The impact of a carbon label introduction on food orders: A natural field experiment in a full service restaurant

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Abstract

Consumers play a fundamental role in achieving a more sustainable global food supply chain through their dietary choices. Consumers have a positive attitude toward sustainable food consumption. However, this attitude hardly translates into behavior. Policy intervention can help drive consumers towards a more sustainable behavior. Labels are considered the main effective tools to overcome information asymmetries related to sustainable practices while affecting consumers' food choices. To test the responsiveness of restaurant customers to a carbon label introduction, we conducted a natural field experiment in a restaurant. We introduced a carbon label on the menu providing information on dishes' CO2 emissions .We aimed to test how the provision of carbon information impacted the choices of a restaurant's one-time customers versus habitual ones. Results show that the label introduction does not affect a one-time customer's ordering choice, but instead, it affects returning customers' choices. We show that the label introduction positively affects returning clients' behavior, generating awareness and driving them from including zero climate-friendly options per order to include at least one. From this, we can argue that it is an effective tool for modifying the ordering routine for habitual customers but not the choices of random customers who visit a restaurant only once. Policymakers should account for the importance of familiarity and trust when designing a carbon label.

1. Introduction

The food supply chain (FSC) is responsible for a large portion of the global anthropogenic greenhouse gas emissions (GHG), one of the main drivers of climate change. However, there is uncertainty on the exact numbers of the FSC environmental impact. Poore and Nemecek (2018) estimated that FSC accounted for one-quarter of global greenhouse gas (GHG) emissions, but a more recent (Crippa et al; 2021) study showed that the FSC impact is even higher, accounting for one-third of global GHG emissions.

As the most impactful stage of FSC is agricultural production (Garnett et al; 2016, Poore and Nemecek, 2018, Crippa et al; 2021), it is vital to look for more sustainable production processes to shrink it. Yet, despite that, producers alone cannot conclusively mitigate climate change. Through their dietary choices, consumers play a fundamental role in achieving a more sustainable global FSC by driving producers' choices and delivering benefits on a larger scale (Poore & Nemecek, 2018).

The literature reported that consumers have a positive attitude toward sustainable food consumption (Vecchio and Annunziata, 2015; Bastounis et al; 2021). However, this attitude has to translate into behavior, where their high level of concern towards sustainability translates into a purchase choice (Campbell-Arvai et al., 2014, Abrahamse, 2020).

Policy intervention can help driving consumers towards a more sustainable behavior. The policies more strongly directed toward consumers are price incentives and information interventions, such as information provision tools (Soregaroli et al; 2021). Price incentives alter the incentive structure of choice and can produce a more sustainable purchased basket. However, this result is contingent to the observed relative prices. Differently, policies focusing on information aim at altering consumers' preferences. Information provision can allow consumers to uptake more environmentally-friendly choices when purchasing (Vermeir & Verbeke, 2006), enabling them to match their food choices and preferences (Verbeke, 2005). Information provision can include educational programs communication campaigns, and visuals and texts on product packages at the point of sales. Specifically, labels are considered among the main effective tools to overcome information asymmetries related to sustainable practices meanwhile affecting consumers' food choices (Grunert et al., 2014).

Sustainability labels are designed to convey to consumers the different aspects of sustainability (i.e., social, economic, and environmental) (Canavari and Coderoni, 2020). There is a wide array of sustainability labels on food products: the EU commission identified 129 schemes, either public or private, in the agri-food sector (Grunert et al; 2014), most of those adopted voluntarily (Manta et al; 2021). A vast literature is available concerning health-related attributes of food. Differently, evidence concerning the effects of information provision related to environmentally friendly attributes is still scarce. Most of the previous studies aimed at measuring the effect of providing customers with information on product's sustainability are based on stated preferences (e.g., Onozaka and McFadden, 2011, Van Loo et al; 2015, Menozzi et al; 2020). These studies are helpful in assessing the possible effectiveness of alternative claims and visuals but can hardly determine the effect of a label in a natural context. Natural filed experiments can help filling this gap. However, focusing on environmentally-friendly attributes, such experiments are still scarce and some examples can be found in supermarket settings (Vanclay et al; 2011, Elofsson et al; 2016), ice-cream shops (Menapace and Raffaelli, 2017), and restaurants concerning both wine choices (Soregaroli et al., 2021) and food choices (Brunner et al; 2018).

In this study we aim at filling some of the gaps concerning the revealed preferences toward environmentally-friendly attributes focusing on food choices in a restaurant's setting. Over the last decades, households' food consumption away from home has increased, weighing more heavily on the overall food system's carbon footprint (Dai et al., 2020). The restaurant industry contributes highly to the overall GHG emissions because of the extensive use of energy, water, supply materials, generation of non-recyclable trash, and food waste (Tehrani et al., 2020). Therefore, understanding customers' choices of sustainable-labeled menu options could help reduce restaurants' GHG emissions and contribute to tackling climate change (Dai et al., 2020; Babakhani and Dolnicar, 2020). Namkung and Jang (2017) showed that customers are willing to pay a premium price for restaurants investing in environmentally-friendly practices, indicating an interest in the restaurant's sustainability commitment. However, empirical evidence scarce and seems to suggest a small effect of such labels (Brunner et al, 2018). Moreover, most of the previously conducted field experiments were conducted in university canteens/cafeterias partly because such an environment is usually simpler and offers a higher degree of control from one authority toward consumption (Lehner et al., 2016). However, university canteens interact with a limited sample of the population, mainly researchers and students; thereby, the sample might not represent the average consumer (Schjøll and Alfnes, 2017). Given these consideration we decided to conduct our experiment in a full-service restaurant. As a typical restaurant's clientele base is composed of both habitual and non-habitual clients we decided to account for that in designing our research questions.

RQ1: What is the effect on one-time customers' choices of a labeling intervention concerning environmentally-friendly attributes when ordering in a full-service restaurant in a "business as usual" context?

Improving the understanding of how consumers' choice reacts to a label introduction is important from a policy perspective. Developing effective tools could help and support economic activities by investing in environmentally-friendly practices. However, in assessing the impact of such tool food consumption habits of customers could play an important role. The literature argues that food choices are habitual (Kujala and Johnson, 1993, Carrasco et al; 2005), and as such, these are harder to be modified by information provision tools (Verplanken and Whitmarsh, 2021). Assessing information provision to a consumer out of its daily routine in hypothetical or non-hypothetical lab experiments can suggest a potential of such information. However, it can hardly take into account for inhibitors to change embedded in a daily routine and within a choice taken in a natural context. Also, it cannot capture how information provision affects customers over time. While the literature researched the effects of interventions on consumers' habitual choices in food grocery shopping and restaurant orders, to our knowledge repeated purchase behavior has not received attention in a natural context when assessing an environmentally-friendly label in a restaurant. Therefore in a second research question we address the following:

RQ2: Does repeated purchase behavior have a role in the effectiveness of a labeling intervention concerning environmentally-friendly attributes when ordering in a full-service restaurant in a "business as usual" context?

We address RQ1 and RQ2 conducting a natural field experiment in a full-service restaurant located in the north of Italy. Using a life-cycle assessment (LCA) method, which measures the carbon dioxide emitted in production processes, all of the dishes of the restaurant menu were assessed. Our intervention consisted in introducing a carbon label on the menu on the least carbon-emitting dish per food category. The experiment was structured to investigate revealed preferences for all restaurant customers and a subset of *returning* customers who habitually ordered before and after the label introduction. The availability of information on returning customers allows us to add some innovative insights on how information provision affects them. Generally, especially in randomized control trials (RCT), the researcher's problem is to identify returning customers as they could be exposed to multiple treatments and introduce sources of bias in the data. Therefore, to assure the validity of the entire experiment and according to feasibility, returning customers are excluded ex-ante from a treatment or ex-post from the data analysis. Differently, in our experimental design returning customers constitute an important source of information as they allow to investigate the effect of the newly introduced label on habits. Moreover, returning customers represent a typical real-life scenario as many restaurants have a habitual customer base. Our results reveal that the carbon label introduction does not have an impact on one-time customers choices, whereas it has an effect on returning client's choices increasing the number of customers willing to order a labeled dish.

The paper is organized as follows. First, we will describe carbon labeling in the food industry, referring to both stated and revealed preferences literature. In Section 3, we will describe the experimental design and procedure. Section 4 will provide information on the model empirical specification. Finally, in Section 5, we will present the results and, in Section 6 we will provide the discussions and conclusions.

2. An overview of carbon labeling in the food industry

2.1 Stated preferences

The literature has widely investigated consumers' stated preferences toward some sustainability-related labels (such as organic) (e.g., Brooks et al; 2010, Van Loo et al; 2011). Comparatively, carbon labels have been less explored.

Specific research on carbon labels is needed because consumers perceive them differently than other labels, even if there are some common traits with other environmentally-friendly labels. For example, organic labeling brings a halo effect on consumers, indicating personal benefits, which hasn't been observed on carbon labels, making the two labels incomparable (Vermeir et al; 2020).

The general issues highlighted sustainability-sounding labels (i.e., information overload and confusion) recur for carbon labels. For example, in their study Feucht et al; (2018) report that participants "tended to subsume climate indications together with the attributes local' and 'organic production' under the umbrella term 'eco-friendly behavior."

The issue is that the climate information brought by carbon labels seems less critical when compared to other sustainability claims such as free-range, organic, or locally produced (Feucht et al; 2018, Lombardi et al; 2017). For example, Onozaka and McFadden (2011) analyzed the interaction of three sustainability claims (organic, fair trade, and carbon footprint) plus a location claim. The authors showed that "locally grown" was the most important claim. Moreover, they showed that negative carbon footprint claims (i.e., a high footprint) resulted in less importance in consumers' eyes when combined with other claims like an organic and fair trade. Moreover, Dudinskaya et al; (2021) showed even if customer's value positively carbon information, among other attributes, they have the lowest WTP for it. It is also worth to note that a vast number of sustainable-sounding claims and labels in the food market can bring to an information overload that could reduce the effectiveness of the label with respect to the desired sustainability goal (Van Loo et al; 2014, Janßen and Langen, 2017).Carbon label design can help consumers sort their confusion out and increase the value they put on carbon label information. According to the literature, consumers prefer carbon labels with a traffic light logo shape and quantitative information such as the absolute number of C02-equivalents (Klein and Mendrad, 2018, Feucht et al; 2018). Moreover, Zhou et al; (2019) showed that the position of the label on a product package is also important.

As far as demographic characteristics are concerned, Rondoni and Grasso's (2021) literature review showed that older females with higher income have a higher WTP toward carbon-label products. Cross-country differences are also significant, bringing heterogeneity in consumers' attitudes and affecting their choices (Grebitius et al; 2016).

2.1 Revealed preferences

The above described studies reported consumers' stated preferences toward carbon labeling. Despite the stated preferences method having internal validity, there are issues embedded in its external validity. Indeed, this method can easily generate "deviation from real market evidence", also defined as hypothetical bias (Hensher, 2010). Nevertheless, the stated preferences method can help retrieving valuable information to investigate consumers' revealed preferences. The revealed preferences method uses actual choices to measure consumers' preferences avoiding the bias related to stated preferences methods (Hicks, 2002). To elicit revealed preferences, researchers make use of experiments. In particular, natural filed experiment elicits revealed preferences in a naturally-occurring settings with participants usually unaware of being part of an experiment (List, 2007). Such studies enable to observe human actors in a real-life scenario, in a context where they express their true preferences avoiding those biases encountered when applying other methods. On the other side, natural field experiments have the problem of controlling the experimental setting as a lot of noise could be present in the collected data. Moreover, they do not allow a deep investigation of the underlying reasons behind an observed behavior.

While in the literature, natural field experiments exploring the introduction of labels are available (e.g., Vermeer et al; 2011, Duke et al; 2021), there is a scarcity of studies investigating carbon label introduction, at least in the food industry. As Table 1 shows, we found only six studies that fit our scope. The natural field experiments were conducted in either grocery stores (Vanclay et al; 2011, Elofsson et al; 2016), university canteens/cafeterias (Spaargaren et al; 2013, Brunner et al; 2018, Slapø and Karevold; 2019), or restaurants (Soregaroli et al; 2021).

Vanclay et al; (2011), in a grocery store, introduced a color-based carbon label on a selection of groceries, showing that the label, even if with a small effect, modified consumers' choices. Elofsson et al; (2016) conducted a field experiment across retail stores, providing qualitative carbon information on milk. The authors showed that the information provision re-oriented consumers' demand towards labeled products, at least in large stores. In a university cafeteria, Brunner et al; (2018) introduced a traffic light color carbon label showing that it resulted in a significant though small effect leading to more climate-friendly customer choices, at least in the short run. Also, Slapø and Karevold (2019) tested three different labeling systems in a university cafeteria and showed that only the traffic light color carbon label significantly influenced consumers' choices. Other studies found that a carbon label alone does not re-orient customers' choices towards environmentally-friendly options. For example, Spaargaren et al; (2013), in a university canteen, showed that a quantitative carbon label is only effective if supported by further communication techniques. Similarly, but in a restaurant setting, Soregaroli et al; (2021) found that adding carbon information to a wine bottle does not modify customers' choices unless combined with a price incentive.

Table 1: Natural field experiments on carbon label introduction

Citation	Context	Type of carbon label	Country	Main Findings
Brunner et al; (2018)	University cafeteria	Traffic light color label, quantitative label	Sweden	The introduction of a color based label lead 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	Carbon label, providing information on "producer committed" but not specific quantitative info	Sweden	The demand for carbon labeled product (i.e. milk) increased by 6-8%, in supermarkets in the short-term.
Soregaroli et al; (2021)	Restaurant	Carbon footprint information (quantitative) combined with a price incentives on wine cards.	Italy	The carbon label alone isn't enough to affect consumer's choices. Instead, when CF information is combined with a price change (increase in price proportional to the bottle CF), it affects choices, namely price increase reduced C02 emitted per bottle
Spaargaren et al; (2013)	University canteen	The authors introduced two different labeling schemes: a light labeling 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 towards the carbon label is noted, but there are some resistances. The "light" labeling regime showed no effect, whereas when the label was supported by information and other interventions (comprehensive label), carbon labels impact behavior, 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. Labels were introduced on 37 grocery store product.	Australia	The sales of black-labeled products decreased, whereas the green-labeled increased. Moreover, when price and green-label coincide (lowest price-greener product), the shift from black-to green was even greater.
Slapø and Karevold; (2019)	University Cafeteria	Three different labels: • traffic-light labels with three symbols (red, yellow, and green), • single-green label for environmentally friendliest dishes, • single-red label for the least environmentally friendly option. Moreover, the authors put posters to reinforce the information conveyed by the label.	Norway	The only label effectively improving the sustainability of customer choices is the traffic-light one. The traffic light stops consumers from purchasing the most emitting option (red light), but it does not make customers choose the climate friendliest option (green light).

3. Experimental design and procedures

We conducted a natural field experiment in a full-service restaurant in Piacenza, Northern Italy (hereafter, the Restaurant). The experiment was structured based on a protocol approved by an ethical committee of the University and based on research integrity principles. The protocol specified the study objectives and the experiment design and listed the restaurant's parameters to be considered an eligible participant. Specifically, a target restaurant should be interested in *"sustainability practices"* and eager to modify its menu by introducing a voluntary carbon label. Moreover, it should have an online ordering channel that could be adapted to the needs of the experiment. Finally, we deemed it mandatory to specify that only restaurants signing informed consent could participate in the experiment. The Piacenza restaurant we took into analysis filled our parameters.

The Restaurant's business model is oriented to 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, both for lunch and dinner. The menu is based on a typical Italian meal structure. Thus, it contains: first course, second course, sides, dessert. Moreover, it also offers poke bowls, fresh juices, snacks, drinks, and different sauces options.

Customers can place their orders at the Restaurant through different channels: the restaurant-owned app, third-party platforms, mail, phone, website, and sit-down service (from May 2021, previously dismissed because of COVID-19). Except for third-party platforms, an electronic ordering system is common to every other Restaurant's ordering channels. The Restaurant has a digital menu with no printed version, and all orders are placed using this system. For example, customers using the sit-down service or online autonomously place their order using the Restaurant's application. This provides a unique feature for the experiment, as it potentially offers better control of the visuals and information customers are exposed to while placing an order. Even those ordering by phone are exposed to the same visuals and information while browsing the Restaurant's app or website. Moreover, the Restaurant's ordering system allows distinguishing new customers from returning customers. While placing the first order, all customers fill their personal data and are provided with a unique ID number. Returning customers are identified because of the incentive to use the same ID for a simpler ordering process and because, while entering twice the same personal data, the system will identify the already existing user.

Data concerning orders and customers' IDs are available through the electronic register of the restaurant. According to the protocol approved by the ethical committee, each order could be linked to the specific ID number of a customer but, to preserve privacy details, no personal information about the customer could be disclosed to the researcher.

3.1 Dishes description and CO_2 emissions calculations

Based on the composition of dishes provided by the restaurant, we calculated each dish's C02 emissions through the database Eternity: the system includes data on the Life Cycle Assessment (LCA) of food ingredients, adopting the system boundary *"farm to gate,"* which expresses emissions from production to sale.

At the moment of the introduction of the label, a total of 48 options were present on the menu: seven for the first course, seven for the second course, five for sides, eleven poke bowls, ten for desserts, and eight fresh juices.

Since the restaurant has a network of local producers and big-distribution retailers, we highlighted this difference in the calculation. Indeed, when ingredients came from local production, we excluded the average transportation emissions provided by the database from the calculations. The functional unit used to classify and compare dishes inside the menu was the portion. We computed the CO2-eq emissions per dish for each category: if a dish was larger, it embodied more emissions. We excluded from our emissions calculations, and thus from our analysis, the snacks, drinks, and sauces categories as we could not compute the emissions because the restaurant didn't prepare such products but externally purchased them.

In Table 2, we report the least emitting dishes for each category. There are two-second courses reported; this is because, on June 15th, the restaurant replaced the *"Veggie Burger"* with the *"Omelette with asparagus, zucchini, and carrots".*

Table 2: Least emitting dish per category

Category	**Number of dishes per category**	**Least emitting dish**	**Mean gCO2eq**	**Min g CO2eq**	**Max g CO2eq**
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*	7	Omelette with asparagus, zucchini and carrots	479,74	335,29	1121,24
Sides	5	Roasted Potatoes	72,86	24	111,35
Poke Bowl	11	Vegetarian Poke	790,1	520,46	1050,72
Dessert	10	Buckwheat galette with jam	404,74	102,41	1355,71
Fresh Juices	8	Strawberries fresh juice	455,02	62,88	2130,81

***Change of labeled dish on June 15th**

3.2 Label design

Once identified the least emitting dish per category, we elaborated a carbon label to be put on the restaurant's menu. For the design phase we overviewed the main literature to see which essential label features to consider conceiving an efficacious label. Based on Donato and Adıgüzel (2022), the label should be easy-to-understand, eye-catching, and highly visible. A higher visibility implies a higher understanding of the label and a higher attitude toward purchasing a labeled product (Annunziata et al; 2019). Also, Tebbe and von Blanckenburg (2018) specify that "the more isn't always, the merrier", meaning that consumers' willingness to pay (WTP) does not increase with the number of labels. This indicates that it is better to put a single label rather than a combination of sustainability labels on a package.

On the design side, there are no specifics on the visuals of a label. Some field experiments in the restaurant industry used color-themed labels (Brunner et al; 2019) and traffic lights shaped labels (Slapø and Karevold, 2019) which resulted in affecting consumers' choices. However, when dealing with C02 emissions, there is no daily benchmark as there could be for an optimal diet. Therefore, the green-red light classification might only be implemented in relative terms by comparing one dish to another.

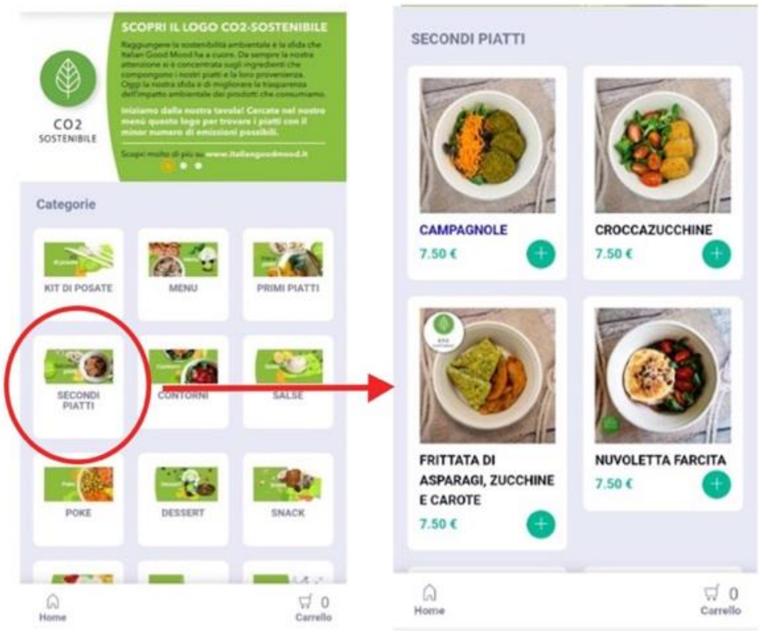
The above considerations suggest that to preserve an effective and meaningful label its design should be simple and clearly understood. For this reason, we designed a carbon-related label which is purposely neutral and not color-based with a simple green circle containing a white leaf (Figure 1). The label identifies the least emitting dish for each food category in the menu. This could be communicated in a simple way to the customers, without having them to process one-to-one dish comparisons. The label on menu was accompanied by a text quoting "CO2 sustainable". This text is the result of a pragmatic choice made with the Restaurant's manager who wanted to promote the "sustainable" attribute of the restaurant's dishes. The label on the menu was accompanied by additional information (Figure 2). More precisely, on top of the menu page, a banner highlighted the novelty introduced by reporting, "Discover the new CO2-sustainable logo". A message on the meaning of the label and on the restaurant's effort on sustainability was reported [1](Figure 2). We introduced the label on the restaurant menu on May 31st.

[1] The banner reported the following claim "Discover the new CO2-sustainable logo". In addition, the message conveyed the restaurant's mission "we want to improve transparency on the environmental impact of our products." Moreover, the banner directly engaged the customers inviting them to "lookout on the menu for this logo to find the dishes with lowest carbon emissions."

Figure 1: Carbon Label

Source: Restaurant Menu

Figure 2: Restaurant's menu



Source: Restaurant App

3.3 Data collection

After the restaurant owner signed the informed consent, we could access the electronic cash register data where each order had a unique customer ID. We collected data for orders either taken at the Restaurant's store or with the Restaurant app while disregarding data collected from third-party apps. Indeed those apps did not have the same electronic ordering system, and thereby we could not keep a trace of the customer's ID.

We collected customer's orders for two different periods: 1) a control period (January 4th -May 31st); and an intervention period (June 1st-July 31st). The intervention corresponded with the introduction of the label on the menu. Except for the label, the Restaurant's environment was kept identical to the usual setting during the observation period.

The full sample counted with 1704 orders. Of these orders 582 were from *one-time* customers and 1122 orders from *returning* customers. In total customers were 581, and 117 of these were returning one or multiple times. Focusing on *returning* customers, of particular interest to study repeated choices are those that placed orders before and after the label introduction. We singled out a subset of 823 orders from 60 such customers. This subset of observations exploits a panel-like data structure and adds an intra-subject analysis to this work, keeping all the other things equal. Overall this subset of observations counted for 48,3% of total restaurant orders, indicating that returning customers deserve specific and dedicated attention.

4. Empirical approach

4.1 Dependent variable

Previous literature analyzed the impact of an information intervention using either binary variable, indicating the probabilities that a customer will choose a labeled dish (Brunner et al; 2019), or continuous such as the sales share of labeled dishes over aggregated sales (Slapø and Karevold; 2019).

In this study, being the unit of analysis, the Restaurant orders collected at the individual level, we opted for a continuous dependent variable. Resembling customers' budget allocation and optimization process, we weighed each dish by its relative importance in economic terms. Therefore, the expenditure for climate-friendly dishes was divided by the total order expense for each order. The resulting "expenditure share of climate-friendly dishes" constituted the dependent variable. Unlike other studies (Slapø and Karevold; 2019), we constructed the dependent variable at the individual level. Customers had a wide variety of choices (i.e., 48 menu options), and as a result, not every order contained the dish identified as climate-friendly. Table 3 reports the share of climate-friendly dishes per order distinguishing between one-time and returning customers. Most orders did not contain one of these dishes, while less than 1% of orders included only climate-friendly options.

4.2 Explanatory Variables

In our model we considered several explanatory variables based on previous studies. Table 3 reports the descriptive statistics distinguishing between one-time customers and returning ones.

Dish Category

Literature accounted for differences across food categories when evaluating consumer’s attitude and WTP towards sustainability. Sánchez-Bravo et al; (2020) showed that the consumer’s awarness sustainability changes across countries and it is dependent on food categories. Li and Kallas (2018) estimating WTP premium prices for sustainable food products showed that this willingness changes for different food categories (i.e. highest for fruits and vegetables, lower for seafood).

Considered this heterogeneity in consumer's choices as a function of food categories, we decided to account for it by designing a set of dummy variables indicating the different categories to which the dishes belong.

As Table 3 shows, the highest selling category in both samples was Poke, followed by the First and Second courses. Sides also have a high frequency of orders, but they usually come for free when customers choose to order a "Second course." Therefore, the first customer's layer of choice is a dish belonging to the Second course category. The high presence of Sides comes automatically with the main dish choice, thereby not relevant to describing the consumer's order's preferences but relevant to define whether they include a climate-friendly option or not.

Weather conditions: temperature and rain

We included a set of variables describing the weather conditions as rain and daily weather both in a restaurant's physical location and online. Soregaroli et al; (2021) reported that rain impacts customers' choices when ordering a bottle of wine, showing when it rains, they choose lower-emitting wines.

Liu et al; (2021) explored consumers' choices for ordering takeaway foods finding that rain, changes in temperatures, and air quality affects consumer choices, but the results are contingent on which food category customers are ordering. We collected weather data using 3B Meteo Piacenza [2] and we designed three binary variables indicating different temperatures: T10 (for temperatures lower than 10°C degrees), T20 (for temperatures that ranged between 10°C and 30°C), T30 (for temperatures higher or equal to 30°C). Using the same data, we defined a binary variable measuring whether the order's day was raining or not.

Time of the order: lunch or dinner

Previous empirical results showed that time does not seem significant in explaining customers' choices toward more sustainable options (Slapø and Karevold (2019), but it is still important for characterizing customer's sustainable food choices (Campbell-Arvai et al.; 2015). Therefore, we designed a variable to measure whether the order was placed for lunch or dinner. Accordingly with the main target of customers that purchase for the daily working lunch, most of the orders were placed for lunch.

[2] https://3bmeteo.com/meteo/piacenza/storico)

Ordering method: in store or online

We included a variable indicating whether the order was made in-store or online. According to the literature, customers' food purchase choices are different when ordering online versus when going to a store. Zatz et al; (2021) showed that consumers have lower spending on unhealthy products when online food grocery shopping. However, Pitts et al; (2018) literature review revealed that such an ordering method might increase unhealthy choices as consumers are reluctant to purchase fresh foods online.

Based on these findings, we want to measure whether ordering online impacts a customer's choice from a menu and, thereby, whether it affects the climate-friendly dish choice. Ordering on-site at the Restaurant was the most frequently used option.

Returning Customer’s frequency of orders

The frequency of purchase or consumption of food is an explanatory variable often considered to explain a consumer's demand for food products. Considering environmentally-friendly food products, Stranieri et al; (2017) showing that food purchase habits play a role in predicting customer’s purchase behavior. Moreover, Annunziata et al; (2019) showed that frequency of purchase plays a role in determining the effectiveness of sustainable labels. We designed a set of binary variables describing different levels of order frequency for returning customers, which we will use as a proxy to describe how habitual these customers are. We envisioned three levels of frequency. High Frequency indicates customers with a high frequency of orders (more than 10 orders), Medium Frequency, customer's with a medium frequency of orders (between 5 and 10), and Low Frequency indicates a low frequency of orders (less than 5 orders). We observe that most returning customers have a high frequency of orders; thereby, we conclude that the restaurant has a strongly habitual customer base.

Intervention persistence

To measure whether the introduction of an information tool has a short or long-run effect on consumers' choices is a policy-relevant issue that should be taken into account (Allcott and Rogers, 2014). Previous literature (Spaargaren et al; 2013,Brunner et al; 2018) found that introducing a carbon label did not impact consumers' short-term ordering choices.

We deem it essential to highlight that we wanted to be confident that customers had been exposed to the label when designing these variables. Given that we could account with individual observations, we decided to first identify the first customer's order after the label introduction. Then, we coded dummy variables for each individual for those orders placed in the same week as the first one or after one/two/three/more than three weeks after. We believe this is the best way to measure whether multiple exposures to the same intervention affect consumers' preferences and thus to measure whether the intervention effect is persistent over time. This variable accounts for customers who ordered at least twice (at least in the observation period) after the label introduction.

Table 3: Variables descriptive statistics

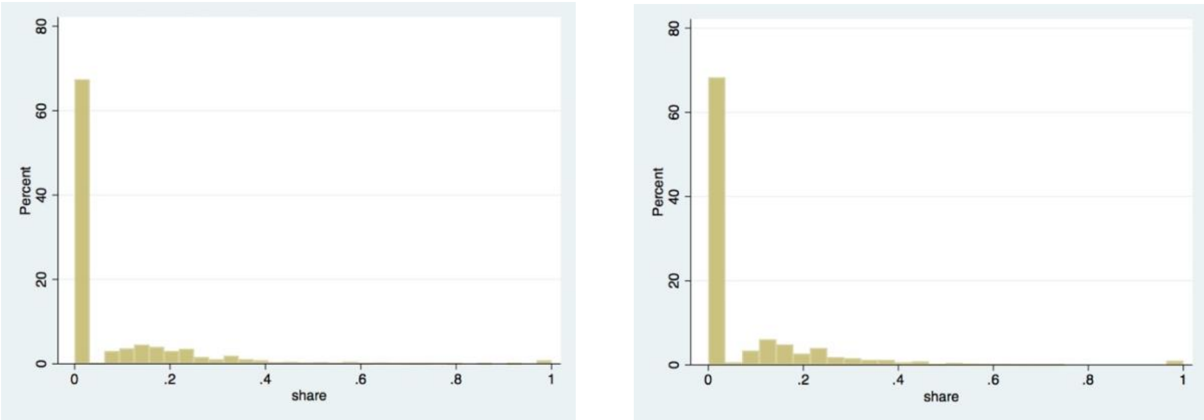
Variable	Unit of measurement	Mean one-time customers (523 obs)	Mean returning clients customers (823 obs.)
	Dependent variable		
Share climate-friendly dishes per order			
0	Continous variable	0.663	0.681
Between 0 and 1	Continous variable	0.327	0.31
1	Continous variable	0.010	0.009
	Explanatory variable		
Intervention			
Intervention	Binary variable	0.307	0.361
No intervention	Binary variable	0.694	0.639
Dish category			
First course	Binary variable	0.196	0.182
Second course	Binary variable	0.156	0.179
Sides	Binary variable	0.182	0.196
Poke	Binary variable	0.261	0.2
Menu	Binary variable	0.020	0.005
Dessert	Binary variable	0.075	0.077
Fresh Juices	Binary variable	0.11	0.161
Temperature			
T10	Binary variable	0.355	0.344
T20	Binary variable	0.341	0.294
T30	Binary variable	0.304	9.362
Weather			
Sun	Binary variable	0.619	0.597
Rain	Binary variable	0.381	0.404
Ordering method			
In store	Binary variable	0.744	0.614
Online	Binary variable	0.256	0.386
Time			
Lunch	Binary variable	0.787	0.849
Dinner	Binary variable	0.213	0.386
Frequency of orders			
High frequency	Binary variable		0.741
Medium frequency	Binary variable		0.19
Low frequency	Binary variable		0.069
Intervention persistence			
Same week	Binary Variable		0,012
After one weeks	Binary Variable		0,049
After two weeks	Binary Variable		0,035
After three weeks	Binary Variable		0,057
After more than three weeks	Binary Variable		0,127
Single order after label	Binary Variable		0,72

4.3 Empirical model

As we previously described in Table 3 and plotted in Figure 3, the share of climate-friendly dishes per order has an uneven distribution [0,1], whose extreme values are particularly interesting for our analysis. Therefore, we choose to model the data following Ospina and Ferrari (2012), who introduced the zero-and-one inflated beta distribution (BEINF), which is appropriate when the response variable takes values in a known range, including endpoints.

Figure 3-Dependent variable distribution

One-time customers **Returning Customer**



Source: Own illustration

The BEINF distribution is defined on four parameters (μ, ϕ, ν, τ) where μ is the mean parameter, ϕ is the precision parameter, ν representing the probability of excess zeroes and τ the probability of observing excess ones. To estimate correctly such distribution, we would need a mixture of a continuous beta distribution (0,1) and a Bernoulli distribution to get non-negative probabilities at 0 and 1 (Ospina and Ferrari, 2012).

For this reason, we will use zero/one inflated beta regression, ZIOB, which accounts for mass points at zero and one, based on the assumption that these are generated qualitatively different from the other proportion.

With the zero-one beta inflated regression (ZIOB) we are modelling a mixture of data-generating processes:

1. A beta regression, that predicts if an outcome is between 0 and 1 which is defined by μ and ϕ parameter. The parameters μ and ϕ are estimated separately, as they impose no restriction on each other. ϕ should be modeled separately if there is the presumption that certain variables influence particularly the distribution dispersion. As we do not believe that this is the case of our analysis, we will model ϕ only with the intercept, with a log link. Instead, we will focus our attention in estimating μ with a Logit link;

2. A Logit regression model that predicts if an outcome is 0 or not, defined by ν;
3. A Logit regression model that predicts if an outcome is 1 or not, defined by τ. As we have only a few observations equal to 1 (see Table 3), we modeled τ only with the intercept (Van Woerden et al; 2019).

To estimate the models we will use the user-developed package ziob, for STATA, with three different model specifications, Model 1, estimated *identically* both for the one-time customers and for the returning customers plus Model 2 and Model 3 estimated only for the returning customers.

We report Model 1 specification for each parameter estimated (μ, ϕ ,ν, τ). From now on, we will refer to Model 1 as Model 1-One-time customers and Model 1-Returning customers. For i=1,…523 & i=1,…823:

$$Logit(\mu) = \alpha + \beta_{intervention} * D_{intervention_i} + \boldsymbol{\theta} * \boldsymbol{A_i} + \varepsilon_i$$

$$Logit(\upsilon) = \alpha + \beta_{intervention} * D_{intervention_i} + \boldsymbol{\gamma} * \boldsymbol{B_i} + \varepsilon_i$$

$$Logit(\tau) = \alpha$$

$$Log(\phi) = \alpha \tag{1}$$

Where α is the intercept, β is the coefficient to the corresponding dummy indicating the label's introduction. θ is a vector of coefficients corresponding to the vector $\mathbf{A_i}$ of exogenous controls used to model the proportion share of climate-friendly dishes containing: dish category, weather conditions, time of the order, and the ordering method binary variables. $\boldsymbol{\gamma}$ is the vector of coefficients corresponding to the vector $\mathbf{B_i}$ of exogenous controls used to model the probability of observing a share equal to zero which contains: dish categories, time of the order and ordering method binary variables. Finally, ε_i is the random error term.

We excluded the weather variables control variables (i.e., temperatures and rain) from the Logit to estimate the probability of observing a share equal to zero as we do not believe they affect the excess zeroes. In other words, we presume that weather variables affect the mean of the distribution, affecting the probability of ordering a certain quantity of climate-friendly dishes (0<share<1), but that they do not specifically influence an extreme choice which is the probability of ordering none (share=0).

We estimated Model 2 only for the returning client's subset. The model has the same baseline variables as Model 1, but introduces the binary variables describing customer's order's frequency. We report Model 2 specification for each component estimated (μ, σ ,ν, τ), with i=1,…,823:

$$Logit(\mu) = \alpha + \beta_{intervention} * D_{intervention_i} + \boldsymbol{\theta} * \boldsymbol{A_i} + \delta_{frequencyoforders} * D_{frequencyoforders_i} + \varepsilon_i$$

$$Logit(\upsilon) = \alpha + \beta_{intervention} * D_{intervention_i} + \boldsymbol{\gamma} * \boldsymbol{B_i} + \delta_{frequencyoforders} * D_{frequencyoforders_i} + \varepsilon_i$$

$$Logit(\tau) = \alpha$$

$$Log(\phi) = \alpha$$

(2)

Finally, We estimated Model 3 only for the returning client's subset. The model has the same baseline variables as Model 1, but introduces the binary variables describing the intervention persistence. We report Model 3 specification for each component estimated (μ, ϕ ,ν, τ), with i=1,…,823:

$$Logit(\mu) = \alpha + \beta_{intervention} * D_{intervention_i} + \boldsymbol{\theta} * \boldsymbol{A_i} + \pi_{interventionpersistence} * D_{interventionpersistence} + \varepsilon_i$$

$$Logit(\upsilon) = \alpha + \beta_{intervention} * D_{intervention_i} + \boldsymbol{\gamma} * \boldsymbol{B_i} + \pi_{interventionpersistence} * D_{interventionpersistence_i} + \varepsilon_i$$

$$Logit(\tau) = \alpha$$

$$Log(\phi) = \alpha$$

(3)

5. Results

As previously explained, ZIOB regression consists of simultaneously estimated components, and in this work, we will focus the discussion on the results obtained for the proportion (0<share<1) and the zero-inflated part of the distribution (share=0). We report the estimated coefficients, the corresponding p-value and their marginal effects for Model 1 in Table 4 and for Model 2 and Model 3 in Table 5.

We will first present each model results for the estimation of Logit (μ), then, we will present each model result for Logit (ν), to see how the label introduction and the other explanatory variables impacts these two outcomes. To ease the interpretation of the coefficients, we computed the marginal effects at means.

Model 1: One-time vs. Returning customers

Considering the proportion of climate-friendly dishes per order, for one-time customers, the carbon label introduction does not affect the likelihood of ordering such dishes. The only explanatory variable influencing it belongs to the dish category. Specifically, one-time customers who order a dish belonging to the first course have a lower probability of choosing the dish identified as climate-friendly (-4,9 %). Similarly, when looking at returning customers the label's introduction does not affect the proportion of climate-friendly dishes per order. The only statistically significant variables belong to the dish category and ordering method group. Ordering a fresh juice (2,3%) or a poke (5.5%) decreases the probability of choosing the climate-friendly item. On the other hand, ordering online positively affects the probability of selecting a carbon-friendly item (1,9%).

Considering the probability of having zero shares of labeled dish per order, for one-time customers ,the intervention does not affect the probability of observing a share of carbon-friendly dishes equal to zero. Instead, the binary variables indicating the first course (21%), poke (36,1%), and fresh juices (14,9%) are statistically significant and decrease the probability of ordering the climate-friendly option.

Instead, the results differ for returning customers. In fact, for such customers the intervention is statistically significant decreasing the probability of observing a share equal to zero (13%), driving them from including zero-carbon friendly dishes per order to having at least one carbon-friendly option.

Instead, first course (19,8%), poke (28,2%), dessert (12,3%), and fresh juices (14%) are statistically significant, increasing the probability of observing a share equal to 0, thereby of not including the carbon-friendly option.

Model 2: Returning customers and order's frequency

In Model 2, we introduced binary variables measuring customers' ordering frequency. Neither the intervention nor the binary variables indicating the customer's frequency of orders influence this distribution component. Instead, Results show that choosing a fresh juice decreases the probability of selecting the carbon-label item in that category ((1,6%). Similarly, ordering online decreases the probability of selecting a carbon-friendly option, even if the effect is small(0,6%). Instead, when looking at the excess zeroes result, we observe that the intervention is statistically significant and positively affects the probability of choosing a climate-friendly option (14,3%). Instead, the variable describing a High Frequency of orders is statistically and positively affects the probability of not ordering a climate-friendly option (18,9%). First course (22,4%), poke (37,5%), dessert (13,9), and fresh juices (13,6%) are statistically significantly decreasing the probability of including the carbon-friendly dish when ordering one of those categories. Similarly, ordering online increases the likelihood of observing a share equal to zero (7,1%), thereby of not choosing a climate-friendly option. Finally,

Model 3: Returning customers and intervention persistence

In Model 3 we introduced the binary variables measuring the intervention persistence.

Results show that the binary variable indicating the orders placed three week after the first one have a lower probability of containing a labeled dish (2,9%). Moreover, we observe that, for the proportion of climate-friendly dishes per order, ordering a poke (6,4%) decreases the probability of including the carbon-friendly option. Likewise, ordering online (0,07%) decrease the probability of including a carbon-friendly option per order. For the excess zeroes model component, ordering a dish belonging first course (25,7), poke (36,6), dessert (14,3) or fresh juices (16,9), similarly to Model 1, decrease the probability of including a carbon-friendly item. We compared Model 2 and Model 3 to the returning customers baseline model (Model 1) using a likelihood ratio test showing that there is an improvement on the overall model's fit when including the variables indicating order's frequency (0.0001) while there is no improvement when including the variables indicating the order's persistence (0.6073).

Table 4: Model 1 ZIOB regression estimates

	Model 1- One time customers			*Model 1- Returning customers*		
Variable	Coefficient	P>|z|	Marginal effects	Coefficient	P>|z|	Marginal effects
			Proportion			
Intervention						
Intervention	0.494	0.393	0.025	0.059	0.837	0.032
No intervention			Omitted			
Time						
Lunch	0.174	0.117	0.010	-0.026	0.801	-0.001
Dinner						
Category						
First course	0.468***	0.008	-0.031	0.196	0.157	-0.043
Second course	-0.005	0.997	0.007	0.087	0.431	0.006
Poke	0.168	0.385	-0.089	0.319*	0.042	-0.066
Menu	-0.08	0.814	-0.023	0.244	0.504	0.075
Dessert	0.256	0.210	0.002	0.085	0.631	-0.029
Fresh juices	0.231	0.245	-0.027	0.267*	0.043	-0.023
Sides			Omitted			
Ordering method						
online	0.105	0.389	0.0195	0.201*	0.026	-0.002
In store			Omitted			
Weather						
Rain	-0.037	0.739	-0.002	-0.021	0.798	-0.001
Sun			Omitted			
Temperature						
T10	-0.179	0.176	-0.002	-0.036	0.751	-0.002
T20			Omitted			
T30	-0.583	0.313	-0.035	-0.090	0.752	-0.004
Intercept	-1.141***	0.000		-1.384***	0.000	
			One- inflate			
Intercept	-3.455***	0.000		-3.458***	0.000	
			Zero-inflate			
Intervention						
Intervention	0.0715	0.724	0.0134	-0.6501***	0.000	-0.133
No intervention			Omitted			
Category						
First course	1.024***	0.001	0.217	1.153***	0.000	0.237
Second course	-0.123	0.617	-0.027	-0.043	0.854	-0.011
Poke	1.699***	0.000	0.361	1.814***	0.000	0.36
Menu	0.316	0.610	0.067	-1.191	0.312	-0.279
Dessert	0.232	0.526	0.049	0.687*	0.034	0.15
Sides			Omitted			
Fresh juices	0.709*	0.035	0.149	0.798**	0.002	0.1655
Ordering method						
Online	-0.2212	0.296	-0.047	0.268	0.114	0.055
In store			Omitted			
Intercept	0.116	0.582		0.384*	0.024	
			ln_phi			
Intercept	2.024***	0.000		2.467***	0.000	
AIC	567.681			639.145		
BIC	672.476			752.253		

Legend: * p<.05; ** p<.01; *** p<.001, p-values reported in parentheses

Table 5: Model 2 and Model 3 ZIOB regression estimates

	Model 2- Frequency of orders			*Model 3- Intervention persistance*		
Variable	Coefficient	P>|z|	Marginal effects	Coefficient	P>|z|	Marginal effects
			Proportion			
Intervention						
Intervention	0.089	0.750	0.036	0.095	0.732	0.027
No intervention			Omitted			
Time						
Lunch	-0.023	0.821	-0.001	-0.035	0.781	--0.0017
Dinner			Omitted			
Category						
First course	0.229	0.100	-0.039	0.184	0.157	-0.048
Second course	0.082	0.460	0.007	0.075	0.539	0.005
Poke	0.302	0.053	-0.070	0.352*	0.025	-0.064
Menu	0.243	0.506	0.077	0.344	0.370	0.075
Dessert	0.126	0.476	-0.025	0.115	0.510	-0.026
Fresh juices	0.305*	0.023	-0.016	0.244	0.063	-0.025
Sides			Omitted			
Ordering method						
Online	0.199*	0.034	-0.007	0.229*	0.012	-0.0007
In store			Omitted			
Weather						
Rain	-0.008	0.922	0.000	-0.034	0.688	-0.001
Sun			Omitted			
Temperature						
T10	-0.030	0.793	-0.001	-0.037	0.730	-0.002
T20			-0.090			
T30	-0.109	0.694		-0.028	0.921	-0.001
Frequency of orders			-0.005			
High frequency	-0.113	0.255	0.011		not inluded	
Medium freqeuncy	Omitted				not included	
Low frequency	-0.237	0.173	0.019		not included	
Time persistence						
Sameweek	not included			-0.404	0.290	-0.007
Oneweekfrom	not included			-0.022	0.905	0.015
Twoweekfrom	not included			-0.154	0.539	-0.013
Threeweek	not included			-0.004*	0.031	-0.029
Morethanthreeweek	not included			0.004	0.980	
Intercept	-1.317***	0.000		-1.390***	0.000	
			One- inflate			
Intercept	-3.458***	0.000		-3.450***	0.000	
			Zero-inflate			
Intervention						
Intervention	-0.703***	0.000	-0.143	-0.049	0.078	-0.101
No intervention			Omitted			
Category						
First course	1.093***	0.000	0.222	1.258***	0.000	0.257
Second course	-0.058	0.808	-0.012	-0.035	0.881	-0.007
Poke	1.857***	0.000	0..378	1.789***	0.000	0.366
Menu	-1.434	0.227	-0.292	-1.274	0.288	-0.260
Dessert	0.681*	0.039	0.138	0.699*	0.034	0.143
Sides			Omitted			
Fresh juices	0.678**	0.009	0.138	0.826**	0.001	0.169
Ordering method						
Online	0.357*	0.040	0.073	0.262	0.131	0.053

In store			Omitted			
Frequency of orders						
High frequency	0.932***	0.000	0.189	not included		
Medium frequency	Omitted			not included		
Low frequency	0.476	0.166	0.097	not included		
Intervention persistence						
Sameweek	not included			-0.289	0.711	-0.057
Oneweekfrom	not included			-0.351	0.403	-0.071
Twoweekfrom	not included			0.128	0.793	0.026
Threeweek	not included			0.120	0.799	0.024
Morethanthreeweek	not included			-0.374	0.260	0.076
Intercept	-0.399	0.097		0.277	0.123	
			ln_phi			
Intercept	2.476***	0.000		2.486***	0.000	
AIC	623.7938			646.438		
BIC	755.7566			797.136		

Legend: * p<.05; ** p<.01; *** p<.001, p-values reported in parentheses

6. Discussions and Conclusions

This natural field experiment evaluated how introducing a carbon label on a menu affected consumers' choices in a full-service restaurant.

Specifically, we investigated how introducing the carbon label, affected the share of carbon-friendly dishes per order highlighting differences between one-time a restaurant's returning customers. Considering RQ1, we showed that introducing the carbon label does not affect the previous ordering choices of one-time restaurant customers. This result agrees with the previous literature, which concluded that a carbon label *per se* is not enough to impact consumers' food choices (Spaargaren et al; 2013, Soregaroli et al; 2021).

Instead, considering RQ2, we show that the label introduction positively affects returning clients' behavior, generating awareness and driving them from including zero climate-friendly options per order to include at least one. The label's potential is enhanced if we consider that our results showed that highly-returning customers before the label introduction preferred not to order carbon-friendly items. This implies that the intervention can affect consumers' previous not environmentally-conscious habits driving them to a more environmentally-friendly consumption. The carbon label has the power to increase the number of returning customers willing to order a carbon-friendly dish. From this, we can argue that it is an effective tool for modifying the ordering routine for habitual customers but not the choices of random customers who visit a restaurant only once.

This result opens to policy-relevant considerations reminding us of the importance of accounting for repeated choices when designing a label. Habitual clients will be exposed multiple times to a label as they look at the menu more than once, and this induces familiarity with the information tool. Familiarity and trust with a label increase its usage (van Herpen et al; 2012). From this, we understand that a carbon label conceived as we currently do is not powerful enough to affect the choices of those who are exposed occasionally or even once to it. Customers seem more skeptical toward brands claiming "climate-friendly" food attributes (Sirieix et al; 2013). Policymakers should consider this lack of trust when designing a carbon label. If consumers do not find a message believable, they will not change their preferences.

Results suggest that carbon labels should be considered an integrated tool and not *per se*. The market's wide range of environmental claims does not help customers make conscious choices and transform their attitudes into actual purchase choices. Trust plays a fundamental role when customers evaluate a product's credence attributes (Karstens and Belz, 2006), as a product's carbon-friendliness. Literature shows that an organization promotes it generates a role in promoting a label (Zepeda et al; 2020, Khachatryan et al; 2021). In this work, we introduced only voluntary instruments, and customers might not put too much trust in claims made by individuals in a market that is already saturated with sustainability claims. We believe that a public carbon label with a recognizable logo could improve the effectiveness of such an instrument as it would increase the trust and familiarity that customers place in it.

Indeed, our results show that customers exposed multiple times to a label positively react to it. This makes us presume that a well-designed and well-understood information tool has the potential to modify customers' choices effectively in a long time frame.

The conducted study has different elements of novelty. This study is among the first attempts to assess differences between one-time and returning consumers' food choices after a carbon-label provision in a natural choice scenario. Moreover, data availability at an individual level allowed us to truly evaluate the same customer's pre and post-label behavior, allowing us to uncover new behavioral patterns.

However, it presents some limitations.

We could not identify whether the effect of the label is short-run or long-run; therefore, we cannot draw definitive conclusions about the instrument's persistence on customers' choices. This lack of identification is linked to the fact that we do not have a long period of observations after the label introduction, and we believe that more research is needed to understand the bond between labels and time. Moreover, we collected results only for one restaurant in a specific geographical; therefore, the results might lack of external validity. We believe more observations could help us understand consumers' reactions over time. Finally, we tested the introduction of only a design of a carbon label. We consciously choose a simple design, but we believe it would be worth investigating the impact of different logos such as traffic lights or color-based labels to see how consumers' choices react to it.

To conclude, we believe that accounting for returning customers' choices taught us an important lesson on how to improve the way to vehiculate carbon information to every customer. However, to truly achieve sustainable development goals and curb carbon emissions, a better conceptualization of these information tools is needed, and this poses an urgent challenge to be tackled by policymakers.

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