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What Factors Drive Inequalities in Carbon Tax Incidence? Decomposing Socioeconomic Inequalities in Carbon Tax Incidence in Ireland

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Abstract: Carbon taxes increase the cost of necessary household energy expenditures. In many developed countries, carbon taxes are regressive as they comprise a greater proportion of a poorer household's income. Certain socioeconomic groups are more negatively affected by these impacts than others. While inequality of incidence by income group has received great attention in the literature, a gap exists to quantify the inequality associated with socioeconomic characteristics. This information is policy-relevant as it may inform the most effective means to offset negative welfare impacts through changes to taxes and/or social transfers. This paper provides this contribution. First, the inequality of carbon tax incidence across the income spectrum is quantified using the concentration index methodology. A subsequent multivariate decomposition quantifies the contribution each socioeconomic factor makes towards this inequality of incidence. This is carried out for electricity, motor fuel and all other home fuels to elicit variation of socioeconomic incidence by source. While income contributes a great deal towards inequality of incidence for other home fuels, socioeconomic characteristics are the primary determinants of electricity and motor fuel-related carbon tax incidence. The relative importance of each characteristic in determining regressive impacts is quantified and this varies by carbon tax source.

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1. Introduction

International environmental agreements have motivated binding national targets to reduce CO_2 emission [e.g. 1, 13]. Around 40 countries and more than 20 cities, states and provinces have either implemented or are planning to implement a carbon tax or similar carbon pricing scheme [15, 45, 44]. In many developed economies, a carbon tax has been found to be regressive, having a proportionally greater impact on the incomes of poorer households than richer households [6, 15]. Understanding this impact has been the subject of much analysis to date [e.g. 29, 6, 23]. Regression-based analyses [e.g. 5] have identified the socioeconomic determinants of carbon tax expenditure, while microsimulation-based analyses [e.g. 6] have shown the distribution of incidence across the income spectrum and broad social groupings. Combining these methods to identify the impact socioeconomic variables have in determining overall inequality across the income spectrum has been overlooked. This paper addresses this gap, decomposing inequalities associated with carbon tax incidence using the concentration index, a method commonly employed to decompose socioeconomic inequalities in health outcomes [41, 37, 46, 39].

As [8] states, "it is almost essential to attempt to 'account for' the level of, or trend in, inequality by components of the population" [12]. While this understanding is important in its own right, it is of added benefit when one considers revenue 'recycling' measures to redistribute carbon tax receipts via the tax-benefit system [2, 6]. Existing revenue recycling mechanisms and associated analyses have focussed on providing a progressive post-redistribution pattern of incidence [2, 6, 11, 19], showing that many redistributive mechanisms yield a net benefit for many income groups in aggregate. Despite this pattern of incidence, losers may still prevail. This is because different socioeconomic groups incur different carbon tax burdens and these do not necessarily correspond to those positively impacted by a given redistribution measure. Indeed, an unintended consequence of an otherwise progressive redistributive mechanism is the persistent negative incidence amongst a particular socioeconomic group, despite a redistributive mechanism being in place. As carbon tax rates are expected to grow through time [35, 36] the negative distributional effects will grow in magnitude. Effectively designing offsetting measures that target negatively impacted households, and thus minimising the prevalence of 'losers' of carbon tax policy, will thus be of greater importance [16] and will become an additional consideration in the design of traditional social transfer policy. Alongside this primary driver, the political acceptability of carbon taxation is heavily influenced by measures enacted to effectively mitigate negative income impacts [11, 18, 23].

This paper is thus the first to decompose the inequality created by a carbon tax according to socioeconomic determinant. This contribution is demonstrated by means of an Irish example. Ireland has income and consumption patterns representative of many developed countries, with levels of income inequality at the EU average, post-taxes and transfers [14]. Alongside this, there exists detailed microdata on household income and expenditure, allowing for analysis of incidence that is differentiated by source. Such insight is of importance as, in many EU countries, electricity-related emissions are subject to a carbon price set by the EU Emissions Trading Scheme (EU ETS), whilst emissions from motor and household fuels are subject to a domestic carbon price [15]. The imposition of carbon taxation in Ireland is thus representative of that experienced in many countries.

This paper proceeds as follows. Section 2 reviews the previous literature in the field of carbon taxation, concentration indices and decompositional analysis, highlighting the gap addressed by this paper. Section 3 outlines the data and methodology employed. Section 4 presents the results. First, the regressive impact of each carbon tax is explicitly quantified using the concentration and Kakwani indices. Next, regression analyses are presented to identify the determinants of carbon tax consumption. Following the methodology of [40], the total regressive impact is decomposed according to constituent socio-economic drivers. Presenting the results in this fashion allows for more complete insight into how carbon taxes affect the income distribution, while emphasising the benefit of adopting the decomposed concentration index methodology. Section 5 offers insight into the important policy implications of these findings. Section 6 offers some concluding comments.

2. Literature Review

[6] have comprehensively reviewed the literature analysing the distribution of carbon tax incidence amongst households. Microsimulation-based methods are most-often used to analyse the incidence of cost relative to income. Most analyses to date focus on changes in income as a result of direct emission of CO_2 [31, 32, 30, 29, 33, 6]. Tax-benefit microsimulation models have been used to consider the distributional impact relative to the full tax and benefit system [6, 29]. Advances in this field have generally focussed on incorporating further sources of emission or incorporating a behavioural response to price changes. Indirect consumption of CO_2 embedded in goods and services has been incorporated through integration with an input-output or CGE model [2, 7, 11, 21, 24, 26, 38, 43]. [23] analyse the distributional effects of taxing multiple greenhouse gases. They find that the tax is less regressive and more cost-effective than taxing carbon alone. Analyses by [3, 24, 34] include a system of demand equations to incorporate demand response to carbon tax-induced price changes, with these studies also finding regressive impacts.

Despite the wide range of methodological developments, the literature to date has not decomposed regressive impacts by socioeconomic determinant. A number of methods have been applied to approximate these impacts. [5] use a regression-based analysis to elicit the determinants of carbon tax emission. Comparing the socioeconomic determinants of carbon emission with the determinants of income gave qualitiative insight into distributional impacts. However, quantification of distributional effect and ranking of importance is not facilitated by this analysis. This is important information to effectively offset negative income effects through social transfer design.

Presenting incidence by income or socioeconomic cohort [6, 11, 19] gives intuitive insight into incidence amongst population groups. However, it is difficult to compare between-factor impacts in this manner, such as comparing the influence of education vs. social class in determining the regressivity of a carbon tax, as determinants are confounded in such analyses. Indeed, when such an analysis is extrapolated out over a number of determinants, easy comparison, quantification of effect and ranking of importance is difficult. Such information may be important when designing an effective suite of social transfer policies.

To address this deficiency, this paper quantifies the contribution each socioeconomic factor makes towards unequal carbon tax incidence using regression-based decomposition methods. Regression-based decomposition methods have been used by [17], [28] and [47] to quantify the relative influence of different socio-economic determinants in overall income inequality. [28] used this measure to identify the socio-economic determinants of income inequality for a number of income quintiles in rural China. [17] used this method to identify the influence of socio-economic factors in both the overall rate of inequality in 1979 and 1999 in the USA, whilst also proposing a method to quantify the influence of each factor in the change in inequality between time periods. [4] have carried out a similar analysis to track the relative contribution of each factor to change in inequality over a number of intervals from 1968-2009.

Similarly, regression-based methods have been used to decompose the unequal prevalence of a certain factor such as a health outcome, using the concentration index. The concentration index is a metric of inequality commonly employed to analyse the socioeconomic gradient of health outcomes, with multivariate decomposition of this metric widely applied in the field of health economics. Applications to date have analysed socioeconomic inequalities in obesity [41], vaccine uptake [10], malnutrition [39], doctor utilisation [37] and disease [46]. This paper augments the field of application to analyse socioeconomic inequalities in carbon tax incidence. The concentration index is used for this paper as it explicitly focuses on the regressive determinants of a particular outcome variable. We do not employ a full tax-benefit microsimulation model which allows for understanding in the broader context of the entire system of taxes and social transfers. Such models explicitly consider measures that may offset any regressive impacts of carbon taxation. Instead, we focus on the distributional impact of carbon tax in isolation. In doing so, we elicit the distributional impact of this particular taxation measure. As carbon taxes grow as a proportion of general taxation, these findings of may inform measures to counteract regressive impacts of carbon taxation in the context of the wider tax-benefit system.

3. Data and Methodology

3.1. Data

The anonymised Irish Household Budget Survey (HBS) for 2009/10 [9] are the primary data used in this analysis. The HBS details household-level income and expenditures for a representative random sample of all private households in Ireland over a two week period. In 2009/2010, 5,891 private households participated with a response rate of just under 40% [9]. Responses are weighted to minimise any bias that may occur due to participant non-response.

The impact of a carbon tax is analysed with respect to three categories of emission source; motor fuels, electricity and 'other' fuels (light fuel oil, diesel, petrol, liquid petroleum gas (LPG), gas (bulk purchase), peat, coal, anthracite and gasoil). We thus elicit the distributional impact of carbon prices differentiated by source. Differentiated prices according to carbon tax source is a common occurrence in many countries [15], especially for those where electricity generation is subject to the EU Emissions Trading Scheme (EU ETS). In such circumstances, the carbon price for electricity is set by the EU ETS, with carbon consumption sourced from other fuels priced at a different rate [15].

As the focus of this paper is on presenting a decomposed measure of income inequality, we follow the analyses of [6, 29, 31, 30, 32] and [33] to concentrate on direct impacts. Indirect carbon consumption comprises a small proportion of total carbon tax incidence and tends to be progressively distributed [38]. Taking an Irish case study, [38] show that indirect costs are €0.50-1.50/week, assuming no ETS-related carbon taxation, while the direct cost is €3-4 per week. Of greater importance, however, is the positive distribution of this impact. Indeed, the proportional impact is constant for deciles 2-10 and comprises about 10% of the proportional impact for all carbon taxation for the lowest income decile. Thus, direct emission through the consumption of electricity and fuels is the primary driver of regressive impacts and thus of most importance for policymakers when considering revenue redistribution mechanisms. To concentrate on the primary contribution of this paper, the use of the decomposed concentration index, and to avoid superfluous analysis of predominantly non-regressive impacts, we limit this analysis to direct effects of carbon taxation. An extension to consider indirect effects will be carried out in future work.

Household-level carbon emissions are calculated by first converting expenditures to quantities consumed and then deriving the carbon content of consumed items. To do this, we divide total expenditure by unit price data following the approach of [6], [5] and [25]. For each quarter of analysis, the Sustainable Energy Authority of Ireland (SEAI) have provided average retail price data for for gas, light fuel oil, diesel, petrol, liquid petroleum gas (LPG), peat, coal, anthracite, gas (bulk purchase) and gasoil. For electricity, we use unitary prices and standing charges applicable for the 2009/2010 survey period. This is carried out by reducing the gross expenditure amount by 13.5% to account for VAT and then deducting the standing charge for the standard ESB (Electricity Supply Board) Customer Supply electricity tariff (ESB, 2009). To calculate the quantity of electricity consumed, the remaining electricity expenditure amount is divided by the unitary cost of electricity (CER, 2010c, 2011b). Once the number of units consumed are identified, emissions coefficients are taken from [33] from which the quantity of CO_2 emitted may be identified. This quantity is then multiplied by the carbon price to elicit the carbon tax paid per household.

To calculate the unequal incidence of a carbon tax, we compare the cost to equivalised household disposable income. Disposable income is income after taxes and social transfers. Equivalisation is a weighting procedure to account for household size-related economies of scale. The 'OECD-modified scale' is the preferred equivalence scale of Eurostat and the OECD and is used for this analysis. This scale weighs household income according to the number and status of household inhabitants. A weight of 1 is assigned to the first adult, a weight of 0.5 to each additional adult and a weight of 0.3 to each child [20].

For 'other' fuel-related expenditures, we notice outliers that indicate unfeasibly high levels of usage. For example, some households report spending €200 on peat briquettes, where the median value for those who consumed peat briquettes was €3.83. We follow [5] and omit these observations as they can lead to biased regression results. We omit values in excess of three standard deviations from the mean of consumption for each constituent fuel in the 'other' fuel category. This is calculated conditional on consumption being greater than zero. This trims 79 observations or 1% of the total sample. Trimming the data in this way minimises any potential bias introduced by implausibly high data points [5]. This restricted sample is used for analyses pertaining to emissions sourced from 'other' fuels and total fuel usage.

3.2. Methodology

The analysis of this paper is carried out with respect to a €20/tCO_2 carbon tax. €20 corresponds to the current carbon tax in place in Ireland, however, the relative distribution of impacts should prevail for all carbon tax values, assuming a zero demand response.

Regression-based decompostion of an inequality index requires estimation of the inequality index and regressions to predict carbon tax expenditure as constituent calculations. Each of these constituent analyses are presented in this paper to give a complete insight into the distributional impact of carbon taxation while also emphasising the added value of the decompositional methodology. Each step will now be outlined in turn.

3.2.1. Measuring inequality of carbon tax incidence

The unequal incidence of each carbon tax is first estimated in aggregate. The Concentration Index (CI) is used to quantify the degree of income-related inequality in carbon tax incidence. The CI is easily quantified and is measured between the ranges -1 and 1, with zero representing perfect equality. The CI can be constructed according to a number of methodologies. Following [22] and [10], we calculate the CI in the following way:

$$CI = \frac{2}{N\mu}\sum_{i=1}^{N} y_i R_i - 1 \tag{1}$$

where y_i represents carbon tax payments for household i, μ is mean of carbon tax payments, R_i is the fractional rank of households along the income distribution, where household i is ranked 1 if at the bottom of the income distribution and N if at the top of the income distribution.

While the concentration index gives insight into how carbon taxes are distributed across the income distribution, it is also important to understand the progressivity of this incidence with respect to income. To carry this out, the CI for the carbon tax must be compared to a measure of income inequality. An index of income inequality provides a metric of how evenly income is distributed across the population. The Gini coefficient (G) is the most commonly employed index of income inequality and is related to the CI. Once again ranking households by income, the Gini coefficient may be calculated as follows:

$$G = 2\frac{\sum_{i=1}^{N} R_i(a_i - \bar{a})}{N^2\bar{a}} \tag{2}$$

where a_i is equivalised disposable income for household i, $\bar{a}$ is mean equivalised disposable income and all other variables are as previously defined. The Kakwani Index (K) is commonly used to measure the progressivity of a tax intervention such as a carbon tax. This can be calculated in a number of ways. In this paper, it is calculated as the concentration index for the analysed carbon tax, less the Gini coefficient of income inequality. The larger the Kakwani index, the more progressive the distribution of the carbon tax.

$$K = CI - G \tag{3}$$

3.2.2. Determinants of carbon tax incidence

A multivariate regression-based decomposition is carried out to elicit the socioeconomic determinants of inequitable carbon tax incidence. This comprises a number of stages. First the determinants of carbon tax incidence are identified by means of a multivariate OLS regression, following the analysis of [5]:

$$y_i = \alpha + \sum_j \beta_j x_{j,i} + \epsilon_i \tag{4}$$

where the dependent variable (y_i) is carbon tax cost per household i, the x_j variables are j explanatory variables, β_j is the average partial effect of variable j on carbon tax expenditure and ϵ is the error term. This is analysed for each source of carbon expenditure: electricity, motor fuels and all other fuels (previously defined).

Explanatory variables included in this analysis represent a range of socioeconomic and household variables that explain household consumption of carbon and the gradient of this consumption across the income distribution, informed by economic theory and the literature [5, 25]. The following independent variables are included. Location is coded according to three dummies representing Dublin; Border, Midland, West; and South, Mid West, Mid East excluding Dublin. Dummy variables are used to represent each category of occupation, education and age of the Household Reference Person (HRP). The presence of adults and children and OAPs are also categorised by dummy variables. Equivalised disposable income is log-transformed to model a linear relationship with emissions and following the approach taken in the literature [5, 10, 41]. The existence of a loan indicates the degree of indebtedness for a household and may affect their propensity to consume across the income distribution and this is thus included as a dummy variable [42]. Household size and type, along with water heating, space heating and cooking method, affects the consumption of electricity and other fuels [25] and these variables are included in the analysis for these regression specifications only. Preliminary analyses found that the only appliances that varied sufficiently across the income spectrum to influence the socioeconomic gradient of carbon tax incidence were the number of motor vehicles in a household, along with dishwasher and tumble dryer ownership. These are thus included in the analysis.

While appliance ownership, dwelling characteristics and heating method have been found to be determinants of energy usage [25] and thus carbon tax incidence, such variables are often not observable by policymakers. Omitting these variables and comparing the results gives further insight into the socioeconomic variation of incidence. Thus, regression specifications are imposed that respectively include and omit these variables. When specifying these regressions, variance inflation factors are calculated to test for multicollinearity, with no variables reporting a value in excess of 6.51, well below the recommended threshold of 10.

3.2.3. Multivariate Decomposition of Inequality

[39] have shown that by coupling the concentration index (Sections 3.2.1) with regression analysis (Section 3.2.2) total inequality can be partitioned into inequalities for a set of J determinants. drawing on the relationship between y_i and $x_{j,i}$ illustrated in equation (4), equation (1) can be rewritten as (5):

$$CI = \sum_j \left(\frac{\beta_i \bar{x}_j}{\mu} \right) C_j + \frac{C_\epsilon}{\mu}, \tag{5}$$

where $\bar{x_j}$ is the mean of x_j; C_j is the concentration index for determinant x_j (defined analogous to CI); and all other variables are as previously defined. [37] gives a good interpretation of Equation (5).

Equation (5) shows that CI is equal to a weighted sum of the concentration indices of the j regressors, with the contribution each j regressor makes towards CI is calculated according to $\left(\frac{\beta_i \bar{x}_j}{\mu}\right) C_j$. The weight or 'share' for x_j, is the elasticity of y with respect to x_j $\left(\frac{\beta_i \bar{x}_j}{\mu}\right)$. The second term may be interpreted as a residual and reflects the inequality in the outcome variable that is not explained by systematic variation across income groups in the x_j variables. As our dependent variable (carbon tax expenditure) is continuous, we use the standard concentration index in our decomposition [37].

It is important to bear in mind equation (5) when interpreting results in Section 4.3. If C_j is negative, variable j has a greater association with lower incomes, and vice versa. If the elasticity term for variable j is negative, variable j has a greater association with lower carbon tax incidence, and vice versa. Should both parameters be negative, variable j will contribute towards increasing the inequality associated with carbon tax incidence. Should both parameters be positive, variable j will contribute positively. Should one parameter be negative and one positive, the greater parameter will determine the association.

4. Results

4.1. Inequality

We first analyse the distribution of carbon tax expenditure across the income spectrum. The Concentration Index (CI) (Table 1) reports a single metric to summarise the distribution of carbon tax expenditures across the income spectrum. As all CI values are positive, it follows that richer households pay a greater proportion of total carbon taxes than poorer households. This is greatest for expenditure on motor fuels. Carbon tax expenditure on electricity and 'other' fuels shows less variation across the income distribution, however, we find that rich households spend more by a modest amount. Together, these findings sum to indicate that total carbon tax expenditure is skewed towards wealthy households. Interpreting the CI value for total carbon tax expenditure, we follow [10] and [37] by saying that an 8.34% redistribution of carbon tax payments from rich households to poor households would result in equal payments across the income spectrum.

Table 1: Indices of inequality by emission source

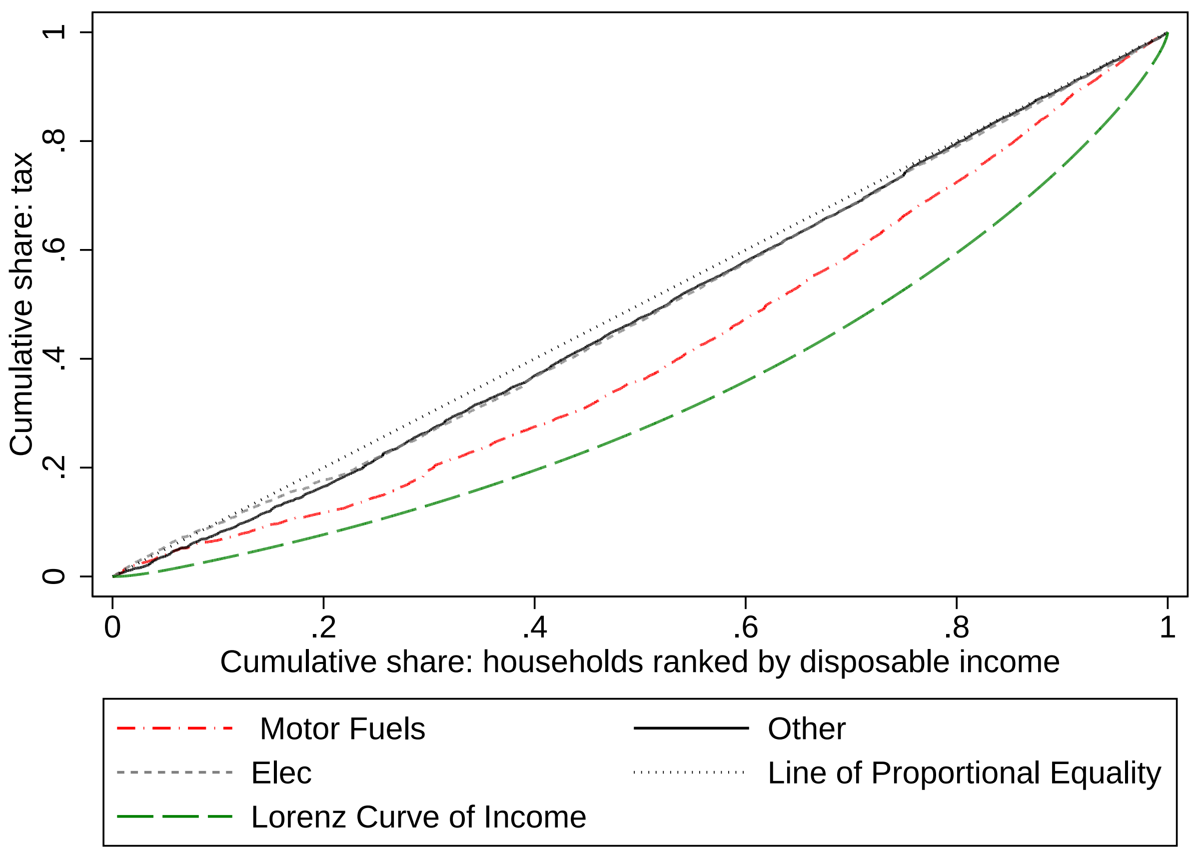
Source	Concentration Index	Standard Error	Kakwani Index
Electricity	0.0362	0.0060	-0.2934
Motor Fuels	0.1653	0.0083	-0.1643
Other	0.0380	0.0080	-0.2916
Total	0.0834	0.0053	-0.2462

Figure 1 demonstrates the socioeconomic gradient of carbon tax expenditure by means of a concentration curve. Each point on the concentration curve represents the cumulative portion of total carbon tax paid by the cumulative number of households, where households are ranked by pre-carbon tax equivalised disposable income. Alongside this, we graph the 'Lorenz' Curve of income inequality, which displays the cumulative proportion of pre-carbon tax equivalised disposable income paid by households ranked by pre-carbon tax equivalised disposable income. The dotted 45° line represents perfect equality; a curve along this line suggests equal distribution amongst all households. A curve above this line indicates a greater burden on the poor and a curve below this line indicates a greater burden on the rich.

Analysing Figure 1, one can see that a carbon tax for all carbon tax sources is pro-rich. Figure 1 shows that motor fuels and electricity-based carbon taxes have the greatest pro-poor gradient, with a greater pro-poor gradient for electricity-based carbon taxes amongst the lowest 20%.

While the concentration index shows trends of usage across income categories, a full understanding of the impact relative to ability to pay. The Kakwani index carries this out. We see that for all carbon tax payments, a negative Kakwani index is observed (Table 1). This suggests that, when payment incidence is interpreted in the context of income, carbon taxes are regressive. Carbon consumption in relation to electricity and 'other' fuels has a greater pro-poor bias as the Kakwani index is more negative. Figure 1 provides further insight into this trend, where we see that each concentration curve lies above the Lorenz curves of pre-carbon tax income. This suggests that, at any cumulative income level, the fraction of cumulative premiums paid is more than the fraction of cumulative pre-carbon tax income received by those households. Thus, a greater proportion of the carbon tax cost is borne by those with lesser proportion of total income.

Figure 1: Lorenz curve and concentration curves

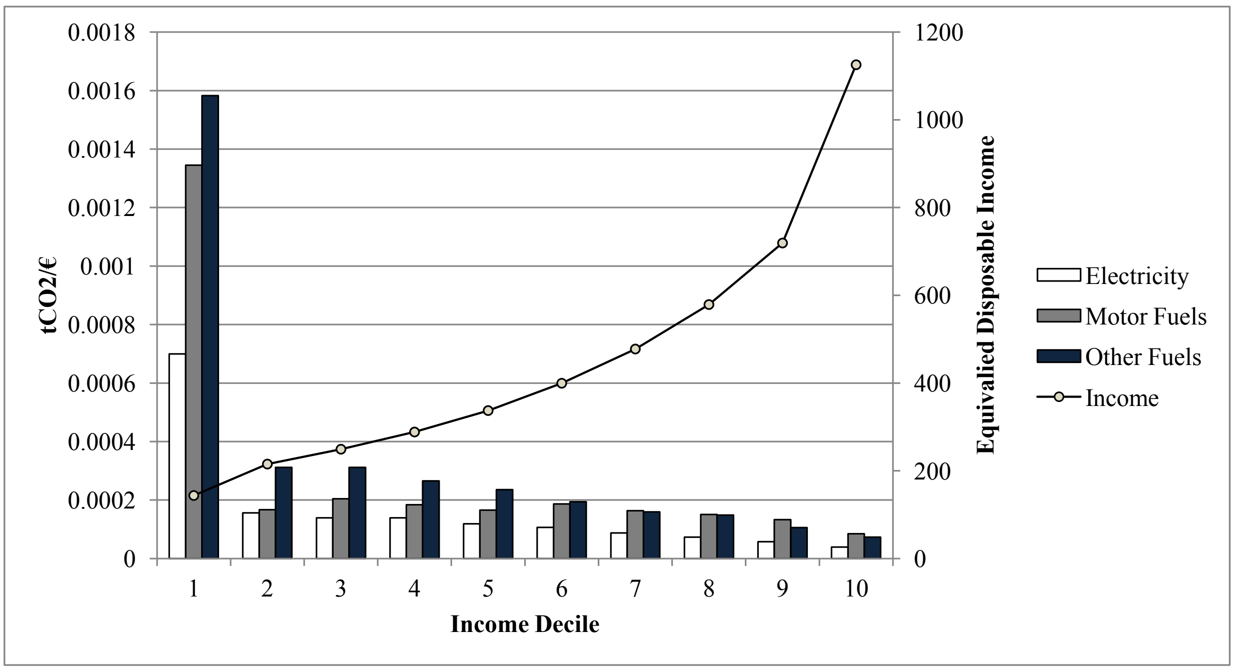


This incidence relative to income is explored further in Figure 2. Where Figure 1 showed the proportion of cost by income group, Figure 2 shows the average ton of CO_2 per € of equivalised disposable income for ten income groups or 'deciles'. This allows for the magnitude of incidence between income groups to be compared. We see that households consume, on average, more carbon per unit of income due to 'other' fuel consumption, followed by motor fuel consumption and then electricity.

The magnitude of incidence is of greatest concern for the first decile. We see that households in the first decile consume, on average, more carbon per unit of income than households in other deciles. The average carbon consumed per unit of income for 'other' fuels is over 4 times greater for the lowest income decile than for higher income deciles. A similar trend is observed for motor fuels and electricity-related CO_2 emission, however the magnitude is lower.

Motor fuel-related carbon consumption shows a progressive trend for deciles 2-6, falling slightly for deciles 7-10. Electricity and 'other' fuel-related carbon consumption shows a regressive pattern of incidence across the entire income distribution. Given the great magnitude of incidence, negative income impacts of 'other' fuel-related carbon taxes are likely to be of greatest concern for policymakers. Despite demonstrating a less-regressive trend of incidence, negative income effects of a motor-fuel related carbon tax are likely to be of a greater magnitude than those related to electricity.

Figure 2: CO_2 Incidence by income group (tCO_2/€)



4.2. Multivariate analysis

The second stage of analysis is to assess the determinants of carbon tax expenditure. Following [5] and [25], we model this impact using OLS regressions with robust standard errors to correct for heteroskedasticity. These findings are reported in Tables 2 and 3. We split determinants by category and discuss each category in turn.

4.2.1. Location

Living outside of Dublin is associated with higher motor fuel-related carbon tax expenditure and lower electricity-related carbon tax expenditure. These effects are of a greater magnitude for residents in Border, Midland and Western (BMW) regions than those in south, midwest and mideastern rural areas. Greater motor fuel-related expenditure may be explained by a more dispersed population in rural locations and thus greater use of motor vehicles. Lower electricity-related carbon tax expenditure suggests that urban areas use more electrical devices and appliances. When we do not control for appliance usage and dwelling characterisitics, living in a rural area has an insignificant effect on electricity-related carbon tax incidence. This may be explained by the higher prevalence of larger and detached households in rural areas which are associated with greater electricity-related carbon tax incidence and thus countering the negative effect observed when these factors are controlled for.

When we control for appliance usage and dwelling characterisitics, living in a rural area has an insignificant effect on ‘other’ fuel-related carbon taxes for BMW residents and significantly negative for south, midwest and mideastern rural areas. However, this becomes significantly positive when appliance and household variables are omitted from the analysis (Table 3). This would suggest that while rural residents incur greater ‘other’ fuel-related carbon tax costs, this is largely due to urban/rural differences in space heating method, appliance ownership and dwelling characteristics.

4.2.2. Occupation

Occupation is of importance for motor fuel and electricity-related carbon taxes only. Own account workers and farmers incur the greatest cost associated with motor fuel and electricity-related carbon taxes, perhaps due to the high levels of independent travelling and spillover domestic usage associated with these professions. ‘Professionals’ incur the next greatest motor fuel cost. Other fuel-related carbon tax does not vary by profession.

4.2.3. Education

Relative to a postgrad degree or higher, those with secondary school education (or lower) incur a significantly greater level of carbon tax cost related to the consumption of ‘other’ fuels. However, this is countered by a lower use of motor fuels, resulting in an insignificant difference in total carbon tax cost by education level.

4.2.4. Age

Households where the Household Reference Person (HRP) is aged 35 and older pay more carbon tax for the consumption of ‘other’ fuels than those where the HRP is younger than 35. This impact is greater in magnitude when not controlling for appliance usage and dwelling characteristics, suggesting that appliance usage and dwelling characteristics are contributory factors driving differences in costs incurred between age groups. Indeed, we see that age has a significant impact on motor fuel-related carbon tax incidence when the number of motor vehicles is not controlled for, indicating that age-related differences in motor fuel-related carbon tax incidence exists, explained by age-related differences in motor vehicle ownership.

4.2.5. Household Structure

A greater number of household inhabitants leads to greater carbon tax cost. The magnitude of impact, and carbon source responsible, varies depending on the household structure. The presence of 3 or more adults is associated with greater motor vehicle-related carbon tax cost. ‘Other’ fuels show the lowest rate of change with respect to the number of adults, reflecting economies of scale associated with cooking and heating requirements. Having 3 or more children is associated with the highest carbon tax cost, especially in relation to ‘other’ fuels and electricity usage. This is perhaps due to the presence of children resulting in greater time spent at home along with greater heating, cooking and appliance usage.

There is a lower cost for electricity and motor fuel-related carbon taxes if one or more inhabitants are OAPs. While other fuels shows no significant difference, this becomes significant in the restricted model, suggesting that variation in dwelling size and type, along with heating fuel and appliance usage, explain much of the OAP-related variation in ‘other’ fuel consumption.

Higher incomes are associated with a greater carbon tax cost for ‘other’ fuels and motor fuels. Income has an insignificant effect on electricity-related carbon tax cost, suggesting that income-related variations in electricity usage are determined by other factors controlled for in the model. This is confirmed by Table 3 where income is positively significant. This suggests that appliance ownership, heating/cooking method and dwelling characteristics are responsible for much of the income-related variation in electricity-related carbon tax expenditure.

If the household has a loan, the incurred carbon tax cost tends to be lower, perhaps due to a more prudent spending pattern as a result of indebtedness. This is particularly evident for motor fuel and 'other' fuel usage, suggesting that, on foot of being in debt, households are more likely to reduce motor fuel and 'other' fuel consumption.

4.2.6. Dwelling characteristics, heating system and appliance ownership

Larger, detached houses incur a greater carbon cost associated with electricity and other fuels. Owning a dishwasher and tumble dryer is associated with greater carbon tax cost for electricity, with ownership of a dishwasher translating into a significantly different cost for total carbon tax. The number of motor vehicles in a household is the primary determinant of motors-related carbon tax cost, as one would expect.

Space heating is found to be the more important than cooking or water heating method when determining carbon tax cost. Relative to electricity-related space heating, oil, backboiler, solid fuel and gas technologies incur a greater carbon cost. Finally, households that own dishwashers and tumble dryers incur a much greater level of electricity usage and thus a much greater carbon tax cost, however this only translates to a significantly different level of total carbon tax incidence for dishwasher use.

Table 2: Determinants of carbon tax expenditure: full model

	(1) All sources	(2) Electricity	(3) Motor Fuels	(4) Other fuels
Location				
Dublin	Base category			
Border, Midland, West	0.297**	-0.0932**	0.626***	-0.0243
SW, SE, MW, ME, excl. Dublin	0.0404	-0.0508*	0.375***	-0.132*
Occupation				
Professional	Base category			
Non-manual	-0.118	0.0305	-0.231***	0.0367
Manual (semi) skilled	-0.0935	0.0554*	-0.203**	0.0206
Unskilled and agri	0.0289	0.0132	-0.243***	0.183
Own a/c and farmers	0.451*	0.191**	0.382**	-0.0791
Other Gainfully Employed and Unknown	-0.350**	-0.0188	-0.372***	-0.0280
Education				
Secondary school or less	0.0619	-0.00242	-0.153**	0.212**
Post-secondary, degree	0.110	0.0216	0.0878	0.0565
Postgrad degree	Base category			
Other	-0.171	0.641	-0.502*	-0.234
Age				
HRP: <35	Base category			
HRP: 35+	0.123	0.00967	0.0494	0.161**
Household structure				
1-2 Adults	Base category			
3+ Adults	0.974***	0.324***	0.553***	0.160*
No Children	Base category			
1-2 Children	0.495***	0.194***	0.160**	0.172**
3+ Children	1.091***	0.399***	0.341**	0.444***
Ln. Household disposable income	0.236**	-0.00232	0.138**	0.156***
OAP Present	-0.338**	-0.245***	-0.227***	0.167
Household has loan	-0.810***	-0.130**	-0.319**	-0.366**
Period of analysis				
Q1	-0.846***	-0.301***	0.146	-0.679***
Q2	-0.434***	-0.0932**	0.0559	-0.394***
Q3	Base category			
Q4	-0.324***	-0.0269	0.0824	-0.374***
Q5	-1.008***	-0.129***	-0.0835	-0.787***
Dwelling characteristics				
1-3 rooms	Base category			
4-6 rooms	0.0468	0.0822*		0.127*
7+ rooms	0.470**	0.262***		0.376***
Apartment/bedist	Base category			
House: detached	1.205***	0.138**		0.736***
House: semi-d/terrace	0.560***	0.0254		0.410***
Other	0.285	0.208		-0.153

Water heating				
Immersion heater	Base category			
Gas	0.0275	-0.0124		-0.0343
Solid fuel	0.510*	-0.00918		0.548**
Central	0.0879	-0.0328		0.0423
Other and none	-0.345	0.0243		-0.489**
Renewable	-0.282	0.191		-0.538*
Space heating				
Electric	Base category			
Oil, backboiler, solid fuel	0.619***	-0.357***		0.847***
Gas	0.389**	-0.349***		0.784***
Renewable	0.190	0.732		-0.960***
Other	0.590*	-0.195*		0.809***
Cooking method				
Electric	Base category			
Solid fuel	0.0299	0.0191		-0.152
Oil	0.312	0.00274		0.232
Central	-0.462	-0.198		-0.307
Combined fuel	0.0332	0.0422		-0.211
Gas	-0.0927	-0.0410		-0.0344
LPG	-0.186	-0.141***		-0.00382
Motor Vehicles				
No motor vehicle	-0.724***		-0.739***	
1 motor vehicle	Base category			
2+ motor vehicles	0.946***		0.903***	
Appliances				
Dishwasher	0.339***	0.148***		0.0491
Tumble dryer	0.137	0.0882***		-0.0120
Constant	1.232*	0.984***	0.335	-0.347
Observations	5797	5876	5876	5797
R^2	0.355	0.272	0.336	0.148
Adjusted R^2	0.350	0.266	0.334	0.141

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Determinants of carbon tax expenditure: restricted model

	(1) All sources	(2) Electricity	(3) Motor Fuels	(4) Other fuels
Location				
Dublin	Base category			
Border, Midland, West	1.078***	-0.0164	0.728***	0.379***
SW, SE, MW, ME, excl. Dublin	0.775***	0.0218	0.542***	0.197***
Occupation				
Professional	Base category			
Non-manual	-0.341***	-0.0149	-0.300***	-0.0310
Manual (semi) skilled	-0.370**	-0.00249	-0.276***	-0.0721
Unskilled and agri	-0.328*	-0.0623*	-0.384***	0.0995
Own a/c and farmers	0.776***	0.223***	0.472***	0.0470
Other Gainfully Employed and Unknown	-0.970***	-0.0671	-0.732***	-0.170*
Education				
Secondary school or less	-0.0814	-0.0613*	-0.297***	0.281***
Post-secondary, degree	0.137	0.0151	0.0589	0.104
Postgrad degree	Base category			
Other	-0.136	0.678	-0.666**	-0.142
Age				
HRP: <35	Base category			
HRP: 35+	0.652***	0.0535**	0.129**	0.467***
Household structure				
1-2 Adults	Base category			
3+ Adults	1.558***	0.407***	0.871***	0.295***
No Children	Base category			
1-2 Children	0.833***	0.227***	0.284***	0.317***
3+ Children	1.792***	0.503***	0.587***	0.693***
Ln. Household disposable income	0.680***	0.0402*	0.387***	0.262***
OAP Present	-0.143	-0.229***	-0.236***	0.320***
Household has loan	-0.977***	-0.136**	-0.439***	-0.400**
Period of analysis				
Q1	-0.915***	-0.303***	0.0979	-0.697***
Q2	-0.518***	-0.0918**	0.00561	-0.417***
Q3	Base category			
Q4	-0.375***	-0.0223	0.0521	-0.399***
Q5	-1.022***	-0.133***	-0.118*	-0.769***
Constant	-0.393	0.631***	-1.040**	-0.0499
Observations	5797	5876	5876	5797
R^2	0.257	0.207	0.244	0.086
Adjusted R^2	0.254	0.204	0.241	0.082

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.3. *Multivariate decomposition of unequal incidence*

The analysis of Section 4.2 identifies the socioeconomic characteristics associated with a greater carbon tax cost. However, households that incur a greater cost do not necessarily coincide with households that incur the most regressive impacts. Results presented in Tables 4 and 5 decompose the concentration index to quantify these impacts. Table 4 shows a number of details relating to the incidence of total carbon tax expenditure. We present the contribution each determinant gives towards the overall regressive incidence of the carbon tax total, in both actual and percentage terms, alongside the elasticity of the CI with respect to each determinant and the CI of the determinant variable. Table 5 shows the percentage contribution made by each socioeconomic variable for each constituent carbon tax source. A negative contribution increases the regressivity of incidence while a positive contribution increases the progressivity of incidence. We split determinants by category and discuss each category in turn.

4.3.1. *Location*

Being located in the BMW region is associated with a more regressive carbon tax incidence, primarily due to greater motor fuel and other fuel use. A progressive association with electricity use tempers the overall regressive impact. However, as the proportional cost of motor fuel-related carbon taxes are greater than those arising from electricity usage (see Figure 2), this results in a negative total contribution. This pattern prevails for the south, midwest, mideast rural regions but the effect is of a lesser magnitude.

4.3.2. *Occupation*

Tables 2 and 3 have shown that own account workers and farmers are associated with a greater incidence of motor fuel and electricity-related carbon tax costs. Table 4 shows that these occupations are negatively distributed along the income distribution and thus this results in farmers and own account workers being associated with a regressive contribution towards the unequal incidence of carbon taxation. Households where the HRP is gainfully employed in an unknown occupation are associated with lower incomes and lower carbon tax incidence and thus a positive contribution to overall inequality is observed.

4.3.3. *Education and Age*

Households with a secondary education or less consume a significantly higher level of ‘other’ fuels and have a pro-poor concentration index (see Table 4). Such households thus contribute towards increased regressivity of carbon tax incidence. A similar pattern is observed with respect to age, however, we find that the proportional contribution is of a much lower magnitude.

4.3.4. *Household structure*

Household structure has a considerable impact on carbon tax incidence and it is through the analysis of this determinant, in particular, that the contribution of the decomposed concentration index can best be illustrated. Tables 2 and 3 have shown that the number of adults has a greater impact on incurred carbon tax costs than the presence of 1-2 children, with an impact of slightly lesser magnitude than the presence of 3+ children. However, Table 4 shows that a greater number of adults is associated with a progressive equity impact while a greater number of children is associated with a regressive impact. Examining Table 5, we see that the magnitude of these impacts is of greatest concern with respect to electricity-related carbon tax incidence. Thus, should policymakers make recommendations based on the traditional regression-based analyses of Tables 2 and 3, revenue redistribution measures focussing on household size and the number of adults in particular may be pursued. However, the findings of this paper show that to offset regressive impacts of carbon tax, transfers corresponding to the number of children are more effective, especially when offsetting electricity-related carbon tax inequalities.

Further benefits associated with the decomposed concentration index methodology can be observed with respect to OAPs. The presence of OAPs increases the progressive incidence of total carbon tax incidence.

Although OAPs have lower incomes, they also use less electricity. This reduction in electricity usage outweighs their lower income levels and thus a negative elasticity exists with respect to the concentration index for total carbon taxes (Table 4). Thus, the CI methodology allows us to quantitatively compare these competing effects on the distribution of incidence to determine that OAPs contribute positively towards the progressive incidence of total carbon tax expenditure.

However, when we delve deeper into the socioeconomic gradient of carbon tax by source, we find that different carbon taxes affect this socioeconomic cohort in different ways. Given the lower propensity to incur electricity and motor fuel-related carbon taxes, these OAPs are associated with a progressive distribution of this cost. Given a higher propensity to incur 'other' fuel related carbon taxes, OAPs are associated with a regressive distribution of this cost. Thus, OAPs are an important consideration in relation to the negative impact of carbon taxes associated with 'other' fuels, but of lesser concern with respect to electricity and motor fuels.

4.3.5. Income

Income accounts for a substantial portion (24.45%) of the pro-rich distribution of total carbon tax incidence. Table 5 shows that this is largely driven by income-related gradient in 'other' fuel usage. A lower income gradient is found with respect to motor fuel-related carbon taxes, with socioeconomic differences in usage thus playing a more important role in the unequal incidence of motor and other fuel-related carbon taxes. A negative value exists with respect to electricity usage. As the coefficient for electricity usage in Table 2 is negative and insignificant, this suggests that all income-related gradient in electricity usage-related carbon tax is controlled for by the socioeconomic determinants in the model.

4.3.6. Dwelling characteristics, heating system and appliance ownership

Dwelling characteristics contribute a great deal towards the variability of carbon tax incidence. Relative to living in an apartment, living in a detached house has a positive impact on the overall progressive impact. This is because inhabitants of houses consume more electricity and other fuels but also have higher incomes. The positive gradient in income across this socioeconomic group outweighs the positive gradient in usage and thus a progressive impact prevails. This implies that a more regressive impact is imposed on inhabitants of apartments. The number of rooms has the same pattern of incidence. We find that a greater number of rooms is positively associated with a progressive carbon tax incidence for both electricity and 'other' fuels, suggesting that smaller households incur a more regressive impact.

Tables 4 and 5 show that ownership of electricity-intensive appliances such as a dishwasher or a tumble dryer contributes a considerable degree towards the pro-rich distribution of carbon tax incidence, especially in relation to electricity-related carbon taxes. This is due to the considerable pro-rich association of these appliances and the highly positive contribution towards electricity usage (see Table 2).

Space heating method is of considerable importance for carbon tax incidence, with water heating and cooking method contributing to a much lesser extent towards inequality. Relative to electricity-based central heating, households with oil, backboilers or solid fuels increase the inequality of carbon tax incidence, while households with gas reduce this inequality.

Analysing this socioeconomic variable gives further insight into the added value offered by the CI methodology, as the drivers of this inequality may be identified. For oil, backboilers and solid fuel space heating, the elasticity parameter is of a much greater magnitude than this determinant's CI. Thus, the regressive impact associated with this space heating technology is primarily driven by the carbon content and thus elasticity of carbon tax expenditure with respect to usage. Conversely, the progressive association of gas-based space heating is primarily driven by a strongly positive association with income.

4.3.7. Relative weighting of each category

While the preceding analysis has highlighted the factors contributing towards the negative impact of carbon tax incidence, the relative importance of each socioeconomic determinant is a further important contribution of this paper. Tables 4 and 5 present the relative weighting of importance that each socioeconomic determinant contributes towards overall inequality of incidence, where we find that different socio-economic traits are responsible for incidence amongst each emission source. For electricity, we find that the contribution of income is overshadowed by the presence of electricity-using appliances, with dishwasher and tumble dryer ownership, an indicator of ownership of electricity intensive goods associated with high income households, accounting for around 50% of unequal incidence across the income spectrum. Income-related consumption of electricity-intensive goods is thus the most important factor. This is followed by the number of rooms of the household (28%); the number of adults (12.61%) and children (-11%); location (11%) and space heating technology (-16%). For motor fuels, the number of motor vehicles is the predominant determinant (58.6%), followed by income (19.55%), occupation (12%) and location (-10%). For 'other' fuels, income is the overriding concern, contributing 85.51% of unequal incidence. This is followed by education (-26%), number of rooms (19.79%) and house type (10.27%). The presence of children and OAPs leads to an unequal pattern of incidence for 'other' fuels, contributing -8.41% and -5.99% respectively. Water heating and space heating technologies are also important considerations, with the presence of an oil, backboiler, or solid fuel space heating technology increasing the regressive impact of total carbon tax by -5.92%.

Table 4: Decomposition of concentration index for total carbon tax

Concentration Index	0.0834			
Projected Concentration Index	0.0774			
Residual term	0.0060	92.87%		
Decomposition results	Contributions	% Contributions	Elasticities	CI (determinants)
Location				
Dublin	Base category			
Border, Midland, West	-0.0024	-2.91%	0.021	-0.12
SW, SE, MW, ME, excl. Dublin	-0.0001	-0.14%	0.004	-0.03
Occupation				
Professional	Base category			
Non-manual	-0.0002	-0.29%	-0.005	0.05
Manual (semi) skilled	0.0003	0.33%	-0.004	-0.07
Unskilled and agri	0.0000	-0.05%	0.001	-0.07
Own a/c and farmers	-0.0019	-2.30%	0.012	-0.16
Other Gainfully Employed and Unknown	0.0082	9.82%	-0.015	-0.54
Education				
Secondary school or less	-0.0012	-1.44%	0.005	-0.26
Post-secondary, degree	-0.0003	-0.31%	0.005	-0.05
Postgrad degree	Base category			
Other	0.0000	0.02%	0.000	-0.05
Age				
HRP: <35	Base category			
HRP 35+	-0.0003	-0.42%	0.023	-0.01
Household structure				
1-2 Adults	Base category			
3+ Adults	0.0029	3.52%	0.068	0.04
No Children	Base category			
1-2 Children	-0.0011	-1.29%	0.032	-0.03
3+ Children	-0.0014	-1.69%	0.018	-0.08
Ln. Household disposable income	0.0204	24.45%	0.358	0.06
OAP Present	0.0027	3.24%	-0.016	-0.17
Household has loan	0.0026	3.08%	-0.189	-0.01
Period of analysis				
Q1	-0.0007	-0.85%	-0.022	0.03
Q2	-0.0005	-0.64%	-0.024	0.02
Q3	Base category			
Q4	0.0000	0.02%	-0.020	0.00
Q5	-0.0001	-0.12%	-0.041	0.00
Dwelling characteristics				
1-3 rooms	Base category			
4-6 rooms	-0.0003	-0.37%	0.008	-0.04
7+ rooms	0.0050	5.94%	0.028	0.18
Apartment/bedsit	Base category			
House detached	0.0026	3.16%	0.114	0.02

House semi-d/terrace	0.0000	0.03%	0.070	0.00
Other	0.0000	0.01%	0.000	0.05
Water heating				
Immersion heater	Base category			
Gas	0.0001	0.08%	0.000	0.14
Solid fuel	-0.0030	-3.62%	0.011	-0.28
Central	0.0008	0.92%	0.015	0.05
Other and none	0.0002	0.23%	-0.001	-0.25
Renewable	-0.0001	-0.13%	0.000	0.35
Space heating				
Electric	Base category			
Oil, backboiler, solid fuel	-0.0049	-5.92%	0.079	-0.06
Gas	0.0050	5.98%	0.037	0.13
Renewable	0.0000	0.05%	0.000	0.44
Other	-0.0003	-0.40%	0.004	-0.08
Cooking method				
Electric	Base category			
Solid fuel	0.0000	-0.04%	0.000	-0.28
Oil	0.0000	0.02%	0.001	0.02
Central	0.0001	0.11%	0.000	-0.25
Combined fuel	0.0000	-0.01%	0.000	-0.09
Gas	-0.0001	-0.06%	-0.002	0.02
LPG	0.0007	0.84%	-0.003	-0.22
Motor vehicles				
No motor vehicle	0.0131	15.73%	-0.035	-0.37
1 motor vehicle	Base category			
2+ motor vehicles	0.0232	27.82%	0.077	0.30
Appliances				
Dishwasher	0.0073	8.80%	0.054	0.14
Tumble dryer	0.0014	1.63%	0.023	0.06

Table 5: Decomposition of concentration index for each carbon tax source

	Electricity		Motor fuels		Other fuels	
Concentration Index	0.0362	**100.0%**	0.1653	**100.0%**	0.0380	**100.0%**
Projected Concentration Index	0.0358	**99.0%**	0.1508	**91.2%**	0.0344	**90.6%**
Residual term	0.0004	**1.0%**	0.0145	**8.8%**	0.0036	**9.4%**
Decomposition results	*Contributions*					
Location						
Dublin		Base category				
Border, Midland, West		9.6%		-8.4%		1.3%
SW, SE, MW, ME, excl. Dublin		1.9%		-1.8%		2.3%
Occupation						
Professional		Base category				
Non-manual		0.8%		-0.8%		0.5%
Manual (semi) skilled		-2.0%		1.0%		-0.4%
Unskilled and agri		-0.2%		0.5%		-1.5%
Own a/c and farmers		-10.2%		-2.7%		2.1%
Other Gainfully Employed and Unknown		5.6%		14.4%		4.2%
Education						
Secondary school or less		0.6%		4.9%		-25.9%
Post-secondary, degree		-0.6%		-0.3%		-0.8%
Postgrad degree		Base category				
Other		-0.7%		0.1%		0.1%
Age						
HRP: <35		Base category				
HRP 35+		-0.3%		-0.2%		-2.9%
Household structure						
1-2 Adults		Base category				
3+ Adults		12.6%		2.8%		3.1%
No Children		Base category				
1-2 Children		-5.3%		-0.6%		-2.4%
3+ Children		-6.5%		-0.7%		-3.6%
Ln. Household disposable income		-2.5%		19.5%		85.5%
OAP Present		24.9%		3.0%		-8.4%
Household has loan		5.1%		1.7%		7.3%
Period of analysis						
Q1		-3.3%		0.2%		-3.6%
Q2		-1.5%		0.1%		-3.1%
Q3		Base category				
Q4		-0.1%		0.0%		0.1%
Q5		-0.2%		0.0%		-0.5%
Dwelling characteristics						
1-3 rooms		Base category				
4-6 rooms		-7.0%		-		-5.3%
7+ rooms		35.2%		-		25.0%

Apartment/bedsit	Base category		
House detached	4.1%	-	10.2%
House semi-d/terrace	0.0%	-	0.1%
Other	0.1%	-	0.0%
Water heating			
Immersion heater	Base category		
Gas	-0.4%	-	-0.6%
Solid fuel	0.7%	-	-20.5%
Central	-3.6%	-	2.3%
Other and none	-0.2%	-	1.8%
Renewable	1.0%	-	-1.3%
Space heating			
Electric	Base category		
Oil, backboiler, solid fuel	35.8%	-	-42.8%
Gas	-56.1%	-	63.6%
Renewable	2.2%	-	-1.4%
Other	1.4%	-	-2.9%
Cooking method			
Electric	Base category		
Solid fuel	-0.3%	-	1.1%
Oil	0.0%	-	0.1%
Central	0.5%	-	0.4%
Combined fuel	-0.1%	-	0.2%
Gas	-0.4%	-	-0.1%
LPG	6.8%	-	0.1%
Appliances			
Dishwasher	40.4%	-	6.7%
Tumble dryer	11.0%	-	-0.8%
Motor vehicles			
No motor vehicle	-	22%	-
1 motor vehicle	Base category		
2+ motor vehicles	-	36%	-

5. Discussion

Our results are the first to apply the concentration index methodology to give novel and policy-relevant insight into the incidence of carbon taxation by socioeconomic group. While [5] have compared determinants of carbon incidence with determinants of income to provide qualitative insight into distributional implications, providing quantitative evidence to confirm many of these distributional hypotheses was identified as a gap in the literature [5]. This paper provides that contribution, giving insight into the relative importance of each socioeconomic characteristic in addressing negative income effects. As has been argued by [27], it is of lesser concern that a single tax measure is regressive, but rather of greater importance that a tax-benefit system in its entirety is progressive, as regressive measures may be offset by those that are progressive. Thus, losers identified in this paper may be compensated elsewhere in the tax-benefit system and this has not been accounted for. While this paper does not offer this context, it highlights socioeconomic groups that are most negatively affected by a carbon tax alone. As carbon taxes grow as a proportion of total tax revenue, and regressive impacts grow in magnitude, offsetting these impacts becomes of greater concern for the wider tax-benefit system. This paper provides information for a policymaker who wishes to augment existing taxes or benefits to account for losers of such carbon tax growth.

A number of key policy insights are offered by this analysis. Should different fuel sources be faced with different carbon tax rates, then policymakers will need to consider measures to offset negative income impacts from each carbon source seperately, confirming the findings of [5]. This is the case in many countries, particularly those partipicating in the EU ETS [15]. This paper has shown that, for the considered Irish case study, 'other' fuel-related carbon taxes have regressive effects of the greatest magnitude, followed by motor fuel and electricity-related carbon taxes. Redistributive mechanisms by source should take this into account when apportioning revenue. The channels that are most effective for offsetting negative income impacts associated with each source of carbon tax have also been identified and the policy implications of these findings will now be outlined.

The CI methodology of this paper finds that income is associated with 85.51% of 'other' fuel-related inequality. Income-based redistribution measures such as cash transfers may thus be most appropriate to counteract regressivity associated with this carbon tax source. This finding corresponds to that of [42] who state that fuel poverty is a subset of total poverty as opposed to something that requires seperate treatment.

Despite the importance of income-based measures in treating 'other' fuel-related carbon tax inequalities, there is evidence to support incentives for less carbon-intensive space heating technologies. The analysis of Section 4.2 found that a non-negligible proportion of incidence is attributable to the method of space heating. Space heating technology is a long-term, capital investment and as carbon taxes affect the marginal cost of consumption, a temporal disconnect exists with respect to the fuel choice decision. While weekly cash transfers may subsidise fuel purchase and thus alleviate regressive impacts in the short term, they are unlikely to affect a consumer's decision to change technology and the unequal effect may persist. Incentives to switch space heating technologies may be more effective in mitigating these regressive impacts. However, given the weighting of such factors observed in our analysis, a lesser proportion of the total carbon tax revenue should be used for this purpose.

While confirming the recommendations of [42], the CI methodology of this paper suggests that income is of lesser importance with respect to electricity or motor fuel-related carbon tax incidence. To offset the negative effects of electricity-related carbon taxes, and to a lesser extent those related to 'other' fuels, this paper is able to identify that household-related variables are of considerable importance. Household size is found to represent 28% of the unequal incidence of carbon tax for electricity, with a smaller household size being associated with a more regressive impact. Similarly, apartments tend to incur a more regressive impact. These impacts are not inconsiderable, representing 8.78% of the total socioeconomic gradient, an impact quantitatively greater than the presence of OAPs or the number of children. Thus, measures that take account of household characteristics are of importance for electricity-related carbon taxes. The relative importance of these variables may be overlooked through normal regression techniques.

The number of motor vehicles is predictably the predominant determinant of motor fuel carbon tax incidence. However, income, occupation and location are also of considerable importance. Farmers and own account workers are associated with regressive effects, with redistributive measures such as tax adjustments for the self-employed potentially useful in countering these negative income effects. Redistributive measures that discriminate recipients spatially are important to counteract regressive impacts on rural inhabitants.

Our findings correspond with those of [5] who find a positive relationship between education and all sources of emission except home energy. Our analysis gives further insight into the role education may have in mitigating both carbon tax consumption and the unequal incidence of its imposition. Tables 2 and 3 show that households with higher education are associated with greater motor fuel and electricity usage (due to variances in dwelling characteristics and appliance usage) and lower levels of 'other' fuel usage. This suggests that more educated people are more likely to employ less carbon-intensive heating systems, but use more motor fuels and electricity-consuming appliances. Low levels of education contribute a great deal towards the regressive incidence of ‘other’ fuels (-25.9%), with impacts associated with electricity and motor fuels of much lesser magnitude. Given the high degree of quantified inequality associated with ‘other’ fuel usage amongst those with low education, addressing this issue should perhaps be a priority for policymakers, both in an effort to reduce carbon emissions but also to reduce the regressive impacts associated with their imposition.

Differentiated carbon prices based on emission source will require careful consideration with respect to the net incidence for OAPs, as they are particularly vulnerable to changes in carbon taxes on ‘other’ fuel sources. This is in contrast to their propensity to incur lesser degrees of motor fuel and electricity-related carbon tax which outweighs their reduced levels of income. This is insight that is quantifiable through the presented CI methodology.

Household structure is a further important consideration when policymakers are designing revenue redistribution measures. While a greater number of inhabitants increases the household’s carbon tax cost, this impact is only regressive in relation to the number of children present. This paper builds on the research of [23] and [5] to show that households with children are associated with regressive impacts, especially in relation to electricity-related carbon tax incidence. Revenue redistribution measures that take this into account, such as child benefit adjustments, are thus important. A policymaker should bear in mind that the number of children in a household contributes -3% towards the total concentration index, with this being of lesser importance than income-based transfers or household-related inequalities. The quantification of incidence offered by the methodological approach of this paper allows for this added insight.

6. Conclusion

This paper has addressed a previously identified gap in the literature by decomposing carbon tax-related inequality by socioeconomic determinant for an Irish case study. This is considered for three carbon tax emission sources of electricity, motor fuels and all other direct fuel consumption in the home. This paper provides a number of contributions to the literature. First, the total regressive effect of each carbon tax source is quantified. ‘Other’ fuels used in the home are regressively distributed and comprise the greatest proportion of household equivalised disposable income across the income spectrum. It is found that while motor taxes are the most progressively distributed across the income spectrum, the cost is of greater proportional magnitude than electricity-related expenditures and thus the negative income effect is greater.

Second, the multivariate decomposition of carbon tax incidence allows for a number of insights that have not been identified in the literature previous. The relative importance of each socioeconomic determinant in unequal carbon tax incidence is quantified. Socioeconomic determinants vary in importance according to carbon tax source. For electricity, it is found that appliance ownership, income, dwelling characteristics, household composition, location and space heating technology are of greatest importance. For motor fuels, the number of motor vehicles, income, occupation and location are important factors. For all other fuels consumed in the home, income, education, dwelling characteristics and choice of space heating technology are important determinants. The methodology of this paper allows for further insight. In some circumstances, the distributional impact amongst a certain socioeconomic cohort is unclear, and the progressivity of incidence is determined by the effect the variable has on carbon tax incidence and distribution of the socioeconomic determinant across the income distribution. The methodology employed in this paper provides a means to decompose progressive or regressive impacts according to the mechanism driving a resulting distributional impact.

The policy relevance of these findings has been discussed. Should revenue recycling measures ignore these quantified trends in inequality, then the identified vulnerable socioeconomic groups may persistently lose out from the incidence of carbon taxation, despite the presence of revenue redistribution mechanisms.

Furthermore, the findings of this paper imply that revenue should be recycled via a combination of adjustments. This is particulary important should carbon tax rates differ by emission source, as is the case in many countries, as different socioeconomic groups are negatively affected by carbon taxes arising from each source.

This paper provides an important first step in isolating the contribution each socioeconomic determinant may have in the incidence of carbon tax expenditure, informing efficient policy measures to offset negative income impacts of carbon tax policies. This will be of increasing relevance for policymakers as environmental targets progress and offsetting the inequalities created by carbon taxes grows in importance for effective social policy design.

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