Environmental and Resource Economics (2025) 88:2595–2627
https://doi.org/10.1007/s10640-025-01012-x

Nudging, Fast and Slow: Experimental Evidence from Food Choices under Time Pressure

Paul M. Lohmann[1] · **Elisabeth Gsottbauer**[2,3] · **Christina Gravert**[4] · **Lucia A. Reisch**[1]

Accepted: 13 June 2025 / Published online: 26 June 2025

Abstract

Understanding when and why nudges work is crucial for designing interventions that consistently and reliably change behaviour. This paper explores the relationship between decision-making speed and the effectiveness of two nudges – carbon footprint labelling and menu repositioning – aimed at encouraging climate-friendly food choices. Using an incentivized online randomized controlled trial with a quasi-representative sample of British consumers ($N = 3{,}052$) ordering meals through an experimental food-delivery platform, we introduced a time-pressure mechanism to capture both fast and slow decision-making processes. Our findings suggest that menu repositioning is an effective tool for promoting climate-friendly choices when decisions are made quickly, though the effect fades when subjects have time to revise their choices. Carbon labels, in contrast, showed minimal impact overall but reduced emissions among highly educated and climate-conscious individuals when they made fast decisions. The results imply that choice architects should apply both interventions in contexts where consumers make fast decisions, such as digital platforms, canteens, or fast-food restaurants to help mitigate climate externalities. More broadly, our findings suggest that the available decision time in different contexts might at least partly explain differences in effect sizes found in previous studies of these nudges.

Keywords Carbon-footprint labelling · Choice architecture · Food-delivery apps · Low-carbon diets · Dual-process models · System 1

JEL Codes C90 · D04 · I18 · D90 · Q18 · Q50

✉ Paul M. Lohmann
pml44@cam.ac.uk

1 El-Erian Institute of Behavioural Economics and Policy, Judge Business School, University of Cambridge, Cambridge, UK

2 Competence Center of Economic, Ecological and Social Sustainability, Free University Bolzano, Bolzano, Italy

3 Grantham Research Institute of Climate Change and the Environment, London School of Economics and Political Science (LSE), London, UK

4 Center for Economic Behavior and Inequality, Department of Economics, University of Copenhagen, Copenhagen, Denmark

1 Introduction

Behavioural nudges have shown promise across various domains, but their generalizability, scalability, and transferability remain contested (Szaszi et al. 2018; Al-Ubaydli et al. 2021). Improving our knowledge about the circumstances under which nudges work is crucial to foster realistic expectations about their impact and support the development of welfare-enhancing interventions (Bryan et al. 2021; Allcott et al. 2022; DellaVigna and Linos 2022). While a number of meta-studies explored variations in techniques (defaults, reminders, social proof, etc.), demographics (such as gender, age or political orientation), behavioural domains (such as food, electricity or financial decisions) or research methods (such as sample size and publication bias) to explain heterogeneity in the effect of nudges (DellaVigna and Linos 2022; Mertens et al. 2022), more recent studies have suggested examining contextual factors instead. For example, Saccardo et al. (2023) analyse data from 123 randomized controlled trials, finding that the efficacy of nudges depends on factors such as baseline uptake, time horizon, and breadth of outcomes.

In this paper, we investigate the effect of decision time on the effectiveness of nudges. Inspired by Daniel (Kahneman's 2011) dual-process theory of choice, we hypothesize that nudges are more effective under time pressure than when subjects are given ample time to deliberate. Kahneman's theory posits that the human mind has two different "cognitive systems": one cognitive process is fast and intuitive (System 1), and one is slow and analytical (System 2). System 1 is quick; most of the time it runs on auto pilot. It enables fast decisions but leaves individuals more susceptible to cognitive biases, such as primacy and order effects (Kahneman 1973; Rey et al. 2020). System 2, in contrast, is slow. It encourages careful, deliberate reasoning and reflection, thereby demanding more time, cognitive effort and self-control. System 2 is harder to manipulate. Given that a majority of nudges are designed to affect System 1 decisions – described as "architectural nudges" (Reisch and Sunstein 2021) or "pure nudges" (Carlsson et al. 2021) – it is surprising how little work has been done to learn whether these nudges are effective only in fast decisions, or if they can also affect slower System 2 decision-making.).[1]

If nudges mostly affect fast System 1 decisions, this can help explain differences in the effectiveness of nudges across studies, settings and domains. For example, changing the menu order in a busy lunch restaurant might have a much stronger effect on choices than the same changes of item positioning on the menu at a relaxed diner. Ordering take-out in an app on the way home from work might also lead to different choices compared to leisurely browsing on a Sunday night on the couch (e.g., Jesse et al. 2021). Some studies have aimed to measure the effect of nudges under varying levels of cognitive load (Bruns 2019; Altmann et al. 2022), yet the evidence on decision-making speed has mostly been anecdotal or endogenous to the decision maker's speed (Lohmann et al. 2024a).

We focus on two popular nudges, carbon footprint labelling and menu repositioning, proposed to encourage more climate-friendly food choices, mostly by avoiding ruminant meat (Reisch et al. 2021; Ammann et al. 2023; Lohmann et al. 2024b).[2] Menu repositioning

[1] We acknowledge that System 1 and System 2 is a simplified classification. Other classifications exist, such as distinguishing between pro-self and pro-social nudges (e.g., Sunstein 2014). Additionally, some nudges may not neatly fall into either category.

[2] This rapidly expanding body of literature has examined various approaches, including manipulating the availability of options (Garnett et al. 2019; Lambrecht et al. 2023; Klatt and Schulze Tilling 2024; Merk et

moves low-carbon dishes to the top of the menu, making them easier to choose and creating an anchoring effect such that choices further down the menu will be compared to those at the top (Tversky and Kahneman 1974). It has consistently been found effective in encouraging more sustainable choices in restaurants, canteens and food delivery apps (Gravert and Kurz 2021; Jostock et al. 2024; Lohmann et al. 2024a). Carbon footprint labels often use a combination of descriptive information and traffic-light colour schemes to guide food choices, making lower-carbon options salient and providing a visual warning against high-carbon meals through colour cues (Reisch et al. 2021).)[3] Carbon footprint labels have been evaluated in a range of field settings, including supermarkets Elofsson et al. (2016), Muller et al. (2019), Bilén (2022), Maier and Fesenfeld (2024), university canteens (Brunner et al. 2018; Lohmann et al. 2022; Schulze Tilling 2023; Beyer et al. 2024) and restaurants (Casati et al. 2023), and the results suggest that labels are able to achieve modest increases in climate-friendly choices.

We conducted an incentive-compatible online randomized controlled trial with a quasi-representative sample of UK consumers (N=3,052) in which participants ordered dinner through an experimental food-delivery platform. Modelled after popular real-world food-delivery apps, the experimental platform offered a selection of restaurants with a variety of meal options to replicate an authentic consumer choice environment. Importantly, choices were incentivized through a random incentive mechanism offering a one in 30 chance to actually receive one's meal choice. Participants were randomly assigned to a control group or one of two intervention conditions: (1) a menu-repositioning nudge that placed low-carbon meals at the top of the menu, and (2) a traffic-light coloured carbon footprint label with 5-levels that provided environmental-impact information for each meal. To observe both fast (intuitive) and slow (reflective) decision-making for each individual, we put respondents under time pressure, utilizing a continuous time-pressure choice-process elicitation mechanism (Crosetto and Gaudeul 2023). They were given 90 seconds to choose a meal on the platform and were incentivised to make an initial rapid choice (by the 10-second mark), with the option to subsequently revise their choice within the allotted total timeframe. This design captured each participant's perceived optimal meal choice at any moment and tracked all choice revisions, enabling us to observe when and how decisions shifted over time. We hypothesized that in a choice setting with little time where food choices are fast and intuitive, both carbon labelling and menu repositioning would increase climate-friendly choices compared to presenting choices in random order and without carbon labels. However, in choice situations with enough time to engage System 2, we expected these effects to decline.

al. 2024), education and information-based interventions (Imai et al. 2022; Perino and Schwirplies 2022; Jalil et al. 2023; Fosgaard et al. 2024; Pizzo et al. 2024), fiscal interventions and other financial incentives (Panzone et al. 2018; Faccioli et al. 2022; Lohmann et al. 2024a) and a range of nudge-type strategies (Kurz 2018; Panzone et al. 2021, 2024; Banerjee et al. 2023; Dannenberg and Weingärtner 2023; Dannenberg et al. 2024). For a comprehensive overview of effect sizes across intervention categories, see the systematic review and meta-analysis by Lohmann et al. (2024b).

[3] Traffic-light carbon labels may act as intuitive choice heuristics (e.g., 'Red should be avoided'), leveraging System 1 processes, particularly under rapid decision-making. Their effectiveness may also stem from negativity bias (Rozin and Royzman 2001) and loss aversion (Kahneman and Tversky 1979; Tversky and Kahneman 1991). Labels that provide more detailed emissions information can also serve as information provision tools, engaging System 2 through more deliberate cognitive processing. In practice, labels likely incorporate both intuitive and deliberative elements, though preliminary evidence suggests their influence on choices is driven more by salience than by informational effects (Schulze Tilling 2023; Ho and Page 2024).

Results showed that menu-item repositioning is an effective strategy for promoting climate-friendlier choices when individuals make quick choices. However, this influence only occurs under fast decision-making conditions. When individuals are given sufficient time to reconsider their choices, the climate impact of their decisions under this nudging intervention aligns with that of the control group. This finding implies that menu repositioning is most likely to achieve its aim in situations where people spend little time deliberating about their food choices, and rapid, intuitive (System 1) decision-processes dominate. In contrast, carbon footprint labels were unable to achieve a reduction in emissions of food choices, on average, both under time pressure and after people had sufficient time to reflect on their selection. The only exception was the group of highly educated and climate-conscious consumers. For them the labels did lower meal emissions for fast decisions, suggesting that for this group, they are an effective nudge, when they make fast decisions.

Our results show that considering the time under which decisions are made can help explain why the same nudge might work in some context and not in others. Further, to maximize the effectiveness of a nudge, policymakers should prioritize implementing nudges in decision contexts where they expect consumers to make quick decisions (System 1) rather than slow decisions (System 2). This policy advice, however, triggers a more fundamental question of the alignment between the preferences of choice architects and decision makers, which we take up in the discussion section.

2 Methods and Data

2.1 Experimental Set-Up

In September 2024 we conducted an incentive-compatible online randomized controlled trial using a simulated food-delivery app[4] with a nationally quasi-representative sample of 3,052 adults in the UK, which we recruited with the help of a survey panel provider (Predictiv). Participants were tasked with ordering a meal on our app and completed brief pre- and post-intervention surveys. The experiment was pre-registered via AEA Trial Registry[5] and received ethical approval through the Cambridge Judge Business School Ethics Review Group.

Participants first completed a brief pre-intervention survey to capture food-consumption habits and preferences, experience with delivery platforms and their political identity. Prior to the food-choice task, they had to pass an attention check[6] and were subsequently given detailed instructions about the task and the mechanism used to determine payoff-relevant choices (see Appendix A3 and A4 for details).

The simulated food-delivery platform consisted of nine restaurants, closely based on real-world equivalents, offering a range of popular cuisines representative of the UK food-deliv-

[4] The platform "Take a BITe" was developed by the Behavioural Insights Team (BIT) and has been employed in prior research (Bianchi et al. 2023; Lohmann et al. 2024a).

[5] AEARCTR-0014349: https://doi.org/10.1257/rct.14349-1.0

[6] Participants who failed the attention check once were allowed to revise their responses and finish the study. However, those who failed the attention check twice were not permitted to continue with the experiment.

ery landscape.[7] Restaurant menus were limited to main meal bundles, providing a complete and substantial meal (e.g., burger with fries, or curry with rice), and prices were adjusted to match market prices from July 2024 for a realistic experience. Participants could choose from a total of 87 unique meals, for which carbon footprint and corresponding impact scores were calculated.[8] Appendix Figure A displays the distribution of available meals across five climate-impact categories (A–E). Appendix Table 1 reports summary statistics on menu prices and GHG emissions intensity by food category.

All choices on the platform were incentivised using a random incentive mechanism, whereby a subset of participants received one of the meals they selected on the app within a £20 budget. To receive their meal, participants selected a date and time for delivery in a follow-up survey, and the research team placed the order using Deliveroo. The remaining balance was transferred directly to the participants' bank accounts. Afterwards, a post-intervention survey was conducted to measure the factors influencing participants' choices and to assess their satisfaction, attention to the interventions, and other attitudes and preferences. This included attitudes towards climate change and food variety that may have overly primed participants in the pre-intervention survey.

2.2 Experimental Groups

We randomly and equally allocated participants ($N=3{,}052$) to different versions of the food-delivery platform across three experimental groups using a simple randomisation procedure: First, the control group used a version of the platform without any interventions, and menus were displayed in random order. Second, in the carbon label group, participants were shown a carbon footprint label on each menu item, indicating a low to high environmental impact. The order of restaurants and menu items was randomly presented. The third group, the menu repositioning group, was shown a platform where both restaurants and menu items were re-arranged based on their climate impact. Menu items were ranked by GHG intensity (kg CO_2e / kg) thus aligning with the carbon footprint labels. Restaurant rankings were ranked by the average GHG intensity of their meals.

The label and its life-cycle calculations were developed in collaboration with our industry partner Foodsteps.[9] The label was pre-tested with a sample of 150 participants from the UK, recruited via Prolific in August 2024 (see Appendix A5, Tables A8–A11). Three alternative label designs were evaluated, with participants rating them on various criteria, including the quality of information provided, clarity, conciseness, comprehensibility, trustworthiness, visual appeal and suitability for food-delivery apps. Participants each evaluated one label design under time pressure (30 seconds) and the remaining two with unlimited time. The label with the highest overall score under time pressure was subsequently used in the main experiment. The selected design combines both informational and behavioural elements, featuring a descriptive, traffic-light coloured, 5-point scale ranging from A (very

[7] The selection included chain restaurants operating nationwide, with the exception of Chinese and Indian cuisines, for which broadly available popular menu items were chosen.

[8] As recipes for meals of major restaurant franchises are not publicly available, simplified recipes consisting of the most important (main) ingredients were developed based on the available meal descriptions. Carbon footprint information, impact ratings (ranging from low to high) and labels were provided by the Foodsteps platform.

[9] See https://www.foodsteps.earth/

low) to E (very high). The descriptive label categories enable a comparison of the relative impact of different meals on the menu, while the traffic-light coloured scale provides a normative signal of what is considered 'good' or 'bad'. Impact scores (A–E) were based on the Greenhouse Gas (GHG) emissions intensity (kg CO_2e / kg) of a given meal, calculated based on the meal's individual ingredients. Impact score cut-offs were determined by the Global Carbon Budget for Food (2019 EAT-Lancet Commission), whereby only products aligning with the Paris Agreement targets are given an A rating.[10]

Figure 1 illustrates the food-delivery app interface and decision environment encountered by participants during the experiment. Panel A displays the carbon-labelling condition, and Panel B the menu-repositioning condition. From left to right, participants first selected from nine restaurant options, which led to the display of the respective restaurant's menu. After they chose an item, a pop-up window appeared, providing key details (item name, price, description, dietary information, and carbon labels) and allowing participants to add the item to their basket. Although participants could view their basket throughout the process, they were automatically checked out at the end of a decision period, with no option to

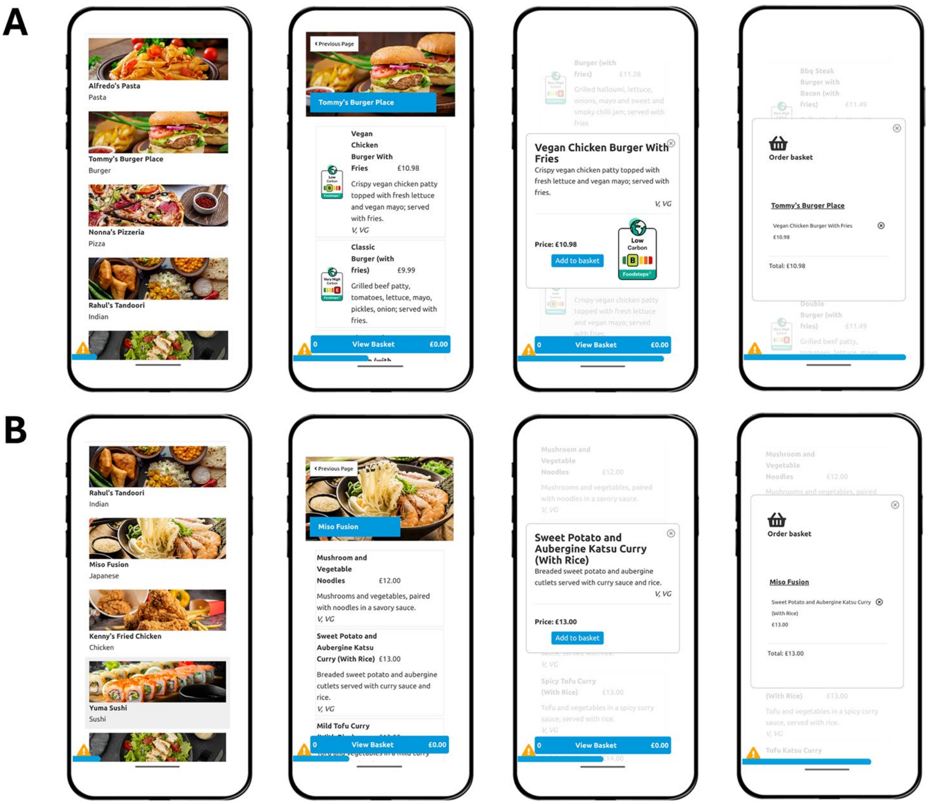

Fig. 1 Illustration of the choice environment within the food-delivery app for the carbon-labelling condition (Panel **A**) and the menu-repositioning condition (Panel **B**)

[10] Impact score boundaries are the following (kg CO_2e / kg): A/B (1.81), B/C (2.90), C/D (4.63) and D/E (7.5).

check out manually. We explain the setup of the decision period and the timing of decisions in the next section.

2.3 Elicitation of Meal Choices and Time-pressure Mechanism

After completing a brief pre-intervention survey, participants received detailed instructions about the meal-choice task, which was framed as ordering dinner (one meal) for themselves through a food-delivery app. Each participant was given a virtual budget of £20 to spend on the app, with a one in 30 chance of receiving their order delivered to their home at a preferred date and time. Participants were also informed that any remaining balance would be paid out via bank transfer. They were encouraged to use the food-delivery app as they normally would, allowing them to browse multiple restaurants, view the respective menus, and add or remove items from their shopping basket.

Participants were then familiarized with the time-choice elicitation mechanism, adapted from Crosetto and Gaudeul (2023) and originally proposed by Caplin et al. (2011). This mechanism induces continuous time pressure using an ex-post random stopping mechanism, incentivising participants to make a first rapid meal choice but allowing for subsequent choice revisions that encourage deliberation. Unlike alternative commonly used time-pressure mechanisms, such as randomly assigning participants to different time allocations, this approach allows us to observe both 'fast' and 'slow' choices for each individual and causally investigate the effects of time on participants' meal choices.

Participants were informed that they had 90 seconds to add meals to their shopping basket and were able to make as many choice revisions as they wanted. Any new item added to the basket automatically replaced the current choice if a previous selection had been made. Participants were unable to manually check out before 90 seconds, yet al.l their choices over the time period were saved. A progress bar at the bottom of the screen indicated the remaining time. After 90 seconds, participants were automatically checked out and proceeded to the post-intervention survey.

This mechanism imposed acute time pressure through a random stopping rule, where a second – between 10 and 90 – was randomly selected after completion of the choice task to determine the meal that participants would ultimately receive if they were selected as a winner. If their basket was empty at that second, no meal was ordered, and no payout was made. Participants were thus incentivized to make a fast, potentially provisional choice, with the option to revise their choices during the remaining time. Ten seconds was chosen as the lower bound to allow for meaningful first choices, and to avoid choices that were neither reflective nor influenced by context effects.,[11] Figure 2 illustrates a possible choice pattern and three alternative scenarios.

In this example, Meal A was chosen at 33 seconds, Meal C at 46 seconds and Meal B at 70 seconds. In Panel A, the randomly drawn second is 39, and the payoff-relevant meal is thus Meal A. In Panel B, the randomly drawn second is 78, indicating that Meal B would be the ordered meal. Finally, in Panel C, the randomly drawn second is 18, at which no choice had been made (i.e., the basket was empty), resulting in no payout or meal delivery if this participant were to be declared a winner.

[11] Pre-testing indicated that a meaningful first choice could be made within 5–10 seconds, aligning with Crosetto and Gaudeul (2023), who found initial clicks occurred after around 5 seconds.

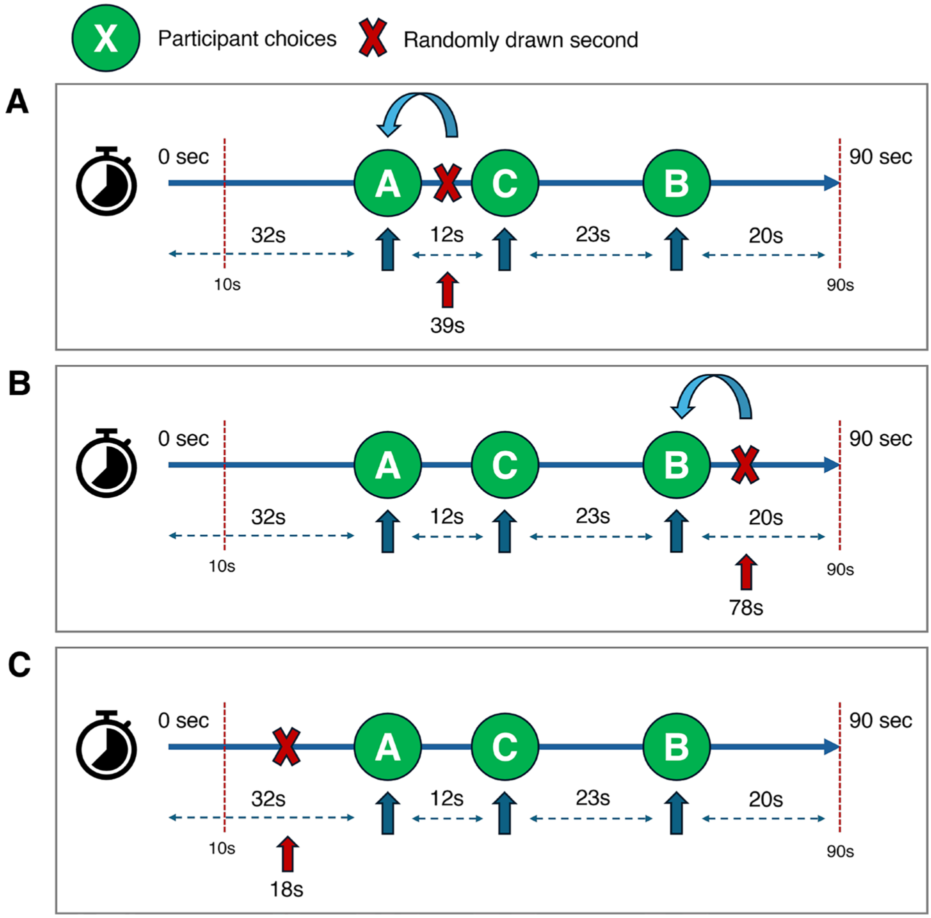

Fig. 2 Illustration of the time-pressure mechanism with a hypothetical choice sequence where a participant selected three different items: meal A at 33 seconds, Meal C at 46 seconds and Meal B at 70 seconds. The dotted lines indicate the time passed in between choices. Each panel displays an example of the random stopping rule with randomly drawn seconds at 39 (Panel A), 78 (Panel B) and 18 (Panel C)

Participants were clearly instructed about the time-pressure mechanism and had to complete a series of comprehension-check questions prior to starting the food-choice task (see Appendix A3 for details). The average number of correct responses was 4.3 (out of 7), indicating that the majority of respondents understood the time-pressure mechanism. If questions were answered incorrectly, the correct answers were shown to participants before they could proceed. In our primary analysis, we thus utilise all participant responses, including those who did not answer all questions correctly. In robustness checks, we show that a lack of understanding of the time pressure mechanism did not significantly affect our results.

2.4 Incentivisation

Participants were given a virtual budget of č 20 to spend on their online food order, allowing them to select any meal available on the platform. The average meal price was £11.72, with the most expensive option priced at £16.50. Choices were made incentive-compatible using a random incentive mechanism: One in 30 participants (3.3%) was randomly selected to receive their meal order (or the closest possible match) after completion of the experiment. In a companion survey, winners were subsequently asked to choose a date and time (from a selection of dates) on which they would like to receive their meal. Meal orders were then placed by the research team using Deliveroo. Any remaining budget was paid out to participants via an online transfer. Alternatively, winners were given the option to donate the value of their meal to a UK-based food bank.[12]

2.5 Data and Key Outcomes

The data collected from every participant consist of a record of all the meal choices added to their basket during the 90-second time window of the food-choice task. From this data, we identify several food-choice outcomes. Specifically, we assess the carbon footprint (GHG emissions intensity measured in kg CO_2e / kg) of their meal order, whether they opted for a meal with a high carbon impact (classified as an impact score of D or E), and if they selected a meat-based main meal. We differentiate between initial choices (first choices) and any subsequent changes (all other choices).

We also set three cut-off points to look at how participants make decisions in different time windows. In the absence of prior benchmarks for 'fast' decisions in this setting, we based our thresholds on the observed distribution of choices in the experiment and our pre-registered thresholds. We found that approximately 50% of participants made their first selection within 15 seconds and 80% (our pre-registered threshold) within 30 seconds. We thus consider these to represent 'very fast' and 'fast' decision-making, respectively. 'Slow' decisions were assessed at the full 90 seconds, based on the median decision time in a similar experiment with more complex menus and no time limits (Lohmann et al. 2024a). While stylised in this context, these thresholds reflect plausible real-world decision-making patterns, such as group ordering, ordering while commuting, or making quick selections in cafeteria queues.

In addition to the key outcomes, we collected socio-demographic information (e.g., gender, age, location, income, education) and other relevant variables including dietary preferences, meal-delivery habits, attitudes towards climate change and choice decision factors.

2.6 Sample Characteristics

The experiment included 3,052 participants recruited via an online survey panel (Predictiv) developed by the Behavioural Insights Team.[13] The sample is quasi-representative of the UK population that frequently orders food online. Furthermore, it aligns with the general UK population in terms of age, gender, and education. Table 1 presents the socio-demographic characteristics of the sample, which consists of 51% female participants with an

[12] Incentivisation summary statistics are provided in Appendix Table 11. As our sample included both rural and suburban participants, a subset of deliveries (35%) were not possible due to the unavailability of Deliveroo (the service used to process deliveries). Affected participants were compensated accordingly. It is unlikely that rural and suburban participants anticipated not being able to receive their order, as all participants were regular users of delivery apps. Additionally, other food delivery services (including restaurant home delivery) may have been available in their area. Therefore, we believe this is unlikely to have influenced our results.

[13] For details see: https://www.bi.team/bi-ventures/predictiv/

Table 1 Sample socio-demographic characteristic

	Mean	Std. Dev.	Min	Max
Female	0.52	0.5	0	1
Age	40.42	14.18	18	88
Income	42273.14	27864.33	2500	100000
Bachelor's degree or higher	0.32	0.47	0	1
Location				
Rural	0.16	0.37	0	1
Suburban	0.46	0.5	0	1
Urban	0.37	0.48	0	1
Political Views				
Left-leaning	0.31	0.46	0	1
Neither left nor right	0.46	0.5	0	1
Right-leaning	0.23	0.42	0	1
Diet				
None in particular	0.82	0.38	0	1
Flexitarian	0.07	0.25	0	1
Pescatarian	0.02	0.15	0	1
Vegetarian	0.04	0.21	0	1
Vegan	0.02	0.14	0	1
Other	0.02	0.15	0	1

Note: $N = 3{,}052$

average age of 40.5 years. Most participants (84%) live in urban or suburban areas, and 32% have higher education. Politically, participants are 31% left-leaning, 46% neutral and 23% right-leaning. Dietary preferences are mainly unrestricted (82%), with smaller proportions following specific diets such as flexitarian (7%) and vegetarian (5%). Only 2% identify as vegans, which is closely aligned with the overall UK population (YouGov 2024). Moreover, the experimental groups are balanced on observable variables; see Appendix Table A2 for balance tables and summary statistics.

2.7 Estimation

The primary specification used to test our main hypotheses is as follows:

$$Y_{it} = \alpha + \beta_1 \, \mathrm{Labelling}_i + \beta_2 \, \mathrm{Repositioning}_i + \sigma X_i + e_i \tag{1}$$

where Y_i represents the primary outcomes of interest: GHG_i, High_i, and Meat_i at time t. Outcomes are assessed at three time points: $t = 15s($ very fast choices), $t = 30s($ fast choices), and $t = 90s($ slow choices). $\mathrm{Labelling}_i$ and $\mathrm{Repositioning}_i$ are treatment indicators equal to one if individual i was randomly assigned to the carbon-labelling intervention or menu-repositioning intervention, respectively. X_i is a vector of socio-demographic variables for individual i, including age, gender, income, education, device used, and time taken to complete the survey. The latter variable attempts to control for a participant's overall ability and speed in completing survey-based questionnaires, which may be correlated with their ability to navigate the food-delivery app.

We focus our analysis on the following pre-registered outcomes for each individual i: (1) GHG emission intensity associated with an individual's food basket (GHG_i), estimated with Ordinary Least Squares (OLS); (2) high carbon footprint meal choices, defined as a binary variable that equals 1 if the selected main meal has a high carbon impact score (D or E) and 0 otherwise (A, B, or C) (High_i), with estimation via a Linear Probability Model (LPM); and (3) meat meal choice, a binary variable equal to 1 if the main meal contains meat and 0 otherwise (vegan, vegetarian, or fish-based) (Meat_i), also analysed with LPM. Heteroscedasticity-robust (Eicker-Huber-White) standard errors are applied.

The exploratory heterogeneity analysis was conducted following Equation 2:

$$\begin{aligned} Y_i = \alpha + \beta_1 \text{ Labelling}_i + \beta_2 \text{ Repositioning}_i + \gamma_1 \mathrm{INT1}_i + \delta_1(\mathrm{INT1}_i \times \text{Labelling}_i) \\ + \delta_2(\mathrm{INT1}_i \times \text{Repositioning}_i) + \sigma X_i + e_i \end{aligned} \tag{2}$$

where $\mathrm{INT1}_i$ refers to the interaction variable of interest, which enters both as a main effect and is interacted with the treatment indicators (Labelling_i and Repositioning_i). For ease of interpretation, we plot the predicted differences between the treatment and control groups for each level of the interaction variable, rather than the interaction terms themselves. The full regression outputs, including the interaction terms, are available in the Appendix.

3 Results

We begin by presenting an overview of the descriptive statistics and a graphical analysis of consumption choices over time, categorized as 15-second (very fast), 30-second (fast), and 90-second (slow) decisions. We then examine how the interventions (menu-item repositioning and labels) influence participants' consumption choices using OLS and LPM. Following this, we conduct a heterogeneity analysis to determine whether the main results vary across different population segments.

3.1 Descriptive Statistics

We start by summarizing some key features of the choice task and the choice environment to provide a good understanding of participants' decision-making context (Table 2). Most participants completed the task at home (82%) using a mobile device (83%). The average

Table 2 Food-choice task summary statistics

	Mean	Std. Dev.	Min	Max
Survey taken at home	0.82	0.39	0	1
Survey taken during work	0.22	0.42	0	1
Mobile	0.83	0.38	0	1
Hungry	50.47	28.04	0	100
Number of revisions	2.75	3.72	0	94
Time of first choice (seconds)	20.29	12.81	2	90
Time of last choice (seconds)	52.99	24.35	4	90
Difficulty finding pref. choice				
Not at all easy	0.04	0.2	0	1
A little easy	0.2	0.4	0	1
Somewhat easy	0.3	0.46	0	1
Very easy	0.46	0.5	0	1

Note: N = 3,052

first choice was made within 20 seconds (median = 17s), and participants made an average of 2.75 subsequent choice revisions. Final revisions were made, on average, at the 53-second mark. Previous studies indicate that hunger can significantly influence decision-making (e.g., Lohmann et al. 2024a). In this experiment, the average hunger level of 50 on a 0–100 scale suggests that participants were moderately hungry, potentially impacting their choices. A large portion (46%) found it very easy to choose their preferred option, while only 4% struggled to make a choice, which suggests that the decision environment and the options presented were generally clear and matched expectations of a food-delivery platform.

3.2 Graphical and Regression Analysis

Our primary outcome variables are the carbon footprint of the meal order (GHG intensity), whether the meal has a high carbon impact (rated D or E) and if a meat-based main meal was selected. Before proceeding with the regression analysis, we first provide some graphical evidence. Figure 3 depicts the three outcomes in the control and intervention groups separately during the 90-second decision window. The orange bars indicate the distribution of first choices.

All three main outcomes are clearly lowest in the Repositioning group, with a significant difference evident in the first 15 seconds, and they then gradually converge to similar levels as the other interventions after half a minute or more. In fact, repositioning led to significantly lower GHG emissions intensity (4 kg CO_2e / kg vs. 6–8 kg CO_2e / kg), reduced high-impact choices (around 10% vs. 25–30%), and there were fewer meat meal selections (around 20% vs. 75%) compared to both control and labelling conditions. Furthermore, order effects are most pronounced through quick and intuitive decision-making (first 15 seconds). At the 30-second mark, where approximately 80% of all choices had been made,

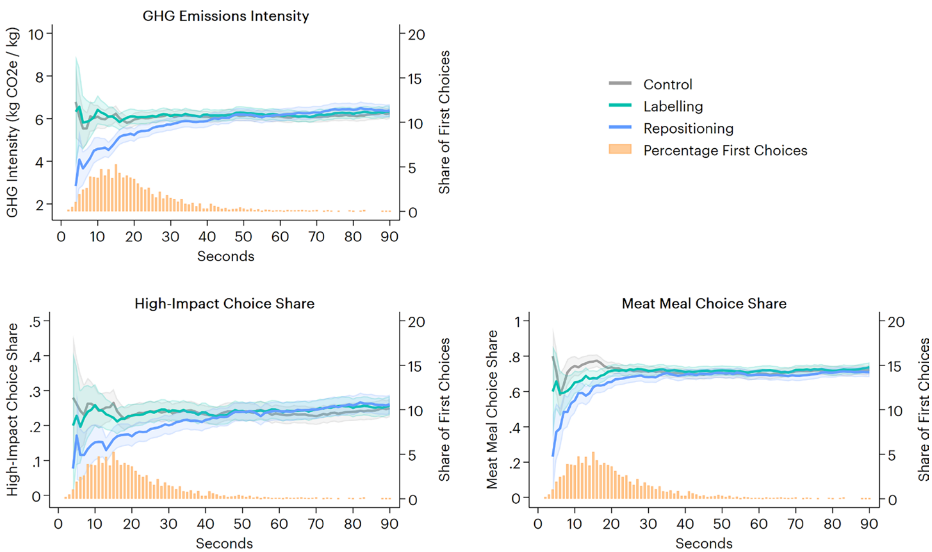

Fig. 3 Primary outcomes over the entire decision-making window (90 seconds). Note: the orange bars indicate the percentage of first choices. GHG emissions intensity is measured in kg CO_2e / kg of meal. High-impact and meat meal choice shares range from 0 to 1

the differences begin to diminish. By the 90-second endpoint, all three conditions largely converge.[14]

The labelling intervention, interestingly, shows minimal differences in relation to the control group throughout the entire decision window, indicating that carbon footprint labels are, on average, not effective at influencing meal choices compared to structural interventions like menu-item repositioning, nor do they become effective with additional decision time.

Table 3 reports the estimates of regressing the three main outcome variables on the treatment indicators. We run the regression for the main outcomes at three points: the 15-second, the 30-second and the 90-second marks. Consistent with the graphical evidence, we observe significant treatment effects for the repositioning intervention at the 15- and 30-second intervals, but these effects are not significant at the 90-second mark. More specifically, for very fast choices (15 sec), repositioning reduces GHG emissions intensity by 1.294 kg CO_2e / kg ($p < 0.01$), decreases high-impact meal selection by 10.4% points ($p < 0.01$) and lowers meat main dish selection by 14.4 posercentage points ($p < 0.01$). For fast choices (30 seconds), the repositioning effects weaken but remain significant for GHG intensity and high-impact meal selection, while the effect on meat main choices becomes insignificant. For slow choices (90 seconds), all interventions show no statistically significant effects across any outcomes, as indicated by the smaller coefficients and larger standard errors. Note that the sample size increases across time windows (from 1,297 to 2,527 to 3,017 observations), as more participants completed their choices as time progressed.[15] Appendix Table A4 reports estimates for all 'first choices' regardless of their timing (see the orange bars in Figure 3 for their distribution). We find that these estimates are comparable to those of 'very fast' choices. Finally, Appendix Table A5 confirms that the results remain robust

Table 3 Main results

	Very Fast Choices (15 sec)			Fast Choices (30 sec)			Slow Choices (90 sec)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	GHG Intensity	High-impact Main	Meat Main	GHG Intensity	High-impact Main	Meat Main	GHG Intensity	High-impact Main	Meat Main
Menu Repositioning	-1.294***	-0.104***	-0.144***	-0.431**	-0.043**	-0.026	0.162	0.013	-0.011
	(0.279)	(0.028)	(0.031)	(0.210)	(0.020)	(0.022)	(0.207)	(0.019)	(0.020)
Carbon Labelling	-0.238	-0.044	-0.093***	-0.039	-0.005	0.008	0.092	0.008	0.017
	(0.296)	(0.029)	(0.030)	(0.213)	(0.021)	(0.022)	(0.199)	(0.019)	(0.020)
Observations	1297	1297	1297	2527	2527	2527	3017	3017	3017

Note: Standard errors in parentheses. Estimates of Equation (1). LPM used for binary outcomes

* p < 0.1, ** p < 0.05, *** p < 0.01

[14] Summary statistics for each outcome at the three assessed time points are presented in Appendix Table A3 and illustrated in Appendix Figure A1.

[15] A small number of participants ($n=35$) emptied their baskets by 90 seconds, after having made an initial choice.

when limiting the sample to participants who correctly answered at least half of the comprehension check questions on the time-pressure mechanism (i.e., at least four out of seven).[16]

The regression results also confirm the graphical evidence that carbon labelling has little impact on consumer choices across all time windows and outcome variables. However, there is one statistically significant effect showing a 9.3% point reduction in meat main selection during very fast choices (15 seconds, $p < 0.01$). Yet this effect completely disappears in fast (30 seconds) and slow (90 seconds) decision-making windows. This could be explained by the fact that nearly all red-labelled dishes on the menu were meat options, with only a few exceptions among fish dishes (see Figure A3). The red labels could have acted as a visual warning, quickly steering individuals away from these higher-impact choices without deeper consideration—a response supported by previous evidence on nutritional labelling (Scarborough et al. 2015).[17]

3.3 Heterogeneity Analysis

Next, we examine whether the treatment effects differ for several subpopulations. We focus on GHG emissions intensity of the chosen meal and explore heterogeneous treatment effects across key sociodemographic characteristics, including gender, income, education and concern about climate change. Figure 4 presents the subgroup-specific treatment effects estimated following equation (2), representing the treatment effects for each subgroup relative to the equivalent group in the control condition. Full regression outputs including interaction terms are presented in Appendix Table A6. Note that given the smaller sample sizes in some subgroups, the wide confidence intervals suggest that the findings should be interpreted with caution. Focusing first on menu repositioning, we notice a gender gap in very fast and fast decisions. The repositioning intervention appears slightly more effective for females than males in the 15-second window, but this relationship is reversed at 30 seconds. It becomes clear that participants with lower socio-economic status, based on income and education, are not necessarily more susceptible to nudges, a potential concern voiced in the literature (e.g., Ghesla et al. 2020).

While all subgroups respond similarly under very fast decision-making (15 seconds), individuals with higher education and climate concern also make lower-carbon choices at 30 seconds, whereas those with lower education and concern have already revised their selections toward higher-carbon options. By 90 seconds, all groups have converged towards higher-carbon meal choices, similar to those of the control group. Thus, the primary difference between these groups lies in the speed at which they revise their choices towards higher-emission options. However, some absolute differences remain: at 90 seconds, the

[16] This robustness check excludes 1,073 participants (35.2% of the sample) who answered fewer than four out of seven comprehension questions correctly. We acknowledge that the questions may have been relatively demanding, as participants could not revisit the instructions or view an example before responding. While correct answers were shown before the task began, and the correlation between response time and comprehension scores is near zero ($r = 0.0025$), future studies using similar designs should consider including practice rounds or visual aids to further support comprehension.

[17] Experimenter demand effects are unlikely to be driving our findings for several reasons. First, as our primary research question concerns differences between experimental conditions, any potential demand effects (e.g., from survey wording) should be consistent across conditions. Second, the only visible intervention, the carbon label, was integrated naturally into the shopping environment. While it made climate information salient, it did so in a way that aligned with typical shopping contexts. If demand effects were influencing choices, they would be most apparent in this condition, which we find not to be the case.

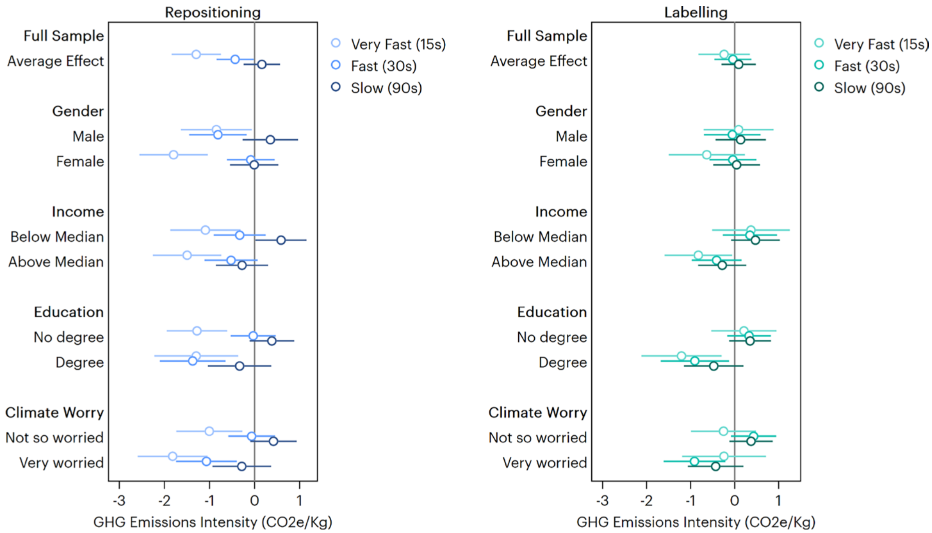

Fig. 4 Subgroup-specific treatment effects based on Equation (2). Error bars represent 95% confidence intervals. Full regression output presented in Appendix Table A6 average effect of the full sample corresponds to estimates presented in Table 3

GHG emissions of choices made by high-income individuals and those with greater climate concern remain lower than those of individuals with below-median income and less concern about climate change.

Similarly, we find that the labelling intervention appears to be more effective for participants with a degree, above-median income and greater concern about climate change. This suggests that while labelling has limited impact overall, it may resonate more quickly with these subpopulations, likely due to greater environmental awareness or familiarity with carbon footprint information among better educated groups. The results for these subgroups suggest that labelling also engages System 1 processes, potentially serving as a salient decision prompt under time pressure, as its effects diminish and lose statistical significance by 90 seconds.

Appendix Figure A4 displays heterogeneity across additional sociodemographic characteristics, including age, meat consumption frequency, rural-urban classification, and political views. Consistent with the above, menu repositioning reliably reduces GHG emissions under ‘very fast’ decision-making, whereas labelling shows no significant effects across these subgroups. We find no notable heterogeneous effects by age or political ideology.

4 Discussion and Conclusion

Our findings can be summarized into three main insights. First, we find that repositioning affects choices when individuals are making fast decisions. In our exploratory analysis, we find no heterogenous effects, suggesting that, on average, all participants are affected by repositioning. Second, we find that, on average, carbon labels do not affect choices. Exploratory analysis suggests they may influence individuals who are highly educated or strongly concerned about the climate. Third, we show that in all three conditions, choices converge to high carbon meals when participants are given more time to decide. We will now discuss potential mechanisms, implications for implementation of these interventions in practice, and what our results imply for welfare considerations of nudging as a policy tool.

Confirming earlier evidence, our study shows that menu repositioning can be an effective System 1 nudge to promote climate-friendly choices, particularly when decisions for meals are made quickly (Kurz 2018; Gravert and Kurz 2021; Lohmann et al. 2024a). The nudge achieves an economically and environmentally meaningful reduction in GHG emissions for fast choices, with decreases of 21% at 15 seconds and 7% at 30 seconds into the food choice task. Despite the more stylized nature of this framed field experiment, the effect sizes are slightly smaller than those found in natural field experiments with higher external validity, such as Kurz (2018) and Gravert and Kurz (2021). This mitigates concerns that our stylized setting artificially overstates the effect sizes. Moreover, the added complexity of real-world food decision contexts may suggest that repositioning under time pressure could be even more effective in practice. Exploratory analysis shows that the repositioning nudge appears to be effective at 15 seconds, regardless of socio-economic status. However, at 30 seconds, the remaining reduction in emissions is driven by individuals with higher education, greater climate concern, and male participants. By 90 seconds, all groups shift towards higher-carbon options, with factors such as taste, cravings, value for money, and type of cuisine taking priority (see Appendix Figure A5). There are multiple explanations for why repositioning affects choices under rapid decision-making. The most straight-forward explanation is that repositioning makes it easier to find and choose low-carbon choices. With 83% of participants using their smartphone in our experiment, choosing the restaurant and dishes at the top of the list is faster and easier than scrolling further down the menu. As long as the meals encountered first were regarded as better than no meal, it was in the individuals' best interest to make a first rapid choice and then revise their choice once they find something they like more than their first choice.

Carbon labels, in contrast, showed minimal impact on carbon intensity of meal choices, on average. This finding is also in line with previous literature and natural field experiments with by design higher external validity (Muller et al. 2019; Maier and Fesenfeld 2024; Lohmann et al. 2024a). We propose two main explanations for the lack of effect in our setting: Either, participants did not notice the labels, or, they noticed them, but decided not to use the information.[18] From our post-experimental survey, we learn that only 30% of participants in the labelling condition reported noticing the carbon footprint labels, supporting the first explanation. This lack of perception is surprising, as we pretested the employed carbon label intensively. The label was designed according to the most recent insights on effective label design (Thøgersen et al. 2024) and pretesting found that it is well-suited to convey the intended information. The difference in label effectiveness in the pre-test and the experiment is not atypical for laboratory experiments, where the focus is solely on the label. In a real-life context such as in a food delivery platform, carbon labels compete for attention with other relevant information such as prices, meal descriptions, photos, ads, and so on. Even well-designed labels may fail to be salient enough to cut through the information noise and capture consumers' attention. We also find evidence that is in line with the second

[18] One could also imagine that some individuals may interpret labels as attempt to manipulate their choices by inducing guilt, prompting reactance behaviour (e.g. intentionally choosing a red-labelled meal). However, we find no evidence of this, as the proportion of high carbon choices is similar to that of the control condition.

explanation of choosing not to use the information. The average participant in our study appears to have limited environmental preferences for climate-friendly food choices: Only 15% indicated in the pre-intervention survey that it was "very important" for their food consumption to be climate-friendly, and only 5% stated "climate" as a factor influencing their decision after completing the task. If environmental factors are not a priority for consumers, then information on climate impact may lack relevance, which could explain why labelling did not significantly affect choices. This phenomenon of ignoring information not perceived as relevant to 1's own decision utility is known in economics as "rational inattention" (Sims 2003; Maćkowiak et al. 2023).[19]

Rational inattention theory could explain why in our exploratory heterogeneity analysis we find that certain groups did respond to the climate labels when making a fast choice – namely, those with higher income, higher education, or strong climate consciousness. When people care about making climate-conscious decisions (or have the means and education to do so), they might use the labels as a decision heuristic when decision time is limited. By "fast"-checking the labels, they can avoid making 'red' choices that warn them of high climate impact meals, or they can focus on 'green' choices that could even have a rewarding effect: choosing green might make them feel good about doing the right thing (Schwartz et al. 2020; Lohmann et al. 2022). Future research could investigate the exact mechanism using, e.g., eye tracking methods and manipulating the label design (e.g. traffic-light vs monochrome labels). Yet, whether choices are fast or slow, expectations of the direct effects of carbon labels on consumer choice should be modest. As food policy scholars have argued, the real potential of labels might lie in their indirect effects on the supply side, with industry, retail, and online platforms adapting processes, reformulating menus or recipes with the aim of avoiding unattractive 'red' labels (Robertson et al. 2023). Nonetheless, our results suggest that targeting carbon footprint information at those most likely to use it, for instance through personalised interventions (Mills 2022; Sunstein 2022), may be an effective strategy for nudging more sustainable food choices in fast decision-making.

Our results suggest that both interventions are most effective in contexts where consumers make fast decisions. In most cases, it will not be feasible or ethical for policymakers to deliberately impose time pressure. Nevertheless, there are many plausible endogenous and exogenous factors that can naturally lead individuals to make decisions more quickly or slowly. For instance, the hectic environment of a coffee shop during Monday morning rush hour will encourage faster decisions than the same coffee shop on a quiet Sunday evening. Similarly, a person running late for work will make faster decisions than a tourist taking shelter from the rain. Focusing nudges on contexts with many fast decisions will be most promising.

In addition to the practical implications of our results, our study also raises the question of whether these nudges work as originally intended as a tool to "help people make better choices as judged by themselves" (Thaler and Sunstein 2008). The premise of nudging, as introduced by Thaler and Sunstein (2008), also known as asymmetric paternalism (Camerer et al. 2003), was that it "creates large benefits for those who make errors, while imposing little or no harm on those who are fully rational." In our setting this would imply that choices made quickly might be mistakes (System 1) while slower choices are in line with

[19] This concept is, however, anything but new: Daniel Kahneman discussed the observation that attention is effortful and that therefore individuals select what things to pay attention to, more than fifty years ago in "Attention and Effort" (Kahneman 1973).

the decision makers' true preferences (System 2). A classic nudge should help decision makers avoid these mistakes and guide them towards a choice that aligns with their true preference, i.e. help to overcome internalities. In practice, though, as well as in our experiment, many nudge applications are found in settings where they are implemented to help reduce externalities, such as lowering GHG emissions. These nudges are defined as green or prosocial nudges (Carlsson et al. 2021). Green nudges help people make better choices as judged by a choice architect - which might not be in line with the individual's preference.

Given that we observe a convergence toward higher-carbon choices in both treatment groups and control eventually, it seems that the choice architects' and the decision makers' preferences were not aligned. All three groups revise their choices equally often (Control: 2.96, Repositioning: 2.64, Labelling: 2.62) and ultimately select higher-emission meals. Instead of "correcting a mistake", the repositioning intervention appears to nudge choices temporarily toward lower-carbon options, thus reducing the externality of the meal choices. Our results imply that choice architects should be aware that encouraging climate-friendly food choices through repositioning or labelling might stand in contrast to what individuals would prefer to consume if they had time to deliberate. The results highlight the need for a responsible nudging approach by regulators and platforms alike, such as, informing customers about the intention to guide their choices towards less climate-intensive options (Bruns et al. 2018; Michaelsen 2023). We leave the important discussion of welfare consequences of nudges in the case of aligned vs. misaligned preferences for further research.

To conclude, readers should interpret our results both as one possible explanation for heterogenous effect sizes in nudging studies and as guidance on the types of settings where implementing these nudges would be most meaningful. Nudging fast, or slow, may be one important piece of the puzzle in fully understanding how to implement effective interventions.

A1. Additional Tables

Table A1 Menu sample statistics

	Price (č)	*GHG (Kg CO2e / Kg)*	*N*
Fish	11.45	4.55	13
Meat	11.84	7.20	46
Vegan	12.04	2.22	16
Vegetarian	11.13	3.09	12
All items	11.72	5.32	87

Note: Table displays average menu item price (č) and GHG emissions intensity (Kg CO_2e / Kg) by food category (fish, meat, vegan, vegetarian)

Table A2 Balance checks

	Control	Carbon Labelling	*p* value	Menu Repositioning	*p* value
	n=1,070 (35.1%)	*n*=995 (32.6%)		*n*=987 (32.3%)	
Mobile	0.83 (0.38)	0.84 (0.37)	0.500	0.83 (0.38)	0.983
Survey Duration	755.11 (1740.55)	657.07 (716.19)	0.099	680.11 (961.90)	0.232
Female	0.51 (0.50)	0.51 (0.50)	0.979	0.53 (0.50)	0.535
Age	41.17 (14.51)	39.91 (13.89)	0.043	40.13 (14.09)	0.099
Income (mid)	41802.10 (27276.82)	43615.95 (28176.29)	0.137	41430.09 (28155.32)	0.761
Degree	0.30 (0.46)	0.34 (0.48)	0.047	0.32 (0.47)	0.319
Political Views					
Left leaning	325 (30.4%)	302 (30.4%)	0.999	323 (32.7%)	0.461
Neither left nor right	497 (46.4%)	463 (46.5%)		451 (45.7%)	
Right leaning	248 (23.2%)	230 (23.1%)		213 (21.6%)	
Diet					
None in particular	883 (82.5%)	823 (82.7%)	0.299	801 (81.2%)	0.584
Flexitarian	67 (6.3%)	72 (7.2%)		74 (7.5%)	
Pescatarian	27 (2.5%)	15 (1.5%)		24 (2.4%)	
Vegetarian	40 (3.7%)	47 (4.7%)		48 (4.9%)	
Vegan	24 (2.2%)	18 (1.8%)		19 (1.9%)	
Other	29 (2.7%)	20 (2.0%)		21 (2.1%)	

Note: Table displays summary statistics and balance checks for key socio-demographic variables. P-value column displays the p-value from balance tests between the control group and the respective treatment group. Means and standard deviations (in parentheses) and p-value from linear regression displayed for continuous variables. Frequency and percent (in parentheses) and p-values from Pearson Chi-squared test displayed for categorical variables

Table A3 Summary statistics of primary outcomes for very fast, fast and slow decision-making

	Control			Carbon Labelling			Menu Repositioning		
	Mean	SD	*N*	Mean	SD	*N*	Mean	SD	*N*
GHG Emissions Intensity									
15 Seconds	6.23	(4.33)	468	5.99	(4.52)	419	4.93	(3.87)	410
30 Seconds	6.17	(4.40)	911	6.12	(4.40)	810	5.72	(4.29)	806
90 Seconds	6.25	(4.47)	1057	6.32	(4.46)	983	6.39	(4.82)	977
High-Impact Meals									
15 Seconds	0.26	(0.44)	468	0.22	(0.42)	419	0.16	(0.37)	410
30 Seconds	0.24	(0.43)	911	0.24	(0.43)	810	0.20	(0.40)	806
90 Seconds	0.25	(0.43)	1057	0.26	(0.44)	983	0.26	(0.44)	977
Meat Meals									
15 Seconds	0.77	(0.42)	468	0.68	(0.47)	419	0.62	(0.48)	410
30 Seconds	0.71	(0.45)	911	0.72	(0.45)	810	0.68	(0.47)	806
90 Seconds	0.72	(0.45)	1057	0.73	(0.44)	983	0.71	(0.45)	977

Note: Table displays summary statistics for primary outcomes by treatment condition for each decision-making speed: very fast (15 seconds), fast (30 seconds), slow (90 seconds)

Table A4 Main analysis for first choices

	First Choices		
	(1) GHG Intensity	(2) High-impact Main	(3) Meat Main
Menu Repositioning	–1.039***	–0.068***	–0.100***
	(0.183)	(0.018)	(0.021)
Carbon Labelling	0.102	–0.002	–0.006
	(0.193)	(0.019)	(0.020)
Observations	3052	3052	3052

Note: Table displays estimates of Equation (1). Standard errors in parentheses. LPM used for binary outcomes (columns 2 and 3)

* p < 0.1, ** p < 0.05, *** p < 0.01

Table A5 Main analysis excluding participants who failed the majority of comprehension checks

	Very Fast Choices (15 s)			Fast Choices (30 s)			Slow Choices (90 s)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	GHG Intensity	High-impact Main	Meat Main	GHG Intensity	High-impact Main	Meat Main	GHG Intensity	High-impact Main	Meat Main
Menu Repositioning	–1.135***	–0.084**	–0.154***	–0.482*	–0.034	–0.025	–0.095	–0.005	–0.017
	(0.370)	(0.036)	(0.040)	(0.265)	(0.025)	(0.028)	(0.263)	(0.025)	(0.025)
Carbon Labelling	–0.068	–0.036	–0.089**	–0.062	–0.007	0.020	–0.238	–0.031	–0.000
	(0.387)	(0.037)	(0.038)	(0.265)	(0.025)	(0.027)	(0.252)	(0.024)	(0.024)
Observations	792	792	792	1635	1635	1635	1965	1965	1965

Note: Standard errors in parentheses. Estimates of equation (1). LPM used for binary outcomes. Table presents the main regression analysis including only those participants that correctly responded to at least half (4 of 7) of all comprehension check questions on the time-pressure mechanism. This excludes n = 1, 073 or 35.16% of the sample

* p < 0.1, ** p < 0.05, *** p < 0.01

Table A6 Heterogeneity analysis

	Full Sample			Female			Income			Education			Climate Worry		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	Very Fast	Fast	Slow	Very Fast	Fast	Slow	Very Fast	Fast	Slow	Very Fast	Fast	Slow	Very Fast	Fast	Slow
Labelling	-0.238	-0.039	0.092	0.090	-0.051	0.137	0.372	0.348	0.472*	0.212	0.329	0.351	-0.252	0.431	0.374
	(0.296)	(0.213)	(0.199)	(0.404)	(0.328)	(0.291)	(0.450)	(0.314)	(0.282)	(0.378)	(0.252)	(0.242)	(0.376)	(0.263)	(0.250)
Repositioning	-1.294***	-0.431**	0.162	-0.847**	-0.811**	0.351	-1.090***	-0.330	0.587**	-1.277***	-0.030	0.383	-1.004***	-0.065	0.420
	(0.279)	(0.210)	(0.207)	(0.400)	(0.325)	(0.314)	(0.398)	(0.293)	(0.289)	(0.341)	(0.255)	(0.252)	(0.373)	(0.264)	(0.263)
INT				0.076	-0.867***	-0.510*	0.557	0.280	0.809***	-0.293	0.374	0.039	-0.310	0.504	0.021
				(0.409)	(0.292)	(0.278)	(0.407)	(0.291)	(0.276)	(0.427)	(0.338)	(0.305)	(0.411)	(0.311)	(0.288)
INT × Labelling				-0.723	0.011	-0.093	-1.195**	-0.756*	-0.754*	-1.419**	-1.232***	-0.826*	0.010	-1.342***	-0.803**
				(0.601)	(0.425)	(0.396)	(0.596)	(0.425)	(0.395)	(0.601)	(0.469)	(0.421)	(0.612)	(0.442)	(0.406)
INT × Repositioning				-0.950*	0.727*	-0.358	-0.405	-0.192	-0.865**	-0.017	-1.342***	-0.715	-0.813	-1.003**	-0.702*
				(0.557)	(0.422)	(0.415)	(0.553)	(0.420)	(0.412)	(0.583)	(0.451)	(0.438)	(0.544)	(0.432)	(0.422)
Female	-0.456*	-0.656***	-0.646***	0.000	0.000	0.000	-0.475**	-0.635***	-0.661***	-0.435*	-0.621***	-0.651***	-0.407*	-0.619***	-0.637***
	(0.240)	(0.175)	(0.170)				(0.240)	(0.174)	(0.170)	(0.241)	(0.175)	(0.170)	(0.239)	(0.173)	(0.170)
Age	-0.007	0.003	0.005	-0.006	0.002	0.005	-0.007	0.003	0.005	-0.007	0.002	0.005	-0.005	0.003	0.006
	(0.008)	(0.006)	(0.006)	(0.008)	(0.006)	(0.006)	(0.008)	(0.006)	(0.006)	(0.008)	(0.006)	(0.006)	(0.008)	(0.006)	(0.006)
High Edu (Degree)	-0.779***	-0.411**	-0.500***	-0.774***	-0.460**	-0.472***	-0.788***	-0.472**	-0.467***	0.000	0.000	0.000	-0.720***	-0.432**	-0.427**
	(0.252)	(0.191)	(0.181)	(0.250)	(0.188)	(0.178)	(0.248)	(0.189)	(0.178)				(0.249)	(0.189)	(0.178)
Mobile	0.032	0.109	0.513**	0.039	0.116	0.504**	0.058	0.127	0.497**	0.067	0.115	0.503**	-0.021	0.098	0.474**
	(0.306)	(0.236)	(0.220)	(0.306)	(0.235)	(0.219)	(0.306)	(0.236)	(0.219)	(0.305)	(0.236)	(0.218)	(0.309)	(0.236)	(0.220)
Survey Duration	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)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
High Income				0.029	-0.021	0.285*	0.000	0.000	0.000	0.025	-0.018	0.289*	0.068	-0.025	0.287*

Table A6 (continued)

	Full Sample			Female			Income			Education			Climate Worry		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	Very Fast	Fast	Slow	Very Fast	Fast	Slow	Very Fast	Fast	Slow	Very Fast	Fast	Slow	Very Fast	Fast	Slow
				(0.243)	(0.175)	(0.170)				(0.243)	(0.176)	(0.171)	(0.242)	(0.175)	(0.170)
Constant	6.800***	6.635***	5.876***	6.550***	6.631***	5.917***	6.550***	6.344***	5.737***	6.641***	6.283***	5.852***	6.879***	6.282***	5.938***
	(0.514)	(0.399)	(0.377)	(0.522)	(0.413)	(0.383)	(0.525)	(0.406)	(0.379)	(0.509)	(0.390)	(0.372)	(0.533)	(0.397)	(0.379)
R^2	0.027	0.010	0.009	0.029	0.011	0.009	0.030	0.011	0.011	0.032	0.014	0.010	0.032	0.015	0.013
Observations	1,297	2,527	3,017	1,297	2,527	3,017	1,297	2,527	3,017	1,297	2,527	3,017	1,297	2,527	3,017

Note: Table displays estimates of equation (2). Standard errors in parentheses. The interaction variable of interest is presented in the column header and estimated for each decision-making speed: very fast (15 seconds), fast (30 seconds), slow (90 seconds). The outcome variable is the GHG Emissions Intensity (kg CO^2e / Kg) of the chosen meal in all columns.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A7 Incentivisation summary statistics

Winners contacted	118
Could not be contacted	5
No response	49
Incomplete response	2
Deliveroo/Restaurant/Item unavailable	20
Successful deliveries	34
Failed deliveries	3

A2 Additional Figures

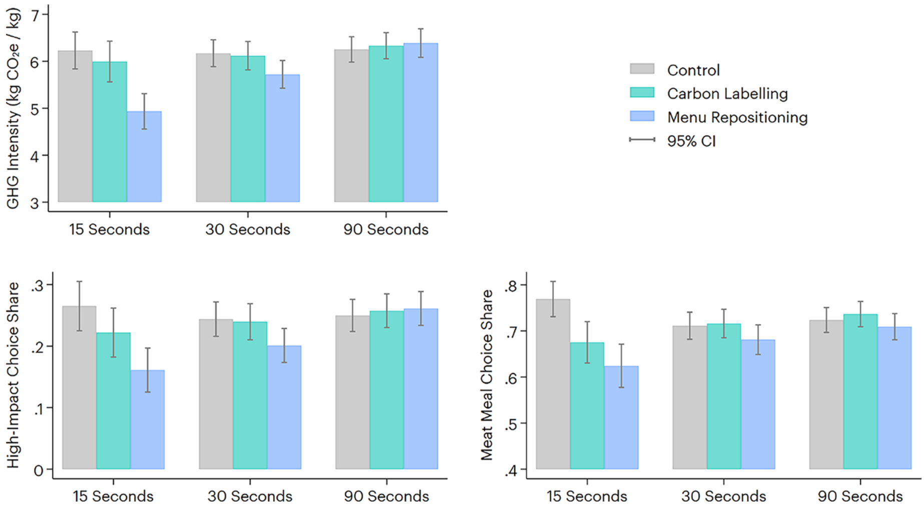

Fig. A1 Primary outcomes by treatment condition and decision-making speed. Error bars are 95% confidence intervals

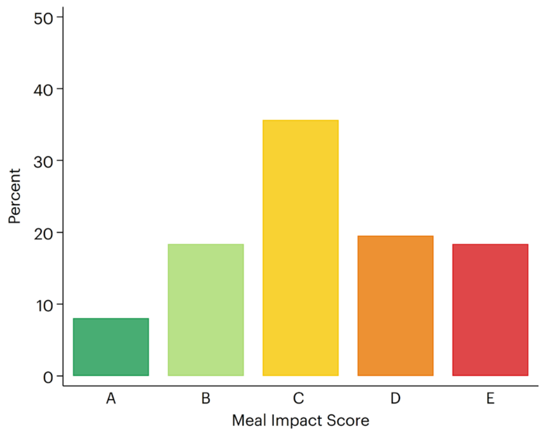

Fig. A2 Distribution of impact scores (AE) for all meals available on the platform (n=87)

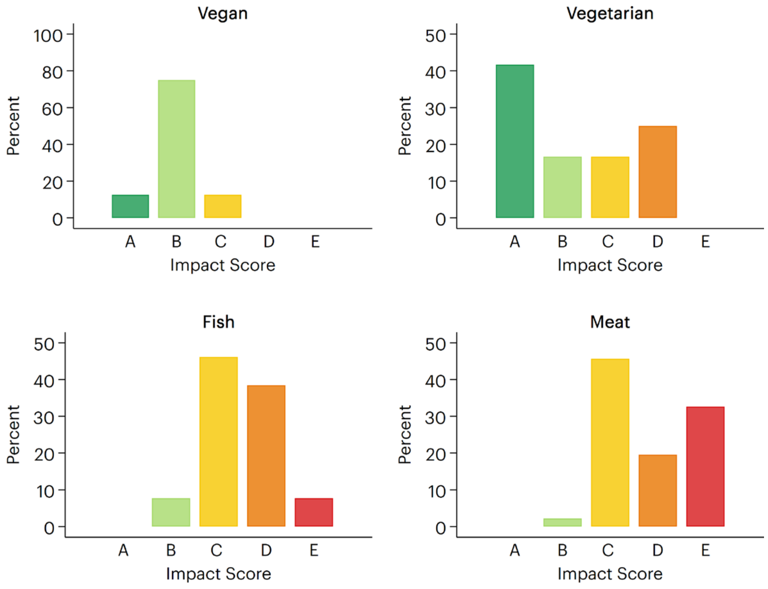

Fig. A3 Distribution of impact scores (AE) across each meal type category

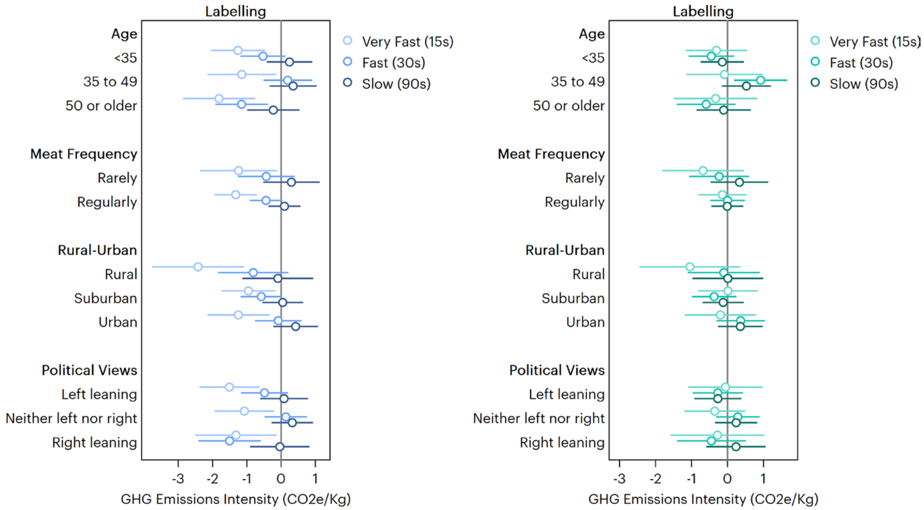

Fig. A4 Additional Heterogeneity Analysis

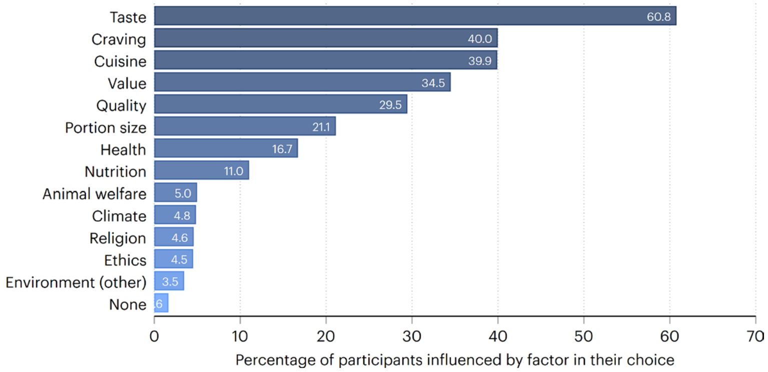

Fig. A5 Decision factors elicited in the post-intervention survey based on the question: *Which factors most influenced your food choice? Select all that apply*' A3. Experimental Instructions

General Study Information

The aim of this study is to study food purchasing on online food delivery platforms. You have been invited to take part because you are aged 18 and over and have previously used online delivery platforms.

This study contains a short survey where we will ask you some questions about yourself and your food consumer behaviour and attitudes to purchase food online. You will then be asked to order food for dinner. Note that for some of you this order will have real consequences, as every 30th participant will actually receive the ordered food which will be delivered to their homes. In total, we expect 4000 participants to complete this study.

No background knowledge is required to complete the study. The study will take about 5–10 minutes to complete.

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 you will actually receive the order you place, and if selected as a winner, we will also pay you 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.

How we record your choices:

- You will have 90 seconds to add items to your basket.
- If you add a new item, it will replace the current item in your basket.

- You cannot check out before time is up, but all your choices are saved.
- A bar on the top or bottom shows the remaining time.

After 90 seconds:

- You will be checked out automatically.
- A random second between 10 and 90 will be chosen.
- The item in your basket at that moment will be the ordered meal.
- If your basket is empty at that second, you won't receive a meal or payout.
- It's in your best interest to make a quick, possibly provisional choice by 10 seconds to avoid getting nothing. You can always change your mind later, as often as you like.

Meal prize draw:

- A random draw (1 out of 30) will determine meal winners.
- You will be notified if you are selected at the end of the survey.
- Winners will be contacted by email after the study and can choose a date and time for meal delivery.
- Your remaining budget will be paid out via bank transfer.

Comprehension Check

Before you place your order on the meal delivery app, please answer the following questions:

1. How many seconds do you have to make meal choices on the app? *Answers: a) 60s, b) 90s, c) 120s*
2. Can you change your mind by removing and re-adding items to the basket? *Answers: a) Yes, as many times as I like; b) Yes, but only twice; c) No*
3. What determines your ordered meal? *Answers: a) The item in your basket at a randomly drawn second between 10 and 90; b) The first item you added; c) The last item you added.*
4. If you made a first choice after 30 seconds and the randomly drawn second is 15, what is your ordered meal? *Answers: a) A random meal; b) your chosen meal; c) No meal*
5. If you made a first choice after 30 seconds and the randomly drawn second is 39, what is your ordered meal? *Answers: a) A random meal; b) your chosen meal; c) no meal*
6. If you changed your meal to a different one after 60 seconds and the randomly drawn second is 46, what is your ordered meal? *Answers: a) your first choice; b) your second choice; c) no meal*
7. If you changed your meal to a different one after 60 seconds and the randomly drawn second is 78, what is your ordered meal? *Answers: a) your first choice; b) your second choice; c) no meal*

A4 Questionnaire

Pre-Survey

1. Where are you right now while taking this survey? *[At work; at home (not working); at home (working); traveling (e.g., commuting, on a trip); during leisure time (e.g., at a cafe, park, social event, with family/friends); other (please specify)]*
2. How hungry are you feeling right now? *[0 - "Not at all hungry" to 100 - "Extremely hungry"]*
3. 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]*
4. 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]*
5. What diet do you follow, if any? *[None in particular; Vegan; Vegetarian; Flexitarian; Pescatarian; Other (please specify)]*.
6. How often do you eat a sweet dessert with your meals? *[Every day; Between 3 and 5 times a week; 1–2 times a week; Less than once a week; Never]*
7. How often do you eat meat or fish? (including sausage, salami, steak etc). *[Every day; Between 3 and 5 times a week; 1–2 times a week; Less than once a week; Never]*
8. How important is it that the food you normally choose is healthy? *[1: Not at all important - 4: very important]*
9. How important is it that the food you normally choose is climate friendly? *[1: Not at all important - 4: very important]*
10. How important is it that the food you normally choose is cheap? *[1: Not at all important - 4: very important]*
11. How important is it that the food you normally choose is tasty? *[1: Not at all important - 4: very important]*
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? *[Strongly left; Moderately left; Slightly left; Neither the left nor the right; Slightly right; Moderately right; Strongly right]*
13. If you are running a race and you are passing the person in the second place, which place are you in?
14. A bat and a ball cost 22 dollars in total. The bat costs 20 dollars more than the ball. How many dollars does the ball cost?
15. If it takes 7 machines 7 minutes to make 7 widgets, how many minutes would it take 100 machines to make 100 widgets?

Post-Survey

1. How easy did you find it to find your preferred meal? *[Not at all satisfied; Not very satisfied; Neither unsatisfied nor satisfied; Satisfied; Very satisfied]*

2. Which factors most influenced your food choice? *[Select all that apply] Multiple choice [Taste; craving; quality; price (value for money); climate impact; animal welfare concerns; ethics; other environmental concerns (water pollution, air pollution, land use change, biodiversity loss); portion size; cuisine; nutritional content; health; cultural/religious reasons; none of the above; other (please specify).]*
3. Do you recall seeing any of the following labels on the menu? *[Multiple choice - Calorie labels; organic labels; carbon labels; fair trade labels.]*
4. How worried are you about climate change? *[Not at all worried - Extremely worried]*
5. How worried are you about your health? *[Not at all worried - Extremely worried]*
6. To what extent do you feel a personal responsibility to try to reduce climate change? *[0 - Not at all; 10 = A great deal]*
7. To what extent do you feel a personal responsibility to adopt habits that promote a healthy lifestyle? *[0 - Not at all; 10 = A great deal]*
8. AHS-4 items, 1 ("strongly disagree") to 7 ("strongly agree") *[Please indicate your level of agreement with each of the following statements: everything in the universe is somehow related to each other; it is more desirable to take the middle ground than go to extremes; future events are predictable based on present situations; it is more important to pay attention to the whole context rather than the details.]*
9. Love of variety: 5-point Likert scale, ranging from "completely disagree" to "completely agree". Item 7 is reverse-scored. *[When I eat out, I like to try the most unusual items, even if I am not sure I would like them; While preparing foods or snacks, I like to try out new recipes; I think it is fun to try out food items one is not familiar with; I am eager to know what kinds of foods people from other countries eat; I prefer to eat food products I am used to. (reverse-scored)]*

A5. Label Pre-test Results

Note: Figures A6 and Tables A8, A9, A10, A11 displayed here.

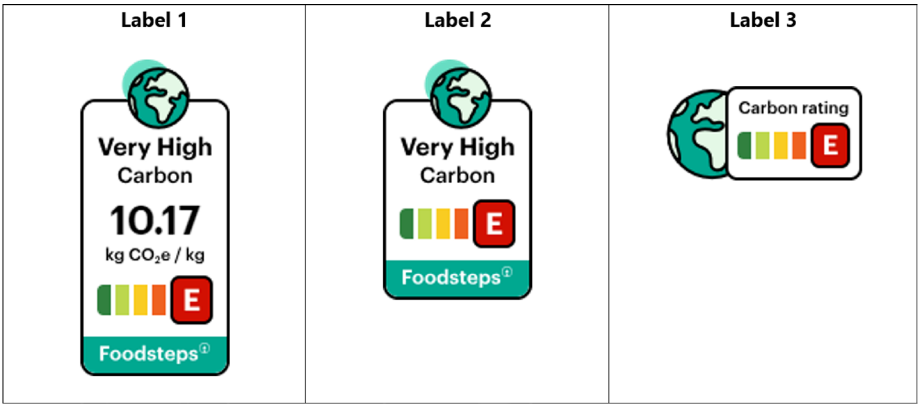

Fig. A6 Labels tested in the label pre-test survey

Table A8 What does the label show?

	Label 1	Label 2	Label 3
The climate impact of the meal	90%	84.5%	84%
	(45)	(38)	(42)
The energy required to prepare the meal	10%	13.3%	14%
	(5)	(6)	(7)
The healthiness of the meal		2.2%	2%
		(1)	(1)
Observations	50	45	50

Note: Percentage responses per category. Number of responses (in parentheses) differ due to enforced time pressure (30 seconds). Initial allocation of participants to each group: Label 1 = 50, Label 2 = 46, Label 3 = 51

Table A9 Ratings under time pressure

	Label 1	Label 2	Label 3
Info provided	6.35	6.72	5.72
	(43)	(43)	(46)
Clear/Concise	6.48	6.75	6.43
	(42)	(40)	(44)
Easy to understand	6.14	7.36	6.11
	(37)	(36)	(37)
Trustworthy	5.20	5.81	5.94
	(30)	(32)	(32)
Visual appeal	6.33	5.85	6.83
	(24)	(26)	(29)
Appropriate for apps	6.00	6.15	6.39
	(19)	(20)	(23)
Average score	6.20	6.58	6.05
	(43)	(43)	(48)

Note: Average score per item and overall average score under time pres- sure (30 seconds). Items were scored on a scale of 010. Number of re- sponses (in parentheses) differs due to enforced time pressure (30 sec- onds). Initial allocation of participants to each group: Label 1 = 50, Label 2 = 46, Label 3 = 51

Table A10 Ratings without time pressure

	Label 1	Label 2	Label 3
Info provided	7.65	5.96	5.71
	(2.06)	(2.35)	(2.35)
Clear/Concise	7.15	6.36	6.32
	(2.14)	(2.51)	(2.61)
Easy to understand	6.76	6.23	6.11
	(2.48)	(2.69)	(2.66)
Trustworthy	6.42	5.67	5.25
	(2.48)	(2.74)	(2.55)
Visual appeal	6.60	6.66	6.28
	(2.56)	(2.45)	(2.40)
Appropriate for apps	5.91	5.71	5.27
	(2.83)	(2.96)	(3.07)
Average score	6.57	6.13	5.85

Table A10 (continued)

	Label 1	Label 2	Label 3
	(2.08)	(2.12)	(2.11)
Observations	97	101	96

Note: Average score per item and overall average score, without time pressure. Items were scored on a scale of 010. Standard deviation in parentheses

Table A11 Ranking

	Label 1	Label 2	Label 3
First	70	52	25
Second	32	71	44
Third	45	24	78
Overall Score	2.17	2.19	1.64
Observations	147	147	147

Note: Number of times a label was chosen as First, Second or Third, without time pressure. Average Score based on allocating 3 points for First, 2 points for Second and 1 point for Third

Acknowledgements We are grateful to the Behavioural Insights Team for facilitating this study, with special thanks to Abigail Mottershaw, Bobby Stuijfzand, and Thea House for their invaluable support. The activities of CEBI are financed by the Danish National Research Foundation, Grant DNRF134.

Data Availability Data and code to replicate the analysis will be made publicly available via OSF repository: https://osf.io/4n9e8.

Declarations

Competing Interests The authors declare no competing interests.

References

Al-Ubaydli O, Lee MS, List JA, Mackevicius CL, Suskind D (2021) How can experiments play a greater role in public policy? Twelve proposals from an economic model of scaling. Behav Public Policy 5(1):2–49

Allcott H, Cohen D, Morrison W, Taubinsky D (2022) When do" nudges" increase welfare? Technical report, National Bureau of Economic Research.

Altmann S, Grunewald A, Radbruch J (2022) Interventions and cognitive spillovers. Rev Econ Stud 89(5):2293–2328

Ammann J, Arbenz A, Mack G, Nemecek T, El Benni N (2023) A review on policy instruments for sustainable food consumption. Sustain Prod Consumption 36:338–353

Banerjee S, Galizzi MM, John P, Mourato S (2023) Sustainable dietary choices improved by reflection before a nudge in an online experiment. Nat Sustain 6(12):1632–1642

Beyer B, Chaskel R, Euler S, Gassen J, Großkopf AK, and Sellhorn T (2024) How does carbon footprint information affect consumer choice? A field experiment. J Account Res 62(1):101–136

Bianchi F, Luick M, Bandy L, Bone J, Kelly S, Farrington J, Leung J, Mottershow A, Murar F, Jebb SA, Harper H, Pechey R (2023) The impact of altering restaurant and menu option position on food selected from an experimental food delivery platform: a randomised controlled trial. Int J Behav Nutr Phys Act 20(1)

Bilén D (2022) Do carbon labels cause consumers to reduce their emissions? evidence from a large-scale natural experiment. Technical report, Mimeo, Gothenburg University.

Brunner F, Kurz V, Bryngelsson D, Hedenus F (2018) Carbon label at a University restaurant – label implementation and evaluation. Ecol Econ 146(August 2017):658–667

Bruns H (2019) No evidence that distracted people are easier to nudge. An Experiment On The Interaction Of Cognitive Scarcity And Defaults In a Public Goods Game.

Bruns H, Kantorowicz-Reznichenko E, Klement K, Luistro Jonsson M, Rahali B (2018) Can nudges be transparent and yet effective? J Econ Psychol 65:41–59

Bryan CJ, Tipton E, Yeager DS (2021) Behavioural science is unlikely to change the world without a heterogeneity revolution. Nat Hum Behaviour 5(8):980–989

Camerer C, Issacharoff S, Loewenstein G, O'Donoghue T, Rabin M (2003) Regulation for conservatives: behavioral economics and the case for" asymmetric paternalism". Univ PA Law Rev 151(3):1211–1254

Caplin A, Dean M, Martin D (2011) Search and satisficing. The Am Econ Rev 101(7):2899–2922

Carlsson F, Gravert C, Johansson-Stenman O, Kurz V (2021) The use of green nudges as an environmental policy instrument. Rev Environ Econ Policy 15(2):000–000

Casati M, Soregaroli C, Rommel J, Luzzani G, Stranieri S (2023) Please keep ordering! A natural field experiment assessing a carbon label introduction. Food Policy 120

Crosetto P, Gaudeul A (2023) Fast then slow: choice revisions drive a decline in the attraction effect. Manag Sci 70(6):3711–3733

Dannenberg A, Klatt C, Weingärtner E (2024) The effects of social norms and observability on food choice. Food Policy 125

Dannenberg A, Weingärtner E (2023) The effects of observability and an information nudge on food choice. J Environ Econ Manag 120

DellaVigna S, Linos E (2022) Rcts to scale: comprehensive evidence from two nudge units. Econometrica 90(1):81–116

Elofsson K, Bengtsson N, Matsdotter E, Arntyr J (2016) The impact of climate information on milk demand: evidence from a field experiment. Food Policy 58:14–23

Faccioli M, Law C, Caine CA, Berger N, Yan X, Weninger F, Guell C, Day B, Smith RD, Bateman IJ (2022) Combined carbon and health taxes outperform single-purpose information or fiscal measures in designing sustainable food policies. Nat Food 3(5):331–340

Fosgaard TR, Pizzo A, Sadoff S (2024) Do people respond to the climate impact of their behavior? The effect of carbon footprint information on grocery purchases. Environ Resour Econ

Garnett EE, Balmford A, Sandbrook C, Pilling MA, Marteau TM (2019) Impact of increasing vegetarian availability on meal selection and sales in cafeterias. Proc Natl Acad Sci USA 116(42):20923–20929

Ghesla C, Grieder M, Schubert R (2020) Nudging the poor and the rich – a field study on the distributional effects of green electricity defaults. Energy Econ 86

Gravert C, Kurz V (2021) Nudging à la carte: a field experiment on climate-friendly food choice. Behav Public Policy 5(3):378–395

Ho L, Page L (2024) Got beef with beef? evidence from a large-scale carbon labeling experiment. Evidence From a Large-Scale Carbon Labeling Experiment. (April 23, 2024)

Imai T, Pace DD, Schwardmann P, van der Weele JJ (2022) Correcting consumer misperceptions about CO2 emissions. (10138.

Jalil A, Tasoff J, Bustamante AV (2023) Low-cost climate-change informational intervention reduces meat consumption among students for years. Nat Food

Jesse M, Jannach D, Gula B (2021) Digital nudging for online food choices. Front Psychol 12

Jostock C, Luick M, Jebb SA, Pechey R (2024) Changing the availability and positioning of more vs. less environmentally sustainable products: a randomised controlled trial in an online experimental supermarket. Appetite 200

Kahneman D (1973) Attention and effort

Kahneman D (2011) Thinking, fast and slow. Farrar, *Straus and Giroux*

Kahneman D, Tversky A (1979) Prospect theory: an analysis of decision under risk. Econometrica 47(2):263–291

Klatt C, Schulze Tilling A (2024) Tastes better than expected: post-intervention effects of a vegetarian month in the student canteen. Technical report, ECONtribute Discussion Paper

Kurz V (2018) Nudging to reduce meat consumption: immediate and persistent effects of an intervention at a university restaurant. J Environ Econ Manag 90:317–341

Lambrecht NJ, Hoey L, Bryan A, Heller M, Jones AD (2023) Limiting red meat availability in a university food service setting reduces food-related greenhouse gas emissions by one-third. Clim Change 176(6)

Lohmann PM, Gsottbauer E, Doherty A, Kontoleon A (2022) Do carbon footprint labels promote climatarian diets? Evidence from a large-scale field experiment. J Environ Econ Manag 114

Lohmann PM, Gsottbauer E, Farrington J, Human S, Reisch LA (2024a) Choice architecture promotes sustainable choices in online food-delivery apps. PNAS Nexus 3(10)
Lohmann PM, Pizzo A, Bauer JM, Khanna TM, Reisch LA (2024b) Demand-side interventions for sustainable food systems: a meta-analysis of food-policy interventions targeting food consumption and waste behaviours. Available at SSRN 4811931.
Maćkowiak B, Matějka F, Wiederholt M (2023) Rational inattention: a review. J Econ Lit 61(1):226–273
Maier M, Fesenfeld LP (2024) Carbon food labels unlikely to close intention-behavior gaps in grocery shopping. Working paper.
Merk C, Meissner LP, Griesoph A, Hoffmann S, Schmidt U, Rehdanz K (2024) No need for meat as most customers do not leave canteens on veggie days. Npj Climate Action 3(1):79
Mertens S, Herberz M, Hahnel UJ, Brosch T (2022) The effectiveness of nudging: a meta-analysis of choice architecture interventions across behavioral domains. Proc Natl Acad Sci USA 119(1):e2107346118
Michaelsen P (2023) Transparency and nudging: an overview and methodological critique of empirical investigations. Behav Public Policy 1–11
Mills S (2022) Personalized nudging. Behav Public Policy 6(1):150–159
Muller L, Lacroix A, Ruffieux B (2019) Environmental labelling and consumption changes: a food choice experiment. Environmental and Resource Economics.
Panzone LA, Auch N, Zizzo DJ (2024) Nudging the food basket green: the effects of commitment and badges on the carbon footprint of food shopping. Environ Resour Econ 87(1):89–133
Panzone LA, Ulph A, Hilton D, Gortemaker I, Tajudeen IA (2021) Sustainable by design: choice architecture and the carbon footprint of grocery shopping. J Public Policy & Mark 40(4):463–486
Panzone LA, Ulph A, Zizzo DJ, Hilton D, Clear A (2018) The impact of environmental recall and carbon taxation on the carbon footprint of supermarket shopping. J Environ Econ Manag 109:102137
Perino G, Schwirplies C (2022) Meaty arguments and fishy effects: field experimental evidence on the impact of reasons to reduce meat consumption. J Environ Econ Manag 114
Pizzo A, Bauer JM, Reisch LA (2024) What shapes sustainable food choices? A field experiment on the impact of a behaviorally informed intervention and a price variation on sustainable food choices
Reisch LA, Sunstein CR (2021) Plant-based by default. One Earth 4(9):1205–1208
Reisch LA, Sunstein CR, Andor MA, Doebbe FC, Meier J, Haddaway NR (2021) Mitigating climate change via food consumption and food waste: a systematic map of behavioral interventions. J Cleaner Production 279:123717
Reisch LA, Sunstein CR, Kaiser M (2021) What do people want to know? Information avoidance and food policy implications. Food Policy 102:102076
Rey A, Le Goff K, Abadie M, Courrieu P (2020) The primacy order effect in complex decision making. Psychol Res 84(6):1739–1748
Robertson DA, Andersson Y, Lunn PD (2023) How consumer and provider responses to nutritional labelling interact: an online shopping experiment with implications for policy. Food Policy 121
Rozin P, Royzman EB (2001) Negativity bias, negativity dominance, and contagion. Pers Soc Psychol Rev 5(4):296–320
Saccardo S, Dai H, Han M, Raja N, Vangala S, Croymans D (2023) Assessing nudge scalability. Available at SSRN 3971192.
Scarborough P, Matthews A, Eyles H, Kaur A, Hodgkins C, Raats MM, Rayner M (2015) Reds are more important than greens: how UK supermarket shoppers use the different information on a traffic light nutrition label in a choice experiment. Int J Behav Nutr Phys Act 12(1):1–9
Schulze Tilling A (2023) Changing consumption behavior with carbon labels: causal evidence on behavioral channels and effectiveness. Technical report, technical report, Mimeo, University of Bonn.
Schwartz D, Loewenstein G, Agüero-Gaete L (2020) Encouraging pro-environmental behaviour through green identity labelling. Nat Sustain 3(9):746–752
Sims CA (2003) Implications of rational inattention. J Monet Econ 50(3):665–690
Sunstein CR (2014) Nudging: a very short guide. J Consum Policy (Dordr) 37:583–588
Sunstein CR (2022) The distributional effects of nudges. Nat Hum Behaviour 6(1):9–10
Szaszi B, Palinkas A, Palfi B, Szollosi A, Aczel B (2018) A systematic scoping eview of the choice architecture movement: toward understanding when and why nudges work. J Behav Decis Mak 31(3):355–366
Thaler RH, Sunstein CR (2008) Nudge: improving decisions about health, wealth, and happiness. Yale University Press, New Haven, CT, US
Thøgersen J, Dessart FJ, Marandola G, Hille SL (2024) Positive, negative or graded sustainability labelling? Which is most effective at promoting a shift towards more sustainable product choices? Bus Strategy Environ
Tversky A, Kahneman D (1974) Judgment under uncertainty: heuristics and biases: biases in judgments reveal some heuristics of thinking under uncertainty. Science 185(4157):1124–1131

Tversky A, Kahneman D (1991) Loss aversion in riskless choice: a reference-dependent model. Q J Econ 106(4):1039–1061

YouGov (2024) Dietary choices of brits. https://yougov.co.uk/topics/society/trackers/dietery-choices-of-brits-eg-vegeterian-flexitarian-meat-eater-etc