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Do carbon footprint labels promote climatarian diets? Evidence from a large-scale field experiment

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ABSTRACT

We estimate the causal effect of carbon footprint labels on individual food choices and quantify potential carbon emission reductions, using data from a large-scale field experiment at five university cafeterias with over 80,000 individual meal choices. Results show that carbon footprint labels led to a decrease in the probability of selecting a high-carbon footprint meal by approximately 2.7 percentage points with consumers substituting to mid-carbon impact meals. We find no change in the market share of low-carbon meals, on average. The reduction in high-carbon footprint meals is driven by decreases in sales of meat meals while sales of mid-ranged vegan, vegetarian and fish meals all increased. We estimate that the introduction of carbon footprint labels was associated with a 4.3% reduction in average carbon emissions per meal. We contrast our findings with those from nudge-style interventions and discuss the cost-effectiveness of carbon footprint labels. Our results suggest that carbon footprint labels present a viable and low-cost policy tool to address information failure and harness climatarian preferences to encourage more sustainable food choices.

1. Introduction

There is growing awareness around the impact of dietary choices on climate change. It is estimated that the food system alone is responsible for 26%–34% of global greenhouse gas (GHG) emissions (Crippa et al., 2021; Poore and Nemecek, 2018), of which at least 15% are attributed to livestock farming (Gerber et al., 2013; Godfray et al., 2018).[1] Recent modelling suggests that even if fossil fuel emissions were immediately halted, current trends in global food systems would prevent the achievement of the IPCC's 1.5 °C target and, by the end of the century, even threaten the attainment of the 2 °C target (Clark et al., 2020). Studies also show that a shift towards diets with lower carbon footprints, so called climatarian diets, have the potential to meaningfully reduce carbon

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[1] Beyond climate impacts, ongoing agricultural expansion and intensification (in particular related to livestock production) have further far-reaching consequences for land degradation, deforestation and biodiversity loss (Daskalova et al., 2020; Williams et al., 2020).

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emissions and alleviate pressures on the environment (Kim et al., 2019; Poore and Nemecek, 2018; Willett et al., 2019).[2] With food related emissions being largely demand driven, policies that target food-demand management hold a significant greenhouse gas (GHG) mitigation potential (Bajželj et al., 2014; Temme et al., 2020; Reisch, 2021).

In a first best world, a Pigouvian intervention in the form of a widely discussed carbon tax targeting emissions from all products, or a more directed meat and dairy tax, can directly price in environmental externalities from livestock production and consumption and incentivise people to change their diets.[3] However, such taxes have faced fierce resistance in practice, due to a lack of popularity among voters. Taxes are also costly to design and implement, and simulations point out that particular carbon-based food taxes tend to be slightly regressive (García-Muros et al., 2017; Säll, 2018).

In response, academics and policy makers have turned to explore more subtle behavioural interventions, so called 'nudges', which constitute small changes in the choice architecture that can promote behavioural changes, without forbidding any options or significantly changing economic incentives (Thaler and Sunstein, 2009). Nudges have gained increasing popularity as an environmental policy instrument (for a review see Carlsson et al., 2021a). In the realm of food choices, numerous studies have attempted to encourage more sustainable food choices through a range of behavioural interventions in different settings, including supermarkets and restaurants (Vandenbroele et al., 2020).[4] More recently, there has been a particular focus on interventions targeting meat and vegetarian consumption (Bianchi et al., 2018b; Çoker and van der Linden, 2020). Interventions explored include changing the salience, order or positioning of meals in cafeteria and restaurant settings (Bacon et al., 2018; Garnett et al., 2020; Gravert and Kurz, 2019; Kurz, 2018). Overwhelmingly, the results suggest that these stimuli are associated with positive and significant increases in the share of vegetarian meals consumed. While the aforementioned behavioural interventions – targeting different aspects of the choice architecture (i.e., different ways in which choices can be presented) – have the ability to nudge consumers towards more sustainable meal choices, they usually fail to address the information asymmetries underlying the market failure associated with food production in the presence of environmental externalities. It remains unlikely that consumers will make socially optimal consumption decisions in a sustained manner if markets do not convey relevant information about the external costs of production and consumption (Moran, 2021).

In an effort to address the information asymmetry around the environmental impact of food, recent experimental studies have explored the efficacy of information and educational interventions in cafeteria (Jalil et al., 2020; Schwitzgebel et al., 2020) and supermarket settings (Elofsson et al., 2016; Kanay et al., 2021; Lanz et al., 2018). For instance, results from Jalil et al. (2020) show that a one-off lecture on the environmental impact of meat consumption increases vegetarian sales, however effects fade over time.[5] These findings suggest that consumers may fundamentally lack sufficient knowledge about the consequences of their food choices, or this information may not be salient at the time of purchase. Both issues may be addressed by providing clear environmental impact information in the form of carbon footprint labels. For instance, Camilleri et al. (2019) find that consumers misperceive the environmental impact of their diets and consistently tend to underestimate the carbon footprint of their food consumption. In addition, the study also shows that carbon labels can reduce such consumer misperceptions (Camilleri et al., 2019). Recent research corroborates that carbon footprint labels operate through improvements in consumer knowledge and are effective in reducing estimation biases for the carbon footprint of food (Panzone et al., 2020).

Only a small set of experimental studies have explored the impact of providing information on greenhouse gas emissions on actual meal choices via labels.[6] For instance, Osman and Thornton (2019) study hypothetical meal choices in a laboratory experiment and find that carbon labels can encourage sustainable meal choices compared to a condition where only basic meal information is provided. In a cafeteria setting, Spaargaren et al. (2013) find emissions reductions of less than 2% from a comprehensive climate labelling scheme on snack-like items. Slapø and Karevold (2019) find that traffic-light labels on warm dishes significantly reduced sales of meat dishes, but only during the first 20 days of the intervention at a university cafeteria in Norway. The study closest to ours is Brunner et al. (2018) who conducted an impact evaluation of the introduction of a carbon label at one university restaurant using a before–after intervention design. They find that sales of high-emission meat dishes decreased by 2.4 percentage points and low-emission meat dishes increased by 5.6 percentage points, resulting in an overall decrease in emissions of 3.6%. Although the aforementioned studies were conducted in a field setting, all three studies utilise data from only a single restaurant with a limited number of purchase decisions.

Our study contributes to this literature by experimentally assessing the causal effect of carbon footprint labelling on individual meal choices in a university cafeteria setting using a large-scale field experiment. The study allows us to explicitly explore whether

[2] A climatarian diet is a diet that aims to reduce the carbon footprint from food consumption and mitigate climate change. Such a diet does not generally involve strict rules, but rather places a focus on mindfulness about food-related emissions. Climatarian diets may encompass a range of behaviours to lower one's carbon footprint from food consumption (e.g., reducing meat consumption, substituting to lower-impact meat alternatives, reducing food waste and packaging, or eating locally) and are consistent with a range of environmentally motivated diets (including plant-based and flexitarian). In this paper, climatarian diet is defined as a diet that involves making consumption choices based on the carbon footprint of different foods.

[3] Experimental research shows that carbon taxation can reduce the carbon footprint of food consumption (Panzone et al., 2018, 2021).

[4] A complementary experimental literature has explored the effect of behavioural interventions on healthier food choices. For recent reviews see Vecchio and Cavallo (2019) and Cadario and Chandon (2020).

[5] For a broader review of interventions targeting demand for meat including information provision, see Bianchi et al. (2018a).

[6] There are a considerable number of empirical studies on consumer response to carbon footprint and environmental sustainability food labels that come from hypothetical surveys or stated preference methods (see Rondoni and Grasso (2021) and Potter et al. (2021) for recent reviews; see Edenbrandt and Lagerkvist (2021) and Carlsson et al. (2021b) for recent applications). Though this body of work is informative, the literature review in this paper focuses on the relatively small number of field experimental studies on this topic, as these are more suitable for assessing the causal links between carbon food labels and actual food choices. Finally, a separate literature provides field experimental evidence on the effect of fair trade labelling on consumers' ethical food choices (e.g. Hainmueller et al., 2015).

carbon footprint labels can induce more climatarian food choices and simultaneously quantify potential emissions reductions that can be attained from such changes in food consumption patterns. The experiment was conducted in partnership with five college cafeterias catering to students and staff at the University of Cambridge between October 2019 and March 2020. Carbon footprint labels were introduced at three of the five cafeterias on all cafeteria main meals served during an intervention period, while two cafeterias served as our control. We collected baseline (pre-treatment) meal choice data as well as a post-intervention follow-up exit survey data. The final dataset consists of over 80,000 individual dining decisions made by 2228 individuals.

The present paper makes multiple contributions to the literature. First, our experimental field setting allows us to observe actual food choices in a real-world setting, while previous literature primarily relied on laboratory experiments or vignette studies, which do not accurately represent a real food choice setting. Second, our experimental design improves substantially on previous comparable field studies by implementing a difference-in-differences (DID) identification strategy with a significantly larger dataset. In contrast to previous studies, the availability of both treatment and control data, as well as baseline data, allows a causal interpretation of the results. Third, access to individual-level data enables us to track purchase decisions of the same individuals over time, allowing us to control for unobserved preference heterogeneity. Finally, our study is the first to provide insights into potential mechanisms and heterogeneous effects of carbon footprint labels by linking food purchase data with exit survey data collected at the treatment cafeterias after the intervention had been completed.

Our results indicate that carbon footprint labels have statistically significant effects on food choices. We find a significant substitution pattern between high and mid-carbon impact meals of approximately 2.7 percentage points. The reduction in high-carbon footprint meals is primarily driven by decreased sales of orange and red-labelled meat dishes, while the choice probability for yellow labelled vegan, vegetarian and fish dishes increased. Sales of low-carbon meals appear to be unaffected by labelling, on average. We find further evidence that the effect of labels on meal choices differs by pre-intervention preferences. Those individuals who followed a pre-dominantly high-carbon footprint diet in the pre-intervention period were most likely to reduce their consumption of high-carbon meals and increase mid-carbon meal purchases. Drawing on exit-survey data, we document that the information provided by the labels was perceived as trustworthy, useful and easy to understand. A supplementary analysis suggests that labels had a larger effect the happier they made customers feel about their food choices. With respect to emissions reduction, our estimates suggest that the carbon footprint labels caused a statistically significant average reduction of 27 g CO_2 per 100 g serving, corresponding to a 4.3% decrease in emissions.

2. Methods and data

2.1. Experimental design

We conducted a field experiment of carbon footprint labels on meals at five university cafeterias.[7] Each cafeteria was located within a University of Cambridge College, comparable to a hall of residence, which caters to its own (in residence) student population, academics and staff that are members of the College as well as a small number of guests. Our study focuses on the student populations of these five colleges, which range from approximately 500 to 1100 students. All colleges in our sample host both undergraduates and postgraduates as well as students from any academic discipline.

All cafeterias offered lunch and dinner services on weekdays, whereas three cafeterias were also open on weekends. The menu compositions in each cafeteria were planned by the cafeteria chefs before the start of each academic term and followed a pre-defined menu rotation. The menus were designed to cater towards different tastes and dietary preferences serving a variety of vegan, vegetarian, fish and meat dishes. The exact menu composition and the number of dishes available varied from day-to-day but generally included at least one vegan/vegetarian meal and a combination of fish and meat dishes. One treatment cafeteria did not serve ruminant meat (beef and lamb). We thus take specific care to control for time-varying availability of different meal alternatives in our econometric models. Only minor changes were made to the menus between baseline and intervention periods: 8% of dishes were replaced with comparable dishes in the treatment cafeterias and 15% in the control cafeteria employed in our main analysis. However, menu compositions – the average availability of meal options – remained largely unchanged between baseline and intervention period for both treatment and control cafeterias (see Appendix Table A1). This feature uniquely benefits our identification, as diners faced recurring choice sets every four to six weeks throughout the experiment.

For all cafeterias, we obtained individual-level meals sales data, which were recorded via electronic sales registers. Whilst cash and/or credit card payments were generally accepted for guests, college members could conveniently pay by swiping their university ID cards, which is the most common form of payment. Meal purchases made by college members were identified with an anonymous identifier, which allows us to track their meal choices over time. Alternatively, students have the possibility to eat out, order takeaway or cook their own food. However, the majority of undergraduate students do not have fully equipped kitchens in their student accommodation, which makes dining at the cafeteria a popular option. It is important to note that students were unlikely to switch between cafeterias in our study due to the college cafeteria system. Each college only allows its own members to conveniently dine at the college cafeteria, offering subsidised rates and automated purchases for student members via their ID cards. Students cannot use their ID cards at other colleges and therefore do not receive discounted rates. While it is possible to dine at other colleges upon invitation, this only happens occasionally, as students generally form a strong social network within their own college.

[7] Ethical approval for the experiment was granted by the Department of Land Economy Ethics Research Committee.

Fig. 1. Carbon footprint label design. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

The experiment took place over the course of two academic terms, running from 7th October to 8th December and January 13th to March 15th. While the academic year consists of three terms – two teaching terms and one exam term – the university requires all students to be physically present in Cambridge during the first two terms in which our experiment was conducted, thus allowing us to observe meal choices of a consistent sample of students. Moreover, the study period covered both autumn and winter months during which weather patterns were relatively stable and unlikely to confound our results. The first academic term, as well as the first two weeks of the second term served as our baseline data collection period at all participating cafeterias. In total, the baseline period covered 9 weeks. At three treatment cafeterias, carbon footprint labels were introduced on Monday 27th January and in one case on Tuesday 28th 2020 and displayed throughout the 7-week intervention period at lunch and dinner services for all cafeteria main meals.[8] The remaining two cafeterias served as a control group which displayed no additional carbon footprint information.

2.2. Intervention

To inform the design of the label, we calculated individual carbon footprints for 743 unique cafeteria main meals using detailed ingredient information provided by the cafeteria chefs.[9] Calculations were conducted in cooperation with Foodsteps Ltd., a UK-based sustainability consultancy in the food sector. The greenhouse gas emission values for individual ingredients were taken from three Life-cycle Assessment Databases (Clune et al., 2017; Poore and Nemecek, 2018; Hilborn et al., 2018) and adapted to reflect a British food procurement system where possible. A detailed description of the methodology used to estimate the carbon footprints can be found in Appendix E.

In addition, we conducted an extensive literature review to further inform important design elements of the carbon footprint label used for our study purposes. This literature has identified a combination of traffic-light design with a scale that puts information into context as the most comprehensible and more frequently trusted label design (e.g. Feucht and Zander, 2018; Meyerding et al., 2019; Muller et al., 2019; Panzone et al., 2020; Spaargaren et al., 2013; Thøgersen and Nielsen, 2016). We employed two UK-based graphic designers to create a set of label designs for the experiment and conducted an online survey with a small student sample from UK universities to validate the most promising design. We found that the most preferred design elements included a differentiated scale providing both numerical and normative guidance (i.e., numerical cut-offs and traffic-light colours) presented using a dial-shaped layout. See Fig. 1 for a graphical representation of the final design.

The label depicts the carbon footprint (CO_2 equivalent) per 100 g serving of each meal, combined with a traffic-light coloured scheme and a numerical scale. For means of comparability across meals and cafeterias, the numerical value of the footprint was displayed in CO_2 per 100 g serving. The numerical cut-offs for each label colour category were determined by splitting the sample of unique cafeteria meals into quintiles based on their estimated carbon footprint. The 20% of meals with the lowest carbon footprints had a footprint less than 150 g CO_2 per 100 g whilst the 20% of meals with the highest footprints had a footprint greater than 800 g CO_2 per 100 g. At all three cafeterias, the labels were displayed in the servery directly above the cafeteria meals during lunch and dinner. See Fig. 2 for a picture of the experimental setting in one of the treatment cafeterias.

[8] The experiment was originally designed to run throughout the entire academic year and end after the third academic term (mid-June 2020). Labels were thus introduced in the third week of the second term in order to balance the length of the baseline and intervention period and allow all students to have returned to their term-time accommodation after the Christmas break. Unfortunately, all cafeterias were forced to close by 24th March due to the COVID-19 national lockdown which somewhat shortened the intervention period.

[9] Recipe information was only available for treatment cafeteria dishes. However, for analysis purposes, we used our database of 743 unique cafeteria meals to impute carbon footprint estimates for comparable dishes served in the control cafeterias. We followed a systematic procedure: First, we matched dishes which were found on both treatment and control cafeteria menus (e.g. battered fish). Second, For the remaining dishes, we extracted comparable dishes based on the primary ingredients (usually the type of protein) and selected the dish with the greatest overlap of typical ingredients (e.g. ham and leek pie matched with ham and mushroom pie). This matching procedure was supported by the expertise of our industry partner, who specialises in footprint calculations for the food industry.

Fig. 2. Experimental setting.

2.3. Data

We rely on individual-level sales data obtained from the cafeterias' Point of Sale providers. Sales data cover the entire experimental period (16 weeks) including the 9-week baseline period and the 7-week intervention period. While all cafeterias distinguished between sales to college members, staff and guests and applied different pricing regimes accordingly, only sales to student members could be effectively identified and tracked over the entire study period. We thus focus our analysis on college student members whose food choices could be associated with individual diners via their university IDs. Students can only use their IDs at their own college, which implies that there is no cross-contamination in the analysis sample. Finally, we limit the analysis to cafeteria main meals only (excluding sides, desserts and salads), as this is the primary focus of our study.[10] We acknowledge that a complete analysis of the carbon footprint of meal choices would incorporate all components of a meal to fully capture any instances of behavioural compensation. However, sales of sides, desserts and salads are recorded in our sales data using generic identifiers which do not allow us to accurately identify which additional items were purchased.

Daily menu sheets were collected for the entire experimental period to track any deviations from the planned menu. Menus were merged with the sales data in order to identify which meal alternatives (i.e., choice sets) were available at a given service and which meal option was chosen by each individual. Sales coding in two treatment cafeterias and one control cafeteria allow us to observe the exact dishes chosen. In the third treatment cafeteria, sales coding does not distinguish between vegan or vegetarian sales, thus allowing us to only observe the exact meal choices for a subset of observations where either a vegan or vegetarian meal was available. In the second control cafeteria, the sales coding is limited to vegan/vegetarian or fish/meat. Sales data from this cafeteria can, therefore, only be used in a binary choice model with two aggregate alternatives. In the remainder of this article, we thus distinguish between the 'full dataset', consisting of 81,401 individual purchase decisions in all five cafeterias, for which we observe only vegan/vegetarian and fish/meat choices, and the 'main analysis dataset' (N = 59,492) for which we observe the exact meal choices in only four cafeterias. The latter is employed to provide our main results on changes in climatarian meal choices. Prior to our analysis, choice sets were adjusted to reflect the alternatives available at any given time. For instance, if an alternative had run out after a certain time, it was removed from all subsequent choice sets, or adjusted, if a replacement was made available. Fig. 3 utilises the full dataset to plot the total sales of cafeteria main meals aggregated on a weekly basis. Total sales decreased in both treatment and control cafeterias over the course of the academic year, due to increasing workload, alternative commitments and social dynamics (i.e., students eventually rely less on the cafeteria as a social hub). This is a common pattern observed every academic year.

To provide further insights into potential mechanisms, we collected qualitative data via an exit survey conducted among customers of all three treatment cafeterias at the end of the intervention period. The exit survey was designed to collect basic demographic information and assess how labels were perceived with respect to their credibility, importance, comprehensiveness and usefulness. Participants were also asked to self-report in which situations the labels influenced their choices. Finally, participants had the option to provide consent for their responses to be linked to sales data using anonymised identifiers. The surveys were distributed via each college's mailing lists and participation was incentivised with a prize draw.

[10] Note that we excluded any individual diners who bought more than one meal at a given cafeteria service (N = 18,147, 1.8% of all observations), as we were not able to determine whether additional meals were purchased for themselves or other people.

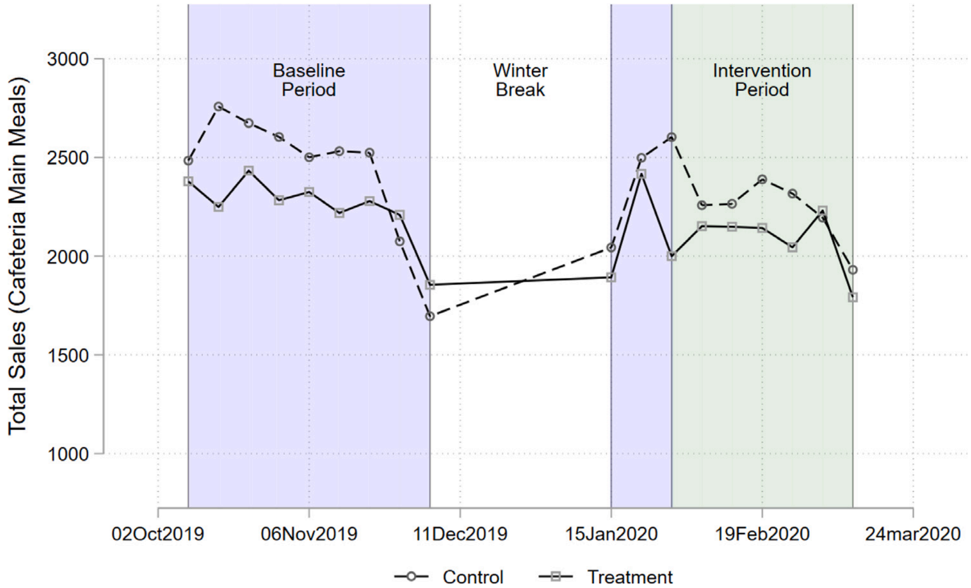

Fig. 3. Total weekly cafeteria main meals sold in treatment and control cafeterias. *Note:* Based on the full dataset, $N = 81{,}401$ individual sales.

2.4. Outcome variables & hypotheses

Our data allows us to explore the impact of treatment (exposure to carbon label) on multiple outcome variables related to whether participants make more climatarian meal choices. To do so, we construct three binary outcome variables equal to one if an individual selected a low-carbon impact meal with less than 250 g CO_2 per 100 g serving, mid-carbon impact meal between 250 g and 500 g CO_2 per 100 g serving or a high-carbon impact meal with more than > 500 g CO_2 per 100 g.[11] Moreover, to directly estimate the effect of the labelling intervention on the average carbon footprint of meal choices, we construct a continuous outcome variable for the CO_2 content of each meal choice.

Previous literature on interventions to reduce meat consumption has primarily focused on how the share of vegetarian/vegan dishes responds to an intervention (Garnett et al., 2019, 2020; Kurz, 2018). To provide comparable results, we construct an aggregated binary indicator equal to one if an individual selected a meat or fish dish and zero if the vegan or vegetarian alternative was chosen. However, it is important to note that using meat/fish or vegetarian/vegan choices as a proxy for more sustainable food choices may mask some of the complexities associated with the carbon footprint of different foods. In particular, vegetarian dishes in our data are found across all five label-colour categories. Similarly, fish dishes have an equally diverse range of carbon footprints (excluding the lowest-carbon category). We visualise the frequency distribution of vegan, vegetarian, fish and meat dishes across each of the five label categories in Appendix Figures A1 and A2. While the majority of combined vegan and vegetarian dishes (65%) are low-carbon dishes, labelled dark-green or light green, the remaining 35% are either mid or high-carbon impact (see Figure A1). Consequently, utilising aggregate choice variables may not accurately capture changes in preferences for climatarian diets (i.e., diets specifically aimed at reducing the carbon footprint). We thus provide a more nuanced analysis in Section 3.5 in which the choice setting is defined as a choice between vegan, vegetarian, fish and meat alternatives. Moreover, we allow the treatment effect to vary corresponding to the label colour with which each alternative is labelled.

We expect carbon footprint labels to decrease the market share of high-impact carbon meals and shift consumer preferences to more sustainable options. Both hypotheses are based on findings from previous research suggesting that carbon labels on food items aid customers to make more sustainable consumption choices (Brunner et al., 2018; Camilleri et al., 2019). We expect this effect to be partially reflected by a decrease in meat/fish sales and an increased demand for vegan/vegetarian meal options.

2.5. Estimation strategy

To estimate the effect of carbon footprint labels on the previously discussed outcome variables we implement an incremental estimation strategy, with each estimation step building the case for the robustness of our analysis. First, our main results come from a generalised difference-in-differences (DID) model with unit and time fixed effects to control for individual-specific heterogeneity and any exogenous factors that could affect food choices during the experimental period (Baker et al., 2022).

$$Y_{its} = \alpha_i + \lambda_t + \delta^{DD} D_{is} + X_s + \varepsilon_{ist} \tag{1}$$

[11] In each case, the comparison group encompasses all other available alternatives.

where Y_{its} is the binary dependent variable of meal choice or continuous variable of the carbon footprint of a particular meal choice made by individual i at cafeteria service s in week t. Individual fixed effects are captured by α_i and λ_t are week fixed effects. Individual fixed effects account for unobserved preference heterogeneity such as dietary preferences or restrictions and week fixed effects capture common shocks over time (e.g., midterm exams). X_s is a vector of time-varying control variables specific to cafeteria service s.[12] Controls include day-of-week dummies, an indicator for dinner services, the total number of sales and total number of options available at cafeteria service s, as well as the hourly temperature. For binary meal choice indicators, we also control for the number of options available for the dependent variable in question and the average price differential between high and low-carbon alternatives. Both availability and price have been found to play an important role in food purchase decisions (Garnett et al., 2021, 2019).[13]

$D_{is} = Treat \times Post$ is an indicator for a treated individual (Treat) during the labelling period (Post), with both main effects being subsumed by the individual and week fixed effects. The coefficient of interest is the DID estimator δ^{DD} which is unbiased in settings where there is a single treatment (Baker et al., 2022). We estimate linear probability models of Eq. (1) by OLS for each binary meal choice outcome (Y_{its}) separately and exclude observations where Y_{its} was either not available to choose as an alternative, or the only option available. The effective sample size thus varies depending on which dependent variable is analysed.

To probe the robustness of Eq. (1), we additionally model individual purchase decisions within a random utility maximisation framework using random-parameter mixed logit (MXL) models. The panel-data MXL models the probability of selecting each alternative for each choice situation (cafeteria service). Importantly, the MXL model uses random coefficients to relax the Independence-of-Irrelevant Alternatives (IIA) assumption, a restrictive assumption which implies that the error terms cannot be correlated across alternatives or over time. Moreover, the MXL model has the ability to account for preference heterogeneity by allowing the utility parameters to flexibly vary across choice makers (Train, 2009). For instance, individuals may hold heterogeneous preferences over the carbon-impact of meals, the meal-type itself and may be subject to varying degrees of price sensitivity. Formally, we model the probability (P_{it}^j) that alternative j is selected by individual i at cafeteria service s.

$$P_{is}^j = Prob\left[Y_{is} = j\right] = \frac{exp\left(\beta_{0,j} ASC^j + \beta_1 price_{is}^j + \beta_2 nroptions_{is}^j + \rho Treat + \gamma Post + \delta^{DD}\left(Treat \times Post\right) + X_{is} + \varepsilon_{is}\right)}{\Sigma_{k=1}^{j} exp\left(\beta_{0,j} ASC^j + \beta_1 price_{is}^J + \beta_2 nroptions_{is}^J + \rho Treat + \gamma Post + \delta^{DD}\left(Treat \times Post\right) + X_{is} + \varepsilon_{is}\right)} \quad (2)$$

Corresponding to the binary outcome variables discussed above we consider two specifications of Eq. (2), the first with three alternatives (j) capturing low, mid and high-carbon dishes and the second with two alternatives for meat/fish and vegan/veggie dishes. We include alternative-specific constants (ASC^j) and two alternative-specific variables for the price of each option ($price_{is}^j$) and the availability of each meal option ($nroptions_{is}^j$). In addition, we include a set of case-specific controls as in Eq. (1).[14] To identify the DID estimator δ^{DD} capturing the treatment effect of the labelling intervention, we use a standard DID specification with indicator variables $Post$ for observations in the intervention period and Treat for sales recorded in treatment cafeterias.[15] To account for unobserved preference heterogeneity, we allow the alternative-specific constants (ASC) as well as the price attribute to be randomly distributed in the population (Hensher and Greene, 2003; Train, 2009). All MXL models are estimated via simulated maximum likelihood with 300 Halton draws. To obtain interpretable estimates, we compute the marginal treatment effects following Puhani (2012) and account for unbalanced choice sets by restricting the sample for each alternative to the subpopulation of cases which include that alternative in their choice set.[16]

To explore the more nuanced effects of carbon footprint labels on meal choices, we consider a choice setting in which consumers choose between four alternatives: vegan, vegetarian, fish and meat. Moreover, we extend Eq. (2) to allow the treatment effect on the choice probability of alternative j to vary by label colour. The mixed logit model takes the following form:

$$P_{is}^j = Prob\left[Y_{is} = j\right] = \frac{exp(\beta_{0,j} ASC^j + \beta_1 price_{is}^j + \beta_2 nroptions_{is}^j + \beta_3 label^j + \beta_4(label^j \times T) + \beta_5(label^j \times P) + \beta_6(label^j \times T \times P) + \rho T + \gamma P + \delta^{DD}(T \times P) + X_{is} + \eta_{is})}{\Sigma_{k=1}^{j} exp(\beta_{0,j} ASC^j + \beta_1 price_{is}^j + \beta_2 nroptions_{is}^j + \beta_3 label^j + \beta_4(label^j \times T) + \beta_5(label^j \times P) + \beta_6(label^j \times T \times P) + \rho T + \gamma P + \delta^{DD}(T \times P) + X_{is} + \eta_{is})} \quad (3)$$

where $label^J$ represents a vector of four indicator variables for each label colour of alternative j in choice situation t (yellow is omitted as the base-category) and T and P are abbreviations for $Treat$ and $Post$, respectively. We estimate the marginal effects of the intervention for each combination of alternative and label-colour by restricting the sample to subpopulations of cases in which the respective combination was part of the choice set.

[12] Note that individuals are only observed at the specific cafeteria which they are affiliated to, hence control variables are limited to *time-varying* cafeteria characteristics.

[13] Note that the price-differential between meat/fish and vegan/vegetarian options is used in the analysis of meat/fish choices.

[14] Note that in Eq. (2) the vector of control variables X_{it} no longer includes availability and price differential controls as these are now directly captured by the alternative-specific variables $price$ and $nroptions$.

[15] We estimate a standard DID model to avoid computational difficulties when estimating conditional and mixed-logit models, resulting from the inclusion of a large number of unit and time fixed effects.

[16] Yet, despite the advantages of the MXL model to analyse choice data, estimation via maximum-likelihood simulation is computationally demanding if the number of choice sets or covariates is large. We are, therefore, required to exclude individual and week fixed effects from our MXL specifications, although these may capture important unobserved individual characteristics as well as common temporal shocks, thereby making our estimates more precise. For this reason, we will discuss Eq. (1) estimated by OLS as providing the main results and Eq. (2) as providing the basis for our robustness analysis.

Table 1
Treatment and control sample statistics over the experimental period.

	Treatment cafeterias		Control cafeterias	
	Baseline	Intervention	Baseline	Intervention
Days	77	48	76	49
Cafeteria services	143	90	139	90
Individuals	1112	1112	1116	1116
Mean visits per individual	22	13	24	14
Individual sales	24,541	14,512	26,390	15,958
Total sales	N = 39,053		N = 42,348	

Note: Table provides an overview of the analysis sample using all available meal choice observations (N = 81,401) of the full dataset (cafeterias = 5). Cafeteria services refers to the number of mealtimes (i.e. lunch and dinner services).

2.6. Statistical inference

Following Bertrand et al. (2004), we cluster standard errors at the individual level to account for within-individual error correlations. In the context of food choices, accounting for within-individual serial correlation is important due to differences in diet preferences and tastes, as well as cultural dietary restrictions or allergies. However, we may also be concerned about clustering at the cafeteria level as each cafeteria has slightly different practices, menus and employs different chefs. Moreover, individual diners are assigned to treatment at the cafeteria-level which justifies cluster-adjustments at this level (Abadie et al., 2017). In Section 3.3.2 we explore the robustness of our main results to clustering at the cafeteria-level by implementing the wild bootstrap-t procedure to account for the small number of clusters (Cameron et al., 2008; Roodman et al., 2019).

Identification in DID analysis depends crucially on the assumption that both treatment and control group would follow the same trend in outcomes, in the absence of an intervention. Whilst this assumption is not directly testable, we are able to draw on our 9-week baseline period to explore whether meal choices followed similar trends in treatment and control groups prior to the intervention. Appendix Figure B1 plots the raw data for treatment and control groups showing the average weekly sales of each dependent variable. The samples used to plot average weekly sales for a given dependent variable are restricted to the respective observations employed in the main analysis. A visual assessment of the pre-trends suggests that both treatment and control groups follow a comparable pre-intervention trend for all key outcome variables. However, it is also apparent that average sales are highly volatile on a week-by-week basis. This variation is likely due to unobserved differences in popularity of certain dishes available in a given week. As treatment and control cafeterias do not follow the same menus, it is to be expected that sales differ between treatment and control group on a weekly basis. This is confirmed by estimating unconditional event study plots (Figure A3), which visualise the estimated differences between treatment and control groups in bi-weekly intervals during the baseline and intervention periods for each of the main "climatarian" outcome variables. However, over the entire baseline period, sales in treatment and control cafeterias do not appear to systematically diverge. To provide greater clarity whether long-run trends are comparable between treatment and control groups, we perform a formal statistical test for the equality of pre-trends using data from the pre-intervention period between October 2019 and January 2020. We estimate a model with the previously discussed indicators for meal choices as the dependent variables, regressed on the same set of controls and fixed effects specified in Eq. (1), as well as a linear time trend (number of cafeteria services since 7th October) and its interaction with the treatment group indicator. The parameter of interest is the estimated coefficient on the interaction term between the linear time-trend and the treatment group dummy. The results from this exercise are shown in Appendix Table B1. We find no statistically detectable difference in the trends prior to the labelling intervention for treatment and control cafeterias.

3. Results

3.1. Descriptive statistics

Table 1 provides summary statistics of the full sample, including all observations made during the study period. We observe a total of 39,053 and 42,348 individual purchase decisions in the treatment and control group, respectively. The full sample spans observations from 81,401 individual meal choices, made by 2228 individuals during 232 cafeteria services (i.e., lunch or dinner services) over a period of 125 days. Students visited the cafeteria on average 37 times over the entire study period, equivalent to consuming either lunch or dinner in the cafeteria twice per week. Table 1 shows that observations are evenly distributed across treatment and control cafeterias.

Table 2 shows the meal sales shares for our main outcome variables for both the baseline and intervention period across treatment and control cafeterias. The sample used to compute the sales share for a given dependent variable is restricted to those observations where the respective meal option was available as one of multiple options and the exact choice could be observed. If a high-carbon meal was available, it was chosen approximately 50% of the time in treatment cafeterias and slightly more frequently in the control cafeterias (57%) during the baseline period. Moreover, approximately every third meal choice in the treatment cafeterias was a low-carbon or mid-carbon meal if these options were available to choose from. In the control cafeterias, low- and mid-carbon meals

Table 2
Share of dishes sold in treatment and control cafeterias over the experimental period.

Meal sales share	Treatment cafeterias				Control cafeterias			
	Baseline		Intervention		Baseline		Intervention	
Low-Carbon[a]	0.33	(0.47)	0.34	(0.47)	0.29	(0.45)	0.26	(0.44)
Mid-Carbon[a]	0.30	(0.46)	0.33	(0.47)	0.25	(0.43)	0.24	(0.43)
High-Carbon[a]	0.52	(0.50)	0.50	(0.50)	0.57	(0.49)	0.59	(0.49)
Meat/Fish	0.59	(0.49)	0.59	(0.49)	0.63	(0.48)	0.65	(0.48)
Vegan/Vegetarian	0.41	(0.49)	0.41	(0.49)	0.37	(0.48)	0.35	(0.48)
Carbon footprint[a]	573.23	(520.34)	564.48	(525.39)	671.27	(635.07)	688.40	(631.42)

Note: Table shows the percentage of meals *sold* for each dependent variable during the entire baseline and intervention period in both treatment and control cafeterias. "Low-Carbon" includes meals labelled dark and light green; "Mid-Carbon" includes yellow labelled meals and "High-Carbon" includes orange and red labelled meals (see Fig. 1). Carbon Footprint in grams of CO_2 equivalent per 100 g serving. Meal shares are computed based on observations where the exact meal choice could be identified as one of multiple alternatives for each respective dependent variable (i.e., excluding observations where the dependent variable was not available). For this reason, the sum of meal sales shares for low, mid and high-carbon alternatives is greater than 1. Standard deviation in parentheses.

[a]Main analysis dataset for which the exact meal-choices can be observed (cafeterias = 4).

Table 3
Main results.

	Climatarian preferences				
	(1) Low	(2) Mid	(3) High	(4) GHG	(5) Fish/Meat
Post × Treat	0.002	0.027***	−0.027***	−26.740***	−0.017**
	(0.008)	(0.009)	(0.008)	(8.803)	(0.007)
ID & Week FE	Yes	Yes	Yes	Yes	Yes
Individuals	1694	1658	1693	1714	2224
Observations	56,352	38,510	56,891	59,458	75,659

Note: OLS estimates of Eq. (1). The dependent variables in columns (1)–(3) are indicators for low, mid and high-carbon meal choice, respectively, and zero if any other alternative was chosen. The dependent variable in column (4) is a continuous variable for the carbon footprint of meal choice. The dependent variable in column (5) is an indicator for fish/meat meal choice. Post × Treat is the difference-in-differences estimator (δ^{DD}) capturing the treatment effect. Controls include total sales, total number of options available, number of options available of Y (for binary meal choice indicators), price differential between veg and meat or high-carbon and low-carbon alternatives, indicator for dinner service, hourly temperature and day-of-week dummies. All models include individual and week fixed effects. Standard errors clustered at the individual level in parentheses. Climatarian preferences are estimated using the main analysis dataset (cafeterias = 4). Fish/Meat draws on the full dataset (cafeterias = 5). Full model results shown in Appendix C.

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

were slightly less popular, making up 29% and 25% of choices in the baseline period, respectively. Meat and fish meals were consistently more popular than vegan and vegetarian alternatives. Between baseline and intervention periods, we observe minor changes in the sales shares of treated cafeterias in the expected directions (decrease in high-carbon sales, increases in mid and low-carbon sales) while in the control cafeterias we observe changes in the opposite direction.

3.2. Main results

We first examine the average treatment effect of the labelling intervention obtained by estimating Eq. (1) and substituting the outcome variables described in Section 2.5 to explore changes in both climatarian and vegetarian meal choices. Fig. 4 visualises the average treatment effects, while Table 3 presents results for the main coefficients of interest (the full results are shown in Appendix C). Columns (1) to (3) in Table 3 show the effects of carbon footprint labels on the probability of selecting a low, mid or high-carbon impact meal. Note that the three categories correspond to the label colours representing a range of CO_2 emissions: 'Low' combines choices of dark green and light green meals (<250 g CO_2 per 100 g), 'mid' represents yellow-labelled (250 g–500 g CO_2 per 100 g) meals and high encompasses orange and red labelled meals (>500 g CO_2 per 100 g). Column (4) shows the average treatment effect of the labels on the carbon footprint of meal choices. Columns (1) to (4) reflect climatarian preferences and are estimated using data from the four cafeterias in which we observe individuals' exact meal choices. Finally, column (5) shows the effects of carbon footprint labels on the likelihood of selecting fish or meat dish, estimated utilising data from all five cafeterias.

Focusing on our main dependent variables capturing climatarian preferences (columns 1 – 4) we find evidence that carbon footprint labels decreased the market share of high-carbon impact meals by 2.7 percentage points and led to a corresponding increase (2.7 percentage points) in the share of mid-carbon impact meals. Both estimates are highly statistically significant at the 1% level. We find no effect of the labels on low-carbon meal choices. Column (4) reports the effect of the labelling intervention on a continuous

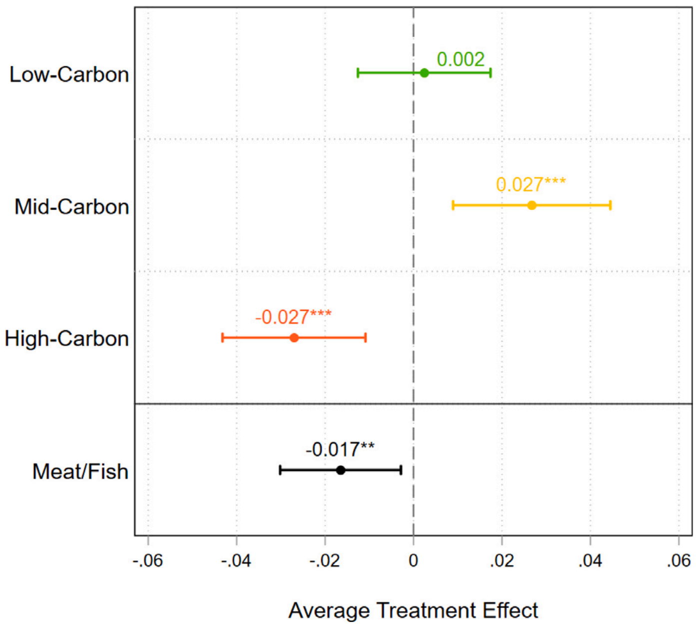

Fig. 4. Average treatment effects. *Note:* OLS estimates of Eq. (1). The dependent variables are binary meal choice indicators for low-, mid-, high-carbon and meat/fish choice. Error bars indicate 95% confidence intervals. Low-, mid- and high-carbon effects estimated using the main analysis dataset (cafeterias = 4). Meat/fish uses the full dataset (cafeterias = 5). See Table 3 for the exact sample size for each regression. Full model results shown in Appendix Table C1.

variable capturing the carbon footprint of meal choices. The negative coefficient indicates that carbon footprint labels caused a reduction of 27 g CO_2 in the average footprint consumed per 100 g serving, significant at the 1% level.

With respect to preferences for the meat/fish alternative (column 5), we find that carbon footprint labels caused a decrease in the market share of fish and meat sales by 1.7 percentage points which corresponds to an increase in vegan and vegetarian sales by the same amount, significant at the 5% level. However, it is important to note that an aggregate indicator combining both meat and fish masks important substitution patterns between meat and fish alternatives. More nuanced results of the treatment effect on both meat and fish alternatives are provided in Section 3.5.

3.3. Robustness

3.3.1. Mixed-logit choice model

This section demonstrates robustness of our main results when estimated via simulated maximum likelihood using a random parameter mixed-logit model as specified in Eq. (2). Table 4 presents the marginal effects of the labelling intervention on the choice probabilities for each of the outcomes which are selected from a set of possible alternatives. Columns (1) to (3) are obtained from a MXL model, in which the choice alternatives are defined as low, mid and high-carbon impact alternatives. Column (4) reflects a binary choice setting in which the consumer chooses between vegan/vegetarian or fish/meat alternatives.

We find comparable, yet slightly smaller marginal treatment effects (Post x Treat) across all four dependent variables. On average, carbon footprint labels increased the probability of selecting a mid-carbon meal by 1.6 percentage points (Column 2) and decreased the probability of selecting a high-carbon meal by 2.1 percentage points (Column 3), significant at the 10% and 1% level, respectively. The findings thus confirm the substitution pattern from high to mid-carbon alternatives shown in Section 3.2, which is reflected by a reduction in the probability of selecting a fish or meat dish (Column 4). Appendix C reports the full model results for the mixed-logit specifications in Tables C2 and C3. Both appendix tables additionally present the estimated standard deviations for the alternative specific constants and price variables obtained from the mixed-logit model. The estimated means and standard errors indicate that there is a highly statistically significant degree of preference heterogeneity in our sample, suggesting that individuals vary in their level of appreciation of low and high carbon meals, as well as vegetarian dishes. We also document a significant negative correlation between low and high-carbon alternatives, significant at the 1% level.

Our analysis, so far, has focused on examining the average treatment effects of the intervention on food choices, which provide a useful indication of the overall efficacy of carbon footprint labelling. However, an interesting question relates to whether effects differ with changes in the choice set composition. For instance, one might explore whether consumers substitute from high-carbon to low-carbon dishes if no mid-carbon impact dish is available to choose from. The mixed-logit choice model allows us to conveniently estimate the marginal treatment effects for each possible combination of low, mid and high-carbon alternatives (i.e., the different choice sets which occur in our data). This is achieved by restricting the sample to those cases that constitute a specific choice set and estimating the corresponding marginal effects with this subpopulation of observations. In our data, all three alternatives were

Table 4
Robustness: Mixed-logit estimates.

	(1) Low	(2) Mid	(3) High	(4) Fish/Meat
Post × Treat	0.011	0.016*	−0.021***	−0.016***
	(0.007)	(0.009)	(0.007)	(0.006)
ID & Week FE				
Observations	151,901	151,901	151,901	151,326
Nr. cases	59,360	59,360	59,360	75,663

Note: Mixed-logit estimates of Eq. (2). Marginal effects are computed for each alternative based on the subpopulation of cases with that alternative in their choice set. The choice alternatives in columns (1) to (3) are defined as low, mid and high carbon meals. The base category is the mid-carbon meal alternative which is constrained to zero. Column (4) is based on the binary choice scenario between Fish/Meat and Vegan/Vegetarian alternatives and the base category is meat/fish. Alternative specific attributes account for the price and availability of each alternative. Additional case-specific covariates include controls for total sales, total number of options available, average hourly temperature, an indicator for dinner service and day-of-week dummies. Standard errors clustered at the individual level in parentheses. Climatarian preferences are estimated using the main analysis dataset (cafeterias = 4). Fish/Meat draws on the full dataset (cafeterias = 5). Full model results shown in Appendix Tables C2 and C3.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5
Robustness: Climatarian preferences by choice set.

	(1) Low	(2) Mid	(3) High
Panel A: Low & Mid & High			
Post × Treat	0.008	0.016*	−0.024***
	(0.007)	(0.009)	(0.008)
Obs.	99,543	99,543	99,543
Panel B: Low & Mid			
Post × Treat	−0.004	0.004	
	(0.010)	(0.010)	
Obs.	4864	4864	
Panel C: Low & High			
Post × Treat	0.017**		−0.017**
	(0.007)		(0.007)
Obs.	41,564		41,564
Panel D: Mid & High			
Post × Treat		0.026***	−0.026***
		(0.010)	(0.010)
Obs.		5930	5930

Note: Mixed-logit estimates of Eq. (2). The choice alternatives in columns (1) to (3) are defined as low, mid and high carbon meals, respectively. The base category is the mid-carbon meal alternative which is constrained to zero. Panels A, B, C and D display the marginal effects estimated for sub-populations grouped by available choice set. The sample in Panel A is restricted to choice sets in which all three alternatives are available. The samples in Panels B, C and D are restricted to choice sets in which one of the three alternatives is not available, thus resulting in different combinations of low, mid and high alternatives. Post × Treat is the marginal effect capturing the treatment effect. Standard errors clustered at the individual level in parentheses. Estimates obtained from the main analysis dataset (cafeterias = 4).
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

available in 33,181 choice situations (N = 99,543). In 2432 cases (N = 4864) only low and mid alternatives were available. In 20,782 cases (N = 41,564) only low and high alternatives were available and in the remaining 2965 cases (N = 5930) only mid and high-carbon dishes were available to choose from. The results from this analysis are presented in Table 5.

Several interesting findings emerge. First, we find that labels decreased the choice probability of selecting a high-carbon meal regardless of which other alternatives were available to choose from. Interestingly, the substitution effect is most pronounced (2.6 percentage points) if the only other alternatives were mid-carbon meals (Panel D). If all three alternatives were available (Panel A) the decrease in the choice probability for high-carbon meals was 2.4 percentage points. However, if no mid-carbon meals were available in the choice set, consumers still decreased their consumption of high-carbon meals by 1.7 percentage points and increased low-carbon meal choices by 1.7 percentage points. These findings suggest that, if at least one mid-carbon option is available, consumers will prefer to switch from high-carbon to the mid-carbon alternatives. However, if only high-carbon and low-carbon alternatives are available on the menu, labels retain their effect but to a lesser extent. If only low and mid-carbon alternatives were available (Panel B), labels had no impact on consumer choice.

3.3.2. Additional robustness checks

Appendix A contains additional robustness checks and supplementary analysis. Table A2 shows the main results obtained from an adjusted version of Eq. (1) which excludes all time-varying controls (X_s). With this specification, we find that some of the treatment effects are slightly larger than those presented in Section 3.2 and all estimates are highly statistically significant. Moreover, we observe a statistically significant positive effect of labels on choices of low-carbon dishes, which is not encountered in our main results. Finally, we note that our main results are unchanged if the sample is restricted to weekdays only.

Table A3 shows the p-values for the DID estimator obtained from estimating (1) using both our preferred clustering approach (on the individual diner) and wild bootstrap clustered standard errors at the cafeteria level. We recover comparable p-values and the statistical significance of our main results presented in Section 3.2 remain statistically significant at the 5% level for vegetarian choice variables and at the 10% level for climatarian choice variables. However, we find that the estimate for the continuous carbon footprint outcome variable does not reach statistical significance when clustering at the cafeteria-level.

3.3.3. Rebound effects and attrition

A further concern relates to the possibility that the introduction of carbon footprint labels leads to avoidance behaviour and may deter individuals from dining at the cafeteria. Not only may this result in potential behavioural rebound effects (e.g. individuals consuming a high-carbon meal elsewhere), but may also lead to selective attrition over time if certain groups of individuals are differentially affected by the labels. For instance, if labels lead to avoidance behaviour amongst individuals who follow a high-carbon impact diet prior to the intervention (e.g. by evoking feelings of guilt), our estimates would no longer be unbiased. We address the first concern by aggregating the sales data to the "cafeteria service" level for each cafeteria (see Table 1) and estimating an adapted version of Eq. (1) with total meal sales at a given cafeteria service as the dependent variable.[17] Results are shown in column (1) of Appendix Table A4 and suggest that there is no statistically significant effect of the label intervention on total sales.

To address the second concern, we assign each individual to one of four equally sized groups, ranging from 'Least Green' to 'Most Green', based on their frequency of low-carbon meal consumption during the baseline period (discussed in detail in the following section). We then aggregate the data at the 'cafeteria service' level and calculate the share of customers in each quartile relative to the total customers for each cafeteria service. Next, we estimate the DID model with each share as the dependent variable. The DID estimator indicates whether the labelling intervention caused an increase or decrease in the share of customers of each category. Results are shown in columns (2) to (5) of Appendix Table A4. We find that the introduction of carbon footprint labels had no effect on the share of customers in each preference quartile and conclude that differential attrition does not threaten the internal validity of our results.

3.4. Preference heterogeneity

In this section we explore whether carbon footprint labels have heterogeneous effects on meal choices for individuals with different pre-intervention dietary habits. We classify frequent customers (with at least 10 cafeteria visits during the baseline period) into eight groups based on their pre-intervention consumption patterns.[18] Specifically, we assigned individuals into four equally sized groups ranging from 'Least Veg' to 'Most Veg', based on how frequently they consumed vegetarian or vegan meals during the baseline period. Additionally, we defined four climatarian preference quartiles based on the frequency of low-carbon meal consumption ranging from "Least Green", those individuals who were least likely to choose a low-carbon alternative (<250 g CO_2 per 100 g serving), to "Most Green" which captures those individuals who already pre-dominantly followed a low-carbon footprint diet. Tables 6 and 7 show the estimated average treatment effect of the carbon footprint labels on climatarian meal choices for each sub-sample of vegetarian and climatarian preferences, respectively, estimated by OLS using the generalised DID specification shown in (1).

With respect to baseline vegetarian preferences, the results indicate that the carbon footprint labels had the largest effect on individuals who were least likely to consume vegetarian or vegan meals in the baseline period (i.e., followed a meat-heavy diet). Individuals in this preference quartile (Least Veg) decreased their consumption of high-carbon meals by on average 4.2 percentage points and increased mid-carbon meal consumption by 6.7 percentage points, with both estimates statistically significant at the 1% level. Individuals in the second and third preference quartiles (Less Veg & More Veg) showed a comparable decrease in high-carbon meals (4.1 & 3.8 percentage points), significant at the 5% and 10% level, respectively. Interestingly, those individuals who already followed a predominantly vegetarian diet (Most Veg) significantly decreased their consumption of mid-carbon impact meals, significant at the 10% level.

As for climatarian preferences, the results indicate that individuals who followed a predominantly high-carbon footprint diet (i.e. consumed low-carbon meals less or least frequently in the pre-intervention period) were most likely to change their behaviour due to the carbon footprint labels. We observe a 3.3 percentage point decrease in the probability of selecting a high carbon meal for the "Least Green" preference quartile and a 4.9 percentage point decrease for the "Less Green" quartile, with estimates being

[17] As the data are aggregated at the cafeteria service level, subscript i as well as the individual fixed effects are removed. We control for additional external factors that may influence total sales, including average rainfall and humidity during the cafeteria service.

[18] Following Garnett et al. (2019), we selected 10 observations as the minimum number of cafeteria visits to accurately classify individual dietary preferences. While setting a higher threshold would further increase accuracy, this would result in a smaller sample size by restricting the sample to the more frequent customers. Ten cafeteria visits correspond to approximately one visit per week over the entire baseline period and thus should offer a varied picture of people's food preferences.

Table 6
Heterogeneity analysis: Veg.

	(1) Least Veg	(2) Less Veg	(3) More Veg	(4) Most Veg
Panel A: DV = Low carbon choices				
Post × Treat	−0.007 (0.012)	0.023* (0.013)	0.022 (0.021)	0.023 (0.017)
Obs.	14,496	13,510	12,301	12,270
Panel B: DV = Mid carbon choices				
Post × Treat	0.067*** (0.017)	0.028 (0.018)	0.015 (0.021)	−0.033* (0.018)
Obs.	10,247	9261	8179	8110
Panel C: DV = High carbon choices				
Post × Treat	−0.042*** (0.016)	−0.041** (0.017)	−0.038* (0.020)	−0.006 (0.015)
Obs.	14,907	13,670	12,307	12,181
ID & Week FE	Yes	Yes	Yes	Yes

Note: Results obtained from 12 separate OLS regressions of Eq. (1) using four equally sized subsamples (quartiles) grouping individuals by pre-intervention consumption frequency of vegan/vegetarian meals. The dependent variable (DV) in Panel A, B and C capture low, mid and high-carbon meal choices, respectively. Post × Treat is the difference-in-differences estimator (δ^{DD}) capturing the treatment effect. Controls include total sales, total number of options available, number of options available for Y, price differential between veg and meat or high-carbon and low-carbon alternatives, indicator for dinner service, hourly temperature and day-of-week dummies. All models include individual and week fixed effects. Estimates obtained from the main analysis dataset (cafeterias = 4). Standard errors clustered at the individual level in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7
Heterogeneity analysis: Green.

	(1) Least Green	(2) Less Green	(3) More Green	(4) Most Green
Panel A: DV = Low carbon choices				
Post × Treat	−0.001 (0.012)	0.022* (0.013)	0.016 (0.018)	0.029 (0.018)
Obs.	12,847	13,631	12,850	12,707
Panel B: DV = Mid carbon choices				
Post × Treat	0.045** (0.017)	0.040** (0.018)	0.009 (0.020)	−0.018 (0.018)
Obs.	9010	9229	8808	8391
Panel C: DV = High carbon choices				
Post × Treat	−0.033* (0.017)	−0.049*** (0.016)	−0.032* (0.019)	−0.021 (0.015)
Obs.	13,182	13,771	12,948	12,614
ID & Week FE	Yes	Yes	Yes	Yes

Note: Standard errors clustered at the individual level in parentheses. Results obtained from 12 separate OLS regressions of Eq. (1) using four equally sized subsamples (quartiles) grouping individuals by pre-intervention consumption frequency of low-carbon (green) impact meals. The dependent variable (DV) in Panel A, B and C capture low, mid and high-carbon meal choices, respectively. Post × Treat is the difference-in-differences estimator (δ^{DD}) capturing the treatment effect. Controls include total sales, total number of options available, number of options available for Y, price differential between veg and meat or high-carbon and low-carbon alternatives, indicator for dinner service, hourly temperature and day-of-week dummies. All models include individual and week fixed effects. Estimates obtained from the main analysis dataset (cafeterias = 4). Standard errors clustered at the individual level in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

statistically significant at the 10% and 1% significance level, respectively. Both groups increased their consumption of mid-carbon meals (4.5 and 4.0 percentage points, significant at the 5% level), whereas the "Less Green" preference quartile also increased consumption of low-carbon meals by 2.2 percentage points, significant at the 10% level.

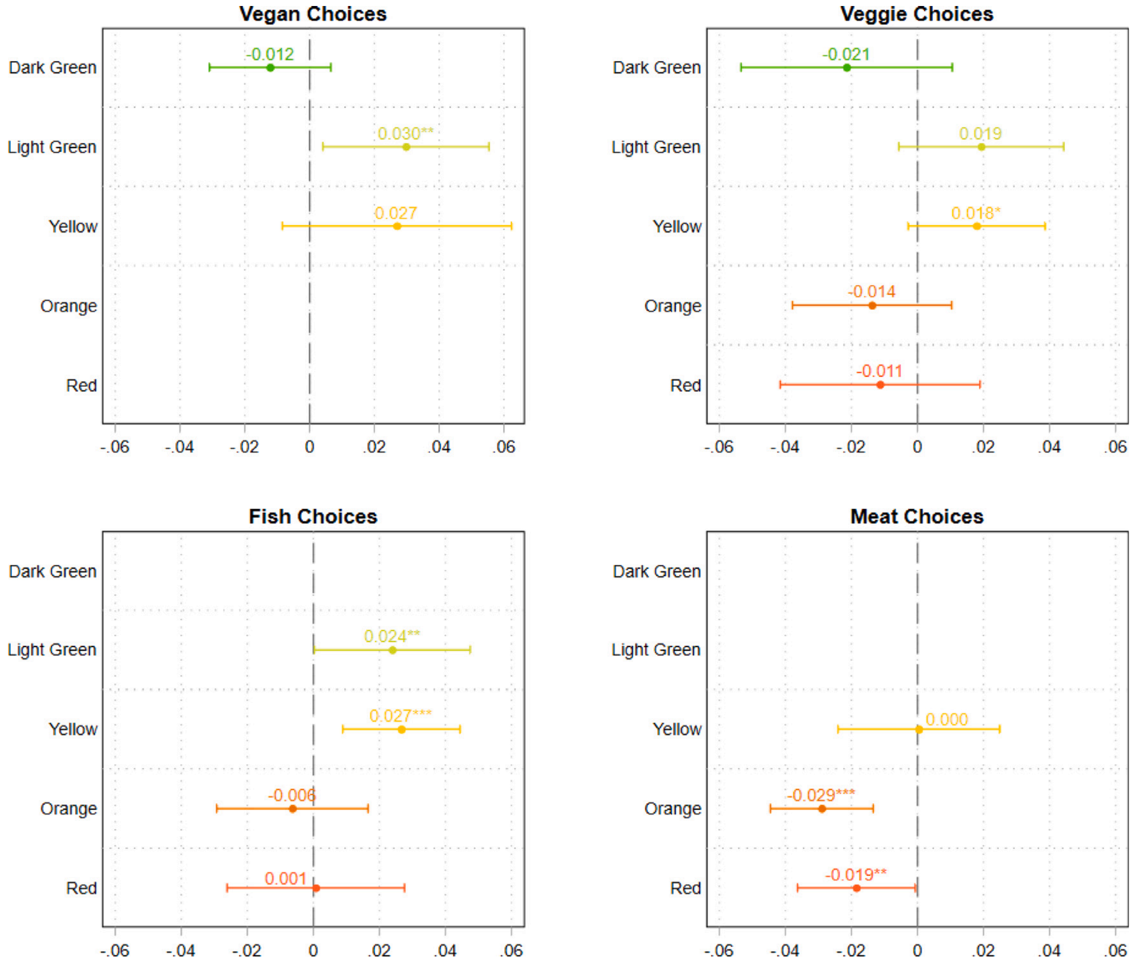

Fig. 5. Marginal effects of the treatment for each label colour. *Note:* Mixed-logit estimates of Eq. (3) via simulated maximum likelihood estimation where the choice alternatives are defined as vegan, vegetarian, fish and meat meals. The base category is the vegetarian meal alternative which is constrained to zero. Error bars indicate 95% confidence intervals. Full model results shown in Appendix Table C4. Estimates obtained from the main analysis dataset (cafeterias = 4).

3.5. Treatment effect by label colour

The results presented so far show that carbon footprint labels encourage consumers to substitute high-carbon meals with mid-carbon alternatives, which is reflected by a decrease in meat/fish sales and an increase in vegan/vegetarian choices. However, as previously discussed, aggregating vegan and vegetarian, and fish and meat choices into two categories may mask some of the nuances related to food preferences. Furthermore, we may suspect the treatment effect to differ depending on the colour with which dishes of the same category are labelled (i.e., their relative carbon footprint). For instance, the effect of the label may differ between yellow and red labelled fish dishes. To shed light on the more nuanced effects of carbon footprint labels on meal choices, we estimate (using Eq. (3)) the marginal effects of the treatment on the predicted probabilities of vegan, vegetarian, fish and meat choices for different sub-populations of choice scenarios representing all possible combinations of each alternative and label colour. Results are shown in Fig. 5.

In line with our expectations, the results indicate that the treatment effect of the labels on each of the four alternatives depends on the relative carbon footprint of the meal and the corresponding label colour with which it was labelled. We find that labels increased the sales of vegan meals if they were labelled light green by 3 percentage points (significant at the 5% level) but had no statistically significant effect if they fell into the dark-green or yellow category. This finding suggests that the relatively higher carbon vegan alternatives gained in popularity, but choices of the lowest carbon vegan meals were unaffected by the labels and even display a slight decrease. Turning to vegetarian sales, we observe that these remain largely unchanged by carbon footprint labels, apart from sales of yellow labelled vegetarian meals which increased by 1.8 percentage points, significant at the 10% level. With respect to fish dishes, labels caused an increase of 2.4 percentage points in the sales of light-green labelled fish meals and an even larger increase (2.7 percentage points) if they were labelled with yellow, significant at the 5% and 1% level, respectively.

However, the labels had no statistically significant effect on choices of orange and red-labelled fish dishes. Finally, labels led to a 2.9-percentage point decrease in orange labelled meat dishes, significant at the 1% level and a 1.9-percentage point decrease in red-labelled meat dishes, significant at the 5% level. Choices of meat dishes in the mid-carbon range were unaffected by the labels. Taken together, these results confirm our hypothesis that the efficacy of labels in changing meal choices is specific to the type of meal *and* with which colour it is labelled. The results provide an additional layer of detail to aid our interpretation of the main findings presented in Section 3.2. We observe that the increase in mid-carbon impact (yellow-labelled) meals stems from increased sales of vegan, vegetarian and fish dishes, whereas the reduction in high-carbon sales was primarily driven by a decrease in orange-labelled meat dishes and to a lesser extent by red-labelled meat dishes. Moreover, these findings imply that relying on aggregate measures of meat/fish to proxy sustainable food choices may lead to inaccurate conclusions, due to the diversity in carbon footprints in both categories.

3.6. Mechanisms

In this section we explore potential mechanisms and sources of heterogeneity driving the observed effect of carbon footprint labels on food choices. To obtain additional individual-level information to assess how carbon footprint labels were perceived by customers, we conducted an exit survey in all three treatment cafeterias after the intervention period. Specifically, we asked respondents how frequently they consulted the labels and whether the information provided by the labels was easy to understand, trustworthy, useful and important to be displayed. Additionally, we asked respondents to indicate the effect the labels had on their choices in a range of different scenarios, as well as how the labels made them feel about their meal choices. Respondents were given the option to provide their student ID numbers allowing us to link survey responses to their individual sales history. Below we will present a range of exploratory findings from a supplementary analysis using a sub-sample of observations from the sales data ($N = 8598$) to which we were able to link exit survey responses. In total, 159 respondents who regularly dined in the cafeteria in both baseline and intervention periods provided consent for their survey responses to be linked to the sales data. It is important to note that the sample of survey respondents does not accurately represent the sample population of the full sales data. First, the sample of survey respondents is biased towards regular customers, with an average of 54 cafeteria visits over the experimental period, compared to 37 in the full sample. With respect to pre-intervention preferences, the survey subsample is biased towards individuals who already favoured low-carbon diets, with approximately 67% being in the highest two low-carbon quartiles.[19] Hence, results must be interpreted with caution. Nonetheless, the findings provide additional insights into how labels were perceived and potential mechanisms driving the observed treatment effects.

Using this sub-sample of the data, we conduct a before–after analysis regressing Y_{its} on the post-treatment indicator and an interaction of the post-treatment dummy with a selection of variables elicited in the exit survey.[20] For Y_{its} we focus on the binary variable for selecting a high carbon footprint meal, as reducing consumption of these meals holds the largest GHG mitigation potential. We estimate the marginal effect of the post-intervention variables for different levels and categories of the survey questions.

First, we ascertain whether survey respondents replied truthfully to the survey questions by assessing the effect of self-reported influence of the labels on their meal choices. Respondents were asked to indicate, on a scale from 1 (not at all) to 10 (very much), whether the labels influenced their meal choices. The estimated marginal treatment effect is shown for all values in Fig. 6.

Here we find a statistically significant decrease in the probability of selecting a high-carbon meal for values greater than 6 on the self-reported label influence scale (significant at the 10% level). A similar pattern emerges when interacting a variable based on the statement: Labels motivated me to choose a meal with a lower carbon footprint (see Appendix Figure D1). Taken together these results support the internal consistency between the exit survey responses and actual observed meal choice behaviour.

Next, we explore avoidance behaviour and general perceptions towards the labels. To assess potential avoidance behaviour and attention towards the labels, we asked survey respondents how often, if at all, they saw and read the labels. Appendix Figure D2 shows that the majority of individuals paid attention to the labels on most occasions (31% most meals, 32% always). However, 11% stated to have never seen or read the labels. To assess general perceptions, we asked respondents to indicate, on a scale from 1 (not at all) to 10 (very much), how easy to understand, trustworthy/reliable, useful and important the information provided by the labels was. Appendix Figure D3 shows that overall, the labels were well received. The majority of individuals believed that the information was easy to understand and important to be displayed ($M = 9$), as well as trustworthy ($M = 7$) and useful ($M = 8$). We hypothesised that differences in attention and perceptions may influence the effectiveness of the labels in reducing high carbon meal choices, however, logit regressions show no statistically significant difference for both attention and perceptions.

We further hypothesised that a potential mechanism driving the efficacy of labels in changing behaviour could be the emotional response to the labels (Taufik, 2018; Thunström, 2019; Schneider et al., 2021). 'Warm Glow', the positive emotional reward from acting pro-socially, has recently received increasing attention as an important motive for meat reduction (Taufik, 2018) and pro-environmental behaviour in general (Van Der Linden, 2018). To measure experienced positive and negative emotions, we asked survey participants to indicate how the labels made them feel about their meal choices, using the Qualtrics graphic "smile" slider,

[19] The surveys were administered via the college mailing lists and sent to the entire student population of each college. Participation in the surveys was optional and incentivised with a prize-draw for a £20 Amazon Voucher for each college. Survey uptake was low, and a significant proportion of individuals did not fully complete the survey. As individuals self-selected into the sample, the observed bias in diets and cafeteria visits was expected.

[20] We estimate logit models for the following specification: $Y_{its} = \alpha_1 + \beta_1 S_i + \gamma_1 Post + \theta_1 Post \times S_i + X_t + \epsilon_t$, with S_i being the survey variable of interest, X_t representing the same control variables and day-of week fixed effects specified in Eq. (1). The coefficient of interest is θ_1 capturing the post-intervention differences associated with S_i. To visualise the differences, we compute marginal effects at representative values of S_i.

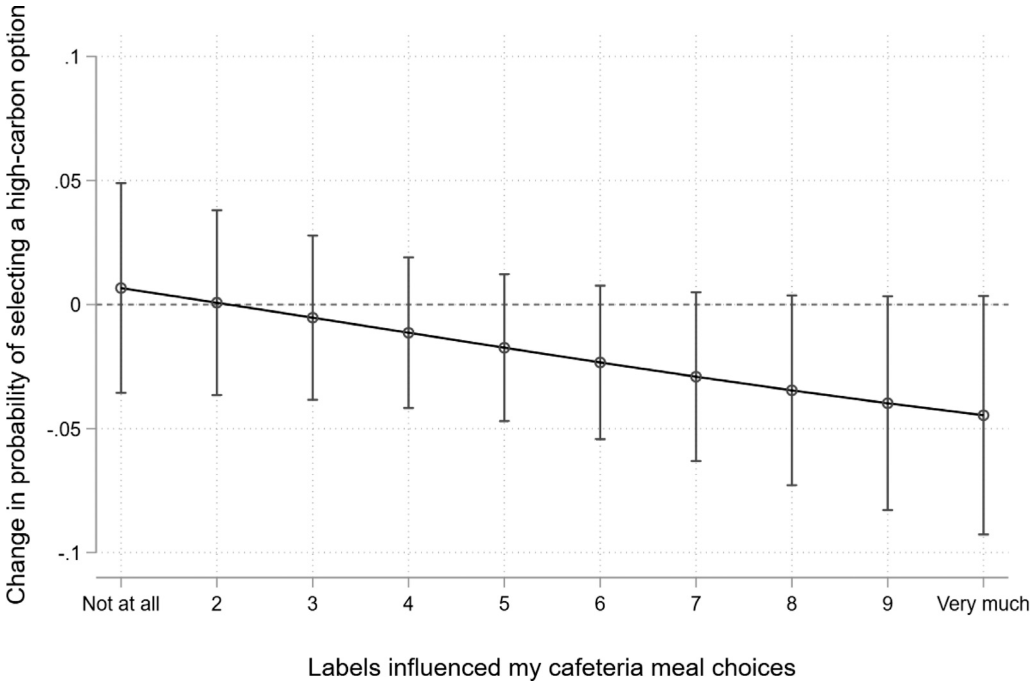

Fig. 6. Change in the probability of selecting a high-carbon footprint meal by stated effect on meal choice (general influence). *Note:* Error bars indicate 95% confidence intervals; $N = 7650$, Individuals = 158.

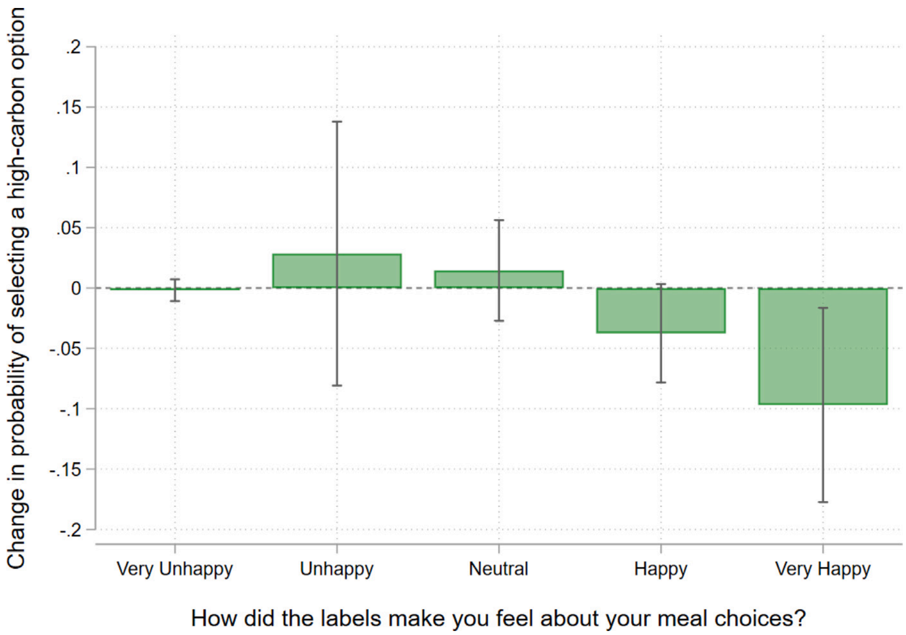

Fig. 7. Difference in treatment effect by emotional response to the labels. *Note:* Error bars indicate 95% confidence intervals; $N = 7650$, Individuals = 158.

ranging from 1 (very unhappy) to 5 (very happy). In Fig. 7 we plot the marginal treatment effect of the labels on high-carbon meal choices for each of the five categories of emotional response.

The results show that only those individuals who experienced positive emotions in relation to the labels decreased their consumption of high-carbon meals (significant at the 10% and 5% levels, respectively). Moreover, respondents who reported feeling very happy reduced their consumption of high carbon meals to a greater extent (6 percentage points) than individuals who felt happy, however, the difference is not statistically significant at conventional levels ($z = 0.20$). Nonetheless, the findings presented in Fig. 7 suggests that 'warm glow' may be a potential mechanism through which labels encourage more sustainable carbon choices.

4. Discussion & conclusion

Consumers are becoming increasingly aware of the environmental impact of their food consumption. Whilst taste, price and quality remain the most important determinants of food choices, there is a growing share of the population that holds climatarian preferences and actively pursues diets that aim to reduce their environmental impact. According to recent consumer research by the Carbon Trust, almost two-thirds of consumers say they would feel more positive towards companies that have reduced the carbon impact of their products.[21] However, a lack of consumer knowledge on the carbon footprint and environmental impact of foods remains a significant barrier for individuals to align their actions with their pro-environmental values.

Carbon footprint labels address the market failure of information asymmetry and aim to bring about sustainable behaviour change in many consumer domains, given sufficient demand for low-carbon alternatives (Vandenbergh et al., 2011; Taufique et al., 2022). This paper reports findings from a large-scale field experiment in a real-world cafeteria setting, measuring the impact of carbon labels on meal choices and consumer demand for lower-carbon meal options. We find that carbon footprint labels have statistically significant impacts on meal choices. Specifically, we show that labels shifted consumer choices from high-carbon impact meals to mid-carbon impact meals by 2.7 percentage points and decreased sales of meat and fish dishes by 1.7 percentage points (with an equivalent increase in vegan/vegetarian dishes). Effects are most pronounced for individuals who followed a high-carbon footprint diet prior to the intervention. While the effect sizes appear modest, they are highly statistically significant and robust across numerous alternative specifications, providing clear evidence that climatarian preferences exist in our sample population which can be leveraged by providing carbon footprint information.

How do carbon footprint labels compare to frequently used behavioural nudges designed to encourage sustainable diets? To allow for meaningful comparisons, we compare our estimates with findings from other behavioural interventions conducted in similar cafeteria settings. For instance, Kurz (2018) shows that changing the menu order and salience of the vegetarian meal option increased the probability of selecting a vegetarian meal by 6 percentage points. Similarly, Garnett et al. (2020) find that changing the order of vegetarian and meat options, by placing the vegetarian option first, increased the probability of selecting vegetarian options by on average 5.4 percentage points if choices were placed more than 1.5 meters apart. Taken together, the findings from this literature suggest that nudges have a more pronounced impact on food choices than carbon labels do. In contrast to behavioural interventions, however, carbon footprint labels serve as an information instrument, which can affect both the salience of information at the time of purchase and consumer awareness and knowledge. While the effects of nudges appear to be more impactful, they might also be more short-lived (e.g. Allcott and Rogers, 2014). In contrast, labels have the potential to have a sustained long-run impact on consumers by gradually building a stock of knowledge with respect to the carbon footprint of food. To that end, it may require a considerable amount of time for new information to "sink in" before it starts to consistently impact decision-making and may eventually also spill-over into other food choice contexts. While there exist few long-term evaluations, Thorndike et al. (2014) provide results from a 2-year trial on the effectiveness of a food labelling intervention to promote healthier choices in a cafeteria setting and find that the intervention led to sustained improvements in healthy food and beverage choices. Therefore, our results, although comparably small, support the viability of labels as a complementary policy instrument. More research is required to establish the long-term effects of carbon-footprint labels.

In addition, it is important to point out that the previously discussed behavioural interventions were specifically designed to nudge consumers towards choosing vegetarian dishes. However, the primary intention of carbon footprint labels is to encourage more sustainable choices, regardless of whether the lower-carbon alternative is a vegetarian, fish or meat meal. Our analysis in Section 3.5 shows that labels have much more nuanced effects on food choices which are not accurately captured by aggregate measures of vegan/vegetarian and fish/meat meal choices. For instance, we find that labels decreased the probability of selecting the highest carbon meat alternatives (orange and red labelled) but had no effect on mid-carbon meat dishes and even increased the sales of light-green and yellow-labelled fish dishes. These promising findings suggest that consumers indeed respond to carbon footprint information regardless of which type of meal is being offered, yet it significantly complicates a direct comparison of labels to the previously discussed behavioural interventions. More generally, we acknowledge that it is difficult to compare treatment intervention effect sizes from different studies, conducted in different contexts and experimental settings. Further research is needed to implement direct experimental testing, in the form of multi-treatment studies, to provide truly comparable estimates for different policy instruments.

When assessing the efficacy of different policy tools for sustainable behaviour change, including information provision, it is important to also evaluate welfare effects (Sunstein, 2021). So far, only few studies have considered welfare effects of labels (and nudges) and results from these welfare evaluations are mixed (Allcott and Kessler, 2019; Bulte et al., 2020; Damgaard and Gravert, 2018; Thunström, 2019; Ho et al., 2021). For instance, Thunström (2019) suggest that calorie labels on restaurant menus pose an "emotional tax" on some individuals, while she also ascertains considerable heterogeneity in the emotional response to the label.[22] Our supplementary analysis using survey data provides tentative evidence that emotions may be a key pathway through which labels

[21] See Carbon Trust, Consumer Research 2020: Product carbon footprint labelling. Accessed from https://www.carbontrust.com/resources/product-carbon-footprint-labelling-consumer-research-2020 [October, 2021].

[22] Relatedly, people may actively avoid food product information if it imposes hedonic costs (Sunstein, 2019; Reisch et al., 2021; Edenbrandt et al., 2021).

affect consumer choices. We find that labels only changed behaviour for those individuals who reported that the labels made them feel 'happy' or 'very happy' and had no effect on individuals who felt 'neutral' or 'unhappy'. These results need to be interpreted with caution, due to the small and self-selected sample in the exit survey. Nonetheless, the survey data reveals that 7% of individuals reported that the labels made them feel 'unhappy' or 'very unhappy' which indicates that the net-benefits of carbon footprint labels may be lower, after accounting for such emotional costs. More research is needed to assess whether carbon labels may have other unintended consequences and potential negative welfare effects, which could undermine their policy relevance.

A further key marker to judge the efficacy of carbon footprint labels as a policy tool is to evaluate the overall emissions mitigation potential. Our data allow us to directly estimate the average emissions reduction per 100 g serving. Using the observed carbon footprint of meal choices as the dependent variable in our main specification, we estimate a direct treatment effect of 27 g CO_2 (or 4.3%) reduction per 100 g serving. This value is in line, yet slightly larger than previous findings from the labelling literature.[23] Although the reduction in emissions may appear modest, a reduction of 27 g CO_2 (or 4.3%) per 100 g serving should not be understated. For our intervention period, in which about 26,000 meals were sold in the treatment cafeterias, each with an average footprint of 2 kg CO_2e, the labelling intervention thus led to a reduction of 2.21 tons of CO_2. If we scale up this estimate for all 31 college cafeterias in Cambridge for a typical term time of 8-weeks with a total of roughly 350,000 meals sold (accounting for different college sizes), this could lead to savings of approximately 30 tonnes of CO_2 per term.

Conducting a simple back-of-the-envelope calculation for a typical university cafeteria, we obtain the following estimates for the costs of avoided CO_2 emissions from our labelling intervention. Given that in our university cafeteria setting, a label intervention is able to avert 4.3% of carbon emissions of every meal with an average impact of 2 kg CO_2e per serving, we scale up this point estimate to a representative university cafeteria which serves 1000 meals per day. Doing so results in savings of 86 kg CO_2/day, which is about 2.5 tonnes per month. Based on pricing estimates by Foodsteps Inc. the average cost faced by the cafeteria for implementing the label programme on all meals using professional carbon footprinting and labelling software amounts to approximately £80/month. We treat this amount as the programme cost, however, there may be minor personnel costs for administering the programme (e.g., printing the labels). For one month, the total abatement cost is thus £31 per tCO_2 emissions avoided.

To summarise, our results suggest that labels are an effective tool to leverage pro-environmental preferences in a cafeteria setting and promise considerable GHG emission reductions at the individual level. Whilst our study is limited to the cafeteria setting, carbon labels will have a much larger role to play in a broader set of food consumer choices, in particular in supermarket purchase decisions (the volume of which is much larger than cafeteria choices). Additional experiments in these food choice settings with non-student samples will be important to solidify our understanding of how carbon footprint labels affect consumer choices. We leave this to future research.

Moreover, labels allow for product differentiation on sustainability grounds and hence provide clear signals to consumers who hold environmental preferences. Product differentiation aids consumer choices and in turn may bring about significant changes on the producer side if market dynamics continue on their current trend in favour of low-carbon alternatives and increasing climatarian dietary preferences. For instance, labels may incentivise suppliers to substitute high-carbon alternatives in favour of lower-carbon alternatives, which could result in substantial decreases in food production emissions. If future carbon footprint labels are based on full life-cycle assessments capturing emissions from 'farm to fork', this could further encourage innovations along the entire supply chain. Labels in other areas have in the past proven to set industry standards, such as the 'GMO-Free' labels and animal welfare labels (e.g., dolphin-safe tuna). In both cases, labels were introduced to achieve product differentiation capitalising on changes in consumer preferences which eventually became the industry standard.

Our study and results are particularly relevant under the current policy climate in the UK, the EU and elsewhere where pilot voluntary carbon food labelling schemes are emerging (e.g. the UK's Carbon Trust label) and advanced discussions are underway for introducing carbon food labels as part of many countries' decarbonisation agendas. This momentum is partly a reaction to an increasing consumer shift towards climatarian diets (i.e. diets aimed at reducing the carbon footprint). Yet, the reality remains that rolling out carbon food labels across the entire food industry is an immensely challenging and complex endeavour, while at the same time, causal hard evidence-based studies on the impact of these labels on actual behaviour are lacking (Rondoni and Grasso, 2021). This paper provides one of the first large-scale field experiments specifically assessing these impacts in a causal manner. We find that carbon footprint labels on food could induce carbon reducing behavioural changes. The challenges that remain are how to scale up the use of such labels in a manner that is unambiguous to consumers and also cost-effective.

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[23] For instance, Muller et al. (2019) find that labels induced a reduction between 14 and 19 g per 100 g for a basket of goods in an experimental online store setting. Brunner et al. (2018) estimate that the carbon footprint labelling scheme at a university restaurant reduced overall GHG emissions by 3.6%.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jeem.2022.102693.

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