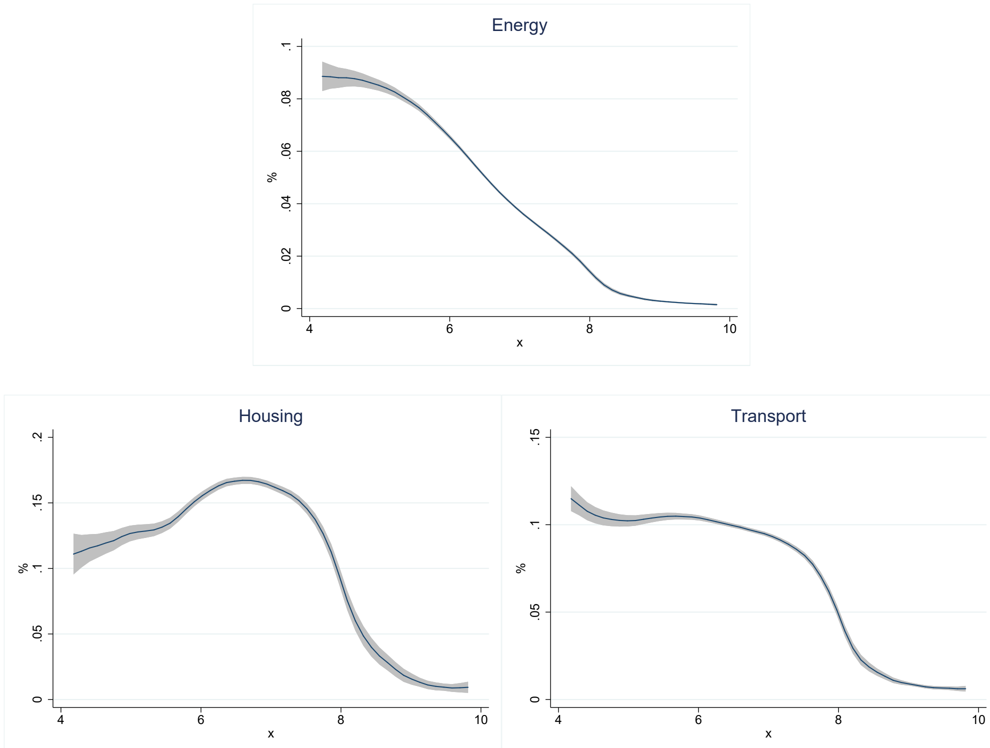

Figure 1: Engel curves across the logarithm of total expenditure

Figure 1 shows the Engel curves for expenditure on energy, housing and transport. These commodities make up a larger share of expenditure in lower income households. The nonlinearity evident in the Engel curves justifies the EASI demand system approach, as an AIDS or QUAIDS specification would be unable to capture the expenditure functions that describe the underlying data.

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. Figure 2 shows the average energy requirement of dwellings by income quartile, which decreases as incomes increase, indicating that more affluent households live in more energy efficient properties. The equivalised energy demand in kWh is also shown, which increases across income quartiles.

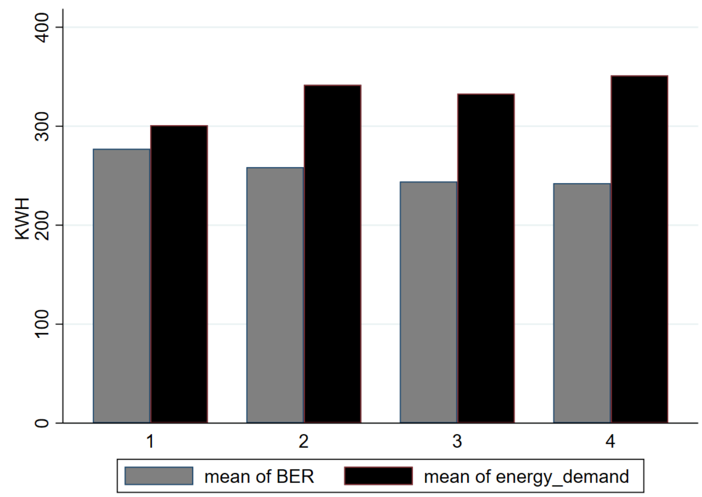

Figure 2: Energy requirement and energy consumption

3.2. *Microsimulation scenarios*

We determine the impact on energy poverty of several potential scenarios via microsimulation. We simulate the impact of increasing carbon taxation by 94 €per tonne, which according to [3] is the level required in order to reach the goals set in the Paris agreement. A carbon tax was introduced in 2010 in Ireland which applies to non-ETS emissions and currently stands at €26 per tonne. Consequently, the carbon tax that we simulate is of 120 €per tonne. Fuel for heating and fuels for private transportation are affected under this scenario. We apply the tax increase to both heating and transportation commodities, and we also increase the cost of housing (rent or mortgage repayment) by 30%. We model the impacts of both sets of cost increases when combined with an increase in energy efficiency, by decreasing the energy requirement of each dwelling by 50 kWh/m^2. Finally we model the impact when combined with a revenue recycling scheme, where the revenue from carbon taxation is distributed via a lump sum payment to each household, colloquially known as a "green cheque". Table 5 summarises these scenarios.

Scenario	Description	Income change	Price change
NoTax	No increase to tax or housing	NO	NO
Tax	Tax and housing increase	NO	YES
TaxRev	Tax and housing increase; lump-sum	YES	YES
TaxEff	Tax, housing and energy efficiency increase	NO	YES

Table 5: Scenario overview

4. Results

4.1. EASI demand system estimation

The results of the results of the EASI demand system estimation are shown in Table 4.1. We find statistically significant and greater than zero parameters for the polynomials of up to degree six. This confirms the non-linearity of the Engel curves and justifies the EASI demand system approach used.

The columns in Table 4.1 give the polynomial coefficients for the equations describing expenditure on each commodity group. The inclusion of the variable for 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. The positive sign on this coefficient in the case of energy expenditure is intuitive: as the energy requirement of a dwelling increases, so too does the expenditure on energy. The negative coefficient on housing reflects the fact that low efficiency houses tend to be of poorer quality and therefore have a lower rent or mortgage repayments. The positive coefficients on the other commodity groupings may be driven by the fact that families in less energy efficient households spend less time at home or consume more alcohol or tobacco (which are included in the "food" category). The exact identification of the drivers of these results are beyond the scope of this paper.

4.2. Elasticities

Table 7 shows the own-price and cross-price elasticities of each commodity group for the lowest income quartile. The expenditure elasticity of energy is lowest of all commodity groups, which is a natural consequence of the fact that energy is (a) a necessary good and (b) has few substitutes. Transport's own price elasticity is second lowest, for similar reasons. The cross price elasticities show that increases in housing prices will reduce the demand of essential commodities such as food, energy, transport and education. Increases in the price of transportation have the same effect.

Regressor:	Dependent variable: budget share for...				
	Food	Housing	Energy	Transport	Education
Polynomial coefficient:					
y1	1.080***	0.416	0.133	0.104	-0.602
y2	-0.789***	-0.329	-0.099	-0.147	0.538*
y3	0.285***	0.151	0.024	0.069	-0.263**
y4	-0.057***	-0.038	-0.002	-0.017	0.072***
y5	0.006***	0.005*	0.000	0.002*	-0.010***
y6	-0.000***	-0.000**	0.000	-0.000*	0.000***
Household types:					
z1	-0.067***	-0.010	-0.011***	-0.010**	0.021*
z2	-0.086***	-0.046***	-0.010***	0.011*	-0.022
z3	-0.007	-0.030*	0.002	-0.015**	0.010
z4	0.000	0.000	0.000	0.000	0.000
z5	0.005	-0.087***	-0.001	-0.009**	0.032***
z6	0.020***	-0.060***	-0.002	0.004	0.013
Interaction term:					
yz1	0.007**	0.006	0.001	0.002	-0.001
yz2	0.014***	-0.010*	0.002	-0.009***	0.020***
yz3	-0.003	0.007	0.000	0.003	0.003
yz4	0.000	0.000	0.000	0.000	0.000
yz5	-0.002	0.014***	-0.000	0.003**	-0.006**
yz6	0.003	0.007***	0.000	0.003***	-0.003
Interaction between price and expenditure ($b_{i,j}$):					
ynp1	-0.038***	-0.006***	0.001	-0.002	0.047***
ynp2	-0.006***	-0.003	0.001	0.004***	-0.003
ynp3	0.001	0.001	-0.008***	0.002***	0.003***
ynp4	-0.002	0.004***	0.002***	-0.014***	0.007***
ynp5	0.047***	-0.003	0.003***	0.007***	-0.084***
Price parameter ($a_{i,j,l}$)					
np1	0.143***	-0.018***	-0.005**	-0.010***	-0.102***
np2	-0.018***	0.050***	-0.008***	-0.015***	0.007
np3	-0.005**	-0.008***	0.047***	-0.011***	-0.012***
np4	-0.010***	-0.015***	-0.011***	0.072***	-0.018***
np5	-0.102***	0.007	-0.012***	-0.018***	0.175***
Log(Energy requirement) 0.022***	-0.054***	0.003***	-0.004***	0.015***	
constant	-0.370**	0.304	0.015	0.168**	0.298
N	18504				

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

Table 6: Results of the EASI demand system estimation. Iterated 3SLS, 3 digits

	Food	Housing	Energy	Transport	Education	Services
Food	-0.669	0.093	0.133	0.092	0.140	0.107
Housing	-0.109	-0.780	-0.029	-0.050	-0.028	0.110
Energy	0.000	-0.021	-0.450	-0.028	-0.032	-0.094
Transport	-0.128	-0.049	-0.026	-0.455	-0.017	-0.068
Education	-0.066	-0.102	-0.112	-0.099	-0.877	0.034
Services	-0.287	-0.189	-0.283	-0.280	-0.210	-1.170

Estimates are statistically significant at 5% level of significance.

Table 7: Own- and cross-price elasticities for the lowest expenditure quartile

Given the fact that this is the first attempt to estimate these elasticities for Ireland using the EASI demand system, and the aggregation approach used here is also not used in the previous literature for Ireland, a direct comparison with previous estimates is not possible. Our estimated own price elasticities for lighting and heating and transport are nonetheless in line with estimates found in the literature for other countries: [31] in the case of Germany, [37] in the case of Ireland, and [38] for six different European countries. In terms of transport, a wide range of estimates exists in the literature: [38] finds a weighted average of 0.47, while [39] report an average expenditure elasticity for transport across 45 OECD countries as 1.58. Our estimates are within these two estimates.

Table 8 shows the expenditure elasticities for each commodity group by income quartile. One can see that expenditure elasticities for food, housing, energy and transport are inelastic. Consequently these commodities are necessary goods. Increases in the price of these commodities will have regressive effects. Increases in household expenditure will have the largest response in the demand for energy and housing for the lowest income quartile. This is important when modelling lump-sum transfers as this will lead to a greater proportional increase in disposable income and consequently in consumption of these commodities for low income households.

Table 9 shows the elasticity of each commodity group when the energy requirement of each dwelling decreases. Decreases in the kWh/m^2 (i.e. energy requirement of each dwelling) reduces energy demand. This elasticity increases across income quartiles, which may reflect a budget constraint. Vulnerable households are constrained in their ability to decrease energy demand as the energy requirement decreases. The positive sign on the elasticity for

Quartile:	Food	Housing	Energy	Transport	Education	Services
1	0.522	0.861	0.212	0.589	1.373	1.889
2	0.607	0.734	0.167	0.651	1.679	1.530
3	0.654	0.650	0.142	0.679	1.739	1.345
4	0.693	0.320	0.315	0.614	1.536	1.246

Estimates are statistically significant at 5% level of significance.

Table 8: Expenditure elasticities by income quartile

housing indicates that energy inefficient dwellings are concentrated in poorer quality housing stock, which have a lower market value. In general, these elasticities reflect the coefficient on energy requirement that was estimated by the EASI system (see Table 4.1).

Quartile:	Food	Housing	Energy	Transport	Education	Services
1	-0.071	0.390	-0.040	0.034	-0.154	-3.821
2	-0.085	0.318	-0.054	0.035	-0.131	-3.508
3	-0.096	0.312	-0.074	0.036	-0.115	-3.161
4	-0.126	0.382	-0.119	0.044	-0.077	-2.690

Estimates are statistically significant at 5% level of significance.

Table 9: Energy requirement elasticities by income quartile

4.3. Microsimulation results

Table 10 shows mean values of energy consumption, expenditure and equivalised income net of housing and energy costs in the NoTax case, as well as proportional changes of these quantities under the various scenarios considered (see Table 5) for each income quartile. After carbon tax and housing costs increase, low income households have the largest reduction in energy consumption and the largest fall in equivalised income. Under the TaxRev scenario, where revenues from carbon taxation are distributed via a lump sum, the equivalent income of low income households increases relative to the NoTax scenario, prompting increases in energy consumption and expenditure. For higher income households, there is a slight reduction in income and a greater reduction in energy consumption. In the TaxEff scenario energy demand decreases even further, as a result of both the carbon tax and the increase in energy efficiency. More affluent households experience larger reductions in energy expenditure, showing that they profit more than poor households from improvements in energy efficiency. In the scenario TaxEff_2, improvements in energy efficiency are targeted towards low income households: the energy requirement of the lowest quartile's dwellings is reduced by 50kWh/m^2, as in TaxEff. The improvements in energy efficiency reduce gradually across expenditure quartiles, where the most affluent households get a reduction in energy requirement of 10 kWh/m^2. One can see that changes in energy expenditure are distributed homogeneously across income levels.

	Income quartile:			
	1st	2nd	3rd	4th
NoTax:				
Energy (KWH)	301.038	341.825	333.041	351.332
Expenditure (€)	21.434	24.535	24.349	25.870
Income(€)	129.016	336.502	586.235	938.747
	Δ w.r.t. the NoTax scenario (%)			
Tax:				
Energy	-7.650	-6.235	-5.203	-6.614
Expenditure	6.980	7.355	8.000	6.340
Income	-2.302	-1.395	-1.184	-1.149
TaxRev:				
Energy	-5.715	-5.437	-4.828	-6.420
Expenditure	9.238	8.238	8.415	6.560
Income	2.924	0.297	-0.295	-0.628
TaxEff:				
Energy	-8.313	-7.211	-6.780	-8.828
Expenditure	6.174	6.170	6.130	3.739
Income	-4.450	-2.782	-2.431	-2.325
TaxEff_2 :				
Energy	-8.313	-6.776	-5.770	-7.002
Expenditure	6.174	6.695	7.317	5.884
Income	-4.450	-2.167	-1.626	-1.352

Table 10: Changes in energy consumption, expenditure and equivalised income under different scenarios (%)

4.3.1. Expenditure-based energy poverty metrics

We now examine the impact of the various microsimulation scenarios considered, outlined in Table 5, on energy poverty. First, we examine the metrics DispInc, AboveMed and MISLI, as per [8] and Table 1, shown in Figure 3.

Regarding the expenditure base metrics, the first panel of Figure 3 shows the energy poverty metric DispInc under the NoTax and Tax scenarios. The DispInc metric classifies households as experiencing energy poverty if their expenditure on energy is greater than 10% of their disposable household income. The second panel in Figure 3 represents the proportion of households considered to be experiencing energy poverty under the AboveMed metric, which binds when a household spends more than the national median energy expenditure. The third panel shows the proportion of households experiencing energy poverty as defined by the MISLI metric, where disposable income after energy costs must be below the median income of the poorest 40% of households after housing and energy costs.

Surprisingly, only the simplest of these three metrics, DispInc, shows a consistent increase in energy poverty after the increase in carbon taxation. This increase, however, is very slight. There is no discernible difference after the introduction of carbon taxation in the proportion of households experiencing energy poverty under the MISLI metric, while the AboveMed metric actually sees a decrease in energy poverty for low income households from carbon taxation, and an increase or no effect for high income households. Furthermore, the AboveMed metric shows that the proportion of households experiencing energy poverty increases, rather than decreases, in income. This suggests that AboveMed is not an appropriate metric for determining energy poverty by any criterion, and that MISLI is also limited in its ability to capture changes in prices and expenditure brought about from carbon taxation. A clear policy response is therefore difficult to determine on the basis of these metrics, but our results suggest that these metrics are not fit for purpose.

We now examine the impacts of policy measures designed to decrease energy poverty, TaxRev and TaxEff described in Table 5. We present the results for a €100 increase in carbon taxation, shown in Figure 4.

In general the DispInc metric show increases in energy poverty after increases in housing and carbon prices. TaxRev shows a very slight decrease in energy poverty relative to the Tax scenario, while TaxEff make no difference. The pattern of the AboveMed metric is similar to the NoTax scenario, show-

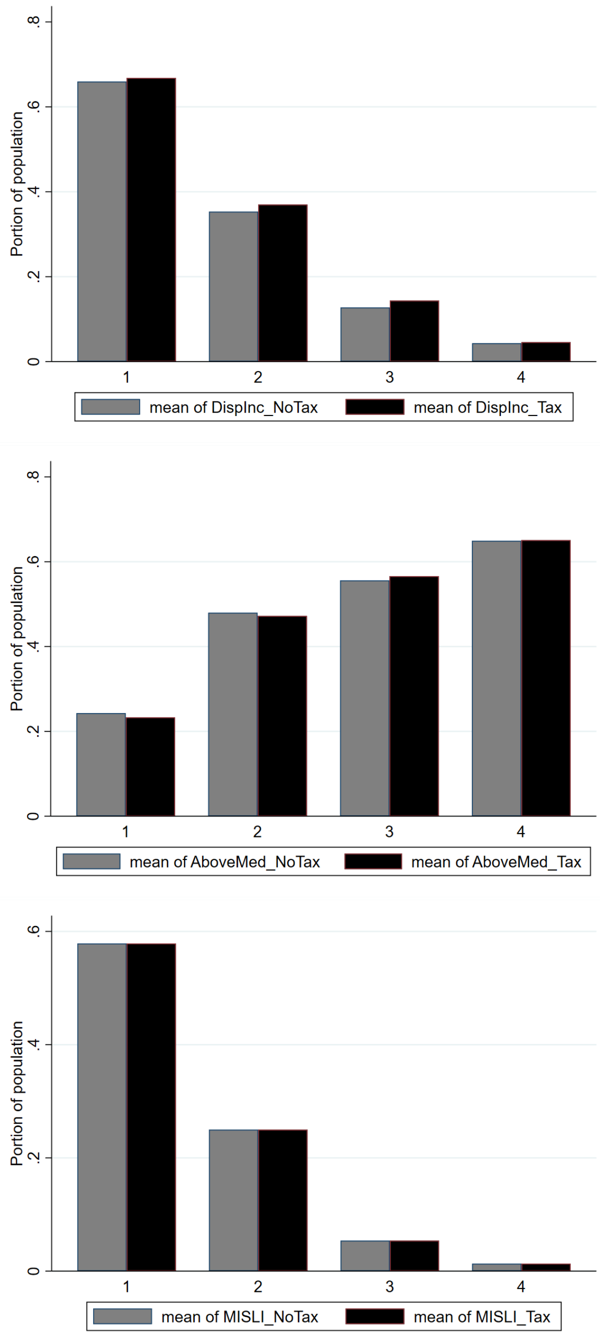

Figure 3: Portion of households determined to be experiencing energy poverty under the base and a carbon tax scenario of an increase of carbon taxes by €100/t

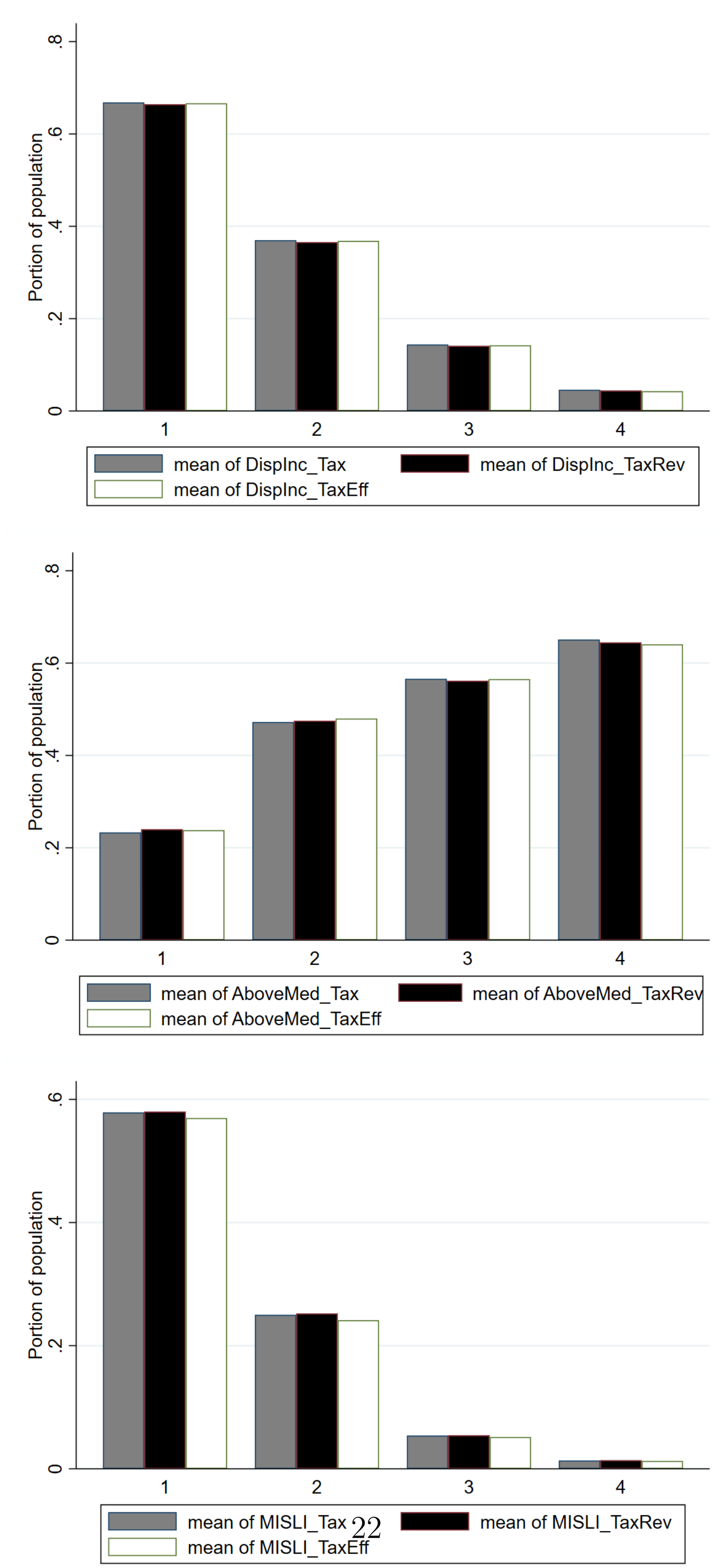

Figure 4: Percentage of households determined to be experiencing energy poverty under various metrics and scenarios

ing only a small proportion of energy poor households in the lowest income quartile, with very slight impacts from the policy measures and with unexpected results (eg, energy poverty increases in quartile 1 under the TaxRev scenario). The MISLI metric moves in the right direction after tax. However, both this metric and the AboveMed metric show increases in energy poverty after transfers. The TaxEff policy, however, shows a very slight decrease in energy poverty.

The results here suggest that the results reported by [11], which found that energy poverty is not a distinct type of deprivation, may actually understate the unsuitability of energy poverty as a policy metric. In fact, the expenditure-based metrics above lead to misleading conclusions, rather than a mere meaningless distinction between poverty and energy poverty, as argued in [11]. The microsimulation exercise used here allows us to model changes in energy consumption and expenditure after changes in both income and commodity prices. The lump-sum transfer modelled here increases the energy demand (i.e. as shown by the income elasticities) and expenditure, which increases the number of households in energy poverty as defined by these metrics. In other words, these metrics indicate that the optimal policy for combating energy poverty in the presence of carbon taxation is to do nothing. This is hardly the case.

4.3.2. Multidimensional poverty results

We now present the results of the multidimensional poverty analysis. Tables 11 and 12 show the proportion of households experiencing multidimensional poverty in all scenarios. We analyse three dimensions of deprivation: equivalised income, energy consumption and energy efficiency, with the thresholds chosen described in section 2.

Table 11 shows the head counting ratio (H), the average weighted number of deprivations (A), the multidimensional poverty index (M_0), the average poverty gap (M_1) and the average severity of deprivations (S) for the NoTax scenario. Rows 2-4 show the relative changes of these metrics with respect to the NoTax scenario.

The estimation of poverty metrics allows us to weight each dimension of poverty equally or unequally. [11] show that fuel poverty is not a distinct dimension of general deprivation that can be better explained by householders characteristics than by dwelling characteristics. Following this finding in Table 11, weights are allocated as follows: energy efficiency (0.35), equivalised income (0.45), energy demand (0.2). In addition, we show that energy

	H	M_0	M_1	A	G	S
NoTax	0.195***	0.173***	0.095***	0.888***	0.547***	0.506***
	Δ w.r.t. the base scenario (%)					
Tax	0.205	0.526	1.543	0.320	1.012	2.897
TaxRev	-0.363	-0.223	-0.906	0.141	-0.685	-0.940
TaxEff	-9.705	-9.690	-2.478	0.016	7.986	10.750
TaxEff_2	-13.457	-13.522	-11.974	-0.075	1.790	4.534

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

Table 11: Multidimensional poverty metrics when income has the largest weight

efficiency is distributed unequally across income levels. In order to check the robustness of our findings, in Table 12 the weights are distributed equally.

	H	M_0	M_1	A	G	S
NoTax	0.425***	0.312***	0.135***	0.734***	0.432***	0.338***
	Δ w.r.t. the base scenario (%)					
Tax	0.313	0.600	0.031	0.286	-0.566	0.499
TaxRev	0.235	0.310	-1.665	0.075	-1.969	-2.923
TaxEff	-5.429	-5.809	1.331	-0.402	7.581	10.776
TaxEff_2	-4.336	-5.236	-3.709	-0.940	1.611	3.427

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

Table 12: Multidimensional poverty metrics when all the deprivation dimensions are equally weighted

The proportion of households experiencing multidimensional poverty increases as carbon tax increases in the absence of any mitigation poverty measures (M_0). This is driven by the breadth of poverty (A), showing that there is an increase in the number of people facing a deprivation in a new dimension. Note that the average poverty gap also increases, driving up M_1, showing that a poor household becomes more deprived in a given dimension. Finally, a carbon tax increases the average shortfall of the total population from the poverty line, as indicated by G. The depth of deprivation of those already facing poverty increases (i.e. severity S).

When the carbon tax is combined with a lump-sum payment to each household (TaxRev), the opposite effect of the carbon tax is observed. In fact, the average poverty gap and its severity decreases relative to the NoTax scenario. Note that breadth of poverty (A) has increased under this scenario. Re-allocation policies where vulnerable households receive a larger proportion of the additional revenues could be an option to reduce the average deprivation magnitude. Increasing energy efficiency equally across households (TaxEff) reduces the number of households experiencing energy poverty by a greater proportion. This will consequently reduce the breadth of poverty (A) because in the dimension of efficiency, households have become more energy efficient. However, the situation for those already experiencing energy poverty gets worse. Note that under this scenario, the average poverty gap (G) and severity increase (S). Increases in energy efficiency across all dwellings, i.e. energy efficiency increases that are not targeted to low income households, will therefore worsen the situation of those already in poverty.

The final scenario, TaxEff$_2$, finds a greater reduction in the number of households experiencing poverty than the untargeted scenario. Furthermore, the average poverty gap and severity have a much smaller effect on those experiencing poverty than in the untargeted energy efficiency scenario. Thus an energy efficiency scheme targeted towards low income households reduces both the number of households experiencing multidimensional poverty and lessens the severity of poverty exprienced by those already in poverty.

Table 12, which weights the dimensions of poverty equally, with the exception of the scenario TaxRev, sees a similar pattern. However, the number of households in energy poverty is much higher than in the weighted results. A head counting metric is therefore dependent on the weights attached to each dimension. We argue that a weighted scheme could better identify the number of households in energy poverty.

The Almost Ideal Demand System (AI-DS) model proposed by [23] was improved in the Quadratic Almost Ideal Demand System (QUAIDS) proposed by [24] by allowing quadratic Engel curves. As a robustness check we also estimated a QUAIDS model. The coefficients for this model are displayed in Table 6 in the appendix of this paper. Table 13 and Table 14 display the metrics for the multidimensional poverty for the weighted and unweighted deprivation dimensions. One can see that the trends in energy poverty are almost the same across the two models. However, in the case of the scenario related to the equal improvement in energy efficiency (TaxEff), there is increases in energy poverty. This shows that imposing quadratic linear curves can lead to misleading conclusions when measuring energy poverty.

	H	M_0	M_1	A	G	S
NoTax	0.205***	0.182***	0.100***	0.889***	0.551***	0.509***
	Δ w.r.t. the base scenario (%)					
Tax	0.195	0.584	1.588	0.388	0.998	2.808
TaxRev	-0.463	-0.275	-0.853	0.189	-0.579	-0.902
TaxEff	0.146	0.327	5.250	0.181	4.907	7.546
TaxEff_2	-12.469	-12.754	-7.305	-0.326	6.246	18.604

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

Table 13: Multidimensional poverty metrics when income has the largest weight. QUAIDS model parameters.

	H	M_0	M_1	A	G	S
NoTax	0.432***	0.319***	0.138***	0.737***	0.433***	0.339***
	Δ w.r.t. the base scenario (%)					
Tax	0.425	0.775	0.173	0.348	-0.597	0.483
TaxRev	0.491	0.579	-1.452	0.088	-2.019	-3.002
TaxEff	0.572	0.704	4.515	0.132	3.784	6.873
TaxEff_2	-6.556	-7.493	-5.331	-1.003	2.337	4.854

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

Table 14: Multidimensional poverty metrics when all the deprivation dimensions are equally weighted. QUAIDS model parameters.

5. Discussion and conclusion

This paper provides a robust examination of various metrics for energy poverty, motivated by the impact of carbon taxation. The EASI demand system was used to parameterise a microsimulation model which examines the impact of both carbon taxation and increases in housing costs on energy poverty, as well as exploring the potential policy responses of revenue recycling and improved energy efficiency.

We found that expenditure-based energy poverty metrics, such as those recommended by the European Commission in [8], perform poorly both in measuring baseline rates of energy poverty and in capturing any changes to energy poverty from carbon taxation. They also fail to capture any impact of policy responses. The only metric that behaved as one would expect was the simplest, that which designates a household as experiencing energy poverty if they spend more than 10% of their income on energy.

Multidimensional poverty metrics prove far more intuitive. Increasing carbon tax and housing costs are found to increase poverty, but revenue recycling decreases poverty even in the presence of increases to carbon and housing costs. Energy efficiency improvements, on the other hand, while reducing the number of households in energy poverty, worsen the situation of those already experiencing energy poverty. Targeting energy efficiency upgrades toward less affluent households mitigates, but does not reverse, this effect. The results suggest that policy responses that increase revenue to households are more effective in reducing the number and the intensity of energy poverty than energy efficiency upgrades.

6. Appendix

References

[1] S. Pye, A. Dobbins, C. Baffert, J. Brajkovic, I. Grgurev, R. De Miglio, P. Deane, Energy poverty and vulnerable consumers in the energy sector across the eu: analysis of policies and measures, Policy 2 (2015).

[2] P. Heindl, R. Schuessler, Dynamic properties of energy affordability measures, Energy Policy 86 (2015) 123 – 132. doi:https://doi.org/10.1016/j.enpol.2015.06.044.
URL http://www.sciencedirect.com/science/article/pii/S0301421515300112

[3] D. Klenert, L. Mattauch, E. Combet, O. Edenhofer, C. Hepburn, R. Rafaty, N. Stern, Making carbon pricing work for citizens, Nature Climate Change 8 (8) (2018) 669–677.

[4] C. Bruegge, T. Deryugina, E. Myers, The distributional effects of building energy codes, Journal of the Association of Environmental and Resource Economists 6 (S1) (2019) S95–S127. arXiv:https://doi.org/10.1086/701189, doi:10.1086/701189.
URL https://doi.org/10.1086/701189

Regressor:	Dependent variable: budget share for...				
	Food	Housing	Energy	Transport	Education
Polynomial coefficient:					
y1	-0.124***	0.043***	-0.071***	-0.061***	0.130***
y2	0.011***	-0.010***	0.007***	0.005***	-0.010***
Household types:					
z1	-0.088***	-0.030**	-0.013***	-0.013**	0.074***
z2	-0.130***	-0.083***	-0.015***	0.007	0.088***
z3	-0.025*	-0.048***	0.001	-0.017**	0.058***
z4	0.000	0.000	0.000	0.000	0.000
z5	-0.004	-0.100***	-0.001	-0.011***	0.063***
z6	0.016**	-0.064***	-0.002	0.004	0.024***
Interaction term:					
yz1	0.014***	0.012***	0.002*	0.003	-0.017***
yz2	0.029***	0.003	0.004***	-0.008***	-0.018***
yz3	0.002	0.013**	0.000	0.004	-0.012**
yz4	0.000	0.000	0.000	0.000	0.000
yz5	0.001	0.018***	-0.000	0.003***	-0.016***
yz6	0.004**	0.008***	0.001	0.004***	-0.006**
Interaction between price and expenditure ($b_{i,j}$):					
ynp1	-0.033***	-0.004**	0.002**	-0.002**	0.040***
ynp2	-0.004**	-0.005	0.001*	0.004***	-0.001
ynp3	0.002**	0.001*	-0.009***	0.002**	0.003***
ynp4	-0.002**	0.004***	0.002**	-0.014***	0.008***
ynp5	0.040***	-0.001	0.003***	0.008***	-0.082***
Price parameter ($a_{i,j,l}$)					
np1	0.129***	-0.024***	-0.008***	-0.009***	-0.076***
np2	-0.024***	0.058***	-0.009***	-0.015***	-0.000
np3	-0.008***	-0.009***	0.048***	-0.009***	-0.010***
np4	-0.009***	-0.015***	-0.009***	0.071***	-0.019***
np5	-0.076***	-0.000	-0.010***	-0.019***	0.166***
Log(Energy requirement) 0.022***	-0.055***	0.003***	-0.004***	0.018***	
constant	0.387***	0.526***	0.159***	0.241***	-0.247***
N	18504				

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

Table 15: Results of the QUAIDS demand system estimation. Iterated 3SLS, 3 digits

[5] K. Csiba, Energy poverty: handbook, European Union, 2016.

[6] Council of Europe Development Bank, Energy poverty in Europe: How Energy Efficiency and Renewables Can Help, Technical Report, available online: https://coebank.org/media/documents/CEB$_{S}tudy_{E}nergy_{P}overty_{i}n_{E}urope.pdf$ (2019).

[7] S. Bouzarovski, Energy poverty:(Dis) assembling Europe's infrastructural divide, Springer, 2017.

[8] K. Rademaekers, J. Yearwood, A. Ferreira, S. Pye, I. Hamilton, P. Agnolucci, D. Grover, J. Karásek, N. Anisimova, Selecting indicators to measure energy poverty, Trinomics: Rotterdam, The Netherlands (2016).

[9] S. Alkire, J. Foster, Counting and multidimensional poverty measurement, Journal of public economics 95 (7-8) (2011) 476–487.

[10] S. Scott, S. Lyons, C. Keane, D. McCarthy, R. S. Tol, Fuel poverty in ireland: Extent, affected groups and policy issues, Tech. rep., ESRI Working paper (2008).

[11] D. Watson, B. Maitre, Is fuel poverty in ireland a distinct type of deprivation?, The Economic and Social Review 46 (2, Summer) (2015) 267–291.

[12] B. Legendre, O. Ricci, Measuring fuel poverty in france: Which households are the most fuel vulnerable?, Energy Economics 49 (2015) 620–628.

[13] A. Burlinson, M. Giulietti, G. Battisti, The elephant in the energy room: Establishing the nexus between housing poverty and fuel poverty, Energy Economics 72 (2018) 135–144.

[14] P. Heindl, Measuring fuel poverty: General considerations and application to german household data, ZEW-Centre for European Economic Research Discussion Paper (13-046) (2013).

[15] S. Kahouli, An economic approach to the study of the relationship between housing hazards and health: The case of residential fuel poverty in france, Energy Economics 85 (2020) 104592.

[16] A. Krauss, How natural gas tariff increases can influence poverty: Results, measurement constraints and bias, Energy Economics 60 (2016) 244–254.

[17] P. Heindl, R. Schüssler, Dynamic properties of energy affordability measures, Energy Policy 86 (2015) 123–132.

[18] P. Baker, R. Blundell, J. Micklewright, Modelling household energy expenditures using micro-data, The Economic Journal 99 (397) (1989) 720–738.
URL http://www.jstor.org/stable/2233767

[19] J. Creedy, C. Sleeman, The distributional effects of indirect taxes : models and applications from New Zealand, Cheltenham, UK [u.a.] : Edward Elgar, 2006.

[20] X. Labandeira, J. Labeaga, M. Rodriguez, A residential energy demand system for Spain, The Energy Journal Volume 27 (Number 2) (2006) 87–112.
URL http://EconPapers.repec.org/RePEc:aen:journl:2006v27-02-a06

[21] P. Pashardes, N. Pashourtidou, T. Zachariadis, Estimating welfare aspects of changes in energy prices from preference heterogeneity, Energy Economics 42 (C) (2014) 58–66.
URL https://ideas.repec.org/a/eee/eneeco/v42y2014icp58-66.html

[22] M. A. Tovar-Reaños, N. M. Wölfing, Household energy prices and inequality: Evidence from German microdata based on the easi demand system, Energy Economics 70 (2018) 84 – 97. doi:https://doi.org/10.1016/j.eneco.2017.12.002.
URL http://www.sciencedirect.com/science/article/pii/S0140988317304206

[23] A. Deaton, J. Muellbauer, An almost ideal demand system, The American Economic Review 70 (3) (1980) 312–326.
URL http://www.jstor.org/stable/1805222

[24] J. Banks, R. Blundell, A. Lewbel, Quadratic engel curves and consumer demand, The Review of Economics and Statistics 79 (4) (1997) 527–539.
URL https://ideas.repec.org/a/tpr/restat/v79y1997i4p527-539.html

[25] R. Burgess, M. Greenstone, N. Ryan, A. Sudarshan, Demand for electricity in a poor economy (2019).

[26] S. Renner, J. Lay, H. Greve, Household welfare and co2 emission impacts of energy and carbon taxes in mexico, Energy Economics 72 (2018) 222–235.

[27] S. Renner, J. Lay, M. Schleicher, The effects of energy price changes: heterogeneous welfare impacts and energy poverty in indonesia, Environment and Development Economics 24 (2) (2019) 180–200.

[28] W. A. Pizer, S. Sexton, The distributional impacts of energy taxes, Review of Environmental Economics and Policy 13 (1) (2019) 104–123.

[29] A. Lewbel, K. Pendakur, Tricks with Hicks: The EASI Demand System, American Economic Review 99 (3) (2009) 827–63.
URL https://ideas.repec.org/a/aea/aecrev/v99y2009i3p827-63.html

[30] M. A. Tovar Reaños, N. M. Wölfing, Household energy prices and inequality: Evidence from german microdata based on the easi demand system, Energy Economics 70 (2018) 84–97.

[31] F. Pothen, M. A. Tovar Reaños, The distribution of material footprints in germany, Ecological Economics 153 (2018) 237 – 251. doi:https://doi.org/10.1016/j.ecolecon.2018.06.001.
URL http://www.sciencedirect.com/science/article/pii/S0921800918302076

[32] H. Varian, Microeconomic theory, W. W. Norton & Company, New York (1992).

[33] A. Lewbel, Identification and Estimation of Equivalence Scales under Weak Separability, Review of Economic Studies 56 (2) (1989) 311–316.
URL https://ideas.repec.org/a/oup/restud/v56y1989i2p311-316..html

[34] D. Pacifico, F. Poege, Estimating measures of multidimensional poverty with stata, The Stata Journal 17 (3) (2017) 687–703.

[35] C. Böhringer, F. Landis, M. A. Tovar Reaños, Cost-effectiveness and incidence of renewable energy promotion in Germany, ZEW Discussion Papers 17-004, ZEW - Zentrum für Europäische Wirtschaftsforschung / Center for European Economic Research (2017).
URL https://ideas.repec.org/p/zbw/zewdip/17004.html

[36] J. Curtis, N. Devitt, A. Whelan, Using census and administrative records to identify the location and occupancy type of energy inefficient residential properties, Sustainable Cities and Society 18 (2015) 56–65.

[37] M. Savage, Indirect tax reform and the specification of demand: the case of ireland, International Tax and Public Finance 23 (2) (2016) 368–399.

[38] S. Salotti, L. Montinari, A. F. Amores, J. M. Rueda-Cantuche, Total expenditure elasticity of non-durable consumption of european households, in: JRC Technical Report EUR 27081 EN, European Union, 2015, p. 2015.

[39] K. W. Clements, Y. Wu, J. Zhang, Comparing international consumption patterns, Empirical Economics 31 (1) (2006) 1–30.