Political Feasibility and Distributional Implications of Carbon Pricing: the Scope for Revenue Recycling

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Abstract

We investigate the extent to which revenue recycling addresses the regressive impacts of carbon pricing and improves its political feasibility by studying the distributional implications of different recycling schemes, including transfers, scale up of social security payments and a reduction of the income tax. We highlight consequences for vertical and horizontal equity as well as public approval rates. We find that recycling via transfers renders carbon pricing progressive, and rebating revenues via social security payments yields the largest increases in consumption and highest approval rates, albeit with the lowest emission reductions. Decreasing the income tax is regressive, does not generate substantial consumption gains nor high approval rates. In fact, we are unable to generate majority approval rates via recycling, emphasizing the political economy limitations of carbon pricing.

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Contents

1 Introduction

Market-based instruments have been proposed as cost-effective approaches to address the climate crisis since the 1980s. Yet, jurisdictions today with a moderately ambitious carbon price of $40 per tonne of CO_2e (CO_2 equivalent [1]) account for less than 1% of global emissions (Cullenward and Victor, 2020). Market-based instruments have been effective in very limited cases[2], but most market-based systems currently in place operate at very low prices which do not provide strong incentives to alter behaviour at scale. Despite their potential to create strong incentives to reduce emissions, carbon pricing schemes have largely failed to convince the public and are often perceived as ineffective, regressive policies that disproportionately impact low-income and rural households (Douenne and Fabre, 2020). This thesis contributes to the literature around the distributional implications of carbon pricing and the role of revenue recycling in mitigating regressive outcomes and increasing public support.

The failure of efforts to implement effective market-based climate policies stems largely from the lack of support from key stakeholders, especially voters. While public concern around climate change has increased, public opposition to carbon taxes and other instruments has fueled debates around their political feasibility. A notable example is the response of French citizens in 2018 to the planned increase of the federal carbon tax to €86.2 per tonne of CO_2e, which fueled large-scale opposition against what was perceived to be an ineffective additional tax that would reduce the purchasing power of low-income and rural households (Douenne and Fabre, 2020). These concerns were, in this context, correct; Douenne (2020) shows large distributive effects of energy taxes despite neutralizing revenue recycling. Despite general commitments to a 'just transition', policy-makers have largely failed to administer credible climate policies that adequately offset the detrimental distributional effects of carbon prices.

[1]Greenhouse gas (GHG) emissions, including from carbon dioxide, methane and nitrous oxide, are converted into CO2 equivalents for ease of comparison. In 2020, the High-Level Commission on Carbon Prices recommended that carbon prices need to be $40-80 per tonne of CO_2e by 2020 and $50-100 per tonne of CO_2e by 2030 to be consistent with UN Paris Agreement pledges.

[2]Notably in support of the United Kingdom's shift away from coal and towards natural gas and renewable energy for electric power.

Rebating carbon tax revenues may compensate households for the price increase and offset regressive consequences. To better understand the extent to which revenue recycling can address distributive objectives and increase public support, we analyze the distributional impacts of a carbon tax of £100 per tonne of CO_2e using detailed microdata from 11 years of UK representative household surveys. We are interested in heterogeneity in tax incidence, across income and household composition. We seek to capture household responses in consumption and labour supply by estimating a demand system and labour supply elasticities within our sample of households, which we then use to calibrate a simple static model that allows us to investigate the implications of different policy scenarios. To quantify the welfare effect, we compute equivalent variations of policy packages, or monetary equivalents used for standard inter-household comparisons which capture not only the tax burden but the net effect accounting for adjustments in consumption and labour supply. We first consider the impact of a carbon tax with no revenue recycling, then analyze three policy scenarios: (1) undifferentiated per capita lump-sum rebates to households, where we adjust for family size, channel proceeds to the bottom 40% of the equivalized income distribution or adjust for geography; (2) a proportional increase in social security payments; and (3) income tax reductions. We are interested in implications for efficiency (as reflected by aggregate consumption changes), equity (both across and within income deciles) and effectiveness (measured by percent reductions in CO_2e emissions).

We show that an uncompensated carbon tax is regressive, but that transfers can be used to offset this regressivity; recycling via transfers or social security decreases inequality, while recycling via an income tax reduction is regressive. Transfers which target the bottom 40% benefit low-income households the most, but increasing social security benefits proportionally yields the highest overall approval rate (34%), albeit with the smallest emissions reduction. Increasing social security benefits also yields the largest consumption increases, while reduction in the income tax does not result in overwhelming efficiency gains. Income tax reductions benefit richer households the most, with an overall approval rate of only 11%. These results are not fully consistent with findings from Germany by Van der Ploeg, Rezai and Tovar (2020), who show that lowering the income tax yields higher consumption increases than lump-sum transfers (confirmed by our data) but that such reforms imply a majority approval rate. While we also impose that the government's budget constraint must hold such that the income tax must *increase* following complete recycling via transfers, since the increase in the price level from the carbon tax erodes the real wage and therefore the tax base, we do not find that this offsets the consumption gains from channeling proportionately more income to low-income households. Differently from their assumption of fixed savings, we assume a fixed propensity to save. We also consider social security benefits, which effectively allow for greater needs-based targeting across all deciles. Finally, we find that income and heating fuel are the most important determinants of welfare costs. Interestingly, we do not find evidence of a rural-urban divide — as was highlighted by the Yellow Vests movement in France (Douenne, 2020) — nor of systematic differences across regions.

We make three original contributions to the literature. First, we estimate consumer demand from an EASI demand system using 11 years of UK survey data and differentiating across seven product categories, which allows us to account for substitution effects in household responses to price changes. Previous assessments of carbon tax incidence in the UK do not estimate price and income elasticities. Second, we consider both implications for inequality and political feasibility, testing for determinants of heterogeneous incidence in the UK. Finally, we build a new dataset of household expenditures, prices, incomes, labour outcomes, and emissions, which can be used by other researchers interested in testing climate policy designs.

This paper is structured as follows: in Section 2, we review existing literature on the distributional impacts of carbon pricing. In Section 3, we present a simple static partial equilibrium model that allows us to quantify the impacts of carbon pricing and recycling on households. Section 4 describes the data and Section 5 presents our estimation strategy for the relevant elasticities of consumer demand and labour supply. Section 6 reports our estimates, equivalent variations of policy simulations and the implications of our exercise. Section 7 discusses limitations and further research opportunities, and Section 8 concludes.

2 Related Literature

The literature around the distributional and equity implications of carbon pricing is vast and old, but yields ambiguous results (Ohlendorf et al., 2021). In addition to recent theoretical uncertainty around the effectiveness of carbon pricing over regulation-based instruments in the presence of market frictions and behavioural agents, theoretical and empirical evidence around distributional implications has proliferated. The literature has generally found regressive implications of energy taxes (Metcalf, 1999; Poterba, 1991; Grainger and Kolstad, 2010; Metcalf and Weisbach, 2009; Rausch, Metcalf and Reilly, 2011; Williams III et al., 2015), as these increase the price of fuel-intensive goods which constitute high shares of low-income households' expenditures (Pizer and Sexton, 2019; Flues and Thomas, 2015). To address this regressivity, economists have considered revenue recycling to render carbon pricing distributionally-neutral. In principle, the distributional impacts of carbon taxes depend on how income is defined and measured, on the producer and consumer shares of tax incidence, on the carbon intensity of households' consumption baskets and their ability to reallocate, and on any complementary changes to governmental taxes and transfers.

While consumer expenditure data from the U.S. and European countries shows that poor households devote greater shares of incomes to energy purchases (much like they devote greater shares of incomes to food and other necessities), inter-household comparisons of the tax burden depend on how income is defined. Measures of regressivity based on annual income typically differ from those evaluated against annual consumption; annual incomes fluctuate due to temporary or permanent shocks and due to life-cycle effects in earnings and savings (Poterba, 1989). Using annual consumption as a proxy of permanent income (as suggested by Friedman et al. (1957)'s permanent income hypothesis, which posits that households smooth consumption over the life cycle through savings) typically reduces the regressivity found when using annual income. We confirm this in our data: effort rates evaluated against expenditures are less regressive than these evaluated against disposable income. Which of these approaches is more relevant is subject to debate; while the true regressivity of the policy might be lower than when measured against annual income, in practice political feasibility is defined by perceived welfare costs likely based on current, not lifetime, income.

The distributional implications of climate policy include vertical and horizontal dimensions, i.e. reallocations across and within income groups. Much empirical evidence shows that the incidence of taxes on fuels and electricity falls more intensely on poor households, while taxes on transport fuels vary non-linearly with income in the OECD (Flues and Thomas, 2015). In the UK, spending on energy goods constitutes the biggest expense after food for the poorest decile, but the smallest expense for the richest decile (Advani et al., 2013). Analyses of policy design have suggested that lump-sum rebates or scaling up existing social programs can fully compensate low-income households; for example, Mathur and Morris (2014) study a carbon tax as part of broader US fiscal reform and find that the poorest income quintile can be fully compensated for an increase in \$15 per tonne of CO_2 emissions by rebating only 11% of revenues. Similarly, Metcalf and Weisbach (2009) design a revenue-neutral package that rebates revenues to households by scaling up the Earned Income Tax Credit (EITC). While the double-dividend literature posits that using revenues to decrease distortionary taxes, like income taxes, combines the benefits of correcting for externalities with reducing inefficient taxation, the equity implications are likely negative; using revenues to decrease the most distorting taxes that are currently progressive, like those on corporate and capital income, may increase the overall regressivity of the tax system. Indeed, Williams III et al. (2015) find that, in the US, recycling revenues via capital income tax cuts increases regressivity, via lump-sum rebates increase progressivity and via income tax reductions represents a middle ground.

Implications for horizontal equity have received less attention than implications for vertical equity. Recent evidence documents horizontal distributive effects within income groups that are larger than across income groups; for example, Douenne (2020) and Berry (2019) find that rural residents exhibit a relatively high demand for transport but less access to public transport, inhabit larger dwellings and are more exposed to weather fluctuations, which result in higher demand for heating. While the energy economics literature has focused primarily on the income (Goulder et al., 2019) and geographic (Cronin, Fullerton and Sexton, 2019; Berry, 2019) dimensions of horizontal equity, a growing body of work has highlighted racial disparities in the energy burden. For example, Reames (2016), Bednar, Reames and Keoleian (2017) and Kontokosta, Reina and Bonczak (2020) find that the energy burden is larger in high-minority neighbourhoods than low-minority neighbourhoods. Lyubich et al. (2020) find that African Americans bear a disproportionate energy burden in the US, both through disproportionate exposure to pollution and disproportionate costs likely due, as the authors suggest, to persistent racial disparities in wealth and housing. Overall, heterogeneity within income deciles depends on family size, home ownership status, climate, electricity-generating infrastructure, home size and vintage, vehicle miles travelled and energy efficiency of durable goods. Horizontal inequities are larger than vertical inequities (Pizer and Sexton, 2019) and more difficult to address via transfers, as any compensation which conditions on factors that determine energy use mutes price effects and offsets the original corrective objectives of the instrument. Cronin, Fullerton and Sexton (2019) first assess the capacity of existing transfer mechanisms to mitigate vertical and horizontal redistributions following the imposition of an energy tax in the US, simulating the effects of per capita lump-sum taxes, decreases in the payroll tax and scaling up of social security and EITC. While they do not account for quantity changes (such that any change in expenditure is driven only by price changes), they find large horizontal redistributions that remain unmitigated and are even exacerbated by revenue recycling. Per capita transfers render the carbon tax progressive, decreasing total taxes borne by the average family in the lowest consumption decile by nearly 700% and increasing them by 1.13% for the richest families. However, while each rebate type considered mitigates the variation in tax burden across income groups, it also increases variation in the tax burden within most deciles, introducing a trade-off between vertical and horizontal equity objectives. Their study is the first to highlight that aggregate decile statistics do not accurately capture welfare, showing that a tax cut for the average family conceals small tax increases for many. From a normative perspective, horizontal equity may be understood as a component of inequality aversion (Bentham, 1843), but large heterogeneity within income groups has important positive implications on whether a policy is passed; a minority of winners is less likely to generate enough public support to offset a majority of losers.

Finally, the design of price mechanisms (broad homogeneous tax vs. sector-specific charges) and the models used to evaluate their implications can yield different results. Sectoral differences in energy efficiency imply that market-based instruments targeted towards specific sectors can have different distributional implications. For example, progressive outcomes for transport sector policies are driven by smaller car ownership rates for low-income households, making fuel a luxury product, while home heating is typically a necessity. With respect to research designs, modeling demand-side adjustments, general equilibrium effects or applying a life-cycle approach result in contrasting implications. Demand-side adjustments ambiguously influence study outcomes; Zhang (2015) finds larger demand elasticities for richer households, while West and Williams III (2004) estimate larger demand-size adjustments to transport fuel taxes for poorer households, resulting in more progressive outcomes. Our estimates instead show larger elasticities for poor households, consistent with findings from Douenne (2020). Extending the analysis to general equilibrium models considers the effect of energy policy on factor prices as well as output prices, i.e. on both the "sources side" and "uses side". A carbon tax may disproportionally burden capital-intensive industries, reducing the return to capital; if the capital income share is higher for richer households, incidence from the "sources side" may by progressive. Fullerton and Heutel (2011) find that incidence from both sources and uses is regressive, but sensitive to parameter values.

Carbon pricing has played an important role in the UK's climate policy strategy; a report from energy regulator Ofgem (2019) estimates that, between 2010 and 2018, carbon pricing was the single most effective electricity decarbonisation policy, reducing emissions more and more efficiently than other policies, like subsidies and standards. Vivid Economics (2020) studies, for the first time, the distributional effects of a tax of £50 per tonne of CO_2e in 2020, rising to £75 in 2030, on UK households. The authors analyze the impacts of this tax on household types, differentiated by income levels and fuel type. They find regressive vertical distributive effects of a carbon tax; low-income households are hit hardest, despite UK households in the top income decile earning 9.4 times as much as households in the lowest decile, and emitting 3.7 times more CO_2e in 2030. Modelling flat and targeted transfers, they find that a carbon tax at these rates on energy, food and transport costs households in the bottom three income deciles 2–4% of their income, and the top three income deciles 1–2% of income. The carbon tax on transport is progressive, as the share of income spent on transport increases with income, while a tax on energy is most regressive. As they do not estimate price elasticities of energy, food and transport, their analysis ignores potentially important substitution and income effects. This research builds on past work by estimating household responses, broadening the set of consumption aggregates, investigating determinants of net welfare effects and integrating dynamics of labour supply, including income tax reductions.

3 Theoretical Framework

3.1 Households

To evaluate welfare effects and political feasibility of increasing carbon prices for different household types, we build a static partial equilibrium model of households and government following Van der Ploeg, Rezai and Tovar (2020). We consider H households with population weight N_h who receive gross hourly wage W_h for their labour l_h, lump-sum transfers from the government t_h, social security benefits ss_h and exogenous non-labour income $\bar{y_h}$, which includes income from investment and pensions. Households spend their disposable income on consumption goods and savings $\hat{s_h}$; as we are primarily concerned with short-run effects and political feasibility, we abstract from dynamic consumption-saving decisions and assume a constant marginal propensity to consume, such that the share of disposable income allocated to savings is constant. Households are subject to a piece-wise linear income tax schedule $\tau_h = f(W_h l_h)$, which depends on labour income and exhibits marginal rate $\tau_h^M = \frac{d\tau_h}{d(W_h l_h)}$.

In this static model, households maximise a within-period, additively-separable, quasi-linear utility function capturing utility from consumption goods net of disutility from labour. The quasi-linearity of the utility function allows us to abstract from cross-price effects between consumption and leisure and estimate utility from consumption v_h, given disposable income and prices, from a demand system. We essentially embed a demand system within a model which includes labour supply to test for double dividends. We do not include disutility from aggregate emissions, as this heterogeneous parameter is difficult to calibrate and households take emissions as given, resulting in the climate externality. We instead assume that aggregate welfare is net of the social disutility from total emissions.

A static partial equilibrium model is the simplest way to capture the short-run effect of a carbon price on households, modelling the intra-temporal behavioural response to changes in prices. We abstract from any inter-temporal dimension and focus on demand-side adjustments only, assuming full pass-through of price changes onto consumers. Diamond and Mirrlees (1971) discuss the conditions under which optimal taxation involves production efficiency (competitive markets, constant returns to scale, flexibility in choosing producer and consumer prices, and exogenous government revenue constraint with no lump-sum taxes). To achieve production efficiency, all producers must face the same prices, whether private or public. Treating the environmental good as an additional output (or input) of productive sectors, a production efficiency result follows directly, such that we focus on consumer prices. We consider both direct and indirect effects of an increase in the price of carbon; direct effects from changes in the price of goods that directly contain CO_2e, like fuels, and indirect effects from price changes of goods in the consumption basket due to CO_2e emissions embedded in their value chain. In principle, one could capture intertemporal dynamics through a life-cycle approach or general equilibrium effects by adding firms to the model.

Households maximize utility subject to the flow budget constraint, such that the problem for each household h is:

$$\max_{x_h, l_h} u_h = v(c_h) - \phi_h \frac{l_h^{1+1/\epsilon}}{1+1/\epsilon} \quad \text{s.t.} \quad c_h + \hat{s_h} = W_h l_h + \bar{y_h} + ss_h + t_h - \tau_h \tag{1}$$

where $c_h(\boldsymbol{p}, \boldsymbol{x})$ is total spending on consumption goods $x_1, ..., x_J$ (we assume utility maximizing households, so total consumption equals total income devoted to consumption goods), $\phi > 0$ is the disutility of labour, which differs across households, and $\epsilon > 0$ is the wage elasticity of labour supply.

Aggregate emissions are given by:

$$E = \sum_{h=1}^{H} N_h \boldsymbol{e_h} c_h \boldsymbol{w_h}^T \tag{2}$$

where $\boldsymbol{e_h}$ represents a vector of carbon intensities — in kgCO_2e per £— for each consumption good consumed by household h, and $c_h \boldsymbol{w_h}$ is a vector of expenditures on each good; $\boldsymbol{e_h x_h}^T$ is the total footprint of household h, which depends on the composition of the consumption bundle[3]. Total emissions are measured in weekly kgCO_2e and total expenditure is measured in weekly monetary terms. The parameter ϕ converts the disutility cost of labour into £. Households take transfers as exogenous, and maximise utility with respect to consumption goods and the labour supply to yield the labour supply schedule:

$$l_h^* = \left(W_h (1 - \tau_h^M) \frac{\mu_h}{\phi_h} \right)^{\epsilon} \tag{3}$$

where μ is the marginal utility of wealth, and consumption such that:

$$\frac{dv_h(c_h^*)}{dc_h^*} = \mu_h \tag{4}$$

$1/\mu_h$ is then equal to $\frac{dc_h}{dv_h}$, which is the marginal cost of utility and denoted by P_h^M. There is no income effect of labour supply given the quasi-linearity of utility, and labour dynamics are entirely driven by substitution effects due to changes in relative prices. Labour supply therefore increases in the after-tax wage, decreases in the disutility of labour and in the marginal cost of utility (it effectively increases in the real wage). If the prices of consumption goods increase, the marginal cost of holding utility fixed increases, i.e. the real wage decreases and the labour supply falls. As the price index is specific to each household and depends on the consumption basket, the extent to which this changes with a carbon tax depends on the carbon intensity of the goods that make up that basket and their own-price and cross-price elasticities, i.e. the ability of each household to substitute towards low-carbon-intensity goods.

We approximate indirect utility v_h by estimating an Exact Affine Stone Index (EASI) demand system. The EASI demand system relies on Sheppard's Lemma to derive optimal budget shares of different consumption groups as a function of observables (a measure of in-

[3]Note that the vector of carbon intensities is specific to each household as it depends on the intensities of disaggregated categories. For example, the intensity of heating depends on fuel type.

direct utility — essentially real expenditures —, prices and household characteristics). We are then able to recover heterogeneity in price and income elasticities for each consumption aggregate, which capture how different household types reallocate consumption after small relative price changes. An EASI demand system allows for general Engel curves which depend on household characteristics, such that we can allow for heterogeneous demands and capture more convincingly the distributional dimension. We consider 7 consumption aggregates: food, energy (fuels, gas and electricity), transport, housing (other housing costs), services, durables, and other goods. We first estimate a system of J = 7 budget shares which depend on observable prices, total expenditure and T = 8 households characteristics (i.e. 8 different household types), where each share is:

$$w_j = \sum_{r=0}^{R} b_{rj} \ln(v)^r + \sum_{t=2}^{T} d_t z_t \ln(v) + \sum_{k=1}^{J} a_{jk} \ln(p_k) + e_j \tag{5}$$

and where v is a measure of indirect utility given by:

$$\ln(v) = \ln(c) - \sum_{j=1}^{J} w_j \ln(p_j) + \frac{1}{2} \sum_{j=1}^{J} \sum_{k=1}^{J} a_{jk} \ln(p_j) \ln(p_k) \tag{6}$$

We have omitted the subscript for households, but each budget share and indirect utility equation is household-specific, including a household-specific price vector, household type vector, measure of indirect utility and consumption. The EASI demand system is preferable to standard Almost Ideal Demand System (AIDS) estimations because it allows for flexible, nonlinear Engel curves and accounts for unobserved heterogeneity in preferences. We provide more detail on the estimation of budget shares in Section 5 and in the Appendix.

From 6, we derive the average cost-of-living index for each household:

$$\ln(c) - \ln(v) = \sum_{j=1}^{J} w_j \ln(p_j) - \frac{1}{2}\sum_{j=1}^{J}\sum_{k=1}^{J} a_{jk} \ln(p_j)\ln(p_k) \tag{7a}$$

$$\frac{c}{v} = P^A = \left(\prod_{j=1}^{J} p_j^{w^j}\right) e^{-\frac{1}{2}\sum_{j=1}^{J}\sum_{k=1}^{J} a_{jk}\ln(p_j)\ln(p_k)} \tag{7b}$$

This is simply the Stone price index if the own and cross-price elasticities are zero, such that budget shares are constant and $P^A = \left(\prod_{j=1}^{J} p_j^{wj}\right)$. To derive the marginal cost of utility, we differentiate 6 and 5 with respect to total spending on consumption goods:

$$\frac{\partial w_j}{\partial c} = \left(\sum_{r=1}^{R} b_{rj}\, r\, \ln(v)^{r-1} + \sum_{t=2}^{T} d_t z_t\right)\frac{d\ln(v)}{dc} \tag{8a}$$

$$\frac{d\ln(v)}{dc} = \frac{1}{v}\frac{dv}{dc} = \frac{1}{c} - \sum_{j=1}^{J} \ln(p_j)\frac{\partial w_j}{\partial c} \tag{8b}$$

and combine to derive:

$$P^M = \frac{dc}{dv} = \frac{c}{v}[1 + (\sum_{r=1}^{R} b_{rj}\, r\, \ln(v)^{r-1} + \sum_{j=2}^{T} d_t z_t)\sum_{j=1}^{J}\ln(p_j)] \tag{9}$$

This marginal cost of utility corresponds to the average cost of utility only if demand is homoethetic, i.e. if the terms b_{rj} and d_t are zero and the budget shares depend only on prices and constant terms. Then, $P^M = \frac{c}{v} = P^A$.

3.2 Policy Instruments and Government

The government imposes a carbon tax π on energy sources and we assume full pass-through from firms to consumers. As this is a partial equilibrium model, prices before the carbon tax are taken as exogenous, such that the after-tax consumer price for good j faced by household h is:

$$p_{jh} = q_{jh}(1 + \pi e_{jh}) \tag{10}$$

for $j = 1, ..., J$ and where e is the carbon intensity (kgCO_2e per $\pounds$), π is the carbon tax (in $\pounds$ per kgCO_2e) and the prices are in $\pounds$ per unit.

The government can use carbon tax revenues to finance exogenous spending R, to lower the income tax homogeneously by decreasing the factor λ, to increase lump-sum rebates to households t, and to increase social security benefits proportionally. Lump-sum rebates are per capita, adjusted for household size or geographic variables, and can be targeted to the bottom two income quintiles. Prior to implementing a carbon tax, the government budget constraint is:

$$\lambda \sum_{h=1}^{H} N_h \tau_h = R_0 \tag{11}$$

where λ captures a scaling degree: $\lambda = 1$ captures the initial income tax revenue. After implementing a carbon tax and channelling all revenues to finance government spending R, the budget constraint is:

$$\lambda \sum_{h=1}^{H} N_h \tau_h + \pi E = R_0 + R \tag{12}$$

When recycling carbon tax revenues as lump-sum transfers, the budget constraint is:

$$\lambda \sum_{h=1}^{H} N_h \tau_h + \pi E = R_0 + \sum_{h=1}^{H} N_h t_h \tag{13}$$

When recycling carbon tax revenues by increasing social security benefits, the budget constraint is:

$$\lambda \sum_{h=1}^{H} N_h \tau_h + \pi E = R_0 + (\nu - 1) \sum_{h=1}^{H} N_h ss_h \tag{14}$$

where ν is a scaling degree, such that $\nu = 1$ captures the initial level and $\nu - 1$ is the increase after recycling. When recycling as income tax reduction, the budget constraint is:

$$\lambda \sum_{h=1}^{H} N_h \tau_h + \pi E = R_0 \tag{15}$$

where $\lambda < 1$. We note that we are assuming a proportional decrease in total taxes paid by all households, which translates into a proportional decrease in the marginal tax. Combining these scenarios, the post carbon tax budget constraint is:

$$\pi E = R + \sum_{h=1}^{H} N_h t_h + (1 - \lambda) \sum_{h=1}^{H} N_h \tau_h + (\nu - 1) \sum_{h=1}^{H} N_h ss_h \tag{16}$$

Since λ is simply a constant, we can derive the new marginal tax faced by households as $\frac{d\lambda\tau_h(W_h l_h)}{d(W_h l_h)} = \lambda \frac{d\tau_h(W_h l_h)}{d(W_h l_h)} = \lambda \tau_h^M$.

3.3 Equivalent Variations

Equivalent variations are used widely in welfare analysis to capture the income that a household is willing to forego to implement a policy, defined as $E(p^0, U^1) - E(p^0, U^0) = E(p^0, U^1) - c$. This is the difference in expenditures required to reach the new utility level given original prices; in other words, EVs are the amount that induces the same utility change as a price change. In this case, EVs capture changes in utility due to changes in real incomes, relative prices and real expenditures after carbon tax increases and recycling. Naturally, price increases with no compensation yield negative equivalent variations, since the impact on welfare is always negative; households are not willing to forego any income to implement the policy, and instead require compensation to maintain their original level of utility. Reaños and Wölfing (2018) derive the EV for an EASI demand system with a price change from q^0

to p^1:

$$EV = \exp\left\{ \ln(c^1) + \sum_{j=1}^{J} \left(w_j^0 \ln(q_j^0) - w_j^1 \ln(p_j^1) \right) + \frac{1}{2} \sum_{j=1}^{J} \sum_{k=1}^{J} a_{jk} [\ln(p_j^1) \ln(p_k^1) - \ln(q_j^0) \ln(q_k^0)] \right\} - c^0 \quad (17)$$

where the superscripts 0 and 1 denote prices and implicit utility before and after the policy change. We report EVs for each type of household to investigate heterogeneity. Importantly, the reader is cautioned that these metrics may be lower than the true welfare effects of these policies for households with higher carbon intensities of consumption and high demand elasticities. Households may experience a fall in energy-intensive consumption that is detrimental for those who are close to subsistence consumption levels, leading some to fall below the fuel or expenditure poverty line. Moreover, these equivalent variations do not fully capture the disutility from working and, more importantly, the disutility from aggregate emissions.

Beyond making inter-household welfare comparisons, we are interested in whether recycling schemes increase the likelihood of a policy package gaining enough public support to pass a majority vote. In our framework, a household supports the proposed reform if the EV is positive, i.e. if it would be willing to forego some income in exchange for its implementation. For each policy proposal, we report the percent of households which would support and oppose it.

Finally, we define aggregate welfare as simply a weighted sum of consumption net of the social cost of aggregate emissions:

$$SWF = \sum_{h=1}^{H} N_h \omega_h u_h - \psi E \quad (18)$$

where ω_h is the marginal Pareto weight[4] (normalized such that $\sum_{h=1}^{H} N_h \omega_h = 1$ and

[4] We can derive ω_h from a social welfare function by specifying its functional form. For example, we consider

$\mathbb{E}[\omega_h] = 1$), u_h is total utility of household h and $\psi > 0$ is the social cost of aggregate emissions. ψ is an approximation of the equity-weighted sum of damages from aggregate pollution — an approximation because we assume the same damages for all households, although in practice damages are clearly heterogeneous across households. The two components in SWF are essentially a money-metric capturing household utility, u_h, and a money-metric capturing disutility of emissions, since we set ψ as the carbon tax. The household weights in total emissions are also normalized to one.

4 Data and Descriptive Statistics

To study welfare impacts of carbon taxes, we build a rich dataset of household characteristics, incomes, expenditures and carbon footprints, using surveys administered to UK households in the years between 2006 and 2017. We combine data on household characteristics, incomes and expenditures from the Living Costs and Food Survey (LCF) with data on the monthly consumer price index (CPI) from the UK Government's official statistics (ONS). We also match each product category with carbon intensities provided by the UK Government, which we cross-check with data on aggregate expenditures and emissions.

4.1 Living Costs and Food Survey

The Living Costs and Food Survey is a cross-sectional representative survey administered annually to around 4,000 UK households, and is the most comprehensive survey on household spending in the UK. Implemented by the Office for National Statistics, the LCF

a social welfare function:

$$\frac{1}{H}\sum_{h=1}^{H} U(c_h + \bar{s_h}) \tag{19}$$

$$U(c_h + \bar{s_h}) = \frac{(c_h + \hat{s_h})^{1-\eta}}{1-\eta}$$

where the social value attached to household h's income $c_h + \bar{s_h}$ is $\omega_h = \frac{dU(c_h+\hat{s_h})}{d(c_h+\hat{s_h})} = (c_h + \hat{s_h})^{-\eta}$ and $\eta > 0, \eta \neq 1$ reflects the concavity of U, i.e. inequality aversion. $\eta = 0$ corresponds to the utilitarian welfare function, while $\eta \to \infty$ corresponds to the maximin. We can generalize these weights to represent "generalized social welfare weights", and allowing them to depend on non-welfarist objectives like fairness, hard work and sacrifice (Saez and Stantcheva, 2016).

provides data on a clustered, multi-stratified random sample of UK households.[5] To avoid seasonal variation, it is administered in multiple waves throughout the year. Given the granularity of micro-data provided by the LCF, it is the most appropriate data source from which to estimate a demand system for households and study the incidence of a carbon tax. It is primarily used to inform the Retail and Consumer Prices Indices, National Accounts estimates of household consumption expenditure and the analysis of the effect of taxes[6].

Household-level data. The LCF includes diary and household questionnaires. The household questionnaire collects households-level data, with the household reference person (HRP) responding on behalf of the household. It includes questions on family relationships, ethnicity, employment details and the ownership of household durables. It is also the source of all expenditure information not recorded in the LCF diary, principally that which concerns regular payments typically made by all households and large, infrequently purchased items such as vehicles, package holidays and home improvements.

Income and employment. The income questionnaire is administered to each household member and collects key person-level variables, covering income from employment, benefits and assets. The household and income questionnaires together form an overview of the total income received by each household, as well as each household member individually. We build aggregate measures of weekly hours worked (including both employee and self-employed, paid and unpaid overtime, summing hours worked by all adults), such that we derive hourly wages by dividing total household labour income by total hours worked. For

[5]A representative sample of the household population is drawn from the Postcode Address File (PAF) with 'small user' postcodes; in the Great Britain sample, postcode sectors are the primary sampling units and are drawn from a list stratified by region, socio-economic classification of household head and car ownership. In Northern Ireland, a systematic sample is drawn, stratified geographically only.

[6]A notable limitation of the LCF is the procedure of anonymization, which ensures that data users do not have access to identifiable information about individuals; this includes anonymising variables like council tax charges, which are calculated by pooling several authorities within a region and estimating the pooled average; anonymized versions of variables such as total expenditures, which include anonymized council tax charges; and top-coding and re-cording variables, including age of HRP (anyone over 80 is anonymized), rooms occupied (households with more than 6 rooms are anonymized), and income variables (top-coded to the value of the 96th percentile.) Unanonymized versions of this data are available on the UK Data Service Secure Access platform to accredited researchers. A follow-up to this study will repeat the analysis on the unanonymized data, which also provides data on household postcodes, which would allow us to link households geographically to neighbourhoods and analyze spatial variation in tax burden more accurately. As access to the unanonymized version of this data is through a Secure Lab, which complicated merging datasets, we chose to simply use the anonymized version for the purposes of this thesis.

the purposes of this thesis, we treat households as units and abstract from within-household bargaining. Importantly, the LCF provides data on income taxes (gross and net), National Insurance contributions and other transfers. **Total weekly household income** includes income from salaries and wages, self-employment, investments, pensions and annuities, social security payments, and other sources. We define **savings** (or borrowing) as total weekly income net of household expenditures, **taxable income** as weekly income net of social security payments, **disposable income** as total income net of deductions (income tax and NI contributions), **nonlabour income** as total income net of salary and self-employment income, and income from **social security** payments to include social security for retirement and other purposes (including welfare transfers).

Expenditures. In addition to the two questionnaires, individuals record daily expenditures for two weeks, thus providing a comprehensive account of household expenditure. Commodities recorded in the LCF diary are grouped by category based on the Classification of Individual Consumption by Purpose (COICOP), which allows aggregation and matching to monthly price indices and carbon emissions. All monetary values appear as weekly equivalents, and have been appropriately scaled when annual amounts are required. Quarterly bill payments on gas and electricity are reported outside of the diary, such that there is complete coverage in the survey of these expenditures at the household level. The other types of fuel (coal, coke, paraffin, oil) are reported as weekly expenditures and are typically bought in bulk, such that we cannot distinguish between households who genuinely do not consume from those with no recorded expenditure. As the LCF aggregates expenditure on electricity, liquid fuels, solid fuels (coal, wood, coke, paraffin) and gas with other expenditures on housing (water supply, rents, maintenance), following Baker, Blundell and Micklewright (1989), we disaggregate this expenditure variable into separate variables for gas, fuels, electricity and housing (including water supply, household maintenance and rents), and match each subgroup to the corresponding price. In our EASI estimations, we use an aggregate variable for housing energy spending and a derived household-specific price. 97.5% of households report having central heating, and most rely on natural gas. We differentiate transport costs between purchase of vehicles, operations of personal transport equipment and transport services, which include expenditures on transport by rail, road, air, sea and other. All variables are screened for expenditures on durables, which are aggregated into a single variable and include purchased vehicles, home furnishing and expenditures on clothing.

Income Tax. Income taxes are the largest source of government revenue in the UK (30%), followed by National Insurance (NI) contributions (20%). All household members are taxed separately, and while there exists a transferable allowance for married couples and civil partners, by which individuals may transfer 10% of their personal allowance to their partners, it is relatively minor and we abstract from this complication. The main rates are applied to non-dividend income, including income from savings, employment, property or pensions. Dividend rates are applied to dividend income, but we focus on the base rates in this thesis. The LCF provides household-level payments towards income taxes, as well as individual labour and gross personal income for each household member. We also use marginal tax rates in 2017 to model the UK tax system: the personal tax-free allowance for under-65s is £11,500, the basic rate for incomes between £11,501 and £45,000 is 20%, the higher rate for incomes between is £45,001 and £150,000 is 40% and the additional rate for incomes above £150,001 is 45%. We find evidence of measurement error in the income tax values reported by the LCF, so we use our imputed taxes instead.

For inter-household comparisons, we stratify by household income and report welfare metrics as shares of both household disposable income and household expenditure (consumption), all equivalized according to the OECD equivalence scale[7]. While household expenditure may be interpreted as a proxy for lifetime income and therefore provide more accurate measures of well-being, we are also concerned with political feasibility and public support. Households' voting decisions are likely informed by the **perceived** regressivity of the policy, shaped by perceived costs compared to current incomes, not their lifetime incomes. Table 1 shows the distribution of income and consumption in our sample. We rank households by equivalized household consumption deciles; the bottom decile holds 2.9% of total household consumption and 4.8% of income. Importantly, consumption appears more un-

[7]The OECD equivalence scale assigns the value of 1 to the the first household member, 0.7 to each additional adult and 0.5 to each child.

equal than income in our data: while the top decile accrues 25% of total consumption, these households hold only 19% of income. This is likely due to top-coding of income in the LCF and under-reporting of income (survey questions about household spending are typically seen as less sensitive than questions about income). Therefore, we evaluate welfare using both measures of well-being but, given our data limitations, favor those based on expenditure.[8].

[8]We check for reported equivalized consumption levels below half of the expenditure poverty line, and find that 0.6% of households (284) fall below this threshold. Following Cronin, Fullerton and Sexton (2019), families whose estimated consumption falls short of this threshold are assumed to finance this minimum consumption from unmeasured transfers or debt financing.

Table 1: Distribution of Income and Consumption, by Consumption Decile

Full sample

Consumption Decile	Avg. Disposable Income	Avg. Consumption	% Distribution of Consumption	% Distribution of Income	Freq.
1	£187.4	£74.1	2.8%	4.5%	6,186
2	£232.5	£116.4	4.5%	5.8%	6,183
3	£270.3	£146.7	5.6%	6.8%	6,183
4	£299.9	£174.0	6.7%	7.7%	6,179
5	£329.9	£202.3	7.8%	8.7%	6,182
6	£364.5	£233.0	9.0%	9.7%	6,185
7	£402.4	£269.7	10.4%	10.8%	6,180
8	£456.4	£318.3	12.3%	12.4%	6,182
9	£519.1	£395.3	15.3%	14.2%	6,183
10	£708.9	£661.6	25.5%	19.4%	6,177
N					61,820

Estimation sample

Consumption Decile	Avg. Disposable Income	Avg. Consumption	% Distribution of Consumption	% Distribution of Income	Freq.
1	£231.9	£104.7	3.8%	5.3%	4,128
2	£281.3	£145.7	5.3%	6.6%	4,122
3	£309.0	£173.6	6.3%	7.4%	4,122
4	£335.0	£200.2	7.3%	8.1%	4,123
5	£366.3	£226.6	8.2%	9.0%	4,119
6	£391.5	£256.0	9.3%	9.7%	4,125
7	£432.5	£290.2	10.5%	10.8%	4,123
8	£477.8	£336.5	12.2%	12.0%	4,122
9	£536.4	£407.4	14.7%	13.6%	4,122
10	£683.5	£621.5	22.5%	17.5%	4,117
N					41,218

2017 Only

Consumption Decile	Avg. Disposable Income	Avg. Consumption	% Distribution of Consumption	% Distribution of Income	Freq.
1	£231.7	£88.0	2.9%	4.8%	493
2	£296.2	£137.6	4.5%	6.3%	493
3	£329.3	£173.6	5.7%	7.0%	493
4	£344.9	£203.1	6.7%	7.4%	493
5	£381.6	£235.6	7.7%	8.4%	493
6	£435.6	£272.7	8.9%	9.7%	493
7	£487.4	£316.1	10.4%	10.9%	493
8	£542.6	£374.7	12.3%	12.3%	493
9	£623.5	£463.2	15.2%	14.3%	493
10	£833.7	£786.3	25.8%	18.9%	493
N					4,930

Note: This table reports the distribution of income and consumption by equivalized consumption deciles, for the full sample of households, our estimation sample and 2017 only. Families are ranked each year according to consumption adjusted for household size, using the OECD equivalence scale. We report average household disposable income and consumption, equivalized, and the shares of total income and consumption held by each decile.

Prices. We match each product group with the corresponding monthly consumer price index. As we use 11 years, we have 132 different prices for each product category. These indices track the evolution of the prices over time compared to the 2015 = 100 benchmark, and this variation identifies the demand system. As we lack regional consumer price indices, we introduce household-level variation by exploiting differing intra-group consumption allocations and compute household-specific Stone-Lewbel prices (Lewbel, 1989). Figure 1 illustrates the evolution of energy and transport prices over time. Prices mostly reflect trends in inflation, except the price of liquid fuels, which tracks the price of oil and exhibits more evident cyclical pattern.

To derive percentage changes in prices which result from imposing a carbon tax (of £100 or £40 per tonne of CO_2e for comparison), we use the carbon intensity factors. A carbon tax directly impacts the price of fuels according to carbon intensities, as well as indirectly impacts the price of other commodities which rely on fuels as inputs across the production process[9]. The intensity factors for electricity, gas, coal, oil for central heating and the resulting price changes are reported in Table 2. Figure 2 illustrates the resulting household-specific percent price changes; a tax of £100 results in an average 49% increase in the price of heating and 26% increase in the price of transport. Heating and transport, naturally, are subject to the largest changes, with small changes in the price of the other goods (food 7%, housing 3%, services 8%, durables 2% and other goods 2%). These changes assume full pass-through from producers to consumers[10].

Table 2: Effect of a Carbon Tax on Fuel Commodity Prices

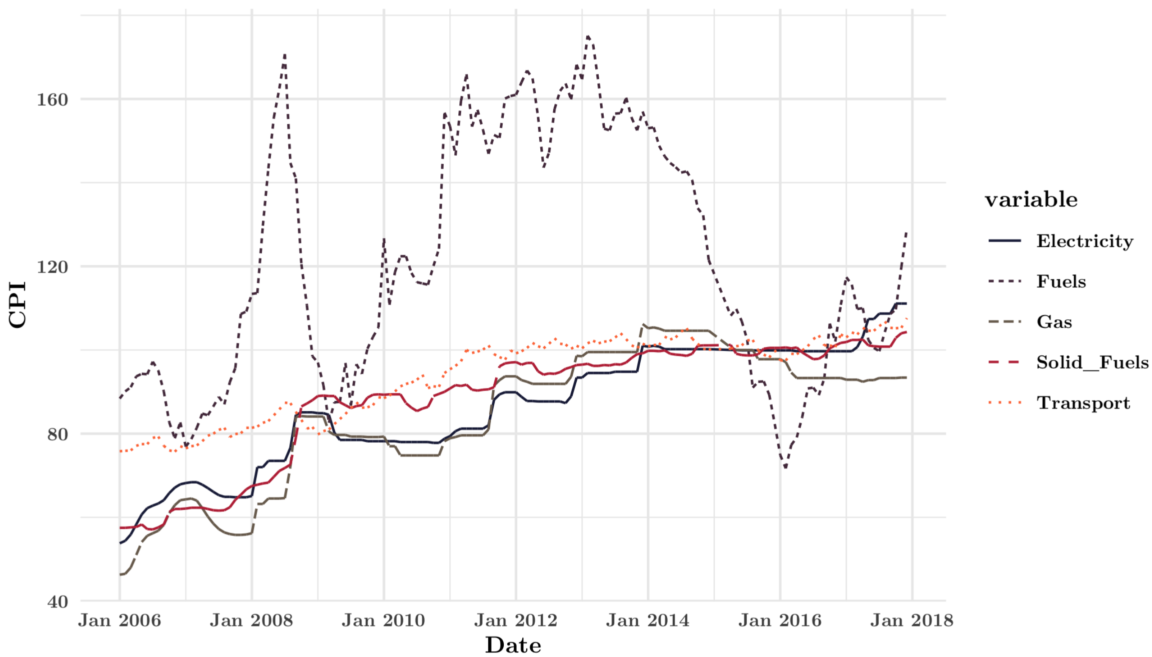
COICOP	GHG (kgCO2e per £)	Carbon Tax (£ per 1,000 kgCO2e)	Price Change (%)
Electricity	3.674	100	37%
Gas	6.306	100	63%
Coal and coke	1.072	100	11%
Oil for central heating	1.072	100	11%
Paraffin, weed, peat, hot water etc	1.072	100	11%
Petrol	4.519	100	45%
Diesel oil	0.728	100	7%

Weighting. To estimate distributional consequences of energy taxes on the population of UK households, we require estimated *population* quantities. The LCF is a voluntary survey, so non-response rates and other sources of bias are of key concern for credible inference. Response rates range from 50% in 2004 to 42% in 2017, and there are considerable differences

[9] Note that $\frac{p}{q} - 1 = \pi e$

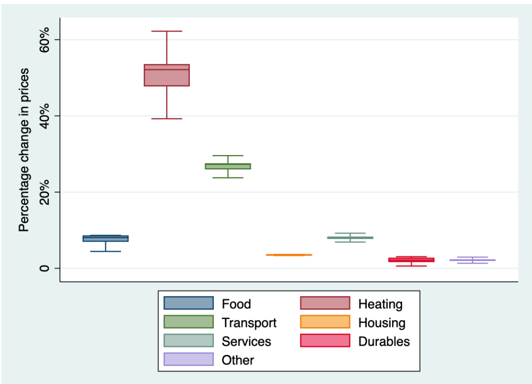
[10] Beyond full pass-through, we are assuming pass-forward, i.e. firms pass costs to purchasers. This is a standard assumption in the literature, but studies have shown that whether costs are assumed to be passed forward to consumers or backwards to factors of production matters for regressivity (Parry, Morris and Williams III, 2015). Moreover, during the transition, a carbon tax may displace workers in affected industries (e.g. coal miners), or may be capitalized into stock prices or land prices such that the costs are borne by particular human or physical capital owners. We do not assess these dynamics (Cronin, Fullerton and Sexton, 2019).

Figure 1: Monthly CPI: Electricity, Gas, Liquid and Solid Fuels, Transport

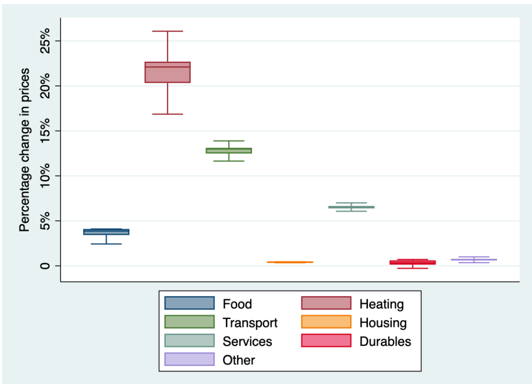


Notes: consumer price indices for heating (electricity, solid and liquid fuels and gas) and transport variables normalized to 100 in 2015. The price of (liquid) fuels is effectively the price of oil, and experiences a steep decline after the financial crisis and after 2014.

Figure 2: Price Changes from Carbon Tax



£100 per tonne CO_2e



£40 per tonne CO_2e

Notes: We plot percentage changes in prices of aggregates that result from imposing a carbon tax of £100 and £40 per tonne of CO_2e. Using carbon intensity estimates of goods sub-categories, we compute new household-specific Stone-Lewbel prices.

between non-responding and responding households; for example, the percentage of single-adult households is higher among non-responding households (for e.g. 40% in 2016) than responding households (32% in 2016). The LCF's weighting approach compensates for non-response and matches the sample distribution to population distributions in terms of region, age group and sex[11].

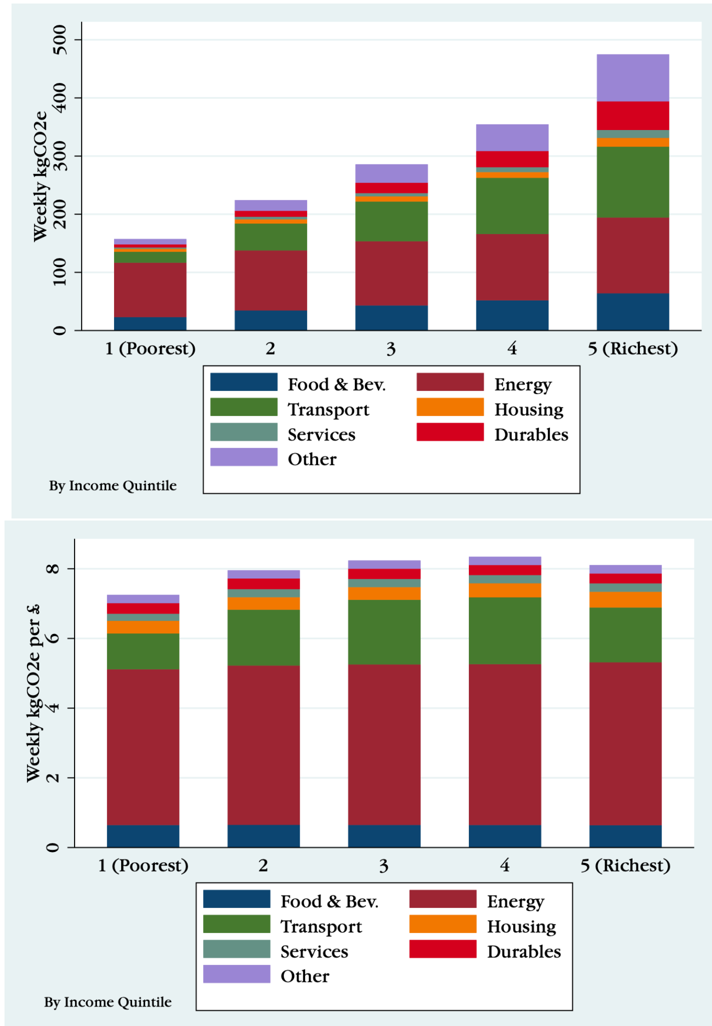
Out of 64,690 initial households, we drop households with positive electricity and gas rebates and negative transport costs. Following Baker, Blundell and Micklewright (1989), we exclude households with non-positive budget shares, and further drop households with budget shares above (below) the 99th (1st) centile. Our final sample includes 41,218 households from which we estimate the demand system. We further exclude retirees and students when estimating labour supply, on a sample of 27,748 households. We perform various robustness checks to validate our estimates.

4.2 GHG Emissions

UK greenhouse gas emissions are calculated by researchers at the University of Leeds and the UK Government's Department of Environment, Food and Rural Affairs (Defra). A multi-region input-output (MRIO) model links flows of goods and services with emissions generated during production, calculating total carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) tonnes attributed to the consumption of goods and services of UK residents. The UK's carbon footprint refers specifically to emissions associated with spending of UK residents — regardless of where these emissions arise along the supply chain — and those generated by UK households through energy consumption (UK Department of Environment and Affairs, 2020). Notably, it excludes emissions arising from (domestically-produced) exported goods. Defra estimates of the uncertainty around consumption-based CO_2e emissions between 1992 and 2004 find standard errors for total CO_2e emissions in any given year between 3.3% and 5.5%. We match these carbon intensities to expenditures by COICOP classification and calculate household-level carbon footprints.

[11] Weighting is assigned in two stages; the data are first weighted to compensate for non-response (sample-based weighting), followed by population-based weighting to match population distribution. Weighting is carried out separately for each quarter of the survey, and two weights are provided to researchers, one quarterly and one annual. Weights are assigned using ONS population estimates, such that the sum of weights is equal to the total number of UK households. The number of households represented by each weight is equal to the weight multiplied by 1,000.

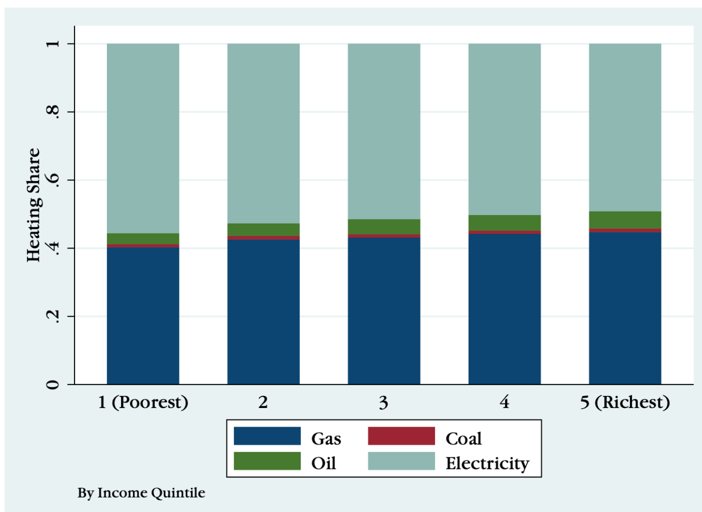
Figure 3: Household Footprints: Emissions and Carbon Intensity



Notes: We plot household footprints (top) and carbon intensity (bottom) of product categories by income quintiles in 2017, with footprints given as CO_2e per weekly expenditures and carbon intensity is given as KgCO2e per £. The first quintile captures the bottom 20% of the income distribution, while the fifth quintile captures the top 20%.

Figure 3 illustrates household footprints and carbon intensity of products by quintiles of household non-durable expenditure. Carbon emissions are naturally increasing with non-durable expenditure towards each product group, with the total average weekly emissions of the highest quintile (559 $kgCO_2e$) 3.6 times those of the bottom quintile (155 $kgCO_2e$). The largest contributions to carbon emissions are are domestic energy use (electricity and heating) and transport expenditures (largely vehicle fuels), followed by food beverages. We observe large differences in emissions from transport expenditures across expenditure groups, while a smaller gap in emissions attributed to heating. Carbon intensities are similar across expenditure groups, suggesting that there are no large differences in fuel type. This is confirmed by Figure 4; richer households spend a slightly larger share of heating on gas and oil compared to electricity, but the differences are minor. Therefore, any regressivity of a tax on fuel is driven by overall expenditures on heating as a share of total expenditure, instead of by different carbon intensities of individual goods products. Naturally, as poor households spend a larger proportion of income on energy and food, the carbon intensity of their total expenditures is higher than those of rich households.

Figure 4: Heating Shares by Fuel Type, Quintiles



Notes: Average share of heating spent on each fuel type in 2017, by non-durable expenditure quintile.

4.3 Descriptive Statistics

We differentiate between 8 households types, where the majority of households is working singles with no children, working couples with up to 2 children and other households (which include a higher number of adults). Mean weekly labour income is £548 (an annual income of £28,469), the average pretax wage is £9.49, and the average weekly hours worked is 28 hours for HRPs and 14 hours for spouses. 92% of HRPs are white, 35% are female and 97% of households own at least one car. 97% of households have central heating, with natural gas as the most popular type of central heating (92% of those with central heating rely on gas), followed by electricity and oil. Table 3-6 report descriptive statistics, including labour and income variables, households types, average budget shares and prices.

Table 3: Household Labour and Income

	Mean	SD	Min	Max
Unemployed	0.02	0.12	0.00	1.00
Employed	0.69	0.46	0.00	1.00
Weekly Labour Income	£547.95	£555.63	0.00	2342.01
Weekly Nonlabour Income	£273.32	£329.46	-0.00	6583.00
Weekly Total Income	£821.27	£493.57	60.00	6797.62
Weekly Disposable Income	£672.32	£373.44	-259.35	6286.01
Weekly Consumption	£460.91	£293.12	42.71	6797.62
Pretax Wage	£9.49	£12.39	0.00	760.49
Expenditure Share of Income	0.91	0.07	0.10	1.00
Weekly Hours Worked HRP	27.65	21.23	0.00	100.00
Weekly Hours Worked Spouse	14.01	18.24	0.00	100.00
Income Tax	£75.71	£105.11	0.00	507.74
N	41,218			

Table 4: Household Types

	Absolute	Relative (%)	Variable
Students	151	0.36	z_1
Working: Single with Children	844	2.05	z_2
Working: Couple with No Children	1,275	3.09	z_3
Working: Couple with Up to 2 Children	7,877	19.11	z_4
Working: Couple with >2 Children	1,428	3.46	z_5
Other	16,660	40.41	z_6
Retirees	9,456	22.94	z_7
Working: Single with No Children (Baseline)	3,527	8.56	z_8
N	41,218	100	

Table 5: Household Characteristics

	Mean	SD	Min	Max
Household Char.				
Household size	2.58	1.25	1.00	12.00
Number of children	0.58	0.94	0.00	10.00
Number of adults	2.00	0.78	0.00	9.00
HRP Char.				
Female HRP	0.35	0.48	0.00	1.00
White	0.92	0.26	0.00	1.00
Black	0.02	0.14	0.00	1.00
Asian	0.04	0.20	0.00	1.00
Mixed	0.01	0.09	0.00	1.00
Other_ethnicity	0.00	0.05	0.00	1.00
Household Durables				
Cars	0.97	0.17	0.00	1.00
Cars owned or used	1.36	0.83	0.00	7.00
Dishwasher	0.49	0.50	0.00	1.00
Washing machine	0.99	0.12	0.00	1.00
Dryer	0.62	0.48	0.00	1.00
Dwelling Char.				
Whole House	0.85	0.35	0.00	1.00
Flat	0.12	0.33	0.00	1.00
Rented	0.24	0.43	0.00	1.00
Owned	0.75	0.43	0.00	1.00
Heating				
Central Heating	0.96	0.19	0.00	1.00
Electricity	0.05	0.23	0.00	1.00
Gas	0.83	0.38	0.00	1.00
Oil	0.06	0.23	0.00	1.00
Solid Fuel	0.01	0.08	0.00	1.00
Other	0.01	0.10	0.00	1.00
Region				
North East	0.04	0.20	0.00	1.00
North West	0.11	0.32	0.00	1.00
Yorkshire	0.09	0.28	0.00	1.00
East Midlands	0.08	0.27	0.00	1.00
West Midlands	0.09	0.28	0.00	1.00
Eastern	0.10	0.30	0.00	1.00
London	0.10	0.30	0.00	1.00
South East	0.14	0.35	0.00	1.00
South West	0.09	0.29	0.00	1.00
Wales	0.05	0.22	0.00	1.00
Scotland	0.09	0.28	0.00	1.00
Northern Ireland	0.02	0.14	0.00	1.00
Urban[a]	0.75	0.43	0.00	1.00
N	41,223			

[a] This variable is only available for years 2015-2017, i.e. 8,783 households.

Table 6: Budget Shares and Prices

		Mean	SD	Min	Max
Budget Shares	Food	0.18	0.09	0.02	0.47
	Heating	0.06	0.04	0.01	0.26
	Transport	0.11	0.08	0.00	0.41
	Housing	0.09	0.11	0.00	0.52
	Services	0.06	0.05	0.01	0.38
	Durables	0.16	0.13	0.00	0.62
	Other	0.33	0.14	0.06	0.73
Energy Mix	Gas	0.45	0.23	0	1
	Coal	0.01	0.07	0	1
	Oil	0.04	0.16	0	1
	Electricity	0.51	0.21	0	1
Log Price Index	Food	4.39	0.27	3.76	4.92
	Heating	4.17	0.29	2.97	5.04
	Transport	4.11	0.28	3.40	5.44
	Housing	3.84	0.29	3.25	4.75
	Services	4.19	0.29	3.13	5.14
	Durables	4.02	0.33	3.38	4.72
	Other	4.37	0.19	3.35	4.66
N		41,218			

Notes: This table reports summary statistics for budget shares of the seven aggregates, shares of each energy source of total spending on heating and price indices.

5 Empirical Framework

5.1 EASI Demand System

We estimate the Exact Affine Stone Index (EASI) demand system to recover the behavioural responses of different types of households to price changes across product categories. EASI demand functions can have any rank, such that Engel curves can be polynomials of any order in real expenditure (importantly, they are not constrained to linearity, as in the commonly used AIDS demand system). The final system of equations that we estimate is:

$$w_j = \sum_{r=0}^{R} b_{jr} \ln(v)^r + \sum_{t=2}^{T} d_t z_t \ln(v) + \sum_{k=1}^{J-1} a_{jk} \ln(p_k/p_J) + e_j \tag{20}$$

for $j = 1, ..., J-1$ goods, exploiting the constraints defined in the Appendix to recover the coefficients for the last product category. We use $J = 7$, $T = 8$ and $R = 4$. As suggested by Lewbel and Pendakur (2009), we implement an iterated three stage least square estimation. First, we use total expenditures c, commodity prices, and sample averages of the budget shares to construct an instrument for implicit utility v. Then, we use this instrument for v to estimate the system of equations: more details on this estimation are included in the Appendix. We iterate this procedure until we reach convergence in a_{ij} and v. We calculate bootstrapped standard errors by drawing observations with replacement from our sample and iterating this estimation 50 times. Figure 15 confirms that the Engle curves are not linear, and Figure 5 plots quadratic fits of budget shares on total expenditure. While budget shares of food, heating and electricity fall with income, budget shares of durables and services increase, as expected by necessity and luxury goods. The budget share of transport exhibits a humped shape, suggesting that demand for motor fuels plateaus after reaching a threshold expenditure level.

Table 7 shows expenditure elasticities across equivalized income quintiles. We measure elasticities lower than 1 for food, heating and services — suggesting inelastic demands — and higher than 1 for transport, housing, durables and others, suggesting that these are luxury goods. The expenditure elasticity of food is highest among the bottom quintile and decreases with income, suggesting that low-income households have a high marginal propensity to consume with respect to food. The heating elasticity is also highest for low-income households, and falls with income (except for the top quintile). The fact that heating, food and services are necessities is a potential source of carbon tax regressivity, and the larger responses may push low-income households to energy consumption under poverty lines. The expenditure elasticity of transport is greater than 1 for the bottom quintile but lower than 1 for the top four, suggesting that fuel is a luxury for low-income households but a necessity for middle-

Table 7: Expenditure Elasticities, by Income Quintile

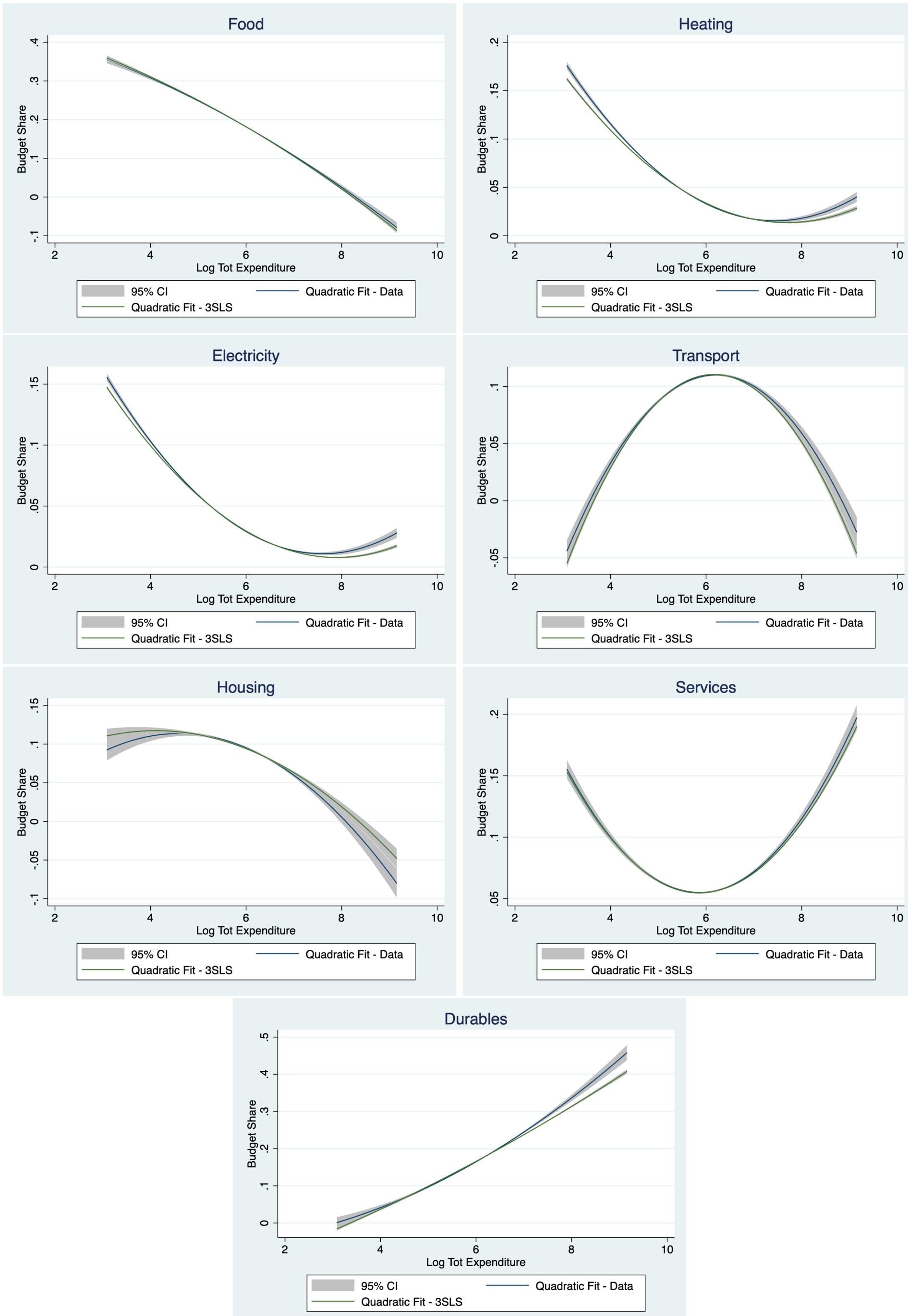
Quintile	Food	Heating	Transport	Housing	Services	Durables	Other
1st	0.71	0.40	1.07	1.09	0.74	1.51	1.19
2nd	0.59	0.32	0.99	0.10	0.76	1.50	1.21
3rd	0.52	0.30	0.96	0.94	0.79	1.48	1.20
4th	0.46	0.29	0.94	0.89	0.82	1.46	1.19
5th	0.37	0.33	0.90	0.83	0.91	1.44	1.17

and high- income households, who are more likely to own cars and commute to work. Our estimates are in line with Reaños and Wölfing (2018)'s expenditure elasticities of electricity and heating in Germany.

Table 18 and Table 17 report Marshallian and Hicksian price elasticities by income quintile and product category. Substitution effects (Hicksian elasticities) are stronger for food and energy (heating and electricity) among lower income households, while we find similar elasticities across income quintiles for the remaining product categories. The own-price elasticity of heating ranges from -0.68 (1st quintile) to -0.38 (5th quintile), and of transport from -0.87 (1st quintile) to -0.88 (5th quintile). Cross-price elasticities are not significantly different from zero. This suggests that low-income households respond more to food and energy price changes, readjusting consumption baskets, while there are no systematic differences across quintiles in response to transport costs (expenditure elasticities are more important than price elasticities for transport goods). We emphasize again that, while this stronger response to energy costs among low-income households leads to a smaller income effect of price changes, if these households are already consuming low levels of food and energy, i.e. they are close to subsistence levels, this reallocation of consumption across categories might place them below the fuel poverty line.

Our results are in line with estimates from the literature. Douenne (2020) finds expenditure elasticities of 0.5 for both transport and housing energies and uncompensated price elasticities of -0.45 for transport fuels and -0.2 for housing energies, which decrease with income, size of urban unit and number of children. Still on French data, Combet et al. (2010) find transport and housing energy elasticities of -0.5 and -0.11. On German data, Reaños and

Figure 5: Household Budget Shares



Wölfing (2018) find own price elasticities for energy services — which differentiate between electricity and heating — of different households types along the income distribution ranging from -0.6 to -0.21, with more elastic reactions of poorer households, with little variation among household types within the same income group.

5.2 Labour Supply

We estimate a continuous static model of labour supply (Hausman and Ruud (1984), Hausman (1985*b*), Hausman (1985*a*)) to recover the disutility parameter ϕ_h and the elasticity ϵ. On a sample of 27,748 households where at least one parent is working (and for whom all occupation-related variables are available), we follow traditional estimation methods relying on cross-sectional variation in working hours and in the after-tax wage. While state-of-the-art methods exploit quasi-experimental variation in income taxes, our cross-sectional data and context do not allow for these types of comparisons. We follow West and Williams III (2007) using group-, occupational- and region-specific wages as instruments for the after tax wage (i.e. net of marginal tax rates), and correct for selectivity bias (the extensive margin work decision) following Heckman (1979). We estimate selection models for single women, single men and couples, and report estimates for the total sample. We approximate the labour supply schedule by taking logs of our first order condition:

$$
\begin{aligned}
l_h &= \left(\frac{w_h(1-\tau_h^M)}{\phi_h P_h}\right)^{\epsilon} \\
\ln(l_h) &= \epsilon \ln\left(\frac{w_h(1-\tau_h^M)}{\phi_h P_h}\right) \\
&= \epsilon \ln\left(\frac{1}{\phi_h}\right) + \epsilon \ln\left(\frac{w_h(1-\tau_h^M)}{P_h}\right)
\end{aligned}
$$

And we estimate the baseline model:

$$
\ln(l_h) = \beta \ln\left(\frac{w_h(1-\tau_h^M)}{P_h}\right) + \boldsymbol{\gamma}'\boldsymbol{X_h} + u_h \tag{21}
$$

where $\ln(l_h)$ is log total weekly hours worked (for the entire household), $\frac{w_h(1-\tau_h^M)}{P_h}$ is the net of tax real hourly wage (net of tax labour income for the household divided by total hours worked), $\boldsymbol{X_h}$ is a vector of household characteristics and controls that includes a constant, the inverse Mill's ratio[12], dummies for HRP sex, presence of children, single households,

[12] Heckman (1979) introduced the inverse Mill's ratio to correct for selectivity bias, proposing a two-stage estimation procedure: in the first stage, we fit a probit model on the full sample of 31,109 households (including

as well as region, month and year controls. We estimate this baseline model by OLS and IV, progressively adding controls to examine robustness of estimates. Our estimate of the elasticity ϵ is β, while the remaining variables capture the disutility of labour ϕ_h. ϵ is then the percentage change in labour supply l_h given a 1% change in after-tax real wage $\frac{w(1-\tau^M)}{P}$.

A plethora of empirical challenges traditionally plagues the estimation of labour supply elasticities. The net wage may be endogenous because (a) the taste for work (or ability) is correlated with both hours worked and earnings, (b) the marginal income tax depends on income and (c) the gross hourly wage is obtained by diving labour income by total hours worked, and both may be measured with error. This endogeneity may result in an bias in the coefficient of a simple OLS regression of log hours on log real wage; mechanically, if total hours worked is used both as a dependent variable and as the denominator used to compute hourly wages, we expect a negative coefficient. We have addressed this by instrumenting the real after-tax wage faced by each household with gender, occupation, and region-specific means; these are arguably exogenous to household-specific work preference (as long as the number of households falling within these groups is not too small[13]), but mechanically correlated with the household-specific wage, satisfying the relevance $\mathbb{E}[\bar{w}\, w_h] \neq 0$ and exogeneity $\mathbb{E}[\bar{w}\, u_h] = 0$ conditions required of valid instrumental variables (where in this case we use w_h to denote the real, after-tax, not nominal, pre-tax wage). As hourly wages are calculated from weekly labour income and total hours worked (both at the household level), they are likely subject to measurement error; while an individual may report a 40 hour week, the true number of hours worked may be much higher or lower. The LCF provides data on overtime (paid and unpaid), which allows us to address potential measurement error in total hours worked to some extent.

The average labour supply elasticity in the sample ranges from -0.221 (1) for the OLS es-

non-working households) to estimate a probability of working. Following West and Williams III (2007), we use HRP age, sex, education, ethnicity, household size, a dummy for the presence of children, a dummy for public transfers constituting the majority of weekly household income, log price of gas, and region and year dummies as predictors. We estimate selection models separately for female singles, male singles and couples, where we add a variable controlling for spouse's employment condition in our regression for couples. The estimated parameters are used to calculate the inverse Mills ratio, which is then added as an additional explanatory variable in our OLS and IV estimations.

[13]For 3,411 households within groups comprised of less than 50 households, we instrument the net wage with national occupation and gender-specific means.

timates to 0.29 (4) for the IV estimates, confirming the hypothesized downward bias of OLS. An elasticity of 0.29 implies a 0.29% response of hours worked to a 1% increase in real net wages. At our average real wage of £15.8 and average of 58 hours worked at the household level, this suggests that *decreasing* the real wage by £1.58 (10%) leads hours worked to fall to 56.3 (by 2.9%). Importantly, we are abstracting from any notion of household bargaining and treating each household as one entity, such that the estimates are an average of single households and couples. Column 5 in Table 8 reports estimates of the baseline specification with an added interaction term between the log net real wage and the HRP male dummy, effectively distinguishing between labour supply elasticities of households with male and female HRPs. The average labour supply elasticity of households with female HRPs is higher than males, confirming that females generally have lower labour market attachment. The intercept is higher for households with male HRPs and for households with children, suggesting that these households supply on average more hours. We report estimates of models fit to couples and single households separately in Table 19 and Table 20. When fit only on couples, we find a female elasticity to be higher than for males; the strongest response is then that of married women, who are more likely to rely on the financial support of their partner.

In our calibration, we use $\beta = \epsilon = 0.29$, since this is the average elasticity across groups estimated by the model with all controls. We then derive the labour disutility parameter using the coefficients on the remaining regressors of column 4 of Table 8; for example, the disutility parameter for households inhabited by couples, with the HRP female, without children and not living in London is $\ln(\phi_h) = \frac{-\gamma_1}{\beta}$, where γ_1 is simply the constant. We find a mean parameter $\phi = £0.024$.

There are important limitations to this static approach. We fail to capture the inter-temporal dimension of life-cycle models, as well as issues related to joint participation decisions and the allocation of resources within the family. State-of-the-art identification methods rely on using policy reforms as natural experiments, without attempting to estimate structural models; these reduced-form approaches offer the most credible sources of identification for labour supply elasticities. As we are interested in measuring elasticities to the extent that they allow us to compute realistic simulations, we are confident that our estimates reflect average

Table 8: Labour Supply: UK Households, Total

	(1) OLS	(2) OLS	(3) IV	(4) IV	(5) IV
Log Net Real Wage	-0.221***	-0.227***	0.315***	0.289***	0.486***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.04)
HRP Male × Log Net Real Wage					-0.257***
					(0.04)
Inverse Mill's Ratio		-1.075***	-0.814***	-0.825***	-0.795***
		(0.01)	(0.03)	(0.03)	(0.03)
Dummy: London		0.052***	-0.119***	-0.107***	-0.116***
		(0.01)	(0.02)	(0.02)	(0.02)
Dummy: HRP Male		0.064***	0.023**	0.023***	0.678***
		(0.01)	(0.01)	(0.01)	(0.11)
Dummy: Children		-0.076***	-0.036***	-0.022***	-0.017***
		(0.01)	(0.01)	(0.01)	(0.01)
Dummy: Single		-0.446***	-0.575***	-0.552***	-0.565***
		(0.01)	(0.01)	(0.01)	(0.01)
Constant	4.542***	4.683***	3.352***	3.404***	2.903***
	(0.02)	(0.02)	(0.06)	(0.06)	(0.11)
Controls: Region	No	Yes	Yes	Yes	Yes
Controls: Month	No	Yes	Yes	Yes	Yes
Controls: Year	No	Yes	Yes	Yes	Yes
SE Bootstrap	No	No	No	Yes	Yes
N	27,695	27,695	27,695	27,695	27,695
R^2	0.047	0.387	0.130	0.156	0.126

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Columns 1-5 report regressions with respect to total weekly hours worked at the household level. We report OLS and IV estimates, where IV estimates use occupation-, region- and group-mean real wages as instruments. We include the inverse Mills ratio as a control for selectivity bias (Heckman, 1979), and allow the intercept to change across household HRP sex, children presence and for households living in London. We add controls for regions and time (month and year) and calculate bootstrapped standard errors. Labour supply wage elasticities range from -0.22 (OLS) to 0.29 (IV); since column 4 reports the average elasticity after applying all controls, we use these estimates in our simulation.

responses (direction, magnitude). On UK data, previous estimates of the elasticities for couples include female wage elasticities of [.29,.71] (Arellano and Meghir, 1992), [.11–.17] (Blundell et al., 2000) and [.13,.37] (Blundell, Duncan and Meghir, 1998). For males, Blundell and Walker (1986) estimate a wage elasticity of .024 in the UK, while others find similarly small magnitudes in other countries (.05 in Denmark by Frederiksen, Graversen and Smith (2008), [.05,.08] in Germany by Bargain and Doorley (2011), .03 in Switzerland by Gerfin and Leu (2003)). For single parents, Blundell, Duncan and Meghir (1992) report a participation elasticity of 0.34, but not a wage elasticity. Our estimates are then slightly higher than previous estimates, but we consider income from both salary and self-employment in our definitions.

5.3 Equivalent Variations

We use the latest year in our sample, 2017, to estimate welfare effects of a carbon tax of £100 per tonne of CO_2e for policy scenarios. Our 2017 sample includes 3,367 households, which effectively represents 12,317 households following our weighting approach. We solve a system of nonlinear equations comprised of the household budget shares as functions of the estimated EASI parameters, indirect utility, labour supply and the household budget constraint. We solve this problem for each household, and, given their behavioural response, simulate revenue neutral policies, i.e. we find values of transfers, social security benefits (ν), and income tax reductions (λ) such that the government's budget constraint holds. From the resulting budget shares and indirect utility, we calculate EVs and investigate the share of households for whom welfare increases — our measure of political feasibility —, as well as the implications for vertical and horizontal equity. As none of the reforms generate enough public support to pass a majority vote, we investigate the implications of including supply-side adjustments by modeling endogenous intensity factors; the carbon intensity of goods falls as the price of carbon increases, as firms attempt to lower marginal costs. This very stylized rendition of supply-side responses nevertheless allows us to capture the magnitude of the differences between households' and firms' responses. Finally, we investigate optimal recycling by examining aggregate welfare given different levels of recycling and inequality aversion.

6 Results

For each scenario, we report changes in aggregate quantities — consumption, hours worked and emissions —, and investigate implications for inequality and political feasibility. Aggregate consumption is not adjusted for price increases, such that changes reflect both quantity and price responses, while aggregate emissions are adjusted to reflect quantity changes only. We report Gini coefficients for disposable income and expenditure to capture vertical inequality, coefficients of variation – the standard deviation of consumption divided by the mean of consumption for each income decile (in the Tables section) – to capture horizontal inequality, and investigate thoroughly heterogeneity across income deciles and household types. Households are stratified by equivalized income, where the 1st decile represents the bottom 10% of the income distribution, and box plots report the 25th, 50th and 75th quantiles.

6.1 No Recycling

We first investigate aggregate implications of carbon pricing with no recycling in Table 9. Following an average increase of 4% in the marginal cost of utility (with dispersion between 5% and 17%), the real wage falls; since we are considering only substitution effects, labour supply falls. As the government must balance its budget and the fall in labour supply from the price increase erodes the tax base, the income tax increases by 5%, inducing a further decrease in labour supply which reaches 3.3%. Households are not compensated in any way, such that income falls; as savings remain proportional to disposable income, consumption falls by 3.1%. The combination of lower consumption and households reallocating expenditures towards commodities with lower carbon intensities leads to a 14% fall in emissions; notably, the average budget share of heating *increases* after the price change (from 5.7% to 7.2%), due to the low elasticity of heating demand. Among households in the bottom (top) income decile, the average share spent on heating increases from 9% (3%) to 11% (4%), while the transport share falls from 9.5% to 9.2% (with no change for the top decile).

Table 9: £100 per tonne of CO_2e; No Recycling

	Emissions (kg CO_2e)	Total Hours	Consumption[a]	EV $\geq 0(\%)$	Gini Disp. Income	Gini Exp.
Baseline	29,260,789	30,497,032	345,536,349		0.2764	0.2990
No Recycling	-13.97%	-3.28%	-3.07%	0%	0.2714	0.2954

[a]Consumption is not adjusted for price increases.

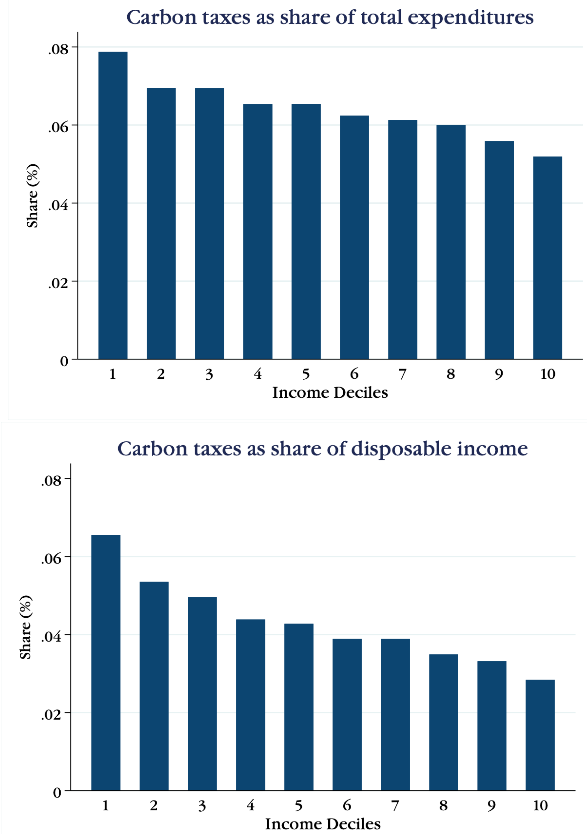
6.1.1 Tax Incidence and Determinants

To investigate incidence heterogeneity, we plot effort rates[14] as shares of both disposable income and total expenditure. Figure 6 confirms that carbon pricing with no recycling is regressive, with carbon taxes representing almost 8% of weekly expenditures for the lowest income decile and around 5% for the richest households. While we observe rates decreasing with income in both cases, using total expenditure as a denominator yields less heterogeneity across deciles, suggesting that impacts of the policy on living standards are less regressive than when evaluated against income. The trade-off between these two methods applied to energy taxes was originally discussed by Poterba (1989) and Metcalf (1999), who argued that especially when analyzing samples that include students, self-employed and retirees, expenditures capture welfare more accurately than income. However, since we are interested in political feasibility, understanding regressivity with respect to income is complementary; voting decisions are likely shaped by current, not lifetime, income. Since utility is quasi-linear in our model, labour supply dynamics are driving consumption changes, and these are shaped by the increase in the income tax required to offset the eroded tax base and the overall price increase from the tax. Indeed, the percent reductions in the after-tax wage and labour supply responses are larger for the top deciles than the bottom deciles, such that the net effect of carbon pricing on the distribution of consumption and income is small. We are effectively broadening the channels through which a carbon tax impacts households, such that net effects capture tax burden as well as responses in consumption and labour supply.

Figure 7 shows the distribution of EVs across income deciles and household types. EVs range from -£597 to -£4, or from -41% to -0.5% of weekly income. Low-income households

[14]The carbon tax as a share of income or expenditure.

Figure 6: No Recycling: Tax burden

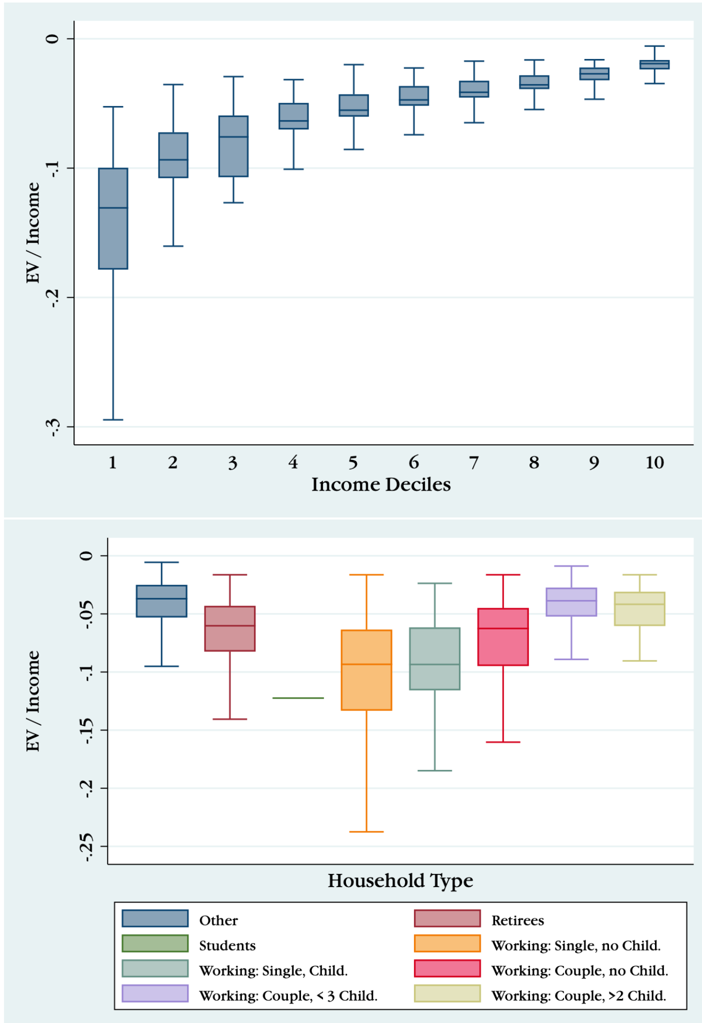


Notes: Tax paid by each household as a share of total expenditures and disposable income, ranked by equivalized income deciles.

are willing to forego a larger share of income to avoid the policy, and there is substantial heterogeneity in welfare costs among the bottom deciles. Singles are hurt most, while working couples with children are hurt least; this is capturing the income dimension, with single workers with and without children over-represented in the low income deciles (working singles with no children are 26% of the bottom quintile and 13% of the top quintile). Overall, no household would be willing to accept the policy without compensation, confirming that public opposition to carbon pricing without recycling is warranted. Before recycling, a carbon tax generates £22 million in revenue for this representative sample of 12,675 households (essentially 6% of GDP), which can be used to offset negative welfare effects.

We observe a higher degree of heterogeneity among the bottom deciles, and explore determinants by regressing EVs on many characteristics. As EVs are negative, positive coefficients

Figure 7: No Recycling: Equivalent Variations



Notes: Box plot showing EV income shares by income decile (top) and household type (bottom). We show 25th, 50th and 75th quantiles. We impose a carbon tax of £100 per tonne of CO_2e without recycling.

indicate a smaller welfare cost. While the literature focuses on determinants of the tax burden, we focus on determinants of net welfare effects. We test for household characteristics, like income composition, number of children, race and ethnicity, e.g. Lyubich et al. (2020), geography and dwelling characteristics, energy sources and commute characteristics. Table 10 reports regressions of EV and EV/Income on many characteristics, where EV/Income obviously controls for income. While rural households appear to bear larger welfare costs, the negative and significant coefficient disappears once we control for income. Tax incidence has been found to be higher for rural households in other contexts, e.g. in France by Douenne

(2020), but this rural-urban divide does not manifest in our data. Similarly, we do not find large effects of regions, except for a positive coefficient on living in London. Indeed, the income dimension captures many of the effects found across other dimensions when income is not controlled for; while ethnicity dummies exhibit significant effects in column 1, these are null in column 2. Single households, those with consumption below the expenditure poverty line, households who live in houses instead of flats, and those with high motor costs experience higher welfare costs. The coefficient on the share of public transport spending in column 4 is positive and significant, suggesting that those who spend more on public transport than on motor fuels are less hurt by the policy and highlighting the potential mitigating role of access to public transport. Interestingly, owning cars and dwelling size (proxied by number of rooms) exhibit a positive and significant coefficient; this may capture the income dimension, with richer households living in larger houses and owning more cars (that they do not necessarily drive).

Table 10: No Recycling: Determinants of Welfare Effect

	(1) EV	(2) EV/Income	(3) EV	(4) EV/Income
Rural	-6.552***	0.003	-0.694	-0.001
	(1.88)	(0.00)	(1.87)	(0.00)
London	-20.919***	0.020***	-12.193**	0.014***
	(4.89)	(0.00)	(4.57)	(0.00)
South East	-10.505*	0.009*	-2.157	0.002
	(4.39)	(0.00)	(4.07)	(0.00)
HRP Male	3.838*	-0.002	3.999*	-0.001
	(1.70)	(0.00)	(1.57)	(0.00)
With Children	-11.743***	0.007***	-12.485***	0.008***
	(1.76)	(0.00)	(1.64)	(0.00)
Single	38.872***	-0.047***	28.637***	-0.036***
	(1.85)	(0.00)	(1.80)	(0.00)
HRP Asian	10.536**	-0.003	2.060	0.006
	(3.91)	(0.00)	(3.63)	(0.00)
HRP Black	11.444*	-0.003	3.788	0.005
	(5.04)	(0.00)	(4.68)	(0.00)
Below Poverty Line			28.517***	-0.034***
			(2.06)	(0.00)
Maintenance			-7.961**	0.002
			(2.50)	(0.00)
House (not Flat)			8.322***	-0.004*
			(2.29)	(0.00)
Owned			-3.498	0.005***
			(1.92)	(0.00)
Rooms in Dwelling			-7.212***	0.004***
			(0.49)	(0.00)
Central Heating			-1.023	-0.015**
			(6.46)	(0.01)
Heating: Electricity			4.769	0.008
			(6.29)	(0.01)
Heating: Gas			-0.877	0.013**
			(5.52)	(0.00)
Heating: Oil			-0.661	0.008
			(6.09)	(0.00)
Own Cars			-7.518**	0.025***
			(2.68)	(0.00)
Motor Costs			3.428	-0.072***
			(16.60)	(0.01)
Public Transport			-115.090**	0.074*
			(41.66)	(0.03)
Constant	-65.620***	-0.054***	-23.961***	-0.089***
	(4.19)	(0.00)	(6.13)	(0.00)
N	3,367	3,367	3,367	3,367
R^2	0.170	0.299	0.431	0.432

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Maintenance = maintenance costs as share of total housing costs, imperfect proxy for dwelling vintage; Motor costs = spending on motor fuels as share of total transport costs, imperfect proxy for mileage; Public transport = spending on public transport, as share of total transport costs.

6.2 Recycling

6.2.1 Policy I: Per Capita Lump-sum Rebates

To model lump-sum recycling, we draw inspiration from the Canadian system, which applies a federal carbon tax to jurisdictions that do not administer their own pricing schemes and returns direct proceeds to residents via lump-sum rebates. In the Canadian system, payments are adjusted for family size and geography (both by province and for urban vs. rural communities). Similarly, we first model per capita lump-sum rebates adjusted by household size, applying a weighting scheme that assigns one to the first adult, 0.5 to the second adult or first child if single household, and 0.25 to the the remaining household members. We then investigate the implications of targeted transfers by applying the same adjustment but channeling all revenues to the bottom 40% of the equivalized income distribution and by scaling up social security benefits. Finally, we adjust for geography, increasing rebates by 10% for rural households and by 50% for households living in Scotland, Norther Ireland, North East and North West,[15], which experience sharper climates. As geography is not a significant determinant of welfare costs in our data, the implications of targeting rural households and provinces do not differ substantially from the un-targeted transfers, so we leave these Figures for the Appendix.

Table 11 reports aggregates. Carbon tax revenues fund a 34% increase in social security payments, an average of £32 weekly (£1,664 annual) rebates to all households or an average £84 weekly (£4,368 annual) rebates to the bottom 40% of the equivalized income distribution. Emissions fall by less than with no recycling, between 9.5% and 11%; this is a consequence of a smaller consumption fall due to transfers — consumption effectively increases in nominal terms. Labour supply falls similarly across all transfer mechanisms, driven by increases in the price level (3.98-4.12%) and the 5% increase in the income tax required to keep the government budget balanced following a tax base reduction. Consumption increases most when rebating via social security payments (by 2.99%), suggesting that social

[15] We are again inspired by the Canadian system, which adjusts for geography, increasing payments by 20% for households in Manitoba, 70% for Manitoba, 60% for Alberta, compared to Ontario.

security payments target households with higher marginal propensities to consume. While some households experience net welfare gains, the overall percentage with positive EVs never reaches 50%; none of these policies would pass a majority vote.

Table 11: £100 per tonne of CO_2e; Per Capita Lump-sum Transfers

	Emissions (kg CO_2e)	Total Hours	Consumption[a]	$EV \geq 0(\%)$	Gini Disp. Income	Gini Exp.
Baseline	29,260,789	30,497,032	345,536,349		0.2764	0.2990
Per Capita Transfers[b]	-11.03%	-3.24%	1.25%	19%	0.2569	0.2825
Targeted Per Capita Transfers[c]	-10.54%	-3.24%	1.67%	30%	0.2382	0.2669
Per Capita Transfers, HE [d]	-11.02%	-3.23%	1.26%	19%	0.2565	0.2822
Increase Social Security[e]	-9.52%	-3.26%	2.99%	35%	0.2714	0.2724

[a]Consumption is not adjusted for price increases.
[b]Adjusted for family size.
[c]Adjusted for family size and targeted to bottom 40% of equivalized income distribution.
[d]Targets horizontal inequality. Adjusted for family size, rural dwellings = 1.1 and urban dwellings = 1, households who live in Scotland, Northern Ireland, North East or North West = 1.5 while households in other regions = 1.
[e]34% increase in social security payments.

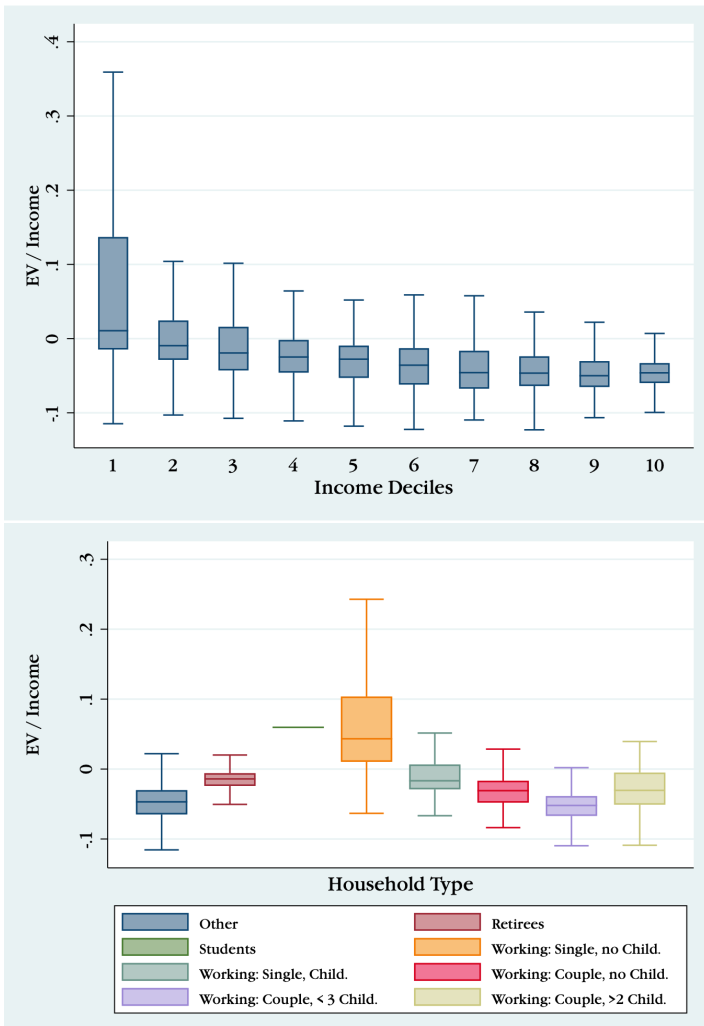
Figure 8 explores vertical and horizontal equity implications of recycling via non-targeted transfers. Transfers adjusted only for family size lead to EVs between -£571 and £45, which increase with income. The bottom income deciles benefit most, mitigating the regressivity of the carbon tax; while 54% of the bottom decile benefits, only 1% of households benefit in the top decile and only 9.8% among the top 5 deciles. The majority of households in all but the first decile loses. The fall in Gini coefficients, both income and expenditure, suggests an improvement in vertical equity, but the benefits are mostly concentrated among low-income households (which include singles, retirees, students and the unemployed).

Yet, heterogeneity in welfare costs amongst the lowest deciles is still large. Singles, with and without children, benefit most, while large working families benefit least. The coefficient of variation captures changes in horizontal equity and is reported in Table 21 for all scenarios. The CV is lower than in the baseline and no recycling cases, across all deciles but especially at the bottom; horizontal equity improves, suggesting that transfers are successful to some extent in offsetting heterogeneous incidence within income groups. As found by Cronin, Fullerton and Sexton (2019), the largest within-decile heterogeneity is at the top of the distribution, reflecting the long tails of consumption distributions. Overall, we observe improvements in both horizontal and vertical equity, especially at the bottom of the distribution.

Income-targeted transfers yield lower emission reductions, as consumption (in nominal terms) increases by 1.67% compared to the 1.25% of non-targeted transfers. Targeting transfers shifts the dispersion of EVs to between -£597 and £137, and Figure 9 explores the implications for equity. As expected, the bottom 40% of the distribution benefits most; average EVs are positive amongst the bottom four deciles and negative for the remaining households. In fact, no households in the top six deciles benefit. These transfers result in substantial gains for bottom 10%, with a 93% approval rate and the average household willing to forego 21% of income to receive transfers. Consumption inequality is lowest with income-based targeting, and all approval rates for the bottom four deciles are above 50%. There is less heterogeneity across household types than following the non-targeted transfers, with approval rates among working singles increasing further. The effect on larger families is ambiguous (with different approval rates depending on whether couples have no children, up to two children or more), but most household types exhibit approval rates of at least 30% (except 'others' and working couples with up to children). This suggests that targeting transfers to the bottom four deciles benefits low-income families, i.e. low-income households not in the bottom decile (which is largely comprised of single households). Indeed, couples with up to two children are over-represented in the 2nd and 3rd quintiles. As expected, the CV falls even further among the bottom 40% with targeted transfers, but is higher than with no income targeting in the top six deciles. Therefore, the decrease in horizontal inequality at the bottom occurs at the expense of equity at the top.

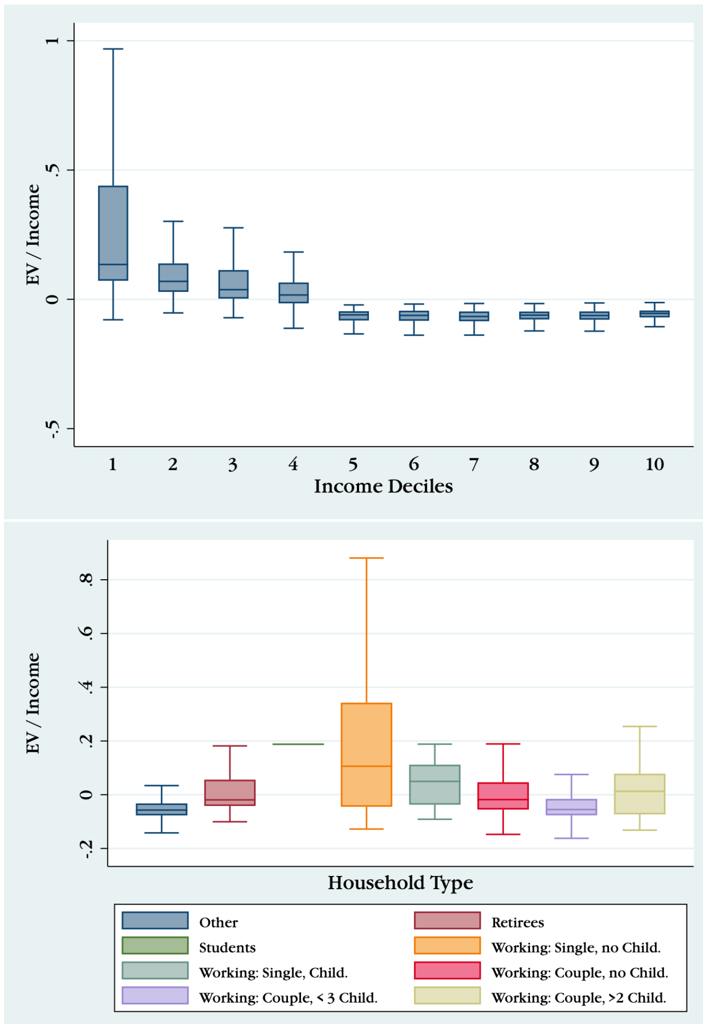
Finally, we explore recycling via social security payments in Figure 11. Social security includes transfers for retirement and other welfare programs, such as child, housing, disability benefits, etc. Income from social security does not include short-term payments like unemployment or sickness benefits. Increasing social security payments proportionally by 34% yields the lowest emission reductions of all transfer scenarios (9.5%), and the largest increase in consumption (2.99%). The overall approval rate of 35% is the highest of all recycling schemes, with gains more dispersed across income groups. Households in all deciles receive some amount; households in the bottom two deciles receive on average £163 weekly,

Figure 8: Recycling: Equivalent Variation, Per Capita Transfers



Notes: Box plot showing EV income shares by income decile (top) and household type (bottom). We show 25th, 50th and 75th quantiles. Transfers are adjusted by family size only, and recycling all revenues results in average transfers of £32 weekly.

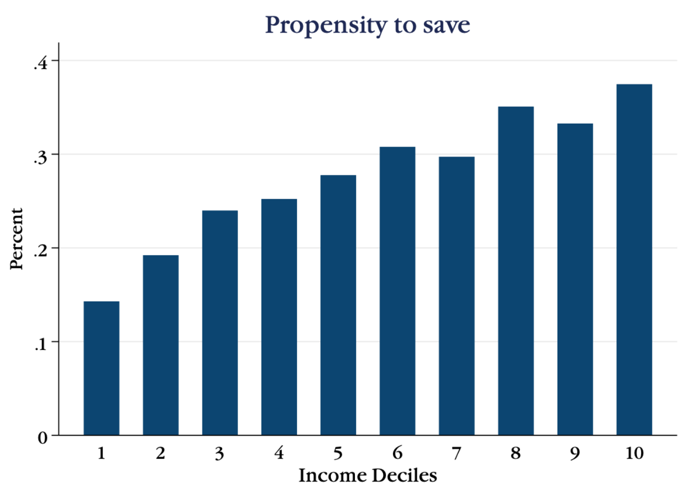
Figure 9: Recycling: Equivalent Variation, Per Capita Transfers, Targeting Bottom 40% of Income



Notes: Box plot showing EV income shares by income decile (top) and household type (bottom). We show 25th, 50th and 75th quantiles. Transfers are adjusted for family size and targeted to households in the bottom 40% of the income distribution. When all revenues are recycled, the average transfer (for households in the bottom two quintiles) is £84 weekly.

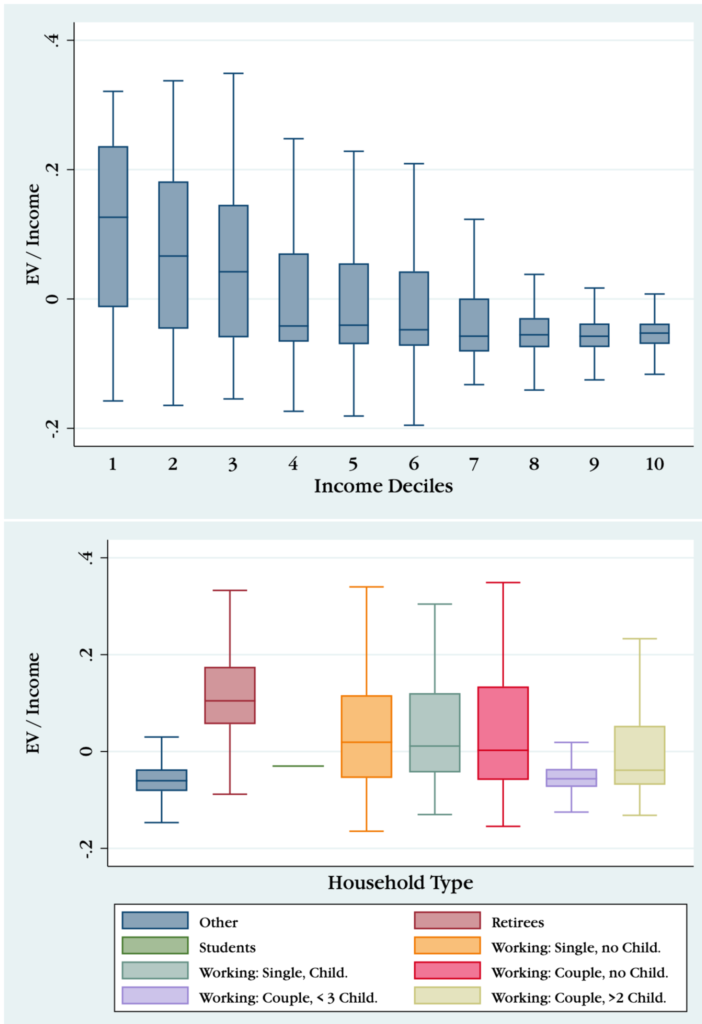
while households in the top two deciles receive on average £47. A proportional increase in benefits then implies that low-income households receive more, such that transfers are progressive. At the same time, low-income households have a lower propensity to save (and therefore higher propensity to consume), as shown in Figure 10. This combination implies that larger transfers to low-income households translate into consumption gains, in contrast with the implications of an income tax reduction discussed in the next section. Indeed, the bottom three deciles exhibit higher than 50% net positive EVs, with approval rates decreasing with income. Moreover, the dispersion of EVs is higher than following other transfer types within all deciles, reflecting the fact that households across all deciles receive social security payments. The Gini coefficients fall, both income and expenditure, suggesting that vertical equity improves.

Figure 10: Propensity to Save, by Income Deciles



Retirees gain most (as expected), and generally the unemployed gain more than the employed (55% vs. 36% approval rates) along with singles and couples with no children (all $>50\%$ approval rates). Larger families, who likely do not rely on social security benefits to the same extent as single households, lose most. However, the contrast between winners and losers is not as accentuated across household types as following per capita transfers. This is reflected by the CV, which is overall the highest across deciles of all transfer scenarios (capturing higher levels of horizontal inequity), but lower than the baseline no carbon tax case. The equity improvement compared to the baseline is then less concentrated at the bottom of the distribution. Overall, this reform results in a net improvement in vertical and horizontal equity, an increase in aggregate consumption and higher approval rates, at the expense of a smaller fall in emissions.

Figure 11: Recycling: Equivalent Variation, Increase Social Security



Notes: Box plot showing EV income shares by income decile (top) and household type (bottom). We show 25th, 50th and 75th quantiles. We recycle all revenues by increasing social security benefits by 34%. Social security includes social security for retirement and welfare transfers.

Of course, we did not consider all possible transfer schemes. Alternative revenue recycling designs may attempt to address horizontal heterogeneity without creating adverse incentives or muting price effects by administering the carbon tax based on the mean consumption of families that are similar in size, location and income category, as suggested by (Cronin, Fullerton and Sexton, 2019), but this may result in a collective action problem. Indeed, perfectly offsetting heterogeneity in welfare effects may not be possible, highlighting the complementary role of energy efficiency standards and other regulation-based instruments, and public investments in infrastructure.

6.2.2 Policy II: Income Tax Reduction

Turning to income tax reductions, we investigate whether decreasing the (distortionary) income tax via carbon tax revenues improves efficiency, yielding double dividends, and its distributional consequences. Tax revenues are large enough to decrease the income tax by 18%. The implications for aggregate consumption are somewhat disappointing, with a 2.81% increase compared to the baseline. This change is smaller than when recycling via social security payments, and driven by both a muted responses of labour supply and the fact that the most benefiting, high-income households also have the lowest propensities to consume. Labour supply now responds to the higher price level but lower income tax, which have contrasting effects on the real wage. This recycling scheme results in the lowest acceptance rate of all scenarios (11%), and smaller fall in emissions (-10.27%) than no recycling and even the un-targeted transfers.

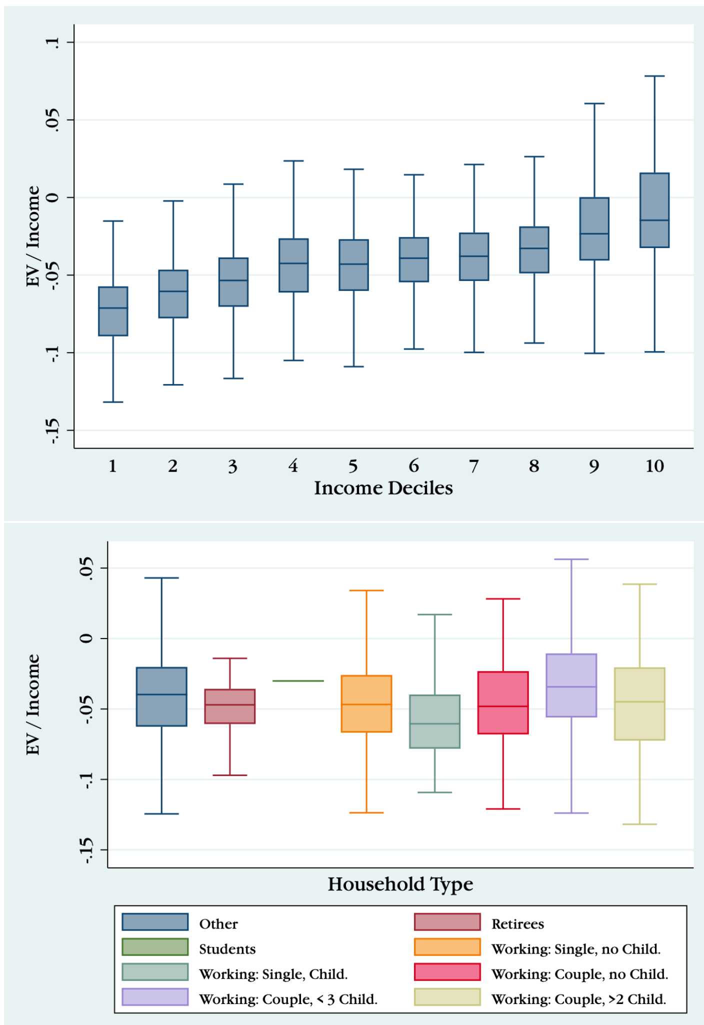
Figure 12 shows that this policy fails to offset the initial regressivity of the carbon tax, with EVs becoming progressively more positive with income and ranging from £-791 to £206. Inequality across income deciles increases, with both income and expenditure Gini higher than the baseline. Among the top decile, 51% of households have positive EV, while among the bottom four deciles, none do. The variance of EVs is approximately equal across deciles, in contrast with the large dispersion differences found following transfers. The differences across household types are less stark than following transfers, with average EVs negative across all income levels and household types. Moreover, the CV is not systematically different from the baseline, suggesting that there is no clear pattern in horizontal equity gains; the most substantial reallocation occurs across income deciles. Retirees are hurt the most (none would accept), along with working singles (who exhibit a 2% approval rate). Unemployed, rural households and households with female HRPs have lower share of positive EVs than the employed, urban and male HRP households (circa 8% vs. 11%). Recycling via income tax reductions does not yield double dividends to the extent suggested by the literature, and its negative effects on equity are not offset by effectiveness or consumption increases.

Table 12: £100 per tonne of CO_2e; Across the Board Income Tax Reduction

	Emissions (kg CO_2e)	Total Hours	Consumption[a]	$EV \geq 0(\%)$	Gini Disp. Income	Gini Exp.
Baseline	29,260,789	30,497,032	345,536,349		0.2764	0.2990
$\lambda = 0.82$	-10.27%	-1.60%	2.81%	11%	0.2868	0.3074

[a]Consumption is not adjusted for price increases.

Figure 12: Recycling: Equivalent Variation, Across the Board Income Tax Reduction



Notes: Box plot showing EV income shares by income decile (top) and household type (bottom). We show 25th, 50th and 75th quantiles.

Table 13: £100 per tonne of CO_2e; All Policies

	Emissions (kg CO_2e)	Total Hours	Consumption[a]	EV $\geq 0(\%)$	Gini Disp. Income	Gini Exp.	Mean Price Change
Baseline	29,260,789	30,497,032	345,536,349		0.2764	0.2990	
No Recycling (A)	-13.97%	-3.28%	-3.07%	0%	0.2714	0.2954	4.40%
Increase Social Security[b] (B)	-9.52%	-3.26%	2.99%	35%	0.2714	0.2724	4.02%
Per Capita Transfers[c] (C)	-11.03%	-3.24%	1.25%	19%	0.2569	0.2825	4.12%
Targeted Per Capita Transfers[d] (D)	-10.54%	-3.24%	1.67%	30%	0.2382	0.2669	3.99%
Per Capita Transfers, HE [e]	-11.02%	-3.23%	1.26%	19%	0.2565	0.2822	4.12%
Decrease Income Tax[f] (E)	-10.27%	-1.60%	2.81%	11%	0.2868	0.3074	4.32%

[a]Emissions are adjusted for price increases, such that the change reflects quantity changes instead of price changes.

[b]34% increase in social security payments.

[c]Adjusted for family size.

[d]Adjusted for family size and targeted to bottom 40% of equivalized income distribution.

[e]Targets horizontal inequality. Adjusted for family size, rural dwellings = 1.1 and urban dwellings = 1, households who live in Scotland, Northern Ireland, North East or North West = 1.5 while households in other regions = 1.

[f]Across the board 18% income tax reduction, $\lambda = 0.82$.

6.2.3 Combined Policies

Beyond discrete recycling, we consider combinations of policies. Recycling only via income tax reductions allows for an 18% decrease. We now explore dynamics when we progressively increase the percent reduction of the income tax (decrease λ) from 0% to 20% and allow social security payments to adjust such that the governments' budget constraint holds (note that we need to reduce social security payments with a 20% income tax reduction). Table 14 shows the resulting increase in social security payments, aggregates and the share of net winners from each policy. As we decrease the income tax, labour supply increases, but consumption falls. This reflects the fact that the largest consumption gains are generated by social security payment increases, not income tax reductions. Approval rates drop with the income tax, and emissions fall.

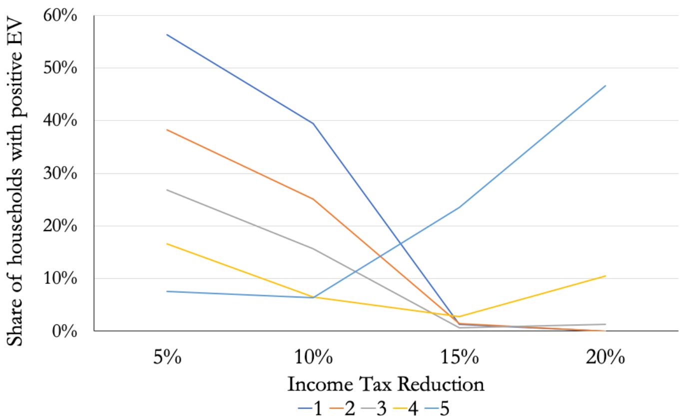
Table 14: £100 per tonne of CO_2e; Revenue Neutral Policy Packages

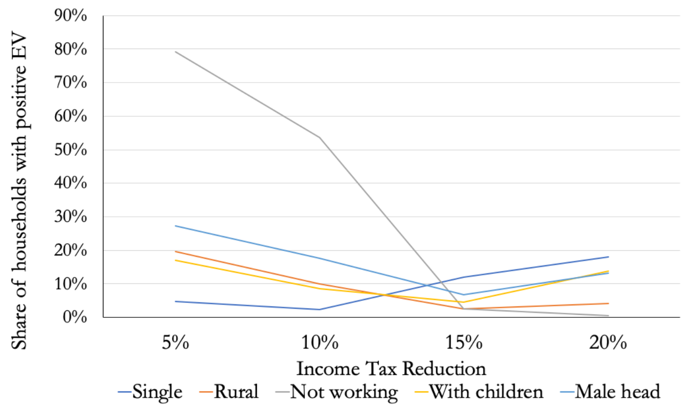
Income Tax	Social Security	Emissions (kg CO_2e)	Total Hours	Consumption	EV ≥ 0
$\lambda = 1$	$\mu = 1$	29,260,789	30,497,032	345,536,34	0%
$\lambda = 0.95$	$\mu = 1.19$	-9.79%	-2.52%	2.93%	27%
$\lambda = 0.90$	$\mu = 1.12$	-9.96%	-2.17%	2.89%	18%
$\lambda = 0.85$	$\mu = 1.05$	-10.14%	-1.82%	2.84%	7%
$\lambda = 0.80$	$\mu = 97.16$	-10.36%	-1.14%	2.79%	14%

Notes: We report policy packages where we allocate revenues to income tax reductions or social security transfers. We start by channelling most revenues towards social security payments (only a 5% reduction in the income tax, $\lambda = 0.95$, and a 19% increase in social security payments, $\nu = 1.19$.) and direct progressively more revenue towards income tax reductions by reducing λ.

Figure 13 shows approval rates across income quintiles and household types as we increase the share of revenue recycled via income tax reduction and decrease the share channeled towards social security payments. As the income tax reduction increases, approval rates in the top income quintile increase and fall among all other quintiles. The bottom quintiles benefit most when revenues are mostly channeled towards social security payments, with an approval rate of almost 60%. This trend is reflected by non-working households, while there are no stark differences based on other household characteristics. Singles have the lowest approval rates, and the response of rural households mostly follows the average population's

Figure 13: Approval Rates Across Income Quintiles (left) and Household Types (right)





Notes: we show approval rates (i.e. the share of households with positive EVs) across income quintiles and household types as we shift recycling revenues between income tax reduction and social security payments (decreasing the income tax entails lower social security payments as the policies are revenue neutral).

(the overall approval rates reported in Table 14).

6.3 Endogenous Emission Intensities

In our model, emissions fall only because of demand-side adjustments: shifting expenditure across households, consuming less and less carbon-intensive goods. Due to the low demand elasticities and limited extent to which households can reallocate or consume less, emissions only fall by around 10% after a quite large increase in the carbon price. We now explore the implications of including supply-side adjustments in our model; we follow Van der Ploeg, Rezai and Tovar (2020) and allow for endogenous emission intensities for each good. Still taking pre-tax prices as given, we now allow firms to reduce the emission intensities of inputs to offset the increase in marginal cost. We consider a backstop technology which is available at a fixed price across all sectors, and take the cost function from Nordhaus' DICE model:

$$R(\rho) = \beta \frac{\rho^{1+\xi}}{1+\xi} \tag{22}$$

where β is the backstop price and ξ is the price elasticity of emissions reduction ρ. In equilibrium, the marginal cost of emissions reduction is the carbon price, such that $R'(\rho) = \pi$ and $\rho = (\pi/\beta)^{\xi}$. We calibrate $\beta = \pounds 500$ per tonne of CO_2e and $\xi = 0.625$, following Van der Ploeg, Rezai and Tovar (2020); this means that, if the carbon price is $\pounds 500$, the carbon intensity falls to zero as $\rho = 1$ as firms avoid all carbon taxes. The carbon content of commodities is then $1 - \rho$, such that prices are now:

$$p_{jh} = q_{jh}[1 + (1-\rho)\pi e_j] \tag{23}$$

and emissions are:

$$E = \sum_{h=1}^{H} N_h (1-\rho) \boldsymbol{e_h} \boldsymbol{x_h}^T \tag{24}$$

Table 15 reports aggregates with endogenous carbon intensities. Emissions fall much more than with no firm responses, by 40-42.7%, while the average price increase is smaller and the response of aggregate labour supply and consumption is muted. Lower emissions levels imply a smaller revenue, such that the scope of recycling is limited; the income tax falls by 11% instead of 18%, and social security payments increase by 22% instead of 34%. Consumption increases by maximum 2.67%, compared to 2.81% with fixed intensities, but now income tax reductions yield the highest consumption gains. The contrasting effects of the lower price increase and smaller compensations result in similar approval rates as with fixed intensities.

A carbon tax then is much more effective when encouraging production-side adjustments than changing households' consumption patterns, and the scope of recycling is weaker given lower carbon revenues. However, we are entirely ignoring the welfare effects of lower emissions on households; such large emission cuts entail a higher probability of mitigating climate change, lower pollution levels, and generally improved environmental conditions which may offset any negative welfare costs from higher prices.

Table 15: £100 per tonne of CO_2e; All Policies with Endogenous Intensities

	Emissions (kg CO_2e)[a]	Total Hours	Consumption	EV $\geq 0(\%)$	Gini Disp. Income	Gini Exp.	Mean Price Change
Baseline	29,260,789	30,497,032	345,536,349		0.2764	0.2990	
Govt Exp.	-42.68%	-2.69%	-2.52%	0%	0.2721	0.2959	2.80%
Per Capita Transfers[b]	-41.41%	-2.67%	0.32%	18%	0.2624	0.2872	2.64%
Targeted Per Capita Transfers[c]	-41.18%	-2.66%	0.59%	29%	0.2497	0.2761	2.55%
Per Capita Transfers, HE [d]	-41.40%	-2.66%	0.33%	19%	0.2621	0.2869	2.64%
Increase Social Security[e]	-40.75%	-2.67%	1.44%	34%	0.2721	0.2796	2.58%
Decrease Income Tax[f]	-40.92%	-1.45%	2.67%	11%	0.2857	0.3065	2.75%

[a]Emissions are adjusted for price increases, such that the change reflects quantity changes instead of price changes.

[b]Adjusted for family size.

[c]Adjusted for family size and targeted to bottom 40% of equivalized income distribution.

[d]Targets horizontal inequality. Adjusted for family size, rural dwellings = 1.1 and urban dwellings = 1, households who live in Scotland, Northern Ireland, North East or North West = 1.5 while households in other regions = 1.

[e]22% increase in social security payments.

[f]Across the board 11% income tax reduction, $\lambda = 0.8861$.

6.4 Discussion and Robustness

Through these policy exercises, we show that all recycling schemes fail to generate above 50% majority approval rates. Recycling by increasing social security benefits generates the highest approval rates and the largest increases in consumption, at the expense of emission reductions. Vertical equity does not improve as much via social security payments as with the other transfers, since benefits are not as concentrated in bottom deciles; generally, different recycling schemes have different vertical and horizontal equity implications, which may result in trade-offs. The income dimension matters most for welfare impacts, while geography does not play as large a role as has been found in other contexts; access to public transport, commute characteristics and fuel type appear most important. By modeling supply-side adjustments, we show that the price mechanism is more effective at incentivizing reductions in the carbon intensity of goods, as the extent to which households can reallocate is limited.

As robustness checks, we estimate the EASI demand system with alternative specifications of our budget shares equations, for example testing for higher order polynomials and using different aggregations of goods. When estimating elasticities separately for electricity and household heating, the high share of households with zero expenditures results in imprecisely estimated coefficients. As a robustness check to our sample selection and to avoid dropping 25% of households with zero expenditure[16] in one of our main aggregates, we impute expenditure values of 50% of the "poverty rate" in each aggregate (the poverty rate is considered to be 60% of median expenditure). Finally, to address the possibility of high inter-household variation in expenditures due to the brevity of the coverage period (reported spending reflects only two weeks' expenses), we compute average monthly expenditures by household type (region, composition, sex of HRP, household income, ethnicity) and re-estimate elasticities on this sample. We find no stark differences in estimates.

[16] Completely excluding these households might, in principle, bias our estimates, as households reporting non-positive expenditures are likely to be systematically different from households with positive expenditures. We indeed confirm that the distribution of zero-expenditure households is skewed towards the lower end of the income distribution, as captured by Figure 14.

7 Limitations and Future Research

Finally, we outline a series of limitations of this study and propose avenues for further research. First, survey data is subject to measurement error and recall bias, and expenditures are reported over a short period of time (two weeks). This may cause excessive variability across households — potentially not offset by our robustness check —, which may overestimate the degree of tax incidence heterogeneity across households. Using third-party administrative data (for e.g. households tax records) for income variables, as in Cronin, Fullerton and Sexton (2019), and recovering expenditure data directly from household bills (for e.g. from utility companies) would limit measurement error and reporting effects. Moreover, more comprehensive data on dwelling and commute characteristics would allow us to better understand determinants of household energy expenditures. Access to more granular spatial data on dwellings (at the very least linking households to city sizes) would enable a better understanding of the spatial distribution of tax incidence. The LCF does not include detailed information on households' geographic location, appliance vintage, commuting distance to work, access to public transport, etc., which affect exposure to carbon taxes. In his own investigation of determinants, Douenne (2020) augments household surveys with a more detailed transport survey using matching techniques; we could similarly match the LCF to the English Housing Survey (based on household characteristics such as household reference person demographics, region, household income variables and economic status). This national survey includes data on housing and energy efficiency of households, including characteristics of dwellings, neighbourhoods, access to infrastructure like parking, mains gas and types of space and water heating systems; it would especially allow us to investigate implications of a carbon tax for fuel poverty, i.e. the inability of households to adequately meet energy needs. There is scope for better understanding the trade-offs between alleviating energy poverty and achieving climate goals (and especially the links between climate and energy poverty policies), determinants of energy poverty beyond energy efficiency and income (especially with respect to racial and ethnic dimensions) and determinants of energy poverty on socioeconomic outcomes (especially well-being). Matching these data-sets would allow us to explore these questions.

Second, our model captures the effects of a broad tax, a single rate on all carbon emissions, instead of sector-specific prices. This limits the number of calculations required, but ignores important network effects of sector-specific policies, which are in practice more common. For example, King, Tarbush and Teytelboym (2019) theoretically study sector-specific carbon taxes, showing that carbon tax reforms which target sectors based on their position in the production network can achieve larger reductions in aggregate emissions than reforms that target sectors based on their direct emissions alone. Incorporating network effects and production linkages to understand macroeconomic dynamics is a growing area of research, and its applications to climate economics would allow for a better understanding of spillovers (amplifying mechanisms) and scope of targeted reforms (see Farmer et al. (2019) on sensitive intervention points).

Finally, and most importantly, ignoring behavioural considerations and public attitudes when designing climate policy undermines the prescriptive objective of economic models; public support or antagonism towards a policy proposal ultimately determines its implementation. Beyond investigating 'true' incidence and welfare effects, the political economy of climate policy literature highlights that measuring discrepancies between actual impacts and subjective beliefs and identifying the relationship between beliefs and attitudes is an important avenue for further research (Carattini, Carvalho and Fankhauser, 2018; Klenert et al., 2018). On the theoretical front, Gabaix, Farhi et al. (2017) reexamine the classical theory of corrective taxation with behavioural, i.e. "inattentive" agents, showing that first-best policies are never possible with heterogeneous behavioural biases (so even when Engel curves are linear). On the empirical front, mounting evidence of motivated political beliefs suggests that the relationship between beliefs and attitudes may be bidirectional. For example, Douenne and Fabre (2020) investigate the formation of beliefs and attitudes around carbon taxation in France, in the context of the Yellow Vests movement, finding that informing individuals largely *fails* to change pessimistic beliefs. Respondents revise beliefs asymmetrically, giving more weight to new information that confirms pre-existing convictions. While the causal effects of convincing people of the actual incidence and effectiveness of the policy are high, increasing the acceptance rate by 50% percent, they document belief inertia, and find that those who are more opposed to the tax are more pessimistally biased. This evidence falls within a larger literature exploiting large-scale surveys to understand determinants of attitudes towards policies; for example, Stantcheva (2020) studies the mental models of US tax-payers and finds partisan divergences not just in the final policy views, but at every step of the reasoning about the underlying mechanisms of taxes, and most starkly on the fairness considerations. This literature leads to two natural extensions of our study; theoretically, we can incorporate behavioural biases in our model and investigate the implications of heterogeneous inattention for the effectiveness of recycling schemes. Empirically, we can exploit large-scale surveys to measure discrepancies between true welfare effects and perceived tax burden in the UK, experimentally implementing information treatments to identify potential motivated reasoning channels. Finally, we can exploit these surveys to understand public beliefs and attitudes towards *policy packages* instead of independent policies, studying interactions between climate and other economic or social policies, which would further inform our analysis of revenue recycling.

8 Conclusion

The legally binding Climate Change Act (2008) commits the UK to net zero emissions by 2050. In December 2020, the UK communicated to the UN Framework Convention Climate Change (UNFCCC) its new Nationally Determined Contribution (NDC) under the Paris Agreement: reducing economy-wide greenhouse gas emissions by at least 68% by 2030, compared to 1990 levels. The cross-party, not-for-profit think tank Policy Connect, that follows the UK's progress towards decarbonization, highlights that the country is **not** on track to meet future carbon budgets or NDCs. Accelerating the implementation of policy that effectively reduces carbon emissions is crucial to meeting these targets. We study the distributional implications of implementing a carbon tax of £100 per tonne of CO_2e in the UK, investigating both horizontal and vertical equity, and impacts of recycling schemes on inequality and political feasibility, measured via approval rates. We show that a carbon tax is indeed regressive with respect to both income and expenditure, and that recycling succeeds in offsetting this regressivity, rendering the tax progressive. The income dimension is the most important determinant of welfare costs, while other characteristics, like geography, are not significant predictors. We model different recycling schemes, both transfers and income tax reduction, but find that none of these induce an overall majority approval rate. While carbon pricing has received much attention and should play a role in sensible climate strategies (especially considering the currently-in-place fossil fuel subsidies), the overall empirical evidence around the effectiveness of carbon prices at current levels is pessimistic. For example, Rafaty, Dolphin and Pretis (2020) study five sectors in a panel of 39 countries over 1990-2016, finding that the introduction of carbon pricing has reduced growth in CO2 emissions by 1% to 2.5% on average relative to counterfactual emissions. As there are few countries with carbon prices high enough to result in any significant effect, policy-makers must increase the political feasibility of carbon pricing through improvements in design, which take into account distributional implications, and urgently focus on complementary instruments. It is unlikely that a carbon tax, on its own, will effectively incite the economy-wide transformation required to avoid the devastating impacts of unmitigated climate change.

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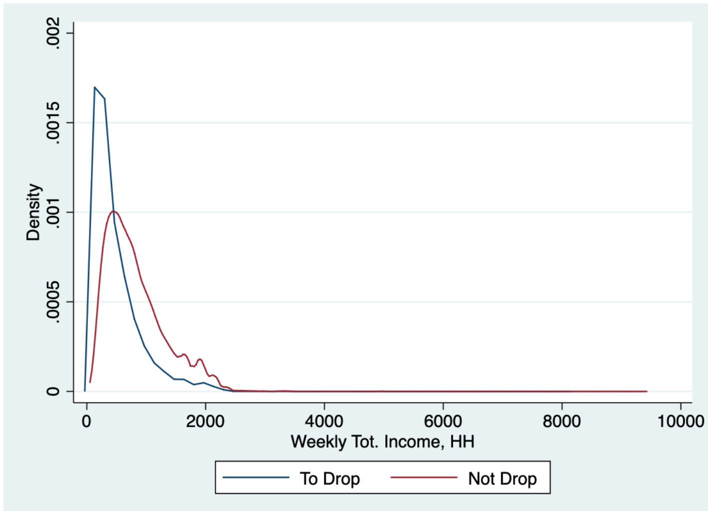
Tables

Figure 14: Kernel Density of Income



Notes: (Epanechnikov) Kernel density of income for households with positive expenditure on all product aggregates compared to households with at least one zero ("To Drop"). The distribution of dropped households is clearly skewed towards low-income households, which biases our sample towards high-income households.

Table 16: EASI Demand Coefficients

Variable Names	Food	Heating	Transport	Housing	Services	Durables
$\ln(v)$	0.009	-0.048	-0.007	0.104	-0.046	0.022
	(0.030)	(0.013)	(0.020)	(0.041)	(0.021)	(0.021)
$\ln(v)^2$	-0.074	-0.028	0.034	-0.036	0.029	0.029
	(0.025)	(0.011)	(0.020)	(0.036)	(0.022)	(0.022)
$\ln(v)^3$	0.017	0.015	-0.019	0.001	-0.013	0.001
	(0.009)	(0.004)	(0.008)	(0.013)	(0.009)	(0.009)
$\ln(v)^4$	-0.001	-0.002	0.003	0.001	0.002	-0.001
	(0.001)	(0.000)	(0.001)	(0.002)	(0.001)	(0.001)
$\ln(v) * z_1$	0.032	0.002	-0.007	0.034	0.003	-0.051
	(0.004)	(0.002)	(0.005)	(0.007)	(0.004)	(0.006)
$\ln(v) * z_2$	0.019	0.004	-0.007	-0.016	0.007	-0.016
	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)	(0.003)
$\ln(v) * z_3$	0.024	0.005	-0.001	-0.011	0.003	-0.021
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
$\ln(v) * z_4$	0.038	0.004	0.001	-0.012	0.004	-0.029
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)
$\ln(v) * z_5$	0.050	0.008	0.001	-0.022	0.003	-0.029

Continued on next page...

... table 16 continued

Variable Names	Food	Heating	Transport	Housing	Services	Durables
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.003)
$\ln(v) * z_6$	0.035	0.004	0.005	-0.011	0.004	-0.029
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)
$\ln(v) * z_7$	0.042	0.006	-0.003	-0.012	-0.001	-0.025
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)
$\ln(v) * z_8$	(Reference group)					
Log Price Food	0.072	-0.005	-0.020	-0.009	-0.007	-0.023
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log Price Heating	-0.005	0.028	-0.005	-0.001	-0.004	-0.008
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log Price Transport	-0.020	-0.005	0.014	-0.005	-0.005	-0.021
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Log Price Housing	-0.009	-0.001	-0.005	0.018	-0.004	-0.020
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Log Price Services	-0.007	-0.004	-0.005	-0.004	0.025	-0.010
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log Price Durables	-0.023	-0.008	-0.021	-0.020	-0.010	0.068
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Dummy: Rent	-0.003	0.005	-0.020	0.187	-0.003	-0.054
	(0.002)	(0.000)	(0.001)	(0.002)	(0.001)	(0.002)
Dummy: Flat	-0.017	-0.013	-0.005	0.035	-0.000	-0.005
	(0.002)	(0.001)	(0.002)	(0.003)	(0.001)	(0.002)
Constant	0.254	0.178	0.090	-0.047	0.084	0.092
	(0.012)	(0.006)	(0.008)	(0.017)	(0.007)	(0.009)
Controls: Regions	Y	Y	Y	Y	Y	Y
Controls: Months	Y	Y	Y	Y	Y	Y
Controls: Years	Y	Y	Y	Y	Y	Y
SE Bootstrap	Y	Y	Y	Y	Y	Y
N	41,218	41,218	41,218	41,218	41,218	41,218

Notes: Coefficients on prices and real expenditure, estimated by EASI. We bootstrap standard errors through 50 iterations of our model estimation.

Table 17: Marshallian (Uncompensated) Elasticities, by Income Quintile

Quintile	Products	Food	Heating and Elec.	Transport	Housing	Services	Durables	Other
1	Food	-0.85	-0.19	-0.25	-0.21	-0.19	-0.26	-0.18
	Domestic Energy	-0.11	-0.70	-0.11	-0.06	-0.08	-0.13	-0.07
	Transport	-0.32	-0.17	-0.98	-0.15	-0.16	-0.32	0.32
	Housing	-0.21	-0.14	-0.16	-0.93	-0.16	-0.29	0.05
	Services	-0.15	-0.11	-0.13	-0.12	-0.65	-0.21	0.05
	Durables	-0.37	-0.26	-0.36	-0.34	-0.27	-0.67	-0.09
	Other	-0.35	-0.35	-0.17	-0.27	-0.31	-0.29	-1.60
2	Food	-0.75	-0.15	-0.22	-0.17	-0.15	-0.23	-0.14
	Domestic Energy	-0.12	-0.59	-0.11	-0.05	-0.08	-0.14	-0.07
	Transport	-0.30	-0.17	-0.98	-0.15	-0.15	-0.30	0.30
	Housing	-0.20	-0.12	-0.14	-0.89	-0.15	-0.28	0.08
	Services	-0.16	-0.11	-0.13	-0.12	-0.62	-0.22	0.06
	Durables	-0.38	-0.28	-0.37	-0.35	-0.29	-0.79	-0.14
	Other	-0.40	-0.39	-0.24	-0.32	-0.36	-0.34	-1.61
3	Food	-0.69	-0.13	-0.21	-0.15	-0.13	-0.22	-0.12
	Domestic Energy	-0.13	-0.52	-0.12	-0.05	-0.08	-0.16	-0.07
	Transport	-0.30	-0.16	-0.99	-0.15	-0.15	-0.30	0.29
	Housing	-0.20	-0.10	-0.13	-0.83	-0.13	-0.30	0.13
	Services	-0.16	-0.11	-0.13	-0.12	-0.62	-0.22	0.06
	Durables	-0.38	-0.30	-0.38	-0.36	-0.31	-0.85	-0.17
	Other	-0.42	-0.42	-0.28	-0.35	-0.39	-0.37	-1.62
4	Food	-0.64	-0.12	-0.20	-0.14	-0.12	-0.21	-0.11
	Domestic Energy	-0.14	-0.45	-0.13	-0.05	-0.09	-0.17	-0.08
	Transport	-0.29	-0.16	-0.99	-0.14	-0.15	-0.29	0.28
	Housing	-0.21	-0.09	-0.12	-0.78	-0.13	-0.32	0.19
	Services	-0.16	-0.12	-0.13	-0.13	-0.61	-0.22	0.06
	Durables	-0.39	-0.31	-0.38	-0.37	-0.32	-0.89	-0.19
	Other	-0.44	-0.44	-0.30	-0.38	-0.41	-0.39	-1.63
5	Food	-0.55	-0.10	-0.20	-0.12	-0.10	-0.21	-0.09
	Domestic Energy	-0.16	-0.37	-0.15	-0.05	-0.10	-0.19	-0.09
	Transport	-0.29	-0.16	-0.98	-0.14	-0.14	-0.29	0.29
	Housing	-0.21	-0.08	-0.12	-0.74	-0.12	-0.33	0.22
	Services	-0.17	-0.12	-0.14	-0.13	-0.64	-0.22	0.05
	Durables	-0.40	-0.32	-0.39	-0.37	-0.33	-0.93	-0.21
	Other	-0.46	-0.45	-0.33	-0.39	-0.43	-0.41	-1.64

Table 18: Hicksian (Compensated) Elasticities, by Income Quintile

Quintile	Products	Food	Heating and Elec.	Transport	Housing	Services	Durables	Other
1	Food	-0.69	-0.03	-0.09	-0.04	-0.03	-0.10	-0.02
	Domestic Energy	-0.07	-0.67	-0.07	-0.02	-0.04	-0.09	-0.04
	Transport	-0.21	-0.06	-0.87	-0.04	-0.05	-0.21	0.43
	Housing	-0.09	-0.02	-0.04	-0.81	-0.04	-0.17	0.17
	Services	-0.11	-0.06	-0.08	-0.07	-0.61	-0.16	0.10
	Durables	-0.18	-0.07	-0.17	-0.14	-0.08	-0.48	0.10
	Other	-0.02	-0.01	0.16	0.07	0.02	0.05	-1.26
2	Food	-0.63	-0.03	-0.11	-0.05	-0.03	-0.11	-0.03
	Domestic Energy	-0.10	-0.56	-0.09	-0.03	-0.06	-0.12	-0.05
	Transport	-0.20	-0.06	-0.88	-0.04	-0.05	-0.20	0.41
	Housing	-0.10	-0.02	-0.04	-0.79	-0.04	-0.18	0.18
	Services	-0.12	-0.07	-0.09	-0.08	-0.58	-0.17	0.11
	Durables	-0.15	-0.05	-0.14	-0.12	-0.06	-0.56	0.09
	Other	-0.02	-0.01	0.14	0.06	0.02	0.04	-1.23
3	Food	-0.60	-0.04	-0.12	-0.06	-0.04	-0.12	-0.03
	Domestic Energy	-0.11	-0.50	-0.10	-0.03	-0.06	-0.14	-0.06
	Transport	-0.19	-0.06	-0.88	-0.04	-0.04	-0.19	0.40
	Housing	-0.12	-0.02	-0.05	-0.75	-0.05	-0.22	0.21
	Services	-0.12	-0.07	-0.09	-0.08	-0.58	-0.17	0.11
	Durables	-0.13	-0.05	-0.13	-0.11	-0.06	-0.60	0.08
	Other	-0.02	-0.01	0.13	0.05	0.02	0.04	-1.22
4	Food	-0.56	-0.04	-0.13	-0.06	-0.04	-0.14	-0.03
	Domestic Energy	-0.12	-0.44	-0.12	-0.03	-0.07	-0.15	-0.06
	Transport	-0.19	-0.06	-0.88	-0.04	-0.04	-0.19	0.39
	Housing	-0.14	-0.03	-0.06	-0.71	-0.06	-0.25	0.25
	Services	-0.12	-0.07	-0.09	-0.08	-0.57	-0.18	0.11
	Durables	-0.13	-0.05	-0.12	-0.10	-0.05	-0.63	0.07
	Other	-0.01	-0.01	0.12	0.05	0.02	0.04	-1.20
5	Food	-0.50	-0.05	-0.15	-0.07	-0.05	-0.16	-0.04
	Domestic Energy	-0.14	-0.36	-0.13	-0.04	-0.08	-0.18	-0.07
	Transport	-0.19	-0.06	-0.88	-0.04	-0.04	-0.19	0.39
	Housing	-0.15	-0.03	-0.06	-0.68	-0.07	-0.28	0.27
	Services	-0.11	-0.07	-0.08	-0.08	-0.59	-0.17	0.10
	Durables	-0.12	-0.04	-0.11	-0.09	-0.05	-0.66	0.07
	Other	-0.01	-0.01	0.12	0.05	0.02	0.04	-1.19

Table 19: Labour Supply: UK Households, Singles

	(1) OLS	(2) OLS	(3) IV	(4) IV	(5) IV
Log Net Real Wage	-0.011	-0.152***	0.203***	0.203***	0.481***
	(0.01)	(0.01)	(0.05)	(0.05)	(0.09)
HRP Male × Log Net Real Wage					-0.498***
					(0.08)
heck_agg		-0.782***	-0.561***	-0.561***	-0.482***
		(0.02)	(0.05)	(0.05)	(0.06)
london		0.046	-0.094*	-0.089*	-0.111***
		(0.03)	(0.04)	(0.04)	(0.03)
sex of household reference person		0.210***	0.185***	0.180***	1.533***
		(0.01)	(0.01)	(0.01)	(0.22)
d_children		-0.254***	-0.158***	-0.160***	-0.126***
		(0.01)	(0.02)	(0.02)	(0.02)
Constant	3.547***	4.001***	3.027***	3.037***	2.279***
	(0.03)	(0.04)	(0.15)	(0.16)	(0.24)
Controls: Region	No	Yes	Yes	Yes	Yes
Controls: Month	No	Yes	Yes	Yes	Yes
Controls: Year	No	Yes	Yes	Yes	Yes
SE Bootstrap	No	No	No	Yes	Yes
N	6,431	6,431	6,431	6,431	6,431
R^2	0	0.256	0.098	0.108	.

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. We restrict the sample to single households. Columns 1-5 report regressions with respect to total weekly hours worked at the household level. We report OLS and IV estimates, where IV estimates use occupation-, region- and group-mean real wages as instruments. We include the inverse Mills ratio as a control for selectivity bias (Heckman, 1979), and allow the intercept to change across household HRP sex, children presence and for households living in London. We add controls for regions and time (month and year) and calculate bootsrapped standard errors. Labour supply elasticities range from -0.01 (OLS) to 0.20 (IV) when hours worked is used, while is increases when taxable income is used.

Table 20: Labour Supply: UK Households, Couples

	(1) OLS	(2) OLS	(3) IV	(4) IV	(5) IV
Log Net Real Wage	-0.208***	-0.182***	0.222***	0.200***	0.583***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.04)
HRP Male × Log Net Real Wage				-0.463***	
					(0.05)
Inverse Mill's Ratio		-0.813***	-0.566***	-0.605***	-0.602***
		(0.02)	(0.05)	(0.03)	(0.04)
Dummy: London		0.049***	-0.065***	-0.058***	-0.068***
		(0.01)	(0.02)	(0.02)	(0.02)
Dummy: HRP London		0.021***	0.002	0.002	1.155***
		(0.01)	(0.01)	(0.01)	(0.12)
Dummy: Children		-0.013*	0.007	0.016***	0.020***
		(0.00)	(0.01)	(0.00)	(0.01)
Spouse Working		0.532***	0.629***	0.615***	0.614***
		(0.01)	(0.01)	(0.01)	(0.01)
Constant	4.638***	4.159***	3.084***	3.144***	2.191***
	(0.02)	(0.02)	(0.06)	(0.05)	(0.11)
Controls: Region	No	Yes	Yes	Yes	Yes
Controls: Month	No	Yes	Yes	Yes	Yes
Controls: Year	No	Yes	Yes	Yes	Yes
SE Bootstrap	No	No	No	Yes	Yes
N	21,264	21,264	21,264	21,264	21,264
R^2	0.050	0.423	0.253	0.279	0.220

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. We restrict the sample to couples. Columns 1-5 report regressions with respect to total weekly hours worked at the household level. We report OLS and IV estimates, where IV estimates use occupation-, region- and group-mean real wages as instruments. We include the inverse Mills ratio as a control for selectivity bias (Heckman, 1979), and allow the intercept to change across household HRP sex, children presence and for households living in London. We add controls for regions and time (month and year) and calculate bootstrapped standard errors. Labour supply wage elasticities range from -0.21 (OLS) to 0.20 (IV) when hours worked is used, while the elasticity of taxable income is larger.

Table 21: Horizontal Heterogeneity: Mean (£), SD (£), CV of Consumption

	Baseline			No Recycling			Per Capita Transfers		
Income Deciles	Mean	SD	CV	Mean	SD	CV	Mean	SD	CV
1	264	117	0.443	262	115	0.440	294	116	0.396
2	343	137	0.399	338	134	0.396	367	136	0.372
3	381	168	0.441	375	163	0.436	401	166	0.413
4	431	174	0.403	422	170	0.403	446	172	0.385
5	489	214	0.437	477	207	0.434	500	211	0.423
6	528	215	0.408	513	208	0.406	534	211	0.395
7	588	245	0.417	570	238	0.417	592	242	0.408
8	610	247	0.405	589	240	0.407	609	244	0.401
9	751	321	0.428	722	309	0.429	742	313	0.422
10	903	506	0.560	866	496	0.573	884	500	0.566

	Income Targeting			HE Targeting			Social Security		
Income Deciles	Mean	SD	CV	Mean	SD	CV	Mean	SD	CV
1	339	121	0.358	295	117	0.396	317	131	0.413
2	407	142	0.349	368	137	0.371	395	143	0.361
3	438	171	0.390	402	165	0.412	428	165	0.386
4	480	176	0.366	447	171	0.383	456	176	0.385
5	477	207	0.434	502	212	0.422	513	210	0.409
6	513	208	0.406	535	211	0.394	547	210	0.383
7	570	238	0.417	593	242	0.408	593	240	0.404
8	589	240	0.407	609	244	0.400	613	247	0.403
9	722	309	0.429	742	313	0.421	739	311	0.421
10	866	496	0.573	884	500	0.566	881	500	0.568

	Income Tax		
Income Deciles	Mean	SD	CV
1	263	117	0.443
2	342	138	0.404
3	383	170	0.445
4	434	176	0.405
5	494	218	0.441
6	536	220	0.411
7	602	254	0.423
8	629	259	0.412
9	785	340	0.433
10	956	523	0.547

Figures

Figure 15: Engel Curves

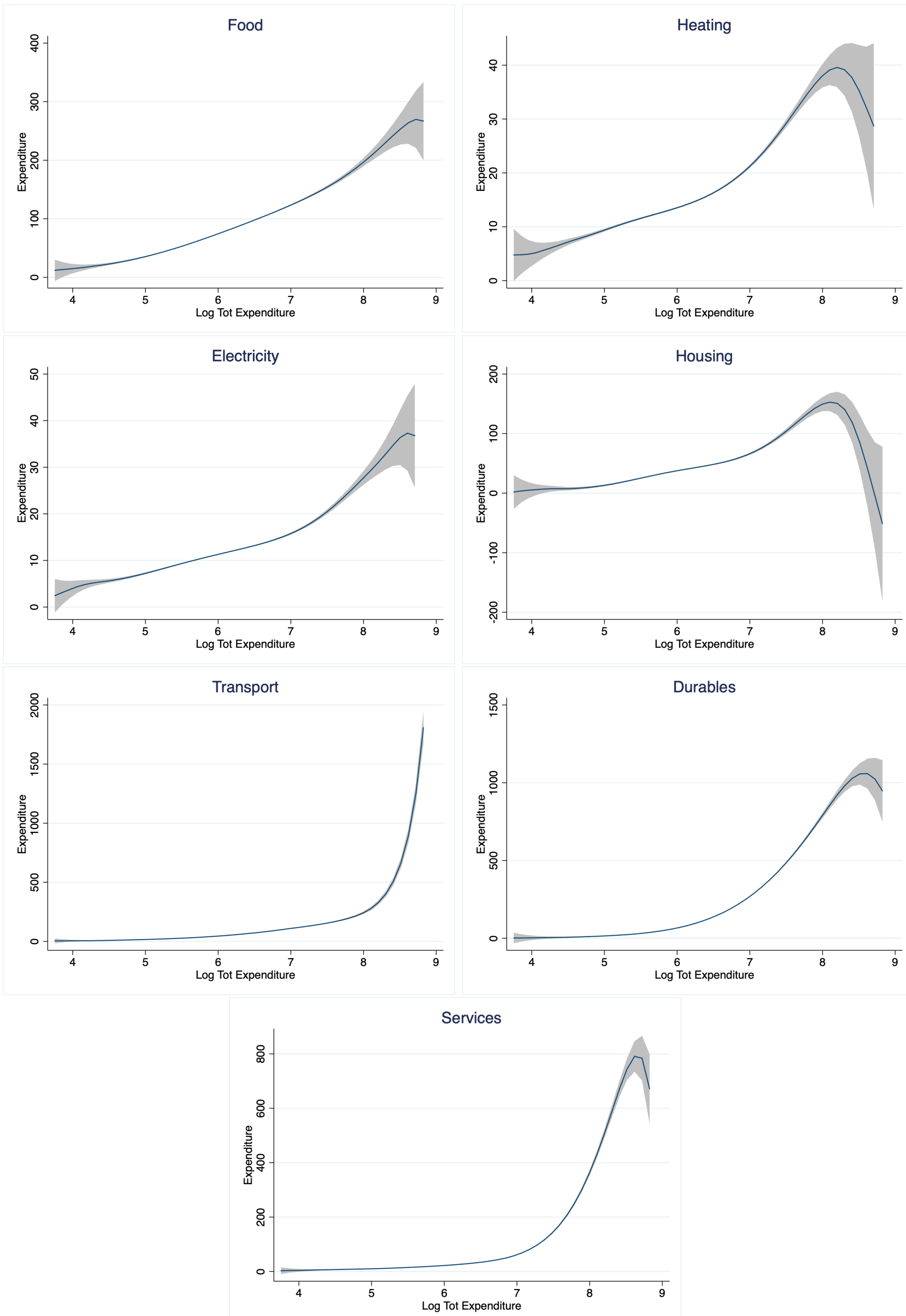
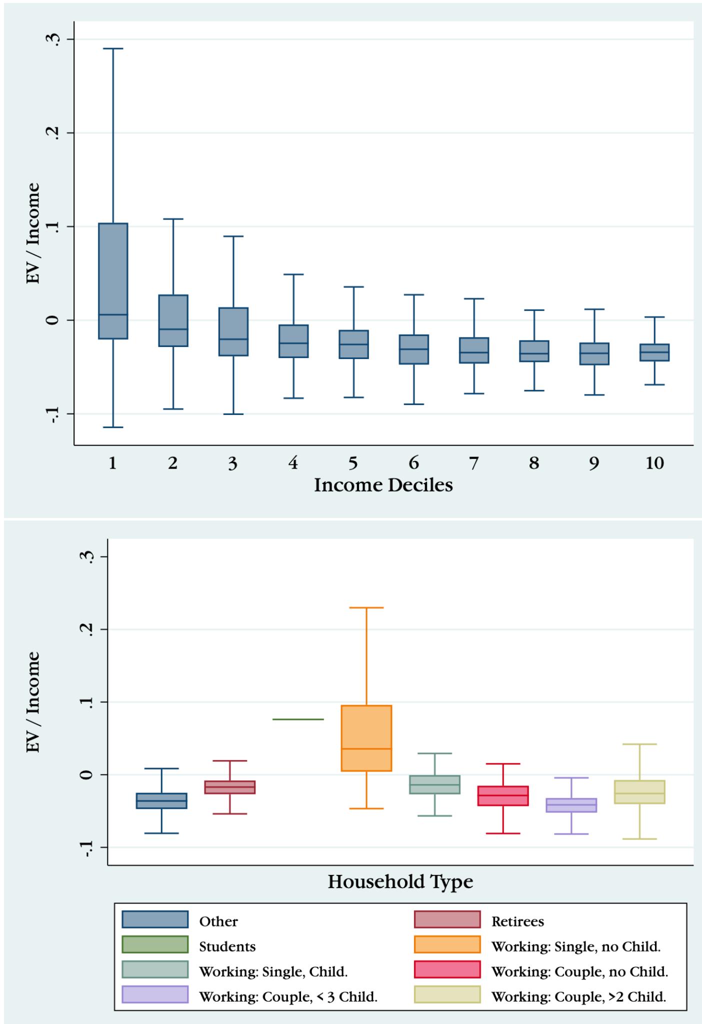


Figure 16: Recycling: Equivalent Variation, Per Capita Transfers, Targeting Regions and Rural Households



Notes: Box plot showing EV income shares by income decile (top) and household type (bottom). We show 25th, 50th and 75th quantiles.

Appendix

8.1 EASI Demand System

8.1.1 Model

Empirical work with consumer expenditure data typically finds Engel curves that are different and nonlinear across goods (Blundell, Chen and Kristensen, 2007). Moreover, observables - prices, expenditure and household demographics - explain no more than half the variation in budget shares, with the remaining attributed to measurement error and unobserved heterogeneity in preferences across consumers (Pendakur, 2009). This may yield biased elasticity estimates; if, for example, an individual exhibits stronger unobserved preferences for food consumption, she will allocate a higher budget share to food - which will be captured by error terms - and will therefore be subject to a higher income effect with prices changes. These ideas are developed by Lewbel (2001), among others. The Almost Ideal Demand System (AIDS) model by Deaton and Muellbauer (1980), while a popular and straightforward model of consumer demand, does not incorporate unobserved heterogeneity and imposes linear Engel curves for all goods. In contrast, the implicit Marshallian demand system expresses budget shares as *implicit* functions of observable prices, expenditures and demographic characteristics; it can accommodate arbitrary variation in observable demographic characteristics, complex Engel curves and additive unobserved preference heterogeneity. The reader is referred to a straightforward exposition of the implicit Marshallian demand system parametric model in Pendakur (2009), whose ideas we briefly outline here for the sake of clarity.

Let $\boldsymbol{\omega}(\boldsymbol{p}, u) = [\omega^1(\boldsymbol{p}, u), ..., \omega^J(\boldsymbol{p}, u)]$ be Hicksian budget-share functions which depend on prices and utility. As utility is obviously unobservable, we exploit properties of consumer demand to obtain functions that we can recover from observables. Let $\omega^j = m^j(u)$ for $j = 1...J$ specify budget-share functions for each commodity group, unrelated across goods and which depend only on utility. By exploiting Sheppard's Lemma, we have:

$$\omega^j(\boldsymbol{p}, u) = \frac{\partial \ln C(\boldsymbol{p}, u)}{\partial \ln p^j} \tag{25}$$

which, given our function for the budget share, implies a cost function of the form:

$$\ln C(\boldsymbol{p}, u) = u + \sum_{j=1}^{J} m^j(u) \ln p^j \tag{26}$$

If we observe budget shares w^j in the data, which we do, we can replace $w^j = \omega^j = m^j(u)$ and total expenditure c for $C(\boldsymbol{p}, u)$ and derive utility entirely from observable budget shares, prices and total expenditures.

$$\ln v = u = \ln c - \sum_{j=1}^{J} w^j \ln p^j \tag{27}$$

Here, $\ln c$ is a form of implicit utility, in line with the notation used in this paper. If the price vector is $\mathbf{1_j}$, and thus the log-price vector $\mathbf{0_j}$, we have $\ln v = \ln c$; v is then a log-money-metric representation of utility for a unit price vector, and hence a form of log real expenditures. The Stone index (Stone 1954), $\sum_{j=1}^{J}(p^j)^{w_j}$, is the deflator which converts nominal expenditures c into real expenditures v. Replacing 27 in our implicit budget shares allows for very general budget shares in terms of observables.

$$\omega^j = m^j(\ln c - \sum_{j=1}^{J} w^j \ln p^j) \tag{28}$$

As suggested by Lewbel and Pendakur (2009), we can estimate these implicit functions with instrumental variables - essentially any function of exogenous $\ln c$ and $\ln \boldsymbol{p}$. To add unobserved heterogeneity, prices and observable demographic characteristics - as is done in our specification - let $\boldsymbol{z} = [z^1, ..., z^T]$ be a vector of demographic characteristics, and let the first element be a constant such that $\bar{\boldsymbol{z}} = [1, 0, ..., 0]$ is the value of $\boldsymbol{z}$ for a reference consumer. We then specify the Exact Affine Stone Index (EASI) cost function, of the form:

$$\ln C(\boldsymbol{p}, u, \boldsymbol{z}, \boldsymbol{e}) = u + \sum_{j=1}^{J} m^j(u, \boldsymbol{z}) \ln p^j + \frac{1}{2}\sum_{j=1}^{J}\sum_{k=1}^{J} a^{jk} \ln p^j \ln p^k + \sum_{j=1}^{J} e^j \ln p^j \tag{29}$$

By Sheppard's Lemma, the Hicksian budget share is then:

$$\omega^j(\boldsymbol{p}, u, \boldsymbol{z}, \boldsymbol{e}) = m^j(y, \boldsymbol{z}) + \sum_{k=1}^{J} a^{jk} \ln p^k + e^j \tag{30}$$

and implicit utility is:

$$\ln v = u = \ln c - \sum_{j=1}^{J} w^j \ln p^j + \frac{1}{2}\sum_{j=1}^{J}\sum_{k=1}^{J} a^{jk} \ln p^j \ln p^k \tag{31}$$

The log of the deflator that exactly converts nominal expenditures c into real expenditures $\ln v$ is $\sum_{j=1}^{J} w^j \ln p^j + \frac{1}{2}\sum_{j=1}^{J}\sum_{k=1}^{J} a^{jk} \ln p^j \ln p^k$, which is affine in the Stone Index $\sum_{j=1}^{J} w^j \ln p^j$. Finally, the implicit Marshallian budget shares are:

$$w^j = m^j(\ln v, \boldsymbol{z}) + \sum_{k=1}^{J} a^{jk} \ln p^k + e^j \tag{32}$$

where $a^{jk} = a^{kj}$ for all j, k (by Slutsky symmetry). Since the function $m^j(\ln v, \boldsymbol{z})$ is unrestricted, Engel curves differ in shapes and degree of variety across goods. In our estimation, we use the specification:

$$m^j(\ln v, \boldsymbol{z}) = \sum_{r=0}^{R} b_r^j (\ln v)^r + \sum_{j=2}^{T} d_t^j z_t(\ln v) \tag{33}$$

with J = 7, R = 4 and T = 8, meaning that we have 7 product categories, 8 household types and we allow for a polynomial of degree 4. Note that the effect of d_1^j is captured by b_0^j. This yields a system of equations of endogenous, nonlinear budget shares:

$$w^j = \sum_{r=0}^{R} b_r^j (\ln v)^r + \sum_{j=2}^{T} d_t^j z_t(\ln v) + \sum_{k=1}^{J} a^{jk} \ln p^k + e^j \tag{34}$$

where

$$\ln v = \ln c - \sum_{j=1}^{J} w^j \ln p^j + \frac{1}{2}\sum_{j=1}^{J}\sum_{k=1}^{J} a^{jk} \ln p^j \ln p^k \tag{35}$$

and with the following restrictions:

$$\begin{aligned}
a^{ij} &= a^{ji} && i,j = 1...I \\
\sum_{k=1}^{I} a^{kj} = \sum_{h=1}^{I} a_{ih} &= 0 && i,j = 1...I \\
\sum_{i=1}^{I} b_r^i &= 0 && r = 1,...,R \\
\sum_{i=1}^{I} b_r^i &= 1 && r = 0 \\
\sum_{i=1}^{I} d^{il} &= 0 && i,j = 1...I
\end{aligned}$$

The parameters b_r^j determine the shape of the Engel curve, d_t^j allow for demographic shifters in budget shares, the a_{jk} determine price effects, and the error terms reflect unobserved preference heterogeneity. We allow for 8 types of households, as captured in the vector of demographic characteristics: students, retirees, single working households with no children, single working households with children, working couples with no children, working couples with up to two children, working couples with more than two children and others. We also control for household characteristics that may determine budget shares, including dummies for whether the dwelling is rented and a flat, the number of rooms in the dwelling as a proxy for dwelling size, and region, month and year fixed effects.

Introducing the constraints into the system, the final system of equations in based on:

$$w^j = \sum_{r=0}^{R} b_r^j (\ln v)^r + \sum_{j=2}^{T} d_t^j z_t (\ln v) + \sum_{k=1}^{J-1} a^{jk} \ln(p^k/p^J) + e^j \tag{36}$$

8.1.2 Elasticities

If we differentiate (36) with respect to the logarithm of real expenditure, v, we derive real expenditure semi-elasticities, which we can then convert into quantity income elasticities:

$$\mu_i = \frac{\partial w^j(\boldsymbol{p}, u, \boldsymbol{z}, \boldsymbol{e})}{\partial \ln v} = \sum_{r=1}^{R} b_j^r r v^{r-1} + \sum_{t=2}^{T} d_t^j z_t \tag{37}$$

$$e_i = \frac{\partial q^i}{\partial v^i}\frac{v^i}{q^i} = 1 + \frac{\mu_i}{w_i} \tag{38}$$

Hicksian (compensated) price elasticities are given by:

$$\frac{\partial w^j(\boldsymbol{p}, u, \boldsymbol{z}, \boldsymbol{e})}{\partial \ln p^k} = a^{jk} \tag{39}$$

$$\epsilon_{ij}^H = \frac{a^{ij}}{w^j} - 1(i == j) \tag{40}$$

Marshallian (uncompensated) price elasticities are given by:

$$\epsilon_{ii}^M = \epsilon_{ii}^H - e_i w_i \tag{41}$$

$$\epsilon_{ij}^M = \epsilon_{ij}^H - e_i w_j \tag{42}$$

8.1.3 Estimation

Like Douenne (2020), we match national, monthly consumer price index data to each household according to the survey year and month. Given than we use 11 years of survey data, we have 132 prices for each good. Following Douenne (2020) and Lewbel (1989), we compute Stone-Lewebel price indices that exploit households' consumption mix to derive personalized prices, specifically for heating and transport. For a bundle i consumed by household h, the price index is:

$$\ln p_{ih} = \sum_{l=1}^{L_i} \frac{w_{lh}}{w_{ih}} \ln p_{lh} \tag{43}$$

where w_{lh} is the consumption share of good l belonging to the bundle i for household h, w_{ih} is the consumption share of good i in the total consumption of the household, and p_{lh}, p_{ih} are their respective price indices. This method introduces heterogeneity by relying on difference in preferences within each bundle.

Equation (23) is estimated by iterated linear methods. After specifying initial values for a^{jk}, we compute an initial value of implicit utility, denoted by v_0, given observed budget shares and prices. We then estimate (23) using initial value v_0. Given new estimated values for a_n^{jk}, we then estimate v_n and iterate in this way until convergence, i.e. until the changes in computed implicit utility are very small. We retain the final estimates of b_r^j, g_t^j, and a^{jk} at convergence. For a more detailed account of this approach, see Pendakur (2009).

Since the linear model $w(c, v(\boldsymbol{w}, \boldsymbol{p}), \boldsymbol{p}, \boldsymbol{z})$ estimated in each linear iteration is endogenous, we can instrument the v polynomial by any function of the exogenous variables $\ln c, z_t, \ln p^j$. These variables are exogenous, and therefore uncorrelated with the error term in (36), but are obviously correlated with v, as we know its functional form. While any function would work, we use the following instrument:

$$\ln v = \ln c - \sum_{j=1}^{J} \bar{w}^j \ln p^j + \frac{1}{2} \sum_{j=1}^{J} \sum_{k=1}^{J} \bar{a}^{jk} \ln p^j \ln p^k \tag{44}$$

Where $\bar{w}$ are sample average budget shares and $\bar{a}^{jk}$ are estimated from an initial estimator. The exogeneity and relevance conditions required by instrumental variable methods are satisfied, and thus allows us to identify our endogenous model.

Finally, we implement this iterative procedure via three stage least squares (3SLS) linear endogenous system estimation, imposing Slutsky symmetry through the constraint that $a^{jk} = a^{kj}$ for all j, k. We estimate the system of J-1 equations and construct the estimates for the jth equation by summing over the estimated parameters.