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Please keep ordering! A natural field experiment assessing a carbon label introduction

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ABSTRACT

We conduct a natural field experiment investigating the efficacy of environmental information provision while considering its relationships with individual consumers' habitual behaviour. A carbon label was introduced to the lowest-emission dish for each food category on the menu of a full-service restaurant; its efficacy was assessed by distinguishing its immediate impact on orders placed by the restaurant's occasional and regular customers as well as the impact over time for repeated orders. We collected 1,737 customer orders – of which 1,200 were placed by 99 regular customers – taking advantage of an electronic ordering system that identified customers through a unique number. Independently of customer type, we find no immediate effect of the carbon label after its introduction. However, the probability of ordering an environmentally friendly dish increases significantly with repeated exposure and additional orders, albeit with a progressively diminishing effect. We discuss the importance of the repetition effect when assessing a new label, including implications for research and policy.

1. Introduction

Agri-food-related processes account for one third of global greenhouse gas (GHG) emissions (Crippa et al., 2021). Globally, there is growing public awareness of the impact of food supply chains on climate change (Poore and Nemecek, 2018). According to Leiserowitz et al. (2019), a large proportion of Americans express concern about global warming, and the same apprehension is shared by Australians and Europeans (Berry and Peel, 2015; Steentjes et al., 2017). Furthermore, a survey recently conducted in Italy showed a significant increase in the percentage of people who consider climate change as their primary concern (EIB, 2022).

Despite these high levels of concern reported by consumers, few are adopting sustainable behaviours regarding food choices. This may be due to the difficulty of recognising sustainable-related product characteristics during grocery shopping and the complexity of identifying the best food behaviours for the mitigation of climate change (Thøgersen, 2021). Indeed, current studies discuss the mitigation potential of low-carbon-emission food consumption on the environment, but related results are still controversial (Poore and Nemecek, 2018; Williams et al., 2021). At present, various policies promote behavioural changes with respect to food choices (Kim et al., 2020; Stranieri et al., 2022), including both price- and information-related normative interventions. Price changes alter the incentive structure and may result in the purchase of a more sustainable basket of goods. However, this result is contingent on the observed relative prices. By contrast, policies focused on information aim to nudge consumers toward sustainable eating habits by creating consumer awareness and knowledge about the environmental impact of their food choices (Vermeir and Verbeke, 2006). Information provision can include educational programmes (Ellison et al., 2019), communication campaigns (Vega-Zamora et al., 2019), and information labelling on food products (Asioli et al., 2020). Specifically, labels are among the most effective tools to overcome information asymmetries related to sustainable food production practices while simultaneously affecting consumers' awareness regarding sustainable consumption and food choices (Grunert et al., 2014).

Existing studies indicate a positive consumer attitude and willingness to pay a premium price for foodstuffs with various sustainability-related labels, with organic certification leading the way (Li and Kallas, 2021). According to the reviews by Rondoni and Grasso (2021) on

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carbon footprint labels and, more broadly, by Majer et al. (2022) on visual sustainability labels, most studies on consumer evaluation of environment-related food attributes use stated preferences analyses (e.g., questionnaires or hypothetical choice experiments). Such approaches fail to consider context and merely approximate the intention of choosing food with environmentally friendly characteristics rather than revealing actual consumer behaviour (Abrahamse, 2020).

By contrast, natural field experiments can overcome such hypothetical bias and offer a good opportunity to observe consumer behaviour in a real market context (e.g., Lohmann et al., 2022). To date, few natural field experiments have investigated climate-friendly certifications such as carbon labels in supermarkets (Elofsson et al., 2016; Vanclay et al., 2011), university canteens (Spaargaren et al., 2013; Visschers and Siegrist, 2015; Brunner et al., 2018; Lohmann et al., 2022), and restaurants (Soregaroli et al., 2021). Such studies used interventions to observe the efficacy of carbon labels and, hence, their ability to impact consumer's choices and to move them towards more environmentally friendly options. The experiments of Vanclay et al. (2011) and Elofsson et al. (2016) both revealed an increase in the choice of carbon-labelled products in grocery stores. Such results are also corroborated by Brunner et al. (2018), Slapø and Karevold (2019) and Lohmann et al. (2022) in university canteens and cafeterias. However, Soregaroli et al. (2021) found that adding carbon information to a wine menu in a restaurant did not modify customers' choices unless combined with a price incentive. Still, empirical evidence remains scarce within the restaurant context (see Appendix A).

Previously conducted natural experiments offer some interesting insights into the impact of carbon-labelled information on consumer behaviour, but they lack in considering the efficacy of the adoption process, (i.e., how labels can affect the repeated choices of consumers). Moreover, the individual and psychological consumer characteristics affecting sustainable food choices (such as trust or social and moral norms) are normally analysed in a static context; such an approach cannot account for their influence on repeated consumer behaviour.

Such considerations are particularly important for food choices, which are characterised mainly by automaticity, the influence of daily routines, resistance to innovation, and a need for variety (Carrasco et al., 2005; Adamowicz and Swait, 2013). All these elements have a role in the formation of consumers' environmentally friendly behaviour, and they can gradually influence the efficacy of labelling as an information-provision tool (Verplanken and Whitmarsh, 2021). Although a few studies have investigated the persistence effect of the introduction of a carbon label in grocery stores (Elofsson et al., 2016) and university canteens (Lohmann et al., 2022), persistence is not independent of the successful initial introduction of a label and its management over time. The evaluation of a label's potential over time is rarely assessed in stated-preference studies or lab experiments. In fact, although it is possible to use these approaches – for example, by introducing a hypothetical time dimension in the experimental framework (e.g., Cirillo et al., 2017) or by repeating the experiment over time to test for consistency and preference stability (Brouwer et al., 2017) – these studies suffer from intrinsic limitations in their ability to assess the evolution over time of a label's effectiveness.

It is more feasible to consider the time dimension in a natural field experiment, even if there remain some practical challenges that might be limiting. Existing studies in supermarkets provide examples of the evolving carbon label effectiveness after their introduction. However, studies such as Vanclay et al. (2011) or Elofsson et al. (2016) monitored the effect of the label introduction at the aggregate level and only for a short period of time. Randomised control trials offer a possible solution to assess revealed consumer behaviour, but they are difficult to apply when choices are repeated. In fact, repeated choices by the same customers are often explicitly avoided in the data collection, especially when the experiment is conducted in a single location (e.g. Soregaroli et al., 2021). In this setting, the usual researcher's challenge is to prevent individuals from being exposed to different treatments within the same experiment, as this could generate biases from experimenter demand effects and compromise the entire experiment's internal validity. As a result, these studies are often focused on a first-reaction assessment. To date, no study has offered insight into the effect of a carbon label on repeated individual behaviour targeting regular customers in restaurants (i.e., consumers making repeated food choices and who are thus exposed to the carbon label several times).

The above considerations have important policy implications because they contribute to understanding the real effectiveness of the carbon label on food products. In this study, we address such research gaps by investigating the efficacy of an information provision considering its relationships with individual customers' habitual behaviour. In a first research question (RQ1) we investigate the initial efficacy of a carbon label introduction in a natural context, while in a second research question (RQ2), we investigate how regular customers' choices are affected by the carbon label from its introduction onward.

We conducted a natural field experiment in a full-service restaurant, located in northern Italy, which provides table service, food delivery and take-away service. We calculated the carbon emissions of the dishes offered by the restaurant through the Life Cycle Assessment (LCA) method and we introduced a carbon label to the lowest-emission dish for each food category on the digital menu. Furthermore, customers were provided with additional information to help them understand the meaning of the carbon label. The restaurant's proprietary ordering channels use an electronic ordering system that assigns each customer a unique identification (ID) number, which allowed us to track repeated customers' orders. We collected customers' orders both before and after the carbon label was introduced. Overall, we collected data on 1,737 orders: 537 orders placed by occasional customers and 1,200 orders placed by 99 regular customers. Moreover, we collected 937 orders for customers who ordered using third-party apps.

Our findings indicate no immediate effect of the carbon label after its introduction. Independently of the type of customers – regardless of whether they developed some potential ordering routine – the probability of including an environmentally friendly dish in an order does not change with the first exposure to the carbon label. In contrast, the introduction of the carbon related information positively influences regular customers' choices, with the probability of individuals placing orders containing environmentally friendly dishes increasing with each order.

This paper contributes to the literature in several ways. First, our experimental field setting allows food choices to be studied in a real-world setting, whereas previous studies relied mainly on hypothetical choices. Second, the restaurant setting for introducing a carbon label has rarely been explored, even though household food consumption away from home has increased worldwide over the last decades (Dai et al., 2020), weighing more heavily on the overall food system's carbon footprint. This also holds true for Italy, where, according to the 2021 report by the Italian restaurant industry, the food-away-from-home-consumption market in Italy has shown steady growth over the last two decades, with a 72% increase at current prices from 2000 to 2019, surpassing the 35% growth of the at-home food consumption market (FIPE, 2021). Moreover, the restaurant industry contributes significantly to overall GHG emissions because of its extensive use of energy, water, and supply materials, as well as its generation of non-recyclable trash and food waste (Tehrani et al., 2020). Third, access to individual-level data allowed us to investigate repeated choices when assessing the effectiveness of a new label. Indeed, as is the case for most innovations, the introduction of a new label on food requires that the consumer go through several cognitive steps, from the creation of awareness to its final use (Grunert et al., 2014). Therefore, assessments exposing customers only once to a label or a message may result in significant underestimations of the effects of such policy tools.

2. Research design

2.1. Experimental design and procedures

The experiment was structured based on a protocol approved by the Ethics Committee of the University of Milan and based on principles of research integrity. The protocol specified the study objectives, described the experimental design, and listed the criteria for a restaurant to be considered eligible for participation in the experiment. The protocol specified that the experiment must be conducted in a real-world setting and must observe consumers who are not aware that they are part of an experiment. Furthermore, the target restaurant needed to be interested in 'sustainability practices' and willing to modify its menu by voluntarily introducing a carbon label. To guarantee respect for the study's ethical issues, we deemed it mandatory that only restaurants formally accepting the protocol could participate in the experiment.

The restaurant we selected satisfied our criteria and signed the protocol after a careful explanation from an experienced researcher about the features of a natural field experiment and the procedures to be followed during data collection.

The restaurant selected is a full-service restaurant located in Piacenza, northern Italy. Such geographical area is of particular interest for our research aim. Almost 80% of Italians consider climate change to be the most significant challenge of the 21st century, and more than 70% state that climate change will dictate changes in people's lifestyles, including a shift towards plant-based diets (EIB, 2022). The highest proportion of Italian consumers worried about climate change is concentrated in the north-eastern part of the country and consists predominantly of young people under 34 years (Istat, 2021).

The restaurant's business model is oriented toward offering a quick meal and attracting a diversified customer base, especially workers who share the desire for a healthy meal. The restaurant is open from Monday to Friday for lunch and dinner. The menu is based on a typical structure for an Italian meal: it contains a first course, second course, sides, and dessert. In addition, the menu offers poke bowls, smoothies, snacks, drinks, and different sauce options.

Customers can place their orders while seated at the restaurant, or through the website, email, phone, and third-party digital platforms (i.e., Deliveroo, Glovo, and Foodracers). Apart from those placed via third-party platforms, orders are managed throughout the restaurant's proprietary electronic ordering system, which relies on an app where customers can consult a digital menu and make their choices. Before placing their first order, customers must enter their personal data and are provided with a unique ID number, which allows the ordering system to recognise customers' identities. Through the ID number, it is possible to collect data on all orders placed by each customer (while preserving their anonymous identity) and to distinguish between occasional and regular customers. This identification system does not apply to orders placed through third-party platforms.

In the experimental setting, a carbon label identifying the dish with the lowest emissions was added to the digital menu of restaurant-owned ordering channels (such as phone apps, websites, and digital in-store menus) to identify the dish with the lowest emissions. The menu interface was the same across all channels, and all customers who used the restaurant-owned ordering system were exposed to the label, as the system did not allow for customisation of exposure. The label was *not* added to menus on third-party platforms, so customers who ordered through those platforms were not exposed to the label. Such orders served as a control sample for robustness checks for the before-after comparison. Except for the label introduction, the restaurant's environment was kept identical to the usual setting during the observation period.

2.2. Dish descriptions and GHG emissions calculations

To identify the dishes with the lowest emissions, we calculated the overall GHG emissions of the restaurant's dishes, expressed in grams of CO_2 equivalent (g CO_2eq) emissions/dish, using the LCA data reported in the Eaternity database (EDB).[1]

The EDB reports the GHG emissions in kilograms of CO_2-equivalent (kg CO_2eq) values for 550 food items, modelled according to the LCA methodology for country of origin, seasonality, farming procedure (i.e. standard, organic, greenhouse, fair-trade, wild-caught, sustainable fish), transportation (i.e. ground or air), conservation (i.e. fresh, frozen, dried, conserved, canned, boiled down) and processing (i.e. cradle to retail) by using life cycle inventory data from the Ecoinvent, Agribalyse, and World Food databases.[2]

The LCA is a methodology used to determine the environmental burden of a product, organisation, or service by considering its whole life cycle. First, the system boundaries are defined; these determine which system is analysed and how far the analysis will go in data collection by delimitating what is included in the LCA. The LCA considers all the inputs used to produce the product or service and allocates the emissions attributed to its production; the set of data related to the inputs and outputs of the system constitutes the life cycle inventory. The LCA identifies various impact categories; this study falls under the category of 'climate change', which is measured in terms of the global warming potential of the GHG emitted across the product life cycle (IPCC, 2014; International Organization for Standardization-ISO, 2018).

The EDB was chosen because it provides a comprehensive database that models LCA data on a sufficient number of food items. Moreover, 150 restaurants already use the EDB to assess the carbon footprint of meals, and awareness of this service is spreading within the restaurant industry (Eaternity, 2023).

Calculating the GHG emissions of a recipe includes assessing the following steps in the system: production, transportation, conservation, processing, packaging, storage, and distribution (i.e. from cradle to retail). Transportation from the retail store to the restaurant, storage at the restaurant, and cooking have been excluded from the analysis for lack of reliable data. Disposal is also not included because the carbon information for dishes is provided before consumption.

For those food items in which ingredients or products are supplied locally, the average transportation emissions have been excluded from the calculations. This follows the EDB modelling approach, which diversifies suppliers into local farmers and large distributors.

The functional unit of the GHG emissions assessment (the unit to which the GHG emissions refer) is the standard portion served by the restaurant, meaning that clients can compare the GHG information for each dish. This is crucial to the experiment objective because it aims at assessing the effect on customers' choices of a labelling intervention concerning the environmentally friendly attributes of the dishes; it is, therefore, customer-based.[3]

We calculated LCA for the 48 dishes that were displayed on the restaurant's menu at the time of the research: seven as a first course, seven as a second course, five as side dishes, eleven poke bowls, ten as desserts, and eight smoothies. We did not calculate LCA for snacks, drinks or sauces because these are purchased externally rather than directly processed by the restaurant.

Table 1 shows the least emitting dishes for each category included in the study.

[1] https://eaternity.org/foodprint/database.

[2] Eaternity Database References [last update: 2022–03-21] are available in https://eaternity.org/assets/edb/EDB-References-current.pdf (consulted on 13th July 2022).

[3] A spreadsheet MS Excel workbook was developed; the workbook reports, for each dish included in the study, the ingredients list, and related quantities, and the total GHG emissions (g CO_2eq /dish).

Table 1
Least emitting dish per category.

Category	No. of dishes per category	Least emitting dish	Mean gCO_2eq	Min gCO_2eq	Max gCO_2eq
First course	7	Vegetable cous cous	393.08	166.37	835.87
Second course	7	Veggie burger	466.78	179.78	1121.24
Second course[1]	7	Omelette with vegetables	479.74	335.29	1121.24
Poke	11	Vegetarian poke	790.10	520.46	1050.72
Dessert	10	Buckwheat galette with jam	404.74	102.41	1355.71
Smoothies[2]	8	Fresh strawberries juice	455.02	62.88	2130.81
Sides	5	Roasted potatoes	72.86	24.00	111.35

Mean gCO_2eq, Min gCO_2eq, Max gCO_2eq are reported by food category and computed on average dish portion; [1]Change of labelled dish on 15 June 2021; [2] Dish discontinued on 31 August 2021.

2.3. Label design

Having identified the least emitting dish per category, we elaborated a carbon label to be placed on the restaurant's menu. There are multiple ways to present carbon-related information to consumers.

Specifically, Lemken et al. (2021) identified five different schemes: 1) Relative reduction labels aim to inform consumers about a reduction in product emissions compared to either competitors or previous points in the past; 2) Best-in-class labels aim to inform consumers that a product has the lowest emissions among products in the same category; 3) Compensation labels aim to inform consumers about a product's climate neutrality, meaning producers purchase compensation certificates to offset GHG emissions; 4) Absolute CO_2eq value labels express the absolute value of GHG emissions per kg, thereby providing customers with quantitative information; and 5) Categorial labels, which are colour-based, rank GHG emissions through normative colour-coding, either reporting the absolute value of GHG or not. Even if there is no agreement as to which scheme will best affect consumers' choices, the literature agrees that to be effective, a label should be easy to understand, eye-catching, highly visible, and accurate (Lemken et al., 2021; Donato and Adıgüzel, 2022).

Some field experiments in the restaurant industry use categorical labels, namely colour-themed labels (Brunner et al., 2018) and traffic-light-shaped labels (Spaargaren et al., 2013; Slapø and Karevold, 2019), which appear to be moderately effective in impacting consumer choices. However, categorising dishes by green or red implies attributing a grade, implicitly telling customers that a dish is 'good' or 'bad'. This strategy may be appropriate for an experiment conducted in a university or school canteen, which is unlikely to be a profit-oriented business. However, it is less feasible in a full-service restaurant or, more generally, in a context of voluntary labelling. Indeed, restaurateurs are reluctant to include colour-coded labelling because it could cause customers to draw incorrect inferences and demonise some dishes, potentially leading to a loss of profit. For this reason, we designed a best-in-class label that is intentionally neutral (i.e. not colour-based) with a simple green circle containing a white leaf (Fig. 1). The label identifies the lowest-emission dish for each food category on the digital menu. It does not report quantitative information on CO_2 emissions, as the literature showed that such information is too vague for consumers to interpret (Meyerding et al., 2019). The label on the menu was also combined with additional information related to the meaning of the label (Fig. 2). More precisely, at the top of the digital menu page, a banner – 'Discover the new CO_2-sustainable logo' – highlighted the novelty being introduced. Moreover, a message explaining the meaning of the label and the restaurant's effort toward sustainability was provided to the right side of the logo (Fig. 2). This text results from a pragmatic choice made by the restaurant's manager, who wanted to inform their customers about the sustainable aspects of the restaurant's dishes.

3. Data and model estimation

3.1. Data collection

After receiving the restaurant owner's signature on the protocol, we accessed the restaurant's electronic cash register data. Using these data, we collected information on customer orders during two distinct periods in 2021. The first period was before the label introduction on the restaurant's menu, from 4 January to 30 May. The second period was after the label was introduced, taking place from 31 May to 30 September.

Overall, we collected data on 1,801 orders from the restaurant's electronic ordering system: of these orders, 64 were dropped because they were taken directly by a waiter in the restaurant store and as such did not have a unique ID identifier. It is important to consider the potential selection bias that may arise from the removal of orders from our sample. Although this operation could introduce bias (as not every order is included in the sample), the fact that only a small number of orders were removed alleviates concerns.

Therefore, we had 1,737 usable orders: 537 orders for occasional customers (i.e., customers who ordered from the restaurant once and did not return) and 1,200 orders from 99 regular customers, who ordered on average 12 times throughout the experimental observation period. Moreover, we also collected 997 orders from third-party apps: these orders served as robustness check on the seasonality of the demand for environmentally friendly dishes and changes that occurred over time common to all individuals (see Appendix B for further details).

3.2. Variables

Previous studies have analysed the impact of an information intervention by using either a binary variable to indicate the probabilities that a customer will choose a labelled dish (Brunner et al., 2018), or a continuous variable such as the sales share of labelled dishes over aggregated sales (Slapø and Karevold, 2019). The former approach is more suitable for our highly skewed distribution that includes a large presence of zeros (i.e. no environmentally friendly dish included in the order), which occurs when a large number of choices (i.e. 48 dishes) is available. We constructed the 'presence' binary dependent variable at the individual level, using restaurant orders as the unit of analysis. Our binary dependent variable takes the value of 1 if customers included one

Fig. 1. Carbon label introduced on the menu. *Source: Restaurant menu.*

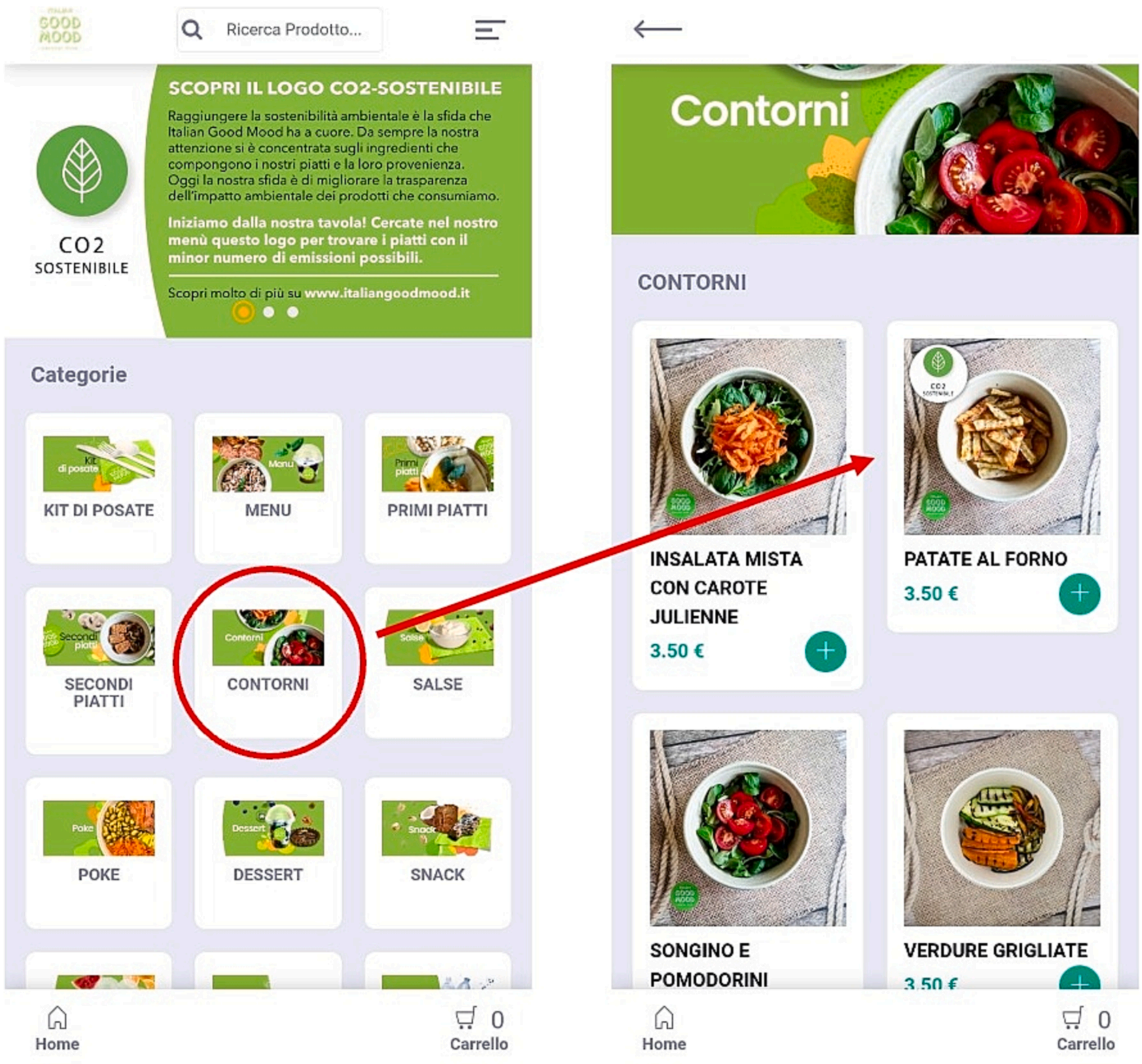

Fig. 2. Example of restaurant's digital menu. *Source: Restaurant app menu.*

of the dishes identified as the least emitting within the first course, sides, poke, or dessert categories, and 0 otherwise. We excluded dishes from the second courses or smoothies categories from the definition of 'presence' to account for the restaurant's menu changes during the analysis period, which were influenced by the seasonal availability of fresh ingredients. This decision was made to avoid potential confounding effects of label introduction on these categories, which could be masked by changes in demand for newly offered dishes. Table 2 reports descriptive statistics for the dependent variable distinguishing between occasional and regular customers.

Based on previous literature, we selected a set of control variables to identify the impact of introducing labels on customers' choices (Table 2). Following Sánchez-Bravo et al. (2020) and Li and Kallas (2021), we included dummy variables that indicated the different types of dishes customers ordered to account for the variability in customers' choices across food categories. Furthermore, as in the restaurant in analysis, prices are constant within category of the dishes (e.g. every first course has the same/slightly different price); such variables can also control for how much consumers were willing to spend on their orders.

We also adjusted for the number of items included in each order, recognising that increasing the number of items increases the likelihood of including environmentally friendly dishes.

Moreover, we included the time of day when customers eat (i.e., lunch or dinner). Although the latter does not appear to explain customers' choices regarding sustainable options (Slapø and Karevold, 2019), it is important for characterising their food choices generally (Campbell-Arvai et al., 2014). Finally, we introduced a variable to measure whether orders were made in-store or online through the restaurant app, because this might influence customers' food purchase decisions (Pitts et al., 2018; Zatz et al., 2021). The inclusion of this variable is even more important given the nature of the restaurant analysed, which had a high percentage of customers ordering from the restaurant's app, and because the experiment was conducted while some COVID-19 restrictions on in-person dining were still in place.

3.3. *Empirical strategy*

To account for panel data structure and time dimension, we categorised the orders collected into those from occasional and regular customers. This distinction is particularly important because the data

Table 2
Descriptive statistics.

Variable	Unit of measurement	Mean occasional customers (537 obs.)	Mean regular customers (1,200 obs.)
Dependent variable			
Environmentally friendly dishes per order			
Present	Binary variable	0.314	0.279
Not present	Binary variable	0.686	0.721
Main explanatory variables			
Intervention			
Intervention	Binary variable	0.403	0.448
No intervention	Binary variable	0.597	0.552
Control variables			
Dish category			
First course	Binary variable	0.459	0.422
Second course	Binary variable	0.484	0.511
Poke	Binary variable	0.450	0.330
Dessert	Binary variable	0.286	0.267
Smoothies	Binary variable	0.305	0.437
Sides	Binary variable	0.527	0.578
Ordering method			
In-store	Binary variable	0.741	0.640
Online	Binary variable	0.259	0.360
Time of the order			
Lunch	Binary variable	0.673	0.850
Dinner	Binary variable	0.327	0.150
Other			
Order size	Continuous variable	3.288 (1.94)*	3.390 (1.87)*

* Standard deviation reported in parentheses.

structure of regular customers is panel data, with the same customers observed multiple times; therefore, we needed to control for unobserved heterogeneity among these individuals (see Appendix B).

We utilised a logit model to investigate whether there was an immediate effect upon first exposure to the label (RQ1). Specifically, we compared the results from two models: one for random occasional customers (Model 1) and another for regular customers (Model 1a).

To allow for a more insightful comparison between these two customers' categories, we considered only the first order after the label introduction for regular customers. Furthermore, we did not incorporate individual fixed effects in the model, but instead accounted for the panel data structure by including robust standard errors that were clustered at the individual level (Rabe-Hesketh and Skrondal, 2008).

The two models are constructed using the same vector $\mathbf{x_{imt}}$ of exogenous control variables to model the presence of environmentally friendly dishes per order; this vector contains dish category, time of the order, and the ordering method binary variables.

For occasional customers $y_{mt} \sim bernoulli(p_{mt})$, Model 1 is expressed as follows:

$$\text{Logit}(\text{P}_{\text{mt}}) = Log\left(\frac{\text{P}_{\text{mt}}}{1-\text{P}_{\text{mt}}}\right) = \theta + \beta_1 \boldsymbol{D_{mt}} + \beta \mathbf{x_{mt}} + \varepsilon_{\text{mt}} \tag{1}$$

where $m = 1, \dots 537$ indicates the number of orders, $t = 04/01/2021, \dots. 30/09/2021$, θ is the intercept, D_{mt} represents the intervention ($D_{mt} = 0$ is the period before the intervention and $D_{mt} = 1$ represents the period after the intervention), and ε_{mt} is the stochastic error term.

For regular customers, with probability $y_{imt} \sim bernoulli(p_{imt})$, Model 1a is expressed as follows:

$$\text{Logit}(\text{P}_{\text{imt}}) = Log\left(\frac{P_{imt}}{1-P_{imt}}\right) = \theta + \beta_1 \boldsymbol{D_{mt}} + \beta \mathbf{x_{imt}} + \nu_{imt} \tag{1a}$$

where $i = 1, \dots 99$, indicates the regular customers, $m = 1$ when $t > 28/05/2021$ and $m = 1, \dots \text{M}_{\text{it}}$ when $t \leq 28/05/2021$ and $t = 04/01/2021, \dots. 30/09/2021$, θ is the intercept, D_{mt} represents the intervention ($D_{mt} = 0$ is the period before the intervention and$D_m = 1$ represents the period after the intervention), and ν_{imt} is the idiosyncratic error term composed by $\nu_{imt} = (\alpha_i + \varepsilon_{imt})$.

Moreover, we estimated three models to explore how the label introduction affected the probability of including an environmentally friendly option in repeated orders (RQ2). In all three models, we incorporated individual fixed effects to control for stable and specific customer characteristics, enabling us to accurately assess the net effect of the predictors on the dependent variable. Additionally, we constructed the models using the same vector $\mathbf{x_{imt}}$ of exogenous control variables as in Models 1 and 1a.

First, we estimated a model (Model 2) that included every order placed by regular customers.

With probability $y_{imt} \sim bernoulli(p_{mt})$, Model 2 appears as follows:

$$\text{Logit}(P_{\text{imt}}) = Log\left(\frac{\text{P}_{\text{imt}}}{1-\text{P}_{\text{imt}}}\right) = \beta_1 \boldsymbol{D_{mt}} + \beta \mathbf{x_{imt}} + \alpha_i + \varepsilon_{\text{imt}} \tag{2}$$

where $i = 1, \dots 99$, $t = 04/01/2021, \dots. 30/09/2021$, D_{mt} represents the intervention ($\text{D}_{\text{mt}} = 0$ is the period before the intervention and$\text{D}_{\text{m}} = 1$ represents the period after the intervention), α_i are individual fixed effects, and ε_{imt} is the idiosyncratic error term.

Second, we estimated a model (Model 3) in which we introduced binary variables distinguishing between the customer's first order after the label introduction and their subsequent orders. The aim of this model is to distinguish whether the label introduction had an immediate effect on customer' choices or whether this effect is to be observed afterwards (from their second order onwards). We introduced a dummy variable to indicate the first order that customers placed after the label introduction and a dummy variable indicating all the remaining orders.

With probability $y_{imt} \sim bernoulli(p_{imt})$, Model 3 is as follows:

$$\text{Logit}(P_{imt}) = Log\left(\frac{P_{imt}}{1-P_{imt}}\right) = \theta + \beta_1 D_{1_{imt}} + \beta_2 D_{2_{imt}} + \beta \mathbf{x_{imt}} + \alpha_i + \varepsilon_{\text{imt}} \tag{3}$$

where $i = 1, \dots 99$, $t = 04/01/2021, \dots. 30/09/2021$, $D_{1_{imt}}$ is a dummy representing the first order after the intervention, $D_{2_{imt}}$ is a dummy representing all the remaining orders after the intervention, α_i are individual fixed effects, and ε_{imt} is the idiosyncratic error term.

Third, we specified Model 4 by introducing a continuous variable that describes the progressive number of orders placed after the label introduction, as well as its square. This allowed us to measure the relationship between the label introduction and the likelihood of including environmentally friendly options in orders over time while accounting for any nonlinearities in this relationship.

With probability $y_{imt} \sim bernoulli(p_{imt})$, Model 4 is as follows:

$$\text{Logit}(P_{\text{imt}}) = Log\left(\frac{P_{\text{imt}}}{1 - P_{\text{imt}}}\right) = \beta_1 x_{1\,imt} + \beta_2 (x_{2\,imt})^2 + \beta \mathbf{x}_{\mathbf{imt}} + \alpha_i + \varepsilon_{\text{imt}} \quad (4)$$

where $i = 1, \ldots 99$, $t = 04/01/2021, \ldots. 30/09/2021$, $x_{1\,\text{imt}}$ indicates the progressive number of orders placed after the label introduction and $x_{2\text{imt}}$ its square, α_i are individual fixed effects, and ε_{imt} is the idiosyncratic error term.

Furthermore, we estimated two models as a robustness check for seasonality, investigating whether time effects had any impact on the control group's ordering decisions. The results indicated that there were no significant seasonal effects on the probability of including an environmentally friendly dish in an order in the control group. For more detailed information, refer to Appendix B. All the estimations were conducted using Stata 17 and reported as odds ratios to facilitate the interpretation of the effects of each variable.

4. Results

Descriptive analysis revealed that the carbon label introduction resulted in a higher probability of selecting environmentally friendly dishes, with the likelihood increasing from 26.26% to 31.51%. This represents an overall increase of approximately 20% relative to the initial probability. Across all food categories, the introduction of the carbon label had a positive effect on the probability of choosing options with lower emissions. The most significant increase was observed in the poke dish category (i.e. the vegetarian poke), suggesting the potential impact of such labels in promoting sustainable dietary choices (see Appendix C for details).

Below, we report the estimated coefficients and respective odds ratios to ease the interpretation and comparison across Models 1 and 1a in Table 3 and across Models 2, 3, and 4 in Table 4.

The results of Models 1 and 1a indicate that there was no significant difference between occasional and regular customers when considering only the regular customers' first order after the introduction of carbon labels. Further analysis of the control variables revealed that occasional customers who included a first course, a dessert, or a side in their orders were more likely to select an environmentally friendly option, whereas regular customers who included a poke in their orders were less likely to include an environmentally friendly option in their orders compared to those who did not include that dish category in their orders. On the other hand, customers who included a side in their orders were 3.43 times more likely to include an environmentally friendly dish compared to those who did not. Additionally, for both occasional and regular customers, order size (i.e. number of dishes included in an order) was positively associated with the probability of selecting an environmentally friendly option, with odds ratios of 1.24 and 1.45, respectively.

Table 4 shows the results for Models 2, 3, and 4, indicating how the label introduction affected the probability of including an environmentally friendly option in repeated orders for regular customers.

Model 2 results shows that the carbon label introduction has a significant effect on the likelihood of ordering environmentally friendly dishes when considering all the regular customer's orders. In fact, as Table 3 shows, the intervention increases the odds of including one environmentally friendly dish per order by 1.74 compared to the period before the label introduction. This effect is then explored in Models 3 and 4 to decompose how the label effect evolves over time. In Model 3, we reinforce the point made in Model 1a showing that that the label is not effective when customers are first exposed to it but that, instead, it does impact their subsequent choices. The results of Model 4 highlight a quadratic relationship between the presence of environmentally friendly dishes in an order and the number of orders placed after the label

Table 3
The impact of carbon label on occasional and regular customers' choices after the first exposure.

	Occasional customers *(Model 1)*			Regular customers *(Model 1a)*		
	Coef.	SE	OR	Coef.	SE	OR
Intervention						
Intervention	−0.019	0.229	0.982	0.277	0.273	1.359
No intervention-Reference category						
Dish category						
First course	0.533**	0.260	1.704	0.049	0.238	1.051
Second course	−0.122	0.387	0.885	−0.391	0.324	0.677
Poke	−0.402	0.279	0.669	−0.681***	0.253	0.506
Dessert	0.789**	0.261	2.202	−0.068	0.305	0.934
Smoothies	−0.367	0.265	0.693	−0.415	0.335	0.660
Sides	1.651**	0.402	5.209	1.235**	0.504	3.439
Ordering method						
Online	0.035	0.248	1.035	−0.184	0.340	0.832
In-store-Reference category						
Time of the order						
Lunch	−0.233	0.235	0.791	−0.269	0.280	0.764
Dinner-Reference category						
Other						
Order size	0.214**	0.092	1.239	0.372***	0.102	1.450
Constant	−2.588***	0.398	0.075	−2.389***	0.410	0.092
Clustered standard errors		No			Yes	
Number of obs.		537			761	
Pseudo R-squared		0.216			0.165	
Log-likelihood		−263.94562			−386.27601	
Akaike crit. (AIC)		546.172			751.326	

Significance levels: *** p <.01, ** p <.05, * p <.1.
SE: Standard error, OR: Odds ratios.

Table 4
The impact of carbon labels on the probability of regular customers selecting an environmentally friendly option over time.

	Model 2			Model 3			Model 4		
	Coef.	SE	OR	Coef.	SE	OR	Coef.	SE	OR
Intervention									
Intervention	0.556***	0.183	1.743	N/I			N/I		
No intervention-Reference category									
Information persistence									
First	N/I			0.553	0.337	1.739	N/I		
Following orders	N/I			0.556***	0.197	1.744	N/I		
Orders progression-after label	N/I			N/I			0.031***	0.010	1.032
Orders progression-squared	N/I			N/I			-0.002***	0.001	0.999
Dish category									
First course	0.086	0.202	1.090	0.086	0.202	1.090	0.071	0.202	1.073
Second course	−0.281	0.320	0.755	−0.281	0.320	0.755	−0.272	0.319	0.762
Poke	−0.472*	0.247	0.624	−0.472*	0.247	0.623	−0.489*	0.248	0.613
Dessert	0.109	0.256	1.116	0.109	0.256	1.116	0.127	0.256	1.139
Smoothies	−0.885***	0.285	0.413	−0.885***	0.285	0.413	−0.880***	0.286	0.415
Sides	1.059***	0.314	2.885	1.059***	0.314	2.885	1.036***	0.315	2.817
Ordering method									
Online	0.071	0.442	1.074	0.071	0.442	1.074	0.095	0.441	1.099
In store-Reference category									
Time of the order									
Lunch	−0.151	0.276	0.859	−0.151	0.276	0.860	−0.181	0.276	0.834
Dinner-Reference category									
Other									
Order size	0.482***	0.820	1.619	0.482***	0.820	1.619	0.488***	0.083	1.629
Individual fixed effects	Yes			Yes			Yes		
Number of obs.	1,053[a]			1,053[a]			1,053[a]		
Pseudo R-squared	0.165			0.165			0.165		
Log-likelihood	−404.226			-404.300			-404.300		
Akaike crit. (AIC)	828.452			830.602			830.602		

[a] 1,200 panel observations; however, 147 observations were lost with the introduction of individual fixed effects because of no variation in the outcome. Significance levels: *** p <.01, ** p <.05, * p <.1, SE: Standard error, OR: Odds ratios, N/I: Not included.

introduction. The results show that orders of the environmentally friendly dishes increased soon after the label introduction, even if the pace of increase tends to reduce as the number of orders increase. As shown by the negative and statistically significant coefficient on the squared term, the label effect fades with subsequent order repetitions. Note that the inverted *u*-shaped quadratic specification would, in principle, imply negative impacts after a high number of orders. However, within the observed maximum number of orders in the sample, the total effect remains positive and increase.

We observed that across model specifications, the presence of an environmentally friendly dish is impacted by which dish category is included in an order. Customers who included a poke or a smoothie in their orders were less likely to select a dish identified as environmentally friendly compared to those customers who did not include one of those categories in their orders. Instead, those customers who included a side dish in their order had a 2.88 odds ratio of including an environmentally friendly option in their orders, suggesting that those who included a side dish were twice as likely to order an environmentally friendly dish compared to those who did not include a side dish. Finally, the results show that increasing order size increases the odds of ordering an environmentally friendly dish. Neither the ordering method nor the time of the order influenced regular customers' ordering preferences.

5. Discussion

Looking at RQ1, we do not find evidence of a difference between regular and occasional customers concerning the probability of including an environmentally friendly dish in their first order after the intervention. In both cases, no different effect from previous purchasing experiences could be detected. Although this might be related to the lack of statistical power (see Appendix D for a post-hoc power calculation), theoretical arguments may also warrant attention.

An initial barrier to the adoption of a label could relate to customer habits; consumers face multiple food choices every day (Sobal and Bisogni, 2009); to streamline their cognitive processes, they base some of these choices on habitual behaviours (Adamowicz and Swait, 2013). The literature shows that grocery purchases are repeated over time, habitual, and performed with little information search (Carrasco et al., 2005; Gardner, 2012; Machín et al., 2020). People with repeated behaviours forming strong habits use less information when making decisions, and they generally appear to be less responsive to information (van t'Riet et al., 2011). In other words, because habits are hard to break, they can pose a hurdle to the effectiveness of an intervention (Verplanken and Whitmarsh, 2021). The literature shows that habits can represent a barrier to adopting environmentally friendly alternatives (Kurz et al., 2015); indeed, when habits come into play – even if consumers have a positive environmental attitude – it might be hard to convert their attitudes into actual behaviour (Verplanken and Whitmarsh, 2021). This attitude–behaviour gap may be even stronger for regular customers to a restaurant than for those who are merely occasional customers; familiarity with a menu and the possible automatisms and ordering routines may play a relatively greater role as a barrier to choosing carbon-labelled dishes as compared to occasional customers.

Together with consumers' eating habits, other factors may play a role as well. For example, the literature shows that the more customers trust the information source, the more prone they are to buy according to a label (Atkinson and Rosenthal, 2014; Gorton et al., 2021). Restaurants cultivate loyalty in their customers by delivering satisfactory experiences that reinforce the consequent willingness to return to a given location (Bowden-Everson et al., 2013). Occasional customers are less likely to trust the restaurant and, therefore, toward the proposed labelling scheme. Regular customers may have greater trust, but its effect in our study might not have been sufficient to compensate for automatism and ordering routines to be detected on the first purchase.

In RQ2, we investigated the purchasing behaviour of customers ordering multiple times under the new labelling system. We found that customers' choices were changing from order to order. The probability of observing an environmentally friendly dish in orders increases progressively, albeit at a diminishing rate. The carbon-related literature contains few empirical results with which to compare ours. Our findings are consistent with those of Vanclay et al. (2011), whose grocery-store study found a positive trend in aggregate sales during the first two months of treatment for those items that were labelled as 'green'. Our results may also be consistent with those of Elofsson et al. (2016), who investigated milk sales in grocery stores and found a positive coefficient for the cumulative effect of the treatment. However, the coefficient in that study was not significant, possibly because of a lack of statistical power.

Several theoretical arguments from the literature could explain this lag in adoption and the cumulative effect. For example, consumer-related models highlight the importance of the cognitive process as a starting point in a sequence of nudging a customer into an environmentally sustainable behavioural change (Grunert et al., 2014; White et al., 2019). The cognitive process is particularly relevant for attributes that can generate an informative process with high customer involvement within a rational decision-making process (Vaughn, 1986). The carbon label, being a 'green' message with a rational appeal, is likely processed following this cognitive, affective, and behavioural sequence.

In all the classical models, such as the hierarchy-of-effects (Lavidge and Steiner, 1961) or the innovation–adoption (Rogers, 1962) models, the cognitive process starts with generating awareness about the attribute, which is followed by a cognitive response that can arouse an individual's interest in a product and its trial and adoption. In this process, repetition helps to generate awareness about a message that might not be noticed in the first encounter. Paying attention to an environmental label is a fundamental step in arriving at a purchase decision; it depends not only on the consumer's motivations but also on the availability and awareness of the label (Thøgersen, 2000). Moreover, repetition reduces uncertainty and conflicts originating from a novel stimulus. Repetition creates positive habituation toward the stimulus and generates cognitive factors that can increase purchase confidence (Burton et al., 2019). The more difficult it is to process label information, the more repetition is expected to increase its effectiveness (Anand and Sternthal, 1990). Therefore, it is highly unlikely that a newly introduced label will be immediately effective on the target customer. This is also in line with the results for RQ1, as the lack of awareness is common to both types of customers.

The concavity of the curve indicates the probability of including a labelled dish in an order as a function of the level of order repetition, highlighting not only the cumulation effect but also emphasising that the increase in the effectiveness of the label diminishes with repeated orders by the customer. In a restaurant setting, this is consistent with at least two types of behaviours that can be formulated from theory, namely: 1) variety seeking and 2) moral licensing.

With excessive exposure to the same message, repetition generates cognitive counterarguments and can create tedium, which reduces the message's effectiveness, especially when customers are less familiar with its source (Campbell and Keller, 2003). In the context of a restaurant menu, the influence tedium may also be evident in the customer's variety-seeking behaviour; that is, to avoid tedium, customers may seek alternative eating-out locations and cuisine choices (Van Trijp and Steenkamp, 1992; Adamowicz and Swait, 2013). Indeed, as Menon and Kahn (1995) point out, even if routinisation in food choices may be helpful at first, it can lead to 'monotony and boredom'. Once a certain level of satiation is reached, customers become willing to seek new stimuli by switching to new menu items. In other words, repeated choices may lead to boredom, which drives customers to try alternatives to labelled items, thereby reducing the overall effectiveness of a label.

Other psychological processes may produce a similar effect. For example, Khan and Dhar (2006) demonstrate how prior decisions could activate a moral licensing effect on subsequent consumption choices. Following this interpretation, a previous climate-friendly behaviour could give consumers a 'licence' to make less environmentally friendly efforts in later choices because they feel that they have already accumulated positive credits or credentials (Burger et al., 2022). Such behaviour is corroborated by Soregaroli et al. (2021), whose findings showed that including an explicit compensation payment for high-carbon-emitting wines increased the probability of making less environmentally friendly choices in restaurants. Burger et al. (2022) show how previous climate-friendly behaviours reduce individuals' subsequent feelings of guilt felt when consuming carbon-problematic dishes such as meat. Moreover, Hurst and Sintov (2022) demonstrate how moral licensing is more evident when related to a pattern of behaviour as compared to an isolated previous environmentally friendly choice. This suggests that such an effect may be more relevant for repeated choices.

6. Policy implications

From a policy perspective, our findings indicate various elements that ought to be considered for the effectiveness of a carbon label intervention. First, the effect of a carbon label intervention is not immediate; rather, it is cumulative. Promoting awareness of the label is important, although this does not mean that strong advertising campaigns are necessary to generate a detectable effect. In our experiment, it was sufficient to provide supporting information and repeated exposure. A must-have characteristic, which was included in our experiment, is the certification of the label by a well-known local university acting as a third party. Gorton et al. (2021) showed that the link between third-party verification and consumers' trust is an important enabler in developing awareness and familiarity with the label as well as the subsequent increase in its usage. Moreover, this effect might be reinforced if customers could also find the label in different outlets.

As Thøgersen (2000) suggests, the prevalence of an eco-label (i.e. its presence in various contexts) makes it easier to notice, generates learning, improves the credibility of the label, and could steadily nudge consumers toward sustainable food choices. It is possible that a spot initiative in a restaurant, such as that presented in this study, could underestimate the effect of label introduction on a larger scale; it is likely that the magnitude of the label effect would remain small in the restaurant context. As remarked by Majer et al. (2022), labels are important, but to be effective they must be part of a more comprehensive set of policy tools.

Indeed, based on the intervention effect found, it is important for policy makers to implement a set of communication and education strategies aimed at creating consumer awareness of sustainability labels, such as carbon labels. Certifying institutions should, therefore, actively inform through short-term interventions. Such normative measures aim to create familiarity with the labels introduced and to build consumer confidence in certified information. Within this context, target-oriented communication strategies, such as information and promotion campaigns addressed to consumers interested in environmentally friendly products, may help to accelerate the process for creating consumer awareness of carbon-labelled information.

Second, the present findings reveal that the efficacy of a carbon label is not independent of a successful first introduction of the label and its management over time. Persistency and habit-formation effects have been studied before: Elofsson et al. (2016) and Lohmann et al. (2022) investigated the persistence of a carbon label introduction in grocery stores and university canteens, and List et al. (2022) assessed the consistency of grocery shoppers' choices with a health habit-formation model. However, little consideration has been given to how persistence can be achieved. Normative intervention aimed at creating consumer knowledge on sustainable-related food attributes can help to achieve a long-lasting cumulative adoption process. For example, educational campaigns are important to create conscious consumers and to reduce information asymmetries related to products' characteristics.

Such policy interventions could also support the preservation of the magnitude of marginal effects in choosing environmentally friendly dishes by reducing moral-licence-related behaviours among consumers. Indeed, robust knowledge about the environmental challenges of food products can counterbalance consumers' inclination to behave in environmentally unsustainable ways because of previous sustainable behaviours. Also, other policy measures could be considered to activate pride and guilt as pro-environmental behavioural motivators (Hurst and Sintov, 2022); indeed, these very psychological factors have been recognised as drivers of moral licensing. Within this context, the adoption of a carbon label could be linked to measurable and tangible environmental targets to be reached by individuals over time.

Also, economic actors of the catering sector can have a role in fighting consumer boredom, which is another of the drivers of moral licensing. In specific, the need for variety can be addressed by restaurant managers providing seasonal dishes and new options over time. Therefore, the effectiveness of a carbon label could push restaurants to introduce more variety in those dishes having a lower environmental impact, leading to a more sustainable food offering. In the long run, this behaviour on the supply side could reinforce the overall policy intervention.

Third, here we have used a 'best-in-class' carbon label (cf. Lemken et al., 2021). It is important to acknowledge that the effectiveness of such a label may be limited by the heterogeneous preferences of restaurant customers as well as their tendency towards variety-seeking. Although the label could substantially simplify decision-making for customers looking to make more sustainable choices, it may not be as effective in influencing behaviour as other approaches. The 'best-in-class' CO_2 label does not fully capture the complexity of carbon footprint considerations. Thus, a 'best-in-class' label may not resonate with all customers – or may even heighten the risk of greenwashing initiatives.

To address these limitations, policymakers may need to consider alternative approaches to promoting sustainable food choices, such as incorporating sustainability criteria into restaurant certification programmes, issuing awards and prizes, or offering incentives for restaurants that prioritise environmental friendliness. They should also be aware that labels have heterogeneous impacts and may not achieve change where it is needed most – i.e., among those who consume products with high carbon impacts (Edenbrandt and Lagerkvist, 2021).

Finally, policymakers must also consider the potential unintended consequences of food labelling policies. For example, some consumers may actively avoid the label (Edenbrandt et al., 2021), or mandatory labelling may disproportionately impact small businesses (e.g. restaurants), or they may inadvertently create incentives for companies to reformulate their products in ways that are not actually more sustainable. On the other hand, consumers may struggle to understand excessive private labels with diverse standards (Banerjee and Solomon, 2003). Therefore, careful consideration of the potential impacts and unintended consequences of food labelling policies is essential to ensure that such policies effectively promote the intended choices without creating unintended negative effects.

7. Conclusions

In this study, we conducted a natural field experiment to evaluate how introducing a carbon label on a menu affects customers' choices in a full-service restaurant. We investigated how introducing the carbon label impacted the probability of including environmentally friendly dishes in an order, highlighting differences between occasional and regular customers. Moreover, we investigated the behaviour of regular customers in consecutive orders after the labelling intervention.

We could not detect a difference in the composition of orders because of a one-time exposure to the label. The orders placed by occasional customers who were exposed to the label were not significantly different from those placed by regular customers in the preceding weeks. Similarly, we did not detect a different behavioural pattern when observing the first orders placed by regular customers after exposure. In other words, the likelihood that a customer will order an environmentally friendly dish significantly increases with repeated exposures and additional orders, albeit with an effect that progressively diminishes. Thus, the label introduction positively affects regular clients' behaviour, generating awareness and driving them to increase the number of climate-friendly options in their orders, even if with a diminishing effect over time.

The results presented and the literature discussed reveal the complexity of introducing a steady, environmentally friendly information intervention and shifting customers towards more sustainable food choices in the context of restaurants. Several elements may interact in this process. First, customers' habits and routines may decrease the effectiveness of a new carbon label. Second, the environmental message may face obstacles in consumers' ability to understand it, and repetition may facilitate habituation and confidence toward the purchase. Third, customers may grow bored of the environmental choice if the menu is not varied over time. Fourth, moral licensing may reduce consistency in environmentally sustainable behaviour. By managing all these elements, we can expect the efficacy of the carbon label intervention to change over time.

Some limitations of this study must be considered. First, we conducted our experiment in only one restaurant within only one specific geographic region, and we tested the effects of only one carbon-label design. To increase the external validity of the results, it would be worth investigating the differential effect of different visuals such as traffic lights or colour-based labels. Second, the lack of additional details on customer IDs poses a challenge in discerning whether the customer is an individual or a group such as colleagues or family members. Consequently, it becomes difficult to determine whether the same person is ordering and paying every time when customers visit the restaurant as a group on multiple occasions. This could potentially affect the order composition and ordering choices, and the repetition effect observed may not be solely attributable to individual consumers. Therefore, to gain a more comprehensive understanding of the impact of a carbon label, there is a need for further investigation that distinguishes between individual and group dynamics. In addition, the statistical power of our research design was limited to the detection of larger shifts in consumption (see Appendix D). Repeating the analysis in a larger sample would therefore be warranted.

Finally, a well-known challenge when evaluating the effectiveness of a policy intervention is the trade-off across expenditure categories. While filling their shopping cart or making an order, customers may compensate for low emission choices within a food category via substitution and income effects with other food categories (Shewmake et al., 2015). In an experimental setting, it becomes quite problematic to consider all possible substitutions. In this paper, we control for the possible alternatives by looking at a whole set of choices on a restaurant's menu. However, we do not monitor customers' overall consumption behaviours, such as their purchases on other eating occasions.

Digital solutions may open the way for future studies to assess the effects of information provision in a more comprehensive way. In grocery stores, loyalty cards are already available for research purposes and have been used in several studies for segmentation and differential impact assessment (e.g. Fearne et al., 2022). Their use could be extended to assess the purchase dynamics determined by information provision. Even greater potential may be realised in randomised control trials targeting single individuals: Online grocery stores or digital ordering from a restaurant could be used to expose the same individual to the same treatment multiple times. Of course, such platforms must allow consistent user-specific text and visuals, which was not the case for the empirical application presented in this study.

CRediT authorship contribution statement

Mirta Casati: Methodology, Data curation, Formal analysis, Writing – original draft, Visualization. **Claudio Soregaroli:** Conceptualization, Methodology, Writing – review & editing, Project administration, Supervision. **Jens Rommel:** Conceptualization, Methodology, Writing – review & editing. **Gloria Luzzani:** Resources, Methodology. **Stefanella Stranieri:** Conceptualization, Methodology, Writing – review & editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

Table A1.

Table A1
Natural field experiments on carbon label introduction.

Author	Context	Type of carbon label	Country	Main findings
Brunner et al. (2018)	University cafeteria	Traffic-light label, quantitative label.	Sweden	The introduction of a colour-based label leads to moderately more climate-friendly consumption. Overall GHG emissions from food sales were reduced by 3.6% due to the label introduction.
Elofsson et al. (2016)	Retail stores	A sign attached to a shelf in the proximity of the milk, explaining that the milk is climate certified. There is no quantitative information provided.	Sweden	The demand for the carbon-labelled product (i.e. milk) increased by 6–8% in supermarkets in the short term.
Lohmann et al. (2022)	University cafeteria	Traffic-light labels with quantitative information.	UK	The carbon footprint label introduction decreased the probability of selecting a meal with a high carbon footprint. Specifically, consumers substituted meat meals with vegan, vegetarian, and fish meals, moving to meals with moderate carbon impact.
Slapø and Karevold (2019)	University cafeteria	Three different traffic-light labels (red, yellow, and green), a single green label for the most environmentally friendly dishes, single red label for the least environmentally friendly option. Moreover, the authors installed posters to reinforce the information conveyed by the label.	Norway	The only label type that effectively improved the sustainability of customer choices was the traffic-light label. The traffic light stopped consumers from purchasing the most carbon-emitting option (red light), but it did not make customers choose the most climate-friendly option (green light).
Soregaroli et al. (2021)	Restaurant	Carbon footprint information (quantitative) combined with a price incentive on wine cards.	Italy	The carbon footprint (CF) information alone was insufficient to affect consumers' choices. Instead, when CF information was combined with a price change (increase in price proportional to the bottle emissions), it affected choices: customers chose wines with a lower CF if the carbon-related expenditure was implicit. Instead, when the carbon-related cost was explicit, they chose wines with comparatively higher CF.
Spaargaren et al. (2013)	University canteen	Two different labelling schemes: a light labelling regime and a comprehensive one. The former presented the factual emissions information without additional intervention, while the latter accompanied the label with a broader set of interventions.	Netherlands	A positive attitude toward the carbon label was noted, but there was some resistance. The 'light' labelling regime had no effect, whereas when the label was supported by information and other interventions (comprehensive label), the carbon label impacted behaviour, even within a limited period.
Vanclay et al., 2011	Grocery store	Three different labels representing different emissions levels: green (below average), yellow (near average), and black (above average).	Australia	The sales of black-labelled products decreased, whereas the green-labelled product sales increased. Moreover, when price and green labelling coincided (lowest price = greenest product), the shift from black to green was more pronounced.

Appendix B

Our study adopts the estimation strategy of a before-after analysis in which each customer functions as its own control. This approach allowed us to identify the intervention effect. However, given the deterministic nature of the intervention and the structure of the analysis, we could not control for the potential presence of seasonality in the consumers' choices.

Previous studies showed that weather conditions, such as rain and daily temperature, could influence customers' food choices in the restaurant's physical location or when ordering online. For example, Soregaroli et al. (2021) report that rain impacted customers' choices when ordering a bottle of wine: when it rained, they chose lower-emission wine. Likewise, Liu et al. (2021) explore customers' choices in ordering take-away foods, finding that rain, temperature changes, and air quality affected consumer choices contingently on the food category that customers were ordering.

We introduced the label on the menu in summer (31 May), and the pre-intervention period spanned from winter to spring. Therefore, we acknowledge that increased temperatures may confound the detected effect of the label's introduction in increasing consumers' probability of ordering an environmentally friendly dish.

To investigate whether any seasonal change was relevant, we used a control group consisting of orders placed through third-party apps, whose menus were not subject to the label introduction. Therefore, the menu's appearance to customers did not change throughout the experimental period (4 January–30 September).

Table B1 shows how the control group and the orders placed via the restaurant's own system behave differently in the absence of the intervention. In fact, during the pre-treatment period, the two groups of observations differ in terms of which categories of dishes the customers preferred to order, as well as their order size and the time when they placed their orders. Additionally, unlike orders placed in the restaurant itself or via the restaurant's proprietary app, orders placed via the third-party system did not assign a unique ID code to each customer. Consequently, we could not determine whether these were repeat or occasional customers. Thus, for these customers, we could not control for unobserved individual heterogeneity holding constant the effect of any time-invariant individual-level difference. Market trends suggest that users of food delivery services tend to be younger, more educated and earn a higher annual household income compared to non-users. Additionally, 56% of restaurant and food delivery users can be characterised as early adopters of new technology – and, thus of new services (Statista Consumer Insights, 2022).

Table B1
Pre-intervention customers' ordering preferences.

Variable	Mean control group (466 obs.)	Mean repeated customers (538 obs.)	p
Dish category			
First course	0.403	0.407	0.907
Second course	0.433	0.526	*** 0.003
Poke	0.356	0.315	0.177
Dessert	0.236	0.252	0.538
Smoothies	0.283	0.388	*** 0.000
Sides	0.489	0.576	*** 0.002
Time of the order			
Lunch	0.568	0.849	***0.000
Other			
Order size	2.688	3.310	*** 0.000

Significance levels: *** p <.01, ** p <.05, * p <.1.

The above description clarifies how the reported differences render the control group unsuitable as a counterfactual to identify the label introduction effect with approaches such as difference-in-differences. However, the group can still provide valuable information when used to investigate the presence of any seasonal change within its consumers' choices of an environmentally friendly dish (i.e. our dependent variable). As Table B2 shows, there is no statistical difference when comparing the means for these dishes of the two samples in the pre-treatment period. Because the pre-treatment condition is valid, we estimated a model observing whether the presence of the environmentally friendly dishes changed over the period of analysis.

Table B2
Pre-treatment customers' orders of environmentally friendly dishes.

Environmentally friendly dish	Mean control group (466 obs.)	Mean repeated customers (538 obs.)	p
Vegetable cous cous	0.060	0.058	0.868
Roasted potatoes	0.193	0.210	0.506
Vegetarian poke	0.021	0.030	0.410
Buckwheat galette with jam	0.032	0.028	0.689

Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.1.

We estimated Models B.1 and B.2 by including monthly dummy variables (January–September) and using June as the reference month (which is when the intervention was implemented) to examine any seasonal variations in the likelihood that third-party app customers (Model B.1) and regular customers (Model B.2) would include an environmentally friendly dish in their orders. In both models, $\mathbf{x}_{\mathbf{imt}}$[4] is the vector of exogenous control variables to model the presence of environmentally friendly dishes per order; this vector contains dish category, time of the order, and the ordering method binary variables.

Model B.1 on third-party app customers reads as follows:

$$\mathrm{Logit}(\mathrm{P}_{\mathrm{mt}}) = Log\left(\frac{\mathrm{P}_{\mathrm{mt}}}{1-\mathrm{P}_{\mathrm{mt}}}\right) = \theta + \eta \mathrm{D}_{\mathrm{month}_{\mathrm{mt}}} + \beta \mathbf{x}_{\mathbf{mt}} + \varepsilon_{\mathrm{mt}} \tag{B.1}$$

where $m = 1, \dots 997$ indicating the number of orders and $t = 04/01/2021, \dots. 30/09/2021$, θ is the intercept, $\mathrm{D}_{\mathrm{month}_{\mathrm{mt}}}$ the binary variables indicating the months, and $\varepsilon_{\mathrm{mt}}$ the stochastic error term.

Model B.2 on regular customers reads as follows:

[4] We did not include the binary variable *Ordering method* in model B.1 because all third-party apps orders were placed online.

$$\mathrm{Logit}(\mathrm{P}_{\mathrm{imt}}) = Log\left(\frac{\mathrm{P}_{\mathrm{imt}}}{1-\mathrm{P}_{\mathrm{imt}}}\right) = \eta \mathrm{D}_{\mathrm{month}_{\mathrm{imt}}} + \beta \mathbf{x}_{\mathbf{imt}} + \alpha_i + \varepsilon_{\mathrm{imt}} \tag{B.2}$$

where $i = 1, \ldots 99$, $t = 04/01/2021, \ldots. 30/09/2021$, $\mathrm{D}_{\mathrm{month}_{\mathrm{mt}}}$ the binary variables indicating the months, α_i are individual fixed effects and $\varepsilon_{\mathrm{imt}}$ the idiosyncratic error term.

The results reported in Table B3 show that we did not detect a difference across months in third-party ordering preferences for the environmentally friendly dishes on the menu. Instead, for the regular customers, we observe that (as predicted) there is a statistically significant difference across months, because in June (i.e. the month when we introduced the label) customers are more likely to include one of the dishes identified as environmentally friendly in their orders.

Table B3
Robustness check for the seasonality on demand for environmentally friendly dishes.

	Model B.1			Model B.2		
	Coef.	SE	OR	Coef.	SE	OR
Month						
January	−0.113	0.506	0.893	−0.756*	0.389	0.469
February	0.462	0.467	1.587	−0.818**	0.348	0.441
March	0.222	0.316	1.249	−0.739**	0.336	0.478
April	0.093	0.316	1.097	−0.233	0.322	0.792
May	0.121	0.327	1.128	−0.387	0.316	0.679
July	0.218	0.310	1.243	0.037	0.299	1.037
August	−0.584	0.539	0.558	0.160	0.524	1.174
September	−0.209	0.326	0.812	−0.060	0.308	0.942
June-Reference category						
Dish category						
First course	0.696***	0.209	2.006	0.129	0.206	1.138
Second course	0.113	0.233	1.120	−0.305	0.320	0.737
Poke	−0.347	0.236	0.707	−0.436*	0.249	0.647
Dessert	0.301	0.243	1.351	0.099	0.256	1.105
Smoothies	−0.767***	0.240	0.465	−0.917***	0.290	0.400
Sides	1.568***	0.242	4.797	1.106***	0.315	3.023
Order size	0.371***	0.083	1.449	0.482***	0.082	1.619
Ordering method						
Online	N/I			−0.010	0.439	0.990
In store-Reference category						
Time of the order						
Lunch	−0.466**	0.182	0.627	−0.171	0.276	0.843
Dinner-Reference category						
Other						
Order size	0.371***	0.083	1.449	0.482***	0.082	1.619
Constant	−2.838***	0.330	0.059			
Individual fixed effects		No			Yes	
Number of obs.		997			1,053[a]	
Pseudo R-squared		0.270			0.170	
Log-likelihood		−439.589			−402.031	
Akaike crit. (AIC)		913.179			838.063	

Significance levels: ***p <.01, **p <.05, *p <.1, SE: Standard error, OR: Odds ratios, N/I: Not included.
[a] 1,200 panel observations; however, 147 observations were lost with the introduction of individual fixed effects because of no variation in the outcome.

Appendix C

The bar graph displays the probability that customer would include an environmentally friendly dish in an order before and after the label introduction across the four dishes identified as the least emitting: cous cous, roasted potatoes, vegetarian poke, and dessert.

Before the label was introduced, cous cous was chosen 4.68% of the times, whereas after the label introduction, the probability of choosing cous cous increased to 5.76%. This represents an increase of 1.08 percentage points, or approximately 23% relative to the initial probability. Similarly, the probability of choosing roasted potatoes increased from 18.27% before the label to 21% after the label, indicating an increase of 2.73 percentage points, or approximately 15% relative to the initial probability (see Fig. C1).

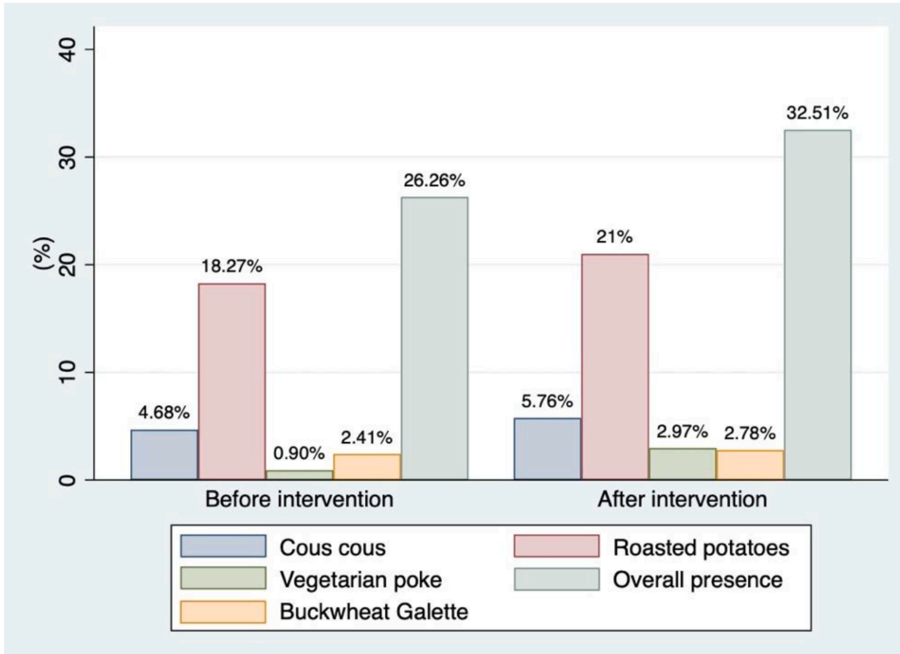

Fig. C1. Presence of environmentally friendly dishes in customers' orders before and after the intervention.

The probability of choosing vegetarian poke showed the largest increase, rising from 0.90% to 2.97%, which represents an increase of 2.07 percentage points, or approximately 230% relative to the initial probability. In contrast, the probability of including dessert increased only slightly from 2.41% to 2.78%, indicating an increase of 0.37 percentage points, or approximately 15% relative to the initial probability.

Appendix D

Research has shown that agricultural economics papers are often underpowered (Ferraro and Shukla, 2023). In addition, researchers in experimental agricultural economics rarely discuss statistical power (Palm-Forster et al., 2019). In this section we perform post-hoc power calculations. We do this (1) to understand our ability to detect label impacts and (2) to understand differences in statistical power to detect label effects in repeated vs. occasional customers.

Post-hoc power calculations are problematic when they assume that the estimated effect size is representative for the population level effect (because the effect is only a realization of a sample and hence a random variable). Consequently, we calculate minimum detectable effect sizes (given our sample sizes, an alpha of 5%, and a beta of 20%, i.e., a power of 80%) and calculate and discuss power for range of plausible effect sizes. Given that power calculations for panel data logit models with binary independent variables can only be simulated, here, we operate under the following simplified assumptions:

- We perform all calculations for occasional customers for the pre-treatment and intervention periods for a *two-sample test of proportions*, i.e., we assume that the data are fully independent and stem from different people.
- We perform all calculations for repeated customers for the pre-treatment and intervention periods for *McNemar's test*, i.e., we assume that the data are interdependent and stem from the same people (abstracting from the fact that there may be more than one observation per customer for the pre-treatment and intervention periods respectively).
- While a hypothesized *increase* in choosing an environmentally friendly dish would call for one-sided tests, we additionally present results for the more conservative two-sided tests.

All calculations were performed with G*power (Faul et al., 2007, 2009).

Table D1 presents the sample sizes and outcomes for occasional and repeated customers. These numbers serve as inputs and basis for discussion in our power calculations:

Table D1
Treatment effects and sample sizes from the study.

	Before treatment	Intervention period
	Occasional customers	
Presence of environmentally friendly dish	103	66
Percentage of environmentally friendly dish	32.09%	30.56%
Total *n* occasional customers	321	216
	Repeated customers	
Presence of environmentally friendly dish	170	165
Percentage of environmentally friendly dish	25.68%	30.67%
Total *n* repeated customers	662	538

For an assumed proportion of environmentally friendly dishes of 32.09% in the pre-treatment period (Table D1), the detectable difference in the treatment period is 42.63% (with alpha = 5% and P =.8 for a one-tailed two-sample test of proportions). The respective proportion is 44.00% for the two-tailed test.

As an additional illustration, Fig. D1 displays how statistical power changes with effect size (for the one-tailed test).

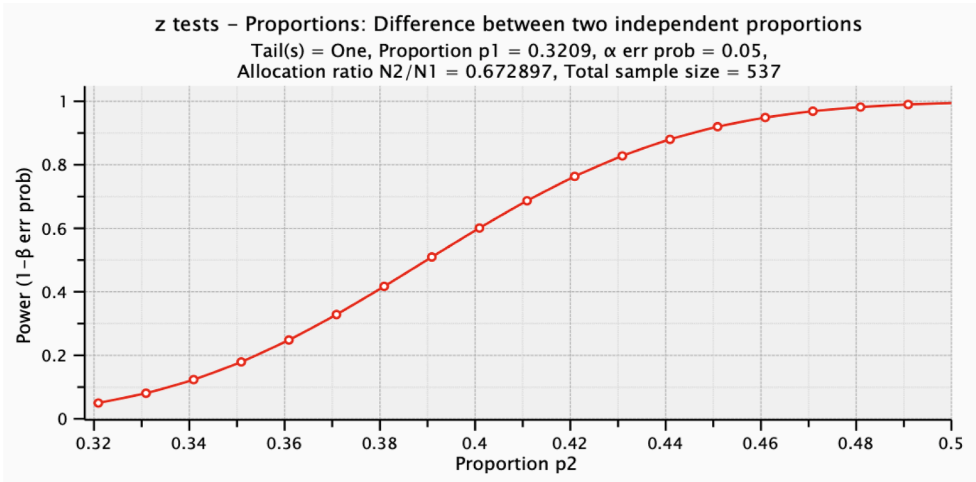

Fig. D1. Power for detecting a difference between the pre-treatment and intervention period (assuming p1 = 32.09% in the pre-treatment period) and plotting for the proportion in the intervention period.

Turning to the repeated customers, and following the G*power manual on McNemar's test, we transform the data from Table D1 into ratios adding up to a total of 100% (see Table D2). Note that we work under the simplified assumption of paired data for these ratios.

Table D2
Simplified ratios for repeated customers.

	Environmentally friendly dish present	Environmentally friendly dish not present
Intervention period	13.75%	31.08%
Pre-treatment period	14.16%	41.00%

The tested hypothesis is that the odds are different from one. As inputs we use the discordant pair proportion from the table 31.08% + 14.16% = 45.24%, a total sample size of 1,200, an alpha of 5% and a power of 0.80. The minimum detectable odds ratio in this scenario is 1.24 (1.28 for the two-tailed test).

Fig. D2 displays statistical power as a function of the odds ratio in this scenario (for the one-tailed test).

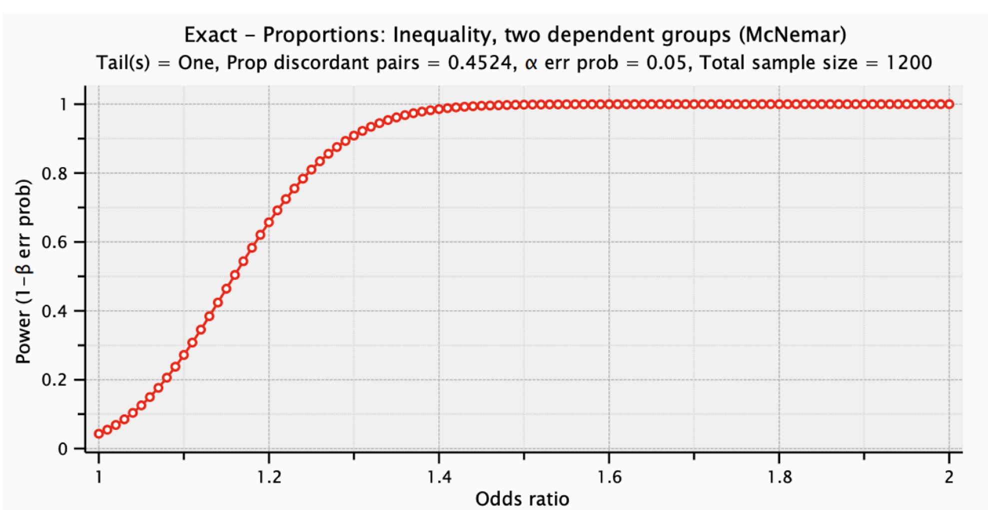

Fig. D2. Power for detecting a difference between the pre-treatment and intervention period assuming different population level odds ratio for McNemar's test.

We can conclude from these power calculations (under some simplifying assumptions), that our research design cannot detect very small effect sizes. However, medium to large shifts in the choice of the environmentally friendly dish (e.g., a ten percentage point increase for the occasional customers) are detectable with reasonable power (80%). While one may not expect such medium to large shifts from climate labelling alone (as such nudges typically only exhibit very small effects, see Mertens et al., 2022 and Maier et al., 2022 for a debate on plausible effect sizes of nudges), we believe that reporting our results can contribute to the aggregation of evidence in future *meta*-analysis of nudges in restaurants – a so far underresearched field of application.

Appendix E. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.foodpol.2023.102523.

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