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Dietary change is a low-cost and scalable strategy for reducing greenhouse gas emissions from the food system, yet little is known about which households emit most, who reduces emissions over time, and how. This paper combines detailed scanner data from Worldpanel by Numerator's Take Home data with product-level emissions from the SHARP-ID database to examine the level and evolution of dietary carbon footprints among GB households from 2017 to 2022. We find differences across household types. Higher footprints are associated with older, less-educated, or female main shoppers, as well as larger, predominantly male, or child-rearing households. These differences reflect both quantities purchased and the carbon intensity of food choices. Over time, households with initially high footprints—especially middle-aged, less-educated, and larger households—were most likely to reduce them. In contrast, households with children and predominantly male ones showed little adjustment. Among reducers, nearly all lowered food quantity, and a majority also reduced carbon intensity, often via substitutions within food groups (e.g., beef to chicken). These findings identify the groups driving emissions, those adjusting, and those requiring policy attention. Supporting lower-carbon substitutions and targeting high-emission groups could improve the effectiveness and equity of food-related climate policies.

JEL Codes:

Q54, Q18, D12, C23

Keywords:

dietary carbon footprint; household heterogeneity; scanner data; carbon intensity

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The authors declare no conflict of interest.

Data Availability Statement:
The contents of this publication are IFS' own analysis and findings. The analysis and findings have been undertaken by IFS on the basis of its own work using data from Worldpanel by Numerator's Take Home data / Worldpanel by Numerator's Out of Home data (all use is subject to Worldpanel by Numerator's terms and conditions) and Worldpanel by Numerator does not represent any endorsement of the efficacy or accuracy of IFS' analysis and findings. The use of Worldpanel by Numerator's data in this work does not imply the endorsement of Worldpanel by Numerator's data from the interpretation or analysis of the data. All errors and omissions remain the responsibility of the authors of this publication.

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1 Introduction

Since the Intergovernmental Panel on Climate Change's (IPCC) first report in 1990, the urgency of curbing human-driven global warming has been widely recognised. Climate action has largely focused on decarbonising the energy system through investments in renewables, carbon capture, and energy efficiency. Yet these technological transformations often come with high marginal abatement costs, sometimes exceeding 100 to 200 USD per ton of CO_2e (Friedmann *et al.*, 2020; International Energy Agency, 2020), posing serious challenges for budget-constrained governments and raising concerns about policy acceptability. In this context, identifying low-cost and scalable mitigation levers is becoming increasingly critical.

One such lever is dietary change, which stands out as both cost-effective and politically feasible in end-use sectors. Recent studies estimate that shifting to more sustainable diets and reducing food waste could mitigate up to 44% of emissions from the food sector alone (IPCC, 2022). The case for dietary shifts is further strengthened by the food system's substantial carbon footprint, which accounts for roughly 26% of global greenhouse gas (GHG) emissions (Ritchie, 2019). Unlike post-production stages, the most carbon-intensive parts of the food supply chain (land use change, on-farm emissions, and animal feed (Poore & Nemecek, 2018)) are not easily addressed through decarbonising energy inputs. Shifting consumption away from high-emission food (e.g., ruminant meat) toward lower-emission alternatives (e.g., poultry or legumes) thus emerges as an impactful and relatively low-cost strategy for emissions reduction.

This paper makes a novel contribution by systematically documenting how dietary carbon footprints vary across demographic groups, and by identifying which households are most likely to reduce these footprints and through which mechanisms. By doing so, it brings two advantages for policymakers. First, it enables the design of more effective targeted policies to promote sustainable diets, for instance by tailoring interventions to specific household types or reduction strategies. Second, it clarifies how factors such as gender, age, education, and household composition shape dietary choices, thereby highlighting the potential distributional consequences of policies like taxes on high-emission food or subsidies for lower-carbon alternatives. Taken together, this evidence helps ensure that climate action in the food sector can be both effective and equitable.

Specifically, this paper examines which household characteristics are associated with higher dietary carbon footprints and with a greater likelihood of reducing, maintaining or increasing those footprints from 2017 to 2022 in the United Kingdom. A central objective is to disentangle the sources of heterogeneity in emissions: whether they stem from differences in the total quantity of food purchased, the carbon intensity of purchases, or both. This level of understanding is highly relevant for policy design and is enabled by the uniquely granular dataset used in this study, which links detailed scanner data on household food purchases from Worldpanel by Numerator's Take Home data with environmental impact estimates from the SHARP-ID database (Mertens *et al.*, 2019), producing estimates of GHG emissions per calorie across 26,752 food products.

The analysis relies on highly granular environmental and food expenditure data. The Sharp-ID provides European averages of the emissions of carbon dioxide (CO_2), methane ($CH4$) and nitrous oxide (N_2O) associated with the life cycle of food products based on studies from Agri-footprint and Ecoinvent. Worldpanel by Numerator's Take Home data provides information at the barcode level on each food product purchased by households (either in shops or farmer markets) during each shopping trip, for as long as the households remain in the sample. Goods from the scanner data are matched to environmental estimates in the Sharp-ID, leading to a total of 26,752 unique emission factors for goods in our consumption data. Armed with this information, we compute the yearly averages of the monthly dietary carbon footprint (in kilograms of CO_2 equivalent), of the monthly amount of calories purchased, and of the monthly carbon intensity of diets (i.e. the amount of CO_2 equivalent emissions associated with 1,000 calories representative of the household's monthly diet).

Unlike food frequency questionnaires or self-reported consumption surveys, scanner data provide continuous and high-frequency records of actual purchases, thereby reducing recall bias and measurement error. In addition, the rich nutritional information available in the Worldpanel by Numerator's Take Home data, together with the wide range of products covered, enables precise estimation of dietary GHG emissions per calorie and allows for a fine-grained investigation of the carbon intensity of individuals' choices: a level of detail rarely attainable in other datasets. The longitudinal structure of the data further makes it possible to track changes in purchasing behaviour within the same households over time. Taken together, these advantages make scanner data particularly well-suited to studying both the level and the evolution of dietary carbon footprints across demographic groups.

However, scanner data measure actual purchases in the home for household use and as such do not measure food consumed out of the home. Under-reporting can also occur if households fail to scan some purchases. Moreover, the income variables are less detailed than those available in national expenditure surveys. We return to these issues in more detail in the following sections. Nevertheless, the richness and granularity of scanner data make them uniquely valuable for our purposes.

We employ a two-step empirical strategy to address the two main questions of the paper. First, we estimate the socio-economic factors associated with household dietary carbon footprints (what we refer to as the static analysis) using Ordinary Least Squares (OLS) regression. Specifically, we examine how dietary footprints vary with household characteristics, and we replicate the analysis separately for food quantities and for category-specific carbon intensities in order to shed light on the drivers of heterogeneity in dietary footprints.

The second part of the analysis focuses on the relationship between time variations in dietary carbon footprints and household characteristics (the dynamic analysis). We classify households according to whether they reduced, maintained, or increased their carbon footprints between 2017 and 2022, and we use a multinomial logit model to examine how household characteristics influence the probability of having maintained or reduced, rather than increased, their footprint. Since the multinomial logit framework does not allow us to account for the timing of changes in household characteristics over time (for instance, a change in the gender of the main shopper), this analysis is restricted to households whose observed characteristics remain stable across the five-year period.

We find substantial heterogeneity in dietary carbon footprints across households, driven by both quantities consumed and the carbon intensity of purchases. Older, less-educated, and female main shoppers, as well as larger and predominantly male households and those with children, tend to have higher footprints. Over time, households with higher footprints are more likely to reduce them, especially middle-aged, less-educated, and larger households, while households with children and predominantly male households show little adjustment. Among reducers, almost all lower the quantity of food purchased, and a majority also reduce the carbon intensity of their diets; while reductions in quantity are widespread, older and smaller households are particularly more likely to lower carbon intensity. Taken together, these results reveal both encouraging signs of adjustment and clear opportunities for targeted policies to foster more meaningful dietary transitions.

Although our results are descriptive rather than causal, they provide clear guidance for policy. They show which households emit more, which are more likely to respond to incentives to reduce quantities or shift toward lower-carbon products, and which (such as younger, highly educated, or child-rearing households) may require additional nudges to reduce their dietary emissions.

2 Related literature

Until recently, much of the literature on the impact of dietary shifts on household emissions focused on typified diets, examining for example the potential benefits of switching from meat-based to plant-based diets (Baroni *et al.*, 2007; Reijnders &

Soret, 2003), or relied on national averages of dietary habits (e.g., Carlsson-Kanyama *et al.* (2003) for Sweden, or van de Kamp *et al.* (2018) for the Netherlands). As noted by Vieux *et al.* (2012), while these approaches are informative, they offer limited insight into the actual effort required by individuals to lower their carbon footprints and do not capture heterogeneity in dietary emissions across the population. Using French data, Vieux *et al.* (2012) was among the first to investigate the environmental impact of self-selected diets, opening the way for a wave of similar studies exploring heterogeneity in other countries. Such studies include Rose *et al.* (2019) in the United States, Strid *et al.* (2019) in Sweden, Auclair & Burgos (2021) in Canada, and Franco *et al.* (2022) in Chile. Our study contributes to this growing literature in several key ways.

First, existing work has focused almost exclusively on the carbon intensity of diets when explaining heterogeneity (Rose *et al.*, 2019; Auclair & Burgos, 2021; Strid *et al.*, 2019). Yet total dietary footprints are determined by both the quantity of food purchased and the emissions associated with each good. Two exceptions are Vieux *et al.* (2012), who examine both dimensions to investigate the reduction potential of different scenarios (e.g., reducing over-consumption versus shifting away from red meat), and Franco *et al.* (2022), who investigate overall dietary emissions' relationship to income. However, the latter does not disentangle the role of quantity and carbon intensity in driving this heterogeneity.

In addition, studies that investigate heterogeneity in the carbon intensity of diets typically compare individuals at the top and bottom of the emission distribution without multivariate controls, making it difficult to isolate specific household traits. Strid *et al.* (2019), Rose *et al.* (2019) and Auclair & Burgos (2021) investigate heterogeneity in carbon footprints by comparing the share of individuals with given characteristics in the top and bottom quintiles of the footprint distribution, while Vieux *et al.* (2012) do so by comparing averages between groups. Franco *et al.* (2022) compute mean dietary carbon footprints by income quintile and describe differences in emissions across groups. In contrast, our econometric specification allows us to evaluate how each household characteristic separately influences purchase quantities, carbon intensity, and the resulting overall dietary carbon footprint.

Many of these studies rely on either 24-hour dietary recalls (Vieux *et al.*, 2012; Rose *et al.*, 2019) or food-frequency questionnaires (Strid *et al.*, 2019), both of which provide only brief snapshots of intakes and are subject to recall bias. Some analyses are also limited in dietary detail: for instance, Vieux *et al.* (2012), Strid *et al.* (2019), and Franco *et al.* (2022) group food into 73, 64 and 59 items, respectively. In contrast, Auclair & Burgos (2021) and Rose *et al.* (2019) incorporate environmental estimates for approximately 6,000 distinct food, offering greater granularity. Building on this, our scanner data provide an even more comprehensive picture by tracking the purchase of over 70,000 food products brought into the home, characterised by more than 26,000 emission factors over a 5-year period.

In addition to identifying which household characteristics are associated with larger dietary carbon footprints, this paper also investigates which characteristics are linked to reductions in emissions over time. Several recent studies have examined time variations in dietary carbon footprints, but they face important limitations. Bassi *et al.* (2022) and Mehlig *et al.* (2021) rely on repeated cross-sectional data, preventing them from following the same individuals over time. Esteve-Llorens *et al.* (2021) use aggregate household purchase data in a descriptive framework, without analysing heterogeneity across individual households. Hjorth *et al.* (2020) do use panel data, but their analysis is limited to a descriptive tracking of emission quintiles and does not attempt to isolate the role of specific household traits. Moreover, most of these studies either focus on average footprint levels or broad trends, with limited attention to disentangling whether changes are driven by reduced quantities or shifts in carbon intensity. In contrast, this paper estimates which household characteristics are associated with a greater probability of having increased or decreased their dietary carbon footprint, and, among those identified as reducers, examines whether the reduction is more likely to have been driven by a decrease in food quantity or a decline in the carbon intensity of purchases. We thus contribute to the literature by uncovering the household traits linked not only to emission reductions overall, but also to distinct mitigation strategies.

3 Data & measurement

The environmental footprint of diets is computed by putting together consumption data from Worldpanel by Numerator's Take Home data, a longitudinal dataset tracking the food purchases of approximately 30,000 GB households yearly, and the SHARP-ID environmental database, which provides European averages of the greenhouse gas emissions associated with the life cycle of 944 food products. By merging these datasets, we convert the detailed purchase information into precise carbon footprint measurements.

3.1 Data sources

Consumption data. Households' food purchases were computed using longitudinal data on the entire shopping basket of a sample of households in Great Britain over the period 2017–2022: Worldpanel by Numerator's Take Home data. These scanner data document expenditures, quantities, and characteristics of food brought into the homes of approximately 30,000 households in Great Britain each year.

Households record all grocery purchases—whether online, in supermarkets, or at farmers' markets—made and brought into the home using handheld scanners. The data are provided at the transaction level (i.e., the barcode level).

Importantly, there might be intervals during which individuals fail to record their grocery purchases (such as during holidays), potentially inflating the perceived heterogeneity in diet-related emissions. Following the literature using scanner data in their analysis, we assume inadequate recording if individuals fail to record any grocery purchases for more than two weeks, and we exclude individual months containing any part of a period of non-recording. We keep in sample households that record purchases consistently for at least 7 months in a year, and drop the month of December to improve comparability.[1]

Households in the sample answer a yearly household characteristics survey. The data includes information at various levels. At the individual level, we use the gender, age, education, and income of the individual mostly in charge of grocery shopping (thereafter called 'the main shopper'). At the household level, we use information on the household composition, whether it is a single or multi-person household, whether kids are present, whether it is a rural or urban household, and the age and gender of each household member.

This information is used to construct two additional variables: first, the share of female household members over the age of 13, allowing us to examine gender effects beyond just the main shopper, and second, the household energy requirement index (HERI).[2] This index is calculated by summing the standardised dietary requirements of all household members, calculated based on their age and gender and following nutritional guidelines for daily caloric needs. For example, an adult man is assigned a requirement of 2.5, while an adult woman is assigned 2. Thus, a household with one man and one woman would have a combined energy requirement index of 4.5. In contrast, a single mother with a 7-year-old daughter would have a total dietary requirement of 3.53 (2 + 1.53). These age- and gender-specific nutritional needs are based on recommendations from the GB Department of Health (Public Health England, 2017).

[1] Note 1: By keeping households who record purchases for at least 7 months in a year, we acknowledge the risk of detecting household heterogeneity based on the seasons in which households record: food consumption is seasonal, inducing households' footprint to be as well. We control in the analysis for the share of total calories purchased in each season to account for this potential confounder.

Note 2: With the end-of-year celebrations, the month of December adds noise to the estimation, and comparing households that record and do not record purchases in December would not be meaningful.

[2] As the proportion of women in a household increases, their preferences are more likely to shape food consumption patterns.

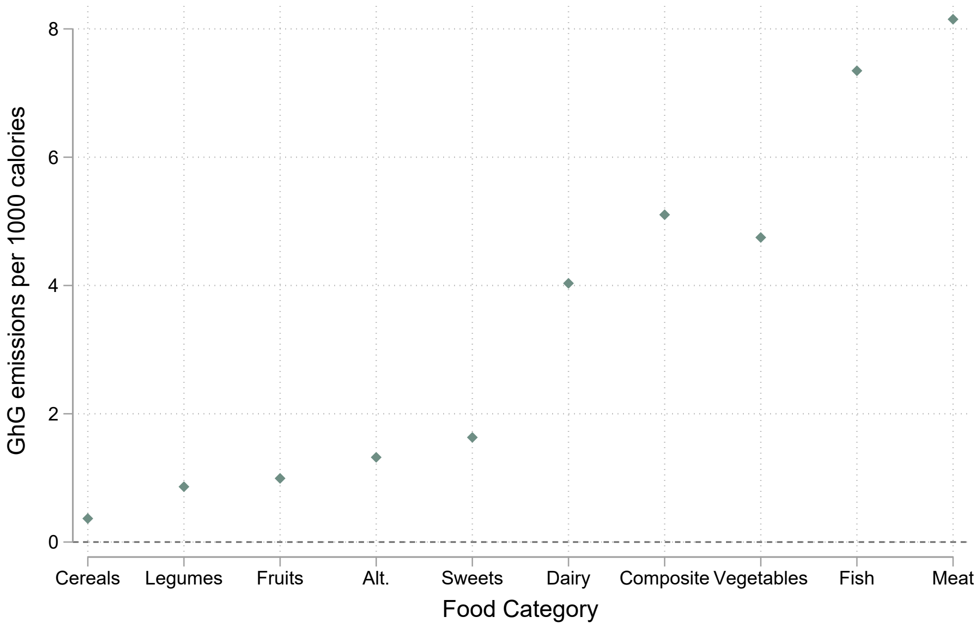
Environmental data. The emission factors used to compute dietary carbon footprints are retrieved from Mertens *et al.* (2019)'s SHARP-ID database. These data provide a European average of the greenhouse gas emissions (including carbon dioxide (CO_2), methane ($CH4$)), and nitrous oxide (N_2O)) associated with the life cycle of 944 food products.

The environmental impact measures are based on primary product life cycle assessments and include emissions associated with the entire life cycle of food products: from the farm to the plate of consumers. Emissions from farming, processing and mass changes, packaging, transportation, and home preparation are included. Emissions multipliers for each stage of the products' life cycle have been retrieved from AgriFootprint 2.0, EcoInvent 3.3 and Capri. Conversion factors for packaging, transportation, and home preparation were computed based on good-specific most frequent packaging type, transportation means and distances, and cooking method. More details on the data creation process are available in Mertens *et al.* (2019).

Importantly, although we compare households' dietary emissions from 2017 to 2022, we apply constant emission factors over time. Time-varying emission multipliers are available from environmentally extended multi-regional input–output models (MRIO), but lack granularity in their food categories. As such, the GB-specific emission factors from the GB-MRIO (DEFRA, 2024) cover only 7 broad categories, and do not allow a precise investigation of the role of carbon intensity in driving heterogeneity in households' dietary emissions. We opt for more granular conversion factors, which enable us to fully exploit the detailed information available in Worldpanel by Numerator's Take Home data. Since consumers rarely observe production technologies directly, they cannot typically choose between more or less carbon-intensive variants of the same product. If, as is likely, all households in our sample were exposed to similar technological changes in the production of their purchased goods, then using constant emission factors does not pose a concern for comparing their dietary emissions.

Merging purchase and environmental data. We match observations in the Worldpanel by Numerator's Take Home data to environmental estimates from the Sharp-ID, and manage to cover over 90% of households' food expenditure in our sample. Products are either directly matched to an environmental estimate available in the SHARP-ID, or approximated using product characteristics (e.g., for a prepared meal: the emission multiplier depends on the primary type of meat found in the meal and the side dish type). The outcome of this process is a highly granular account of food's environmental impact. Table 1 illustrates the level of detail in our environmental estimates for a selected subset of food items. The final dataset includes

Figure 1: GhG emissions associated with 1,000 calories of food by food groups.



Notes: Conversion factors in $kgCO_2$ per 1000 calories, computed combining SHARP-ID's emission factors in $kgCO_2$ per kg of food and nutrition data (energy density) from Worldpanel by Numerator, GB Take Home panel.

26,752 different estimates of CO_2 emissions per calorie.[3]

Figure 1 presents the average emission factors for food products across the 10 main food categories in the dataset. It is important to keep in mind that emission factors expressed in CO_2 equivalent per 1,000 calories increase with the emission intensity of a product's life cycle and decrease with its caloric density. As such, meat has the highest emission factor due to its production-related emissions, while vegetables appear to have relatively high emission factors because they contain few calories per kilogram.

3.2 Measurement

To investigate households' heterogeneity of in-home food purchase GHG emissions, we compute their average monthly dietary carbon footprint. Quantities of each purchased goods are aggregated monthly and multiplied by their emission multiplier, to get households' total monthly carbon footprint in kilograms of CO_2 equivalent ($kgCO_2e$). Monthly footprints are then averaged yearly.

Carbon footprints are driven by two forces: the carbon intensity (CI) of food choices,

[3]The high number of estimates of environmental impacts is due to them being in $kgCO_2e$ per calorie: they are derived by dividing the emissions factor per kilogram by the number of calories per kilogram, with calorie information available at the product barcode level.

Table 1: Example of emissions factors from Sharp ID

Food category	**Example of products**	**GHG (kgCO$_2$e/kg)**
Composite dishes	Pizza and pizza-like dishes	5.56
	Meat-based dishes	17.64
	Legumes-based dishes	1.62
Fish, seafood	Fish fingers, breaded	5.32
	Salmons	4.65
Meat and meat products	Cooked pork ham	10.24
	Bovine, minced meat	34.04
	Meat imitates	2.29
Fruits	Apples	0.74
	Nectarines	0.34
Vegetables	Cauliflowers	1.72
	Spinaches	0.65
Grains and grain-based	Bulgur	0.56
	Dried pasta	0.45
	Croissant	21.9
Dairy and dairy products	Cow Milk	1.58
	Soya drink	0.53

Notes: Selection of emissions factors from the SHARP-ID database, in KgCO$_2$/kg.

depending exclusively on the type of food the shopper purchases (e.g. beef versus chicken) and the quantity of food purchased (Q). We investigate these two drivers to pinpoint the source of household heterogeneity.

Carbon intensity. The carbon intensity metric provides for each household the greenhouse gas emissions in kgCO$_2$e associated with 1,000 calories of food representative of their purchases. It is computed as the calorie-share weighted average of the emission factors of purchased goods. Monthly carbon intensities are then averaged yearly.

Quantity. Households' purchased quantities are given by the sum of purchased calories monthly, and are then averaged yearly.

To better understand the respective importance of food quantity and carbon intensity in driving variation in household dietary footprints, we perform a variance decomposition using the logarithmic identity log(CF)=log(Q)+log(CI). This allows us to express the total variance in log carbon footprint as the sum of the variances in log quantity and log carbon intensity, along with their covariance. Results show that variation in food quantity accounts for 89.4% of the observed variance in carbon footprint across household-year observations, while variation in carbon intensity explains 17.1%. The covariance term is negative (7.4%), indicating that households purchasing larger quantities of food are characterised by a lower carbon intensity, and vice versa. This offsetting relationship reduces the overall variability in carbon footprints. While these results show that variation in food quantity is the dominant driver of footprint heterogeneity, the contribution of carbon intensity is still substantial and policy-relevant. Both dimensions are therefore critical to understanding and reducing household dietary emissions.

3.3 Descriptive statistics

Two samples are used for the analysis. First, to investigate the relationship between households' characteristics and their dietary footprint, we retain all households present in the data from 2017 to 2022. This sample consists of 23,961 households and serves as the main dataset for the static analysis.

Second, to investigate time-variations in dietary footprint, and, more specifically, households' likelihood of having reduced or maintained rather than increased their dietary footprints over the period, we retain all households in sample both in 2017 and 2022 and whose characteristics remain stable over the period. The latter restriction allows us to avoid issues related to the timing of changes in household composition. Specifically, we exclude households where key socioeconomic variables (e.g., income category, household size, or gender of the main shopper) exhibit temporal variations. To minimise the number of households we exclude from the sample, we generate new variables categorising households with respect to their age, dietary requirements, share of women in the household and income, such that a small variation in these variables does not lead us to exclude them. Age becomes a categorical variable with three values, depending on whether the main shopper is younger than 40 years old, older than 60, or between 40 and 60. Income takes three values: low if the main shopper's income is below 20k per year, high if it is above 60k, and medium otherwise. The energy requirement index becomes a binary variable equal to 1 if dietary requirements are low (lower than or equal to 4.5, which is equivalent to an adult man and woman in the household). The share of women over 13 in the households becomes a categorical variable with 3 values: 1 if there is a majority of women, 2 if there are as many adult women as adult men, and 3 if there is a majority of adult men. These variables are less likely to vary on the period than continuous variables, thus helping us maximize the sample size when dropping varying households.

Table 2 provides summary statistics for both samples, and shows that this restricted sample remains comparable to the full sample, with key explanatory variables showing similar distributions. In both samples, the primary grocery shoppers are mostly middle-aged women. Nearly half hold a higher education diploma. The sample primarily consists of urban, childless, multi-person households, with a majority of male members. Income distribution indicates that around 43% of main shoppers fall into the 10-30k annual income bracket.

On average, 1,000 calories in household food purchases are associated with 2.410 kilograms of CO_2 equivalent, and households' average dietary footprint is 226 kgCO_2e. Households purchase approximately 95,712 calories per month. For an average household size of 2.65 members over 30 days, this translates to roughly 1,240 calories per person per day, significantly below official dietary requirements. This discrepancy could be attributed to a number of factors such as not reporting out of home purchasing/consumption. However, as long as under-reporting is not systematically associated with specific household characteristics, this should not bias the analysis. We discuss further the role of food consumed outside the home and reporting issues in Section 4.

4 Static analysis

4.1 Empirical strategy

This section investigates how socioeconomic characteristics are associated with differences in household dietary carbon footprints. We distinguish between characteristics of the main shopper and characteristics of the household. For the main shopper, we focus on age, gender, and education. For household-level traits, we consider the household energy requirement index, the presence of children, and the gender composition.

Importantly, we investigate the role of household and main shopper characteristics separately for single- and multi-person households. Indeed, there is evidence in the literature that preferences are not stable across household compositions (e.g. Hubner (2020)). We emphasize that, although both single women and women in a relationship have more environmentally friendly preferences than men (both in quantities and carbon intensity), this finding does not hold when looking specifically at overall food carbon footprints. Women are found to be more environmentally friendly than men in their food purchases only for single-person households.

The relationships between main shopper and household characteristics and dietary carbon footprints are estimated with ordinary least squares as shown in equation 4.1. We then investigate the role of quantity (total calories purchased) versus carbon intensity (kgCO_2e per 1,000 kcal) to understand the mechanisms behind observed differences. This enables us to disentangle the heterogeneity in dietary footprint as being due to the total quantity of food purchased, the type of food purchased, or

Table 2: Summary statistics - average values for 2017-2022

	Full sample		Restricted sample	
	Mean	SD	Mean	SD
Main shopper characteristics				
Age	52.552	14.351	57.881	13.215
Female	0.737	0.439	0.707	0.455
Higher education	0.522	0.493	0.497	0.500
Household characteristics				
Single	0.189	0.382	0.234	0.424
Household size	2.650	1.275	2.309	1.151
Diet. needs	5.581	2.629	4.976	2.350
Presence of children	0.357	0.466	0.200	0.400
Share of women	53.428	26.036	52.345	27.241
Controls				
Urban	0.841	0.360	0.828	0.378
Main shopper's income				
0-10k	0.059	0.217	0.067	0.228
10-20k	0.216	0.381	0.204	0.390
20-30k	0.214	0.373	0.223	0.386
30-40k	0.172	0.339	0.195	0.343
40-50k	0.125	0.295	0.130	0.287
50-60k	0.085	0.247	0.066	0.215
60-70k	0.050	0.190	0.036	0.170
70k+	0.080	0.256	0.079	0.258
Diet characteristics				
Carbon intensity	2.410	0.482	2.411	0.471
Monthly dietary CF	226.531	106.549	227.376	103.572
Monthly purchased calories	95,712.021	43,551.100	95,892.287	41,954.096
N	23,961		5,883	

Notes: The full sample includes GB households from Worldpanel data present in any year between 2017 and 2022. The restricted sample includes households present both in 2017 and 2022, and whose characteristics have remained more or less stable over the period. The main shopper is defined as the household member mostly in charge of the grocery shopping. Higher education is a dummy variable equal to 1 if the main shopper in the household has any higher education diploma. The variable single is a dummy variable equal to 1 if the household includes one person only, and 0 otherwise. Income is given in thousands of pounds.

both. We control for year fixed effects, and cluster standard errors at the household level. We estimate:

$$Y_{ht} = \alpha + \beta_1 X_{ht} + \beta_2 T_{ht} + \delta_t + \epsilon_{ht} \tag{4.1}$$

where Y_{ht} is the dependent variable at time t. Depending on the model specification, it can be:

1. the dietary carbon footprint from in-home food purchases,
2. the quantity of food purchased in volume in kcal purchased,
3. the carbon intensity of food purchases, in kgCO_2e / 1,000 kcal.

X_{ht} is the vector of characteristics of the household and main shopper at time t, including the age and gender of the individual in charge of the grocery shopping in the household, a binary variable for whether the main shopper has followed some higher education, the household energy requirement index, a binary variable indicating the presence of children in the household, and the share of women among adults.

T_{ht} is the vector of controls at time t. It comprises the main shopper's income to capture variations in financial constraints that may influence household food choices. We however do not discuss it in detail as it is imprecisely measured in the data and refers only to the main shopper. We also control for whether the household is located in a rural or urban area at each period, given that urban households are more likely to consume food outside the home, which could bias our estimates. The limitations of the data regarding food-away-from-home consumption are discussed more in depth in Section 4.4 along with a proposed robustness check to address this issue. Finally, we control for the share of calories purchased each season to account for the seasonality of food purchases (diets might for instance be associated with more emissions in the summer because of the barbecue season, and less from January to June because people tend to start diets and eat more fruits and vegetables at the beginning of each year).

Importantly, when investigating heterogeneity in carbon intensity, we control for total calories purchased to avoid capturing mechanical variations in calorie shares (i.e., shifts in the proportion of calories from a food group that occur solely due to changes in total calorie purchases).[4] For instance, if a household consistently buys 2,000 kcal of meat but increases its total food purchases from 5,000 kcal to 6,000 kcal, the share of calories from meat would fall from 40% to 33%, even though actual meat consumption remains unchanged. Controlling for total calories helps isolating genuine changes in diet composition.

[4]Recall that the carbon intensity measure is equal to weighted average of emission factors, where the weights are the good-specific calorie shares.

Finally, δ_t denotes year fixed effects, capturing common temporal shocks (e.g., price changes, policy shifts, economic trends), and ϵ_{ht} is the error term.

4.2 Results

Table 3 reports results separately for multi-person households (Panel A) and one-person households (Panel B). All models include year fixed-effects and clustered standard errors at the household level. Columns (1) and (4) use total dietary carbon footprint as the dependent variable, Columns (2) and (5) focus on food quantity (calories), and Columns (3) and (6) on dietary carbon intensity (kgCO_2e per 1,000 calories).

Main shopper Characteristics. The characteristics of the person in charge of grocery shopping in the households, namely their age, gender and education level, strongly influence dietary emissions. While the effects of age and education on dietary footprints are consistent across household types, the role of gender differs depending on whether the individual lives alone or shops for a multi-person household.

A 10-year increase in the main shopper's age is associated with a 33.3 kgCO_2e (resp 37.75 kgCO_2e) increase in monthly dietary emissions in multi-person (resp. one-person) households, an increase equivalent to nearly 14.7% of the sample average. In the two household compositions, this increase is driven by older main shoppers purchasing both larger quantities and more carbon-intensive food. In multi-person households, a 10-year age increase corresponds to a 9.3% rise in calories purchased and a 6.2% increase in carbon intensity, relative to the respective sample averages. Similar magnitudes are found for one-person households.

Education shows a comparable effect in both types of household: higher education is associated with lower dietary emissions. Specifically, multi-person households with a highly educated shopper emit 14.6 kgCO_2e less per month: a 6% reduction relative to the sample average, due to both significantly fewer calories purchased (4.3% less relative to the sample average), and less carbon-intensive food choices (a decrease in carbon intensity equivalent to 2% of the average carbon intensity). Again, the magnitude and direction of the relationship between education and quantities and carbon intensities are similar in one-person households.

The effect of gender differs by household composition. In multi-person households, having a female main shopper is associated with higher dietary emissions (+16 kgCO_2e per month), whereas in one-person households the association is negative (–3.2 kgCO_2e). These contrasting results are driven entirely by differences in food quantities, since female shoppers tend to buy more carbon-intensive goods in both household types. The estimated gender effect on carbon intensity is, however, three times larger for one-person households than for multi-person households (2% vs. 0.6% of the sample mean). In terms of food quantities, female shoppers in multi-person households purchase about 6,337 more calories per month than their male counterparts, while in one-person households they purchase about 2,139 fewer calories. We discuss possible mechanisms behind these differences below.

Household Characteristics. Finally, we examine the impact of household-level characteristics for multi-person households, namely their energy requirements, the presence of children in the household and the gender distribution of its members.

Dietary emissions rise with the household energy requirement index. This is fully due to higher calorie purchases, as expected, while food choices become slightly less carbon intensive.[5] One additional adult male in the household (which raises the index by 2.5) increases its monthly dietary footprint by 40.8 kgCO_2e. This increase is entirely explained by higher calorie purchases: an additional adult leads to 20,306 more calories purchased each month on average, while the carbon intensity of purchases falls by 0.04 kgCO_2e per 1,000 calories (equivalent to a 21.2% rise in calories and a 1.6% decline in carbon intensity relative to sample averages).

Independent of households' energy requirement index, the presence of a child in the household is associated with a 8.6% rise in dietary emissions. This increase is entirely driven by higher food quantities, whose effect is however partially offset by the fact that the food consumed tends to be less carbon-intensive, with a reduction of 0.07 kgCO_2e per 1,000 calories equivalent to 2.9% of the average carbon intensity.

The gender composition of the household also plays a significant role. In multi-person households, a 15-percentage-point increase in the share of women over age 13 is associated with a reduction of 7.4 kgCO_2e in monthly dietary emissions.[6] This decline is driven by a lower quantity of calories purchased (a decrease of 2,643 kcal or 2.8% of the sample average), and lower carbon intensity (a decrease equivalent to 0.6% of the sample average).

4.3 The role of diet composition

Variations in carbon footprints reflect both the total quantity of food purchased and the types of food consumed. To better understand differences in the latter, we analyse diet compositions to identify which food categories drive variation in carbon intensity across household characteristics.

[5] Recall that the household energy requirement index reflects household size as well as the age and gender of its members.

[6] A 15 percentage-point increase is equivalent to comparing a new woman arriving in a household of 4 individuals above age 13 where only 1 was a woman prior to her arrival.

Table 3: Between households variations in food carbon footprint, calories purchased and carbon intensity 2017-2022.

	PANEL A Multi-person households			PANEL B One-person households		
	(1) Total CF	(2) Q	(3) CI	(4) Total CF	(5) Q	(6) CI
Main shopper characteristics						
Age	3.554***	937.623***	0.015***	4.075***	1399.430***	0.016***
	(0.343)	(132.122)	(0.002)	(0.417)	(160.570)	(0.004)
Age squared	-0.022***	-5.055***	-0.000***	-0.030***	-10.569***	-0.000***
	(0.003)	(1.191)	(0.000)	(0.003)	(1.336)	(0.000)
Female (ref: Male)	15.961***	6336.984***	0.016*	-3.190*	-2139.242***	0.048***
	(1.818)	(689.933)	(0.009)	(1.883)	(684.292)	(0.018)
Higher education	-14.585***	-4119.560***	-0.049***	-11.463***	-3479.852***	-0.057***
	(1.524)	(583.310)	(0.007)	(1.895)	(690.168)	(0.018)
Household characteristics						
Diet. needs	16.309***	8122.793***	-0.015***			
	(0.466)	(183.834)	(0.002)			
Presence of children=1	19.547***	11229.476***	-0.068***			
	(1.989)	(778.668)	(0.009)			
Share of women	-0.497***	-176.224***	-0.001***			
	(0.043)	(16.820)	(0.000)			
Controls						
Urban (ref: Rural)	1.566	-2428.783***	0.063***	0.549	-1753.684**	0.081***
	(1.877)	(716.848)	(0.009)	(2.383)	(881.848)	(0.022)
Income bracket (ref: 0-10k£)						
10-20k	6.963*	2157.790	0.026	2.554	-330.431	0.069***
	(3.795)	(1495.324)	(0.019)	(2.374)	(861.109)	(0.022)
20-30k	13.763***	3355.860**	0.063***	4.728*	-1113.965	0.137***
	(3.887)	(1525.562)	(0.019)	(2.825)	(1016.070)	(0.026)
30-40k	16.853***	2980.992*	0.108***	9.058**	-1815.451	0.242***
	(3.957)	(1562.302)	(0.019)	(3.572)	(1243.059)	(0.032)
40-50k	14.663***	766.112	0.132***	0.384	-3842.257**	0.202***
	(4.033)	(1586.164)	(0.020)	(4.319)	(1604.847)	(0.042)
50-60k	15.666***	-445.677	0.163***	1.049	-3959.662**	0.169***
	(4.177)	(1635.757)	(0.020)	(5.928)	(1924.127)	(0.052)
60-70k	13.815***	-2427.597	0.187***	9.143	-1656.523	0.202**
	(4.482)	(1727.024)	(0.021)	(9.590)	(2940.517)	(0.085)
70k+	0.449	-6385.843***	0.147***	1.746	-3924.875	0.241***
	(4.331)	(1693.796)	(0.021)	(7.836)	(2863.638)	(0.084)
Seasonality controls	Y	Y	Y	Y	Y	Y
Time fixed effects	Y	Y	Y	Y	Y	Y
Quantity control	N	N	Y	N	N	Y
Constant	25.712**	20877.914***	2.134***	13.337	16887.139***	1.949***
	(10.725)	(4198.532)	(0.054)	(13.606)	(5208.850)	(0.135)
Observations	61523	61523	61523	14982	14982	14982
R^2	0.185	0.260	0.054	0.041	0.042	0.025

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The sample includes GB households from Worldpanel data present in any year between 2017 and 2022. Columns (1) and (4) provide OLS regression results for the relationships between characteristics and total dietary carbon footprint, Columns (2) and (5) focus on food quantity (calories), and Columns (3) and (6) on dietary carbon intensity (kgCO_2e per 1,000 calories). Each model controls for the share of calories purchased each season to account for the seasonality of consumption and for year effects. Quantity purchased is controlled for when investigating carbon intensity to account for mechanical variations due to changes in total calories purchased instead of meaningful dietary shifts. Standard errors are clustered at the household level.

Two mechanisms can drive differences in the overall carbon intensity of diets: variations in the share of calories derived from different food types (e.g., some households obtaining most of their calories from legumes, while others rely more heavily on meat), and differences in carbon intensity within food categories (e.g., some households consuming primarily beef, while others favor chicken for the same quantity of total meat purchased). To investigate the importance of both mechanisms for different household types, we replicate the estimation of Equation 4.1, using two dependent variables: the share of total calories dedicated to each food group, and the carbon intensity of purchases within these food groups.

Table 4 provides the effect of socioeconomic characteristics on the calorie share of each of the 10 types of food in the data (column %) and on the carbon intensity of the food choices within this category of food (column CI) in multi-person households. Results for one-person households are similar and can be found in Appendix A. Importantly, knowing how dietary structure varies with socio-economic characteristics does not directly inform us on the effect of these variations on the carbon intensity of the diet. We need to translate the estimated effects on shares of food and within-group carbon intensity into their impact on total dietary carbon intensity (expressed in $kgCO_2e$ per 1,000 kcal). Given that changes in the share of calories from one food category are offset by proportional changes across all other categories, we translate estimated effects as follows,

$$\Delta CI^{share_f} = \beta_{if} \times (\bar{CI}_f - \bar{CI}_{-f}) \tag{4.2}$$

$$\Delta CI^{CI_f} = \gamma_{if} \times \bar{S}_f \tag{4.3}$$

where ΔCI^{share_f} is the variation in overall carbon intensity due to a change in the share of total calories food f represents, and ΔCI^{CI_f} the one due to the change in category f's carbon intensity. β_{if} is the estimate of the effect of characteristic i on the share of calories from category f (in percentage points) $\bar{CI}_f$ is the average carbon intensity of food purchases in category f in the sample, $\bar{CI}_{-f}$ is the average overall dietary carbon intensity in the sample excluding f, γ_{if} is the estimate of the relationship between the characteristic i and the carbon intensity of category f (in $kgCO_2e$/1,000kcal), and $\bar{S}_f$ is the share of calories dedicated to product category f on average in the sample.[7]

[7] We take the difference between the carbon intensity of category f and the mean without f because shifting calories toward one category implies displacing calories from the rest of the diet, so the net effect on total carbon intensity depends on how much more or less emission-intensive that category is relative to the average.

Results. We discuss below the translation of the results in Table 4, based on Equations 4.2 and 4.3.[8] We focus here on results for multi-person households, as those for one-person households are comparable.[9] Detailed results for the latter are reported in Appendices A and B. The heterogeneity in dietary carbon intensity is primarily driven by four food categories: meat, dairy, composite, and confectionery products.

The rise in carbon intensity with the age of the main shopper is largely explained by meat consumption. Older individuals derive a greater share of their calories from meat, which is the most carbon-intensive food group in the data (7.67 $kgCO_2e$ per 1,000 calories). As a result, a 10-year increase in age is associated with a 0.075 $kgCO_2e$ per 1,000 calories increase in overall carbon intensity due to the higher share of calories devoted to meat (about 3.1% of the sample average). Lower sweet consumption among older individuals also contributes to higher overall carbon intensity. Since sweets are among the least carbon-intensive food groups, their reduced consumption leads, somewhat counterintuitively, to an increase of 0.016 $kgCO_2e$ per 1,000 calories.

Although older individuals consume slightly smaller quantities of dairy products, which lowers carbon intensity by 0.017 $kgCO_2e$ per 1,000 calories (0.7% of the sample mean), they tend to purchase more carbon-intensively in this category, which fully offsets this quantity effect.

The effect of higher education on dietary carbon intensity is again primarily explained by lower meat consumption. Households with a highly educated main shopper obtain a smaller share of their calories from meat, which reduces carbon intensity by 0.04 $kgCO_2e$ per 1,000 calories (about 2% of the sample mean). Although individually modest, this effect is reinforced by other differences in food choices: highly educated main shoppers purchase fewer composite goods and more cereal-based products, both of which further reduce carbon intensity. At the same time, a tendency to purchase more carbon-intensive dairy products partly offsets these reductions.

Although households with greater dietary needs (as measured by a higher household energy requirement index) obtain a slightly larger share of their calories from meat, this effect is more than offset by other factors. The main driver of the lower carbon intensity associated with higher HERI is the reduced carbon intensity of the composite goods they purchased. An increase in the energy requirement of households is associated to a lower carbon intensity of composite good purchases, a shift toward less carbon-intensive meats, and a smaller share of calories from dairy. Together,

[8]The computation results can be find in Tables 8 and 9 in Appendix B.

[9]We do not discuss in this section characteristics whose effect on carbon intensity is lower than 1% of the average overall carbon intensity. As a result, we do not discuss results for the gender of the main shopper and the gender distribution of household members in multi-person households.

these changes reduce overall dietary carbon intensity by 0.023 kgCO_2e per 1,000 calories for a 2.5 increase in the HERI (equivalent to the addition of one adult man to the household), or about 1% of the sample mean.

The lower carbon intensity associated with households with children is mainly explained by a smaller share of meat in their diet and by the lower carbon intensity of the meat they purchase, together reducing emissions by 0.051 kgCO_2e per 1,000 kcal (or 2.11% of the mean). Additional reductions come from less carbon-intensive choices of dairy, composite, and confectionery products, combined with a higher share of sweets, which are relatively low impact. The only counteracting factor is their higher overall dairy consumption, though this effect is too small to offset the reductions from other categories.

A similar role of dietary structure and food-specific carbon intensity is found in explaining heterogeneity by age and education in one-person households. We however discuss here the differences between single men and women, as the gender gap in carbon intensity is significant (unlike in multi-person households). Women's larger carbon intensity of food choices is mostly driven by more carbon intensive dairy and confectionery good choices, and the lower share of calories they allocate to cereal-based products (cereals-based goods have low associated emissions), together accounting for an increase in CI of 0.079 kgCO_2e per 1,000 kcal (3.3% of the sample mean). Single women also buy more vegetables than men, which further contributes to the higher footprint of their diets (recall that vegetables are associated with high emissions per calorie due to their low caloric density). Women however allocate fewer calories to meat and fish, and purchase less carbon-intensive composite goods.

Figure 2 summarizes our findings by depicting the relative contributions of each food type to the heterogeneity in carbon intensity across characteristics estimated in Table 3.[10]

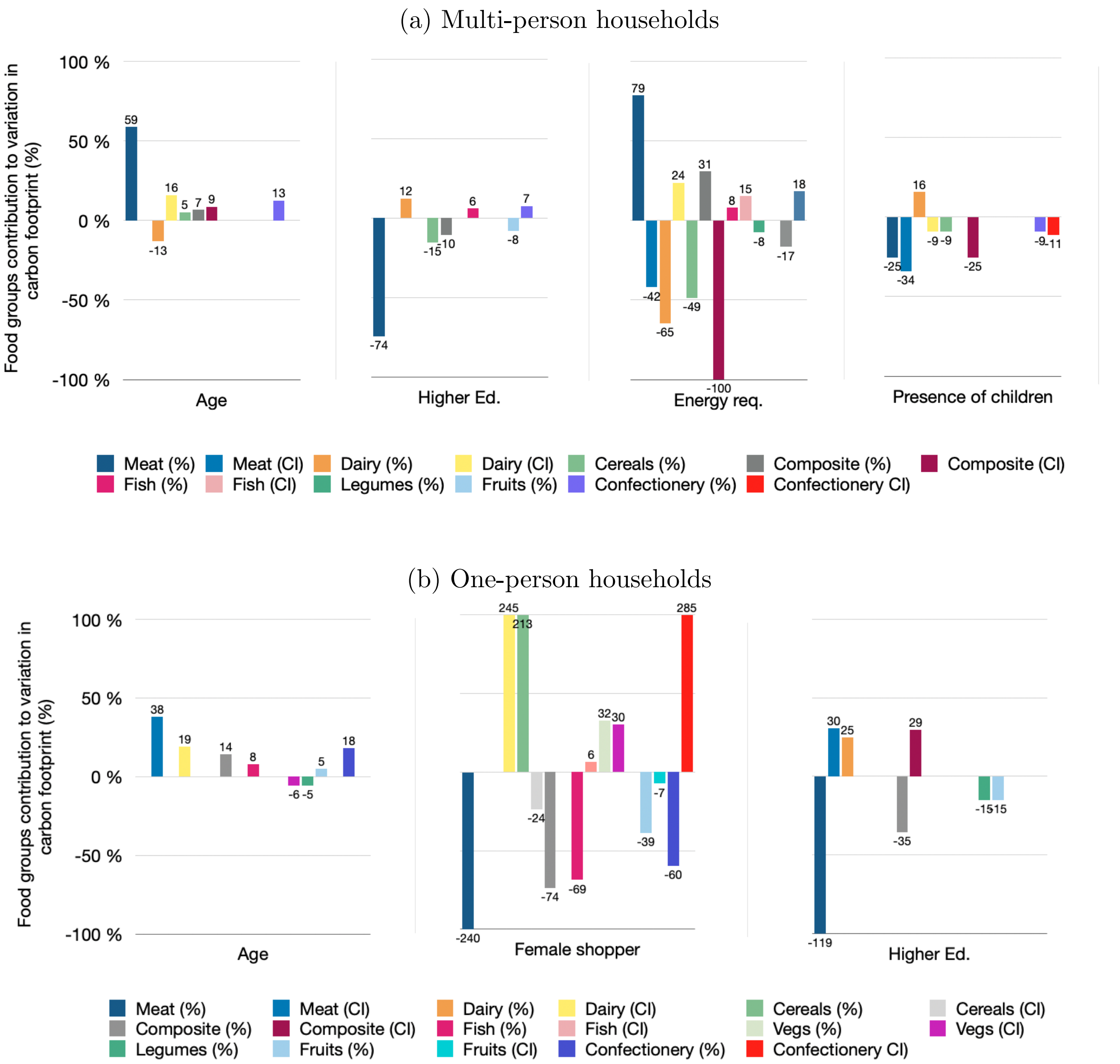
4.4 Discussion

The previous analysis has shed light on older, less educated female main shoppers being associated with a larger carbon footprint, and on the role of household composition in driving heterogeneity in dietary footprints. We discuss in this section potential drivers of these differences, focusing on the potential role of preferences and prices.

A concern in attributing differences in dietary footprints to preferences of the main shopper is that the observed food choices might not reflect the preferences of the

[10]The sum of the bars for each characteristic should amount to 100%, since all these variations explain 100% of the heterogeneity in carbon intensity. However, for the sake of clarity, only food categories explaining at least 5% of the heterogeneity in carbon intensity are depicted on the graph.

Figure 2: Heterogeneity in carbon intensity explained in terms of diet structure and carbon intensity within food categories.



Notes: The sample includes GB households from Worldpanel data present in any year between 2017 and 2022. Figures (A) and (B) illustrate the relative contributions of category-specific calorie shares and carbon intensities to the total effect of household characteristics on overall dietary carbon intensity, for multi- and one-person households, respectively. Effects are obtained by translating regression results from Table 5 into kgCO_2e per 1000 calories and computing, for each characteristic, the share of the total effect attributable to food-specific calorie shares versus carbon intensities.

individual doing the grocery shopping if this person is the secondary earner of the household, as is often the case. Indeed, food purchases in multi-person households, being the outcome of an intra-household bargaining process, are more likely to reflect the primary earner's preferences than the main shopper's according to bargaining theory. However, the similarity of results for the role of education, age, and gender for single- and multi-person households suggests that the main shopper being the primary or secondary earner plays a limited role in driving our results. We thus discuss further potential drivers of dietary footprint heterogeneity below.

Preferences. The increase in carbon intensity with age could partly result from weaker pro-environmental preferences or lower levels of environmental concern for older individuals. There is indeed evidence that younger individuals are generally more likely to express green preferences and to engage in pro-environmental behaviours (Skeirytė *et al.*, 2022). Higher levels of education, however, are not systematically associated with larger environmental concern. The lower CI associated with highly educated main shoppers may thus result from preferences toward healthier diets. More educated people overall are more likely to follow healthier diets (Hiza *et al.*, 2013; Andrews *et al.*, 2017), characterised by lower meat consumption and reliance on composite food, patterns associated with lower dietary emissions (Willett *et al.*, 2019).

The finding of a higher CI among women, especially in single-person households, may seem unexpected given that women are typically associated with greener preferences and healthier preferences (Feraco *et al.*, 2024). A potential explanation lies in the difference in the calorie density of women's food purchases. Less energy-dense food mechanically have a larger carbon intensity per calorie. This explanation is consistent with the larger share of calories women obtain from vegetables, and the larger carbon-intensity of their choices within categories such as dairy products and confectionery goods, alongside lower consumption of calorie-rich but relatively low-emission food such as cereal-based and composite products. As expected, the difference in CI between male and female main shoppers in multi-person households is lower than for singles, as female main shoppers in these households no longer shop according to their own preferences only but for all members.

The presence of children is associated with slightly lower dietary carbon intensity, which could reflect stronger environmental values within the household. In particular, evidence from psychology suggests that parent–child discussions may encourage parents to adopt greener preferences, potentially translating into lower-emission dietary choices (Ding *et al.*, 2024; Shrum *et al.*, 2023).

Prices. Beyond health or environmental preferences, prices and household budget must certainly be a driver of differences in households' purchasing behaviours. Although we control for the main shopper's income to account for heterogeneity in food budgets and thus account for price effects, this only informs us imperfectly since we have no information on the income of other household members. Household budgets play a role both in determining the quantity of food purchased, but also the type of products composing diets. Relative prices help explain part of the heterogeneity in dietary footprints, but they cannot account for all of it.[11]

Older households devote a larger share of their calories to meat despite its high cost, a pattern consistent with looser budget constraints with age. More educated households, by contrast, consume less meat, which is unlikely to reflect affordability since higher education is generally associated with higher incomes; here, preferences for healthier diets are the more plausible driver. In households with higher energy requirements, potentially tighter budgets push consumption toward cheaper protein sources such as poultry and composite goods, and away from costlier categories like red meat and dairy. Similar patterns are observed in households with children, where budget constraints are stronger and substitution toward cheaper, less carbon-intensive products is more pronounced. Gender differences are less easily explained by budgets: female main shoppers purchase less meat, which is consistent with its high relative price, but also fewer cereals, which are among the cheapest foods. This latter pattern points instead to preferences for lower-calorie diets. Taken together, these examples suggest that while relative prices clearly shape some dietary differences (especially in larger households and those with children), preferences play a decisive role for others, notably among older, more educated, and female main shoppers.

Limitations. Understanding differences in quantities purchased is more complex. Since we control for household energy requirements, the remaining variation likely reflects behavioural/financial factors. Our work is however subject to two key limitations, potentially driving differences in quantities. First, our results rely on scanner data, which may be affected by differences in how carefully households report their purchases. However, studies using Worldpanel by Numerator's Take Home data for GB suggest that this is not a major concern. Cherchye *et al.* (2020) find that patterns observed in the scanner data closely align with those from the Living Costs and Food Survey, which is representative of the GB population. Similarly, Griffith & O'Connell (2009) show that excluding periods of non-reporting brings spending

[11] Relative prices by food category are drawn from Numbeo (2025).

levels in line with those recorded in the Living Costs and Food Survey.[12]

The second limitation of our approach to investigating dietary carbon footprints is the absence of data on food consumed outside the home. While individuals' core dietary preferences are unlikely to change significantly when dining out (the vegetarians remain vegetarian, carnivores continue consuming meat, and those who prioritise vegetable consumption are likely to choose healthier options), eating out substantially impacts the quantity of food purchased for home consumption. Household-level heterogeneity in carbon footprint could therefore be influenced by dining-out patterns. For instance, young individuals are likely to eat outside more frequently, which could contribute to their lower observed dietary carbon footprint compared to older individuals. To address this limitation, we incorporate data from the Living Costs and Food Survey (LCFS) to estimate the average proportion of expenditure on dining out across age groups, education levels, gender distributions in the household, household size, and the presence of kids.[13] We then match these estimates to the main shoppers in our dataset to account for food-out consumption. Following a similar method as in O'Connell *et al.* (2022), we integrate this adjustment into our static analysis of the relationship between main shopper and household characteristics and their dietary footprint. Results are presented in Table 10 of Appendix C and are in line with those in the main text. The share of budget attributed to food outside the household is negatively correlated to quantities purchased and overall dietary footprint, although not statistically significantly.

[12]The exclusion of non-reporting periods is common in the literature and applied in this study, as explained in Section 3.1.

[13]Based on our own estimates, these factors show consistent and significant associations with the share of expenditure spent on food out each year. Specifically, age and household size are negatively correlated with food out, while more educated individuals, and childless male-majority households consume more food outside the household.

Table 4: Between-household variations in food types 2017-2022 (multi-person households)

	Meat		Dairy		Cereals		Composite		Fish		Vegs		Legumes		Fruits		Sweets	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	%	CI	%	CI	%	CI	%	CI	%	CI	%	CI	%	CI	%	CI	%	CI
Main shopper char.																		
Age	0.147***	0.008	-0.122***	0.015***	-0.031*	0.001***	0.160***	0.008**	0.006*	0.019**	-0.009	-0.004	0.032***	-0.005***	-0.033***	-0.000	-0.162***	0.001
	(0.020)	(0.006)	(0.020)	(0.002)	(0.017)	(0.000)	(0.022)	(0.003)	(0.004)	(0.009)	(0.006)	(0.005)	(0.006)	(0.001)	(0.007)	(0.001)	(0.035)	(0.002)
Age squared	-0.002***	0.000	0.001***	-0.000***	-0.000	-0.000***	-0.002***	-0.000	-0.000	-0.000***	-0.000	-0.000	-0.000***	0.000***	0.000***	-0.000	0.002***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female (ref: Male)	0.015	0.086***	-0.059	0.014	-0.003	-0.002**	-0.384***	-0.022	-0.025	-0.010	0.001	0.012	-0.022	-0.011*	-0.048	-0.000	0.291*	0.005
	(0.100)	(0.027)	(0.088)	(0.009)	(0.081)	(0.001)	(0.104)	(0.016)	(0.018)	(0.040)	(0.029)	(0.020)	(0.029)	(0.006)	(0.033)	(0.005)	(0.164)	(0.007)
Higher education	-0.795***	-0.017	0.525***	-0.012	0.460***	-0.009***	-0.985***	0.020	0.114***	-0.046	0.293***	0.095***	0.220***	-0.005	0.358***	0.011***	-0.418***	-0.037***
	(0.081)	(0.022)	(0.072)	(0.008)	(0.067)	(0.001)	(0.085)	(0.013)	(0.015)	(0.034)	(0.024)	(0.018)	(0.023)	(0.005)	(0.026)	(0.004)	(0.134)	(0.006)
Household char.																		
Diet. needs	0.061***	-0.018***	-0.199***	0.008***	0.106***	0.001***	0.211***	-0.033***	0.011***	0.041***	-0.008	0.006	0.025***	0.008***	-0.006	0.004***	0.067*	0.003**
	(0.023)	(0.006)	(0.019)	(0.002)	(0.018)	(0.000)	(0.022)	(0.003)	(0.004)	(0.008)	(0.006)	(0.004)	(0.006)	(0.001)	(0.006)	(0.001)	(0.035)	(0.001)
Presence of child.	-0.411***	-0.243***	1.016***	-0.065***	0.405***	-0.006***	0.073	-0.175***	-0.058***	-0.123***	-0.185***	0.040	-0.272***	0.007	0.058	-0.018***	0.780***	-0.038***
	(0.108)	(0.029)	(0.098)	(0.010)	(0.089)	(0.001)	(0.111)	(0.017)	(0.019)	(0.046)	(0.032)	(0.025)	(0.032)	(0.006)	(0.038)	(0.005)	(0.172)	(0.007)
Share of women	-0.013***	-0.002***	-0.004*	0.001***	0.002	-0.000***	-0.013***	0.000	-0.001**	0.003***	0.003***	0.002***	-0.001	0.000	0.004***	-0.000**	0.017***	0.000
	(0.002)	(0.001)	(0.002)	(0.000)	(0.002)	(0.000)	(0.003)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.004)	(0.000)
Controls																		
Urban (ref: Rural)	0.928***	0.039	-0.379***	0.013	0.019	0.008***	0.466***	0.056***	-0.026	0.051	-0.099***	0.011	-0.045	-0.002	-0.079**	-0.012**	-0.390**	0.036***
	(0.098)	(0.029)	(0.094)	(0.010)	(0.086)	(0.001)	(0.108)	(0.017)	(0.020)	(0.044)	(0.030)	(0.021)	(0.030)	(0.006)	(0.032)	(0.005)	(0.173)	(0.007)
Income (ref: 0-10k£)																		
10-20k	-0.218	0.158***	0.090	0.019	0.215	-0.001	-0.309	0.052*	0.042	0.080	0.185***	0.113***	-0.026	-0.019	0.093	-0.008	-0.498	-0.018
	(0.210)	(0.056)	(0.192)	(0.020)	(0.173)	(0.002)	(0.218)	(0.031)	(0.036)	(0.086)	(0.052)	(0.041)	(0.058)	(0.012)	(0.061)	(0.011)	(0.365)	(0.015)
20-30k	-0.197	0.229***	0.341*	-0.000	0.345**	-0.003	-0.130	0.116***	0.042	0.058	0.293***	0.201***	0.049	-0.009	0.174***	-0.003	-1.711***	-0.025*
	(0.212)	(0.056)	(0.194)	(0.020)	(0.174)	(0.002)	(0.220)	(0.031)	(0.036)	(0.086)	(0.053)	(0.042)	(0.059)	(0.013)	(0.062)	(0.011)	(0.364)	(0.015)
30-40k	-0.057	0.289***	0.490**	0.005	0.237	-0.002	-0.103	0.198***	0.052	0.127	0.388***	0.254***	0.048	0.010	0.329***	-0.000	-2.150***	-0.029*
	(0.215)	(0.056)	(0.196)	(0.021)	(0.175)	(0.002)	(0.223)	(0.032)	(0.037)	(0.088)	(0.053)	(0.042)	(0.060)	(0.013)	(0.063)	(0.011)	(0.366)	(0.015)
40-50k	0.115	0.330***	0.406**	0.008	0.215	-0.001	0.036	0.229***	0.080**	0.142	0.480***	0.322***	0.116*	0.012	0.465***	-0.001	-2.528***	-0.032**
	(0.221)	(0.058)	(0.201)	(0.021)	(0.180)	(0.002)	(0.230)	(0.032)	(0.038)	(0.090)	(0.056)	(0.044)	(0.062)	(0.013)	(0.068)	(0.011)	(0.374)	(0.016)
50-60k	0.218	0.298***	0.391*	-0.000	0.273	-0.004*	-0.005	0.275***	0.036	0.157*	0.556***	0.344***	0.044	0.014	0.406***	0.001	-2.901***	-0.021
	(0.231)	(0.060)	(0.207)	(0.021)	(0.186)	(0.002)	(0.238)	(0.034)	(0.039)	(0.094)	(0.060)	(0.046)	(0.064)	(0.013)	(0.068)	(0.011)	(0.389)	(0.016)
60-70k	0.200	0.305***	0.668***	0.003	0.353*	-0.005**	-0.265	0.374***	0.082*	0.165*	0.618***	0.419***	0.125*	0.026*	0.537***	-0.003	-3.379***	-0.010
	(0.246)	(0.065)	(0.221)	(0.023)	(0.200)	(0.002)	(0.260)	(0.038)	(0.045)	(0.097)	(0.065)	(0.049)	(0.070)	(0.014)	(0.076)	(0.012)	(0.408)	(0.018)
70k+	-0.349	0.297***	0.895***	0.004	0.452**	-0.007***	-0.531**	0.394***	0.075*	0.307***	0.708***	0.461***	0.202***	0.025*	0.761***	-0.004	-3.202***	-0.045***
	(0.239)	(0.063)	(0.215)	(0.022)	(0.193)	(0.002)	(0.244)	(0.036)	(0.041)	(0.098)	(0.064)	(0.048)	(0.069)	(0.014)	(0.075)	(0.012)	(0.398)	(0.016)
Quantity control	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Seasonality controles	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Constant	-2.726***	7.635***	4.396***	3.143***	0.992**	0.369***	-3.342***	2.774***	0.282***	6.090***	0.563***	3.354***	-0.286*	1.361***	1.059***	1.209***	2.004*	1.076***
	(0.579)	(0.175)	(0.597)	(0.058)	(0.503)	(0.006)	(0.661)	(0.101)	(0.105)	(0.270)	(0.181)	(0.146)	(0.167)	(0.038)	(0.206)	(0.029)	(1.031)	(0.048)
Observations	61523	61070	61523	61496	61523	61503	61523	61522	61523	59744	61523	61422	61523	61211	61523	60551	61523	61520
R^2	0.058	0.056	0.047	0.023	0.033	0.079	0.034	0.112	0.152	0.054	0.067	0.065	0.070	0.114	0.097	0.029	0.051	0.022

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The sample includes GB households from Worldpanel data present in any year between 2017 and 2022. Columns (1), (3), (5), (7), (9), (11), (13), (15), (17) show regression results for the relationship between household characteristics and the calorie shares each category represents in households' diet. Columns (2), (4), (6), (8), (10), (12), (14), (16), (18) use category-specific carbon intensities as the dependent variables. Each model controls for the share of category-specific calories purchased each season. Quantity purchased is controlled for to account for mechanical variations due to changes in total calories purchased instead of meaningful dietary shifts. Standard errors are clustered at the household level.

5 Dynamic analysis: steady variations in dietary footprints

The ultimate goal of identifying household types with the lowest dietary footprints is to inform effective policies aimed at reducing household GHG emissions. All else equal, the previous analysis has shown that among multi-person households, carbon footprints are highest when the household has an older female main shopper without higher education, includes children, and a higher share of men over age 13, while older men without higher education record the highest dietary footprints among one-person households. However, understanding how household characteristics relate to changes in emissions over time is equally important. Since the focus is on reducing household emissions in the long run, this section examines which types of households have reduced their dietary carbon footprints between 2017 and 2022. Specifically, we investigate the relationship between household characteristics and their probability of having increased, maintained, or decreased their dietary carbon footprint from 2017 to 2022.

5.1 Empirical strategy

The first step of the analysis is to classify households according to the change in their dietary carbon footprint between 2017 and 2022. Households are defined as reducers if their footprint fell by at least 10%, as increasers if it rose by at least 10%, and as stable if the change was within plus or minus 10%.[14] A key challenge, noted by Hut & Oster (2022), is mean reversion: apparent reductions may simply reflect unusually high or low values in the base or end year rather than genuine trends. Because we use annual averages of monthly footprints, single-month outliers are unlikely to drive our estimates. Nevertheless, as a robustness check, we replicate the analysis using an alternative definition of reducers based on the average relative year-to-year variation in dietary footprints. Results are shown in Tables 11 and 12 in Appendix D and are in line with those in the main text.

We investigate how characteristics influence the probability of reducing or increasing dietary footprints over time, with respect to the stable alternative. The set of characteristics we examine in this section is similar to those used in the static analysis. Again, we investigate one-person households separately from multi-person ones for consistency. The only difference is that variables are converted into categorical formats to reduce the number of households with temporal variation, ensuring we retain as many observations as possible as explained in detail in Section 3.3.

We estimate the probability of belonging to each household group (reducers, increasers, or stable) using a multinomial logit model as in Equation 5.1. The depen-

[14] A 10% increase or decrease both correspond to the 30th percentile of their respective distributions.

dent variable Y_h is categorical and takes the value 0 if household h's dietary carbon footprint remained stable (change within plus or minus 10%), 1 if it decreased by more than 10% (reducer), and 2 if it increased by more than 10% (increaser). The increaser group serves as the baseline category.

$$P(Y_h = j) = \frac{e^{\alpha_j + \beta_{1j} X_h + \beta_{2j} T_h + \epsilon_{hj}}}{\sum_{k=0}^{2} e^{\alpha_k + \beta_{1k} X_h + \beta_{2k} T_h + \epsilon_{hk}}}, \quad j \in 0, 1, 2 \tag{5.1}$$

Here, X_h is the vector of socioeconomic characteristics, including the age category of the main shopper, the gender of the main shopper, whether the main shopper holds a higher education diploma, whether the household has high or low dietary requirements,[15] the presence of children, and the majority gender among adult members. T_h is the vector of controls, which includes the household's urban or rural location, the income category of the main shopper (low, medium, or high), and the growth rates of seasonal calorie shares over the study period.

Beyond identifying which household types have reduced their carbon footprints over time, the next step is to explore how these reductions were achieved. Specifically, we investigate whether different household types relied more on reducing the quantity of food purchased (i.e., fewer calories) or on shifting towards less carbon-intensive food choices. To do so, we run two other logistic regressions restricted to the sample of reducers, estimating the effect of socio-economic characteristics on households' odds of having decreased calories purchased, and those of having reduced the carbon intensity of their purchases.

5.2 Results

54% of the sample appear to have reduced their dietary emissions over time, with a median decrease of 17.9%. Considering only sizable changes (in this context, a 10% minimum variation), 29.4% of households had a stable dietary footprint over the period, 32.1% increased it, and 38.4% decreased it. Table 5 presents the estimated relationships between household and main shopper characteristics and the odds of having maintained or reduced rather than increased their dietary carbon footprints between 2017 and 2022, for multi-person households.[16]

Estimation results for one-person households do not reveal any significant associations between individual characteristics and the likelihood of increasing or reducing dietary carbon footprints over time. This is likely due to the small sample size of

[15] A household has low dietary requirements if its dietary requirements are at most equivalent to those of a man and a woman together.

[16] Recall the odds are computed as the ratio of the probability for a household to have reduced (maintained) its dietary carbon footprint between 2017 and 2022 on the probability to have increased it on the period.

single-individual households, which is further split into three outcome categories in the analysis. For this reason, these results are not shown in the main text but are available in Appendix E.

Main shopper characteristics. We find that age is significantly associated with changes in dietary carbon footprints over time. Two patterns emerge from the analysis.

First, households with older members are more likely to maintain a stable dietary footprint rather than increase it. Indeed, households with a main shopper aged more than 60 have 43.1% higher odds of having had a stable footprint from 2017 to 2022 compared with households with a shopper aged between 40 and 60.

Second, households with a main shopper aged 40–60 are relatively less likely to have increased their dietary footprints over the period. In particular, they have 29% higher odds of having reduced (rather than increased) their footprint, and 26.3% higher odds of having maintained (rather than increased) it, compared with younger households.[17]

The gender of the main shopper does not appear to predict dietary footprint trajectories. By contrast, households with a highly educated main shopper have 18.5% lower odds of having decreased rather than increased their dietary footprint compared with households with a less educated main shopper.

Household characteristics. Household characteristics are significantly associated with the likelihood of changes in dietary carbon footprints.

Households with lower dietary needs and with children are considerably more likely to have increased their footprint over the study period: compared with higher-needs households, they exhibit 48.1% lower odds of remaining stable and 61.9% lower odds of having decreased. A similar pattern is observed among households with children, who show 20.3% lower odds of remaining stable and 51.6% lower odds of having decreased, relative to increasing.

Interestingly, although the gender of the main shopper does not drive the likelihood of having increased or decreased dietary footprints, the gender distribution of household members does. Female-majority households are substantially less likely to have increased their footprint, with 61.5% higher odds of remaining stable and more than twice the odds (108.2% higher) of having decreased, relative to mixed households. We do not however estimate significant differences between male-majority and gender mixed households.

[17]These figures are obtained by taking the reciprocal of the odds ratio for households with a main shopper younger than 40 relative to those aged 40–60.

Table 5: Multinomial logit estimates of dietary carbon footprint change by household and main shopper characteristics (base category: increase in dietary footprint)

	(1) Stable	(2) Decrease
Main shopper characteristics		
Age group		
Less than 40	0.792*	0.775**
	(0.103)	(0.097)
More than 60	1.431***	1.036
	(0.144)	(0.096)
Female (ref: Male)	1.120	1.143
	(0.107)	(0.103)
Higher education	0.907	0.815***
	(0.076)	(0.064)
Household characteriscs		
Low diet. needs	0.519**	0.381***
	(0.151)	(0.102)
Presence of children=1	0.797**	0.484***
	(0.090)	(0.052)
Majority gender		
Female	1.615***	2.082***
	(0.274)	(0.326)
Male	1.064	0.887
	(0.240)	(0.192)
Controls		
Urban (ref: Rural)	0.869	0.872
	(0.092)	(0.088)
Income group		
Low	1.024	1.238*
	(0.132)	(0.146)
High	1.056	0.894
	(0.097)	(0.079)
Seasonal controls	Y	Y
Constant	0.981	1.731***
	(0.152)	(0.250)
N	4163	
Pseudo R-squared	0.022	

Exponentiated coefficients; Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The sample includes GB households from Worldpanel data present in 2017 and 2022 with stable socioeconomic characteristics. This table reports multinomial regression results for multi-person households' odds of maintaining (+-15% variation) or decreasing (by more than 15%) their dietary footprint (vs. increasing (by more than 15%) between 2017 and 2022, with seasonal controls capturing variation in calorie shares across seasons.

5.3 Mechanisms

Quantity versus carbon intensity. Table 6 explores how strategies for reducing dietary carbon footprints vary across household and main shopper characteristics, focusing only on the set of individuals who reduced their carbon footprint over time. Specifically, it examines whether certain traits are associated with a greater likelihood of reducing emissions through lower food quantities versus through lower carbon intensity.

Among reducing households, 89.3% have decreased their quantity of calories purchased, and 69.6% have reduced the carbon intensity of their purchases. The results in Table 6 suggest limited heterogeneity across main shopper characteristics in the way households have decreased their dietary emissions. Among reducers, the likelihood of having decreased the quantity of food purchased appears independent from main shopper characteristics. However, we do find significant associations between the age of the main shopper and the likelihood of having reduced the carbon intensity of household diets. Specifically, main shopper above the age of 60 have 34.4% higher odds of having reduced the carbon intensity of their diet compared to main shoppers aged 40 to 60.

We do estimate some heterogeneity in decreasing mechanisms across household characteristics. Specifically, households with lower energy requirements are 185.3% more likely to have reduced the carbon intensity of their purchases.

The opposite is observed for households with a majority of women among adults. These households are 209.7% more likely to have reduced their quantities purchased over time than mixed gendered households, while they are 42.7% less likely of having reduced their carbon intensity.

Diet composition. To examine how the carbon intensity of households that reduced their dietary emissions between 2017 and 2022 has changed, we estimate a logistic regression in which the dependent variable is a binary indicator equal to 1 if a household decreased its dietary carbon footprint over the period, and 0 otherwise. The explanatory variables are food-group-specific calorie shares and carbon intensities. This approach allows us to investigate shifts in dietary composition beyond changes in total quantities purchased.

Figure 3 illustrates how changes in dietary patterns are associated with the probability of having reduced one's dietary carbon footprint.[18] The results suggest that

[18] The figure plots the percentage changes in the odds of having decreased dietary footprints from 2017 to 2022, estimated from a logistic regressions where the dependent variable is the probability of having decreased food emissions and explanatory variables are category-specific calorie shares and carbon intensities. Percentage changes are derived from odds ratios by subtracting one and multiplying by 100.

Table 6: Effect of household characteristics on the probability of having reduced total quantity and carbon intensity of diets, among multi-person households who decreased their dietary footprint.

	(1) Quantity Reducers	(2) Carbon Intensity Reducers
Main shopper characteristics		
Age group		
Less than 40	1.015	1.145
	(0.314)	(0.226)
More than 60	1.038	1.344**
	(0.223)	(0.170)
Female (ref: Male)	1.078	0.877
	(0.225)	(0.114)
Higher education	0.870	0.988
	(0.162)	(0.111)
Household characteristics		
Low diet. needs	0.403	2.853***
	(0.308)	(1.151)
Presence of children=1	0.692	1.037
	(0.176)	(0.164)
Majority gender		
Female	3.097**	0.573***
	(1.460)	(0.103)
Male	0.609	1.148
	(0.265)	(0.378)
Urban (ref: Rural)	0.861	1.090
	(0.206)	(0.151)
Income group		
low	2.079**	0.789
	(0.670)	(0.122)
high	1.147	0.899
	(0.246)	(0.115)
Seasonal controls	Y	Y
N	1630	1630
Pseudo R-squared	0.025	0.013

Exponentiated coefficients; Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The sample includes all GB households from Worldpanel data present in 2017 and 2022 with stable socioeconomic characteristics. Regressions focus on households that reduced their dietary footprint. Column (1) reports results for the odds of having reduced quantities purchased over the period, and Column (2) for the odds of having reduced carbon intensity.

households primarily achieved reductions in emissions by lowering the carbon intensity within food categories, rather than by cutting out high-emission food groups altogether. In particular, higher calorie shares of meat and dairy are positively associated with the likelihood of having reduced dietary emissions, indicating that these households actually increased the share of their diet devoted to these high-emission categories. However, this effect appears to be more than offset by a shift toward lower-carbon options within those categories. For example, among meat eaters, reducers likely substituted red meat with poultry; similarly, changes within dairy also contributed to emissions reduction.

Results show that reducers have significantly decreased the carbon intensity of their meat, dairy, fish, sweets, and composite goods purchases, highlighting the role of within-category substitution in driving overall emission reductions.

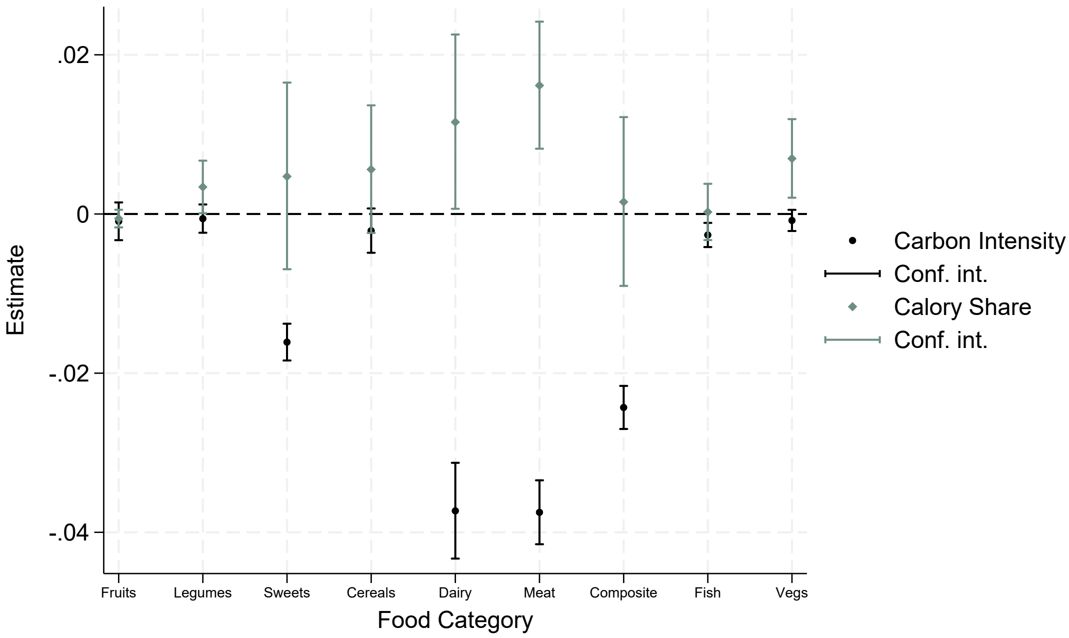
Prices Appendix F illustrates the evolution of consumer price indices across food categories. Examining variation in prices helps us assess whether the dietary changes observed among households that reduced their carbon footprint stem from price effects, preferences, or a combination of both.

Figure 3 shows that reducers did not eliminate meat or dairy from their diet, but lowered their carbon footprint through within-category substitutions such as shifting from beef to poultry and from cheese to milk. When set against consumer price indices between 2017 and 2022 available in Appendix F, these results appear only partially consistent with price incentives.

Poultry and beef indeed experienced similar inflation over the period, suggesting that the substitution toward chicken reflects more than relative prices and is likely driven by preferences or dietary norms. By contrast, the decline in legume prices may have contributed to shifts from meat-based toward legume-based—or more broadly meat-free—composite goods, thereby reducing the carbon intensity of food choices within this category. Turning to dairy, Figure 3 shows that reducers lowered the carbon intensity of their purchases. Since milk became relatively more expensive than cheese, price signals would have predicted a shift toward cheese, raising carbon intensity. The opposite pattern suggests that preferences, not prices, drove the change.

Overall, while we cannot fully disentangle the influence of prices and preferences, price trends alone cannot account for the dietary shifts we observe, pointing to a significant role for preferences in driving reductions in carbon intensity.

Figure 3: Dietary change associations with probability of decreasing dietary footprint.



Notes: The sample includes GB households from Worldpanel data present in 2017 and 2022 with stable socioeconomic characteristics. The figure plots percentage changes in the odds of having decreased dietary footprints from 2017 to 2022, estimated from logistic regressions where the dependent variable is the probability of having decreased food emissions and explanatory variables are category-specific calorie shares and carbon intensities. Percentage changes are derived from odds ratios by subtracting one and multiplying by 100.

5.4 Discussion

Households with higher dietary carbon footprints are generally more likely to have reduced their emissions over time. This pattern is evident among middle-aged individuals (40–60 years old), who are more likely to have decreased their food emissions than younger households. By contrast, this is not observed for those aged 60 and above, likely reflecting more stable consumption habits at older ages. A similar tendency toward reduction is found among less-educated individuals and in larger households (or those with higher energy requirements). Taken together, these results suggest that some of the groups most responsible for elevated emissions have already begun to adjust their consumption patterns—an encouraging sign from a mitigation perspective.

At the same time, our results point to household types that have not reduced their emissions despite having relatively high dietary footprints. These include households with children and those in which adult members are predominantly male. The persistence of high emissions in these groups suggests that they have not yet exhibited clear signs of behavioural adjustment, underscoring the need for targeted policy attention.

We emphasize that these findings are descriptive: they do not allow us to determine whether reductions in dietary emissions are driven by greater environmental concern, economic constraints, or other unobserved factors. While we attempt to account for shifts in purchasing power by controlling for the main shopper's income and food and discuss the potential role of price variations in driving our results, the precise mechanisms underlying these reductions remain unclear. Identifying these mechanisms represents an important avenue for future research.

What we do assess, however, is the nature of dietary footprint reductions among households that have decreased their emissions: whether these reductions result from lower food quantities or from shifts toward less carbon-intensive choices, and how such strategies vary across household types. This analysis not only highlights which reduction pathways have been more common across different groups, but also provides insight into the policy levers most likely to encourage further decreases. If certain households have already tended to reduce through dietary shifts, for instance, this suggests both what has proven feasible in practice and where policy support could most effectively amplify reductions.

Our results highlight that smaller and older households may be particularly responsive to nudges encouraging a shift toward lower-carbon food choices, while female-majority households whose footprints have not decreased might be especially inclined to reduce emissions through lowering overconsumption or limiting food waste.

Overall, our results indicate that while nearly all households have reduced the total quantity of food they purchase, only a subset have also shifted toward lower-carbon food types, mostly by consuming less carbon intensive products within food groups (e.g. shifting from consuming beef to chicken, or from consuming cheese to yoghurt) rather than changing their overall dietary structure (i.e. going from meat eater to vegetarian).

6 Conclusion

This paper has provided new evidence on the heterogeneity of household dietary carbon footprints in the GB and on how these footprints have evolved from 2017 to 2022. Using detailed scanner data, we showed that both household structure and the characteristics of the main shopper are important drivers of dietary emissions. Larger footprints are associated with older, less-educated, and female main shoppers, as well as with larger and predominantly male households and those with children. These differences are shaped not only by the quantity of food purchased but also by its carbon intensity, reflecting a combination of budget constraints and preferences.

Turning to changes over time, our results indicate that households with higher dietary footprints, particularly middle-aged, less-educated, and larger households, are more likely to have reduced their emissions, whereas households with children and gender-mixed or predominantly male households have shown little adjustment. Among those who did reduce, most did so by lowering the quantity of food purchased, while a majority also decreased the carbon intensity of their diets, often through substitutions within food groups rather than broader dietary shifts. Older and smaller households were particularly more likely to lower carbon intensity, suggesting that preferences have played a role alongside prices.

Together, these findings highlight both encouraging signs and persistent challenges. Some of the groups most responsible for elevated emissions have already begun to adjust their consumption, suggesting that mitigation policies could build on these ongoing changes. At the same time, high-emission groups that have not reduced—such as households with children or predominantly male households—require particular policy attention. More broadly, our results indicate that while reductions in food quantities are widespread, more meaningful mitigation will require supporting households to shift toward lower-carbon food types. Policies such as information campaigns, targeted incentives, and support for healthier and less carbon-intensive diets could help turn incremental adjustments into deeper and more lasting dietary transitions, making climate action in the food sector both effective and equitable.

However, this analysis is descriptive and subject to several limitations. Scanner data, while rich and detailed, do not capture food consumed outside the home which may in part be due to under reporting. However this scanner data closely aligns with the Living Costs and Food survey so we do not believe this to be a major concern. In addition, our income measures are less precise than in official expenditure surveys, which may limit the accuracy of our controls for household purchasing power. Finally, our results do not establish causal mechanisms: reductions may stem from environmental concerns, health motivations, or economic constraints, but disentangling these channels remains beyond the scope of this paper. Future research should seek to combine scanner data with complementary sources and causal identification strategies to better uncover the drivers of dietary change and to evaluate the effectiveness of specific policy interventions.

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Appendix A: Between-household variations in diet structures

Table 7: Between households variations in food types 2017-2022 (single-person households)

	Meat		Dairy		Cereals		Composite		Fish		Vegs		Legumes		Fruits		Sweets	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	%	CI	%	CI	%	CI	%	CI	%	CI	%	CI	%	CI	%	CI	%	CI
Main shopper characteristics																		
Age	0.034	0.045***	0.016	0.014***	-0.021	0.002***	0.156***	-0.005	0.028***	0.053**	-0.017	-0.026**	0.038**	0.001	-0.033*	-0.001	-0.183**	0.006
	(0.040)	(0.015)	(0.047)	(0.005)	(0.041)	(0.001)	(0.052)	(0.010)	(0.011)	(0.021)	(0.014)	(0.013)	(0.017)	(0.003)	(0.020)	(0.003)	(0.084)	(0.005)
Age squared	-0.001*	-0.000**	0.000	-0.000***	-0.000	-0.000***	-0.002***	0.000	-0.000***	-0.001***	0.000	0.000	-0.000***	0.000	0.000*	-0.000	0.002***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Female (ref: Male)	-0.426**	-0.008	0.151	0.177***	-1.001***	-0.021***	-2.603***	-0.018	-0.240***	0.287***	0.571***	0.138***	-0.108	0.018	0.258***	-0.031***	0.780**	0.103***
	(0.179)	(0.060)	(0.200)	(0.021)	(0.173)	(0.002)	(0.224)	(0.042)	(0.047)	(0.086)	(0.055)	(0.044)	(0.066)	(0.013)	(0.071)	(0.011)	(0.361)	(0.018)
Higher education	-0.881***	0.150**	0.787***	-0.031	0.008	-0.011***	-1.389***	0.089**	0.008	-0.068	0.210***	0.089**	0.444***	0.006	0.421***	0.016	0.254	-0.000
	(0.178)	(0.060)	(0.198)	(0.020)	(0.167)	(0.002)	(0.217)	(0.040)	(0.046)	(0.085)	(0.055)	(0.043)	(0.067)	(0.013)	(0.068)	(0.011)	(0.357)	(0.019)
Controls																		
Urban (ref: Rural)	0.874***	-0.035	-0.465*	0.025	0.203	-0.001	0.053	0.136***	-0.001	0.294***	-0.096	0.059	-0.039	-0.026	-0.025	-0.007	-0.100	0.088***
	(0.224)	(0.082)	(0.257)	(0.029)	(0.209)	(0.003)	(0.292)	(0.050)	(0.062)	(0.111)	(0.075)	(0.052)	(0.083)	(0.018)	(0.088)	(0.015)	(0.458)	(0.021)
Income (ref: 0-10k£)																		
10-20k	-0.283	-0.002	0.624**	-0.003	-0.923***	-0.003	0.412	0.091*	-0.056	0.215**	0.005	0.161***	-0.000	0.024	0.212***	-0.028*	0.130	0.027
	(0.224)	(0.081)	(0.252)	(0.028)	(0.235)	(0.002)	(0.261)	(0.052)	(0.053)	(0.105)	(0.066)	(0.054)	(0.089)	(0.017)	(0.076)	(0.015)	(0.456)	(0.022)
20-30k	-0.115	-0.001	0.221	0.015	-1.011***	-0.003	1.173***	0.190***	0.086	0.303**	0.143*	0.267***	0.007	0.035*	0.427***	-0.012	-1.124**	0.032
	(0.260)	(0.092)	(0.289)	(0.032)	(0.270)	(0.003)	(0.320)	(0.060)	(0.069)	(0.123)	(0.077)	(0.065)	(0.100)	(0.018)	(0.096)	(0.017)	(0.528)	(0.025)
30-40k	0.586*	0.050	0.090	0.041	-1.278***	-0.003	1.267***	0.342***	0.064	0.390**	0.340***	0.228***	0.004	0.073***	0.578***	-0.024	-2.824***	0.031
	(0.339)	(0.111)	(0.375)	(0.040)	(0.324)	(0.004)	(0.397)	(0.074)	(0.082)	(0.163)	(0.110)	(0.074)	(0.122)	(0.025)	(0.118)	(0.020)	(0.619)	(0.034)
40-50k	-0.565	0.077	0.294	0.030	-1.653***	-0.012**	1.543***	0.440***	-0.022	0.368*	0.039	0.239**	0.257	0.042	0.538***	-0.050**	-1.334	0.055
	(0.397)	(0.174)	(0.422)	(0.049)	(0.397)	(0.005)	(0.563)	(0.096)	(0.112)	(0.196)	(0.125)	(0.101)	(0.170)	(0.033)	(0.154)	(0.025)	(0.837)	(0.048)
50-60k	0.570	-0.195	-0.143	-0.011	-1.703***	-0.009	1.024	0.051	0.096	0.624*	0.442***	0.370**	0.100	0.125**	0.715***	0.002	-1.619	0.058
	(0.565)	(0.174)	(0.559)	(0.063)	(0.552)	(0.007)	(0.948)	(0.126)	(0.138)	(0.353)	(0.165)	(0.182)	(0.220)	(0.049)	(0.260)	(0.041)	(1.118)	(0.076)
60-70k	-0.718	-0.391*	-0.256	0.133	-1.949***	-0.016*	2.337**	0.456**	0.232	0.190	0.085	0.352	-0.084	0.050	0.863***	-0.113***	-1.629	0.059
	(0.829)	(0.206)	(0.680)	(0.087)	(0.593)	(0.009)	(1.143)	(0.197)	(0.212)	(0.330)	(0.200)	(0.225)	(0.242)	(0.059)	(0.293)	(0.042)	(1.510)	(0.073)
70k+	0.483	0.115	0.213	0.027	-1.163*	-0.013	-0.560	0.515***	0.094	1.178***	0.734***	0.440***	0.259	0.082*	1.271***	0.066	-2.310*	-0.076
	(0.732)	(0.281)	(0.702)	(0.076)	(0.624)	(0.012)	(1.144)	(0.174)	(0.190)	(0.388)	(0.267)	(0.160)	(0.288)	(0.046)	(0.392)	(0.048)	(1.356)	(0.056)
Quantity control	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Seasonality controles	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Constant	0.000	6.521***	0.163	3.318***	3.513***	0.406***	-1.394	3.241***	0.366	4.805***	1.213***	4.436***	-0.091	1.277***	1.538**	1.309***	2.390	0.896***
	(1.236)	(0.466)	(1.423)	(0.157)	(1.253)	(0.017)	(1.759)	(0.323)	(0.317)	(0.648)	(0.411)	(0.402)	(0.495)	(0.097)	(0.598)	(0.082)	(2.611)	(0.154)
Observations	14982	14660	14982	14951	14982	14913	14982	14980	14982	13689	14982	14622	14982	14388	14982	13830	14982	14979
R^2	0.074	0.036	0.034	0.029	0.048	0.076	0.075	0.051	0.233	0.040	0.092	0.072	0.114	0.119	0.145	0.038	0.024	0.021

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The sample includes all GB households from Worldpanel data present in any year between 2017 and 2022. Columns (1), (3), (5), (7), (9), (11), (13), (15), (17) show regression results for the relationship between one-person household characteristics and the calorie shares each category represents in households' diet. Columns (2), (4), (6), (8), (10), (12), (14), (16), (18) use category-specific carbon intensities as the dependent variables. Each model controls for the share of category-specific calories purchased each season. Quantity purchased is controlled for to account for mechanical variations due to changes in total calories purchased instead of meaningful dietary shifts. Standard errors are clustered at the household level.

Appendix B: Explaining heterogeneity in carbon intensity

No values are reported when the estimates of the relationship between households characteristics and the share and carbon intensities of food groups are not significant.

Table 8: Effect of diet structure and within-category carbon intensity on overall carbon intensity by multi-person household characteristics

	Meat		Dairy		Cereals		Composite		Fish	
	%	CI	%	CI	%	CI	%	CI	%	CI
Age (+10 years)		0.040		0.020		0.002	0.015		0.009	0.001
Female	-0.026			0.026	0.023	-0.002	-0.03		0.007	0.001
Higher Education	-0.053	0.014	0.011			-0.001	-0.016	0.013		

	Vegs		Legumes		Fruits		Sweets	
	%	CI	%	CI	%	CI	%	CI
Age (+10 years)		-0.006	-0.006		0.005		0.019	
Female	0.003	0.003			-0.004	-0.001	-0.006	0.031
Higher Education	0.001	0.002	-0.007		-0.007			

Table 9: Effect of diet structure and within-category carbon intensity on overall carbon intensity by one-person household characteristics

	Meat		Dairy		Cereals		Composite		Fish	
	%	CI	%	CI	%	CI	%	CI	%	CI
Age (+10 years)	0.075		-0.017	0.021	0.007	0.001	0.009	0.011	0.002	0.003
Higher Education	-0.047		0.008		-0.01	-0.001	-0.007		0.004	
Energy Req.	0.009	-0.005	-0.007	0.003	-0.006		0.004	-0.012	0.001	0.002
Presence of children	-0.024	-0.026	0.025	-0.009	-0.009	-0.001		-0.024	-0.002	-0.002

	Vegs		Legumes		Fruits		Sweets	
	%	CI	%	CI	%	CI	%	CI
Age (+10 years)			-0.004	-0.001	0.005		0.016	
Higher Education	0.002	0.002	-0.003		-0.005		0.005	-0.10
Energy Req.			-0.001				-0.002	0.002
Presence of children	-0.001		0.004				-0.009	-0.011

Appendix C: The role of food out

Table 10: Carbon footprint, quantities, carbon intensity footprint and the role of food-out

	Multi-person households			One-person households		
	Total CF	Q	CI	Total CF	Q	CI
Main shopper characteristics						
Age	3.524***	921.086***	0.015***	4.094***	1406.779***	0.016***
	(0.344)	(132.566)	(0.002)	(0.417)	(160.777)	(0.004)
Age squared	-0.022***	-4.892***	-0.000***	-0.030***	-10.641***	-0.000***
	(0.003)	(1.195)	(0.000)	(0.003)	(1.337)	(0.000)
Female (ref: Male)	15.995***	6371.738***	0.015*	-3.141*	-2130.315***	0.048***
	(1.819)	(690.190)	(0.009)	(1.886)	(684.744)	(0.018)
Higher education	-14.434***	-4026.097***	-0.049***	-11.764***	-3573.865***	-0.058***
	(1.544)	(592.734)	(0.007)	(1.920)	(698.075)	(0.018)
Household characteristics						
Diet. needs	16.306***	8124.653***	-0.015***			
	(0.467)	(184.159)	(0.002)			
Presence of children=1	19.589***	11245.183***	-0.068***			
	(1.994)	(780.145)	(0.009)			
Share of women	-0.497***	-175.907***	-0.001***			
	(0.043)	(16.841)	(0.000)			
Controls						
Urban (ref: Rural)	1.640	-2390.208***	0.063***	0.591	-1743.073**	0.082***
	(1.878)	(716.956)	(0.009)	(2.383)	(882.311)	(0.022)
Food-out budget	-0.584	-343.702	0.000	0.779	230.494	0.005
	(0.770)	(280.200)	(0.004)	(0.695)	(242.113)	(0.007)
Income bracket (ref: 0-10k£)						
10-20k	6.764*	2123.433	0.025	2.498	-357.576	0.069***
	(3.796)	(1492.442)	(0.019)	(2.377)	(861.633)	(0.022)
20-30k	13.501***	3318.154**	0.061***	4.736*	-1103.139	0.137***
	(3.888)	(1522.697)	(0.019)	(2.829)	(1017.312)	(0.026)
30-40k	16.657***	2955.650*	0.107***	8.884**	-1866.480	0.240***
	(3.958)	(1559.690)	(0.019)	(3.577)	(1244.566)	(0.032)
40-50k	14.398***	695.899	0.131***	0.126	-3940.637**	0.202***
	(4.033)	(1582.759)	(0.020)	(4.310)	(1600.371)	(0.042)
50-60k	15.360***	-502.844	0.161***	1.015	-3963.881**	0.168***
	(4.179)	(1633.446)	(0.020)	(5.928)	(1924.429)	(0.052)
60-70k	13.658***	-2469.351	0.186***	8.666	-1459.160	0.178**
	(4.483)	(1724.208)	(0.021)	(9.707)	(2966.925)	(0.080)
70k+	0.227	-6428.814***	0.145***	1.702	-3928.714	0.240***
	(4.332)	(1691.242)	(0.021)	(7.838)	(2864.638)	(0.084)
Seasonality controles	Y	Y	Y	Y	Y	Y
Time fixed effects	Y	Y	Y	Y	Y	Y
Quantity control	N	N	Y	N	N	Y
Constant	27.039**	21463.660***	2.135***	13.001	16790.018***	1.944***
	(10.781)	(4212.321)	(0.054)	(13.598)	(5212.595)	(0.135)
Observations	61393	61393	61393	14953	14953	14953
R^2	0.185	0.260	0.054	0.041	0.042	0.025

Notes: The sample includes GB households from Worldpanel data present in any year between 2017 and 2022. Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Columns (1) and (4) provide OLS regression results for the relationships between characteristics and total dietary carbon footprint, Columns (2) and (5) for food quantity (calories), and Columns (3) and (6) dietary carbon intensity (kgCO_2e per 1,000 calories). Each model controls for the share of calories purchased each season to account for seasonality of consumption, and for year effects. Quantities are controlled for when investigating carbon intensity to account for variations due to changes in total calories purchased instead of meaningful dietary shifts. Standard errors are clustered at the household level.

Appendix D: Identifying dietary footprint reducers

We reproduce the analysis in section 5, using alternative methods to classify households as reducers or not. We use relative year to year growth rate averaged over the whole period, such that the classification is not driven only by the years 2017 to 2022, to avoid the potential noise created by outliers values in these two years.

Results are shown below. Results on the characteristics of households that decreased their carbon footprints and their strategies to do so are similar whether we use the baseline or the average relative year-to-year growth rates.

Table 11: Characteristics of reducing households, average yearly growth.

	(1) Stable	(2) Decrease
Main shopper characteristics		
Age group		
Less than 40	0.744**	0.690***
	(0.091)	(0.093)
More than 60	1.301***	1.021
	(0.118)	(0.094)
Female (ref: Male)	1.187*	1.165*
	(0.104)	(0.106)
Higher education	0.861**	0.798***
	(0.066)	(0.064)
Household characteristics		
Low diet. needs	0.596**	0.519**
	(0.156)	(0.139)
Presence of children=1	0.704***	0.440***
	(0.073)	(0.049)
Majority gender		
Female	1.622***	1.861***
	(0.242)	(0.284)
Male	0.934	0.649*
	(0.189)	(0.149)
Controls		
Urban (ref: Rural)	0.846*	0.905
	(0.082)	(0.093)
Income group		
Low	1.178	1.538***
	(0.138)	(0.181)
High	0.875	0.923
	(0.074)	(0.082)
CPI variation	1.275**	0.835**
	(0.145)	(0.067)
Seasonal controls	Y	Y
Constant	0.016**	21.311**
	(0.031)	(29.501)
N	4289	
Pseudo R-squared	0.029	

Exponentiated coefficients; Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The sample includes GB households from Worldpanel data present in 2017 and 2022 with stable socioeconomic characteristics. This table reports multinomial regression results for multi-person households' odds of maintaining (+-15% variation) or decreasing (by more than 15%) their dietary footprint (vs. increasing (by more than 15%) between 2017 and 2022, with seasonal controls capturing variation in calorie shares across seasons.

Table 12: Characteristics specific reduction mechanisms, average yearly growth.

	(1) Quantity Reducers	(2) Carbon Intensity Reducers
Main shopper characteristics		
Age group		
Less than 40	0.785	1.365
	(0.263)	(0.326)
More than 60	1.412	1.432**
	(0.315)	(0.203)
Female (ref: Male)	1.028	0.853
	(0.235)	(0.126)
Higher education	0.645**	0.957
	(0.131)	(0.122)
Low diet. needs	0.192**	2.531**
	(0.148)	(1.115)
Presence of children=1	1.336	0.980
	(0.399)	(0.182)
Majority gender		
Female	4.563**	0.706
	(2.739)	(0.150)
Male	0.915	1.144
	(0.518)	(0.470)
Urban (ref: Rural)	0.785	0.968
	(0.210)	(0.157)
Income group		
Low	1.850*	0.719*
	(0.612)	(0.122)
High	1.016	0.774*
	(0.227)	(0.112)
CPI variation	1.144	0.955
	(0.180)	(0.112)
Seasonal controls	Y	Y
N	1222	1222
Pseudo R-squared	0.040	0.015

Exponentiated coefficients; Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The sample includes GB households from Worldpanel data present in 2017 and 2022 with stable socioeconomic characteristics. Regressions focus on households that reduced their dietary footprint. Column (1) reports results for the odds of having reduced quantities purchased over the period, and Column (2) for the odds of having reduced carbon intensity.

Appendix E: Singles results: dynamic analysis

Table 13: Relationship between odds of maintaining and decreasing rather than increasing DCF and characteristics among one-person households

	(1) Stable	(2) Decrease
Main shopper characteristics		
Age group		
Less than 40	0.668	0.896
	(0.247)	(0.291)
More than 60	1.243	1.206
	(0.200)	(0.182)
Female (ref: Male)	0.875	1.053
	(0.130)	(0.147)
Higher education	1.171	0.865
Controls		
	(0.176)	(0.122)
Urban (ref: Rural)	0.863	1.334
	(0.180)	(0.281)
Income group High	0.986	1.102
	(0.165)	(0.174)
Low	0.898	0.822
	(0.231)	(0.205)
Seasonal controls	Y	Y
Constant	0.923	0.892
	(0.257)	(0.243)
N	1279	
Pseudo R-squared	0.013	

Exponentiated coefficients; Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The sample includes all one-person GB households from Worldpanel data present in 2017 and 2022 with stable socioeconomic characteristics. This table reports multinomial regression results for one-person households' odds of maintaining (+-15% variation) or decreasing (by more than 15%) their dietary footprint (vs. increasing (by more than 15%) between 2017 and 2022, with seasonal controls capturing variation in calorie shares across seasons.

Table 14: Characteristics specific reduction mechanisms in one-person households

	(1) Quantity Reducers	(2) Carbon Intensity Reducers
Main shopper characteristics		
Age group		
Less than 40	2.705	0.727
	(2.888)	(0.377)
More than 60	0.958	1.327
	(0.306)	(0.318)
Female (ref: Male)	1.819**	1.169
	(0.531)	(0.254)
Higher education	1.014	1.372
	(0.304)	(0.304)
Controls		
Urban (ref: Rural)	0.478	1.737*
	(0.300)	(0.555)
Income group		
Low	1.638	0.757
	(0.545)	(0.192)
High	1.486	0.984
	(0.881)	(0.412)
Seasonal controls	Y	Y
N	493	493
Pseudo R-squared	0.044	0.045

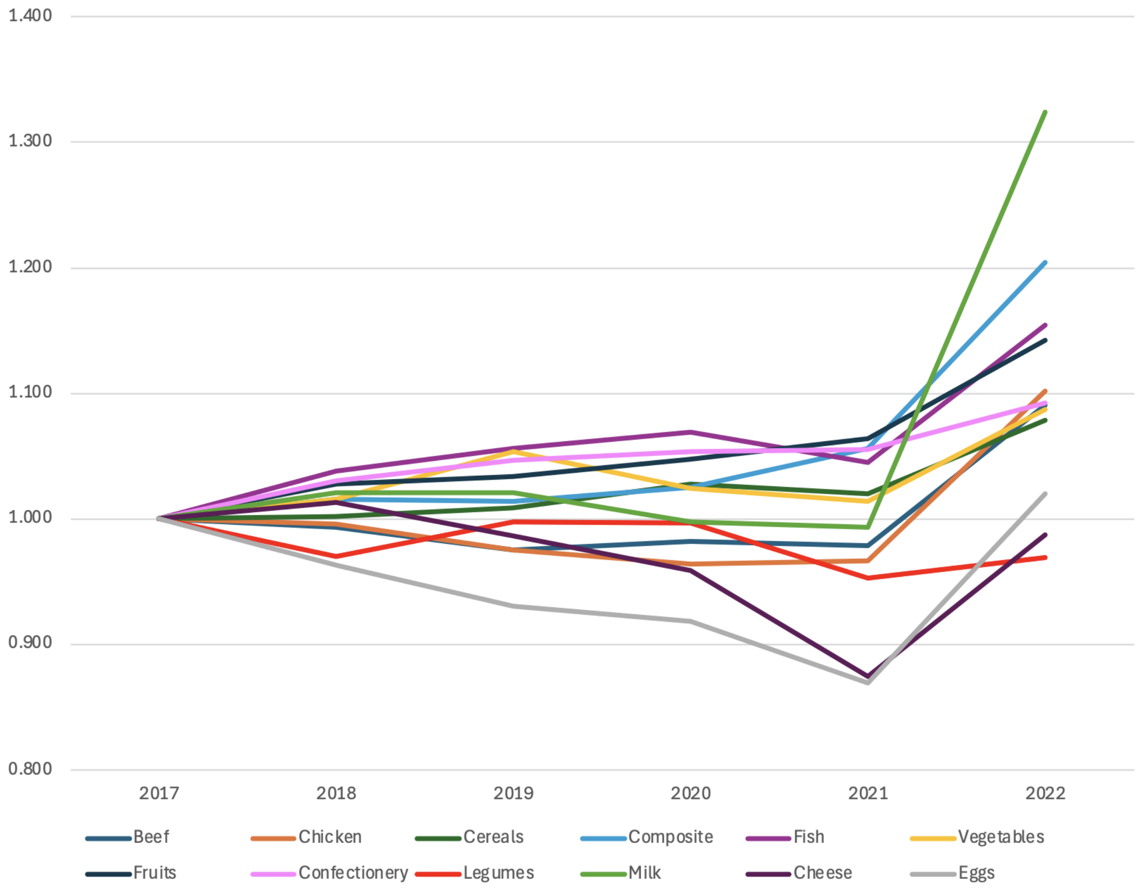
Exponentiated coefficients; Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The sample includes all one-person GB households from Worldpanel data present in 2017 and 2022 with stable socioeconomic characteristics. Regressions focus on households that reduced their dietary footprint. Column (1) reports results for the odds of having reduced quantities purchased over the period, and Column (2) for the odds of having reduced carbon intensity.

Appendix F: Evolution of CPIs between 2017 and 2022

Figure 4: Consumer Price Index between 2017 and 2022.



<u>Notes:</u> Values for the CPI across different categories of products come from the Office for National Statistics with 2015 as the base year (CPI=1).