An online randomised controlled trial of price and non-price interventions to promote sustainable food choices on food delivery platforms

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Abstract

Mitigating emissions from the food system, which constitute about one-third of global greenhouse gas emissions, is a vital goal for research and policy. This study empirically tests the effectiveness of different policy interventions to reduce the carbon footprint of food choices on food-delivery apps, using an incentive-compatible online randomised controlled trial with 4,008 participants. The experiment used an interactive web platform that mimics popular online food delivery platforms (such as Uber Eats) and included three treatment conditions: a sign-posted meat tax, a carbon footprint label, and a choice architecture intervention, which changed the order of the menu so that the lowest carbon-impact restaurants and dishes were presented first. Results show that only the choice architecture nudge significantly reduced the average meal carbon footprint by 0.3 Kg/CO_2e per order (12%), driven by a 5.6 percentage point (13%) reduction in high-carbon meal choices. Moreover, we find evidence of significant health and well-being co-benefits. Menu repositioning resulted in the average meal order being of greater nutritional value and containing fewer calories, whilst significantly increasing self-reported satisfaction with the meal choice. Simple back-of-the-envelope calculations suggest that menu repositioning would be a highly cost-effective policy instrument if implemented at scale, with the return on investment expected to be in the range of £1.28 to £3.85 per metric ton of avoided CO_2 emissions, depending on implementation costs.

Keywords: carbon footprint labelling, carbon tax, choice architecture, food delivery apps, low-carbon diets, repositioning, reordering, meat tax

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1 Introduction

Addressing greenhouse gas (GHG) emissions from the global food system, which account for approximately one third of global emissions, is a critical objective for both research and policy initiatives (Crippa et al., 2021). Transitioning away from high-carbon meat-heavy diets towards more sustainable plant-based diets will be crucial in reducing emissions from the food system and limiting dangerous climate warming (Clark et al., 2020; Scarborough et al., 2023; Willett et al., 2019; Xu et al., 2021). With food related emissions being largely demand driven, demand-side interventions targeting food consumption behaviour hold significant greenhouse gas mitigation potential (Bajželj et al., 2014; Creutzig et al., 2022). However, important questions remain as to which interventions are most effective in driving behaviour change, and where these should be best targeted.

While the majority of food choices in developed nations traditionally occur within supermarket environments, there has been a recent global rise in the prevalence and use of food delivery platforms (Statista, 2022a).[1] Food delivery platforms more broadly include services that deliver prepared meals from restaurants and takeaways, as well as groceries. A rapidly growing sector of the market includes online food-delivery apps which allow users to browse, select, and order food from a selection of restaurants to their preferred location.[2] In the United Kingdom (UK), food prepared away-from-home has already become a major contributor to overall dietary intake (Keeble et al., 2020), and the number of food-delivery app users is projected to continuously increase, reaching 27.8m users by 2027 (Statista, 2022b). While food delivery platforms have received little attention to date, they offer unparalleled opportunities for promoting sustainable and healthy diets, as app-based platforms can seamlessly integrate menu design changes, price adaptations, and provide (emissions) information at the point of purchase (Baragwanath, 2021; Jesse & Jannach, 2021; Mirsch et al., 2017; Ytreberg et al., 2023). Hence, developing and testing interventions uniquely tailored to food delivery apps offers a compelling strategy to accelerate sustainable dietary change.

Conventional economic theory conceptualises behavioural change through the lens of rational choice. This perspective suggests that as consumers, people carefully evaluate their options to make deliberate decisions that aim to maximize personal utility or benefit. In line with this notion, conventional environmental policy offers a range of tools and interventions, such as Pigouvian taxation, education or information provision to influence peoples' decision-making (Sterner & Coria, 2013).

In the context of sustainable food consumption, implementing a Pigouvian carbon tax on all food products or a focused tax on meat and dairy could internalise environmental externalities of food production and incentivise dietary changes (Funke et al., 2022). While carbon-based food taxes can be slightly regressive (García-Muros et al., 2017; Moberg et al., 2021; Säll, 2018), recent research suggests that sophisticated design and framing strategies can enhance the acceptability and effectiveness of these taxes, especially meat taxes, thus making them more politically palatable for both voters and policymakers (Fesenfeld, 2023; Gravert &

[1] Market growth was accelerated by the Covid-19 pandemic. See e.g. https://www.theguardian.com/business/2021/jan/13/just-eat-takeaway-orders-soar-on-back-of-european-lockdowns-covid.

[2] In contrast to conventional modes of food delivery (Restaurant-to-Consumer), food delivery services facilitate online ordering and delivery by serving as an intermediary between restaurants and food outlets (Keeble et al., 2020).

Shreedhar, 2022; Klenert et al., 2023; Perino & Schwickert, 2023). Early experimental research in this area shows that carbon taxation can reduce the carbon footprint of food consumption (Lanz et al., 2018; Panzone et al., 2018).

Another approach, consistent with rational choice theory, would involve educating consumers about the environmental impact of their food choices. Environmental policy tools include education and information provision (e.g. via labelling), and other awareness raising measures, which aim to address the information asymmetries underlying the market failure associated with food production in the presence of environmental externalities and guide consumers towards socially optimal consumption decisions (Barahona et al., 2023; Lohmann, 2023; Taufique et al., 2022). Previous research, conducted in grocery retail and cafeteria settings, has documented significant positive yet generally modest effects of educative interventions (Fosgaard et al., 2021; Jalil et al., 2023; Lohmann, 2023) and carbon footprint labelling (Beyer et al., 2023; Casati et al., 2023; Edenbrandt & Lagerkvist, 2021; Lohmann et al., 2022; Muller et al., 2019).

An alternative approach, which applies a behavioural economics lens to consumer behaviour change, recognises that human decision-making is context-dependent and influenced, in part, by behavioural biases and heuristics, implying bounded rationality (Gsottbauer & van den Bergh, 2011; Hallsworth, 2023; Reisch & Zhao, 2017; Simon, 1955; Thaler, 2016). This approach promotes the use of behavioural interventions (or 'nudges') to effectively steer behaviour in the desired direction, without significantly changing economic incentives, restricting choice or addressing all information asymmetries (Münscher et al., 2016; Thaler & Sunstein, 2008). 'Green nudges' that aim to address environmental externalities have received much attention as an environmental policy tool, as they promise to be relatively inexpensive, easy to implement, and less intrusive than conventional policy measures (Ammann et al., 2023; Carlsson et al., 2021; Gravert & Olsson, 2021). In the context of promoting sustainable dietary changes, behavioural interventions show significant potential, given that consumption habits are deeply affected by factors such as the availability, arrangement, and visibility of options, as well as by subconscious decision-making and sociocultural norms and practices (Vermeulen et al., 2020). Experimental research has produced promising evidence that a variety of choice architecture interventions can bring about more sustainable dietary choices (Banerjee et al., 2023; Betz et al., 2022; Garnett et al., 2019, 2020; Gravert & Kurz, 2019; Kurz, 2018; Meier et al., 2022; Panzone et al., 2021; Reisch et al., 2021).

This paper contributes to our understanding of how price and non-price interventions influence consumers' food choices on app-based food delivery platforms. In a pre-registered incentive compatible experiment,[3] we recruited a representative sample (N=4,008) of the UK internet-using population. We asked them to place a meal order on a simulated food-delivery app closely resembling popular food-delivery services such as UberEats or Deliveroo. The platform was carefully designed to replicate the choice environment and market conditions encountered by users of real delivery apps, enabling the implementation of a randomised incentive mechanism where selected participants received their chosen meal.

Each participant accessing the platform was randomly assigned to one of four conditions: (1) a price condition which introduced a clearly-signposted meat tax that adjusted food prices proportionally to the

[3] https://osf.io/h47yj

carbon content of their meat ingredients, resulting in an average increase in the price of meat items by 10% (N=1,015); (2) an information condition which added information on the carbon footprint of food items through standardized carbon footprint labels with traffic-light colour coding (N=994); (3) a choice architecture condition which utilised a repositioning technique, whereby restaurants and menus were presented in descending order of sustainability and the lowest carbon options were shown first (N=1,009); and (4) a control condition which displayed a "business as usual" version of the platform and served as the comparison group (N=990); We hypothesized that all three interventions would lead to lower consumption of meat and high-carbon dishes resulting in an overall reduction in emissions from food orders.

The present paper contributes to the literature studying environmental policy initiatives for sustainable dietary change in five main ways. First, our experimental design allows us to investigate the relative efficacy of both conventional and behaviourally informed policy interventions in the same experimental setting. Our findings thus contribute to the scarce literature comparing economic incentives against behavioural interventions (see e.g. Chen et al., 2021; Gravert & Olsson, 2021; Ito et al., 2018; Wisdom et al., 2010). We extend the existing literature in the food-sustainability domain by focusing on three of the most widely discussed policy instruments for sustainable food consumption, which have so far only been evaluated in isolation (Ammann et al., 2023). To the best of our knowledge, this study is the first to empirically test the behavioural effect of a sign-posted meat tax in an experimental setting.

Second, we contribute to an emerging literature studying interventions in web and app-based food choice settings (Ytreberg et al., 2023) and more broadly to the research agenda on 'digital nudging' (Baragwanath, 2021; De Bauw et al., 2022; Hummel & Maedche, 2019; Mirsch et al., 2017). Our study is one of the first to focus specifically on food-delivery apps, an underexplored, yet increasingly relevant food choice setting. Our findings thus add to emerging evidence from the food-health domain in online grocery and app-based delivery settings (Bianchi et al., 2023; Finlay et al., 2023; Valenčič et al., 2023) and expand upon field-experimental evidence from grocery and cafeteria settings (e.g. Bilén, 2022; Garnett et al., 2019; Lohmann et al., 2022). More broadly, our study contributes to the wider body of literature that explores how the design of online platforms impacts consumer behaviour and demand (Derakhshan et al., 2022; Dinerstein et al., 2018; Lam, 2021; Sahni & Nair, 2020; Ursu, 2018). Our experimental setting combines elements of a more controlled lab setting with the advantages of recreating a realistic choice environment akin to those encountered in natural field experiments (Harrison & List, 2004).

Third, our findings contribute to the broader research agenda on understanding how to enable diets which are both nutritious and within sustainable food-production boundaries, often referred to as "planetary-health diets" (Reisch, 2021; Willett et al., 2019). Our study explores this dual objective by quantifying the potential health and welfare implications of environmentally motivated interventions, including health co-benefits and hedonic well-being effects, in addition to their climate impact. Our results thus also speak to the literature examining strategies for promoting healthier diets (Bollinger et al., 2011; Cadario & Chandon, 2020; Downs et al., 2009), as well as the literature exploring the hedonic welfare effects of interventions targeting environmental externalities (Allcott & Kessler, 2019; Bulte et al., 2020; Damgaard & Gravert, 2018; E. H. Ho et al., 2021; Sunstein, 2021).

Fourth, our controlled experimental setting allows us to gain insights into potential mechanism underlying the effect of the interventions on food choices, especially for the choice-architecture nudge (Callaway et al., 2022; Löfgren & Nordblom, 2020). As our analysis will show, limited attention, and self-control play an important role in determining the interventions' effectiveness.

Fifth, by drawing on a wealth of individual-level socio-demographic and attitudinal data, further analysis allows us to identify segments of the population most receptive to the interventions and most inclined to support their implementation on real-world food delivery platforms, providing valuable insights into sample heterogeneity (Tipton et al., 2020). Assessing both intervention effectiveness alongside public backing provides a comprehensive view of the feasibility and promise of leveraging food delivery apps to shift eating habits. Our findings not only provide valuable insights for policymakers considering different regulatory approaches to app-based food delivery platforms, but also offer potential avenues for online food-service providers and delivery platforms to contribute towards healthy and sustainable diets.

Our results indicate that only the repositioning nudge significantly reduced the average meal carbon footprint by 0.3 Kg/CO_2e per serving (12%) in the full sample, driven by a 5.6 percentage point (13%) reduction in high-carbon meal choices. None of the interventions were able to achieve a reduction in meat consumption. Notably, menu repositioning also resulted in significant health and well-being co-benefits, with participants consuming, on average, lower-calorie meals with improved nutritional profiles and reporting increased satisfaction with their meal choice. Heterogeneity analysis shows that attention and self-control are two potential mechanisms through which menu repositioning affects food choices. Further subgroup analysis based on individual characteristics suggests that food carbon literacy plays an important role in the effectiveness of the tested sustainable food policy interventions: All three interventions significantly reduced the average meal carbon footprint for individuals who were already more knowledge about the climate impact of food (top quartile), with labels having the largest effect (0.54 Kg/CO_2e per serving). Furthermore, exposure to carbon labelling significantly increased its acceptance as a policy for food delivery platforms, while none of the interventions influenced the acceptability of taxation and repositioning.

2 Methods and data

2.1 Experimental design

We conducted one of the first incentive compatible online randomised controlled trials on interventions to promote sustainable foods choices in a food delivery app setting. For this purpose, we recruited an online representative sample of 4,008 adult consumers in the UK and asked them to complete a food choice task on a platform that closely resembles popular delivery apps such as platforms such Deliveroo, UberEATS or JustEat.[4] The platform included nine restaurants that were based on real-world equivalents and offered a variety of popular cuisines. Each restaurant's menu included a selection of starters, mains, desserts,

[4]Take a BITe was developed on Predictiv by the Behavioural Insights Team (BIT). For details, see: https://www.bi.team/bi-ventures/predictiv/.

and drinks (if applicable), to make the choice environment as realistic as possible. In total, participants could select from 164 unique food items for which we calculated the carbon footprint, calorie content and nutritional profile (details on methodology and calculations provided in Appendix B, Section 1.1). Prices were based on market prices as of December 2022 and adjusted to enable any combination of two items at a given restaurant (one main and one additional item) within a £20 budget, which was at the participant's disposal. An interactive version of the platform in its standard configuration (control condition) can be previewed *here*, and additional details on menu composition and platform calibration are provided in Section 1.2 of Appendix B.

Before placing an order on the simulated delivery app, participants first completed a pre-intervention survey which collected detailed information on food consumption habits and preferences, experience with delivery platforms, climate and consumption attitudes, political identity, and participants' knowledge ("literacy") of the carbon and health impacts of food. Participants then read a short introductory text, which provided information on the platform and food choice task. To avoid overordering, participants were asked to order at least one main and at most one additional item within a budget of £20 for themselves for dinner. To incentivise accurate and honest behaviour, participants were informed that there was a 1 in 30 chance of them actually receiving the meal chosen on the platform, with the remainder of the budget being paid out via bank transfer. After placing their order, participants completed a short post-intervention survey which measured self-reported satisfaction with their food choice, factors which influenced their decision and support for a range of policies that could be implemented on online delivery platforms (the full pre- and post-intervention questionnaires are presented in Appendix C).

2.2 Incentivisation

Participants received a participation fee £0.90 for completing the study. Moreover, participants were given a virtual budget (£20) to allocate towards their online food order. It was mandatory for participants to select at least one main meal. To ensure incentive compatibility, a random incentive mechanism was employed: approximately one in thirty participants were chosen at random to receive their chosen food order from the experiment, or the closest available match, after completing the study. Participants were informed about the incentivisation at the start of the survey and directly before starting the food choice task. Moreover, participants were informed that any remaining budget would be transferred directly to their bank accounts if they were chosen to receive their meal. Winners of the random incentive were subsequently contacted separately and asked to provide their address details so that the actual order could be processed and delivered on a preferred date. Alternatively, winners were given the option to donate the value of their meal to a food bank based in the UK. The research team subsequently placed the meal orders using a real-world food delivery app. If the chosen restaurant/meal was not available in their area, a substitute meal was selected or, if no comparable substitute was available, the full value of the meal was transferred to the participant's bank account. In the event that there was any remaining budget from the participants' virtual funds, it was paid out to them through an email payment service provider. Summary statistics for incentivisation implementation are shown in Appendix Table A1. We observe that incentivisation follow-through was relatively low, with only about 50% of winners responding to the follow-up email. This may be related to factors such as inactive monitoring of email inboxes, spam filters, or inertia stemming from the extra effort involved in arranging meal delivery, but is unlikely to have impacted the efficacy of our incentivisation at the time of choice.

2.3 Interventions

The sample was randomly divided into four groups using a simple randomisation procedure. Approximately one-quarter of participants were assigned to the control group, which did not receive any intervention. The remaining participants were allocated to one of three treatment groups: a monetary intervention (meat tax), an information provision intervention (carbon footprint labels), or a behavioural intervention (menu repositioning), which will be described in detail below.

There were several elements of the platform that could be manipulated: (1) the restaurant page which showed the nine restaurants, (2) the menu page of each restaurant (visible upon selecting a restaurant), which displayed individual menu items including starters, mains, desserts and drinks, (3) the selection pop-up which appeared upon selecting a meal and allowed users to specify the quantity of meals to be added to the basket and (4) the checkout basket which was visible alongside the menu page on the right of the screen (or as a pop-up on mobile) and which had to be reviewed before placing the order. In the remainder of this section, we describe how each of the four elements were varied for the four treatment conditions. As the majority of participants (80%) used a mobile device to complete the experiment, the figures below will illustrate the mobile version of the platform, while screenshots of the web-version can be found in Appendix A1.1, Figures A1 and A2.

2.3.1 Tax condition

In the *Tax Condition*, the platform layout was not changed, but an additional tax was imposed on items containing meat. The menu page of a respective item displayed a red "T" icon and the text "Includes £X.XX of meat tax." In the selection pop-up and in the checkout basket, an extra row indicated the price added by the tax as "+£X.XX meat tax." The additional rows also displayed a small information icon, providing further details about the tax's purpose and impact ("An additional meat tax has been added to this item to reflect its climate impact") if hovered over with the mouse or touched on a mobile device. The order of restaurants and menu items was randomly presented. Figure 1 presents an example of the food-delivery app and choice setting faced by participants (using mobile devices) in the tax condition:

The tax was calculated for each item based on the carbon content of the meat ingredients (in kg CO_2e per serving) and a carbon price of £483 per tonne of CO_2e. This tax rate was chosen to achieve an average price increase of 10% across all meat dishes, equivalent to an average surcharge of 79p. The chosen tax rate aligns with research on carbon taxation in supermarkets (Panzone et al., 2018) and is slightly below the recommendations of Funke et al. (2022), who suggest an average price increase ranging from 20% to 60% to fully account for GHG emissions and nutrient pollution related to meat production and consumption. A

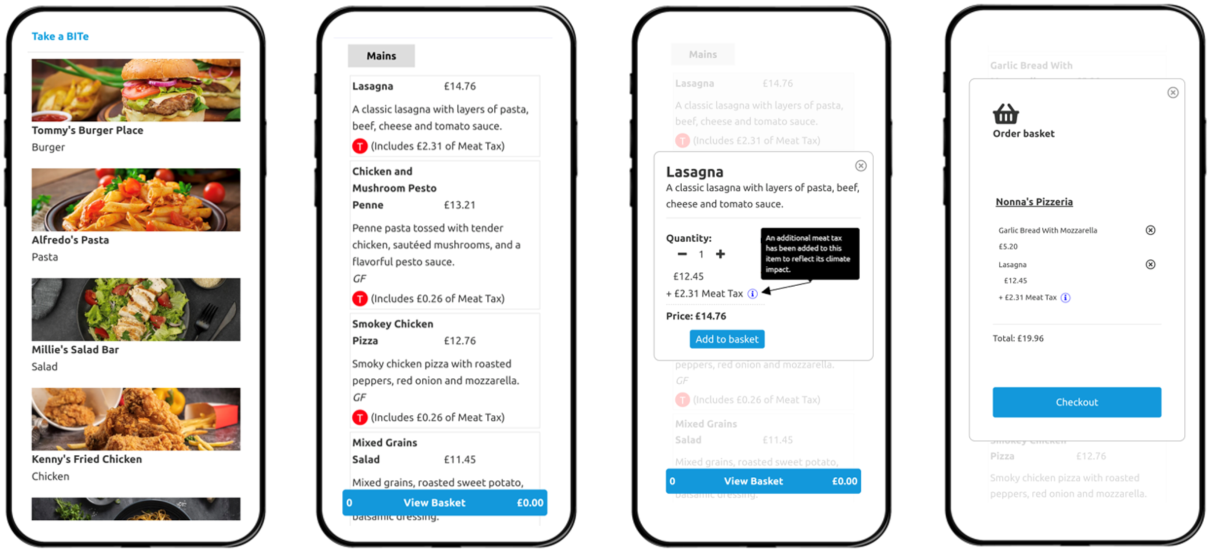

Figure 1: Tax Condition. Example of the choice setting for the meat tax condition. From left to right, the participants first viewed the restaurant page, then the menu page for a chosen restaurant, followed by the selection pop-up for a chosen meal and finally the order basket pop-up to complete their order.

10% average increase in the total price of meat dishes was deemed to reflect a more realistic scenario under which a meat tax could be introduced. The tax was 'sign-posted' to enhance its potential impact (Chetty et al., 2009; Gravert & Olsson, 2021).

2.3.2 Information condition

In the *Information Condition*, the platform design was identical to the Control Group, but additional information in the form of carbon footprint labels were included on the menu page of every food item and selection pop-up. The order of restaurants and menu items was randomly presented. Figure 2 illustrates how the labels were added to the platform.

The label design was informed by previous research (Lohmann et al., 2022) and executed in cooperation with our industry partner (Foodsteps). Meal items are rated based on their carbon footprint per kilogram using categories from A (Very Low) to E (Very High), following the Global Carbon Budget for Food (2019 EAT-Lancet Commission). By choosing A-rated foods, individuals can stay within their daily carbon allowance for food.

2.3.3 Choice Architecture condition

In the *Choice Architecture Condition*, no additional information was presented, but the platform design was altered to emphasize low-carbon alternatives. Both the restaurant and menu pages were re-ordered, presenting options in decreasing order of sustainability, that is, the lowest carbon restaurants and meal items (within each menu category) were presented first. Figure 3 provides an example.

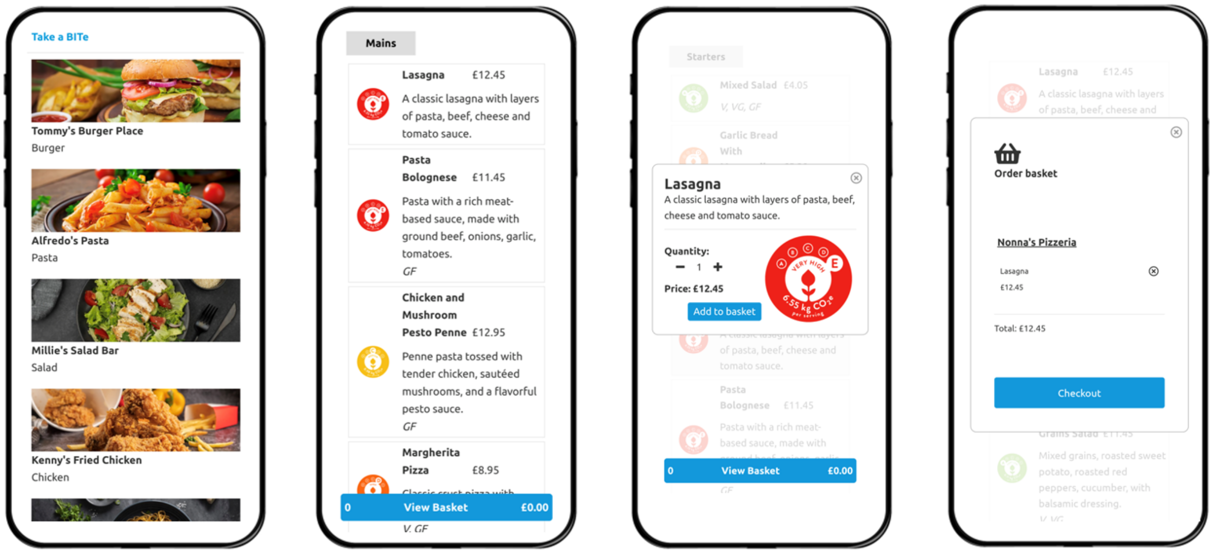

Figure 2: Labelling Condition. Example of the choice setting for the carbon-labelling condition. From left to right, the participants first viewed the restaurant page, then the menu page for a chosen restaurant, followed by the selection pop-up for a chosen meal and finally the order basket pop-up to complete their order.

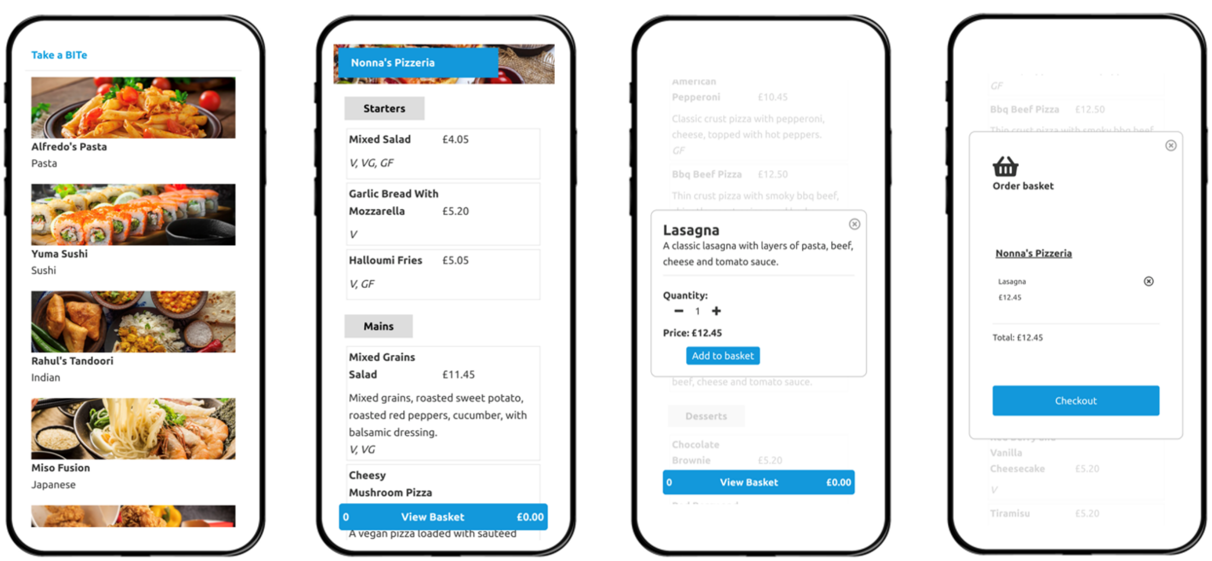

Figure 3: Choice Architecture Condition. Example of the choice setting for choice architecture condition. From left to right, the participants first viewed the restaurant page, then the menu page for a chosen restaurant, followed by the selection pop-up for a chosen meal and finally the order basket pop-up to complete their order.

2.3.4 Control condition

Lastly, in the *Control Condition*, participants experienced the platform in its regular "business as usual" design without any additional information being displayed (as in Figure 3), and the order of restaurants and menu items was presented randomly.

2.4 Data and outcomes of interest

The experiment was conducted in February 2023. Only participants who actively used delivery apps and lived in urban areas were eligible to participate. The aim was to recruit regular users of delivery apps to ensure that the randomly selected meal choices (i.e. the experimental incentivisation) could be successful delivered through real-world delivery platforms. Participants had the flexibility to complete the experiment using desktop computers, tablets, or mobile devices. An attention check question was also included to ensure participants' attentiveness (see Appendix C, Section 1.1). Subjects who failed the attention check once were given the opportunity to adjust their response and complete the survey. Subjects who failed the attention check twice were not able to complete the experiment. Data collection was stopped shortly after the target sample size of 4000 valid responses had been reached. Additional details on ex-ante power calculations and statistics related to survey completion are presented in Section 1.3 of Appendix B.

There are three main outcome variables of interest which were pre-registered, including (1) the sum of carbon footprint (GHG emissions) of the meal order, (2) choices of high-carbon impact main meals (impact score D or E), (3) choices meat-based main meals. Moreover, we pre-registered secondary outcome measures to explore whether the interventions influence health outcomes (i.e., calories purchased and self-reported satisfaction with the food choice), as well as support for public policies on online delivery platforms and restaurant revenue per customer. As calories is generally considered an incomplete measure of healthfulness, we additionally computed the 'Nutri-Score' (Julia & Hercberg, 2017) to serve as an additional health outcome.

We also collected data on sociodemographic characteristics including gender, age, income, location, ethnicity, education, urban and socioeconomic status (which were merged from the Predictiv panel), political orientation, usage of food delivery apps, climate attitudes, dietary preferences and self-control and participant's carbon literacy in relation to food. These variables were used to conduct heterogeneity analyses. Please see Appendix C (Sections 1.1. and 1.2) for a full list of survey questions.

2.5 Sample characteristics

The final sample (N=4,008) was largely representative of the UK internet-using urban population. Summary statistics for key socio-demographic variables are presented in Table 1. Slightly over half (52%) of participants were female with an average age of 38, an average annual income of £35,000, and 34% held a Bachelor's degree or higher. 32% of the sample identified more with the political left, whereas 21% identified more with the political right. The remaining 47% indicated no clear preferences for either left or right. A large majority of participants were omnivorous (87%) with 79% following no particular diet and 8% stating that they were flexitarian. Only 6% of participants were vegetarian and 2% said they were vegan. The distribution of dietary preferences in our sample is thus closely aligned with those found in recent UK-wide dietary surveys (YouGov, 2023; Food and You 2, 2023). Moreover, we find that our randomisation procedure was successful in achieving balance in key socio-demographic characteristics across treatment and control groups (see Appendix Table A2). Summary statistics for all other socio-demographic and attitudinal variables employed in the heterogeneity analysis are presented in Appendix Tables A3.

Table 1: Descriptive Statistics – Full Sample

	Mean	Std. Dev.	Min	Max	UK Mean
Female	.52	.5	0	1	.51
Age	37.9	13.49	18	84	40.2
Income (£ - mid-point)	35,380.46	25,465.38	2,500	100,000	39,328
Bachelor's degree or higher	.34	.47	0	1	.34
Political identity					
Left leaning	.32	.47	0	1	.39
Neither left nor right	.47	.5	0	1	.33
Right leaning	.21	.41	0	1	.28
Diet					
None in particular	.79	.41	0	1	.71
Flexitarian	.08	.27	0	1	.14
Pescatarian	.02	.12	0	1	.03
Vegetarian	.06	.24	0	1	.05
Vegan	.02	.15	0	1	.02
Other	.03	.17	0	1	.03

Note: $N = 4,008$. Column five presents average statistics for the UK population. Gender, age, income and degree are drawn from the 2021 Census. Political identitiy data comes from Wave 6 of the Polarization Tracker (MHP Group, 2023), which tracks a representative sample of the UK population and for which the question used in our survey was developed. Dietary preferences are obtained from YouGov using data from January 2023.

2.6 Estimation

The primary specifications used to test the three primary hypotheses are as follows:

$$Y_i = \alpha + \beta_1 T1_i + \beta_2 T2_i + \beta_3 T3_i + X_i + e_i \tag{1}$$

where Y_i represents the primary outcome of interest: Basket greenhouse gas emissions at checkout (GHG_i), High carbon main meal choice ($High_i$), and meat main meal choice ($Meat_i$). $T1_i$, $T2_i$, and $T3_i$ are treatment indicators equal to one if individual i was randomly assigned to the tax condition, information condition, or choice architecture condition, respectively. X_i is a vector of socio-demographic variables for individual i, including age, gender, income, socio-economic status, region, and ethnicity. The model is estimated by ordinary least squares (OLS), and heteroscedasticity-robust (Eicker-Huber-White) standard errors are computed.

The three pre-registered primary outcomes of interest Y_i are defined as: (1) GHG_i stands for the GHG emission content of the food basket (sum of all items) at checkout of individual i; (2) $High_i$ represents a binary outcome equal to one if the chosen main meal has a high-carbon footprint rating (D or E) and zero otherwise (A, B, and C); (3) $Meat_i$ represents a binary outcome equal to one if the chosen main meal is a meat dish and zero otherwise (vegan, vegetarian, or fish). The first outcome is continuous and is estimated by Ordinary Least Squares (OLS). The latter two outcomes are binary and were estimated using linear probability models (LPM).

We address the threat of multiple hypothesis testing and the possibility of false positives by estimating randomization inference p-values which adjusted for Family-wise Error Rate (FWER) using the procedure developed in Young (2019). As pre-specified, we adjust for three hypothesis tests for our primary analysis (H1), which provide the main finding of this study. Moreover, we adjust for six tests for our secondary analyses (H2 and H3). FWER-adjusted p-values for the above tests are presented in square brackets in our main results table.

The exploratory heterogeneity analysis was conducted following equation 2:

$$Y_i = \alpha + \beta_1 T1_i + \beta_2 T2_i + \beta_3 T3_i + \gamma_1 M1_i + \delta_1(M1_i \times T1_i) + \delta_2(M1_i \times T2_i) + \delta_3(M1_i \times T3_i) + \gamma X_i + e_i \quad (2)$$

Where $M1$ refers to the moderator variable of interest which enters both as a main effect $M1_i$ and interacted with the three treatment indicators ($T1_i$, $T2_i$, and $T3_i$). In some cases, the moderator has a third level ($M2$) which enters the equation in the same way as $M1$, but is omitted here for readability. For instance, the moderator age is a categorical variable with three levels: $M0$ (< 35) the omitted base category, $M1$ ($35 - 49$), and $M2$ (50 or older). We do not adjust for MHT for the exploratory analyses, as these are considered hypothesis generating rather than confirmatory hypothesis testing.

The exploratory analysis of predictors of policy support was conducted following equation 3:

$$Y_i = \alpha + \beta_1 T1_i + \beta_2 T2_i + \beta_3 T3_i + X_i + e_i \quad (3)$$

where Y_i represents a binary outcome of policy support for meat taxation, carbon footprint labelling, and menu repositioning (combining response categories 'support' and 'strongly support' from the 5-point Likert scale response options). $T1_i$, $T2_i$, and $T3_i$ are treatment indicators as in equation 1. X_i is a vector of socio-demographic characteristics (age, gender, income, education, political identity), climate concern (worry and responsibility to act), food self-control, food carbon literacy, frequency of food delivery platform use, and a selection of dietary preferences (diet, meat consumption habits, importance of climate-friendly/cheap food). All models of policy support are estimated by logistic regression, and marginal effects are computed, which allow estimates to be interpreted as a percentage point change in support.

3 Results

3.1 Descriptive statistics

In total, our data contains 4,008 meal purchases, with each participant making a single purchase. On average, participants ordered 1.91 items (i.e., 91% ordered two items) with approximately 66% opting for a meat-based main meal and spent £13.65 on their meal purchase (see Table 2). 77% of participants used a mobile or tablet to place their order, with the remaining 23% using the desktop site. The average energy content of the chosen food items was 1,069 Kcal and the majority of participants were satisfied with their choice. The average carbon footprint of the basket at checkout (sum of all items) was 2.45 Kg CO_2/serving. The majority of participants (66%) chose a meat main meal, and the largest proportion of mains (33%) had a mid-range carbon impact rating (C), followed by high-carbon alternatives (D & E).

Table 2: Descriptive Statistics – Food Choice Task

	Mean	Std. Dev.	Min	Max
Mobile	.77	.42	0	1
Number of items	1.91	.29	1	2
Total price (£)	13.65	2.79	5.99	19.96
Total energy consumed (Kcal)	1069.24	384.95	301	1980
Satisfaction with meal choice	3.82	.91	1	5
Total basket emissions (kg co2/serving)	2.45	2.11	.11	10.22
Main meal carbon impact rating*				
A – very low carbon	.07	.25	0	1
B	.18	.38	0	1
C	.33	.47	0	1
D	.23	.42	0	1
E – very high carbon	.19	.39	0	1
Main meal type				
Meat	.66	.47	0	1

Note: $N = 4,008$. *Meals are rated based on their carbon footprint per kilogram using categories from A (Very Low) to E (Very High).

3.2 Main treatment effects

We first evaluate the direct impact of our three interventions on the climate impact of food choices made by all costumers. Figure 4 depicts the average basket GHG emission per food purchase (A), our primary outcome of interest, as well as the proportion of high carbon main meals (B) and meat main meals (C) purchased by treatment condition. We observe that GHG emissions were about 12% lower in the repositioning condition (2.24 kg CO_2e/serving) compared to control (2.55 kg CO_2e/serving) while emissions were only marginally lower in the meat tax (2.47 kg CO_2e) and carbon labelling conditions (2.54 kg CO_2e). We also find that participants ordered fewer high-carbon dishes in the repositioning condition (13% relative to control) but did not significantly reduce their relative consumption of meat-based dishes.[5] Meat dishes were chosen slightly more frequently in both the meat tax and labelling conditions, compared to the control group. This suggests that additional interventions may be required to effectively reduce the demand for meat-based dishes in online food orders. However, despite limited impact on meat demand, the repositioning intervention did contribute to lowering the total carbon footprint significantly.

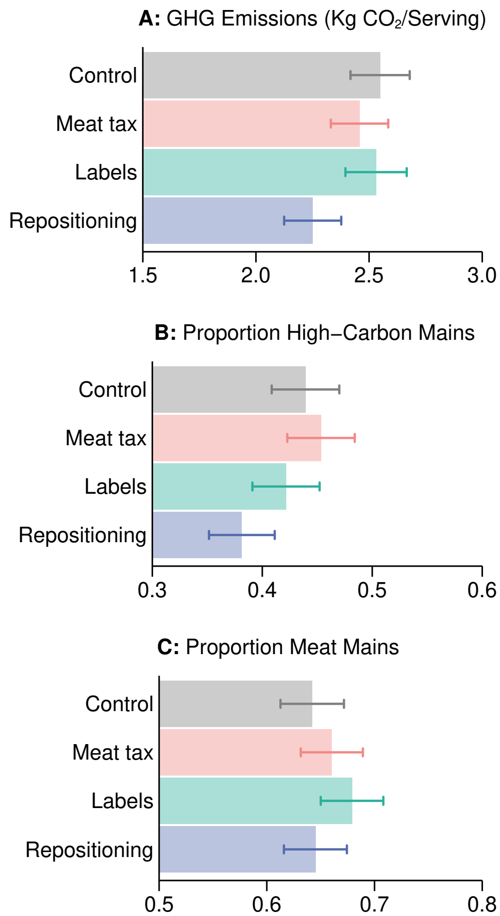

Figure 4: Primary Outcomes. Figure displays summary statistics for sustainable food choice outcomes in the control and three treatment conditions. Panel A shows the average GHG emissions (KgCO_2e/Serving) of the food basket at checkout. Panel B shows the proportion of high-carbon climate-impact mains chosen, and Panel C shows the proportion of meat mains chosen. Error bars represent normal-based 95% confidence intervals for the unadjusted proportions. Please note that the x-axes has been truncated to facilitate visualisation. N=4,008.

Figure 5 visualises the average treatment effects relative to the control group obtained from estimating our pre-registered model specification (see equation (1)), while Table A4 in the Appendix presents the full regression output including p-values adjusted for multiple hypothesis testing. Our empirical analysis confirms that menu repositioning was the only intervention that significantly reduced the carbon impact of food choices, whereas the meat tax and carbon footprint labels had no impact compared to the control group.

The effect of repositioning menus by carbon footprint impact is shown in the first tile (A) of Figure 5. Repositioning led to a statistically significant reduction of approximately 0.3 kg CO_2e in the average greenhouse gas emissions per food basket purchased compared to the control group. The second tile (B) shows that repositioning reduced the likelihood of choosing a high carbon main meal by about 6 percentage

[5]High-carbon dishes include dishes in the two highest impact score categories (D, E).The distribution of choices across the five impact score categories (A-E) by condition is shown in Figure A3

points relative to the control group. Both effects are statistically significant at the 1% level. Finally, the third tile (C) displays the effect of repositioning on the probability of selecting a meat-based main meal. Here, the effect of repositioning is small and not statistically different from zero.

Our results also show that the carbon footprint labelling of the menu had minimal impact on the climate impact of peoples' food choices compared to the control group. As shown in Figure 5, the estimated effects of labelling are small and not statistically significant for GHG emissions and choices of high carbon meals, while labelling even slightly increased the probability of choosing a meat-based main dish by around 2 percentage points compared to the control group (marginally significant at the 10 percent level).[6]

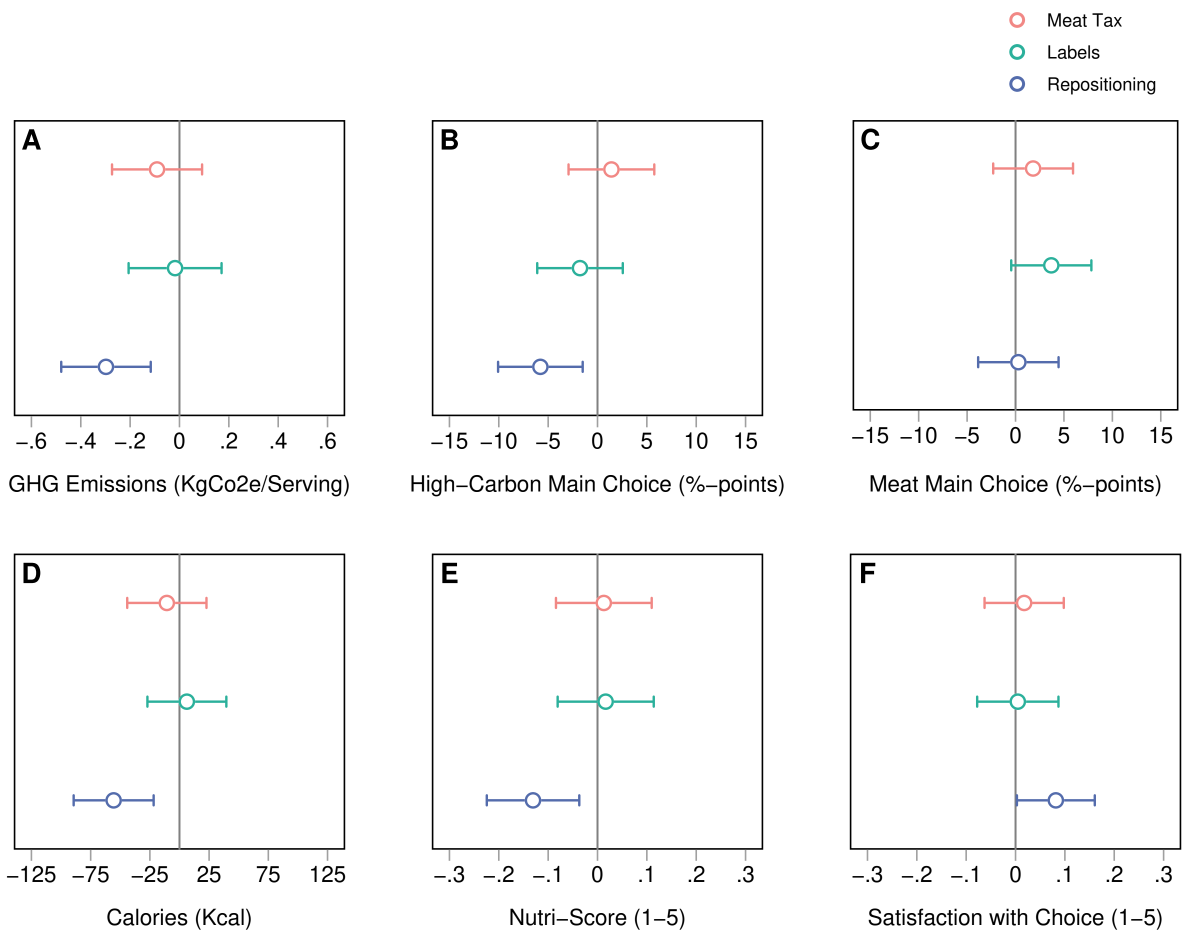

Figure 5: Main Regression Results. Figure displays the regression-estimated effects of the three treatment interventions ('Meat Tax', 'Labels', 'Repositioning') on food sustainability outcomes (A-C) and health and well-being outcomes (D-F), relative to the control group. Estimates of equation (1) estimated by OLS and LPM. Error bars represent normal-based 95% confidence intervals from OLS regressions with heteroscedasticity-robust standard errors. Full regression output presented in Appendix Table A4. N=4,008.

[6]In Appendix Table A5 we provide estimates of the interventions on all four meal-type categories (vegan, vegetarian, fish and meat), which shows that the minor increase in meat main dishes in the labelling condition is related to a reduction in fish dishes

Finally, the meat tax, which increased the prices of meat items by 10% on average across all meat dishes (ranging between 1% and 42%), did not lead to significant reductions in greenhouse gas emissions, low carbon main meal selections, or meat choices compared to the control group. As shown in Figure 5, the estimated effects of the pricing intervention are small and statistically insignificant. We discuss potential explanations for the observed null effects, including high background inflation and potential windfall earning effects, in Section 4.

While both carbon footprint labelling and meat tax show no significant effects on the climate impact of food choices in the full sample, the average treatment effect masks interesting subgroup effects which are discussed in section 3.5.

3.3 Health and well-being co-benefits

In addition to analysing climate impacts, we also examine effects on the total calories (kcal) of purchased food baskets. This is motivated by the concept of a "planetary health diet" which stresses that diets optimized for both human health and environmental sustainability should be a priority (Reisch, 2021; Springmann et al., 2016; Willett et al., 2019). Figure 5, tile D visualizes the main treatment effects and shows that the repositioning intervention significantly reduced average energy consumed by 55 Kcal (or 5%), relative to the control group, decreasing the average calorie count to 1,028 kcal per basket. We acknowledge, however, that calories alone are an imperfect measure of healthfulness. We therefore also computed the Nutri-Score for all dishes included on the menu (see Appendix Section B1.1 for more details). We find that the repositioning intervention decreased the average basket Nutri-Score by 0.13 points (on a 5-point scale) where lower values indicate better nutritional value, thus providing evidence of significant improvements in nutrition.[7] Both findings indicate that interventions aimed at reducing food's climate impact can also have health co-benefits by decreasing calorie consumption and improving nutrition.

We also examine how the interventions affected consumer welfare, an important consideration when nudging choices (Allcott & Kessler, 2019; Laffan et al., 2021; Sunstein, 2021). We assess welfare indirectly through participants' satisfaction with their meal selections, which we measured using a 5-point Likert scale directly after placing the order. Our findings indicate that repositioning resulted in the highest average rating of 3.88 (which is higher and significantly different from control), while at the same time no other interventions reduced consumer satisfaction (see tile F, Figure 5 for average treatment effects).[8] The results should alleviate concerns that efforts to reduce food's environmental footprints come at the expense of enjoyment or happiness with meal selections.[9]

[7]The Nutri-Score is based on key nutrients (see Appendix Section B1.1). For robustness, we also computed a 'Health Score' based on nutrient density (micro and macro nutrients) and USDA recommendations for a healthy diet. When using the Health Score as an outcome we find similar positive effects of repositioning on the healthfulness of food choices.

[8]For ease of interpretation and visualisation, point estimates provided in Figure 5, tile F, are estimated by Ordinary Least Squares (OLS). We obtain similar estimates when using an ordered probit model, which is more appropriate for ordinal (Likert scale) response data. Specifically, we find that people were more likely to say they were "very satisfied" or "extremely satisfied" with their meal choice, and less likely to state that they were "not at all", "a little" or "somewhat" satisfied.

[9]We acknowledge that, due to the nature of our study, we were only able to measure satisfaction with the choice, rather than satisfaction with the meal itself (after consumption). We leave this to future research.

To explore additional dimensions of consumer welfare, we also asked participants to rate their level of satisfaction and guilt with respect to the climate impact of their meal (see full question wording in Appendix Section C1.2). Here, we find no significant effect of any of the interventions on climate satisfaction or guilt, suggesting that the increase in general satisfaction observed in the repositioning condition is unrelated to climate motives.

3.4 Restaurant sales and revenue

Next, we investigate whether any of the treatment conditions led to restaurant substitution and examine the potential implications for restaurant revenue. Table 3 presents the marginal effects of the meat tax, labelling and repositioning intervention on the choice probabilities for each of the nine restaurants available on the platform, relative to the control condition (the omitted base category). The restaurants are listed based on their average carbon footprint (shown in brackets behind each name), reflecting the order in which they were presented in the repositioning condition.

Table 3: Substitution between restaurants

	Meat Tax	Labelling	Repositioning
Pasta (0.49)	0.005	0.004	0.059***
	(0.37)	(0.33)	(4.15)
Sushi (0.74)	0.006	-0.013	0.028*
	(0.49)	(-1.04)	(2.11)
Indian (0.81)	-0.014	-0.021	-0.006
	(-0.97)	(-1.40)	(-0.36)
Japanese (0.84)	-0.013	-0.007	-0.026*
	(-1.11)	(-0.61)	(-2.38)
Fried Chicken (0.87)	-0.014	-0.003	0.007
	(-0.92)	(-0.20)	(0.46)
Salad/Sandwiches (1.12)	-0.014	-0.009	-0.020*
	(-1.46)	(-0.88)	(-2.17)
Pizza (1.18)	0.007	0.021	-0.039**
	(0.42)	(1.30)	(-2.67)
Chinese (1.22)	0.016	0.011	-0.008
	(1.06)	(0.75)	(-0.56)
Burgers (1.57)	0.022	0.016	0.005
	(1.41)	(1.05)	(0.30)

Note: Table reports marginal effect estimates of the three interventions relative to the control condition, obtained from a multinomial logit model where the dependent variable is the choice of restaurant. The restaurants are listed in order of the average carbon footprint across all items. $N = 4,008$.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

As expected, we observe that only the repositioning condition induced substitution between restaurants and the first two restaurants that appeared at the top of the menu page (Pasta and Sushi) were more likely to be chosen. While the repositioning condition decreased the choice probability of restaurants listed further down the menu (most notably Pizza), we find no effect on restaurants with the highest average carbon footprint across all meal items listed at the end of the menu (Chinese and Burgers).[10]

An important question relates to whether substitution between restaurants resulted in differential revenues and profits for the restaurants included on the platform. Table A7 in the Appendix displays the total quantity of meals sold and revenue made by each restaurant under the control and treatment conditions. While shifts between restaurants suggest that some restaurants may have benefited more than others under repositioning, substitution of sales within restaurants may limit revenue gains. Consistent with the shifts in choice probability, we observed that the two restaurants with the lowest average carbon footprints (listed first) significantly increased their revenues by £693 and £469, respectively, under repositioning compared to the control condition. We observe that both the Japanese and Pizza restaurants fare worse under repositioning (£420 and £604 loss, respectively). Nonetheless, no clear pattern emerges to support the idea that menu repositioning systematically harms restaurants listed further down the page, under the assumption that revenues accurately reflect final profits.[11]

3.5 Who is most influenced by choice architecture?

3.5.1 Individual characteristics

Our results show that menu repositioning can effectively nudge more sustainable food choices. However, an important consideration is that individuals may vary in their responsiveness to the nudge, and a comprehensive investigation of this heterogeneity can offer a more nuanced understanding of how interventions should be optimally targeted (Tipton et al., 2020). First, we explore whether treatment effects differ by gender, age and socioeconomic status (SES) including education and income level to identify potential equity effects for disadvantaged groups (Sunstein, 2022). To explore differences between subgroups, we estimate equation (2) which interacts the treatment intervention with each subgroup level (see Section 2.6). Figure 6 plots the treatment effects relative to the control group for each subgroup, while Appendix Table A9 presents the full regression output including the interaction coefficient. We find that male participants were more affected by the repositioning intervention than women, with the difference between the two groups significant at the 10% level. Moreover, we observe no significant differences between age groups. Importantly, we find that repositioning is effective in reducing the carbon footprint of food choices regardless of SES, with both high and low income/education responding similarly to the nudge.

Next, we explore whether repositioning has heterogeneous effects for individuals with different dietary

[10] In Appendix Table A6 we additionally explore substitution patterns within restaurants by estimating equation (1) for each restaurant individually. We find that the repositioning intervention not only induced substitution towards lower-carbon restaurants, but also reduced the average carbon footprint of ordered meals within almost all restaurants, with the exception of Japanese and Fried Chicken. This finding suggests that the combination of restaurant and menu repositioning is likely more effective than implementing either one individually, aligning with earlier research findings in the field of health and nutrition (Bianchi et al., 2023).

[11] It is important to acknowledge that profit margins may differ between menu items within the same restaurant. Here, for the purpose of simplicity, we assume that profit margins are similar for lower and higher-carbon dishes and that restaurant profits are approximately equivalent to 6-9% of restaurant revenues.

habits, food carbon literacy and attitudes towards individual climate action. Based on self-reported frequency of meat consumption, we identify individuals who follow a meat-heavy diet (at least three times per week) and individuals who consume meat less frequently (no more than twice a week). Moreover, we split subjects into groups of low and high carbon literacy, and self-reported personal responsibility to act on climate change (see Section 2.4). We find that all subgroups are significantly influenced by the repositioning intervention, relative to similar individuals in the control group and we find no significant interaction effects (see Appendix Table A9). However, as judged by the effect sizes presented in Figure 6, people who consume less meat, have higher baseline carbon literacy, and perceive a greater responsibility to act on climate change are all more responsive to the repositioning intervention than their counterparts. This finding suggests that people who have greater knowledge about the climate impact of their food consumption or are more willing to act may be more receptive to the environmental signal sent by placing climate friendly options first.

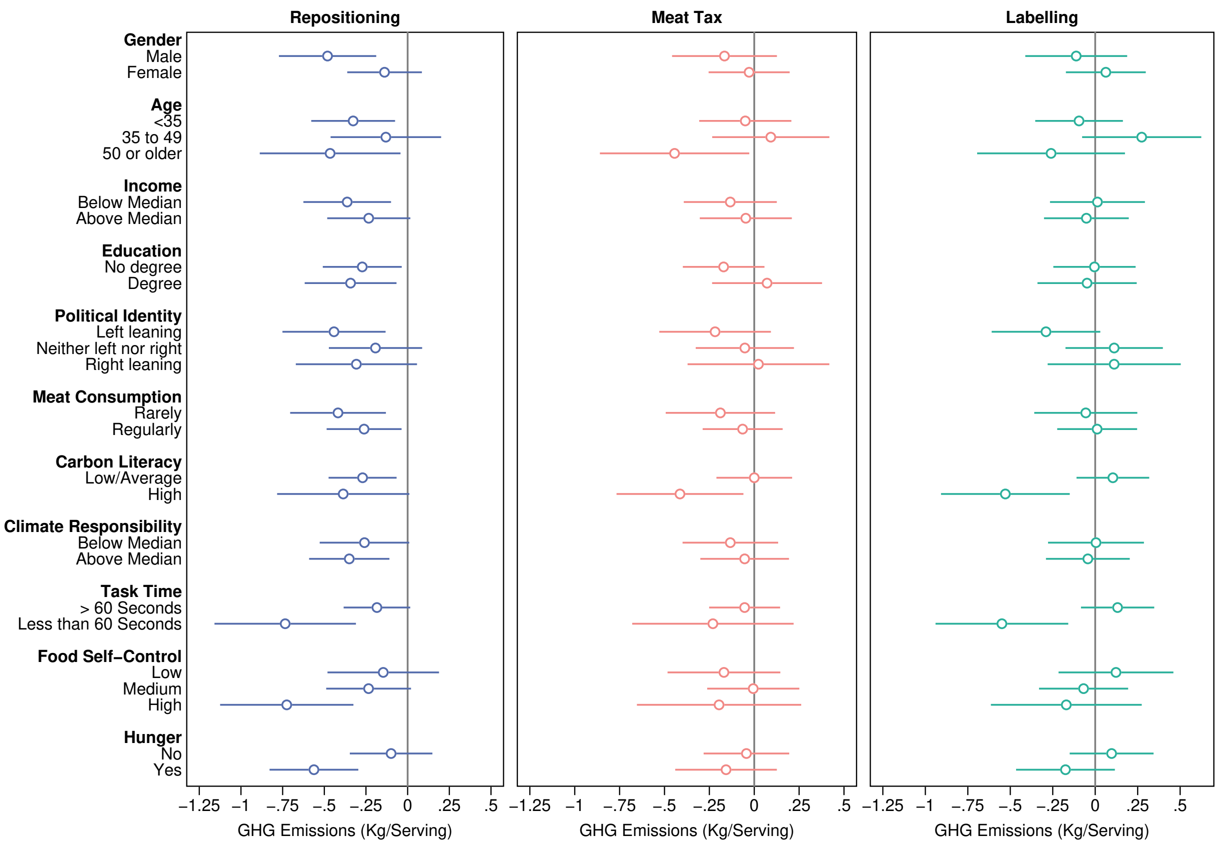

Figure 6: Heterogeneity analysis. Figure displays the regression-estimated effects of the three treatment interventions ('Meat Tax', 'Labels', 'Repositioning') on the average basket GHG emissions, each relative to the control condition, for specific subgroups of the sample. Estimates of equation (2) estimated by OLS. Error bars represent 95% confidence intervals. Full regression output presented in Appendix Table A9 N=4,008.

3.5.2 Mechanisms

Finally, we look at potential (psychological) mechanisms behind menu order effects. In particular, in online environments, factors such as rushed decisions and limited attention could increase susceptibility to the nudge (Valenčič et al., 2023). To proxy attention of participants, we make use of total time spent on the food choice task and distinguish between individuals that made their choice in less than 60 seconds (Median = 41 seconds) or took more than a minute's time (Median= 126 seconds). Furthermore, susceptibility likely depends on individual traits such as willpower and self-control, which can be framed both in terms of sustainability and health goals (White et al., 2019). On the one hand, consumers may hold low- or high-levels of trait self-control to resist food temptations. On the other hand, hunger or appetite may diminish executive functions, deplete cognitive resources and ultimately diminish peoples' momentary self-control to resist food temptations.[12] In both cases, menu-repositioning in favour of lower-carbon food may help people with lower-levels of self-control to make more sustainable choices, by increasing the effort and time involved in finding unhealthier (and generally more unsustainable) options (Münscher et al., 2016).

Table 4: Sales and revenues by restaurant and condition

	(1) Task Time	(2) Self-control	(3) Hunger
Reordering	-0.184*	-0.146	-0.099
	(0.102)	(0.171)	(0.126)
Task Time ≤ 60 seconds	0.348**		
	(0.177)		
Reordering × Task Time ≤ 60 seconds	-0.550**		
	(0.239)		
Medium Self-Control		-0.170	
		(0.151)	
High Self-Control		-0.040	
		(0.199)	
Reordering × Medium Self-Control		-0.088	
		(0.214)	
Reordering × High Self-Control		-0.579**	
		(0.266)	
Hungry=1			0.163
			(0.136)
Reordering × Hungry=1			-0.463**
			(0.186)
R^2	0.021	0.023	0.020
Observations	4,008	4,008	4,008

Note: This table presents OLS estimates of equation (2) from our heterogeneity analysis. The dependent variable is total basket GHG emissions (KG CO_2e/serving). Each column title refers to the moderator variable of interest, which is interacted with the main treatment variables. Meat Tax, Labelling or Reordering capture the treatment effects for the omitted base catgory. The interaction terms represent the difference in the treatment effect between the omitted base category and the respective moderator level. The treatment effect of the moderator levels relative to control are not shown here, but visualised in Figure 6. Robust standard errors in parentheses.

We again estimate equation (2) which interacts the treatment indicators with each of the potential mechanism variables individually. We find evidence for all three of these potential pathways: First, we find that Individuals who spent less time on the task (<60 seconds), held high levels of food self-control, or completed the survey around mealtimes (lunch or dinner) were particularly affected by the choice architecture inter-

[12]To measure *trait* self-control of eating behaviours we utilised the 5-item Self-Regulation of Eating Behaviour Questionnaire (SREBQ), developed and validated by Kliemann et al. (2016) for the UK population. Hunger was proxied based on the timing of participants' involvement in our experiment, specifically noting if it occurred around mealtime (lunch or dinner) or at other times during the day.

vention, relative to their counterparts in the control group (see Figure 6). We find significant interaction effects for all three subgroups, presented in Table 4. These findings suggest that menu-repositioning nudges on online menus may be particularly effective in reducing carbon emissions in settings where people spend little time deliberating over their choices.

In sum, our heterogeneity analysis suggests that menu repositioning is largely effective in reducing carbon emissions from food choices, regardless of individual socio-economic status, attitudes, or intentions. However, we find that men were more responsive to the choice architecture nudge and that attention, hunger, and self-control may all constitute important pathways through which its effectiveness can be enhanced.

3.6 Additional heterogeneity analysis

Next, we explore whether specific subgroups of the population are responsive to meat taxation or carbon footprint labelling (see Figure 6 and Appendix Table A9).

Here, we find that carbon literacy – people's baseline knowledge about the carbon impact of food – appears to be an important factor in determining the interventions' effectiveness. For participants with higher carbon literacy and awareness, both the meat tax and labelling significantly reduced the greenhouse gas emissions of their food choices. Both interaction terms are significant at the 5% and 1% level, respectively. Notably, we find that for this specific subgroup of the sample, labelling leads to the largest reduction in GHG emissions relative to similar participants in the control group (-0.53Kg CO_2e/serving), compared to meat taxation (-0.41Kg) and repositioning (-0.39Kg).

These findings suggest that even a small price change can incentivise more sustainable choices amongst a group of informed, climate-conscious consumers. It is also possible that the environmental sign-posting of the meat tax acted as a form of 'reminder nudge' by increasing the salience of the hidden environmental costs associated with food consumption and thus allowing more knowledgeable individuals to consume more climate friendly meals. Whilst a composite intervention was intentionally chosen for this study, future research should attempt to disentangle the effects of the economic incentive provided by price change and the nudge provided by the sign-posting (see e.g. Zizzo et al. (2021)) for environmentally motivated fiscal interventions.

Similarly, it is likely that labels lead to reductions in GHG emission ordered by increasing the salience of climate considerations in food consumption for this segment of the population. However, for individuals with lower carbon literacy, labels likely require more time and repetition to translate into knowledge gains, and ultimately affect habit formation. In addition to carbon literacy, we find that attention appears to influence the effectiveness of labelling. Subjects who spent less than 60 seconds on the task significantly reduced their GHG emissions by 0.55Kg CO_2e/serving, relative to the control group.

Finally, an important consideration in the evaluation of sustainable food policies is whether they may generate backlash amongst consumers. For instance, L. Ho and Page (2023), find significant backlash effects to a carbon labelling intervention among US consumers who do not believe that individuals have a

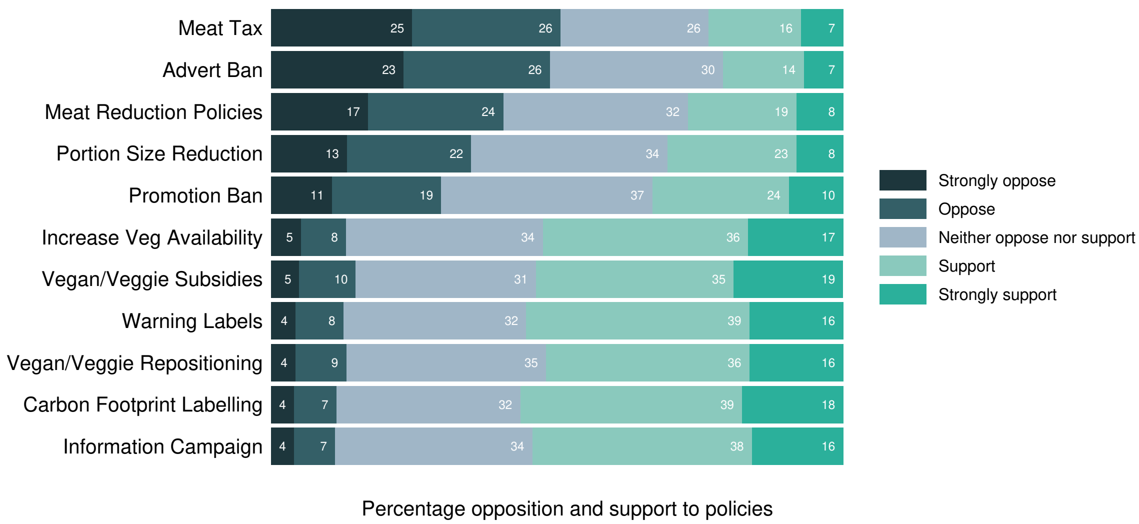

Figure 7: Support for interventions on delivery platforms. Figure displays the percentage responses in each category of policy support, measured on a scale from 1 to 5 from "Strongly Oppose" to "Strongly Support".

moral duty to help address climate. In our sample of UK participants, we find no evidence that any of the interventions resulted in backlash effects among participants: none of the subsamples show a significant increase in GHG emissions ordered in response to the interventions. The equivalent subpopulation in our dataset, with below median perceptions of individual climate responsibility, did not significantly change their food choice behaviour in response to labelling or meat tax interventions and significantly reduced emissions in the choice architecture condition.

3.7 Support for sustainable food policies on food delivery platforms

Understanding public acceptance of and desire for different policies is crucial as experimental efficacy does not always align with support among citizens and consumers. In our ex-post survey, we included a range of policy options which could be implemented on online food delivery apps and asked participants to indicate their support on a scale from 1 to 5 (strongly oppose to strongly support). Figure 7 visualises the distribution of opposition and support for all 11 policies. We find that the majority of policies are supported by more than half of participants. Policies that enjoy the highest levels of support are those that provide sustainability information via information campaigns or carbon labels, while repositioning options is the third most supported policy. Specifically, mean support was greatest for carbon footprint labels (3.59 out of 5), sustainable warning labels (3.55), and making low-carbon options more visible through repositioning (3.51). The latter echoes the effectiveness of choice architecture changes found in the experiment.

We find that more intrusive policies such as meat taxation, portion size reductions, advertising bans and meat reduction policies in general are amongst those which face the highest levels of opposition. Specifically, mean support was lowest for meat taxation (2.55), advertising bans (2.56), and meat reduction policies (2.78). Taken together, our findings suggest that meat taxation is neither supported nor effective in changing behaviour in our experimental setting.

Next, we explore which factors influence individuals' support for meat taxation, carbon labelling and menu repositioning. To do so, we construct a binary variable identifying support for the respective policy by combining response categories 'support' and 'strongly support' and use logistic regressions to model predictors of policy support. We hypothesised that exposure to the interventions may induce support for such policies in the real world. We find that this is not the case, with one notable exception: individuals randomly assigned to the labelling condition were 5%-points more likely to support carbon footprint labelling on food delivery platforms (significant at the 5% level).

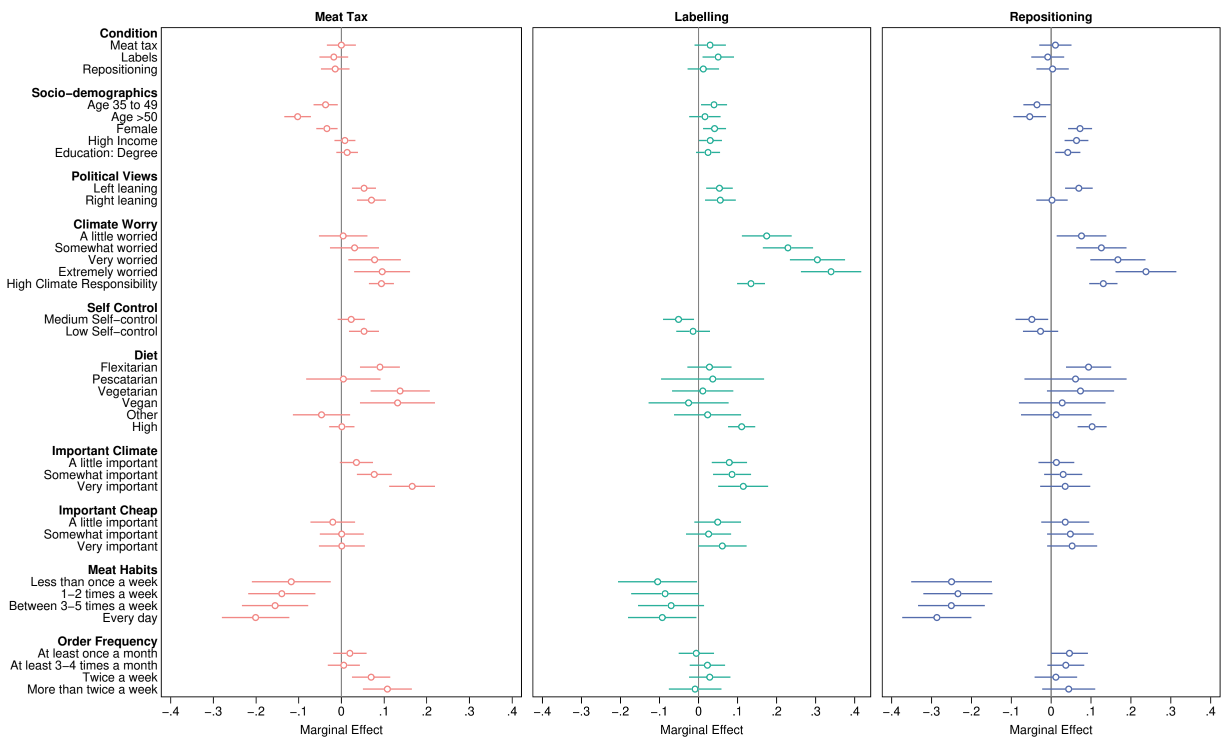

Figure 8: Predictors of Policy Support. Figure shows the predictors of policy support obtained from a logistic regression with a binary dependent variable identifying support for the respective policy (combining response categories 'support' and 'strongly support'). Error bars represent 95% confidence intervals from robust standard errors. The omitted reference categories are younger than 35 (age), male and non-binary (female), below median income (income) no degree education (education), not at all worried (climate worry), below median climate responsibility (climate responsibility), high self-control (self-control), none in particular (diet), not at all important that food is climate-friendly (important climate), not at all important that food is cheap (important cheap), never eat meat (meat habits), a few times a year (order frequency). Full regression estimates (marginal effects) are provided in Appendix, Table A10. N=4,008.

Figure 8 visualises other predictors of policy support. One key aspect revealed by the analysis is that individuals with meat-based diets and frequent meat eaters exhibit lower support for meat taxes, labels and repositioning, which is expected due to their perceived self-interest. On the other hand, those who express greater concern about climate change and feel a sense of responsibility to act are more inclined to support informational interventions such as labels and repositioning in favour of climate-friendly options. Moreover, people to whom it is important that food is climate friendly are more supportive of a meat tax and menu repositioning. This alignment can be attributed to their pre-existing climate-driven food preferences, as they possibly find these interventions reinforcing their current habits. Notably, we find that people with low food self-control are more supportive of meat taxation, in line with previous findings (Kukowski et al., 2023). However, this is not the case for labelling and repositioning. In essence, we find that personal dietary choices and climate concerns play crucial roles in predicting support for different interventions, and in ways that align with expectations. Climate-driven consumers embrace information nudges that reinforce their environmentally friendly habits, while heavy meat eaters resist interventions that could make their preferred options more costly (including search costs).

3.8 External validity

An important consideration when interpreting the results of any experiment is to what degree the findings can be generalised to other contexts or settings. This section thus provides a dedicated discussion of external validity of our experiment, following List's 2020 SANS framework, which encompasses Selection, Attrition, Naturalness, and Scaling considerations.

First, with respect to Selection, our sampling strategy aimed to recruit study participants that most closely align with the population segment that regularly utilizes food-delivery platforms in the UK. We therefore recruited a large sample of individuals who were regular users of home delivery and food delivery platforms. People who never used delivery platforms were not eligible to participate in the survey, which made up around 15% of all people that started the study. Moreover, recruitment was limited to urban areas, as food delivery apps are generally not available in rural areas. Taken together, this strategy makes our selected sample broadly representative of actual users of food-delivery apps. Additionally, our sample shows a relative similarity in key summary statistics when compared to the overall UK population, as indicated in Table 1 ('UK Mean' column). These statistics are derived from the Census and other nationally representative surveys. Notably, our sample exhibits close alignment in terms of gender distribution, educational attainment, and dietary preferences.

Second, while not all participants completed the study in full (due to failed technical checks, non-eligibility, failed attention checks or time-outs), Attrition is not a concern in this study due to the one-shot between-subject design of the experiment. Recruitment was continued until the target sample size of 4,000 participants was reached.

Third, when it comes to Naturalness, our study aimed to replicate the typical consumer experience of interacting with an online food delivery platform. Participants engaged in a choice task that closely resembled the process of searching for meals online, browsing through restaurant and meal options, adjusting their basket by adding or removing food items, and ultimately checking out the desired meal for purchase. While participants utilized the experimenters' funds £20 instead of their own money, it is worth noting that we emphasized the realistic aspect of the task by informing participants that there was a chance of actually receiving the food order they placed. Moreover, any unspent budget was transferred to the participants' bank accounts, providing real financial incentives to minimise "over-buying" on the platform.

Fourth, with regard to Scaling, it is evident that online platforms offer a convenient and adaptable medium for implementing all the interventions (or variants of these) examined in our study. For example, such platforms could voluntarily incorporate features that allow users to sort food items based on different criteria, including sustainability and climate impact. Additionally, online platforms provide flexibility in terms of visual design and layout, making it possible to visually emphasize sustainable food options or accompany them with symbols or labels that highlight their low carbon attributes. One limitation of implementing sustainability sorting or labelling on a webpage for food delivery is the requirement for detailed information and data on life cycle analysis to calculate carbon footprints. However, an increasing number of services are becoming available that facilitate large-scale carbon footprint calculations, which would allow scaling to be implemented in a cost-effective manner.

4 Discussion and conclusion

This study demonstrates that a simple choice architecture interventions in the form of menu repositioning can effectively nudge consumers towards more sustainable food choices in online food delivery settings. Specifically, placing lower carbon options first significantly reduced the greenhouse gas emissions of purchased meal baskets by around 12% (or 0.3 kg CO_2eq per order) compared to the control group. Repositioning also decreased selections of high carbon main dishes by about 13% (5.6 percentage points) relative to the control condition. However, repositioning did not substantially reduce demand for meat-based main meals. Importantly, the repositioning intervention simultaneously improved health outcomes by lowering average calories consumed and improving nutrition while consumer satisfaction was maintained or even enhanced relative to the control condition. Further research could incorporate more comprehensive diet quality indicators and explore synergies between environmental and nutritional goals, as called for by the healthy planetary diets paradigm.

Our findings are thus in line with recent evidence from cafeteria and restaurant experiments (Garnett et al., 2020; Gravert & Kurz, 2019), as well as choice-architecture interventions explicitly targeting healthy food consumption in online food-delivery and retail settings (Bianchi et al., 2023; Valenčič et al., 2023). Moreover, our results lend further support to the notion that plant-based defaults, with menu repositioning as a more subtle implementation, can reliably induce substantial changes in consumption behaviour (Meier et al., 2022; Reisch & Sunstein, 2021).

Our experimental design allows a direct comparison of the effectiveness of different 'types' of interventions within the same choice context. Our results reveal the relative advantage of the choice architecture nudge, over information provision (via carbon labels) and price disincentives (via meat taxation) in this specific experimental setting. Notably, we find that labelling and meat taxation is only effective in encouraging lower-carbon food choices for people with more a priori knowledge of the climate impact of food consumption (i.e. high carbon-literacy).

Our findings thus only partially align with recent field-experimental evidence on carbon footprint labelling in cafeteria and restaurant settings (Beyer et al., 2023; Lohmann et al., 2022), while the lack of repeated exposure to carbon footprint information may explain the limited effects encountered in the full sample (Casti et al., 2022). Specifically, if labels primarily act through improvements in knowledge, repeated exposure will allow consumers to actively process information and cumulatively build awareness about the carbon footprint of food, which could be further reinforced by third-party verification (Casti et al., 2022; Gorton et al., 2021). In our sample, we find that labels were only successful in increasing people's knowledge for the segment of the population that had the lowest food carbon literacy (see Appendix Table A8). For these participants, being exposed to the labelling treatment increased the likelihood of participants correctly categorising their chosen meal into low, medium, or high carbon impact categories by 5.5 percentage points (or a 51%, relative to the control group). Conversely, we find that participants who spent less than 60 seconds on food selection were notably influenced by labelling, offering tentative support for the idea that labels primarily affect choices through salience rather than knowledge (L. Ho & Page, 2023; Pace & van der Weele, 2020; Tilling, 2023), particularly in situations with limited time and attention devoted to the task.

While theory predicts that meat taxes could bring about substantial shifts in consumer demand (Funke et al., 2022), we find limited evidence for its efficacy in this experiment. One possible explanation is that the price increase (which was tied to a substantial carbon price of £483 per metric ton of CO_2) was not large enough to impact choices, especially given high background inflation at the time of the experiment. Furthermore, the experimental budget represented an unexpected windfall gain, and participants' ordering behaviour might have varied if they had earned the endowment (Carlsson et al., 2013).[13] It is also important to acknowledge that, while our meat tax intervention was clearly sign-posted to increase the salience of its environmental motives (Bordalo et al., 2013; Chetty et al., 2009; Gravert & Shreedhar, 2022), we provided no information to participants on revenue-recycling, which may contribute to their perceived effectiveness (Fesenfeld, 2023).

More generally, we find that preferences in the sample for climate-friendly food consumption were low. Only 11% of participants stated climate impact as a decision factor when choosing their meal. Interventions such as carbon labelling or sign-posted meat taxation strongly rely on sufficient preferences for low-carbon food consumption and are likely to be more effective if people understand and support their underlying objective (Lohmann, 2023). In line with previous research (Vermeulen et al., 2020), taste, craving, price and quality were the most important decision factors in our sample (see Figure A4).

Our findings have important policy implications. First, we demonstrate that choice architecture approaches such as strategic menu ordering can nudge climatarian diets without compromising satisfaction or wellbeing. It thus represents a minimally intrusive strategy to support the transition towards more sustainable and healthy diets, whilst maintaining freedom of choice.[14] Moreover, we encounter high levels of pre-existing support for menu repositioning in our sample, with 87% of participants favouring or stating indifference to its implementation, which enhances its potential political feasibility. While restaurants with the lowest-carbon menus experience financial gains under menu repositioning, we do not find a strong indication that

[13] We attempted to mitigate the windfall earnings effect by clearly stating that any remaining budget would be paid out to the participants' bank accounts in the case that they were chosen as a winner.

[14] Comparable choice-architecture regulation was introduced in UK grocery stores in October 2022, restricting the placement of products high in fat, salt and sugar (HFSS) in high footfall areas such as checkouts, store entrances and end-of-aisle units (Muir et al., 2023).

repositioning consistently harms restaurants listed further down the page. Scaling of such an intervention, on a voluntary basis, would nonetheless require the cooperation of all food-service providers to enable standardized carbon footprint calculations. As the demand for carbon footprint quantification in the food industry grows, an increasing number of life-cycle assessment and footprinting services are becoming available, likely leading to reduced costs to the consumer over time.

The cost associated with carbon footprint quantification is also likely to be the key determinant for the cost-effectiveness of menu repositioning interventions. In a hypothetical scenario under which menu repositioning is implemented by the food delivery-app with the largest market share in the UK (JustEat) with annual transactions in order of 260 million,[15] a reduction of 0.3kg/CO_2e on average per order would result in overall emissions savings of 78,000 metric tons per year. If estimated programme costs amount to £150,000 per year (considering only carbon footprint quantification and platform developer costs), the total annual abatement cost would be £1.92 ($2.38) per metric ton CO_2e emissions avoided.[16] Assuming a conservative social cost of carbon in the range of $31-$51,[17] this would be considered a highly cost-effective policy intervention.

Our findings also provide a practical path for industry initiatives to contribute towards healthy and sustainable diets whilst addressing Scope 3 emissions. Food industry and retail sectors are increasingly pressured to contribute to sustainable food systems and diets, not only for their "licence to operate" but also as a show of respect for customers. Moreover, early movers may gain a competitive advantage as consumer preferences and expectations evolve. Consequently, we anticipate the growing adoption of behavioural tools in online choice environments (Ytreberg et al., 2023). An initial voluntary adaptation of a default menu repositioned in order of climate impact, would be to allow customers to self-select the order in which restaurants and menu items are presented, with sustainability (or nutritional content) being one of the possible criteria.

It is important to acknowledge several limitations of our study. First, our study is unable to track long-term adjustments in response to alterations of the delivery platform. It is possible that individuals could adapt to changes in platform design, for instance, by learning to scroll further through the list to find favoured items. Furthermore, carbon labels and sign-posted meat taxation, which partially rely on information processing, might only yield the desired effects after individuals have been repeatedly exposed to them. Further research is necessary to comprehensively investigate dynamic effects and verify the observed null results. Moreover, future research could explore how to better exploit digital food-choice interfaces in combination with machine learning, to learn about customers' intentions and preferences and provide personalised and targeted interventions for healthy and more sustainable diets (Yoganarasimhan, 2020). Finally, a logical extension of our incentivised experiment would involve testing our hypotheses in real-world food-delivery settings, where individuals use their own money and are unaware that their choices are under observation.

Taken together, our study provides compelling evidence for the relative efficacy of choice-architecture nudges on app-based food delivery platforms to promote healthier and climate-friendlier foods without

[15] Data from 2022. See https://www.statista.com/statistics/690645/number-of-orders-from-takeawaycom-by-country/.

[16] Alternative scenarios under which implementation costs are lower (£100,000) or substantially higher (£300,000) result in a range of annual abatement costs spanning from £1.28 to £3.85 per metric ton of avoided CO_2 emissions.

[17] Upper bound based on data up until 2021 (Interagency Working Group on Social Cost of Greenhouse Gases (IWG), 2021)

compromising customer satisfaction. Importantly, our heterogeneity analysis also suggests that repositioning is effective regardless of socio-economic status, educational attainment and dietary preferences, thus making it less likely to further exacerbate pre-existing dietary inequalities. However, gender does appear to play a role in determining the effectiveness of choice architecture, which calls for further research into the optimal design of policies that take gender differences into account. Additional research is also warranted to further explore mechanisms underlying menu-repositioning interventions. While our initial findings are promising, additional strategies may be needed to permanently shift preferences away from meat and animal-based options, which are responsible for nearly 60% of food system emissions (Xu et al., 2021), to further minimize climate and environmental impacts of food delivery orders.

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Appendix A: Additional Tables & Figures

A.1.1 Additional Figures

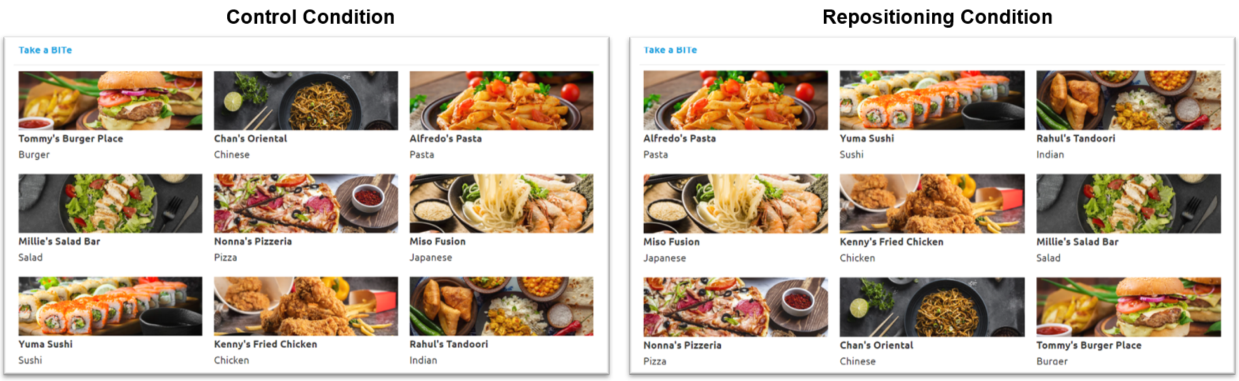

Figure A1: Desktop Version: Restaurants. Restaurant page in the control condition (random order) and repositioning condition (lowest carbon restaurants displayed first).

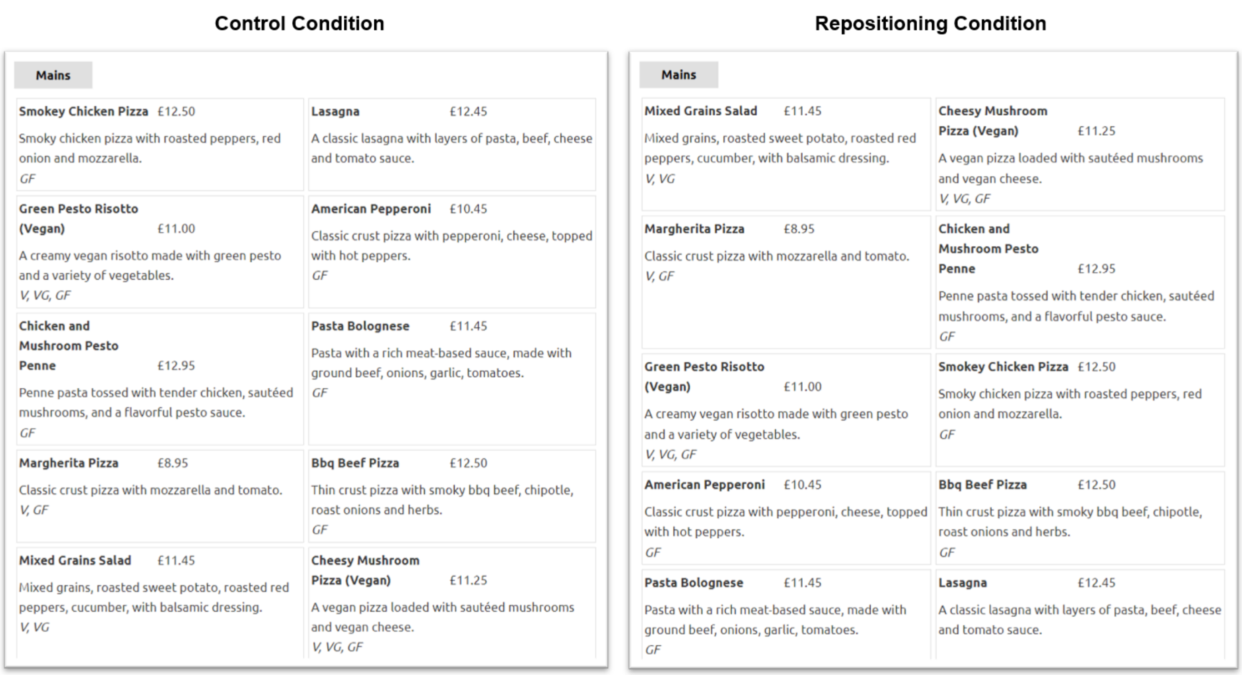

Figure A2: Desktop Version: Menus. Menu page in the control condition (random order) and repositioning condition (lowest carbon dishes displayed first).

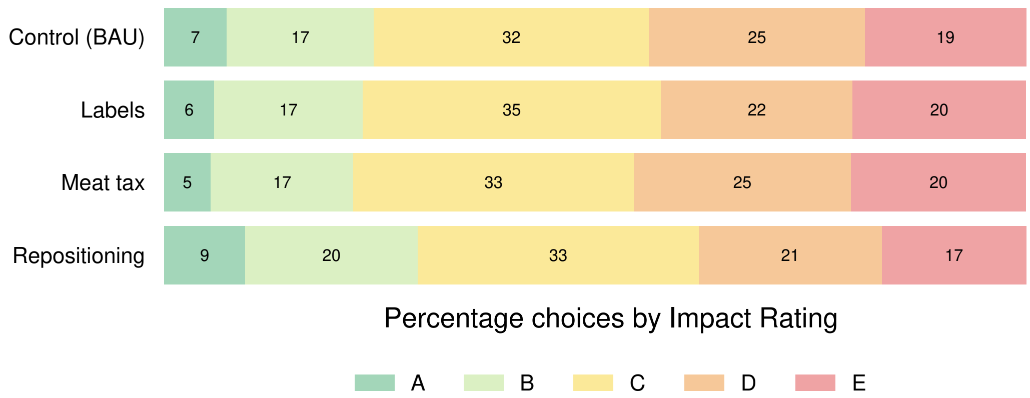

Figure A3: Choices by impact score. Percentage mains chosen according to their climate impact score (A-E) by treatment condition.

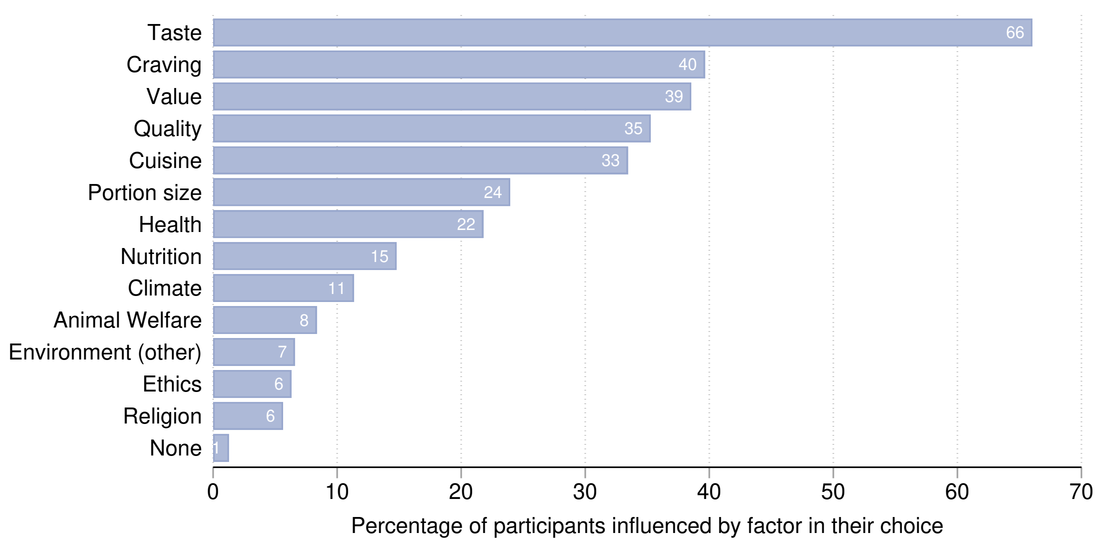

Figure A4: Decision factors.

A.1.2 Additional Tables

Table A1: Balance Checks

Incentivisation Statistics	
Winners contacted	106
No response	56
Incomplete response	5
Restaurant/Item unavailable	6
Attempted deliveries	30
Successful deliveries	27
Failed deliveries	3
Total Delivery Cost	£455.69
Total Email Payments	£420.09
Total Charity Donation	£114.92
Total Incentivisation	£990.70

Note: Incentivisation Statistics

Table A2: Balance Checks

	Control	**Meat tax**		**Labels**		**Reordering**	
	N=990 (24.7%)	N=1,015 (25.3%)	p-value	N=994 (24.8%)	p-value	N=1,009 (25.2%)	p-value
Female	0.54 (0.50)	0.52 (0.50)	0.279	0.52 (0.50)	0.259	0.53 (0.50)	0.259
Age	38.27 (13.80)	38.10 (13.40)	0.788	37.54 (13.50)	0.233	37.68 (13.27)	0.233
Income (£)	35619.57 (25775.07)	34794.09 (25077.67)	0.467	34487.42 (24705.24)	0.318	36615.46 (26256.66)	0.318
Degree	0.35 (0.48)	0.33 (0.47)	0.212	0.33 (0.47)	0.268	0.36 (0.48)	0.268
Political identity							
Left leaning	328 (33.1%)	330 (32.5%)	0.712	319 (32.1%)	0.812	320 (31.7%)	0.812
Neither left nor right	455 (46.0%)	484 (47.7%)		471 (47.4%)		470 (46.6%)	
Right leaning	207 (20.9%)	201 (19.8%)		204 (20.5%)		219 (21.7%)	
Diet							
None in particular	765 (77.3%)	805 (79.3%)	0.681	782 (78.7%)	0.238	809 (80.2%)	0.238
Flexitarian	89 (9.0%)	79 (7.8%)		70 (7.0%)		79 (7.8%)	
Pescatarian	18 (1.8%)	19 (1.9%)		12 (1.2%)		13 (1.3%)	
Vegetarian	60 (6.1%)	57 (5.6%)		79 (7.9%)		59 (5.8%)	
Vegan	28 (2.8%)	20 (2.0%)		26 (2.6%)		22 (2.2%)	
Other	30 (3.0%)	35 (3.4%)		25 (2.5%)		27 (2.7%)	

Note: Mean (Standard deviation): p-value from pooled t-test of equality of means for the control and respective treatment group. Frequency (Percent %): p-value from Pearson Chi-squared test of equality of proportions for the control and respective treatment group.

Table A3: Summary Statistics — variables used for exploratory analysis

Variable	Mean	Std. Dev.	Min	Max
Climate Worry				
Not at all worried	.09	.29	0	1
A little worried	.21	.41	0	1
Somewhat worried	.3	.46	0	1
Very worried	.24	.43	0	1
Extremely worried	.15	.36	0	1
Climate Responsibility				
Below Median	.52	.5	0	1
Above Median	.48	.5	0	1
Food Self-control				
High	.17	.38	0	1
Medium	.5	.5	0	1
Low	.33	.47	0	1
Food Carbon Literacy				
Low/Average	.79	.41	0	1
High	.21	.41	0	1
Important Climate				
Not at all important	.21	.4	0	1
A little important	.32	.47	0	1
Somewhat important	.33	.47	0	1
Very important	.14	.35	0	1
Important Cheap				
Not at all important	.08	.27	0	1
A little important	.28	.45	0	1
Somewhat important	.4	.49	0	1
Very important	.24	.42	0	1
Meat consumption habits				
Never	.06	.24	0	1
Less than once a week	.05	.22	0	1
1-2 times a week	.18	.38	0	1
Between 3-5 times a week	.43	.49	0	1
Every day	.28	.45	0	1
Takeaway Order Frequency				
A few times a year	.16	.36	0	1
At least once a month	.28	.45	0	1
At least 3-4 times a month	.32	.47	0	1
Twice a week	.17	.38	0	1
More than twice a week	.08	.27	0	1
Time spent on task (min)	2.32	2.32	0.11	37.71
Hungry				
No	.57	.49	0	1
Yes	.43	.49	0	1

Note: Table displays the summary statistics for all additional variables not displayed in Table 1, that are used in the exploratory analysis ($N = 4,008$).

Table A4: Main Analysis: Climate-impact outcomes

	(1) GHG	(2) High-impact Main	(3) Meat Main	(4) Calories	(5) NutriScore	(6) Health Score	(7) Satisfaction
Meat tax	-0.091	0.014	0.018	-10.669	0.013	0.015	0.018
	(0.093)	(0.022)	(0.021)	(17.066)	(0.049)	(0.065)	(0.041)
	[0.318]	[0.523]	[0.397]				
Labels	-0.018	-0.018	0.037*	6.232	0.017	0.056	0.005
	(0.096)	(0.022)	(0.021)	(16.996)	(0.050)	(0.066)	(0.042)
	[0.840]	[0.428]	[0.085]				
Repositioning	-0.298***	-0.058***	0.003	-55.571***	-0.131***	0.160**	0.082**
	(0.093)	(0.022)	(0.021)	(17.225)	(0.048)	(0.065)	(0.040)
	[0.004]	[0.005]	[0.881]				
R^2	0.018	0.012	0.020	0.022	0.006	0.005	0.003
Observations	4,008	4,008	4,008	4,008	4,008	4,008	4,008

Note: This table presents the effect of being randomly assigned to one of three treatment groups on our primary outcomes of interest, relative to the control group. Specifically, it presents estimates of β from equation (1) estimated by OLS and LPM. In column (1), the dependent variable is total basket GHG emissions (KG CO_2e/serving). The dependent variables in columns (2) and (3) are the propensity of choosing a high-carbon or meat main dish, respectively. Robust standard errors in parentheses. Multiple testing adjusted p-values in square brackets based on randomisation inference (Young 2019, 2020).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Primary Analysis Meal Type

	(1) Vegan	(2) Vegetarian	(3) Fish	(4) Meat
Meat tax	-0.0210	0.0251*	-0.0223	0.0182
	(0.0134)	(0.0141)	(0.0151)	(0.0210)
Labels	0.00438	-0.00164	-0.0397***	0.0369*
	(0.0142)	(0.0135)	(0.0147)	(0.0211)
Reordering	0.0150	0.00551	-0.0234	0.00293
	(0.0145)	(0.0136)	(0.0152)	(0.0212)
R^2	0.009	0.007	0.010	0.020
Observations	4,008	4,008	4,008	4,008

Note: This table presents the effect of being randomly assigned to one of three treatment groups on choices of meal types, relative to the control group. Specifically, it presents estimates of β from equation (1) estimated by LPM. Depedent variables are binary indicators indicating choices vegan, vegetarian, fish or meat main meals, respectively. Robust standard errors in parentheses.

Table A6: Substitution within restaurants

	(1) Pasta	(2) Sushi	(3) Indian	(4) Japanese	(5) Fried Chicken	(6) Salad Sandwiches	(7) Pizza	(8) Chinese	(9) Burgers
Meat tax	-0.390**	0.036	-0.087	-0.021	0.101	-0.713*	-0.216	-0.147	-0.327
	(0.188)	(0.141)	(0.067)	(0.110)	(0.080)	(0.365)	(0.210)	(0.122)	(0.400)
Labels	-0.032	-0.313**	-0.067	0.129	0.041	-0.057	-0.215	-0.239*	-0.064
	(0.213)	(0.137)	(0.066)	(0.113)	(0.072)	(0.381)	(0.203)	(0.126)	(0.419)
Reordering	-0.317*	-0.317**	-0.119*	0.042	0.014	-0.479	-0.357	-0.311**	-0.328
	(0.185)	(0.127)	(0.062)	(0.125)	(0.073)	(0.333)	(0.230)	(0.127)	(0.422)
R^2	0.026	0.045	0.015	0.015	0.010	0.093	0.017	0.048	0.064
Observations	417	378	502	273	606	182	547	525	578

Note: $N = 4,008$. This table presents estimates of equation (1) estimated by OLS for each restaurant sub-sample individually. The dependent variable is total basket GHG emissions (KG CO_2e/serving). Robust standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Sales and revenue by restaurant and condition

	Control	Meat Tax	Labelling	Repositioning
Pasta				
Total Revenue (£)	978	1090	1047	1671
Total Sales	86	93	91	147
Sushi				
Total Revenue (£)	1156	1221	963	1625
Total Sales	88	94	75	121
Indian				
Total Revenue (£)	2180	2010	1782	2092
Total Sales	135	123	113	131
Japanese				
Total Revenue (£)	1336	1116	1158	916
Total Sales	80	67	71	55
Fried Chicken				
Total Revenue (£)	1751	1762	1780	1886
Total Sales	150	143	152	161
Salad/Sandwiches				
Total Revenue (£)	596	460	490	380
Total Sales	56	43	47	36
Pizza				
Total Revenue (£)	2114	2227	2355	1510
Total Sales	138	148	159	102
Chinese				
Total Revenue (£)	1877	2250	2018	1733
Total Sales	126	145	136	118
Burgers				
Total Revenue (£)	1572	2231	1776	1602
Total Sales	131	159	150	138
Total				
Total Revenue (£)	1634	1794	1670	1649
Total Sales	990	1015	994	1009

Note: Table displays the total revenue (£) and total sales by condition for each of the nine restaurants.

Table A8: Did Labels improve Literacy?

	(1) Full Sample	(2) Low Literacy	(3) Mid Literacy	(4) High Literacy
Meat tax	-0.018	0.008	-0.043	-0.038
	(0.015)	(0.020)	(0.028)	(0.037)
Labels	0.021	0.055**	0.000	-0.019
	(0.016)	(0.022)	(0.029)	(0.040)
Reordering	-0.003	0.014	-0.013	-0.023
	(0.016)	(0.021)	(0.028)	(0.038)
R^2	0.004	0.008	0.004	0.003
Observations	4008	1905	1273	830

Note: This table presents the effect of being randomly assigned to one of three treatment groups on the probability of correctly categorising the carbon footprint of the chosen meal, relative to the control group. Specifically, it presents estimates of β from equation (1) estimated by LPM. Column (1) uses all observations from the full sample. Columns (2), (3) and (4) use sub-samples corresponding to low, average and high baseline carbon literacy. Robust standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A9: Heterogeneity Analysis

	(1) Gender	(2) Age	(3) Income	(4) Education	(5) Politics	(6) Habits	(7) C. Lit.	(8) Clim. Resp.	(9) Task Time	(10) Self-control	(11) Hunger
Meat tax	-0.166	-0.050	-0.133	-0.170	-0.218	-0.188	0.000	-0.133	-0.054	-0.169	-0.044
	(0.149)	(0.131)	(0.132)	(0.116)	(0.159)	(0.155)	(0.108)	(0.136)	(0.101)	(0.160)	(0.122)
Labels	-0.112	-0.095	0.013	-0.004	-0.290*	-0.056	0.104	0.005	0.132	0.122	0.097
	(0.153)	(0.132)	(0.143)	(0.124)	(0.163)	(0.155)	(0.109)	(0.144)	(0.110)	(0.172)	(0.126)
Reordering	-0.480***	-0.327**	-0.363***	-0.272**	-0.442***	-0.418***	-0.270***	-0.259*	-0.184*	-0.146	-0.099
	(0.149)	(0.128)	(0.134)	(0.121)	(0.158)	(0.146)	(0.104)	(0.137)	(0.102)	(0.171)	(0.126)
M1	-0.576***	0.076	-0.126	-0.154	-0.083	0.409***	0.155	-0.261*	0.348**	-0.170	0.163
	(0.136)	(0.147)	(0.153)	(0.136)	(0.156)	(0.139)	(0.163)	(0.134)	(0.177)	(0.151)	(0.136)
M2		0.464**			-0.180					-0.040	
		(0.186)			(0.177)					(0.199)	
M1 × Meat Tax	0.137	0.142	0.086	0.242	0.166	0.124	-0.414**	0.080	-0.177	0.163	-0.113
	(0.188)	(0.212)	(0.186)	(0.195)	(0.211)	(0.192)	(0.210)	(0.185)	(0.250)	(0.207)	(0.189)
M1 × Labelling	0.174	0.369*	-0.065	-0.044	0.401*	0.067	-0.633***	-0.048	-0.681***	-0.191	-0.272
	(0.194)	(0.222)	(0.191)	(0.193)	(0.219)	(0.196)	(0.222)	(0.191)	(0.228)	(0.219)	(0.194)
M1 × Reordering	0.342*	0.196	0.129	-0.070	0.249	0.156	-0.116	-0.091	-0.550**	-0.088	-0.463**
	(0.187)	(0.212)	(0.185)	(0.185)	(0.213)	(0.186)	(0.228)	(0.184)	(0.239)	(0.214)	(0.186)
M2 × Meat Tax		-0.394			0.242					-0.027	
		(0.249)			(0.256)					(0.283)	
M2 × Reordering		-0.138			0.134					-0.579**	
		(0.250)			(0.243)					(0.266)	
M2 × Labelling		-0.165			0.402					-0.292	
		(0.258)			(0.257)					(0.285)	
Female		-0.419***	-0.412***	-0.412***	-0.421***	-0.383***	-0.403***	-0.411***	-0.403***	-0.425***	-0.410***
		(0.067)	(0.067)	(0.067)	(0.068)	(0.067)	(0.067)	(0.067)	(0.068)	(0.067)	(0.067)
Age	0.010***		0.010***	0.010***	0.010***	0.011***	0.010***	0.011***	0.010***	0.011***	0.010***
	(0.002)		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Income	-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)	(0.000)	(0.000)	(0.000)
Degree	-0.118*	-0.122*	-0.121*	0.000	-0.107	-0.117*	-0.121*	-0.100	-0.122*	-0.123*	-0.127*
	(0.070)	(0.070)	(0.070)	(.)	(0.070)	(0.070)	(0.070)	(0.070)	(0.070)	(0.070)	(0.070)
Constant	2.564***	2.742***	2.492***	2.486***	2.554***	2.137***	2.428***	2.559***	2.400***	2.535***	2.406***
	(0.152)	(0.119)	(0.143)	(0.138)	(0.165)	(0.167)	(0.134)	(0.148)	(0.139)	(0.155)	(0.138)
R^2	0.019	0.020	0.019	0.019	0.020	0.030	0.021	0.023	0.021	0.023	0.020
Observations	4,008	4,008	4,008	4,008	4,008	4,008	4,008	4,008	4,008	4,008	4,008

Note: This table presents OLS estimates of equation (2) from our heterogeneity analysis. The dependent variable is total basket GHG emissions (KG CO_2e/serving). Each column title refers to the moderator variable of interest, which is interacted with the main treatment variables. M1 refers main effect of the moderator variable first level of the moderator variable. M2 refers to the second level of the moderator variable (if applicable). M0 is the omitted base category. Meat Tax, Labelling or Reordering capture the treatment effects for the omitted base catgory (e.g. in column (1) they capture the effect of the treatments for male participants). M1/M2 × Meat Tax, Labelling or Reordering, represent the interaction terms for the first/second level of the moderator with the main treatment variables. They provide the difference in the treatment effect between the omitted base category and the respective moderator level (e.g. in column (1) they capture the difference in treatment effects between male and female participants). The treatment effect of the moderator levels relative to control are not shown here, but visualised in Figure 6. Robust standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A10: Predictors of Policy Support

	(1) Meat Tax		(2) Carbon Labels		(3) Repositioning	
Condition						
Meat tax	-0.000	(0.017)	0.030	(0.020)	0.011	(0.021)
Labels	-0.018	(0.017)	0.050**	(0.020)	-0.008	(0.021)
Reordering	-0.014	(0.017)	0.012	(0.021)	0.004	(0.021)
Socio-demographics						
35 to 49	-0.037**	(0.014)	0.040**	(0.017)	-0.036**	(0.017)
50 or older	-0.103***	(0.016)	0.016	(0.020)	-0.054**	(0.021)
Female	-0.034***	(0.013)	0.041***	(0.015)	0.072***	(0.015)
Above Median	0.008	(0.013)	0.030**	(0.015)	0.064***	(0.015)
Degree	0.014	(0.013)	0.024	(0.016)	0.042***	(0.016)
Political Views						
Left leaning	0.053***	(0.014)	0.054***	(0.017)	0.069***	(0.018)
Right leaning	0.070***	(0.017)	0.056***	(0.020)	0.002	(0.020)
Climate Worry						
A little worried	0.004	(0.029)	0.174***	(0.033)	0.076**	(0.032)
Somewhat worried	0.031	(0.029)	0.229***	(0.033)	0.126***	(0.032)
Very worried	0.078**	(0.031)	0.304***	(0.036)	0.167***	(0.035)
Extremely worried	0.096***	(0.033)	0.339***	(0.040)	0.238***	(0.039)
Above Median	0.094***	(0.015)	0.134***	(0.018)	0.131***	(0.018)
Self Control						
Medium	0.023	(0.016)	-0.051**	(0.020)	-0.048**	(0.021)
Low	0.053***	(0.018)	-0.014	(0.022)	-0.027	(0.023)
Diet						
Flexitarian	0.090***	(0.024)	0.028	(0.029)	0.094***	(0.029)
Pescatarian	0.005	(0.044)	0.036	(0.067)	0.061	(0.065)
Vegetarian	0.138***	(0.035)	0.011	(0.040)	0.074*	(0.043)
Vegan	0.132***	(0.045)	-0.026	(0.052)	0.028	(0.055)
Other	-0.047	(0.034)	0.023	(0.044)	0.013	(0.045)
High	0.001	(0.015)	0.110***	(0.018)	0.103***	(0.019)
Important Climate						
A little important	0.035*	(0.020)	0.079***	(0.023)	0.013	(0.023)
Somewhat important	0.077***	(0.021)	0.086***	(0.025)	0.030	(0.024)
Very important	0.166***	(0.027)	0.115***	(0.033)	0.035	(0.032)
Important Cheap						
A little important	-0.020	(0.027)	0.049	(0.030)	0.035	(0.031)
Somewhat important	0.001	(0.026)	0.026	(0.030)	0.048	(0.030)
Very important	0.001	(0.027)	0.061*	(0.032)	0.053	(0.032)
Meat Habits						
Less than once a week	-0.118**	(0.047)	-0.105**	(0.052)	-0.250***	(0.052)
1-2 times a week	-0.140***	(0.040)	-0.086*	(0.044)	-0.234***	(0.044)
Between 3-5 times a week	-0.155***	(0.040)	-0.070	(0.043)	-0.250***	(0.043)
Every day	-0.201***	(0.040)	-0.093**	(0.045)	-0.287***	(0.044)
Order Frequency						
At least once a month	0.020	(0.020)	-0.006	(0.023)	0.046*	(0.024)
At least 3-4 times a month	0.006	(0.019)	0.023	(0.023)	0.037	(0.024)
Twice a week	0.070***	(0.023)	0.029	(0.027)	0.012	(0.027)
More than twice a week	0.108***	(0.029)	-0.009	(0.034)	0.044	(0.034)
Observations	4,008		4,008		4,008	

Note: This table presents the predictors of policy support obtained from a logistic regression with a binary dependent variable identifying support for the respective policy (combining response categories 'support' and 'strongly support'). Robust standard errors in parentheses. The omitted reference categories are younger than 35 (age), male and non-binary (female), below median income (income) no degree education (education), not at all worried (climate worry), below median climate responsibility (climate responsibility), high self-control (self control), none in particular (diet), not at all important that food is climate friendly (important climate), not at all important that food is cheap (important cheap), never eat meat (meat habits), a few times a year (order frequency).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix B: Additional methodological details

B.1.1 Carbon footprint and Nutri-Score calculations

Recipes were developed in collaboration with Foodsteps Ltd. We used the platform provided by Foodsteps Ltd. to calculate the carbon footprints for each meal. We used an online nutrition calculator (https://whisk.com/recipe-nutrition-calculator/) to calculate macro and micro-nutrients for each recipe. This tool was also used to calculate the Health Score. To calculate the Nutri-Score we use the official formula and code adapted from ("Estimating the environmental impacts of 57,000 food products", 2022). See e.g. Julia and Hercberg (2017) for a detailed description of the Nutri-Score, how it was derived and how it is calculated.

B.1.2 Platform design and menu composition

We designed a delivery platform closely mirroring real-world apps like Just Eat or Deliveroo, featuring 9 popular virtual restaurants ranging from burger and chicken fast food, pizza, sandwiches and salad, sushi, pasta, Japanese, Chinese and Indian cuisine. The cuisines represented top dining options on major UK delivery platforms. While restaurant names were generic, every restaurant's offer was modelled after a real-world counterpart, allowing us to deliver actual orders to randomly selected participants. In total, the platform offered approximately 20-25 menu items per restaurant, including main dishes, drinks, desserts and small appetizers. Across all 9 restaurants, 204 items (164 unique items) were available for order.

For this study, recipes for all menu items were developed from scratch in collaboration with Foodsteps, a company specializing in life-cycle assessment and carbon footprint quantification. The recipes were developed to include only the most important (main) ingredients for each dish, based on meal descriptions, and thus only represent an approximation of the equivalent real-world dishes. Associated carbon footprint information and impact rating (low to high) and labels were obtained via the Foodsteps platform. Summary statistics of the average carbon footprint (kg CO_2e) per serving are provided in Table B1.

Table B1: Average Carbon Footprint of Platform Menu

	Mean	Std. Dev	Min	Max	*N*
All Menu Items	1.18	1.34	0.07	9.25	164
Main Meals	1.81	1.60	0.11	9.25	78
Starters	0.81	0.78	0.07	3.61	52
Desserts	0.34	0.12	0.12	0.61	22
Drinks	0.21	0.16	0.14	0.68	12

Note: This table reports the average carbon footprint (kg CO_2e/serving) of all menu items and by menu category.

Figure B1: Climate impact score (A-E) across menu categories.

Figure B2 displays the distribution of meals across the five impact score categories – A (low) to E (high) – which were classified based on the kg CO_2e per kg of the respective meal. Distributions of impact scores are presented for each menu category separately (mains, starters, desserts and drinks).

Figure B1 displays the distribution of meals across the five Nutri-Score score categories – A (best) to E (worst) – which were classified based on nutritional values for each meal. Distributions of Nutri-Scores are presented for each menu category separately (mains, starters, desserts and drinks).

B.1.3 Recruitment

Ex-ante power calculations (see pre-registration) based on data previously collected via the 'Take a BITe' platform indicated that to be able to detect a small effect size (Cohen's d = 0.15), at 80% power, with an alpha of 0.016 (Bonferroni adjusted for three hypotheses), a sample size of 1000 participants per treatment arm would be required.[18]

In total, 6,894 people started the study on Predictiv. Of these, 535 (8%) failed initial technical checks (duplicate responses, tests, or responses that had unclear/unrecognised URLs). Another 1,010 (15%) that started the study were not eligible (i.e., had never used food delivery apps). A further 741 participants (11%) failed the attention check twice and were excluded from the study and 312 participants (7% of those eligible and

[18]Note that the data on which these power calculations were based differ from our final sample with respect to the final selection of restaurants and menu items included on the platform, as well as the ordering restrictions (one main + one starter/drink/dessert) imposed in the current study.

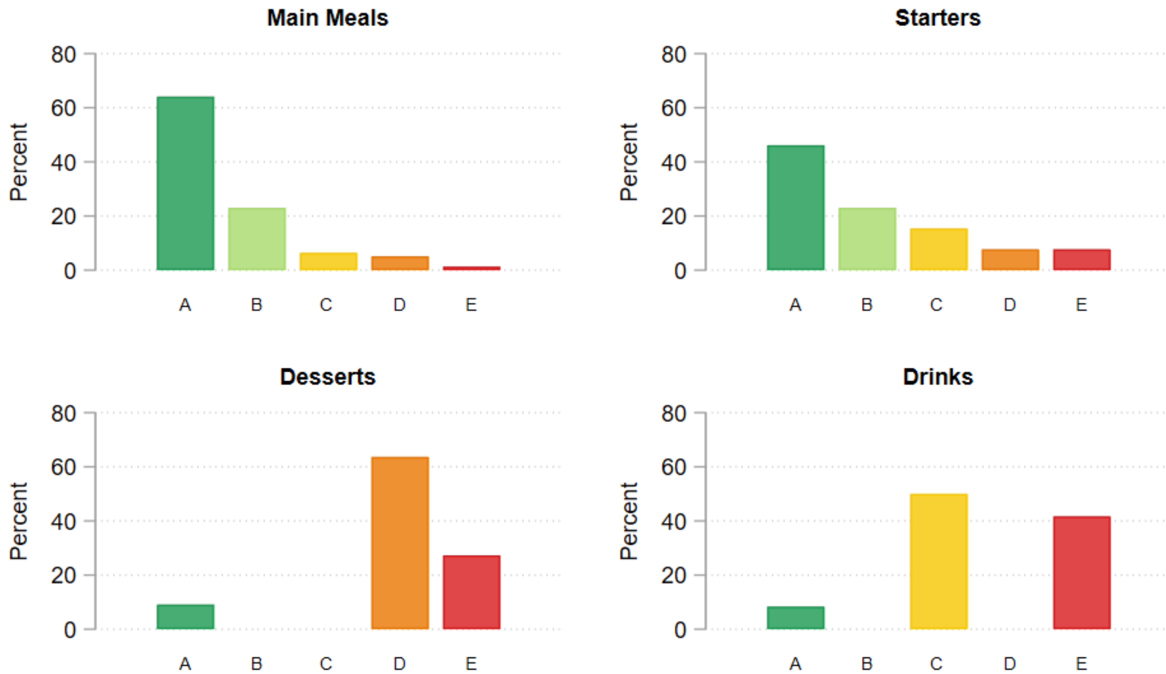

Figure B2: Nutri-Score (A-E) across menu categories.

passed attention check) did not finish the study ('time-outs').

B.1.4 Ethics and Pre-registration

Ethical approval was granted on 14th December 2022 by the Cambridge Judge Business School Ethics Review Group, ensuring adherence to ethical guidelines and protocols (Ref. 22-39). Informed consent was obtained from all participants, demonstrating their voluntary participation and agreement to take part in the study.

The study was pre-registered on the Open Science Framework (OSF) under the registration number h47yj. The pre-analysis plan (PAP) was submitted and registered prior to gaining access to the complete set of cleaned data. Registration DOI: https://doi.org/10.17605/OSF.IO/H47YJ.

B.1.4 Deviations from Pre-analysis Plan

We use a standard linear probability model (LPM) estimated by OLS to conduct confirmatory hypothesis tests of H2 and H3, instead of reporting marginal effects obtained from logistic regressions as previously pre-registered. Results are identical up until the fourth decimal place.

We use the FWER multiple hypothesis testing procedure developed by Young (2019, 2020) which is more appropriate for a small number of tests, instead of the pre-registered FDR step-down procedure (Benjamini et al. 2016).

Appendix C: Survey & task instructions

B.1.1 Carbon footprint and Nutri-Score calculation

[Consumer behavior - Platform]
1. How frequently do you get an online takeaway (i.e., takeaway food order at platforms like Just Eat or Deliveroo)? [A few times a year, At least once a month, At least 3-4 times a month, Twice a week, More than twice a week]

2. Approximately how much do you spend on online takeaways each month? [£0, £10-£30, £30 - £100, £100 - £250, £250 - £500, >£500]

3. If you get an online takeaway, you usually have it... [On my own, With friends, With family, With colleagues (at work), Not sure - it varies]

[Dietary habits]
4. What diet do you follow, if any? [None in particular, Vegan, Vegetarian, Flexitarian, Pescatarian, Other [please specify].]

5. How often do you eat a sweet dessert with your main meal? [Every day, Between 3-5 times a week, 1-2 times a week, Less than once a week, Never]

6. How often do you eat food in the form of meat? (including sausage, salami, steak etc.) [Every day, Between 3-5 times a week, 1-2 times a week, Less than once a week, Never]

7. How important is it that the food you normally eat... [1: Not at all important, 2: A little important, 3: Somewhat important, 4: Very important] • is healthy? • is climate friendly? • is cheap? • is tasty?

[Self-control]
8. Please rate how the following statements apply to you from [1: Never, 2: Rarely, 3: Occasionally, 4: Frequently, 5: Always]. • I'm good at resisting tempting food. • I give up too easily on my eating intentions. • I easily get distracted from my eating intentions. • I find it hard to remember what I have eaten throughout the day. • If I am not eating in the way I intend to I make changes.

[Climate attitudes]
9. How worried are you about climate change? [1: Not at all worried, 2: A little worried, 3: Somewhat worried, 4: Very worried, 5: Extremely worried]

10. To what extent do you feel a personal responsibility to try to reduce climate change? [0: Not at all to 10: A great deal]

[Health assessment]
11. If you judge your health on a scale from 0 to 10, what would you say? [0: Very bad to 10: Excellent].

[Political ideology]
12. Some people in Britain tend to identify more with the political left, while others tend to identify more with the political right. In general, which side do you identify with more? [0: Strongly left, 2: Moderately left, 3: Slightly left, 4: Neither the left nor the right, 5: Slightly right, 6: Moderately right, 7: Strongly right].

[Carbon & health literacy]
In the following, you will see a list of 6 common restaurant meals. For each of these meals, we would like you to rate them according to how climate-friendly you think they are, as well as their calorie content. If you are unsure, give it your best guess. With climate-friendly, we are referring to the carbon footprint of a meal. Carbon footprint refers to the greenhouse gas emissions emitted during a product's life cycle including emissions from farming, packaging, processing, transport and retail. The carbon footprint of food items is calculated in line with average British consumption.

13. Considering the carbon footprint of these meals, please sort them into low, mid or high climate impact categories. [Spinach and Chickpea Curry, Spinach and Mushroom Pasta Bake, Broccoli and Stilton Quiche, Steak and Mushroom Pie, Breaded Haddock, Sweet Chilli Tofu and Vegetable Stir Fry]

With calorie content, we are referring to the calorie count of a meal. Calorie count refers to the amount of energy in food, measured in units of calories. 14. Considering the calorie content of these meals, please sort them into low, medium or high calorie categories. [Spinach and Chickpea Curry, Spinach and Mushroom Pasta Bake, Broccoli and Stilton Quiche, Steak and Mushroom Pie, Breaded Haddock, Sweet Chilli Tofu and Vegetable Stir Fry]

[Attention check]
15. People are very busy these days and some do not properly read survey questions. To show that you've read this much, answer both "Extremely interested" and "Very interested."

C1.2 Post-intervention survey

[Choice factors]
1. How satisfied are you with your meal choice? ... [1: Not at all satisfied, 2: A little satisfied, 3: Somewhat satisfied, 4: Very satisfied, 5: Extremely satisfied]

2. How satisfied are you with your meal choice based on... [1: Not at all satisfied to 5: Extremely satisfied] • its climate impact? • its health (particularly caloric) impact?

3. How would you rate your level of guilt or concern about... [1: Not at all guilty/concerned, to 5: Extremely guilty/concerned] • the climate impact of your meal choice? • the caloric value and health impact of your meal choice?

4. Which factors most influenced your food choice? Select all that apply [Taste, Quality, Craving, Cuisine, Price (value for money), Ethics, Climate impact, Animal welfare concerns, Other environmental concerns (water pollution, air pollution, land use change, biodiversity loss), Portion size, Nutritional content, Health,

Cultural/religious reasons, None of the above, Other]

[Policy support]
5. What do you think about the policies below for online takeaway platforms? [1: Strongly oppose, 2: Oppose, 3: Neither oppose nor support, 4: Support, 5: Strongly support]

• A tax on meat and dairy products. • Reduction in the price of meat-alternatives (vegan and vegetarian meals) via discounts and subsidies. • Labels indicating the carbon footprint of all food/meals. • Sustainable warning labels on high emission food/meals. • Ban on meat advertising. • Restriction of promotions of food/meals high in carbon emissions (e.g., meat dishes). • Information campaign on the importance of sustainable eating. • Reduction of default portion size of meat products/meals. • Making vegetarian options more visible through positioning and changing the menu order. • Decrease availability by reducing the number of available meat options. • Increase availability by increasing the number of available meat-free options.

6. How much are you willing to limit the consumption of meat and dairy products you eat? [Not at all, A little, A moderate amount, A lot, A great deal]

7. Do you recall seeing any of the following information on the menu of the restaurant you ordered from? [Yes, I recall seeing this; No, I do not recall seeing this] • Carbon footprint of the items • Calorie information for each item • Meat tax for meat items • VAT tax costs

8. How would you rate the total calorie content of the food you ordered? [Low, Medium, High]

9. How would you rate the total carbon footprint of the food you ordered? [Low, Medium, High]

C1.3 Food choice task instructions

Your task:

In this next section, we want you to imagine you are ordering dinner for yourself on an online delivery platform. You will be given a virtual budget of £20 to spend on our online food delivery platform. **It is important that you make a careful choice, as there is a chance that you will actually receive the order you place.** If you are selected as a winner, we will also pay you out the remainder of your budget via bank transfer. You can use our food delivery platform just like you would in real life: you can browse through multiple restaurants, view their menus, and add or remove foods from your basket. Once you are happy with your order you can click 'checkout' to complete the task. After you have made your purchase, we will run a random draw [1 out of 30], and you will be notified whether you are selected to receive your purchase at the end of the survey. If you are a winner, we will contact you after the study by email and ask you to provide your name and address details, so that the meal can be delivered to your home. You will be able to choose from a number of dates and times for your order to be delivered. When making your choice please remember:

• You are ordering **a meal for yourself** • Spend between **£5 and £20** • Please order **at least one 'Main'** • Please order **a maximum of two items** including your main (without duplication) • Some of you will **receive your order** and any **remaining budget via bank transfer**