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The welfare impacts of carbon taxes and labels on food demand

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ABSTRACT

Food production and consumption account for a third of global greenhouse gas emissions (Crippa et al., 2021) and, therefore, offer a large mitigation potential. Policies such as carbon taxation and carbon labelling can contribute to correcting such externalities by encouraging consumers to substitute away from carbon intensive food products. We employ data from a survey-based, randomized experiment simulating an online supermarket, administered to a representative sample of the UK population. Using a structural demand system based on the Exact Affine Stone Index model with censoring, we estimate the greenhouse gas emission reductions and welfare effects associated with a range of demand-side policy scenarios, combining carbon labelling and carbon taxation. Our results show that the application of carbon labels leads to a 5.6% decrease in the carbon content of the average food basket. A £60 tax per tonne of CO_2e on the most carbon intensive products would yield a 9.9% reduction in the carbon footprint, while also decreasing consumer welfare by £79 per person per year. Respectively, these policies would yield a decrease in emissions corresponding to about 2.7% and 4.7% of the GHG emissions of the UK. Combining carbon taxation and carbon labelling allows to reach the same CO_2e emissions reduction as the carbon tax, with only a £28 tax rate per tonne of CO_2e, thereby reducing welfare losses to £34 per person per year. These findings imply that carbon taxation and carbon labelling can be combined in order to abate greenhouse gas emissions, while limiting the negative impacts on welfare.

1. Introduction

From production to consumption, the food sector accounts for approximately one third of global emissions of greenhouse gases (GHGs) (Crippa et al., 2021). Accordingly, a shift in dietary choices towards products with smaller GHG footprints offers a large emission mitigation potential (IPCC, 2022; Poore and Nemecek, 2018; Springmann et al., 2018). In order to support these changes in

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behaviour, policy makers have an array of demand-side policy instruments available, ranging from 'harder' (e.g., taxation) to 'softer' (e.g., information provision) measures.[1] Different policies come with different trade-offs: hard policies are generally more effective, but less likely to garner public support, often due to welfare losses (Carattini et al., 2018; Douenne and Fabre, 2022; Timilsina, 2022), while soft policies are generally more palatable, but typically produce smaller-scale impacts (Fesenfeld et al., 2020; Pechey et al., 2022; Pizzo et al., 2026; Taufique et al., 2022). For this reason, a combination of different approaches can be synergetic in overcoming the limitations of each single measure (Fesenfeld et al., 2020). Nevertheless, existing evidence in this regard remains scant. In this paper, we explore the effectiveness, efficiency and distributional impacts of two food demand policies, both as standalone measures and combined, aimed at reducing the carbon footprint of supermarket food purchases: a hard policy (carbon taxation) and a soft one (carbon labelling).

Taxation is, in principle, a theoretically sound policy to internalize the costs associated with excessive GHG emissions (Baranzini et al., 2017). The evidence from the introduction of taxes on fossil fuels suggests that it has been successful also in practice (see Köppl and Schratzenstaller, 2023, for a review). However, no carbon tax has specifically addressed the food sector so far, as the majority of agricultural emissions do not derive from the combustion of fossil fuels (Crippa et al., 2021).[2] Simulations based on demand price elasticities estimate that carbon taxes on food can be highly effective. For example, Kehlbacher et al. (2016) find that a tax rate of £28.41 per tonne of CO_2e applied to all food products with emissions above the average would decrease UK food emissions by 4.3%. However, since lower-income households spend a larger proportion of their income on food (Pineda et al., 2024), one of the main drawbacks of a food carbon tax is its regressivity (Timilsina, 2022; Douenne and Fabre, 2022). For example, Säll (2018) and Schaper et al. (2025) find that the welfare impact of a carbon tax would be more than twice as high for the bottom income quintile, in comparison with the top one. A further issue is that acceptability decreases with the tax rate (Carattini et al., 2018).

On the other hand, providing information about the GHG footprint of food products through front-of-package labels is less controversial (Edenbrandt and Nordström, 2023; Pechey et al., 2022). Consumers typically underestimate their food carbon footprint (Camilleri et al., 2019; Johnson et al., 2024) and, therefore, labelling can represent a low-cost intervention that enables consumers to make more informed decisions (Edenbrandt and Nordström, 2023; Messer et al., 2017). Since there is no real-world example of mandatory public interventions of this type, the available evidence comes from experimental settings, such as choice experiments on a limited number of products (e.g., Edenbrandt and Lagerkvist, 2021; Lanz et al., 2018; Rondoni and Grasso, 2021), and field experiments in specific settings such as university canteens (Brunner et al., 2018; Jalil et al., 2023; Lohmann et al., 2022) and laboratory supermarkets (Muller et al., 2019). These studies show that labelling can significantly reduce the GHG footprint of food purchases with different degrees of effectiveness across sociodemographic groups and settings (Rondoni and Grasso, 2021). Taken together, the current evidence suggests that carbon labelling alone is unlikely to have a sufficiently large impact on emissions (Taufique et al., 2022).

Only few studies in the literature investigate the joint effect of price interventions and information provision in addressing the externalities of food consumption. Most of these works focus on food nutritional content. For instance, both Lacanilao et al. (2011) and Streletskaya et al. (2014) report that the effect of a tax on unhealthy food is stronger when combined with pertinent information. On the other hand, Crosetto et al. (2025) find that nutritional labels outperform both health-focused taxes and subsidies, and that the combination of these policy instruments is sub-additive. Regarding carbon footprint reduction, there is currently scant evidence on the synergistic effects of combining economic incentives with information. Panzone et al. (2021), in an incentivized supermarket experiment with university students, finds no interactive effects of simulated carbon taxes and behavioural nudges. Pizzo et al. (2026), in a field experiment on purchase decisions in a festival food court, report that providing GHG information neither produces significant impacts on its own nor influences the effectiveness of price discounts on vegetarian dishes. Hartmann et al. (2023), in an online experiment with a limited number of products, do not find any impact for carbon labelling but provide evidence that a salient carbon tax may trigger moral licensing, thus reducing its effectiveness.

Against this background, our work examines how the joint implementation of both carbon taxation and carbon labelling affects food demand, carbon emissions and consumers' welfare. We show that a combination of policies can be helpful to maximize effectiveness, while minimizing welfare losses. We analyse a large dataset containing the food-purchase choices collected in a simulated online supermarket from more than 5000 respondents in the UK. The supermarket included a wide range of the most common food and drink products, representing more than 80% of the take-home expenditure of food and beverages. Our paper contributes to the literature in different ways. First, we investigate consumer behaviour across their entire food basket. Our online survey mirrors the familiar setting that households find when grocery shopping and it offers an extensive product assortment. By capturing decisions within this realistic framework, respondents' choices reflect the purchase patterns of the general population rather than context-specific behaviours. Second, by estimating a structural demand system, we move beyond the mere observation of behavioural substitution patterns to the quantification of welfare impacts. Assessing changes in consumer surplus is fundamental to understand the broader socioeconomic implications of a given intervention. Furthermore, our model accounts for heterogeneity by analysing how effects vary across sociodemographic cohorts, with particular emphasis on disparities related to income levels and dietary habits.

[1] For example, Lohmann et al. (2026) distinguish in their meta-analysis between six types of demand-side interventions on food consumption: in addition to incentives (e.g., a tax) and labelling, they consider educational information (e.g., lectures or informational campaigns), and three types of behavioural approaches (i.e. targeted information, such as framing and priming; aid to decision making, such as reminders; and manipulation of the choice environments, such as defaults). In their study, Fesenfeld et al. (2020) consider more broadly the following policy instruments: taxation, regulation, information campaigns, discounts on vegetarian alternatives, producer subsidies and standards. Many of the instruments mentioned above have also been discussed in the context of public health (e.g., sin taxes: Jensen and Smed, 2018; nutritional labels: Barahona et al., 2023).

[2] Denmark is set to become the first country in the world to tax agricultural emissions, starting in 2030 (World Bank, 2025).

Ultimately, our analysis reveals the significant impact that combining two specific climate interventions could have on the everyday lives of millions of UK households.

Our empirical model is underpinned by a structural demand system, based on the Exact Affine Stone Index (EASI) approach (Lewbel and Pendakur, 2009). This method allows us to estimate food substitution patterns and to evaluate the policy impacts on consumer welfare. The EASI model improves upon the popular Almost Ideal Demand System (Deaton and Muellbauer, 1980) by allowing non-linear Engel curves, thus yielding a better representation of the food choices of households with expenditures away from the sample average. In addition, since dietary choices vary significantly across households and often result in corner solutions, we empirically specify our model as a multivariate Tobit, in order to avoid censoring bias. Our econometric approach illustrates how information and labelling can be incorporated within a structural demand system, therefore contributing to a scarce literature in this area (e.g., Capacci and Mazzocchi, 2011; Panzone et al., 2021; Teisl et al., 2002).

Our results show that labelling leads to a significant reduction in the CO_2e content of the food basket of the average household (−5.6% with respect to the baseline without any intervention). However, this change is not as large in magnitude as the reduction achieved by applying a realistic tax rate (Department of Energy and Climate Change, 2009) of £60 per tonne of CO_2e (−9.9%), which comes at the cost of a sizeable welfare loss (£78.7 per person per year). These results correspond respectively to 2.7% and 4.7% of the GHG emissions of the entire UK for the year 2024. A combination of taxes and labels can achieve the same emission reduction as a carbon tax alone at a much lower taxation rate (£27.86), leading to significant net welfare benefits. In fact, considering the avoided carbon emissions (priced at £60 per tonne), the tax revenues for the public sector and the welfare losses for consumers resulting from higher prices, we estimate that combining carbon taxes and labels can lead to net welfare gains of £13.2 per person per year, corresponding to more than two times those achieved by the carbon tax alone (£6.3 per person per year). Considering heterogeneity across respondents, we find that the influence of carbon labelling varies by income: specifically, high-income households demonstrate a stronger response relative to low-income households. We also find that households with a diet rich in meat tend to be very responsive to the display of carbon labels, suggesting that information provision can induce pro-environmental choices also in sociodemographic groups with larger carbon footprints. The carbon tax is the most effective measure in reducing emissions across income levels and dietary profiles, although it produces sizeable losses in consumer welfare that are regressive with income. Nonetheless, these regressive impacts of taxes can be counteracted by a lump-sum redistribution of the tax revenues back to households.

The rest of this article is structured as follows. Section 2 presents the survey and data. Section 3 illustrates the methodological framework, including the theoretical model, the empirical specification and the estimation method. Section 4 presents our demand-system estimates. Section 5 employs the results of the previous sections in order to investigate the impacts of different policy scenarios. Section 6 summarizes our robustness tests. Section 7 concludes.

2. Data

Our dataset was collected as part of a broader project investigating the effects of taxation and information provision on health and environmental impacts of dietary choices (Faccioli et al., 2022). The survey was administered online during autumn 2020 by Accent, a UK market-research company, to a sample of the UK population, representative in terms of dietary profile, age, gender, geographical region of residence and socio-economic status. Study participants were individuals who regularly carried out the food shopping for their household. Survey respondents were asked to report information on the quantity and frequency of purchase of a range of food products under normal circumstances and after the introduction of different policy interventions.

2.1. Survey details

In order to provide a realistic setting and thus reduce the scope for hypothetical bias (Haghani et al., 2021), the survey presented a simulated online supermarket, with a large and comprehensive list of food and beverage items. The supermarket included 72 food items which accounted, according to the Kantar FMCG panel,[3] for 81.1% of the grocery expenditure in Great Britain. For each food item in the experimental supermarket, we displayed a short description of the product, an illustrative image and the price (an example can be found in Appendix Figure B1).

In the first scenario, which we refer to as the "baseline", respondents were asked to indicate the quantity (in units of product) and frequency of purchase (every week, every two weeks, or every month) of each product, according to their regular food-shopping habits.[4] The prices for the different items displayed in this scenario were individual specific and randomly drawn from the distribution of average prices in the Kantar FMCG database, after omitting extreme values. By following this approach, respondents experienced prices that were similar to those found in real supermarkets, but uncorrelated with the unobserved characteristics of the specific food items bought by each individual and, therefore, exogenous.

Next, participants were asked to repeat the food shopping exercise by considering whether and how their responses would change

[3] Kantar FMCG is a database containing real-world scanner data of supermarket food purchases, which is often used in the analysis of food demand (e.g., Caillavet et al., 2019).

[4] The baseline scenario is necessary in order to collect information on respondents' dietary habits, allowing us to categorize them into different groups and thereby explore heterogeneous effects. Furthermore, eliciting baseline preferences prior to the scenarios is recommended to help respondents acclimate to the choice task, which minimizes hypothetical bias (Schläpfer and Fischhoff, 2012). A potential drawback is the possibility of anchoring potentially leading to the underestimation of the treatment effects.

after the introduction of different food-demand policies. Such policies were introduced in the online supermarket experiment through different treatments, that respondents were randomly assigned to. In this paper, we focus on those treatments that introduced either a tax, carbon information, or both simultaneously. We refer to them as “unlabelled tax”, “carbon information”, and “carbon information and tax”.

In the carbon information scenario, respondents were shown the carbon content of each food product using a colour-coded graphical indicator (label) and asked if and how they would change their purchase patterns with respect to the baseline. In the unlabelled tax scenario, respondents experienced a price increase on selected products following the implementation of a generic, unspecified tax. Finally, in the carbon information and tax scenario, participants were shown the carbon content for each food and experienced the implementation of a tax on those food products with an above-average carbon content (i.e., red meat, cheese, and fish). To simulate such tax, baseline prices for those products were increased proportionally to their carbon content by considering three different tax rates (£30, £60, or £90 per tonne of CO_2e per kg of product), which were randomly assigned to respondents.

In order to ensure data quality, we removed observations that were incomplete or contained implausible values, likely resulting from data-entry errors. Specifically, starting from an original sample of 5910 respondents, we excluded those who.

1. Spent more than 90% of their total food expenditure on a single food item (4 respondents);
2. Reported extreme per capita weekly purchase levels for one given item (above the 99.9th percentile of the distribution of answers in the sample) (214 respondents);
3. Experienced a change (either an increase or a decrease) by more than 90% in their food basket expenditure when moving from the baseline to a policy scenario (25 respondents);
4. Had incomplete demographic characteristics (80 respondents).

After cleaning the data, our dataset contained a total of 5587 respondents.

2.2. Food items aggregation

To set up the data for the analysis, following the food demand literature (e.g., Zhen et al., 2014), we aggregated food items into 13 categories, by assuming weak separability between categories which justifies multistage budgeting (Edgerton, 1997). The categories, similar to those considered by other UK-based studies (Kehlbacher et al., 2016; Tiffin et al., 2011), are the following, in decreasing order of carbon intensity per kg of product): 1) beef and lamb; 2) cheese; 3) fish and seafood; 4) pork; 5); other food (the residual category); 6) poultry; 7) eggs; 8) snacks; 9) milk and yoghurt; 10) breakfast cereals; 11) bread, pasta, rice and flour; 12) fruits and vegetables; and 13) beverages. The residual category includes items not frequently purchased and not attributable to other categories. These are plant-based alternatives for milk and meat, and ready meals, both with and without meat or fish. The exact composition of each category can be found in the Appendix (Table A1).

We calculate the aggregate share of expenditure w_{ihs} of food category i, for household h in scenario s as the sum of expenditure shares $w_{\imath hs}$ for each of food items $\imath$ belonging to that category:

$$w_{ihs} = \sum_{\imath} w_{\imath hs} \,. \tag{1}$$

Furthermore, we represent the price for each category as the price index p_{ihs}, defined as the weighted average of the individual prices ($p^{*}_{\imath hs}$) of each food item within the category, where the weights are determined by the average quantities of item $q_{\imath hs}$ reported across all households and all scenarios:

$$p_{ihs} = \frac{\sum_{\imath}\left(\sum_{h}\sum_{s} q_{\imath hs}\right) p^{*}_{\imath hs}}{\sum_{\imath}\sum_{h}\sum_{s} q_{\imath hs}} \tag{2}$$

Similarly, we compute the CO_2e footprint for each food category as the weighted average of the CO_2e footprints of the items contained in the category, where the weights are proportional to the quantity of each item that respondents reported to purchase in the supermarket experiment across all scenarios.[5] The carbon footprint for each food item corresponds to the median value reported in the life cycle assessment database by Poore and Nemecek (2018).

2.3. Descriptive statistics

Our sample is composed by 5587 respondents and 11,173 observations which include 5587 observations for the baseline scenario, 1869 for the carbon information scenario, 1869 for the carbon information and tax scenario, and 1848 for the unlabelled tax scenario.

[5] In Appendix Figure B2, we show that the carbon intensity of each category does not vary substantially from the average across each scenario and therefore we use this figure in our simulation exercises.

Table 1
Descriptive statistics.

Variable	min	mean	median	max	std. dev.
	(1)	(2)	(3)	(4)	(5)
Gender (Male = 1)	0	0.43	0.00	1.00	0.50
Age (years)	18	46.64	47.00	99.00	17.45
Household size (n. of individuals)	1	2.53	2.00	10.00	1.28
Nr. of children	0	0.52	0.00	7.00	0.90
Income (£'000)	10	34.73	30.00	110.00	22.44
Education (years of schooling)	6	13.63	13.00	19.00	2.84

Notes: sample size is 5,587 individuals. See Appendix Table A2 for the descriptive statistics relative to region of residence, ethnic group and employment, not reported here for brevity.

Table 1 reports the descriptive statistics for the main socio-demographic characteristics of our sample, which we compared with the corresponding statistics for the UK population.[6] Additional summary statistics about the region of residence, the employment and the ethnicity are reported in Table A2 in the Appendix. In our dataset, 57% of respondents are female (slightly above the share of women in the UK adult population, equal to 51%; Office for National Statistics, 2021a) and the mean reported age is 47 (compared to 49 years old for the UK population; ONS, 2021a). The average household size in our sample is 2.5 (2.4 is the official average figure in the UK; ONS, 2024a), with values ranging from 1 to 10 family members. The average number of children per household is 0.52 (which is in line with the official statistics figure for the UK, i.e., 0.51; ONS, 2024b). On average, respondents have 13.6 years of schooling (compared with 13.2 years for the UK; United Nations Development Programme, 2020) and indicated a median income of £30,000 per household per year, which is close to the UK figure for the median household disposable income (£30,500; ONS, 2021b).

Table 2 (Panel A) contains descriptive statistics about the weekly reported purchases of food products based on the survey results. Food categories are displayed in decreasing order of carbon footprint, with the amount of carbon emissions per kg of product (carbon intensity) reported in the first column of Table 2. The most carbon intensive category is beef and lamb (56.45 kg of CO_2e per kg of product) and the least one is beverages (0.81 kg of CO_2e per litre of product). The second column reports the share of the food expenditure spent on each category, based on the responses provided in the baseline scenario of the survey. According to our data, the largest shares of food expenditure are on fruits and vegetables (18.1%), beverages (17%), and beef and lamb (10.9%). The third column reports average prices per kg or litre in the baseline: the highest prices are for fish and seafood products (£10.44 per kg), followed by beef and lamb (£8.67 per kg) and cheese (£6.05 per kg). The fourth column reports the share of respondents who did not report any purchased amount across the different food categories. These figures suggest significant heterogeneity in dietary choices. Notably, the categories with the highest rates of reported zero-purchase are animal and fish meats: fish and seafood have the largest share (28.2% in the baseline), followed by pork (19.8%) and beef and lamb (19.0%). The fifth column in Table 2 shows the average purchased quantity of the products in each category in the baseline. The largest reported quantities are of fruit and vegetable (3.5 kg per person per week) and beverages (2.5 l per person per week). The remaining columns indicate the percentage variation in the average reported quantity of food purchases between the baseline and the policy scenarios in the survey. We provide here an overview of the average variation between survey scenarios, while a full descriptive analysis of the experimental results is presented in Faccioli et al. (2022). The food categories in which quantities varied the most are, unsurprisingly, the categories with the largest carbon content, i.e., beef and lamb (respectively, between −19% and −35%), cheese (−6% and −14%), and fish and seafood (−2% and −7%). In the last row of the table (Panel B) we report the average weekly food-expenditure per person, which corresponds to £33.76 in the baseline, slightly decreases in the carbon information and carbon information and tax scenarios (respectively, −3.5% and −2.2%) and increases in the unlabelled tax scenario (+2%).

While our survey simulates in every aspect the environment where households make their supermarket food purchase choices, hence minimizing the cognitive effort and the risk of preferences' misrepresentation (Haghani et al., 2021), the non-incentivized nature of our analysis may raise the question whether respondents answered accurately or rather randomly (Vossler et al., 2012). Thus, to check the external validity of our data, we compared our baseline estimates against the official statistics on food purchase in the UK. We found that, for each food category in our survey, the average reported food quantity, weekly expenditure and carbon footprint align very closely with those reported by the Office for National Statistics and other scientific sources (more details can be found in Appendix C). Furthermore, as shown in the next section, our elasticity estimates are in line with those obtained using real-purchase data. These results provide evidence against response-randomness, showing participants' engagement with the survey and supporting the external validity of our findings.

[6] The interested reader can find a further discussion in the Supplementary Materials of Faccioli et al. (2022), which shows that the sample can be considered representative of the UK population.

Table 2
Descriptive statistics for food categories in the baseline and variation between survey scenarios.

Panel A								
		Baseline				Variation in quantity between policy scenario and baseline (%)		
Category	CO_2e intensity (1)	Budget share (%) (2)	Price (£/kg) (3)	Not bought (%) (4)	Quantity (kg) (5)	*Carbon information* (6)	*Carbon information and tax* (7)	*Unlabelled tax* (8)
Beef and lamb	56.45	10.86	8.67	18.95	0.472	−19.15%	−35.21%	−28.05%
Cheese	12.66	5.28	6.05	5.55	0.278	−6.11%	−12.26%	−13.52%
Fish/Seafood	11.09	4.65	10.44	28.24	0.156	−2.03%	−5.82%	−6.98%
Pork	10.60	6.48	6.00	19.80	0.379	0.58%	−7.33%	−11.24%
Other food	6.42	6.99	3.90	15.54	0.581	0.99%	−1.82%	−9.17%
Poultry	7.50	6.12	4.39	17.84	0.458	1.66%	3.50%	0.29%
Eggs	4.20	1.83	2.57	10.33	0.218	−0.67%	−1.32%	−1.25%
Snacks	2.79	10.86	5.53	4.60	0.642	−1.13%	−2.42%	−12.32%
Milk/yoghurt	2.70	5.25	0.93	4.80	1.750	−2.02%	−3.94%	−1.86%
Breakfast cereals	2.64	2.19	3.23	17.36	0.212	−1.69%	−2.02%	−1.06%
Bread/pasta/rice/flour	1.79	4.33	1.36	2.72	0.982	−0.78%	−1.21%	−0.82%
Fruits/vegetables	1.20	18.13	1.64	0.73	3.516	0.72%	0.80%	−0.60%
Beverages	0.81	17.03	2.48	3.06	2.542	−1.46%	−2.39%	−16.22%
Panel B								
Weekly total expenditure (£)					33.76	−3.53%	−2.18%	2.00%

Notes: statistics refer to the average weekly food purchases by households in our sample, per household member. *CO_2e intensity*, *Budget share*, *Price*, *Not bought*, and *Quantity* refer to the baseline scenario of the survey. *CO_2e intensity* reports the CO_2e content per kg of food category. *Budget share* reports the average budget share spent by respondents on each food category (as a percentage). *Not bought* indicates the percentage of observations that are equal to zero. *Price* reports the average price per kg or litre. *Quantity* reports the average quantity of food purchases in kg. Columns under *Variation with respect to baseline* report the difference (in kg) of the average quantity between each scenario and the baseline. *Weekly expenditure* reports the average expenditure in food based on quantities and prices in the survey, per household member, and its percentage variation in each scenario. Descriptive statistics for every single item are reported in Table A3.

3. Methods

In this section, we discuss our empirical approach: in Section 3.1 we present the derivation of the demand system; in Section 3.2 we describe the empirical specification and in Section 3.3 the estimation method. In Section 3.4 we describe how we derived the compensating variation, a measure of welfare change.[7]

3.1. Demand system specification

We model food demand under different price and information scenarios by specifying a structural demand system. We employ the EASI model (Lewbel and Pendakur, 2009), which improves upon the popular Almost Ideal Demand System (Deaton and Muellbauer, 1980) by allowing non-linear Engel curves. Following Lewbel and Pendakur (2009), we specify a log-cost function $logC(\cdot)$, which indicates the minimal level of expenditure needed for a household to attain a certain utility level from the weekly purchase of food, given a vector of prices for food categories $i = 1, \ldots, R$ and $g = 1, \ldots, G$ households' characteristics $h = 1, \ldots, H$. The log-cost function takes the following form:

$$logC(\boldsymbol{p}, u, \boldsymbol{z}, \epsilon) = u + \boldsymbol{p}'\left(\boldsymbol{\alpha} + \boldsymbol{\beta} u^k + \boldsymbol{\delta z} + \boldsymbol{\delta}_u \boldsymbol{z}_u u\right) + \frac{1}{2}\boldsymbol{p}'(\boldsymbol{\gamma} + \boldsymbol{\zeta} u)\boldsymbol{p} + \boldsymbol{p}'\boldsymbol{\epsilon}, \tag{3}$$

where u is the utility level attained by the household, $\boldsymbol{p}$ is the $R \times 1$ vector of the logarithm of prices for each commodity group, $\boldsymbol{z}$ is a $G \times 1$ vector of socio-demographic characteristics, $\boldsymbol{z}_u$ is a $F \times 1$ subvector of $\boldsymbol{z}$ with socio-demographic characteristics interacted with u, and $\boldsymbol{\epsilon}$ is a $R \times 1$ vector of unobserved characteristics determining unobserved heterogeneity in preferences (Lewbel and Pendakur, 2009).

Invoking the Shepard's Lemma, the derivative in the logarithm of prices of Equation (3) provides Hicksian budget shares $\boldsymbol{w}$ ($R \times 1$):

$$\boldsymbol{w} = \boldsymbol{\alpha} + \boldsymbol{\beta} u^k + \boldsymbol{\delta z} + \boldsymbol{\delta}_u \boldsymbol{z}_u u + \boldsymbol{\gamma p} + \boldsymbol{\zeta p} u + \boldsymbol{\epsilon}. \tag{4}$$

However, Equation (4) cannot be estimated, since it contains the unobserved utility level u. Instead, since we observe budget shares $\boldsymbol{w}$, we can use Equation (4) in Equation (3) in order to express u in terms of observables:

[7] The interested reader can find the derivation of expenditure and price elasticities in Appendix D.

$$logC(\boldsymbol{p}, u, \boldsymbol{z}, \epsilon) = u + \boldsymbol{p}'\boldsymbol{w} - \frac{1}{2}\boldsymbol{p}'(\boldsymbol{\gamma} + \boldsymbol{\zeta}u)\boldsymbol{p}, \tag{5}$$

$$u = \frac{x - \boldsymbol{p}'\boldsymbol{w} + \frac{1}{2}\boldsymbol{p}'\boldsymbol{\gamma}\boldsymbol{p}}{1 - \frac{1}{2}\boldsymbol{p}'\boldsymbol{\zeta}\boldsymbol{p}} = y, \tag{6}$$

where x are observed (log) expenditures that are equal to $logC(\cdot)$ by definition and y is defined as implicit utility: it depends only on observable data and can be seen as a money-metric measure of utility (Lewbel and Pendakur, 2009). The implicit utility y is a nonlinear function of the expenditures and the other observed variables which, following Lewbel and Pendakur (2009), can be approximated by:

$$\tilde{y} = \log x - \sum \overline{w}_i \log p_i, \tag{7}$$

where $\overline{w}_i$ is the average expenditure share for food category i in our sample. In practice, $\tilde{y}$ is the Stone price-deflated real expenditure in food. This approximation, also employed in other analyses (e.g., Zhen et al., 2014; McCullough et al., 2022), is necessary in our application because, for empirical estimation, we are specifying the demand function as a system of censored equations, and a non-linear representation of y would make the estimation excessively computationally difficult. By substituting u with $\tilde{y}$ in Equation (4) we obtain estimable budget shares as *implicit Marshallian demands*:

$$\boldsymbol{w} = \boldsymbol{\alpha} + \boldsymbol{\beta}\tilde{\boldsymbol{y}}^k + \boldsymbol{\delta}\boldsymbol{z} + \boldsymbol{\delta}_u\boldsymbol{z}_u\tilde{\boldsymbol{y}} + \boldsymbol{\gamma}\boldsymbol{p} + \boldsymbol{\zeta}\boldsymbol{p}\tilde{\boldsymbol{y}} + \boldsymbol{\epsilon}, \tag{8}$$

where $\boldsymbol{\alpha}$ $(R \times 1)$, $\boldsymbol{\beta}$ $(R \times K)$, $\boldsymbol{\delta}$ $(R \times G)$, $\boldsymbol{\delta_u}$ $(R \times F)$, $\boldsymbol{\gamma}$ $(R \times R)$, $\boldsymbol{\zeta}$ $(R \times R)$ are the parameters to be estimated. The values in $\boldsymbol{\alpha}$ represent the baseline quantity demanded for each food category; $\boldsymbol{\delta}$ indicates the effect of consumer's characteristics $\boldsymbol{z}$ on demand as linear shifters. We allow for a subset of such parameters, $\boldsymbol{\delta_u}$, to vary with expenditure $\tilde{y}$ in order to allow income effects to vary alongside socio-demographic characteristics. Parameters $\boldsymbol{\beta}$ measure how demand varies with expenditure and thus determine the shape of the Engel curves. Finally, parameters $\boldsymbol{\gamma}$ describe how prices affect demand, while $\boldsymbol{\zeta}$ allows their impact to change with expenditure. In order to ensure properties that are coherent with microeconomic theory, namely homogeneity of degree zero in prices and total expenditure, Slutsky symmetry condition, and adding up of total shares to 1, we impose the following standard restrictions on the parameters: $\mathbf{1}'\boldsymbol{\alpha} = 1$, and $\mathbf{1}'\boldsymbol{\beta} = \mathbf{1}'\,\boldsymbol{\delta} = \mathbf{1}'\boldsymbol{\delta_u} = \mathbf{1}'\boldsymbol{\gamma} = \mathbf{1}'\boldsymbol{\zeta} = 0$. In addition, $\boldsymbol{\gamma}$ and $\boldsymbol{\zeta}$ are symmetric matrices, such that: $\gamma_{ij} = \gamma_{ji}$ and $\zeta_{ij} = \zeta_{ji}$.

3.2. Empirical specification

From Equation (8), we obtain a system of equations that can be jointly estimated for food categories $i = 1, \ldots, 12$:

$$w_{ihs} = \alpha_i + \sum_k \beta_{ik}\tilde{y}_{hs}^k + \sum_j \gamma_{ij} \log p_{jhs} + \sum_j \zeta_{ij} \log p_{jhs}\tilde{y}_{hs} + \sum_g \delta_{ig} z_{gh} + \sum_f \delta_{iu} z_{uhf}\tilde{y}_{hs} + \theta_i D_{hs}^c + \theta_{iu} D_{hs}^c\tilde{y}_{hs} + \sum_f \theta_{if} D^c z_{uhf} + \epsilon_{ihs}, \tag{9}$$

where w_{ihs} is the expenditure share for food category i of household h in survey scenario s, α_i is the intercept for category i, p_{jhs} is the price of category j and $\tilde{y}_{hs}$ is the linear approximation of real expenditure. Parameters β capture how a food-category demand changes with the total expenditure; following Lewbel and Pendakur (2009) and Zhen et al. (2014), expenditure enters the model as a polynomial of 5th degree ($K = 5$) thus allowing highly flexible Engel curves. z_{gh} are the socio-demographic characteristics of respondents: we control for gender, age, household size, number of children in the household, income, education, employment, region of residence, ethnic group, and we include two dummy variables indicating if the household is in the bottom or top quartile of the meat consumption distribution, based on their meat expenditure level in the baseline scenario. Parameters ζ_{ij} and δ_{iu} allow, respectively, the effect of prices and selected socio-demographic variables z_{uhf} (i.e., gender, age, income, education, and meat expenditure level) to vary with the level of expenditure. ϵ_{ihs} is the error component of the regression. In addition, we include a dummy variable D_{hs}^C for carbon-information, taking value 1 if the respondent received the information and 0 otherwise. The corresponding parameter θ_i captures the extent to which respondents adjust their desired expenditure share of food group i as a result of being exposed to the information concerning the food carbon footprint. We also interact D_{hs}^C with a subset of household characteristics z_{uhf}, i.e., gender, age, income, education and meat expenditure, to allow for heterogeneous effects. We also tested for the impact of an additional set of parameters capturing the interaction effect between prices and the carbon information dummy. These parameters measure the influence of a price change when respondents know the food carbon footprints. A Likelihood Ratio test does not reject the null hypothesis that all these additional interaction parameters are equal to zero (Chi-squared test: 67.05 with 78 degrees of freedom, $p = 0.807$) and, therefore, in the results' section we present the most parsimonious specification. This finding is also in line with what reported by Ahn and Lusk (2021), who found little evidence of differences in the impact of taxes motivated by different objectives.

3.3. Estimation

Since our data display a substantial amount of censoring (i.e., household consumption decisions leading to corner solutions, or zero demanded quantity, for some food categories), the OLS estimator of equation (9) would be inconsistent. Therefore, in order to derive a consistent and unbiased estimate of the parameters in our model, we follow Tobin (1958)'s approach, which was extended to the multivariate setting by Amemiya (1974). Adapted to our case, the Tobit specification assumes latent expenditure shares, w_{ihs}^*, defined as:

$$w^{*}_{ihs} = \boldsymbol{m}'_{ihs}\boldsymbol{\omega_i} + \epsilon_{ihs}, \tag{10}$$

where $\boldsymbol{m}'_{ihs}\boldsymbol{\omega}_{\mathbf{i}} + \epsilon_{\mathrm{ihs}}$ corresponds to the right-hand side of Equation (9). Latent shares w^{*}_{ihs} are related to the observed shares w_{ihs} in the following way:

$$w_{ihs} = \begin{cases} w^{*}_{ihs} \text{ if } w^{*}_{ihs} > 0 \\ 0 \text{ if } w^{*}_{ihs} < 0 \end{cases} \tag{11}$$

By imposing a distributional form on the residual term ϵ_{ihs} (i.e., a multivariate normal), the parameters $\boldsymbol{\omega_i}$ can be recovered by maximum likelihood. Following Amemiya (1974), the likelihood function is:

$$L = \prod_{1} \Phi(\epsilon_1, \ldots, \epsilon_{12}) \prod_{2} \left[1 - \int_{-\epsilon_1}^{\infty} \ldots \int_{-\epsilon_{12}}^{\infty} \Phi(\epsilon_1, \ldots, \epsilon_{12}) d\epsilon_1 \ldots d\epsilon_{12} \right], \tag{12}$$

where the first product refers to the non-censored observations ($w_{ihs} = w^{*}_{ihs}$ and $\boldsymbol{m}'_{ihs}\boldsymbol{\omega_i} > \epsilon_{ihs}$) and the second product to the censored observations ($w_{ihs} = 0$ and $\boldsymbol{m}'_{ihs}\boldsymbol{\omega_i} < \epsilon_{ihs}$). The function Φ indicates the density of the multivariate normal distribution. In practice, this likelihood function involves high dimension integrals, which are difficult to optimize. For this reason, we employ the simulated maximum likelihood method, which is often used for the estimation of censored demand systems (e.g., Yen et al., 2003), by relying on the Stata 'cmp' command (Roodman, 2011). Finally, the confidence intervals for all our estimates are calculated via Monte Carlo simulation, by using 2000 draws from the multivariate normal, asymptotic distribution of our parameters' estimate.

3.4. Welfare impacts

Following Zhen et al. (2014), we express the impact of a price change on welfare in terms of Compensating Variation (CV), i.e., the change in expenditure required by a household to keep the same utility level after the variation in (log) prices from $\boldsymbol{p_0}$ to $\boldsymbol{p_1}$. Hence, as described in Lewbel and Pendakur (2009), the CV can be expressed as:

$$CV = C(\boldsymbol{p_0}, u_0, \boldsymbol{z}, \epsilon) \times (\exp(\log C(\boldsymbol{p_1}, u_0) - \log C(\boldsymbol{p_0}, u_0)) - 1), \tag{13}$$

Where $C(\boldsymbol{p_0}, u_0, \boldsymbol{z}, \epsilon)$ is the observed total expenditure (x) at baseline prices $\boldsymbol{p_0}$. The change in expenditure $\Delta\log C = \log C(\boldsymbol{p_1}, u_0) - \log C(\boldsymbol{p_0}, u_0)$ is equal to:

$$\Delta\log C = (\boldsymbol{p_1} - \boldsymbol{p_0})'\left(\boldsymbol{\alpha} + \boldsymbol{\beta}\widetilde{y}^{k} + \boldsymbol{\delta z} + \boldsymbol{\delta}_u \boldsymbol{z}_u \widetilde{y} + \boldsymbol{\epsilon}\right) + \frac{1}{2}(\boldsymbol{p_1} - \boldsymbol{p_0})'(\boldsymbol{\gamma} + \boldsymbol{\zeta}\widetilde{y})(\boldsymbol{p_1} - \boldsymbol{p_0}) \tag{14}$$

$$\Delta\log C = (\boldsymbol{p_1} - \boldsymbol{p_0})'(\widehat{\boldsymbol{w}}_{\mathbf{0}}) + \frac{1}{2}(\boldsymbol{p_1} - \boldsymbol{p_0})'(\widehat{\gamma} + \widehat{\zeta}\widetilde{y})(\boldsymbol{p_1} - \boldsymbol{p_0}) \tag{15}$$

where $\widehat{\boldsymbol{w}}_0$ is the vector of baseline budget shares. The first term in Equation (15) captures the variation in expenditure due to the increase in prices (keeping the consumption bundle fixed), while the second term describes the substitution effects (Lewbel and Pendakur, 2009).

Table 3
Goodness of fit.

Category	Squared correlation	# of significant parameters
	(1)	(2)
Beef and lamb	0.503	48%
Cheese	0.056	36%
Fish/Seafood	0.090	46%
Pork	0.330	42%
Poultry	0.234	49%
Eggs	0.060	25%
Snacks	0.079	43%
Milk/yoghurt	0.083	43%
Breakfast cereals	0.074	46%
Bread/pasta/rice/flour	0.134	48%
Fruits/vegetables	0.142	55%
Beverages	0.192	57%

Notes: goodness of fit (column 1) is calculated as the square of the correlation between observed and predicted shares for each estimated equation. Column 2 reports the share of parameters that are statistically different from 0 at the 90% confidence level.

4. Results

Our model includes 13 equations and 871 coefficients. Given this extensive number of parameters, we do not present them individually in this section. Instead, we discuss the model's features such as goodness of fit, expenditure and price elasticities, and the effect of carbon information. Regarding the goodness of fit, we follow Wooldridge (2002) and express it in terms of the square of the correlation between the observed expenditure shares and the predicted ones from Equation (11). Table 3 reports the estimated squared correlation for each equation: they range from 0.056 for cheese to 0.503 for beef and lamb. The percentage of parameters that are significant at the 90% confidence level in each equation is reported in column 2 and ranges from 25% for eggs to 57% for beverages.

4.1. Elasticities

This section presents both the expenditure and price elasticities derived from our parameter estimates for an average household, i. e., assuming that sociodemographic covariates and prices are at their baseline averages. Expenditure elasticities, which measure the variation in the quantity of food demanded following an increase in total expenditure, are shown in Fig. 1 for the different food categories analysed. Beverages, beef and lamb, and fish and seafood appear to be luxury goods, i.e., goods whose demand tends to increase more than proportionally with expenditure. These findings are consistent with previous estimates based on real food consumption behaviour (e.g., Roosen et al., 2022). Since beef and fish are particularly carbon intensive, the above elasticities imply that the carbon content of the food basket tends to increase more than proportionally with the expenditure in food. This result is confirmed by the estimated Engel curves (Appendix Figure B3), where the demand shares of these food categories strictly increase with expenditure. As shown in the Appendix, these curves exhibit significant nonlinearities that are not captured by linear functional forms (as assumed in the AIDS model) or quadratic functional forms (as in the quadratic AIDS). This finding supports the use of the EASI model to represent more realistically consumer behaviour.

We also compute the Marshallian, or uncompensated, price elasticities. In order to save space, Fig. 2 reports only the own-price Marshallian elasticities, while the full cross-price elasticities can be found in the Appendix (Table A5 and Figure B4). The Appendix also includes cross-price Hicksian, or compensated, elasticities (Table A6 and Figure B5). With respect to the elasticities in Fig. 2, our results indicate that demand curves are fairly inelastic, as the own-price elasticities lie in the interval between −1 and 0. This means that the quantities demanded for the different food categories decrease less than proportionally following an increase in prices. These results align, again, to other studies that examine UK food consumption using real-market food purchase data (Kehlbacher et al., 2016; Tiffin et al., 2011). We find that the own-price elasticity for the category "beef and lamb" is the largest in absolute terms, implying that imposing a tax on this category will have a strong effect on its demand and, therefore, on the carbon content of the food basket.

4.2. The effect of carbon information

We now present our estimates of the effect of carbon information on food demand. In principle, carbon labelling reduces information asymmetry, allowing consumers to correct potential misperceptions (Camilleri et al., 2019; Johnson et al., 2024) and to make more informed choices (Edenbrandt and Nördstrom, 2023).

Fig. 3 reports the effect of carbon labels on the change in the share of expenditure by food category, focusing only on those respondents who are actually buying the food category, i.e., the intensive margin of the impact of carbon information. We find that the consumption of high CO_2e products decreases significantly after presenting respondents with information on their carbon emissions. For example, beef and lamb expenditure decreases by 12.7% and cheese expenditure decreases by 2.5%. In turn, the consumption of less carbon intensive categories increases, in particular fruits and vegetables, suggesting that carbon labels can encourage more sustainable choices. Additionally, the rise in poultry consumption suggests a substitution effect, with consumers shifting toward meat types that are associated with lower carbon emissions. Similarly, the decrease in milk and yoghurt consumption might be explained by the availability of low-carbon substitutes, such as plant-based milk. We find similar dynamics in the probability of purchase of the different food categories, i.e., the extensive margin (see Figure B6 in the Appendix).

Our results are in line with previous findings on the effect of carbon labelling in incentivized settings. For example, both Brunner et al. (2018) and Edenbrandt and Lagerkvist (2021) find an increase in demand for chicken and meat substitutes, as a result of introducing carbon labelling, respectively in a field experiment and in a discrete choice experiment. Lohmann et al. (2022), in their field experiment in university cafeterias, find a decrease in the consumption of meals containing meat or fish, after informing students of the carbon content of the dishes available for purchase. Fosgaard et al. (2024) report that the provision of carbon information in a real supermarket setting reduces the purchase of beef and milk.

We now explore the heterogeneity in the impact of carbon labelling. As described in Section 3.2, we allow the effect of carbon labels to change according to several sociodemographic variables, i.e., gender, age, income, education, and the meat content in the diet, distinguishing between the top and the bottom quartiles of the distribution of meat expenditure per person. Expectations about heterogeneity in the effect of labelling are justified by evidence that information affects people differently according to their characteristics (Rondoni and Grasso, 2021). Based on our data, a likelihood ratio test strongly rejects the hypothesis that the carbon information parameters are constant across socio-demographic groups (Chi-squared = 141.14 with 84 degrees of freedom, $p = 0.000$).

Table 4 reports the effect of carbon information on purchases across different respondents' characteristics. Bold figures indicate that the effect of information is statistically different (at the 90% confidence level) across respondents with different profiles in a specific socio-demographic category. Overall, we do not find strong differences based on gender. Considering age, instead, labelling

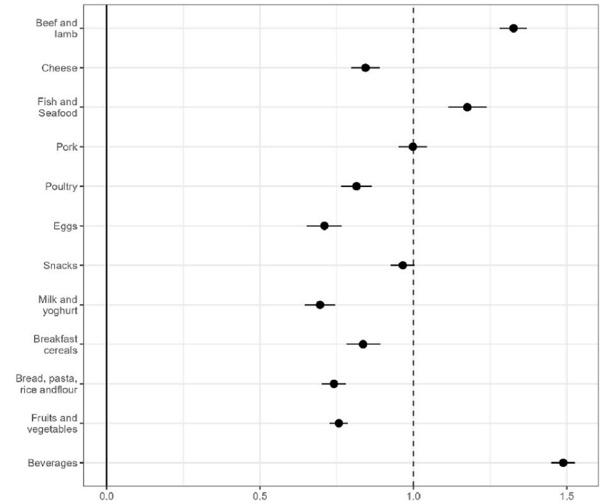

Fig. 1. Expenditure elasticities. Notes: estimated expenditure elasticities for the average household at average baseline prices. The error bars indicate the 90% confidence interval.

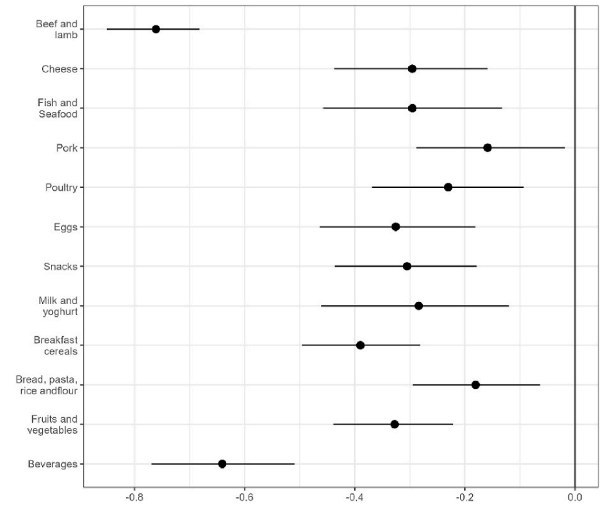

Fig. 2. Own-price Marshallian elasticities. Notes: Marshallian elasticities for the average household at average baseline prices. The error bars indicate the 90% confidence interval.

impacts are more heterogeneous: as a result of carbon labelling, younger individuals increase more their demand for fruits, vegetables, starches and poultry, while older respondents only respond with a slight increase in snacks, beverages and fish consumption. In terms of income, we find that richer households decrease their demand for cheese, beef and lamb more than lower-income ones, who instead increase more their purchase of beverages. Education does not appear to have a strong role, with individuals with more years of schooling experiencing only a small increase in their purchase of fruits, vegetables and pork after the introduction of carbon labels, compared to less educated individuals. Unsurprisingly, more pronounced differences in the effect of labelling can be observed across dietary profiles. Individuals buying larger amounts of meat decrease their overall demand significantly more (−14%) compared to those eating less meat (−7%). On the other hand, individuals buying less meat seem to be more willing to decrease their demand for cheese (−4%). Our findings are in line with those reported in the literature review by Rondoni and Grasso (2021): younger people, individuals with higher income and education tend to react more strongly to carbon labels by switching from carbon intensive goods to less carbon intensive alternatives.

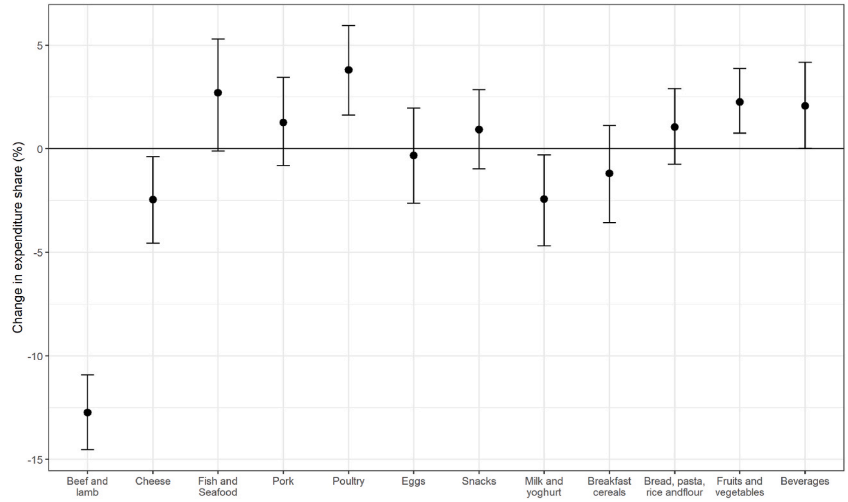

Fig. 3. Change in the expenditure share resulting from the introduction of carbon labelling. Notes: error bars indicate 90% confidence intervals.

5. Policy scenarios

We employ the demand system estimated in the previous section in order to investigate how different policy scenarios involving the introduction of carbon labelling and taxation impact the level of carbon footprint, consumer welfare, and tax revenues for the public sector. Section 5.1 introduces our policy scenarios, Section 5.2 presents the results for the average household and Section 5.3 explores heterogeneous impacts in the effects across different households.

5.1. Description of the policy scenarios

We consider three possible policy scenarios: *a) carbon labelling*, in which a color-coded label indicates the carbon footprint of each food item; *b) carbon tax*, in which a tax is placed on the most carbon intensive food categories, increasing their price proportionally to the carbon content, and *c) carbon labelling and tax*, a scenario introducing simultaneously carbon labels and a carbon tax on selected goods.

In the second (*carbon tax*) and third scenario (*carbon labelling and tax*), the carbon tax is applied only to those food categories with emissions per kg larger than the average, following Briggs et al. (2015) and Faccioli et al. (2022), given that a tax on all products is unlikely to be feasible. The taxed food categories are beef and lamb, cheese, pork, and fish and seafood. While on average these goods account for slightly more than a quarter of the food expenditures, they are responsible for almost 60% of the total GHG emissions of our respondents' baseline food-baskets (Table 2). In the second policy scenario (*carbon tax*), we apply a tax rate of £60 per tonne of CO_2e, which was the central estimate of the UK Government for 2020, based on the marginal abatement cost approach (DECC, 2009). This rate was also the central value for the tax-rate applied in the survey experiment, and therefore our policy scenarios are not based on the extrapolation of the price effects beyond the range used for estimation. Additionally, this figure is around the current allowance prices for the UK ETS, and within the range of values identified by the World Bank to comply with Paris Agreement targets (World Bank, 2023). In the *carbon labelling and tax* scenario, instead of applying the same £60 tax per tonne of CO_2e, we calibrate a tax rate that allows to achieve the same emission reduction as in the *carbon tax* scenario, in order to explore the synergies arising from combining carbon taxes and labels. We find this tax rate to be £27.86 per tonne of CO_2e. When simulating food choices under the scenarios, we keep the total expenditure on food constant, similarly to what was done in Kehlbacher et al. (2016). This choice is also supported by our survey data, which revealed that the total expenditure varied only marginally between survey scenarios (on average 1-2%; Table A7).

We also investigate how a tax recycling scheme can address regressivity concerns, as they constitute one of the major obstacles in the implementation of carbon taxation (Timilsina, 2022). Following Schaper et al. (2025), we assume that all tax revenues are equally redistributed on a per capita (lump sum) basis.

5.2. Impacts on food demand, GHG emissions and welfare

We start by exploring the variations in consumption for the different food categories across the various policy scenarios, as illustrated in Fig. 4. Detailed predicted expenditure shares and quantities can be found, respectively, in Appendix Tables A8 and A9. Based on our results, carbon labelling (red bars) generates a significant shift towards less carbon intensive food categories. The most affected category is, as expected, beef and lamb, which experiences a 16% drop in demand. We also find that carbon labelling encourages an increase in the demand for poultry, which is a low-carbon alternative to red meat. Cheese and other dairy products also experience a decline and are likely replaced by less carbon-intensive alternatives, such as the plant-based options belonging to the

Table 4
Percentage change in expenditure after the introduction of carbon labelling.

Categories	Gender		Age		Income		Years of schooling		Meat content in diet	
	Female	Male	Younger	Older	Lower	Higher	Less	More	Lower	Higher
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Beef and lamb	−12.92***	−9.98***	−11.77***	−11.55***	**−8.35*****	**−13.64*****	−11.45***	−11.84***	**−7.34*****	**−14.18*****
Cheese	−2.67**	−1.39	−2.60**	−1.68	**−0.07**	**−3.36*****	−2.42*	−1.85*	**−3.99****	**1.48**
Fish/Seafood	2.05*	1.58	1.14	2.51**	1.70	1.94*	2.84**	0.96	2.80	−0.51
Pork	1.17	1.06	0.60	1.60	0.15	1.73*	**−1.02**	**3.09****	−1.38	2.49*
Poultry	2.74**	3.98***	**5.41*****	**1.34**	3.43**	3.18***	3.61**	2.98**	2.32	3.90**
Eggs	−0.83	0.49	−0.85	0.27	−2.01	0.83	−0.46	−0.09	0.59	−0.86
Snacks	1.22	0.39	**−0.79**	**2.43****	−0.74	1.89*	0.58	1.12	**−1.78**	**5.02****
Milk/yoghurt	−1.03	−3.54***	−3.35**	−0.98	−2.44*	−1.93*	−1.30	−2.85**	−1.91	−1.55
Breakfast cereals	−0.66	−1.26	0.28	−2.00*	−2.08	−0.20	0.48	−2.16*	−3.19*	1.29
Bread/pasta/rice/flour	0.81	1.35	**3.13****	**−0.86**	1.48	0.77	2.51**	−0.26	0.65	1.30
Fruits/vegetables	2.22**	2.31**	**4.14*****	**0.56**	**4.37*****	**0.98**	**0.59**	**3.79*****	0.00	3.6**
Beverages	1.70	1.86	1.70	1.83*	**−0.74**	**3.32*****	2.60**	1.03	0.94	3.44**

Notes: this table reports the percentage changes in the baseline expenditure shares for household with different sociodemographic characteristics, as a result of the introduction of carbon labels. Changes are predicted by looking at the variation in the expected value of consumed quantity for those respondents with a strictly positive demand for the food category. Demographic characteristics were changed one at the time to single out differences across selected groups. In the case of gender, we consider the difference between females and males. In the case of age, income, schooling and meat content in diet, we compare changes in the expenditure by assuming a respondent located at the 25th and 75th percentile of the distribution of values for the variable. This corresponds to 31 and 61 years old in the case of age, £10,000 and £50,000 in the case of income, 11 and 16 years of education in the case of schooling, and to the bottom or top quartile distribution of meat consumption. Figures in bold indicate that, within a sociodemographic characteristic, the variation is statistically different between the higher and the lower level at the 90% level. *, **, and *** refer to a variation that is statistically different from 0 at the 10, 5, and 1 percent levels, respectively.

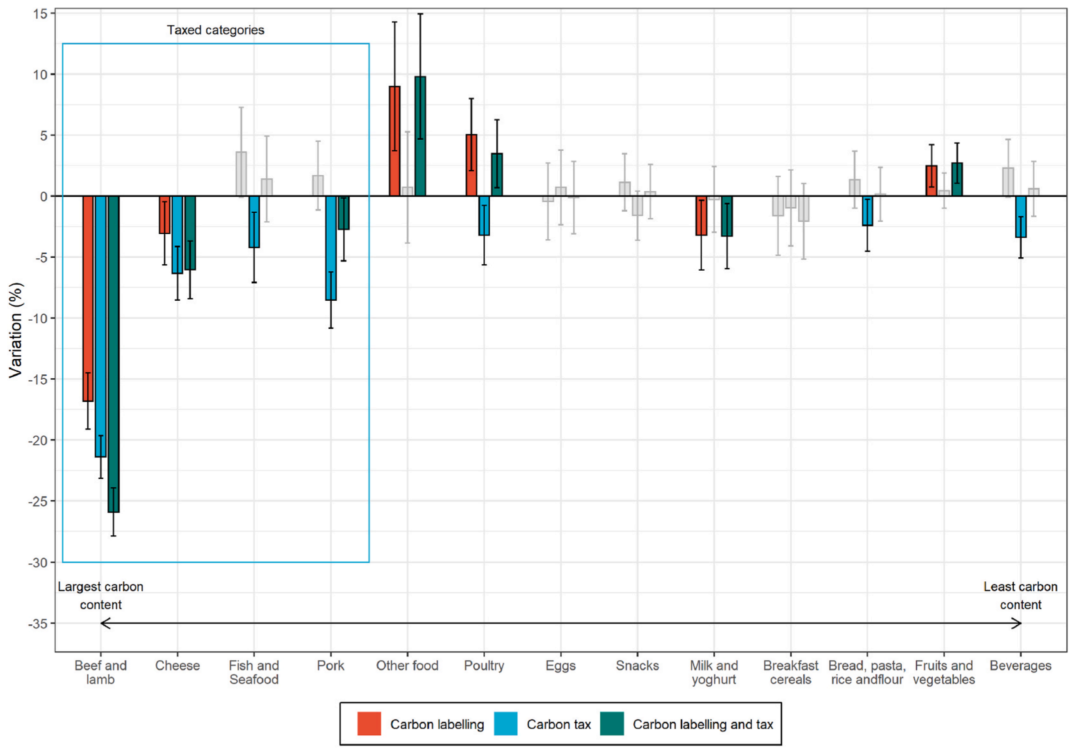

Fig. 4. Variation in food consumption across different policy scenarios. Notes: variations are expressed as a percentage change in the consumption relative to the baseline scenario. *Carbon labelling* refers to the introduction of labels indicating the carbon intensity of the food products. *Carbon tax* indicates the introduction of a £60 per CO_2e tonne tax on food products with an above-average carbon intensity (i.e., Beef and lamb, Cheese, Pork, and Fish and Seafood). *Carbon labelling and tax* refers to a scenario with the combined introduction of carbon labels and a £27.86 tax rate per tonne of CO_2e. The error bars report the 90% confidence interval. Columns in grey indicate that the variation is not statistically different from zero.

other food category, which notably shows a significant increase.[8] These findings suggest that substitution between products is likely to occur between higher-carbon and lower-carbon foods that serve similar purposes in the consumers' diet, as, e.g., substituting between different kinds of meat, rather than from meat to vegetables, which would require a change in the consumer's dietary habits.

The demand effects of the carbon tax scenario are illustrated by the blue bars. As expected, the demand for all taxed categories decreases, driven by the negative and statistically significant price elasticities discussed in Section 4.1. The reduction observed for cheese and beef is even more pronounced than in the carbon labelling scenario and we do not observe an increase in poultry consumption. On the other hand, there is a slight decrease in the demand for poultry probably due to income effects, as taxes overall reduce the budget available for food purchases. An explanation is that, without carbon labelling, consumers might be unable to identify poultry as a low-emission alternative to red meat. Similarly, in the carbon tax scenario there is no noticeable increase in the other food category, which includes low-carbon plant-based meat and milk alternatives.

The effects of introducing both carbon labelling and a carbon tax are represented by the green bars. As mentioned in the previous section, we simulate a carbon tax of £27.86 per tonne of CO_2e, which is the tax rate that needs to be applied to obtain the same carbon emission reductions as in the carbon tax scenario. Under the combined carbon labelling and tax policy scenario, most of the reduction in emissions comes from the drop in the demand of red meat (above 25% and higher than in the previous scenarios). The other food categories experiencing a decrease in demand in the carbon labelling and tax scenario are cheese, milk and yogurt, and pork. Similar to the carbon tax scenario, we observe a shift toward less carbon-intensive food categories, with an increase in demand only for poultry, other food, and fruit and vegetables.

Table 5 compares the different scenarios in terms of both reductions in carbon emissions and welfare impacts. We consider *a*) changes in compensating variation (which measures the reduction in consumer welfare from increasing prices), *b*) revenues for the public sector arising from levying a carbon tax, and *c*) the social welfare benefits that would result from the reductions in GHG

[8] While it would be interesting to distinguish between low-carbon alternatives (e.g., plant-based milk or plant-based meat) and the other food items included in the “Other food” category, in practice our data limit our ability to investigate this. In fact, plant-based meat and milk alternatives are both consumed by a minority of households and represent a very small share of the food budget: estimating an additional equation would likely generate inconsistent results by violating the assumptions underlying the Tobit model. To explore this question, we therefore compared variations across survey scenarios in the expenditure shares of single food items belonging to the “Other food” category: we found that these do not change substantially.

Table 5
The impact of each policy scenario on carbon footprint and welfare.

	Baseline (1)	Carbon labelling (2)	Carbon tax (3)	Carbon labelling and tax (4)
Carbon tax (£/CO_2e tonne)	0	0	60	27.86
Emissions (CO_2e tonne/person/year)	2.52	2.38	2.27	2.27
	(2.51; 2.54)	(2.36; 2.40)	(2.25; 2.29)	(2.26; 2.29)
Change in emissions (%)	0	−5.60	−9.89	−9.89
		(−6.40; −4.81)	(−10.49; −9.34)	(−10.60; −9.23)
Consumer welfare loss (£/person/year)	0	0	−78.71	−33.52
			(−77.41; −80.02)	(−32.96; −34.08)
Tax revenues (£/person/year)	0	0	70.05	31.71
			(67.76; 72.35)	(31.66; 31.77)
Avoided CO_2e (£/person/year)	0	8.47	14.96	14.96
		(7.24; 9.71)	(14.13; 15.87)	(13.92; 16.08)
Net welfare change (£/person/year)	0	8.47	6.30	13.15
		(7.24; 9.71)	(5.17; 7.47)	(12.20; 14.17)

Notes: Consumer welfare is measured in terms of Compensating Variation, tax revenues are obtained as the difference between the baseline price, the new price and the quantity predicted, avoided emissions as the difference in GHG content multiplied by £60. The 90% confidence intervals are reported in parenthesis.

emissions resulting from the different policy scenarios, which we convert into monetary value by applying a price of £60 per avoided tonne of CO_2e.[9] Column 1 reports information on the baseline average emissions per person per year (2.52 CO_2e), which represents the benchmark for our analysis. The second column summarizes the findings for the carbon label scenario. The reduction in emissions is about −5.6%, (from 2.52 to 2.38 tons of CO_2e per person per year), which generates a welfare gain of about £8.47 per person per year. By aggregating this value considering the total the number of households in the UK (27.89 millions; ONS, 2024a), we obtain a reduction of approximately 10 millions tonnes of CO_2e emissions, which corresponds to about 2.7% of all UK GHG emissions in 2024.

The third column reports the impacts of the carbon tax scenario. A £60 tax per tonne of CO_2e achieves a greater reduction of CO_2e (−9.9%, or approximately −17.6 millions of CO_2e tonnes when aggregating at UK level, which corresponds to a 4.7% reduction) relative to the carbon labelling scenario. Interestingly, the magnitude of this effect is proportional to the one found by Kehlbacher et al. (2016), who find that a £28.41 carbon tax per tonne of CO_2e would lead to a 4.3% reduction in GHG emissions, based on a simulation study with reported real food purchase data (i.e., the UK Living Costs and Food Survey). We estimate that the social gain of avoiding these emissions to be £14.96 per person per year. The increase in prices generated by the tax, however, are associated with a loss in consumer welfare, measured through the compensating variation, of £78.71 per person per year. To give an indication of the magnitude of the impact, this figure corresponds to roughly 5% of the yearly expenditure on food consumed at home. In turn, the carbon tax would generate tax revenues for the public sector of about £70.05 per person per year. Considering all this, the net welfare change of the carbon tax policy is positive (£6.30 per person per year), but lower than the corresponding figure associated to the carbon labelling scenario.

The fourth column reports the impacts of a combined carbon labelling and tax scenario. This scenario achieves, by construction, the same emission reductions of the carbon tax scenario (−9.9%). However, applying carbon labelling means that less than half of the tax rate is necessary (£27.86 per CO_2e tonne). In monetary terms, the loss in consumer welfare due to higher prices is less than halved relative to the carbon tax scenario and equal to £33.52 per person per year. In this scenario, the tax revenues collected by the public sector are £31.71 per person per year and the monetary value of the avoided GHG remains £14.96 per person per year. Altogether, the net welfare change associated with this scenario is £13.15 per person per year, which is more than double the one obtained by applying a carbon tax alone, and significantly higher than the one associated with introducing carbon labelling alone. This comparison clearly shows that carbon taxes and labelling can work synergistically and achieve greater efficiency when combined, by leading to higher welfare gains and emission reductions, compared to a scenario in which each policy is implemented independently.

5.3. *Heterogeneous impacts*

In this section we explore the presence of heterogeneous responses across different levels of income and dietary profile in terms of both emission reductions (Fig. 5) and welfare impacts (Table 6) in our policy scenarios.

We begin by examining differences across income groups. We divided the households in our sample by computing their equivalised income, i.e., by adjusting respondents' household income for size and age, following the modified OECD equivalence scale (ONS, 2015). We classified as "low-income" those households in the bottom 5% of the per capita income distribution and as "high income" those in the top 5%. In the first three blocks of columns in Panel A of Fig. 5, we report the absolute amounts of emissions in the baseline (total bar height) and, in colour, the absolute reductions associated with each policy scenario, which is represented by the coloured part of each column. In Panel B, we report the corresponding percentage changes. We find that high-income households, who

[9] We also examined the impact of the different policy scenarios on the nutritional content of the food baskets (proxied by the Nutriscore), but we did not find substantial differences among scenarios and, therefore, we do not report it here in order to streamline our discussion (see Appendix E).

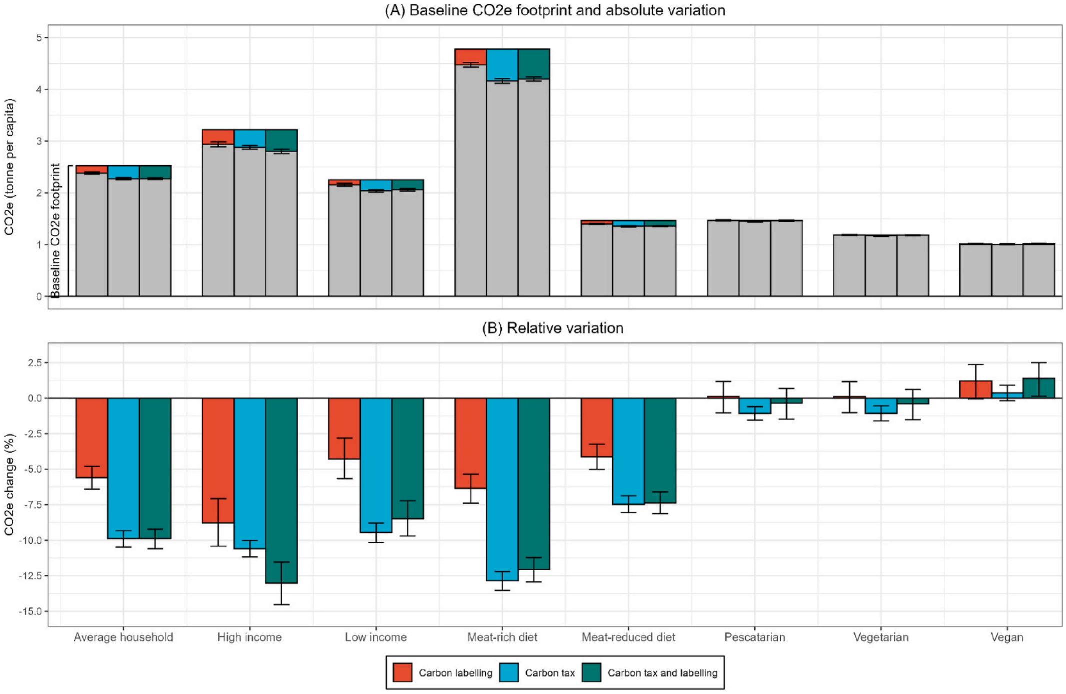

Fig. 5. Change in CO_2e food-related emission levels for different households across the policy scenarios. Notes: both Panel A and B report information on the emission reductions achieved under the different policy scenarios tested (carbon labels, carbon taxes and their combination) for different segments of respondents, in addition to the average household: *High* and *low income* refer to households with an equivalised income respectively in the top and bottom 5%. *Meat-rich diet (Meat-reduced diet)* indicates households in the top (bottom) tercile of the distribution in terms of meat consumption; *Pescatarian* refers to households that do not consume meat, but report a strictly positive quantity of fish and seafood; *Vegetarian* refers to households that do not consume any meat or fish, but report a strictly positive quantity of dairy products and eggs; *Vegan* refers to households that do not consume any product of animal origin. In Panel A, the height of the columns indicate the total absolute level of CO_2e emissions per capita associated with food demand patterns in the baseline, while the coloured segments of the different columns (red, blue, green) refer to the absolute reduction in emissions achieved due to the implementation of the different policies (carbon labels, carbon taxes, and their combination). Panel B reports the relative variation (in % terms) relative to the baseline. The error bars in the graph indicate the 90% confidence interval. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

also tend to have more carbon-intensive diets, respond strongly to carbon labelling. In fact, this group is predicted to reduce emissions by 8.8%, more than doubling the 4.3% value observed among low-income households. On the other hand, a carbon tax produces comparable percentage reductions in emissions across income groups (around 10%). The combined effect of carbon labelling and taxes achieves the largest reduction in carbon emissions amongst high-income households (−13%), while low-income ones respond slightly more strongly to taxation, with the combined policy generating only a 8.5% reduction. Focusing on the welfare impacts, we observe (Table 6, Panel A, odd numbered columns) that both the carbon tax and the combined carbon tax and labelling scenarios generate welfare losses that, in terms of equivalised household income per capita, are proportionately higher for low-income households (16.4‰ of household income in the carbon tax scenario and 7.1‰ in the carbon tax and labelling scenario) relative to high-income households (1.7‰ of household income in the carbon tax scenario and 0.7‰ in the carbon tax and labelling scenario). This result shows that the burden of such tax would be, in proportional terms, relatively higher for low-income households, confirming its regressivity, as suggested by prior research (Klenert et al., 2023).

We also report how welfare impacts would change if our policy scenarios were associated with a redistribution of the carbon tax revenues. We simulate a tax rebate taking the form of a lump-sum transfer that is equal across all households on a per capita basis. In the carbon tax scenario (columns 2 and 6 of Table 6), we find that the welfare burden of the policy becomes proportional to income (0.51‰ and 0.52‰ for respectively high- and low-income households). In turn, in the combined carbon tax and labelling scenario the welfare burden of the tax becomes slightly progressive: high-income households are subject to a welfare loss of 0.15‰ of their income, while low-income households experience a small welfare increase of 0.05‰ (which is represented by the negative CV, columns 4 and 8). This indicates that implementing revenue recycling can alleviate and, in some cases, reverse, the regressivity of carbon taxation.

Table 6
CV for different households across the policy scenarios.

	CV (£ per capita)				CV (‰ of income)			
	Carbon tax	Carbon tax with rebate	Carbon tax and labelling	Carbon tax and labelling with rebate	Carbon tax	Carbon tax with rebate	Carbon tax and labelling	Carbon tax and labelling with rebate
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Average household	78.71	8.66	33.52	1.81	3.68	0.40	1.57	0.08
	(77.42; 80.01)	(7.36; 9.96)	(32.96; 34.07)	(1.25; 2.36)	(3.62; 3.74)	(0.34; 0.47)	(1.54; 1.59)	(0.06; 0.11)
(A) Income								
High income	101.43	31.38	40.59	8.88	1.66	0.51	0.67	0.15
	(98.72; 104.14)	(28.67; 34.09)	(39.17; 42.02)	(7.46; 10.31)	(1.62; 1.71)	(0.47; 0.56)	(0.64; 0.69)	(0.12; 0.17)
Low income	72.33	2.28	31.50	−0.21	16.39	0.52	7.14	−0.05
	(70.62; 74.04)	(0.57; 3.99)	(30.58; 32.42)	(−1.13; 0.71)	(16.01; 16.78)	(0.13; 0.90)	(6.93; 7.35)	(-0.26; 0.16)
(B) Diet								
Meat-rich diet	186.76	116.7	80.38	48.67	8.16	5.10	3.51	2.13
	(183.78; 189.74)	(113.72; 119.68)	(78.97; 81.79)	(47.25; 50.08)	(8.03; 8.29)	(4.97; 5.23)	(3.45; 3.58)	(2.07; 2.19)
Meat-reduced diet	34.58	−35.47	14.79	−16.93	1.76	−1.8	0.75	−0.86
	(33.78; 35.39)	(−36.27; −34.67)	(14.45; 15.12)	(−17.26; −16.59)	(1.72; 1.80)	(−1.85; −1.76)	(0.74; 0.77)	(−0.88; −0.84)
Pescatarian	17.08	−52.98	7.72	−23.99	0.81	−2.5	0.36	−1.13
	(16.34; 17.81)	(−53.71; −52.24)	(7.44; 7.99)	(−24.27; −23.72)	(0.77; 0.84)	(−2.53; −2.46)	(0.35; 0.38)	(−1.14; −1.12)
Vegetarian	9.25	−60.8	4.24	−27.47	0.41	−2.70	0.19	−1.22
	(8.64; 9.86)	(−61.41; −60.2)	(4.04; 4.45)	(−27.67; −27.26)	(0.38; 0.44)	(−2.72; −2.67)	(0.18; 0.23)	(−1.23; −1.39)
Vegan	0.09	−69.96	0.02	−31.69	0.00	−3.14	0.00	−1.42
	(−0.50; 0.69)	(−70.56; −69.37)	(−0.13; 0.17)	(−31.84; −31.54)	(−0.02; 0.03)	(−3.17; −1.54)	(−0.01; 0.01)	(−1.43; −1.42)

Notes: *High* and *low income* refer to households with an equivalised income respectively in the top and bottom 5%. *Meat-rich diet* indicates households in the top tercile of the distribution in terms of meat consumption. *Meat-reduced diet* indicates households in the bottom tercile of the distribution in terms of meat consumption. *Pescatarian* indicates households that do not consume meat, but report a strictly positive quantity consumed of fish and seafood. *Vegetarian* indicates households that do not consume any meat or fish, but that do report a strictly positive quantity consumed of dairy products and eggs. *Vegan* indicates households that do not consume any product of animal origin. In the scenarios with a tax rebate, the tax revenues are equally redistributed on a per capita basis (respectively, £70.05 for the carbon tax and £31.71 for the carbon tax and labelling scenarios). A negative CV indicates positive welfare impacts. Numbers in parentheses report the 90% confidence interval.

We will now consider the emission reductions that would be achieved under the different policy scenarios across households with different dietary profiles: households in the top and bottom tercile of the distribution of non-zero meat consumption (which we indicate, respectively, as households with a *meat-rich* and *meat-reduced* diet), those who report to purchase fish but no other animal meat (*pescatarian*), those that do not buy fish nor meat (*vegetarian*), and those that do not consume any product of animal origin (*vegan*). In our sample, households with a meat-rich and meat-reduced diet represent in total 60.8% of households, pescatarian households correspond to 2.7% of our sample, while vegetarian and vegan households make up respectively 5.2% and 1% of our sample[10]. As shown in the last five blocks of columns of Fig. 5 (Panel A), these different dietary profiles are associated with considerable differences in terms of CO_2e emissions per capita in the baseline. Meat-rich households have the largest amount of carbon emissions (4.78 tonnes of CO_2e emissions per person per year), which is almost twice the value of the average household. On the other hand, meat-reduced and pescatarian households have much smaller but similar carbon footprints among each other (around 1.5 tonnes of CO_2e emissions per person per year). As expected, vegetarians and vegans have the lowest food-related carbon footprints (approximately 1 tonne of CO_2e emissions per person per year).

Considering the impact of the policies, carbon labelling offers the largest emission reduction potential for households with a diet rich in meat (−6.4% relative to the baseline). This result suggests that, despite having a more carbon-intensive diet, households consuming high levels of meat are sensitive to environmental issues and, when stimulated by policy interventions, are willing to decrease their consumption of carbon-intensive goods. On the other hand, the provision of carbon labelling on food products appears to have only minimal impact among pescatarian, vegetarian, and vegan households. This outcome can be attributed to two primary factors. First, these households have limited possibilities to substitute high-carbon products with lower-carbon alternatives, given that their diet is already relatively low-emissions. Second, these households are likely to be more environmentally conscious and better informed, making the additional information provided by labelling potentially redundant for this respondents' group.

In turn, carbon taxation achieves emission reductions that are larger than those obtained via carbon labelling for all dietary profiles. However, as for carbon labelling, the largest reductions are observed among households consuming high levels of meat (−12.9% relative to the baseline). Instead, emission reductions in the carbon taxation scenario are smaller for households consuming low quantities of meat (−7.5%), those who are pescatarian (−1.1%) and those who are vegetarian (−1.1%). Perhaps surprisingly, we find an increase in the levels of emissions among vegan households. While the carbon labelling effect is small (+1.4%) and only marginally significant in the carbon tax and labelling scenario, it may be originating from a form of moral licensing (Khan and Dhar, 2006), as these households may feel entitled to increase their volume of food purchases after being informed (or reminded) that the food products that they consume are low-carbon.

Turning to the analysis of the welfare impacts of carbon taxes across the dietary groups (Table 6, Panel B, column 1), we find that the carbon tax results in losses larger than £180 per person per year in the case of households with meat-rich diets. These impacts decrease significantly for the other dietary groups: about £30 per person per year for households consuming low levels of meat to about £10 per person per year for vegetarians, and almost no welfare losses for vegans. When combining carbon labelling and carbon taxation (Table 6, Panel B, column 3), the welfare loss experienced by consumers reduces by roughly half for all of the dietary groups. When simulating the introduction of a tax rebate (Table 6, Panel B, even numbered columns), we find that all dietary groups witness a small welfare increase (i.e. a negative CV), with the exception of those with a diet with rich in meat. Even in their case, however, the welfare loss is reduced by approximately 40% relative to a scenario without the rebate.

We further investigate the heterogeneity in the welfare impacts of the different policy scenarios by examining the interplay between the dietary profile and the income level of respondents. We first subdivided our sample in income deciles and then further divided each of them in deciles based on the carbon emissions in the baseline scenario. This subdivision generates 100 different subsamples ranked by income and carbon emissions. Fig. 6 reports the welfare impacts of a carbon tax and a combined carbon tax and labelling, with and without the application of tax-revenue recycling. As expected, percentage welfare losses are highest among individuals with lower income and more carbon-intensive diets, and they diminish with income and with lower GHG emission levels in the baseline. Considering the carbon tax scenario (panels A and C), the maximum welfare loss is 55.7‰ of income for households in the first decile of the income distribution and the tenth decile of the GHG emission distribution. The reduction in welfare impacts occurs faster along the GHG emission gradient (CV = 34.0‰ for households in the 9th decile of GHGs and 10th decile of income) than along the income gradient (CV = 43.6‰ for households in the 9th decile of income and 10th decile of GHGs). The patterns are similar, but implying lower welfare losses, when carbon taxation is combined with carbon labelling (panel B). In this policy scenario, the largest welfare losses experienced by respondents are, again, associated with the lowest level of income and highest GHG emissions, and are equal to the 24.5‰ of income. Adding a tax rebate to both the carbon tax scenario (Panel C) and the carbon tax and labelling scenario (Panel D) would starkly reduce the welfare losses for consumers and even induce a small increase in welfare for those individuals with below average food-related GHG emissions (i.e., with food baskets less rich in meat).

6. Robustness tests

In this section we test the robustness of our findings. Table 7 reports the estimated net changes in welfare in the three policy

[10] To compare our sample figures with population statistics, it is interesting to observe that the distribution of the different dietary profiles in our sample closely reflects the situation of the UK population, where 25% of the public described themselves as *still eating but cutting down on meat, dairy and animal products*, a further 5% identify as vegetarian, 3% say they are pescatarian and 2% identify as vegan (Food Standards Agency and Food Standards Scotland, 2022).

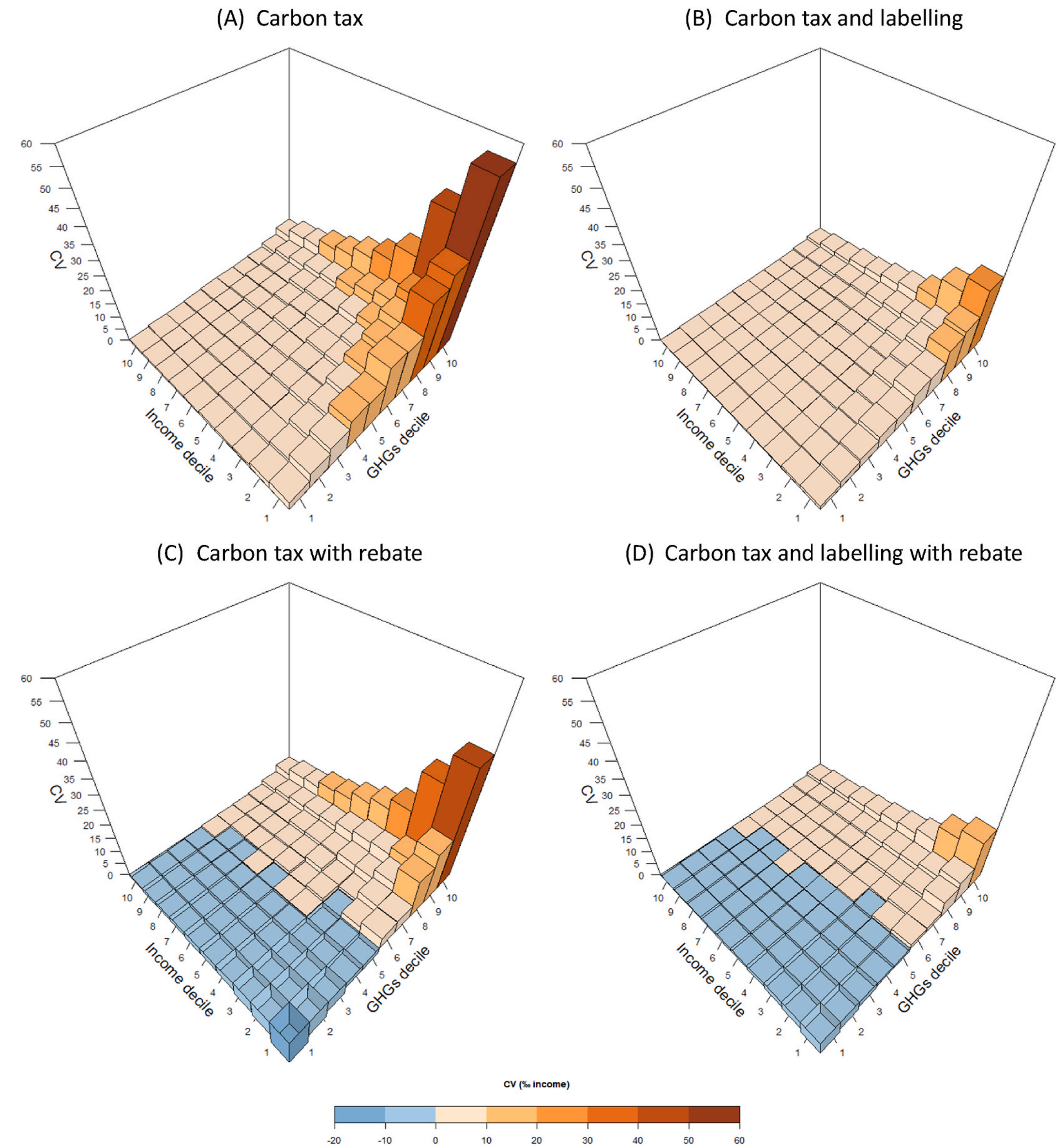

Fig. 6. Welfare impact of policies by deciles of household equivalised income and baseline food. GHGs emissions Notes: income deciles refer to household equivalised income. GHG emission deciles refer to the baseline GHG emission levels from food purchases.

Table 7
Estimated net welfare change (£ per capita) in different robustness tests.

	Carbon labelling	Carbon tax	Carbon labelling and tax
	(1)	(2)	(3)
Main estimates	8.47	6.30	13.15
	(7.24; 9.71)	(5.17; 7.47)	(12.20; 14.17)
Tiffin et al. (2011) elasticities	8.47	6.24	12.18
Kehlbacher et al. (2016) elasticities	8.47	5.34	17.17
Prices and carbon information interaction	8.46	5.86	13.19
EASI (3SLS) without censoring	8.40	5.55	12.76
AIDS	8.48	6.79	13.55

Notes: net welfare changes are obtained as the difference between the loss in consumer welfare (CV), tax revenues, and avoided CO_2e emissions, achieved under the three policy scenarios. More details are reported in Appendix E. In the first row, the values reported in parentheses are the 90% confidence intervals.

scenarios (carbon labelling, carbon tax and a combination of the two) under different modelling assumptions, data and estimation methods. The details of all tests are provided in Appendix E. The first row reports, for comparison, the results obtained with our main specification, summarised in Table 5. In the second and third rows, we report the net welfare gains estimated for the three policy scenarios when using the elasticities estimated in the literature (respectively from Tiffin et al., 2011; Kehlbacher et al., 2016) using UK real food-purchase data. As indicated in Table 7, results vary slightly but are mostly within the 90% confidence intervals of the estimates provided using our data. Moreover, it is worth observing that the relative net welfare ranking of the three policies remains consistent, thus reinforcing the reliability of our conclusions regarding the advantages of combining labelling and taxes. In the fourth row of Table 7, we evaluate the effect of introducing interaction terms between prices and carbon information in our demand model. As anticipated in Section 3.2, we did not find enough evidence in favour of the significance of these interaction effects and therefore including them in the model does not produce a significantly different net welfare estimate. In the fifth and six rows of Table 7, we report the net welfare effects calculated when employing different modelling approaches. In the fifth row we show the results obtained by ignoring the corner-solutions issue and estimating the EASI model without employing the linear approximation (necessary for the multinomial Tobit approach), while allowing for cross-equation correlations by using an iterated 3 stages least squares approach (Lewbel and Pendakur, 2009). All the estimates following this modelling approach are well within the confidence intervals of the estimates obtained with our main model, indicating that both the linear approximation and censoring do not appear to significantly affect our estimates. In the sixth row of Table 7 we report the estimates obtained using an AIDS model (Deaton and Muellbauer, 1980), given that the AIDS remains widely used in the scientific literature. We find similar welfare changes associated with the introduction of each policy. However, a Likelihood Ratio test strongly rejects the hypothesis that the two specifications have equal explanatory power (Chi-squared = 1615.07, df = 210, $p < 0.001$). This suggests that, although the results for the average household are similar, the EASI approach is likely better at capturing heterogeneous effects.

7. Conclusions

This manuscript explores the effectiveness, efficiency and trade-offs involved with the implementation of different demand-side policy interventions aimed at correcting the GHG emission externalities associated with food consumption. By focusing on UK households' purchase choices, we examine the separate and combined effects of a hard policy (a carbon tax) and a soft policy (carbon labelling). Using data collected on a sample of the UK resident population via a survey-based, randomized experiment simulating an online supermarket (Faccioli et al., 2022), we estimate an EASI demand system that considers, in addition to prices and consumer sociodemographic characteristics, the effect of carbon labels on food choices.

Our results indicate that carbon labelling induces a shift away from food categories with the largest carbon footprint (e.g., beef) and/or readily available low-carbon substitutes (e.g., milk). This finding is in line with previous evidence from choice experiments (e.g., Edenbrandt and Lagerkvist, 2021), field experiments (e.g., Brunner et al., 2018), and real supermarkets (Fosgaard et al., 2024). Overall, these substitution patterns imply a decrease in the carbon content of the food basket, which we estimate to decrease by 5.6% for the average household. A carbon tax of £60 per CO_2e tonne on carbon-intensive food categories produces considerably stronger emission reduction (−9.9%). We also show that introducing a policy mix, consisting of the combination of carbon information and taxes, can yield the same emission reductions as a carbon tax, albeit requiring less than half the tax rate. Our results also indicate that the effects of the two interventions are approximately additive, as providing carbon information does not significantly change the impact of prices.

We calculate net welfare gains by considering the benefits of avoided carbon emissions (set as £60 per tonne), tax revenues for the public sector and, where applicable, the loss of consumer welfare resulting from the higher prices imposed by the tax. Based on our results, the overall net welfare gains associated with a combination of carbon taxes and information amount approximately to £13 per person per year, which is more than double the net welfare gains from a carbon tax scenario alone (approximately £6) and significantly larger than those from a carbon labelling scenario alone (approximately £8). Given that the public acceptance of a carbon tax has been shown to decrease with the tax rate (Carattini et al., 2018), combining taxes and labels appears to be a promising policy option to increase the feasibility of climate change mitigation without compromising the possibility to achieve ambitious emission reduction targets. This result highlights the potential for policy makers to exploit the combination of different types of policies in order to maximize social welfare.

We also examine the heterogenous impacts of the policies across household types. In line with previous research (Klenert et al., 2023; Schaper et al., 2025), we find that the impact of carbon taxes on food is regressive and tends to generate welfare losses that, in relative terms, are largest for low-income households. In response to a carbon tax high- and low-income households reduce the carbon content of their food basket by a similar proportion. However, when combining carbon taxes with carbon labels the reduction is proportionally larger for high-income households. This finding suggests that a policy mix can exploit the higher flexibility in dietary choices of wealthy individuals and, in this sense, impose a burden of effort that is less regressive than what would result from a tax alone. Furthermore, we find that introducing a lump-sum tax-recycling scheme can make tax become proportional or even slightly progressive.

Dietary choices create significant horizontal inequality in how a carbon tax affects households of the same income level. This result parallels previous findings on the impact of energy taxes, which are not purely determined by income but also other characteristics (Pizer and Sexton, 2019). The welfare loss of a carbon tax on emissions is largest among the poorest households with the most carbon intensive diet, where, depending on tax rate and rebate scheme, losses can range from 1% to more than 5% of income. Moreover, the relative welfare impact decreases faster along diet footprint deciles than along income deciles, which indicates a substantial inequality within income groups. Nonetheless, all households, especially those with a diet rich in animal products (and therefore with higher food-related emissions), would be willing to decrease their dietary carbon footprint in response to both information provision and price signals. This result supports the finding that most consumers care about their emissions, but either lack the knowledge about the carbon content of food, or the information is not salient enough during grocery shopping (Camilleri et al., 2019; Johnson et al., 2024). Thus, carbon labelling can help individuals with pro-environmental preferences to decrease their carbon footprint. Unsurprisingly, our results also show that vegetarian and vegan households are less affected by the demand policies explored in our study, as they already follow a diet low in carbon emissions and therefore the scope for CO_2e emission reduction in their diet is limited.

While our estimates are based on a hypothetical experiment, the consistency of our findings with those obtained from different studies in the literature using real food consumption data supports the external validity of our results. First, the food purchase patterns in the baseline scenario of our survey are similar to those measured by official statistics. Second, our price elasticity estimates are in line with those from the literature (Kehlbacher et al., 2016; Tiffin et al., 2011). Third, our estimates of the effect of labelling are comparable with those found in previous research using both incentivized choice experiments (Muller et al., 2019), field experiments in canteens (Brunner et al., 2018; Lohmann et al., 2022) and real supermarkets (Fosgaard et al., 2024). Finally, we note that Kehlbacher et al. (2016), using self-reported food purchase data, estimate a 4.3% decrease in food-related emissions following the introduction of a £28.41 tax per tonne of CO_2e: this conclusion is roughly proportional to our result (i.e., a 9.9% emission reduction with a £60 tax per tonne of CO_2e emissions).

Our study has also some limitations, which can be addressed by future research. First, we focus on food consumption at home, ignoring out-of-home food purchases. In the UK, at-home food consumption accounts for the large majority of both food expenditure (64% in 2019; ONS, 2021c) and nutritional energy intake (more than 90%; Department for Environment, Food & Rural Affairs, 2022). However, in other countries food consumption away from home is more prominent, and researchers should also explore the complementarities and substitution patterns between policies targeting different types of consumption, in order to avoid unintended policy effects. Second, we assume a full pass-through of the carbon tax to consumers. As Klenert et al. (2023) note, this is common in this kind of studies, and supported by empirical evidence on carbon taxes in the energy sector (Andersson, 2019; Harju et al., 2022) and on sugar taxes in the beverage sector (Andreyeva et al., 2022). Nevertheless, future research may examine how the tax burden is distributed between food consumers and producers. Third, our experimental design only provides information on the short-term effect of policies, and it does not allow us to understand whether changes in consumption patterns are persistent over time. There is very little literature on the dynamic impact of labelling, but the few existing studies on the effect of taxation on sugar-sweetened beverages suggests that the shift in consumption driven by the tax tends to last at least several months (Lee et al., 2019; Rogers et al., 2023). Similarly, research examining the durability of informational interventions regarding food healthiness (Capacci and Mazzocchi, 2011; Thorndike et al., 2014) and environmental impacts (Jalil et al., 2023; Lohmann et al., 2022) indicates that shifts in consumption persist for several months following the initial treatment. Therefore, we believe that it is unlikely for our results to be only transitory. Finally, consumers may, to some extent, respond to increases in prices by substituting higher-with lower-quality products, while keeping carbon content constant. This effect may reduce the effectiveness of the carbon tax, albeit the impact of carbon labelling would not be affected.

Further avenues for future work include assessing more in detail the nutritional outcomes of changes in diet driven by GHG emission reduction policies, given the strong connection between food and health (Willett et al., 2019). Another important aspect that warrants further exploration concerns the spillover effects of demand-side policies on the food supply chain. Evidence from soda taxes (Dickson et al., 2023) and nutritional labels (Barahona et al., 2023) shows that demand-side food policies can also encourage changes in the production processes. For example, suppliers may be incentivized to innovate and reduce emissions in response to a carbon tax, in order to retain customers and maintain market shares. The analysis of these wider general-equilibrium effects in the economy deserves more investigation in the future, considering the potential for policy making to exploit the behavioural adjustments among suppliers to reduce the pressure on consumers.

Ethical approval

This project received approval from the University of Exeter Business School Research Ethics Committee, UK (reference number eUEBS002059 v.6.0). We have obtained informed consent from all the participants in the research.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work, the author(s) used Gemini in order to improve the linguistic clarity and grammatical accuracy of the manuscript. After using this service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

CRediT authorship contribution statement

Marco Tomasi: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing. **Michela Faccioli:** Conceptualization, Data curation, Funding acquisition, Supervision, Writing – original draft, Writing – review & editing. **Carlo Fezzi:** Conceptualization, Investigation, Methodology, Supervision, Writing – original draft, Writing – review & editing. **Ian J. Bateman:** Conceptualization, Funding acquisition, Writing – review & editing.

Declaration of competing interest

The authors declare no competing interests.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jeem.2026.103387.

Data availability

Data will be made available on request.

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