Carbon information, pricing, and bans. Evidence from a field experiment

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Abstract

How can we encourage the adoption of low carbon footprint (CF) consumption habits? In a large-scale field experiment at a university canteen, we find that adjusting dish prices to positively correlate with their carbon footprint is the most effective policy, leading to a 26.8% reduction in CF. This approach outperforms policies such as banning high-CF dishes once a week (10% CF reduction) or merely informing consumers of dishes' CF (non-significant reductions). In a follow-up survey, when asked to choose between taking no action and these three policies, only 3.5% of respondents preferred no action, while 60% supported the price adjustment policy.

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1 Introduction

Global warming, which is primarily attributed to human activities, has emerged as one of the most pressing global challenges of the 21st century. Most human carbon emissions result from the production of goods and services that ultimately meet people's needs and desires. Until technological progress makes low-carbon options available, affordable and widespread, a reduction in anthropogenic carbon emissions can only be achieved by changing human habits. This paper seeks to answer two key questions: First, what is the most effective policy to encourage people to change their consumption habits in order to reduce their consumption carbon footprint (hereafter CF).[1] Second, which policy is the most socially acceptable and therefore most likely to be actually implemented?

Our study focuses on dietary choices because, among various contributors to greenhouse gas emissions, the production, processing, transportation, and disposal of food account for between 25% and 30% of human carbon emissions (Crippa et al. (2021); Poore and Nemecek (2018)).

Social scientists have identified three broad policy approaches that could influence consumer choices. The first is a prescriptive approach, where regulation prohibits the supply of carbon-intensive goods whenever a low-carbon alternative is available. The second is a pricing policy that makes the low-carbon option less expensive than the high-carbon one, for example through a system of subsidies and taxes. The third approach is to provide consumers with clear and reliable information about the carbon footprint of their choices, without affecting the supply or price of each option. While the effectiveness of the first two policies relies on standard economic channels, the last policy can only be effective if consumers have an intrinsic preference for the low-carbon option but currently lack information about the actual CFs of the available options.

To explore the effectiveness of each policy, we conducted a field experiment in the HEC Paris canteen. We had access to the daily individual lunch choices of all users of the HEC Paris canteen from August 2021 to mid-June 2023, totaling more than 4,000 users and nearly 140,000 meals purchased.[2] To study the effectiveness of the supply regulation policy, we analyzed the introduction of meat-free-Thursday from September 2022 to June 2023. We evaluated the effect

[1] Consumption carbon footprint here refers to all greenhouse gas emissions resulting from the production, use and disposal of consumer goods.

[2] The HEC Paris canteen is open at lunch but not in the evening.

of the information policy by publicly displaying the CF of each main dish at the counter from November 21, 2022 to March 10, 2023. We evaluated the impact of the pricing policy by changing the prices of the dishes for four weeks between March 13, 2023, and April 28, 2023. The price change followed a bonus-malus system that decreased the price of dishes with CF below the median and increased the price of dishes with CF above the median. The sensitivity of a dish's price to its CF varied each week during the bonus-malus period.

We had access to anonymized data that provided each user's key demographic characteristics, as well as the dishes they purchased over the entire period. Using a difference-in-differences approach, we found that the pricing policy was the most effective policy to induce users to choose low-CF dishes. Making low-CF meals slightly cheaper than high-CF meals resulted in a significant reduction (24%) in the average CF of meals purchased. In comparison, eliminating meat one day per week reduced the average CF of purchased dishes by between 10% and 12% on a weekly basis, but also reduced canteen attendance on the meat-free day, suggesting some form of carbon leakage. Providing information about the CFs of the dishes led to inconclusive results, as the change in the average CF of the dishes purchased after the information was displayed was not statistically significant.

To explore the social acceptability of each policy, we conducted an Internet survey between December 2023 and March 2024 among the same population of canteen users, i.e., HEC students and employees.[3] Key elements of the survey included informing subjects about the results of the field experiment and asking them to choose between the status quo situation, in which supply and prices are as in 2021 and the CFs of dishes are not displayed, and three different policies: a supply regulation policy that eliminates read meat two days per week, a bonus-malus pricing policy, and a CF information-only policy. The bonus-malus pricing policy was preferred by about 60% of respondents, while about 30% voted for a supply regulation policy. Only 6.5% and 3.5% chose the information-only policy and the status quo, respectively. This provides clear evidence that the policy that makes the low-carbon alternative less expensive than the high-carbon one is both the most effective in reducing CF consumption and the most politically acceptable.

We think that the specific framework of our experiment is of general interest for three reasons. First, as food consumption accounts for between 25% and 35% of human carbon emissions

[3]Because of student turnover and survey response rates, there is not a perfect match between canteen users during the field experiment and survey respondents.

throughout its life cycle, there is a growing interest in understanding how consumers' choices regarding food consumption can be influenced to reduce this environmental burden.[4] Second, the reduction of anthropogenic greenhouse gas emissions crucially depends on the attitude of firms' managers when making carbon footprint-relevant decisions. Our sample of international business students provides a valuable setting to measure such attitudes in the next generation of managers.[5] Third, we believe that the effectiveness of the pricing policy in reducing the CF of food choices can be extended to other types of goods, particularly those whose desirability is not strongly correlated with their carbon footprint. While food choices are fundamentally influenced by idiosyncratic culinary tastes, which happen to be correlated with the CF of dishes, the same does not apply to other types of goods. For instance, while a substantial change in relative prices might be necessary to persuade a red-meat lover to switch to poultry, a moderate price change could be effective in encouraging households to switch from electricity generated by fossil fuels to that generated by renewable sources.

In the remainder of the paper we first discuss our paper contribution the literature. In Section 2 we describe the setting of the field experiment and its finding. In Section 3.1 we describe the survey its results and how they can be used to better understand the field experiment finding. In Section 4 we discuss external validity and the policy implication of our main findings. Section 5 concludes.

1.1 Contribution to the literature

There are different streams of literature related to our work. First, we contribute to the literature analyzing how individuals react when informed about externalities linked to their choices. This literature includes papers specifically looking at the reaction of food choices to carbon footprint information, but also, more generally, works analyzing the reaction of people to the information about the social sustainability of the firms they interact with, as customers or as investors. The papers in this literature that are closest to our work are: Spaargaren et al. (2018), Brunner et al. (2018), Lohmann et al. (2022), Beyer et al. (2023). Like us, these papers run field experiments at university canteens and measure how users react to the posting of food CF information. Differently from our work, none of the above papers studies the effect of policies aiming at the

[4] In 2022 the estimate of greenhouse emission from HEC food and catering service amounted to 4043 tons and represented 39% of all emissions resulting from internal operation (SouthPole (2023))

[5] HEC Paris is ranked by the Financial Times among the top business schools worldwide (`https://rankings.ft.com/home/regional-rankings`) and more than 90% of its graduates hold managerial positions or run their own companies at some point in their careers.

alignment of dish prices according to their carbon footprint. Whereas the exact CF labeling differs across papers, like in our paper, the CF labels involve traffic light-colored letter grades and numerical indication of the dishes' CF footprint. These papers find that the introduction of CF labels is associated with a relatively small but statistically significant reduction in the average carbon footprint of purchased meals (3.6% in Brunner et al. (2018), 4.3% in Lohmann et al. (2022) and up to 9.2% in Beyer et al. (2023)).

In our study, we find no statistically significant effect of posting information on the carbon footprint of purchased meals. One possible explanation for such differences may arise from variations in the identification strategy.[6] However, it is more likely attributable to the differences in the study's subject population. For example, whereas students in previous experiments come from different fields, the lack of reaction to information that we document could be specific to the business school population in our study.[7] This is in line with the existing empirical and experimental evidence showing that business school or economics students (Carter and Irons (1991)) and professors (Frank et al. (1993)) tend to be more self-interested and money-driven than the rest of the population.[8]

The absence of actual reaction to CF information that we observe substantially differs from the results of survey-based studies that measure subjects' intention rather than their actual behavior in field experiments. Steg (2016) reviews factors influencing and encouraging pro-environmental actions by individuals and households. Among the effective factors she identifies changing the costs and benefits of behavior, reducing cognitive effort, and providing information and feedback[9]. It is well known, however, that there is a gap between consumers' intentions and consumer behavior (Morwitz (2012)). In this perspective, of particular interest for our work is

[6]For example, Beyer et al. (2023) rely on within-day identification, which allows them to control for all calendar day-specific factors, including the menu composition on a given day, whereas in our study, we control for the equal-weighted CO_2 of the dishes offered on a given day to absorb supply-driven effects. However, the result of Beyer et al. (2023) is based on 10 days of experimentation whereas in our study, the information treatment lasted for more than 3 months. Lohmann et al. (2022) compare the behavior of consumers in treated college canteens vs. untreated college canteens in a Diff-in-Diff setting, which allows them to control for time fixed effects. However, in Lohmann et al. (2022), the menus and their evolution differ across treated and non-treated canteens. By contrast, we use the previous academic year data from the same canteen and we rely on the academic calendar fixed effects, which allows us to control for a wide range of academic and calendar seasonality effects. We further control for the local weather and Google Trends associated with carbon footprint, and check that our treatments do not coincide with any school-level environmental policy.

[7]HEC Paris offers only business degrees (such as MBA, pre-experience Master in Management) or degrees that provide a bridge between business and other fields of study (for example, Master in Data Science for Business).

[8]Experimental evidence of business and economic students having a more selfish attitude than other populations has also been provided in Marwell and Ames (1981), Björn and Schulze (2000), Frey and Meier (2003), among others.

[9]See also Rondoni and Grasso (2021) for a literature review specific to consumers' attitude toward carbon footprint labels.

Malaingre (2022) who conducted an internet survey among HEC Paris students and employees during the Spring 2022, a sub-sample of the population in our field experiment. Her survey had a similar research question of the field experiment that we conducted. She compared what people would select in a hypothetical menu of 5 dishes before and after providing information about the carbon footprint of the proposed dishes. From the answers of 642 subjects who completed the online survey, she finds that providing information about the carbon footprint of dishes would reduce the average carbon footprint of purchased meals by about 30%. Our field experiment, shows that when facing actual food choices, subjects seem not to be affected by the provision of carbon footprint information, and only monetary incentives have a significant impact.

Our paper also contributes to the broader literature analyzing consumers' or investors' attitudes and actual behavior when informed about firms' sustainability performance. Christensen et al. (2023), and Leonelli et al. (2023) find that end consumers' reaction to information about firms' sustainability is transitory and only significant for a few highly visible events.

The theoretical literature on sustainable finance literature showed that whether responsible investing can have an impact depends on investors' preferences (see for instance Heinkel et al. (2001), Broccardo et al. (2022), Landier and Lovo (2020), Green and Roth (2020), Bolton and Kacperczyk (2021)) but also on entrepreneurs attitude (see for instance Oehmke and Opp (2019), Edmans and Levit (2023). In this perspective, willingness to pay to contribute to a public good is key. Our findings contribute to the literature suggesting that in actual situations subjects are not keen to change their habits in the general interest, but can be induced to change if appropriately incentivized.

2 The field experiment

2.1 Experimental design and background

Our field experiment was conducted in the canteen of HEC Paris and took place during the academic year 2022-2023. We also have access to users' daily food choices for the academic year 2021-2022. Most HEC students and staff eat their daily lunch in the HEC Paris canteen. Despite its name, HEC Paris is located in the countryside, 25 km southwest of Paris. As a result, students and staff have very few alternatives for their daily lunch besides the HEC canteen. Since HEC Paris heavily subsidizes the canteen's food prices, the quality/price ratio is unbeatable compared to the few nearby restaurants. This ensured that attendance at the HEC cafeteria was not influenced by the change in information or the change in price during the experiment, as shown in Figure 2.[10] Thus we had a relatively robust setting for our field experiment where both information and prices are controlled by the experimenter. Because users pay using their employee or student cards, each user's daily purchase at the HEC canteen is recorded in a database dating back to 2021. We have access to this database after the ID had been anonymized. Anonymized IDs do not change over time, allowing us to follow each user's daily consumption choices across time. For each anonymized ID, we had coarse individual demographic data, so that the user's identity could not be recovered from our database.[11] In particular, we know each user's gender, age bin, continent of origin, academic program for students, and for the employees, we observe whether the user is a faculty member or not. The first phase consisted of simply gathering people's consumption choices in normal conditions, starting from 23 August 2021 until 21 November 2022 (not inclusive). On each main dish stand, the dish name and its price were posted (see panel A of Figure 1).

Between March and April 2022, Malaingre (2022) conducted an online survey with HEC students, staff, and faculty. A total of 642 individuals participated.They were then asked to choose one of five dishes (See Figure 16 panel A). Next, participants were shown the carbon footprint of each dish, either as a letter grade or in kilograms of CO_2 equivalent per portion, and were asked to choose a dish again (See Figure 16 panels B and C). The survey results from Malaingre (2022) show that after viewing the carbon footprint information, the average carbon footprint of the dishes selected was two-thirds of the footprint of the dishes initially chosen. A very promising finding regarding the potential effectiveness of the information-only policy, that encouraged us to run the field experiment of this paper.

At the very end of the benchmark phase, we run a hand-collected survey among users to measure people's knowledge of the carbon footprint of different food in general, which showed a low average level of awareness about the carbon footprint of the dishes (See Table 14).

The information-only treatment phase started on November 21st, 2022, and ended on March 10th, 2023. During this phase, we replaced the original posters on each main dish stand with posters that included the dish CF information. We wanted the carbon label design to be as visible and understandable as possible. Following Brunner et al. (2018) and Lohmann

[10]The same cannot be said for the introduction of the meat-free Thursday, as attendance decreased by a significant 15% compared to Thursdays when a meat was available.

[11]As an example, nationality was at the continent level, and age was provided in bins of 10 years.

et al. (2022), our carbon footprint label design included a letter grade in traffic light color, numerical information, and contextualization to interpret the numerical information. Namely, as illustrated in panel B of Figure 1, next to each main dish stand it was posted, from top to bottom: The dish carbon footprint per portion (as obtained from www.agribalyse.ademe.fr); a letter grade in traffic light colors from $Grade \in \{A^+, A, B, C, D, E, F\}$; a scale with the different letter grades and kg CO_2 eq. thresholds; a contextualization statement "1 kg CO_2 = 7.5 km by car", and the price of the dish. We also posted in different places among the food stands and at the entrance of the restaurant a poster with the letter grades and letter thresholds (see Figure 10).

In price treatment phase, we changed dishes prices during four weeks in the period between 13 March 2023 and 28 April 2023.[12] The weeks were not consecutive and were chosen to be outside the academic and French holidays weeks (see Table 1). The week before the start of the phase, an email was sent by the HEC director to the entire HEC community to inform people that the price would have changed according to the bonus-malus pricing system. Within any given week w the price of carbon did not change. For a given week w, the price of each main dish i was changed according to the following formula:

$$NewPrice_i = OldPrice_i + (FCFP_i - 3)V_{CO2,w} \tag{1}$$

where $FCFP_i$ is dish i's carbon footprint in kg CO_2 eq. per portion, and $V_{CO2,w} \in \{0.1, 0.25, 0.5, 0.1\}$ is the value of CO_2 (in Euros) per kg for week w. The threshold of 3 kg CO_2 eq. corresponds to the median carbon footprint of the main dishes in our sample. Hence, the pricing treatment resulted in a "bonus", i.e. a reduction in the dish price, for dishes whose $FCFP_i$ was below the median (3 kg CO_2 eq.), and into a "malus" i.e., an increase in the dish price for dishes whose $FCFP_i$ was above the median. To minimize the chances that users ignore this change in prices, posters on each main dish stand where changed to incorporate the new price resulting from the bonus-malus information as illustrated in Figure 11. Also, we posted at the entrance of the canteen a large whiteboard indicating the functioning of the bonus-malus system, the price of carbon for that week and a QR code redirecting to a webpage with FAQ about the bonus-malus

[12]Importantly, the pricing phase was nested within the information phase, which ended on May 5th.

system and the experiment in general (see Figure 12).[13] [14]

In order to assess the efficacy of supply regulation, we exploit the implementation of meat-free Thursdays from September 2022 to June 2023, a policy that was decided by the HEC Paris administration before we started the information and the price treatment.

Finally, in a fourth phase, all information about dishes' carbon footprint was removed and the prices went back to their level during the first phase. At the beginning of this phase, we run exactly the same hand-collected survey we run at the end of the benchmark phase. Table 1 provides the calendar dates of the relevant events of the experiment.

2.2 Data description

Our data covers the choices of all HEC canteen users in the period from 23 August 2021 until 16 June 2023. This period can be divided into two sub-periods: the benchmark period from 23 August 2021 until 21 November 2022 (not inclusive), and the period of treatments from 21 November 2022 onward. Summer, Christmas, Winter, and Spring breaks were removed as in those periods there is very little canteen attendance or the canteen is closed.[15] Over the whole period, we observed the individual choice of about 4,000 distinct individuals, for a total of about 140 thousand purchased meals. Each individual had lunch at the canteen an average of about 55 times, although the distribution is skewed with some individuals having up to 300 meals.[16] The population is composed of about 3,500 students, about 500 staff and more than 150 faculty members. Women represent 45% of the population. Users' age spanned from 20s to 60s.[17] Six continents were represented, with the following distribution: 67.7% from Europe, 16.9% from Asia, 7.2% from Africa, 4.7% from South America, 3.4% from North America, and less than 1% from Oceania. See Table 3 for details. Over the whole period, a total of 81 distinct main dishes were offered. In a typical day, a user could choose among 8 to 10 different main dishes. Some

[13]The QR code lead to the FAQ still available at https://people.hec.edu/lovo/food-carbon-footprint-experiment/

[14]During the first days of changes in prices, "ambassador" students were present at the entrance of the canteen and inside the canteen to answer additional questions users might have about the bonus-malus system.

[15]HEC canteen works from Monday to Saturday, but the attendance on Saturday is much lower, while the menu offer is narrower and more volatile. Therefore, we exclude all dish purchases made on Saturday from our sample.

[16]To eliminate customers that do not constitute a typical customer of HEC Paris canteen, we required at least 10 observations per each individual for a given individual to be included in the sample

[17]All individuals aged 29 and younger were grouped in "20s" category, while all individuals aged 60 and older were grouped into "60s" category for the data privacy considerations. In our analysis, whenever a continuous age variable is required (e.g. in regressions), we use the lower bound age for any given age category (and 20 for "20s"). Since we are interested in a relative comparison between different age groups, the level effect does not matter for our conclusions.

dishes were regularly on the daily menu whereas others were offered with a lower frequency. Also, not all dishes that were regularly on the menu encountered the same popularity among users. As a result, the 10 most popular dishes make up 71.3% of the total sale volume (see Table 4).

During the benchmark phase, the original prices of the main dishes ranged from 3.5 to 6.5. The mean price (standard deviation) of the main dishes in the menu constituted 4.16 Euros (0.7 Euros). The mean price (standard deviation) of main dishes actually purchased was 4.46 Euros (0.93 Euros). During the bonus-malus treatment weeks, the average price of the main dish offered in the menus was 4.04 Euros, but not statistically significantly lower than in the rest of the sample. However, the average price users spent for purchased dishes decreased by 4.2%, 7.1%, or 32.8% depending on the value of carbon being of 0.25, 0.50, or 1 Euro/kg CO_2 eq., respectively (see Figure 8).

The carbon footprint of main dishes ranged from 0.1 to 12.4 kg CO_2 eq. per dish portion. The equally weighted (purchase-weighted) average of dishes' carbon footprint during the benchmark period study was 3.28 (3.31) kg CO_2 eq. Note that there is a substantial time variation in the average carbon footprint of the main dishes on the menu, as illustrated in Figure 3. This happens beyond the fact that starting from the third academic week of 2022, following a decision of HEC Paris administration, red meat was not on Thursday's menu. We also find that the carbon footprint of supply on a given day matters. A change in the equal-weighted average carbon footprint of dishes offered on a menu produces about the same change in the average carbon footprint of the dishes actually consumed.[18]

2.3 Food choices in the benchmark period

To isolate the effect of carbon information and pricing on food choices, we first examine how other factors influenced users' choices during the benchmark phase and how these choices translate into the CF of purchased dishes. A user's food choice is influenced by both demographic characteristics and day-specific factors. For each individual, we had the following demographic characteristics: gender, age group, and continent of origin. For each student, we observed the program in which the student was enrolled, and for each employee, we can distinguish between faculty and staff. The day-specific factors we considered were the equal-weighted average of the CF of the dishes on that day's menu, the local weather conditions (temperature, precipitation,

[18]See the regression coefficient corresponding to $CO2.EW$ in column 5 of Table 5.

and cloud cover for that day), and Google Trends worldwide (to reflect the international nature of HEC's student and faculty community) for the keyword "carbon footprint".

We then run the following regression over all meals purchased in the benchmark phase:

$$CO2_{i,t} = \delta_1 Demo_i + \delta_2 DayFactors_t + \epsilon_{i,t} \tag{2}$$

Where $Demo_i$ and $DayFactors_t$ are vectors of the above-mentioned characteristics, and $CO2_{i,t}$ is the carbon footprint in kg of CO_2 eq. of a dish purchased by individual i on day t. In the same spirit, we also consider how individual characteristics and day-specific factors affect the probability of an individual choosing high-CF dishes i.e., a dish with CF of at least 5 kg CO_2 eq. These are the dishes that are labeled E or F in the information phase (see Figure 10). We run the following linear probability regression:

$$CO2\_rank\_EF_{i,t} = \delta_1 Demo_i + \delta_2 DayFactors_t + \epsilon_{i,t} \tag{3}$$

Where $CO2\_rank\_EF_{i,t}$ is a dummy variable equal to 1 if the dish consumed by user i on a day t has a CF of at least 5 kg CO_2 eq. per portion (CF labels E and F). As shown in table 2, we find that women are significantly more (less) likely to choose low (high) carbon footprint dishes. Users' age is negatively correlated with the carbon footprint of their chosen dishes. Being from North America or Asia or enrolled in HEC's Master in Sustainability is negatively correlated with the carbon footprint of the purchased meals. After controlling for gender and age, we find that students tend to opt for higher CF meals compared to the choices of staff and faculty. The most relevant day-specific factor for the average carbon footprint of meals consumed is the equally weighted carbon footprint of the dishes offered on a given day's menu. The average CF is also significantly correlated with the weather conditions of the day, as well as Google Trends for the keywords "carbon footprint". Overall, the OLS regression based on (2) explains up to 8% of the total variability in the carbon footprint.

2.4 Empirical strategy

This section outlines the empirical strategy employed to identify the effect of treatments. Due to institutional constraints, it was not possible to implement an experimental design with a concurrent control group. HEC Paris has a single main canteen, and a randomized provision of information to different consumers would have necessitated the transmission of personalized information regarding the specific day's menu to each customer prior to their visit to the HEC canteen. Such an approach would have posed two significant challenges. Firstly, it would have been practically infeasible for a researcher to guarantee that treated individuals did not pass on the information to their non-treated peers, which would have violated the identifying assumption that the control group did not receive information. Secondly, the treatment effect that we are interested in is the effect of posting information that is publicly visible, which is consistent with how provision of carbon footprint information could be implemented in practice. In addition, for the price treatment, fairness and public relations constraints also apply to price treatments. It would have been practically infeasible for HEC Paris to justify to price-treated individuals why they have to pay according to a different price scale. Therefore, an alternative control group is needed.

We use data from the academic year preceding the treatment year as a control group. Such empirical strategy allows us to control effectively for any academic seasonality effects for different sub-groups of the HEC Paris population, including potential effects of program-specific environment-related curriculum. We further use concurrent weather controls as well Google Trends to control for time-series of searches for the keywords "carbon footprint" to control for slow-moving changes in the interest in the topic of sustainability. We also contacted an HEC environmental student association with a request for the list of all significant environment-related events (e.g. guest lectures and other events outside of the regular curriculum) to make sure that the timing of our information treatment does not coincide with any of these events.

The effect of treatments is estimated in Diff-in-Diff framework, using the preceding academic year as a control group. We saturate the regression specification with fixed effects to control for a set of potential selection effects. We include person-academic year fixed effects to absorb potential differences between individuals who were working or studying at HEC in two different academic years.[19] We absorb potential differences in intra-week behaviour by including weekday fixed effects interacted with academic year (i.e., Thursday effect in 2021-22 is allowed to be different from Thursday effect in 2022-23, which is important in view of "No-meat Thursday" policy introduced at the beginning of 2022-23). We estimate the effect of information and price treatments in two separate regressions, each performed on sample windows surrounding respective treatments. More in details:

[19]Most individuals in our sample are present only for one academic year (1-year long master programs). For those customers who are present in both academic years, person-academic year fixed effect essentially allows for a different average behaviour in the two academic years (which absorbs potential changes in diet across years).

Information-only treatment: For the information treatment, we focus on a window of 11 academic weeks before to 12 academic weeks post-information treatment.[20] To ensure that our estimates are representative of a regular customer at HEC canteen, we require each individual to have at least 5 meals before information treatment and at least 5 meals post-information but pre-price treatment.

Our main specification is therefore:

$$\begin{aligned} CO2_{i,y,t} =& \theta InfoPostTreat_{y,t} + \zeta Controls_{y,t} + Person \times AcademYearFE_{i,y} \\ &+ AcademWeek \times ProgamFE_{i,t} + AcademYear \times WeekdayFE_{y,t} + \epsilon_{i,y,t} \end{aligned} \tag{4}$$

$CO2_{i,y,t}$ is the carbon footprint (in kg of $CO2$ equivalent) of the meal consumed by individual i in academic day t (academic week $\times$ weekday) of the academic year y. $InfoPostTreat_{y,t}$ is an indicator variable equal to 1 if information posters were put in place in the academic day t of academic year y and zero otherwise. Note that in a standard for Diff-in-Diff framework, we would also include $InfoPost_t = 1$ if the academic day t is in academic week #14 or later (in either year) and zero otherwise, and $Treat_y = 1$ if the academic year is 2022-23 (treatment year) and zero otherwise. In our specification, the $InfoPost_t$ variable is fully absorbed by academic week fixed effects, while $Treat_y$ is absorbed by academic year fixed effects.

To test for common pre-trends before information treatment as well as for the potential gradual effect of information, we extend the previous specification by including weekly version of $InfoPostTreat_{y,t}$:

$$\begin{aligned} CO2_{i,y,t} =& \sum_{w \neq -1} \theta_w InfoTreatWeek(w)_{y,t} + \zeta Controls_{y,t} + Person \times AcademYearFE_{i,y} \\ &+ AcademWeek \times ProgamFE_{i,t} + AcademYear \times WeekdayFE_{y,t} + \epsilon_{i,y,t} \end{aligned} \tag{5}$$

Price treatment Similarly to our information treatment regression, for the price-treatment, we focus on a sample of regular HEC canteen customers, which are defined for price treatment as customers that had at least 3 meals post-info but pre-price, and at least 1 meal each price treatment and at least one meal during the placebo breaks (to control for the possibility of

[20] "No-meat Thursdays" were introduced on 3rd academic week of 2022-2023 academic year, which is 11 academic weeks before the information treatment. Therefore, we restrict our window to academic weeks post-"No meat Thursdays" to make sure that our academic year-weekday fixed effects absorb the effects of "No-meat Thursdays".

induced by price treatment trends in behavior).

$$CO2_{i,y,t} = \sum_{w\neq -1} \theta_w PriceTreatWeek(w)_{y,t} + \zeta Controls_{y,t} + Person \times AcademYearFE_{i,y}$$
$$+AcademWeek \times ProgamFE_{i,t} + AcademYear \times WeekdayFE_{y,t} + \epsilon_{i,y,t} \tag{6}$$

No-meat treatment We proceed with a similar strategy to measure the effects of "No-meat Thursday". Since this intervention commenced in the 3rd academic week of the year 2022-2023, we are restricted to only 2 academic weeks before the treatment, and we study 4 weeks following the intervention. As "No-meat Thursday" is affecting the supply of high-CO_2 dishes only on Thursdays, we measure the effect as an interaction.

$$CO2_{i,y,t} = \theta_0 NoMeatPostTreat_{y,t} + \theta_1 NoMeatPostTreat \times d.Thursday_{y,t}$$
$$+\zeta Controls_{y,t} + Person \times AcademYearFE_{i,y} + AcademWeek \times ProgamFE_{i,t} \tag{7}$$
$$+AcademYear \times WeekdayFE_{y,t} + \epsilon_{i,y,t}$$

Dummy $NoMeatPostTreat_{y,t}$ is equal to one strating from academic week #3 in the academic year 2022-23 (when the no-red meat ban has been put in place) and zero otherwise. Thus, θ_1 in the equation above corresponds to the difference between non-treated weekdays and treated by no-meat policy Thursday, while θ_0 is expected to be zero unless meat supply restrictions introduced on Thursday change individual behavior during non-treated weekdays. We refer to θ_1 as the effect of *no-meat policy.*

Similarly to previous studies, we also perform regressions with alternative dependent variables, including natural logarithm of carbon footprint $log(CO2_{i,y,t})$ as well as binary outcome variables $CO2\_rank\_ABC_{i,y,t}$ and $CO2\_rank\_EF_{i,y,t}$ equal to 1 if the dish purchased belongs to A+,A,...,C or E-F $CO2$ categories, respectively, and zero otherwise.

2.5 Results

2.6 The effect of information-only policy

Starting from Monday, November 21st 2022 until Friday, May 5th 2023, on each main dish stand, there was a poster indicating the carbon footprint of the dish. We test whether posting carbon information has an effect on the behavior of consumers using regression specification (5) and focusing on the window of up to 12 academic weeks after the introduction of information to allow for a gradual onset of the effect. Figure 4 plots the estimates of coefficients θ_ω with 95% confidence intervals. Insignificant coefficients before the introduction of information treatment show that our treatment and control groups are comparable, supporting the validity of our identification strategy. We find, however, no statistically significance evidence supporting the hypothesis that posting carbon information affects the behavior of HEC canteen users, neither immediately after the treatment nor in the subsequent academic weeks. Similarly, the introduction of carbon information did not significantly decrease the probability of choosing E- or F-labeled dishes (See Appendix A).

We then check whether users reacted differently to the posting of information depending on their demographic characteristics. We find no significant difference in how women and men reacted to information, nor difference across continents of origin. Also, students, staff, and faculty seem to be equally insensitive to the posting of information (See Table 6).

2.7 The effect bonus-malus pricing

In the bonus-malus pricing treatments, we modified dishes' prices to incorporate their carbon footprint. Rather than introducing a carbon tax that would have increased the price of all dishes proportionally to their carbon footprint, we implemented a bonus-malus pricing that increased the price of relatively carbon-intensive dishes but decreased the price of relatively low-carbon dishes, as illustrated in equation (1). Namely, the prices of main dishes changed *proportionally* to the difference between the carbon footprint of a given dish and 3 kg CO_2 eq. (which is approximately equal to the median carbon footprint across all dishes in our sample). The factor of proportionality is what we call the value of carbon, V_{CO2}. By varying the value of carbon, we could affect the correlation between a dish's price and its carbon footprint. We set the value of carbon at 0.10 $Euros$/kg CO_2 eq., 0.50 $Euros$/kg CO_2 eq., 0.25 $Euros$/kg CO_2 eq., and 1 $Euro$/kg CO_2 eq., during the first, second, third and fourth price-treatment weeks, respectively. In the week between the first and the second price-treatment weeks as well as the week between the third and fourth price-treatment weeks, prices were reverted to their original level, i.e. a situation in which the value of carbon is 0. Importantly during the price treatment weeks, both the price information and the carbon footprint information were present at each main dish stand (see Figure 11).

Whereas original dishes price displayed a negative correlation with the dish carbon footprint, this correlation was close to 0 in the week the value of carbon was 0.10 $Euros$/kg CO_2 eq.

and became positive during the other price treatment week (See Figure 5 and Figure 6).

We test whether the bonus-malus system had an effect on carbon footprint consumption using regression specification (6). Table 7 presents the results of estimation. As for the information treatment, the relatively small change in price resulting from a price treatment with a value of carbon of 0.10 Euros/kg CO_2 eq. had no significant effect on users' average carbon footprint nor did we observe a heterogeneous reaction for demographic characteristics (see Table 8). Things were different for V_{CO2} starting from 0.25 Euros/kg CO_2 eq. and higher: the average carbon footprint of the meals consumed at HEC canteen dropped by 26.8%, 32.9%, or 42.6% for V_{CO2} set to 0.25, 0.50, and 1.00, respectively.[21] Interestingly the reduction in chosen dish CFs becomes large and significant as soon as the correlation between dish prices and their CF becomes positive, whereas as prices revert to their original level, and hence are negatively correlated with dishes CF, users revert to pre-treatment behavior. As illustrated in Figure 7, the effect is monotonically increasing in the value of carbon. We then interact our pricing treatment with a set of demographic characteristics, and we find that only the response of individuals from North America was statistically different at the conventional 5% level of significance. Namely, individuals from North America were less sensitive to the pricing treatment.

2.8 The impact of the red meat ban

We quantify the impact of the HEC Paris administration's decision to ban red meat at the beginning of September 2022. Starting from academic week #3, the supply of main dishes on the menu was limited to vegetarian, fish and chicken options, leading to a significant decrease in the equal-weighted carbon footprint of the offered menu (see Figure 9). Using the regression specification (7), we find that compared to Thursdays before the red meat ban was introduced, the carbon footprint of meals purchased on Thursdays drops by 2.1 kg CO2 eq per portion, or 64.2% (see Table 11), which translates into a reduction of CF of about 12% on a weakly basis.[22] One might expect that severely restricting the supply of red meat on Thursdays might increase the propensity of individuals to consume red meat on other days of the week when there is no such restriction. We find no evidence of such spillovers in our setting, as can be seen in the Table 11. However, after the policy was implemented, Thursday attendance dropped by

[21] We obtain the estimates of the percentage drop in carbon footprint by dividing the coefficients in column 2 of Table 7 by the post-information but pre-bonus-malus average carbon footprint – 3.015 kg $CO2_2$ eq.

[22] We obtain the estimate of the percentage decrease in carbon footprint by dividing the coefficient in column 1 of Table 11 by the average carbon footprint before the ban – 3.31 kg CO_2 eq.

a significant 15%. Depending on whether subjects who deserted the canteen had their usual dishes elsewhere, or they reduced their dishes CF as those who had lunch at the canteen, we can estimate the weakly impact of the Thursday meat-ban between 10% or 12%, respectively.

3 Online Survey

In this section, we describe the results of the online followu-up pre-registered[23] survey that we addressed to the entire HEC community with two main objectives: 1) to understand the channels through which the information treatment affected (or did not affect) individual consumption decisions; 2) to explore consumers' attitudes towards different policies that could reduce the carbon footprint of food.

It is noteworthy that while in the field experiment each individual's dish choice was observed during the sample period, the population of subjects who responded to the follow-up online survey only partially overlapped with those in the field experiment. There are two reasons for this. First, the survey was launched on December 14th, 2023, i.e., the academic year following that of the field experiment. Thus, there was some employee turnover between the end of the field experiment and the start of the survey, as well as a notable change in the student population due to admissions and graduations. Second, although all members of the HEC community were invited to participate in the survey, including all users in the field experiment, not all of them completed the survey. To avoid confusion, the term "user" will be used hereafter to refer to individuals who ate lunch in the cafeteria during the field experiment, the term "subject" to refer to individuals who answered all questions in the follow-up survey, and the term "subject user" to refer to users who answered the follow-up survey.

3.1 Survey description

We used Qualtrix to send a survey to the list of all emails with a hec.fr or hec.edu extension for a total of 10793 addresses.[24] The email contained a personalized link informing the recipient that by answering 100% of the questions in the survey, they would be entered into a raffle to win an Amazon gift card worth 300 Euros. The survey include 23 questions and required about 20' to be completed. On February 29th 2024 we closed the poll. We had a response rate of

[23]RCT ID: AEARCTR-0012583 available at https://www.socialscienceregistry.org/trials/12583

[24]We also manage to retrieve the e-mail address of students who graduated in 2023, hence had no more a hec.ed e-mail, but where on campus during the field expeirment.

12.7% for a total of 1368 subjects who answered the survey. We eliminate from our dataset subject that are likely to have answered at random, that those who completed the survey in less than 5 minute or more than one week and those who did not pass two attention check questions (questions 3 and 7)[25]. This restricted the sample to 874 subject of which 282 are subject-users. Each subject-user was assigned the same anonymized ID in the field experiment and the survey datasets, thus enabling the measurement of correlations between subject-user behavior in the field experiment and responses to the survey.

As a preliminary analysis we first verify that the subject-users are representative of the entire population of users. First, we verify that the subject and the user samples are not statistically different in terms of demographic composition. This is illustrated in Figure 15. We also verify that the main finding of the field experiment remains unchanged when running the field experiment regression analysis on a dataset that only includes subject-users.

The survey question can be classified into three distinct categories. A first group of questions aimed at assessing the subjects' attitude towards the issue of climate change as well as their inter-temporal preferences. A second set of questions was designed to ascertain whether a subject who was present on the HEC campus during the field experiment, noticed, understood and trusted the CF information posted during the field experiment. A third set of questions was designed to ascertain whether the subject would be amenable to HEC implementing a policy to reduce the canteen's carbon footprint. If the subject indicated a willingness to consider such a policy, the survey then inquired as to which policy they would prefer. Third, it could be that people simply are not concerned with global warming related matters.

The list of questions and the distribution of answers are provided in Appendix C.

3.2 Dissecting the information treatment results

From the information-only treatment it resulted that posting information about dish carbon footprint had no significant effect on people dish choice. We can think of three possible explanations for this finding. First, it could be that people already knew the carbon footprint of dishes before posting of the CO2 information was in place. This however is in contrast with the result of the in-person survey we run before posting information. This survey showed that only 4.5% of HEC canteen customers are able to rank correctly 4 typical dishes: roast chicken, roast salmon, roast beef, and roast lamb (see Table 14). Furthermore, For the 328 participants in

[25]The details of the attention check filter a given in Appendix C.

Malaingre (2022)'s survey who were successfully matched with the canteen consumption data, we analyzed their actual dish choice during the benchmark phase. Malaingre (2022) found that after being given the dish carbon footprint (CF) information, respondents selected dishes with a CF that on average was one-third lower than before knowing the CF. However, we found that these respondents' actual dish choices after answering Malaingre et al.'s survey were not significantly different from their choices before answering the survey.[26]

Second, we cannot exclude the possibility that people did not pay attention to the new posters, or that they noticed the new posters but did not understand them, or that they did not consider the information posted to be reliable. We verify these possibilities in the follow-up survey with questions 2, 3, and 4, respectively. It turned out that 98% of the survey respondent correctly interpreted the basic meaning of the poster (and 100% of subject-users by definition). 88.65% of the subject-users noticed the carbon footprint information and 81.56% of them considered the information reliable at level 4 or 5 on a scale of 1 to 5.

More precisely we test the following pre-registered hypotheses:

Hypothesis 1.1. *Individuals who confirm that they noticed carbon footprint information in the canteen did reduce significantly their carbon footprint post-information treatment.*

Hypothesis 1.2. *Individuals who consider estimates of dishes' carbon footprint reliable react stronger to the information treatment.*

Hypothesis 1.3. *Individuals who are more patient react stronger to the information treatment.*

Hypothesis 1.4. *Individuals who care more about climate change react stronger to the information treatment.*

For this purpose, we constructed four dummy variables and interact them with the information treatment indicator in our background study. To test Hypothesis 1.1 we construct an "attention dummy" dummy variable that equals one for subject users who reported in the survey that they noticed that carbon footprint information was provided. We also expect the effect to be stronger among those individuals who indicate in the survey that they care about the environment.[27]

To test Hypothesis 1.2 we construct a "Trust" dummy variable that takes the value 1 for subject users who answered in question 4 of the survey that they consider the CF post

[26]Out of 328 individuals who were successfully matched to the canteen data, only 176 satisfied the regular customer sample criteria.

[27]This is about 80.49% of the subject-users as it results from the answers to the question 12.

information to be reliable for a level of at least 4 out of a maximum of 5 (81.56% of the subject-users' answrs to question 4).

The rationale behind Hypothesis 1.3 is that impatient individuals may view global warming as a distant event, and therefore discount any potential loss in consumption induced by global warming. To test this hypothesis, we use responses of individuals to survey questions 14 and 15, that elicit their impatience as well as the preference for immediacy in quasi-hyperbolic discounting.

We tested Hypothesis 1.4 using responses of individuals to question eliciting the degree to which they care about climate change, ranging from *"I don't care"* to *"I care a lot, it dramatically influences my habits"* (answers to survey question 12).

Each hypothesis is tested using multiple dummy variables, as illustrated in tables 15 to 19. We find no evidence to support Hypotheses 1.1-1.4. Overall, the evidence suggests that users behave as selfish rational agents would when confronted with carbon footprint information. That is, even an agent who is concerned about climate change, after realizing that his/her personal current food choices have no impact on global warming, might simply choose the food that he/she finds tastier, regardless of the food's CF.

3.3 Attitudes towards carbon footprint reduction policies

The second objective of the survey was to explore people's attitudes toward different policies that could reduce the HEC canteen's CF. Namely, we consider three policies: an information-only policy, a supply regulation policy that eliminates red meat two days per week, and a pricing policy that makes low CO_2 dishes 10% less expensive than high CO_2 dishes by decreasing the price of the former and increasing the price of the latter.

We first asked subjects which of these three policies they would expect to be more effective in reducing HEC canteen CF (question 5). We then asked whether they preferred that the carbon footprint of the dishes be posted or not (question 6). We informed subjects of the results of the field experiment and verified that they had incorporated this information and considered it reliable (questions 7 and 8).[28] We then elicit respondents' preference between supply policy and pricing policy (question 9). Finally, in questions 10.A and 11.A, we elicit subjects' preferences among the three policies, but also include among the choices the status

[28]We also used question 7 as an attention check, eliminating from the sample those who clearly answered the survey randomly.

quo situation with no CF information and no change in supply and prices.

Following the dissemination of the field experiment results, it was observed that a proportion of the subjects, 63%, voted in favor of the implementation of the pricing policy. Conversely, a smaller proportion, 29.18%, voted in favor supply regulation policy. While only further 4.92% and 6.63% respectively voted in favor of the information-only and do-nothing option, respectively. Additionally, when presented with the option of selecting between a supply regulation strategy and a pricing policy, approximately two third of subjects indicated a preference for the pricing policy as opposed to the supply regulation policy. It is noteworthy that, a priori, subjects anticipated that the information-only policy would be less effective than the other policies. Furthermore, the efficacy of the information-only policy was perceived to be even lower after the results of the field experiment were revealed. Overall, 92.18% of subjects, expressed a desire for a policy that would effectively reduce the canteen CF.

More in detail we test the following hypothesis

Hypothesis 2.1. *Consumers correctly believe that, on average, posting information about dishes' carbon footprint is less effective in reducing carbon footprint than carbon pricing or reducing the offer of carbon-intensive dishes.*

In fact, only 4.96% of answers to question 5 reported information-only policy to be more effective than other policies. On average subject estimated the effectiveness of the information policy at 2.9, in a scale from 1 to 5, and at 3.9 and 4.1 for the supply regulation and pricing policies, respectively

Hypothesis 2.2. *Consumers are reluctant to see posted information that goes against their consumption habits (cognitive dissonance hypothesis).*

The idea behind this hypothesis is that people who regularly consume red meat might prefer not to be reminded that it is the dish with the highest carbon footprint. Thus, we test whether consumers with high-carbon footprint consumption habits are *less* likely to choose the dish poster *with* carbon footprint information. We find some evidence that subject users who tend to consume more carbon-intensive dishes also tend to prefer the carbon footprint not to be posted (see Tables 20 and 21). Yet, the vast majority of subjects 93.26%—prefers CF information to be posted.

Hypothesis 2.3. *For a fixed level of carbon footprint reduction, consumers prefer to have the flexibility to choose a polluting dish, while paying more for more polluting options.*

We test this hypothesis in Question 15, which asks whether — conditional on the need to implement one of two policies of similar effectiveness — subjects would choose the pricing policy or supply regulation. We find that about two third of subjects prefer the pricing policy (see Figure 13).

In order to better understand how people vote on policy, we verify whether subjects tend to prefer self-serving policies. For example, someone who already follows a low-CF diet would not be affected by a regulation that limits red meat supply, whereas they would strictly benefit from a pricing policy, as this would reduce the price of their preferred dishes. For those with a high-CF diet, the 'do nothing' option seems preferable. It is unclear whether they would prefer a supply regulation policy that keeps red meat cheap on the days it is available or a pricing policy that makes red meat more expensive but always available. This preference might depend on the subject's purchasing power: wealthy individuals, who are not particularly constrained by prices, might prefer the pricing policy, whereas the opposite might apply to less wealthy subjects. Thus we test the following

Hypothesis 2.4. *Do people vote to maximize their own consumption utility? (selfish agent hypothesis)*

The average CO2 footprint of an individual correlates with his/her policy preference. As illustrated in Table 13, for individuals who voted for "do nothing" the average carbon footprint of chosen dish is 5.6 kg CO2/meal. Individuals who vote for carbon reduction effective policies tend to have less CO_2-intensive habits. Individuals voting for the bonus malus pricing or for the red meat ban policies, tend to choose dishes whose average carbon footprint is 21% and 18%,respectively, lower than the one of those advocating for doing nothing.

Hypothesis 2.5. *Will people vote for effective policy? (effective democracy hypothesis).*

We test this hypothesis using the same survey question as above. Specifically, we will look at whether in the setting of a (democratic) referendum, individuals choose a policy that has demonstrated the ability to reduce the food carbon footprint at HEC Paris. We find that indeed 92.18% of subject opt for the two policy that effectively reduced chosen dishes. Notably among the supply regulation and the pricing policy, the latter is twice as popular as the former (See Table 12)

Hypothesis 2.6. *Do people vote differently if put in the manager's position than in a non-pivotal voting position (effective dictator/social planner hypothesis)?*

In question 10.A subjects were asked what policy they would put in place, if any, if they were in charge. In question 11.A they are asked which policy they would vote for in a referendum. Subjects were asked what policy they would vote for whereas in question 10.A, they are asked which policy they would implement, if any, if they were the dean of HEC and had the power to choose any policy.[29] Overall, there is no substantial difference between the answers of these two questions. Compared to a voting framework when put in a hypothetical manager position, the fraction of subjects who opt for no policy or inform-only halves, and the fraction of subject opting for the supply regulation policy slightly increase (see Table 22).

4 Discussion and policy implications

4.1 External validity

It was crucial for the effectiveness of the pricing policy that users had limited access to other restaurants with the same quality-price ratio and that were not linking dish prices to carbon footprints. This means that the experiment can be replicated in other collective restaurants, such as university or firm cafeterias. These cafeterias typically offer prices that are below what commercial restaurants offer, and are thus likely to retain their clients even after the introduction of a bonus-malus pricing system, which rewards low-carbon choices and penalizes high-carbon choices. By contrast, a single commercial restaurant or restaurant chain that would implement such a pricing system is likely to see its red-meat-eating customers move to their competitors.

Our finding that making the low-carbon option slightly cheaper than the high-carbon one can have a substantial effect in shifting demand is likely to also apply to other sectors. The efficacy of this policy depends on how much a product's carbon footprint is connected to other dimensions that a customer values in the product. For example, to induce a red-meat lover to switch to poultry meat, the price difference should compensate the customer for the lower culinary pleasure he or she enjoys from eating chicken rather than beef. Similarly, as long as plane travel is faster and cheaper than train travel for a given journey, there is little hope of observing a significant shift towards train travel over air travel. For this a massive change in price is necessary. By contrast, it is sufficient to make electricity produced from renewable sources slightly cheaper than the one obtained by burning oil or coal to induce households to switch to 'green'-electricity providers. This rises the question of financial cost of a price

[29] Whether a subject had to answer the "dean" question first or "referendum" question first was randomized. Half of the individuals answered first the "dean" questions 10.A, and then the "referendum" question 11.A. The other half (denoted by "B") answered the "referendum" question 10.B first and then the "dean" question 11.B.

adjustment policy.

4.2 Financial cost of the bonus-malus policy

The bonus-malus pricing policy was not designed to be budget-neutral for the canteen. In fact, the reduction in average carbon footprint during the pricing treatment was accompanied by a decrease in the average price users spent per meal. This is contrary to what would have occurred with a carbon tax, which would have increased the price of each meal proportionally to its carbon footprint. The simultaneous increase in the prices of high-carbon dishes and decrease in the prices of low-carbon dishes led to a shift in demand towards low-carbon options. As these dishes were cheaper compared to the average price spent under the original pricing system, this demand shift also resulted in a net reduction in the average meal cost for users. Specifically, the average amount spent per meal decreased by 4.2%, 7.1%, or 32.8%, depending on whether the carbon value was set at 0.25, 0.50, or 1 Euro/$kgCO_2$ equivalent, respectively.

This finding allows us to make a back-of-the-envelope computation of the cost for the canteen per kg of CO_2 reduction. For example, with 0.25 Euros/kg CO_2 eq., the average carbon footprint dropped by 26.8% while per-meal sale proceeds dropped by 4.2%. Thus, each kg of CO_2 reduction costs $\frac{4.46\times 4.2\% \text{ Euro}}{3.31\times 26.8\% \text{ kg } CO_2 \text{ eq.}} \simeq 0.21$ Euro/kg CO_2 eq. Whereas with a value of carbon of 0.5 Euros/kg CO_2 eq. and 1 Euro/kg CO_2 eq., the average cost of CO_2 reduction was 0.29 and 1.04 Euros/kg CO_2 eq., respectively.

It is natural to question whether a bonus-malus pricing system can be implemented without imposing costs on the canteen or the regulator in general. Two possible implementation methods exist. First, a system of taxes on carbon-intensive options could fund subsidies for low-carbon choices. Second, a system of personal tradable carbon permits could be adopted. From the users' perspective, these two policies are economically equivalent to a bonus-malus system. To understand personal carbon permits, imagine each individual receiving a specific number of permits corresponding to the socially optimal per capita emissions level. Individuals who consume more than their allotted carbon would need to buy permits from those who consume less, thereby increasing the cost of high-carbon goods. This mechanism mirrors the bonus-malus system, where high-carbon goods become more expensive due to the added costs of purchasing necessary carbon permits. However, because carbon permits are exchanged among individuals, this policy would be perfectly budget-neutral for the canteen or the regulator in general.

5 Conclusion

Our research demonstrates that a pricing system that rewards low-carbon food choices and penalizes high-carbon ones is the most effective and well-received strategy for reducing the carbon footprint of dietary habits. While supply regulations and providing consumers with information about carbon footprints can have some impact, they are less effective than directly influencing consumer behavior through pricing incentives. Additionally, our findings highlight the social acceptability of such a pricing system, as it was preferred by a significant majority of participants in our survey.

Our study's implications are threefold. First, it highlights the potential for influencing dietary choices to reduce our environmental footprint. Second, it explores the attitudes of future business leaders towards carbon-conscious practices. Finally, it suggests the broader applicability of pricing policies to other goods where low-carbon options exist. While taste preferences might strongly influence food choices, this may not hold true for all goods. For example, a price difference could incentivize switching to renewable energy while not significantly impacting consumer satisfaction.

In conclusion, this research suggests that bonus-malus pricing is the most effective and socially acceptable way to encourage lower-carbon food choices. This finding, coupled with the potential for broader application, offers valuable insights in the fight against climate change.

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Panel A: Dish description without carbon footprint information

Panel B: Dish description in the information phase of the field experiment

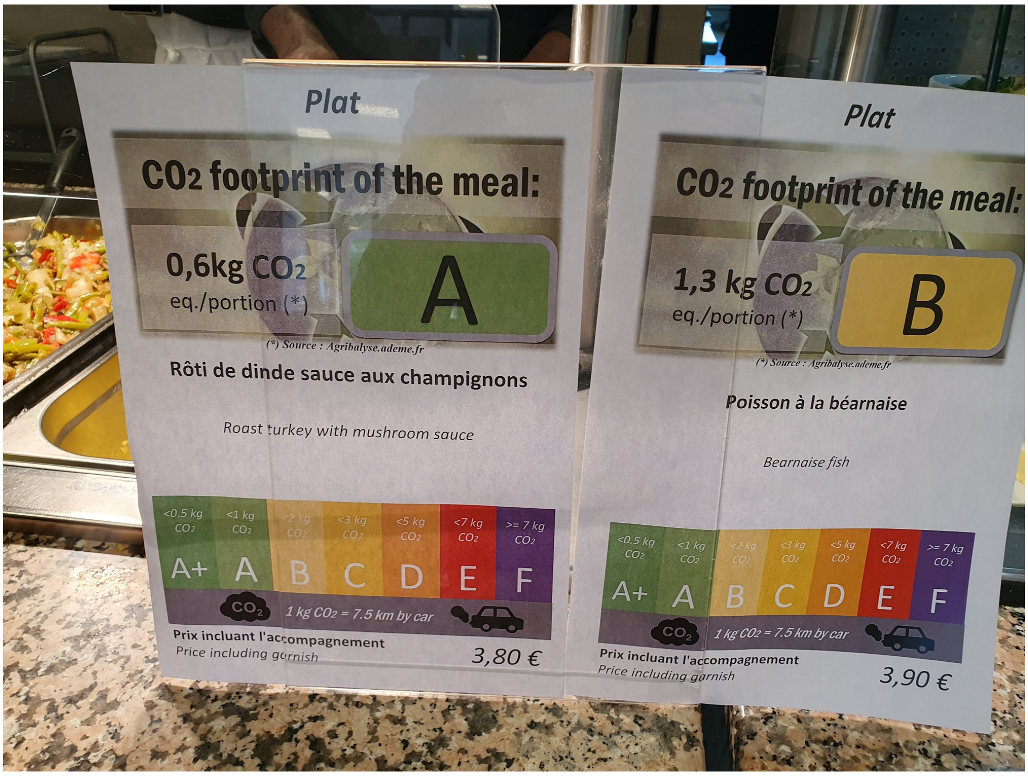


Figure 1: Posted dish description in the information phase in comparison to the original description

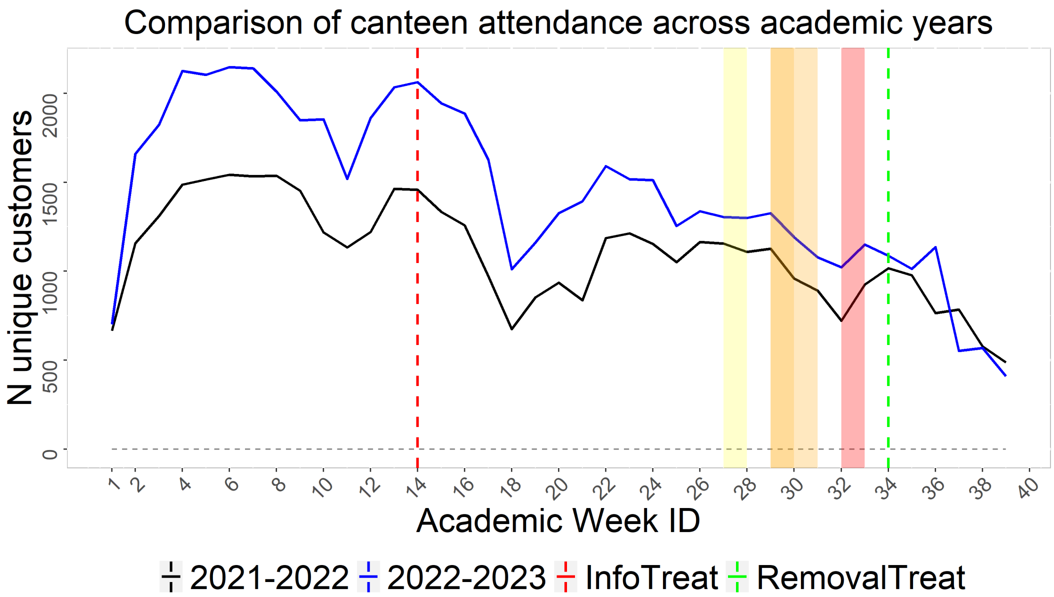


Figure 2: Comparison of HEC canteen attendance by academic week

Note: The figure plots the number of unique individuals purchasing dishes at the HEC canteen across different academic weeks for both academic years. Academic week captures within-academic year seasonality, with the first academic week commencing in late August, and the last academic week taking place in mid-June (we remove Christmas, winter, spring, and summer breaks). The black line corresponds to the academic year 2021-2022, the data of which we use as the control group. The blue line depicts the respective time series in the academic year 2022-2023. The red dotted line marks the first academic week of information treatment, while the 4 yellow-to-red shaded areas correspond to 4 different levels of bonus-malus treatment. Finally, the green dotted line indicates the first week when carbon footprint information has been removed from the HEC canteen.

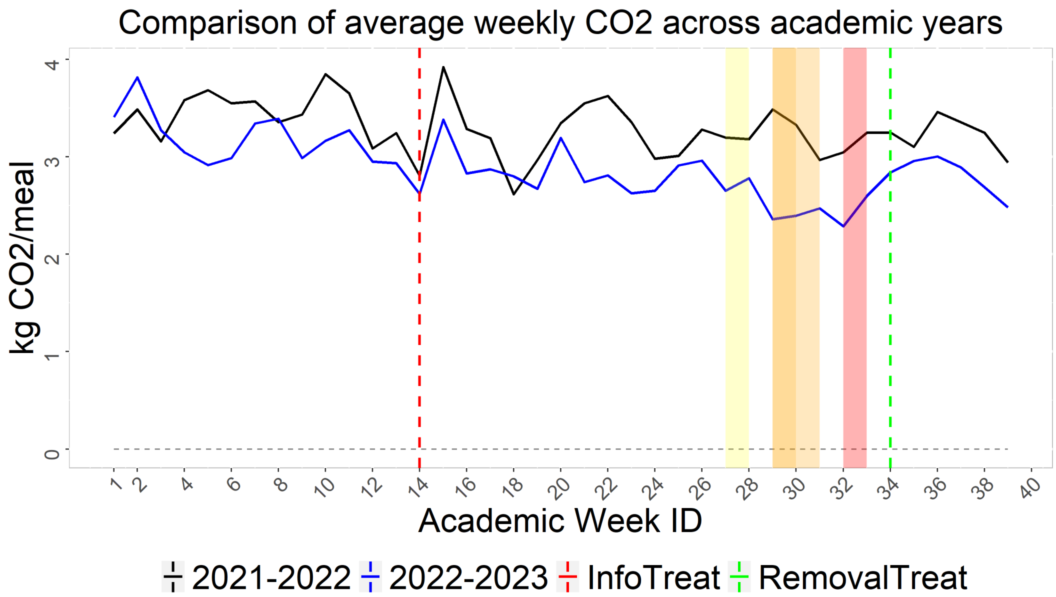


Figure 3: Evolution of average weekly carbon footprint per meal

Note: The figure plots the average weekly carbon footprint per meal across different academic weeks for both academic years. Academic week captures within-academic year seasonality, with the first academic week commencing in late August, and the last academic week taking place in mid-June (we remove Christmas, winter, spring, and summer breaks). The black line corresponds to the academic year 2021-2022, the data of which we use as the control group. The blue line depicts the respective time series in the academic year 2022-2023. The red dotted line marks the first academic week of information treatment, while the 4 yellow-to-red shaded areas correspond to 4 different levels of bonus-malus treatment. Finally, the green dotted line indicates the first week when carbon footprint information has been removed from the HEC canteen.

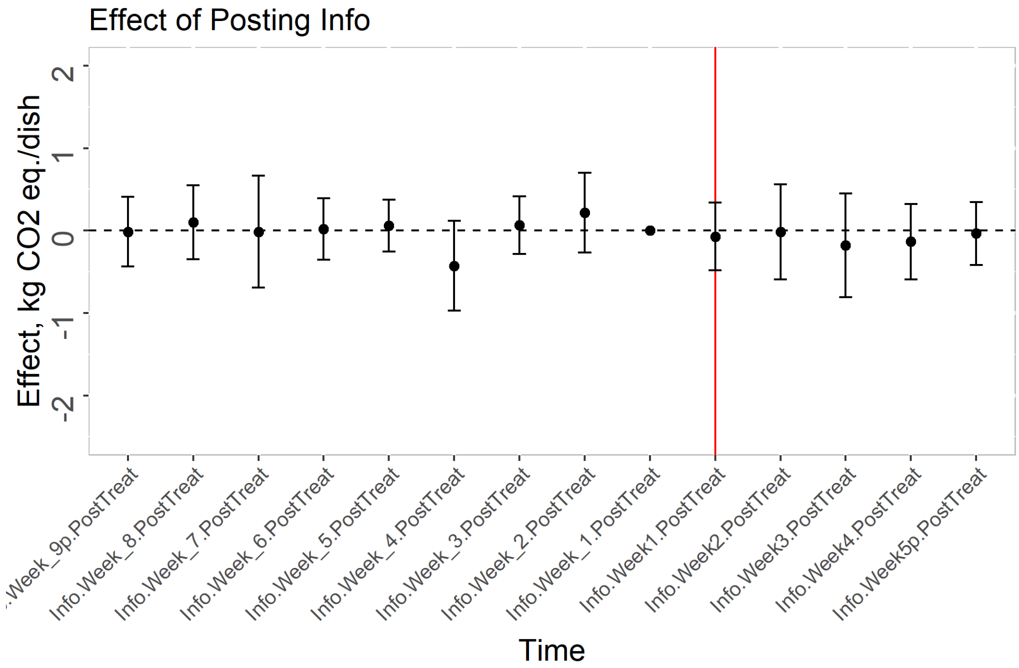


Figure 4: Effect of posting information about dish carbon footprint

The figure plots estimates $\hat{\theta}_w$ from the following estimation equation:

$$\begin{aligned} CO2_{i,y,t} = & \sum_{w \neq -1} \theta_w InfoTreatWeek(w)_{y,t} + \zeta Controls_{y,t} + Person \times AcademYearFE_{i,y} \\ & + AcademWeek \times ProgamFE_{i,t} + AcademYear \times WeekdayFE_{y,t} + \epsilon_{i,y,t} \end{aligned} \tag{8}$$

$CO2_{i,y,t}$ is the carbon footprint of the meal purchased by individual i on academic day t of academic year y (we define academic day as academic week $\times$ weekday, e.g. Friday of academic week #3). Dummy $InfoTreatWeek(w)_{y,t}$ is always equal to 0 in the control academic year of 2021-2022, and is equal to 1 when the academic day in 2022-2023 academic year corresponds to the week w pre-/post-information treatment. The red vertical line marks the first week of information treatment. $Controls_{y,t}$ include equal-weighted average of the carbon footprint of dishes offered on academic day t of academic year y $CO2.EW_{y,t}$; calendar day-specific local temperature, precipitation, and cloud cover; the number of customers making purchase in HEC canteen on a given calendar day; Google Trends worldwide (to correspond to the international nature of HEC student and faculty community) for search phrase "carbon footprint". The equation was estimated on the sample of regular customers defined as individuals who had at least 5 purchases before and at least 5 purchases after the information treatment. For estimation, we focus on the window of 11 academic weeks before and 12 academic weeks after the information treatment (this window does not overlap with price treatment, which commences later). For the ease of exposition, we fit one coefficient $InfoWeek\_9p.PostTreat$ for weeks $-11, ..., -9$ and one coefficient $InfoWeek\_5p.PostTreat$ for weeks $5, ..., 12$. 95% confidence intervals are based on standard errors clustered by person ID and academic day.

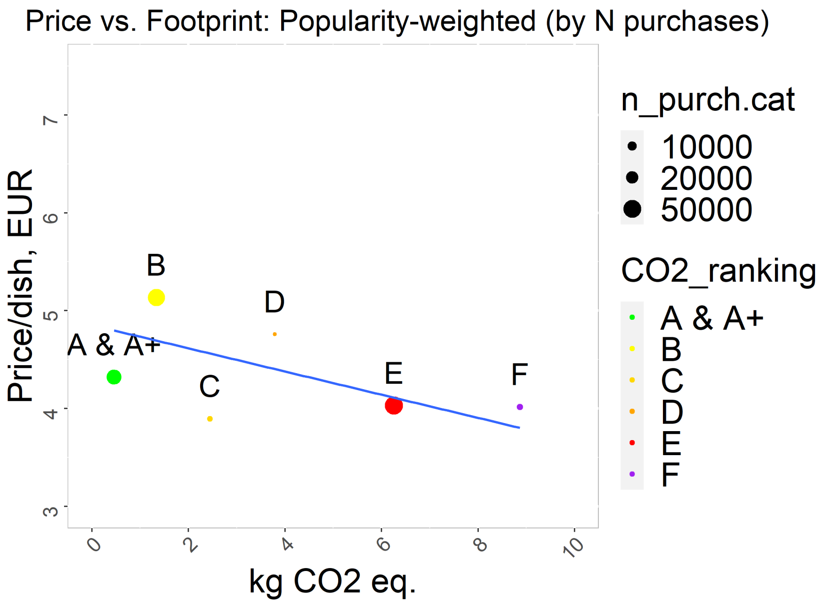


Figure 5: Price-to-CO2 slope in the pre-information period

Note: The figure shows the relationship between original prices and carbon footprint of dishes in the pre-information treatment period. Colors and letter grades on the scatter plot correspond to the carbon footprint categories, defined as in Figure 10. The size of the circle corresponding to each category reflects the popularity of the respective categories (measured in the pre-information period). Both carbon footprint (measured in kg of CO2 equivalent) and prices are popularity-weighted within each category, where dish popularity is also measured in the pre-information period.

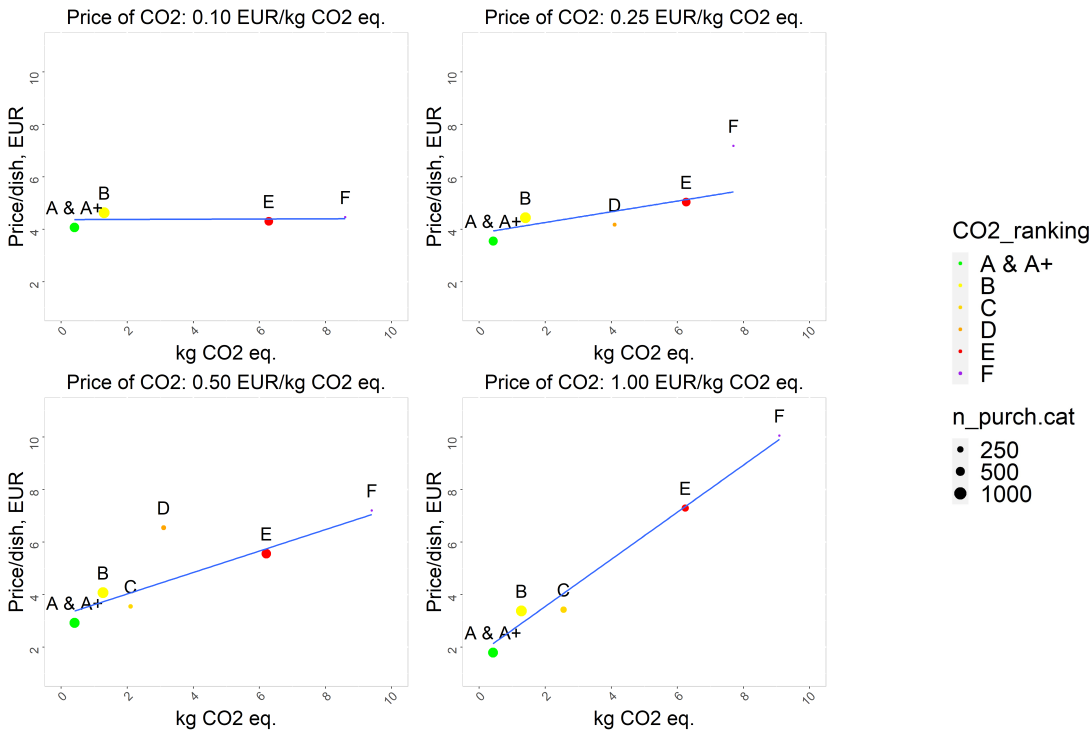


Figure 6: Price-to-CO2 slopes in different bonus-malus treatments

Note: The figure shows the relationship between prices and carbon footprint of dishes during 4 weeks of bonus-malus treatments: 0.10 EUR/kg CO2 eq., 0.25 EUR/kg CO2 eq., 0.5 EUR/kg CO2 eq., and 1.0 EUR/kg CO2 eq., respectively. Colors and letter grades on the scatter plot correspond to the carbon footprint categories, defined as in Figure 10. The size of the circle corresponding to each category reflects the popularity of the respective categories (measured in the week corresponding to each respective level of CO2 value). Both carbon footprint (measured in kg of CO2 equivalent) and prices are popularity-weighted within each category.

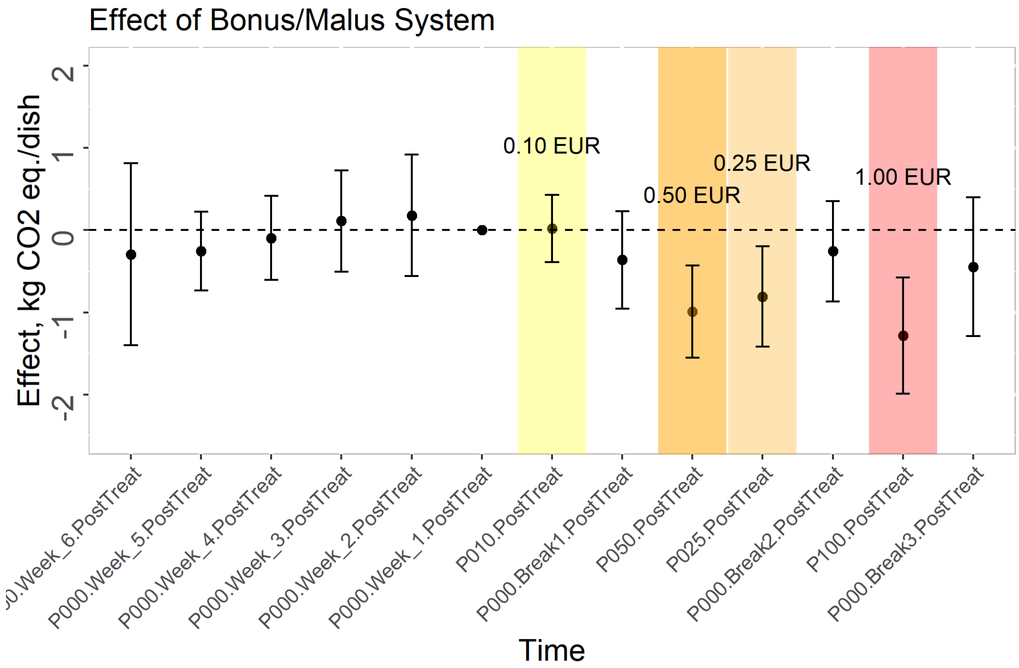


Figure 7: Effect of bonus-malus system on carbon footprint

Note: The figure plots estimates $\hat{\theta}_w$ from the following estimation equation:

$$\begin{aligned} CO2_{i,y,t} = & \sum_{w \neq -1} \theta_w PriceTreatWeek(w)_{y,t} + \zeta Controls_{y,t} + Person \times AcademYearFE_{i,y} \\ & + AcademWeek \times ProgamFE_{i,t} + AcademYear \times WeekdayFE_{y,t} + \epsilon_{i,y,t} \end{aligned} \tag{9}$$

$CO2_{i,y,t}$ is the carbon footprint of the meal purchased by individual i on academic day t of academic year y (we define academic day as academic week × weekday, e.g. Friday of academic week #3). Dummy $PriceTreatWeek(w)_{y,t}$ is always equal to 0 in the control academic year of 2021-2022, and is equal to 1 when the academic day in 2022-2023 academic year corresponds to the week w of the bonus-malus treatment. The 4 yellow-to-red shaded areas correspond to 4 different levels of bonus-malus treatment: 0.10 EUR/kg CO2 eq., 0.25 EUR/kg CO2 eq., 0.50 EUR/kg CO2 eq., 1.0 EUR/kg CO2 eq., respectively. $Controls_{y,t}$ include equal-weighted average of the carbon footprint of dishes offered on academic day t of academic year y $CO2.EW_{y,t}$; calendar day-specific local temperature, precipitation, and cloud cover; the number of customers making purchase in HEC canteen on a given calendar day; Google Trends worldwide (to correspond to the international nature of HEC student and faculty community) for search phrase "carbon footprint". The equation was estimated on the sample of regular customers. For estimation, we focus on the window of 6 academic weeks before and 7 academic weeks after the first price treatment (this window is fully contained within the information treatment). 95% confidence intervals are based on standard errors clustered by person ID and academic day.

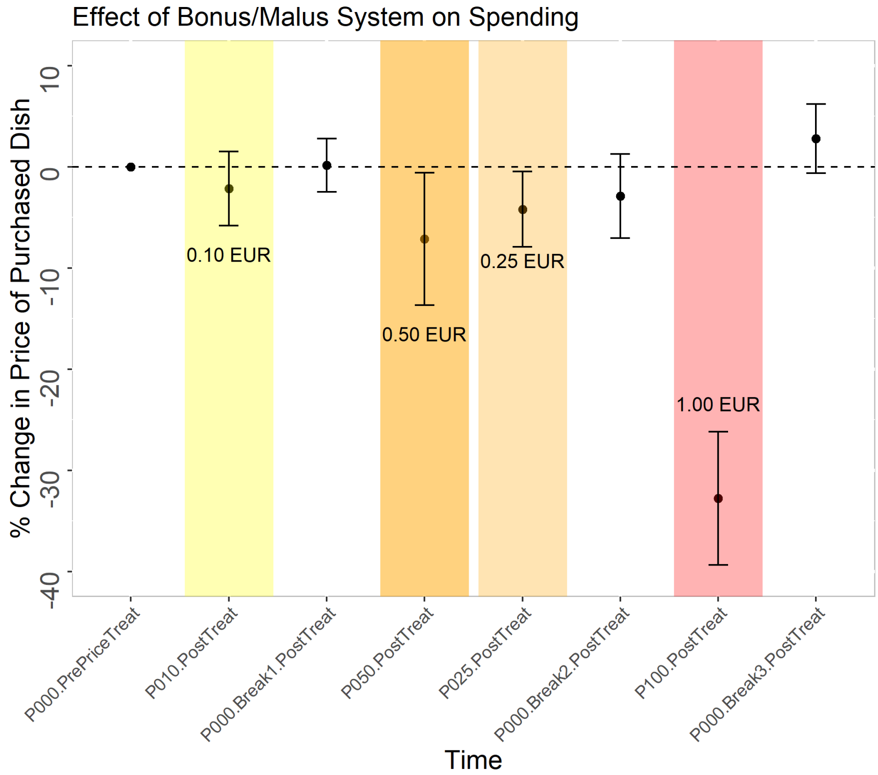


Figure 8: Effect of bonus-malus system on spending

Note: This figure reports estimates from the following regression:

$$log(Price.Actual)_{i,y,t} = \sum_w \theta_w PriceTreatWeek(w)_{y,t} + \zeta Controls_{y,t} + Person \times AcademYearFE_{i,y}$$
$$+AcademWeek \times ProgamFE_{i,t} + AcademYear \times WeekdayFE_{y,t} + \epsilon_{i,y,t}$$

Where $log(Price.Actual)$ is the logarithm of the price of the dish purchased by individual i on academic day t of academic year y (we define academic day as academic week × weekday, e.g. Friday of academic week #3). Dummy $PriceTreatWeek(w)_{y,t}$ is always equal to 0 in the control academic year of 2021-2022, and is equal to 1 when the academic day in 2022-2023 academic year corresponds to the week w of the bonus-malus treatment. The 4 yellow-to-red shaded areas correspond to 4 different levels of bonus-malus treatment: 0.10 EUR/kg CO2 eq., 0.25 EUR/kg CO2 eq., 0.50 EUR/kg CO2 eq., 1.0 EUR/kg CO2 eq., respectively. $Controls_{y,t}$ include the logarithm of an equal-weighted average of the *pre*-price treatment prices of dishes offered on academic day t as well as the logarithm of the equal-weighted carbon footprint of dishes offered on day t. The equation was estimated on the sample of regular customers. For estimation, we focus on the window of 6 academic weeks before and 7 academic weeks after the first price treatment (this window is fully contained within the information treatment). 95% confidence intervals are based on standard errors clustered by person ID and academic day.

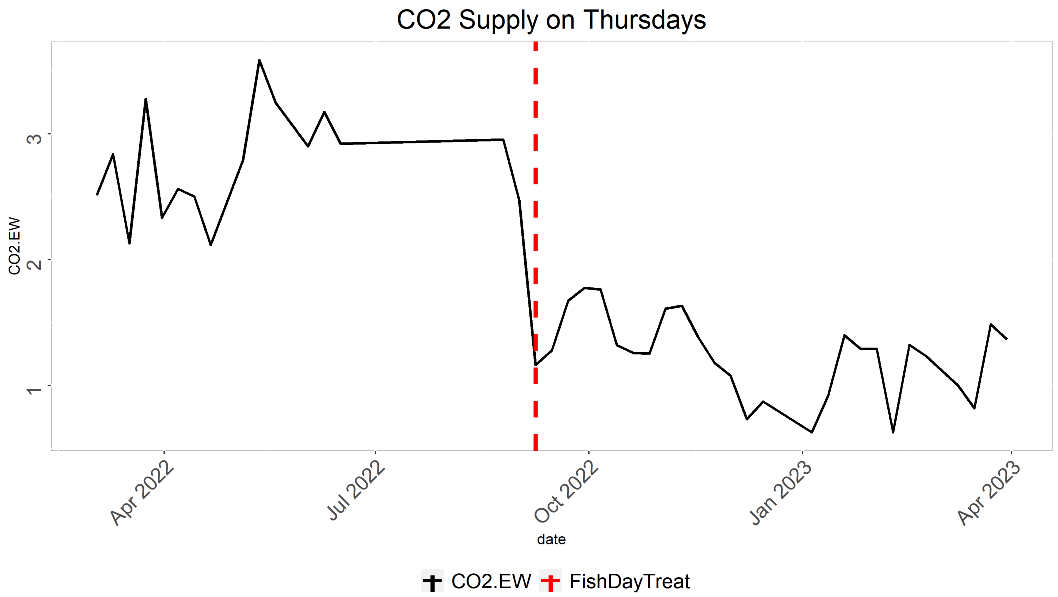


Figure 9: The change in CO2 supply following red meat ban on Thursdays

Note: The figure plots the time series of equal-weighted CO2 of dishes offered on the menu on Thursdays. The red dashed line marks the first week when red meat was excluded from Thursday's menu (corresponding to academic week #3 in our study).

Rating	CO_2 footprint/portion
A+	Less than 0.5 kg CO_2-eq.
A	Between 0.5 and 1 kg CO_2-eq.
B	Between 1 and 2 kg CO_2-eq.
C	Between 2 and 3 kg CO_2-eq.
D	Between 3 and 5 kg CO_2-eq.
E	Between 5 and 7 kg CO_2-eq.
F	More than 7 kg CO_2-eq.

Figure 10: Poster with letter grade legend present between dish stands during the information and the pricing phases

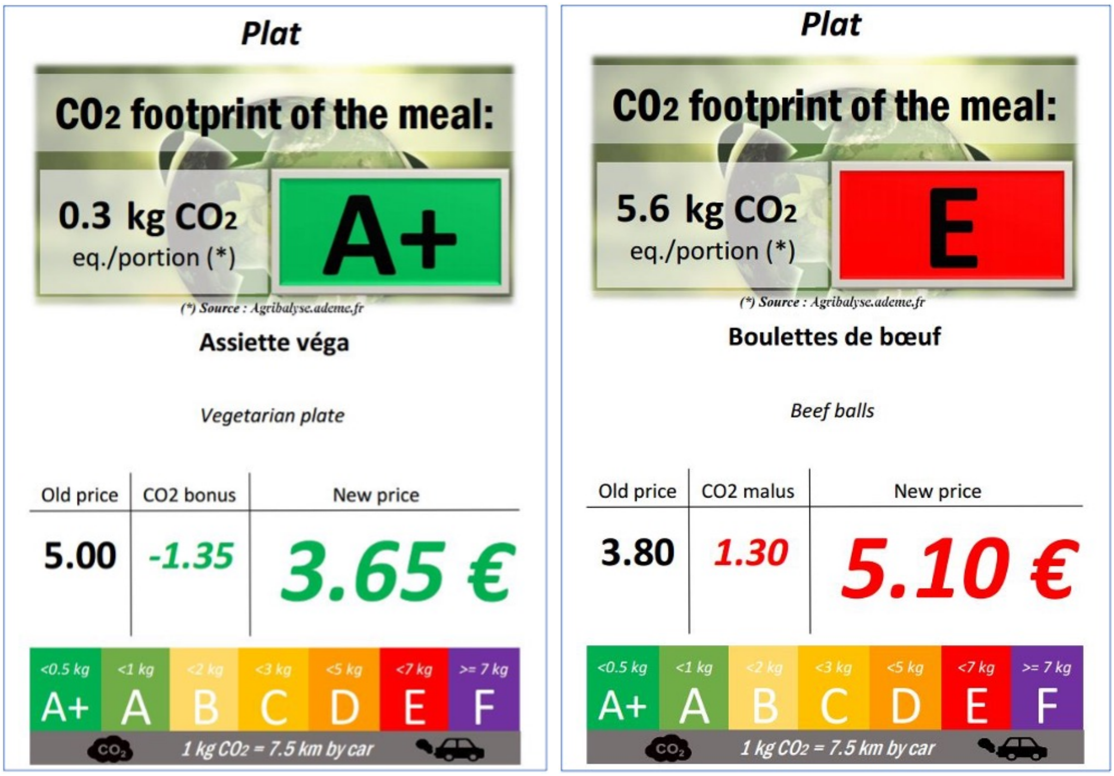


Figure 11: Posted dish description in the pricing phase. The example corresponds to a $V_{CO_2} = 0.25$ Euro/kg CO_2 eq.

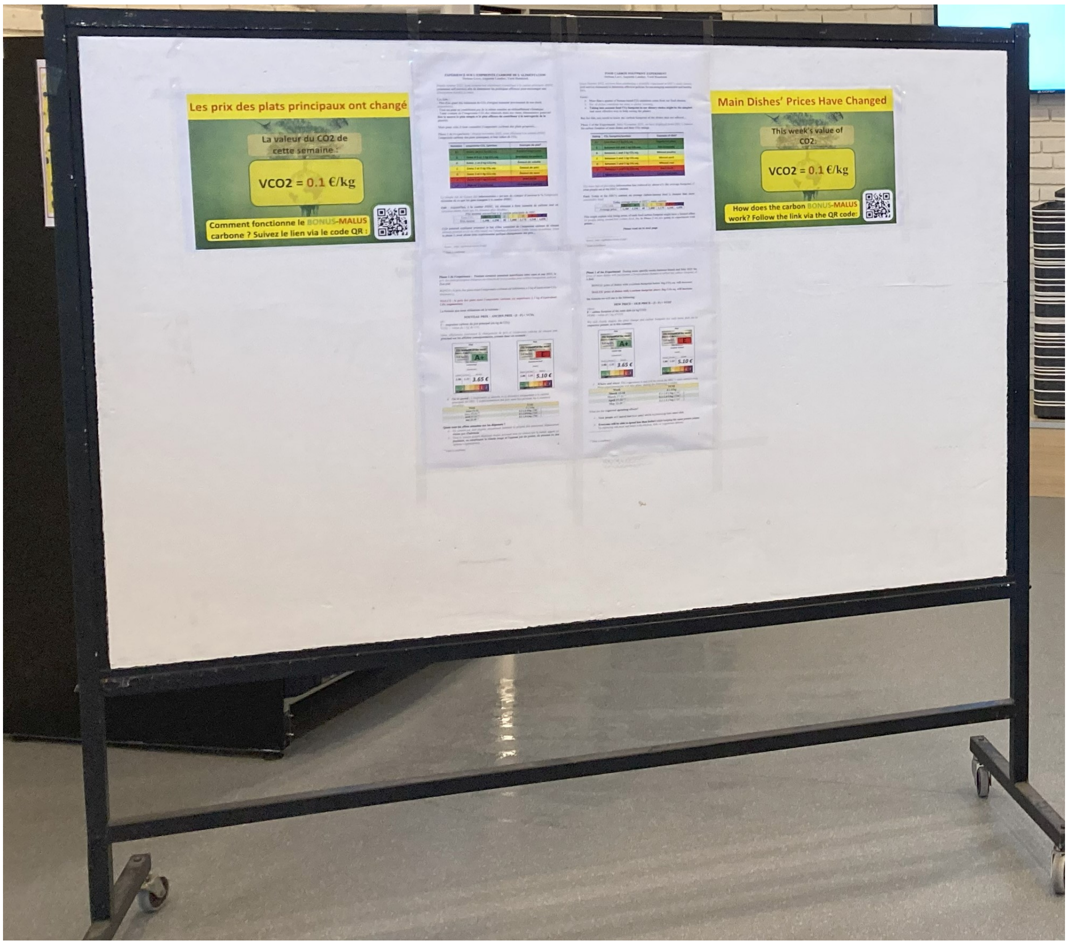


Figure 12: A stand put at HEC canteen during the bonus-malus phase

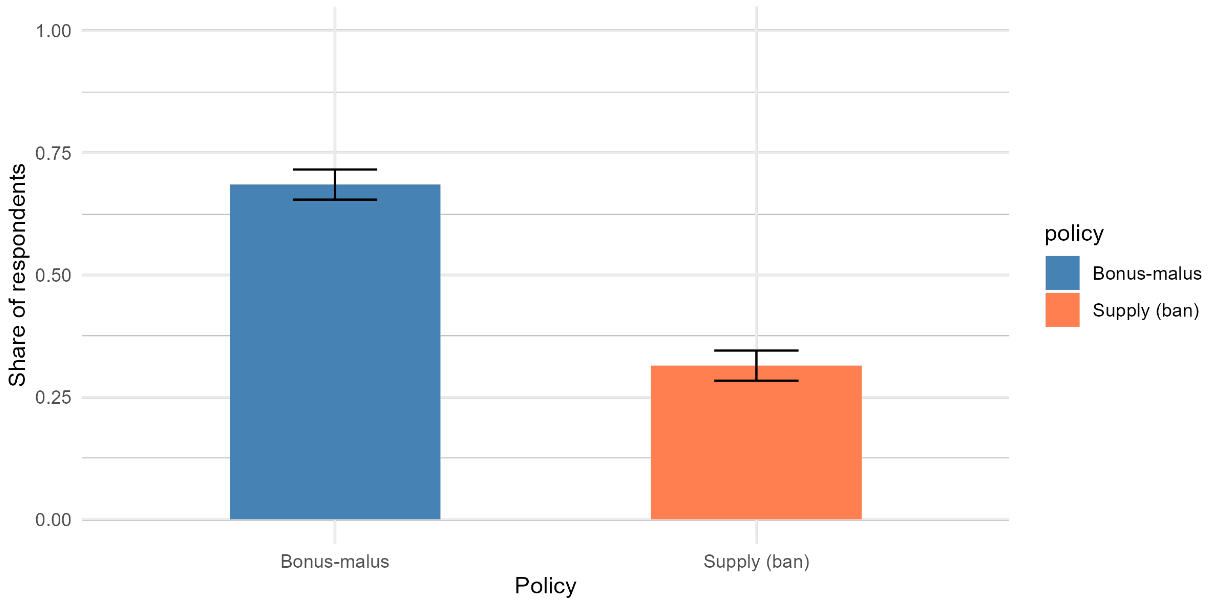


Figure 13: Test of hypothesis 2.3

Note: The error bars indicate the 95% confidence intervals. Standard errors are heteroskedasticity-robust.

Treatment	V_{CO_2} in Euros/kg CO_2 eq.	Start date	End date	Academic weeks (year)
Benchmark phase		23 Aug 2021	18 Nov 2022	1-39 (21-22), 1-13 (22-23)
Malaingre (2022)'s survey		15 Mar 2022	15 April 2022	28-31 (21-22)
On-site CO_2 entry survey		14 Nov 2022	18 Nov 2022	13 (22-23)
Information treatment		21 Nov 2022	5 May 2023	14-33 (22-23)
Price treatment	0.1	13 Mar 2023	17 Mar 2023	27 (22-23)
Price treatment	0	20 Mar 2023	24 Mar 2023	28 (22-23)
Price treatment	0.50	27 Mar 2023	31 Mar 2023	29 (22-23)
Price treatment	0.25	3 Apr 2023	7 Apr 2023	30 (22-23)
Price treatment	0	11 Apr 2023	14 Apr 2023	31 (22-23)
Price treatment	1	17 Apr 2023	21 Apr 2023	32 (22-23)
Price treatment	0	24 Apr 2023	28 Apr 2023	33 (22-23)
Removal of information treatment		9 May 2023	16 Jun 2023	34-39 (22-23)
On-site CO_2 exit survey		9 May 2023	19 May 2023	34-35 (22-23)

Table 1: Calendar of the different phases of the experiment

Note: V_{CO_2} is in Euros/kg CO_2 eq. The benchmark phase includes the control group period: 23 August 2021 - 17 June 2022. We exclude from the span of academic weeks Summer, Christmas, Winter, and Spring breaks. Information treatment lasted through the Spring break of 2023, which took place after academic week 33 and before academic week 34.

Dependent Variables:			CO2				CO2_rank_EF	
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
(Intercept)	3.309***	0.0286	0.8799***	0.8788***	0.4051***	0.0041	0.1800***	0.1797***
	(50.86)	(0.1039)	(2.850)	(2.851)	(35.72)	(0.1038)	(3.987)	(3.980)
CO2.EW		1.287***	1.296***	1.294***				
		(12.35)	(12.49)	(12.47)				
age			-0.0218***	-0.0187***			-0.0050***	-0.0041***
			(-4.534)	(-3.861)			(-6.442)	(-5.329)
female			-0.6764***	-0.6387***			-0.1126***	-0.1044***
			(-13.65)	(-12.74)			(-12.78)	(-11.84)
d.Staff			-0.4738***	-0.6107***			-0.0832***	-0.1216***
			(-3.978)	(-4.765)			(-4.357)	(-5.955)
d.Prof			-0.7682***	-0.8676***			-0.1262***	-0.1536***
			(-6.589)	(-7.076)			(-6.750)	(-7.877)
d.NorthAmerica				-0.4704***				-0.1000***
				(-3.243)				(-4.043)
d.SouthAmerica				0.1442				0.0051
				(1.181)				(0.2334)
d.Africa				-0.1042				-0.0329*
				(-1.076)				(-1.967)
d.Asia				-0.1844**				-0.0626***
				(-2.316)				(-4.610)
d.MBA				-0.1245				-0.0101
				(-0.9624)				(-0.4358)
d.SASI				-0.7396***				-0.1036***
				(-4.673)				(-3.822)
log(CO2.EW)						0.1507	0.1437	0.1376
						(1.464)	(1.401)	(1.338)
frac_dishes.CO2_EF						0.8839***	0.9186***	0.9326***
						(3.376)	(3.546)	(3.607)
Fit statistics								
Sample	Pre-Info	Pre-Info	Pre-Info	Pre-Info	Pre-Info	Pre-Info	Pre-Info	Pre-Info
Cluster S.E.: Academ Day	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster S.E.: Person	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	138,395	138,395	138,395	138,395	138,395	138,395	138,395	138,395
R^2		0.04643	0.08390	0.08672		0.03726	0.07691	0.08071
Adjusted R^2		0.04643	0.08386	0.08665		0.03724	0.07687	0.08063

Clustered (person_id & academ.day_id) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 2: Factors that explain the cross-section of carbon footprint

Note: The table reports estimates from the following linear regression:

$$Y_{i,t} = \delta_1 Demo_i + \delta_2 DayFactors_t + \epsilon_{i,t}$$

Where $Y_{i,t}$ is one of the two measures of carbon footprint: $CO2_{i,t}$ is the carbon footprint in kg of CO_2 eq. of a dish purchased by individual i on day t; $CO2\_rank\_EF_{i,t}$ is a dummy variable equal to 1 if the dish consumed by user i on a day t is labeled E or F, and zero otherwise. $Demo_i$ and $DayFactors_t$ are vectors of demographic characteristics and day-specific factors, respectively. $d.MBA$ ($d.SASI$) is a dummy variable equal to 1 if a given individual is enrolled in MBA (SASI - Master in Sustainability and Social Innovation), and zero otherwise (note that staff and faculty members are assigned 0 by definition). $d.Staff$ and $d.Prof$ are dummy variables equal to 1 if a given individual is a member of staff or faculty, respectively (these are mutually exclusive sets). Dummies $d.NorthAmerica$,...,$d.Asia$ are equal to 1 if the individual's nationality belongs to one of the respective continents.

Panel A: Students

variable	n_indiv	mean	sd	min	max
n_obs.per.person	3486	51.48	40.68	10	281
age	3486	21.34	3.6	20	50
female	3486	0.41			
mean.CO2.preInfo	3371	3.33	1.35	0.14	6.75
sd.CO2.preInfo	3371	2.37	0.63	0	4.03

continent	n_individuals	total_individuals	frequency
Europe	2203	3486	0.632
Asia	692	3486	0.199
Africa	255	3486	0.073
South America	192	3486	0.055
North America	137	3486	0.039
Oceania	7	3486	0.002

Panel B: Staff

variable	n_indiv	mean	sd	min	max
n_obs.per.person	485	65.81	52.55	10	321
age	485	38.99	11.35	20	60
female	485	0.71			
mean.CO2.preInfo	473	2.24	1.17	0.24	6.4
sd.CO2.preInfo	473	1.98	0.87	0	4.06

Panel C: Faculty

variable	n_indiv	mean	sd	min	max
n_obs.per.person	170	57.14	46.37	10	261
age	170	34.35	10.87	20	60
female	170	0.49			
mean.CO2.preInfo	161	2.23	1.03	0.3	4.93
sd.CO2.preInfo	161	2.07	0.81	0	3.86

Table 3: Summary statistics: Customers

Panel A: All Dishes (Pre-InfoTreat)

variable	n_dishes	n_purch	mean	sd	min	max
n_purch	81	139308	1719.85	4006.81	6	24962
freq_purch.pct	81	139308	1.23	2.88	0	17.92
CO2.EW	81	139308	3.28	2.98	0.1	12.4
CO2.PW	81	139308	3.31	2.74	0.1	12.4
price.orig.EW	81	139308	4.16	0.7	3.5	6.5
price.orig.PW	81	139308	4.46	0.93	3.5	6.5

Panel B: Top 10 Dishes by Popularity (Pre-InfoTreat)

code_article	article_ENG	n_purch	CO2	CO2_ranking	price.orig	freq_purch	cum.freq	popularity_rank
512	Eco meat (beef)	24962	6.4	E	4	0.179	0.179	1
1479	Plancha (salmon, tuna, calamari)	18477	1	B	6.5	0.133	0.312	2
721	Minced steak	13839	6.4	E	3.7	0.099	0.411	3
553	Vegetarian plate	12026	0.3	A+	5	0.086	0.497	4
731	Pasta with meat	7887	1.8	B	4.6	0.057	0.554	5
653	Meat casserole	7599	5.6	E	4.5	0.055	0.609	6
739	Quiche	5275	0.8	A	3.8	0.038	0.647	7
1618	Eco vegetarian	3359	0.1	A+	4	0.024	0.671	8
656	Cereal pallet	3161	0.1	A+	3.8	0.023	0.693	9
522	Chicken thigh	2797	1.7	B	3.9	0.02	0.713	10

Table 4: Summary statistics: Dishes

Note: This table presents the summary statistics of the pre-information treatment sample. Panel A describes the cross-section of all dishes. Panel B lists the top 10 dishes by popularity (measured on the sample before the information treatment).

Dependent Variable:			CO2		
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
(Intercept)	3.326***				
	(40.38)				
Info.PostTreat	-0.4178**	0.0066	-0.0824	-0.0561	-0.0825
	(-2.572)	(0.0328)	(-0.6404)	(-0.5108)	(-0.7295)
Info.Post		-0.2149*	-0.0830	-0.1934*	
		(-1.771)	(-0.6598)	(-1.709)	
CO2.EW			1.491***	0.9922***	0.9925***
			(19.74)	(10.92)	(11.73)
Temperature			-0.1268*	-0.0873	-0.1352*
			(-1.739)	(-1.544)	(-1.817)
Precipitation			-0.0575	-0.0984***	-0.0597
			(-1.299)	(-2.884)	(-1.429)
Cloudcover			0.0933**	0.1149***	0.1151***
			(2.221)	(3.466)	(3.148)
N Daily Customers			0.0004*	2.02×10^{-5}	0.0004
			(1.819)	(0.0829)	(1.409)
GoogleTrendsCarbFootprint			-0.0127***	-0.0080*	-0.0103**
			(-2.899)	(-1.971)	(-2.264)
Fixed-effects					
person_id		Yes			
academ.year		Yes			
person_id-academ.year			Yes	Yes	Yes
academ.year-weekday				Yes	Yes
academ.week_id-type_x_program					Yes
Fit statistics					
Cluster S.E.: Acad. Day	Yes	Yes	Yes	Yes	Yes
Cluster S.E.: Person	Yes	Yes	Yes	Yes	Yes
Observations	121,650	121,650	121,650	121,650	121,650
R^2	0.00460	0.22088	0.30105	0.31324	0.31945
Within R^2		0.00177	0.09629	0.02538	0.01977

Clustered (person_id & academ.day_id) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 5: Effect of providing information on carbon footprint

Note: This table reports estimates from the following regression:

$$CO2_{i,y,t} = \kappa InfoPost_{y,t} + \theta InfoPostTreat_{y,t} + \zeta Controls_{y,t} + FEs + \epsilon_{i,y,t} \tag{10}$$

where the set of control variables $Controls_{y,t}$ and fixed effects FEs vary across columns. $CO2_{i,y,t}$ is the carbon footprint of the meal purchased by individual i on academic day t of academic year y (we define academic day as academic week $\times$ weekday, e.g. Friday of academic week #3). Dummy $InfoPostTreat_{y,t}$ is equal to 1 for all academic days t in year 2022-2023 after the information about carbon footprint has been posted (from academic week #14 onward), and zero otherwise. Dummy $InfoPost_{y,t}$ is equal to 1 for observations after the academic week corresponding to the introduction of information posters (academic week #14 onward in *both* 2021-2022 and 2022-2023 academic years), and zero otherwise. $CO2.EW_{y,t}$ is the equal-weighted average of the carbon footprint of dishes offered on academic day t of academic year y. The equation was estimated on the sample of regular customers defined as individuals who had at least 5 purchases before and at least 5 purchases after the information treatment. For estimation, we focus on the window of 11 academic weeks before and 12 academic weeks after the information treatment (this window does not overlap with price treatment, which commences later). Standard errors are clustered by person ID and academic day.

Dependent Variable:	CO2				
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Info.PostTreat	-0.0825	-0.0917	-0.1981	-0.0596	-0.1027
	(-0.7295)	(-0.8399)	(-1.228)	(-0.2994)	(-0.9701)
Info.PostTreat × d.Staff		0.0401			
		(0.2517)			
Info.PostTreat × d.Prof		0.1136			
		(0.6056)			
age × Info.PostTreat			0.0056		
			(0.9101)		
female × Info.PostTreat			-0.0493		
			(-0.5100)		
Quint.mean.CO2.PRE_NORM × Info.PostTreat				-0.0099	
				(-0.1386)	
Quint.sd.CO2.PRE_NORM × Info.PostTreat				-0.0078	
				(-0.1426)	
d.Asia × Info.PostTreat					0.0476
					(0.3393)
d.Africa × Info.PostTreat					0.0822
					(0.5871)
d.NorthAmerica × Info.PostTreat					0.2586
					(1.290)
d.SouthAmerica × Info.PostTreat					0.0554
					(0.2827)
Fixed-effects					
person_id-academ.year	Yes	Yes	Yes	Yes	Yes
academ.year-weekday	Yes	Yes	Yes	Yes	Yes
academ.week_id-type_x_program	Yes	Yes	Yes	Yes	Yes
Fit statistics					
HTE x-Post Interactions	No	FE	Yes	Yes	Yes
Controls:	Yes	Yes	Yes	Yes	Yes
Cluster S.E.: Academ Day	Yes	Yes	Yes	Yes	Yes
Cluster S.E.: Person	Yes	Yes	Yes	Yes	Yes
Observations	121,650	121,650	121,650	121,650	121,650
R^2	0.31945	0.31945	0.31952	0.32187	0.31950
Within R^2	0.01977	0.01977	0.01987	0.02326	0.01983

Clustered (person_id & academ.day_id) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 6: Test for the presence of heterogeneous responses to posting information

Note: *Quint.mean.CO2.PRE.NORM* is the quintile of pre-treatment CO2 of a given individual minus 1. Definition of *Quint.sd.CO2.PRE.NORM* is analogous. Variable *full_tuition_fee_euro_NORM* is a tuition fee of the program minus the minimum tuition fee across programs.

Dependent Variables:	CO2		log(CO2)		CO2_rank_ABC		CO2_rank_EF	
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
P010.PostTreat	-0.0466	0.0189	0.0392	0.0672	0.0297	0.0185	-0.0218	-0.0137
	(-0.2342)	(0.0901)	(0.4192)	(0.6776)	(0.8465)	(0.5371)	(-0.7141)	(-0.4187)
P000.Break1.PostTreat	-0.3836	-0.3629	-0.2189	-0.2025	0.0606	0.0621	-0.0655	-0.0670
	(-1.184)	(-1.202)	(-1.482)	(-1.475)	(1.167)	(1.304)	(-1.326)	(-1.468)
P050.PostTreat	-1.069***	-0.9925***	-0.2802**	-0.2527**	0.1643***	0.1529***	-0.2116***	-0.1992***
	(-3.728)	(-3.469)	(-2.361)	(-2.063)	(4.104)	(4.016)	(-5.025)	(-4.990)
P025.PostTreat	-0.8174***	-0.8082**	-0.1667	-0.1549	0.1261***	0.1259***	-0.2018***	-0.2010***
	(-2.701)	(-2.600)	(-1.336)	(-1.194)	(3.212)	(3.183)	(-4.327)	(-4.344)
P000.Break2.PostTreat	-0.3339	-0.2573	-0.1379	-0.1094	0.0812	0.0698	-0.0608	-0.0463
	(-1.139)	(-0.8256)	(-1.086)	(-0.8155)	(1.252)	(1.046)	(-1.415)	(-1.006)
P100.PostTreat	-1.447***	-1.285***	-0.4165**	-0.3514**	0.2542***	0.2249***	-0.2819***	-0.2527***
	(-4.173)	(-3.565)	(-2.511)	(-2.149)	(5.439)	(4.450)	(-5.653)	(-4.686)
P000.Break3.PostTreat	-0.5284	-0.4453	-0.1400	-0.0904	0.0644	0.0520	-0.0939	-0.0805
	(-1.272)	(-1.031)	(-0.9251)	(-0.5622)	(0.8900)	(0.6861)	(-1.408)	(-1.143)
Fixed-effects								
person_id_AY	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
academ.year-weekday	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
academ.week_id-type_x_program		Yes		Yes		Yes		Yes
Fit statistics								
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Post Indicators	Yes	FE	Yes	FE	Yes	FE	Yes	FE
Cluster S.E.: Acad. Day	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster S.E.: Person	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,347	28,344	28,347	28,344	28,347	28,344	28,347	28,344
R^2	0.31717	0.32240	0.36536	0.36966	0.30891	0.31419	0.30801	0.31317
Within R^2	0.02979	0.02008	0.01320	0.00855	0.02667	0.01390	0.02776	0.01645

Clustered (person_id & academ.day_id) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 7: Effect of bonus-malus system on carbon footprint

Note: This table reports estimates from the following regression:

$$\begin{aligned} CO2_{i,y,t} = & \sum_{w} \theta_w PriceTreatWeek(w)_{y,t} + \zeta Controls_{y,t} + Person \times AcademYearFE_{i,y} \\ & + AcademWeek \times ProgamFE_{i,t} + AcademYear \times WeekdayFE_{y,t} + \epsilon_{i,y,t} \end{aligned} \tag{11}$$

Odd columns include dummies equal to one for each academic week in *both* academic years corresponding to the bonus-malus treatment to capture academic seasonality effects (Post Indicators: "Yes"), while even columns include academic week × program type fixed effects. $Controls_{y,t}$ include equal-weighted average of the carbon footprint of dishes offered on academic day t of academic year y $CO2.EW_{y,t}$; calendar day-specific local temperature, precipitation, and cloud cover; the number of customers making purchase in HEC canteen on a given calendar day; Google Trends worldwide (to correspond to the international nature of HEC student and faculty community) for search phrase "carbon footprint". The equation was estimated on the sample of regular customers. For estimation, we focus on the window of 6 academic weeks before and 7 academic weeks after the first price treatment (this window is fully contained within the information treatment). Standard errors are clustered by person ID and academic day.

Dependent Variable:	CO2					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Price.PostTreat	-1.314***	-1.425***	-2.033***	-1.200***	-1.404***	-1.594***
	(-5.042)	(-5.120)	(-4.272)	(-3.689)	(-5.051)	(-5.032)
Price.PostTreat × d.Staff		0.6891*				
		(1.711)				
Price.PostTreat × d.Prof		0.1415				
		(0.2765)				
age × Price.PostTreat			0.0264*			
			(1.952)			
female × Price.PostTreat			0.1991			
			(0.9796)			
Quint.mean.CO2.PRE_NORM × Price.PostTreat				-0.1908*		
				(-1.838)		
Quint.sd.CO2.PRE_NORM × Price.PostTreat				0.1294		
				(1.060)		
d.Asia × Price.PostTreat					0.4391	
					(1.159)	
d.Africa × Price.PostTreat					0.1359	
					(0.2715)	
d.NorthAmerica × Price.PostTreat					1.158**	
					(2.520)	
d.SouthAmerica × Price.PostTreat					-0.3483	
					(-0.6894)	
full_tuition_fee_euro_NORM × Price.PostTreat						0.0119
						(1.009)
Fixed-effects						
person_id-academ.year	Yes	Yes	Yes	Yes	Yes	Yes
academ.year-weekday	Yes	Yes	Yes	Yes	Yes	Yes
academ.week_id-type_x_program	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
HTE x-Post Interactions	No	FE	Yes	Yes	Yes	Yes
Controls:	Yes	Yes	Yes	Yes	Yes	Yes
Cluster S.E.: Academ Day	Yes	Yes	Yes	Yes	Yes	Yes
Cluster S.E.: Person	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,347	28,347	28,347	28,347	28,347	20,849
R^2	0.32114	0.32128	0.32155	0.32485	0.32137	0.32046
Within R^2	0.01814	0.01833	0.01873	0.02349	0.01846	0.01328

Clustered (person_id & academ.day_id) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 8: Test for the presence of heterogeneous responses to the price treatment

Note: For ease of presenting, in this test, all price treatments were aggregated into a single variable $Price.PostTreat \in \{0, 0.1, 0.25, 0.50, 1\}$. $Quint.mean.CO2.PRE.NORM$ is the quintile of pre-treatment CO2 of a given individual minus 1. Definition of $Quint.sd.CO2.PRE.NORM$ is analogous. Variable $full\_tuition\_fee\_euro\_NORM$ is a tuition fee of the program minus the minimum tuition fee across programs.

Dependent Variables:	price.actual			log(price.actual)		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
P010.PostTreat	-0.1167	-0.2574***	0.1743	-0.0214	-0.0547***	0.0508*
	(-1.2882)	(-2.7408)	(1.1568)	(-1.1454)	(-2.6809)	(1.7018)
P000.Break1.PostTreat	0.0019	-0.0935	0.1050	0.0015	-0.0168	0.0218
	(0.0273)	(-0.9225)	(1.1389)	(0.1085)	(-0.8241)	(1.1713)
P050.PostTreat	-0.1671	-1.1894***	1.7206***	-0.0713**	-0.2993***	0.3596***
	(-1.2287)	(-18.6933)	(14.7364)	(-2.1400)	(-24.8424)	(17.0005)
P025.PostTreat	-0.1579	-0.6542***	0.8260***	-0.0419**	-0.1487***	0.1814***
	(-1.5872)	(-5.4184)	(5.3090)	(-2.2077)	(-5.7512)	(6.3525)
P000.Break2.PostTreat	-0.1539	-0.0980	-0.3372	-0.0290	-0.0201	-0.0675
	(-1.4504)	(-1.0039)	(-1.4387)	(-1.3693)	(-0.9479)	(-1.4760)
P100.PostTreat	-0.7655***	-1.8726***	3.5741***	-0.3278***	-0.5676***	0.6437***
	(-4.9370)	(-16.0354)	(28.0992)	(-9.7606)	(-15.6121)	(33.4929)
P000.Break3.PostTreat	0.1179	-0.0244	0.2100	0.0279	-0.0008	0.0428
	(1.4486)	(-0.2427)	(1.4117)	(1.5942)	(-0.0380)	(1.4142)
Fixed-effects						
person_id_AY	Yes	Yes	Yes	Yes	Yes	Yes
academ.year-weekday	Yes	Yes	Yes	Yes	Yes	Yes
academ.week_id-type_x_program	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Dish Sample	All	A+,A,B,C	D,E,F	All	A+,A,B,C	D,E,F
Cluster S.E.: Acad. Day	Yes	Yes	Yes	Yes	Yes	Yes
Cluster S.E.: Person	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,328	17,488	10,780	28,328	17,488	10,780
R^2	0.2250	0.4668	0.7543	0.2645	0.5120	0.7323
Within R^2	0.0160	0.0813	0.5437	0.0380	0.1175	0.5046

Clustered (person_id & academ.day_id) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 9: Effect of bonus-malus system on spending

Note: This table reports estimates from the following regression:

$$\begin{aligned} log(Price.Actual)_{i,y,t} = &\sum_w \theta_w PriceTreatWeek(w)_{y,t} + \zeta Controls_{y,t} + Person \times AcademYearFE_{i,y} \\ &+ AcademWeek \times ProgamFE_{i,t} + AcademYear \times WeekdayFE_{y,t} + \epsilon_{i,y,t} \end{aligned} \tag{12}$$

Where $log(Price.Actual)$ is the logarithm of the price of the dish purchased by individual i on academic day t of academic year y (we define academic day as academic week $\times$ weekday, e.g. Friday of academic week #3). In columns 1-3, we use the level of price as the dependent variable, while in columns 4-6, we use the natural logarithm of price. Dummy $PriceTreatWeek(w)_{y,t}$ is always equal to 0 in the control academic year of 2021-2022, and is equal to 1 when the academic day in 2022-2023 academic year corresponds to the week w of the bonus-malus treatment. The 4 yellow-to-red shaded areas correspond to 4 different levels of bonus-malus treatment: 0.10 EUR/kg CO2 eq., 0.25 EUR/kg CO2 eq., 0.50 EUR/kg CO2 eq., 1.0 EUR/kg CO2 eq., respectively. $Controls_{y,t}$ include the level (logarithm) of an equal-weighted average of the *pre*-price treatment prices of dishes offered on the academic day t for equations in levels (logarithms). Controls also include the logarithm of the equal-weighted carbon footprint of dishes offered on day t. The equation was estimated on the sample of regular customers. For estimation, we focus on the window of 6 academic weeks before and 7 academic weeks after the first price treatment (this window is fully contained within the information treatment). Standard errors are clustered by person ID and academic day.

Dependent Variables:		CO2			log(CO2)	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
P010.PostTreat	-0.2093	-0.1145	-0.1417	-0.0678	-0.0142	-0.0162
	(-0.9095)	(-0.5165)	(-0.6193)	(-0.6534)	(-0.1378)	(-0.1518)
P000.Break1.PostTreat	-0.4154	-0.4077	-0.4078	-0.2327	-0.2188	-0.2239
	(-1.128)	(-1.286)	(-1.273)	(-1.375)	(-1.495)	(-1.518)
P050.PostTreat	-1.187***	-1.108***	-1.132***	-0.4011***	-0.3586**	-0.3570**
	(-3.393)	(-3.348)	(-3.310)	(-2.918)	(-2.601)	(-2.477)
P025.PostTreat	-1.085***	-1.058***	-1.105***	-0.3729**	-0.3351**	-0.3387**
	(-3.025)	(-3.048)	(-3.032)	(-2.570)	(-2.421)	(-2.351)
P000.Break2.PostTreat	-0.4155	-0.3341	-0.3432	-0.1889	-0.1566	-0.1703
	(-1.323)	(-1.078)	(-1.088)	(-1.412)	(-1.189)	(-1.277)
P100.PostTreat	-1.650***	-1.458***	-1.482***	-0.5515***	-0.4724***	-0.4809***
	(-4.540)	(-3.853)	(-3.845)	(-3.328)	(-2.856)	(-2.899)
P000.Break3.PostTreat	-0.5717	-0.5030	-0.5159	-0.1864	-0.1446	-0.1533
	(-1.309)	(-1.140)	(-1.169)	(-1.205)	(-0.9106)	(-0.9635)
Removal.PostTreat	-0.4074	-0.2834		-0.0993	-0.0407	
	(-1.542)	(-1.139)		(-0.9035)	(-0.3932)	
Removal.Week1.PostTreat			-0.1169			0.0059
			(-0.3766)			(0.0455)
Removal.Week2.PostTreat			-0.4373			-0.1645
			(-1.180)			(-1.162)
Removal.Week3.PostTreat			-0.2946			-0.0379
			(-1.038)			(-0.3106)
Removal.Week4.PostTreat			-0.4932			0.0517
			(-1.353)			(0.3216)
Fixed-effects						
person_id_AY	Yes	Yes	Yes	Yes	Yes	Yes
academ.year-weekday	Yes	Yes	Yes	Yes	Yes	Yes
academ.week_id-type_x_program		Yes	Yes		Yes	Yes
Fit statistics						
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Post Indicators	Yes	FE	FE	Yes	FE	FE
Cluster S.E.: Acad. Day	Yes	Yes	Yes	Yes	Yes	Yes
Cluster S.E.: Person	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30,216	30,207	30,207	30,216	30,207	30,207
R^2	0.30658	0.31415	0.31425	0.36066	0.36693	0.36708
Within R^2	0.03180	0.02173	0.02188	0.01741	0.01021	0.01044

Clustered (person_id & academ.day_id) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 10: Test of the resilience of habits

Note: *Removal.PostTreat* is a dummy variable equal to one for the removal phase of the experiment in 2022-23 academic year and zero otherwise. Variables *Removal.Week1.PostTreat*,...,*Removal.Week4.PostTreat* correspond to the weekly version of *Removal.PostTreat*. Other definitions and the specification design are analogous to those in Table 7.

Dependent Variables:	CO2	CO2_rank_ABC	CO2_rank_EF	CO2	CO2_rank_ABC	CO2_rank_EF
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
NoMeat.PostTreat	-0.1126	-0.0142	0.0140	0.1748	-0.0701*	0.0570
	(-0.4486)	(-0.3285)	(0.2867)	(0.7973)	(-1.842)	(1.152)
Temperature	0.1829	-0.0322	0.0731**	0.0047	0.0027	0.0463
	(1.139)	(-1.103)	(2.448)	(0.0318)	(0.1037)	(1.619)
Cloudcover	0.0943	-0.0042	0.0096	0.0760	-0.0007	0.0069
	(1.467)	(-0.3781)	(0.7596)	(1.381)	(-0.0830)	(0.5875)
Precipitation	0.0446	-0.0147	0.0107	0.0111	-0.0080	0.0056
	(0.4860)	(-0.8963)	(0.6454)	(0.1277)	(-0.5342)	(0.3342)
GoogleTrendsCarbFootprint	0.0389	-0.0032	0.0047	0.0310	-0.0025	0.0042
	(0.7318)	(-0.3544)	(0.4951)	(0.7583)	(-0.3790)	(0.5435)
NoMeat.PostTreat × d.Thu	-2.124***	0.3907***	-0.3904***	-2.353***	0.4352***	-0.4246***
	(-9.122)	(8.877)	(-8.798)	(-12.64)	(13.78)	(-11.34)
CO2.EW.noThu				0.7021***		
				(5.434)		
log(CO2.EW.noThu)					-0.3452***	0.2652***
					(-7.145)	(3.830)
Fixed-effects						
person_id_AY	Yes	Yes	Yes	Yes	Yes	Yes
academ.year-weekday	Yes	Yes	Yes	Yes	Yes	Yes
academ.week_id-type_x_program	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Cluster S.E.: Date	Yes	Yes	Yes	Yes	Yes	Yes
Cluster S.E.: Person	Yes	Yes	Yes	Yes	Yes	Yes
Observations	41,461	41,883	41,883	41,461	41,883	41,883
R^2	0.35519	0.33306	0.33609	0.35992	0.33790	0.33902
Within R^2	0.02210	0.01816	0.02246	0.02928	0.02527	0.02677

Clustered (person_id & date) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 11: Effect of the ban of high-CO2 meat on Thursdays

Note: This table reports estimates from the following regression:

$$\begin{aligned} CO2_{i,y,t} =& \theta_0 NoMeatPostTreat_{y,t} + \theta_1 NoMeatPostTreat \times d.Thursday_{y,t} \\ &+ \zeta Controls_{y,t} + Person \times AcademYearFE_{i,y} + AcademWeek \times ProgamFE_{i,t} \\ &+ AcademYear \times WeekdayFE_{y,t} + \epsilon_{i,y,t} \end{aligned} \tag{13}$$

$CO2_{i,y,t}$ is the carbon footprint of the meal purchased by individual i on academic day t of academic year y (we define academic day as academic week × weekday, e.g. Friday of academic week #3). Dummy $NoMeatPostTreat_{y,t}$ is equal to 1 after the ban on red meat dishes on Thursdays has been put in place (from academic week #3 of the academic year 2022-2023 onward), and zero otherwise. Therefore, the interaction $NoMeatPostTreat_{y,t} \times d.Thursday_{y,t}$ captures the effect on ban, while the non-interacted variable tests for possible spill-over effects on other days. The regression is estimated on the window starts from the academic week #1 (covers 2 academic weeks before the introduction of the red meat ban on Thursdays) and covers 4 academic weeks after the ban (the sample window does not overlap with information or price treatments). For this regression, the full sample of individuals (including both regular and non-regular) is used since we have only 2 academic weeks before the commencement of the ban, and therefore, the definition of regular customers based on pre-treatment behavior is likely to be noisy. Standard errors are clustered by person ID and calendar date (the window span is too short to rely on academic day as a clustering dimension).

Treatment	Relative effect on carbon footprint of purchased dish	Relative effect on users' average spending	% of voters in favor of the policy
Do nothing	$\approx 0\%$	$\approx 0\%$	3.5%
Information only	$\approx 0\%$	$\approx 0\%$	6.5%
Bonus-malus Euro 0.10 / kg CO_2 eq.	$\approx 0\%$	$\approx 0\%$	
Bonus-malus Euro 0.25 / kg CO_2 eq.	-26.8%	-4.2%	60%
Bonus-malus Euro 0.50 / kg CO_2 eq.	-32.9%	-7.1%	
Bonus-malus Euro 0.10 / kg CO_2 eq.	-42.6%	-32.8%	
Red meat-free Thursday	-10%	$\approx 0\%$	30%

Table 12: Efficacy and popularity of the different policies

Among the bonus-malus pricing policy only the 0.25 Euros/kg CO_2 eq. was proposed in the survey.

Dependent Variables:	mean_CO2_habit	median_CO2_habit	mean_CO2_habit	median_CO2_habit
Model:	(1)	(2)	(3)	(4)
Variables				
Constant	5.642***	7.003***		
	(11.73)	(9.878)		
Q17_only_info	-0.2341	-0.4240	-0.2367	-0.4493
	(-0.4509)	(-0.5031)	(-0.3903)	(-0.4737)
Q17_pricing	-1.229**	-1.876***	-1.198**	-1.867**
	(-2.521)	(-2.623)	(-2.072)	(-2.220)
Q17_ban	-1.054**	-1.908***	-1.039*	-1.920**
	(-2.129)	(-2.617)	(-1.786)	(-2.260)
age	-0.0468***	-0.0708***	-0.0015	-0.0105
	(-7.299)	(-8.509)	(-0.1390)	(-0.8692)
female	-0.7810***	-1.207***	-0.7543***	-1.199***
	(-5.570)	(-5.075)	(-5.339)	(-4.757)
Fixed-effects				
type_x_program			Yes	Yes
Fit statistics				
Observations	356	356	356	356
R^2	0.28553	0.24165	0.35898	0.30535
Within R^2			0.14376	0.12130

Heteroskedasticity-robust co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 13: How dish carbon footprint change among groups of users depending on the policy they prefer.

Note: The table reports estimates from the following linear regression:

$$CO2\_habit_i = \alpha + \beta_1 Q17\_only\_info_i + \beta_2 Q17\_pricing_i + \beta_3 Q17\_ban_i + Controls_i + \epsilon_i$$

Consumption habits of the individual i, $CO2\_habit_i$ are measured as the within-individual mean (median) pre-info treatment carbon footprint of dishes, measured in $kg\ CO2$/meal. $Q17\_only\_info_i$, $Q17\_pricing_i$, $Q17\_ban_i$ are dummy variables equal to one if individual i voted for the "only info", "pricing", "ban" policy, respectively, and zero otherwise. Hence, intercept α captures the average $CO2$ habit of individuals who voted for the remaining "do nothing" policy. Standard errors are heteroskedasticity-robust.

Dependent Variables:	CanRank	share.correct	all.correct
Model:	(1)	(2)	(3)
Variables			
(Intercept)	0.6923***	0.3130***	0.0451***
	(29.08)	(25.82)	(4.213)
Removal.Post	0.1060***	0.0502**	0.0372*
	(3.022)	(2.409)	(1.802)
Fit statistics			
S.E.	Heterosk.-rob.	Heterosk.-rob.	Heterosk.-rob.
Observations	620	620	620
R^2	0.01372	0.00977	0.00588
Adjusted R^2	0.01213	0.00817	0.00427

Heteroskedasticity-robust co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 14: Knowledge of about the carbon footprint of dishes: Entry vs. Exit survey

Note: The table reports estimates of the following regression:

$$Y_j = \gamma_0 + \gamma_1 Removal.Post_j + \nu_j$$

where Y_j is one of the measures of carbon footprint knowledge of in-person survey response j, and $Removal.Post_j$ is equal to 1 if the response corresponds to the exit survey wave and 0 otherwise. *CanRank* is a self-reported belief to be able to rank dishes according to their carbon footprint. *share.corret* is the share of dishes that were assigned the correct rank by a given survey respondent. *all.correct* is equal to one if all dishes were ranked correctly, and zero otherwise. In survey, respondents were asked to rank the following 4 dishes according to their carbon footprint: roast chicken, roast salmon, roast beef, roast lamb. The survey was executed as a repeated cross-section.

Dependent Variables:	CO2	log(CO2)	CO2	log(CO2)
Model:	(1)	(2)	(3)	(4)
Variables				
Info.Week1.PostTreat	-0.2843	0.0201	-0.2440	-0.1188
	(-0.9579)	(0.1409)	(-0.4902)	(-0.5397)
Info.Week2.PostTreat	-0.3124	-0.0525	0.4017	0.2148
	(-1.065)	(-0.3440)	(0.6090)	(0.6942)
Info.Week3.PostTreat	-0.1309	0.0287	-0.2371	0.0141
	(-0.4680)	(0.2048)	(-0.3395)	(0.0494)
Info.Week4.PostTreat	-0.2373	0.1188	-0.4668	-0.1088
	(-0.7178)	(0.7228)	(-0.8350)	(-0.4667)
Info.Week5p.PostTreat	-0.4420	-0.0396	-0.6202	-0.1298
	(-1.406)	(-0.2532)	(-1.291)	(-0.5600)
Info.Week1.PostTreat × noticed_CO2_info			-0.0438	0.1484
			(-0.1010)	(0.6879)
Info.Week2.PostTreat × noticed_CO2_info			-0.7587	-0.2839
			(-1.316)	(-1.049)
Info.Week3.PostTreat × noticed_CO2_info			0.1138	0.0159
			(0.1762)	(0.0660)
Info.Week4.PostTreat × noticed_CO2_info			0.2472	0.2434
			(0.5001)	(1.464)
Info.Week5p.PostTreat × noticed_CO2_info			0.1905	0.0969
			(0.5140)	(0.5668)
Fixed-effects				
person_id-academ.year	Yes	Yes	Yes	Yes
academ.year-weekday	Yes	Yes	Yes	Yes
academ.week_id-type_x_program	Yes	Yes	Yes	Yes
Fit statistics				
Controls	Yes	Yes	Yes	Yes
Cluster S.E.: Acad. Day	Yes	Yes	Yes	Yes
Cluster S.E.: Person	Yes	Yes	Yes	Yes
Observations	13,284	13,284	13,284	13,284
R^2	0.37424	0.40082	0.37446	0.40101
Within R^2	0.01248	0.00570	0.01282	0.00602

Clustered (person_id & academ.day_id) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 15: Test of hypothesis 1.1

Note: This table reports estimates from the following regression:

$$CO2_{i,y,t} = \sum_{w \neq -1} \theta_w InfoTreatWeek(w)_{y,t} + \sum_{w \neq -1} \kappa_w InfoTreatWeek(w)_{y,t} \times Noticed\_CO2\_Info_i + FE + \epsilon_{i,y,t} \tag{14}$$

$CO2_{i,y,t}$ is the carbon footprint of the meal purchased by individual i on academic day t of academic year y (we define academic day as academic week × weekday, e.g. Friday of academic week #3). Dummy $InfoTreatWeek(w)_{y,t}$ is always equal to 0 in the control academic year of 2021-2022, and is equal to 1 when the academic day in 2022-2023 academic year corresponds to the week w pre-/post-information treatment. Dummy $Noticed\_CO2\_Info_i$ is equal to 1 if individual i responded in the follow-up survey that they noticed the posters with CO2 information and 0 otherwise.

Dependent Variables:	CO2	log(CO2)	CO2	log(CO2)
Model:	(1)	(2)	(3)	(4)
Variables				
Info.Week1.PostTreat	-0.2843	0.0201	-1.303	-0.5703
	(-0.9579)	(0.1409)	(-1.547)	(-1.338)
Info.Week2.PostTreat	-0.3124	-0.0525	0.1633	0.2374
	(-1.065)	(-0.3440)	(0.2386)	(0.7092)
Info.Week3.PostTreat	-0.1309	0.0287	0.2725	-0.0223
	(-0.4680)	(0.2048)	(0.4911)	(-0.0586)
Info.Week4.PostTreat	-0.2373	0.1188	-0.1814	0.1955
	(-0.7178)	(0.7228)	(-0.2752)	(0.5066)
Info.Week5p.PostTreat	-0.4420	-0.0396	-0.1331	0.1233
	(-1.406)	(-0.2532)	(-0.2867)	(0.5121)
Info.Week1.PostTreat × perceived_reliab			0.2496	0.1448
			(1.355)	(1.584)
Info.Week2.PostTreat × perceived_reliab			-0.1169	-0.0713
			(-0.7090)	(-0.8023)
Info.Week3.PostTreat × perceived_reliab			-0.0991	0.0122
			(-1.049)	(0.1628)
Info.Week4.PostTreat × perceived_reliab			-0.0143	-0.0190
			(-0.1159)	(-0.2702)
Info.Week5p.PostTreat × perceived_reliab			-0.0763	-0.0403
			(-0.9141)	(-0.9202)
Fixed-effects				
person_id-academ.year	Yes	Yes	Yes	Yes
academ.year-weekday	Yes	Yes	Yes	Yes
academ.week_id-type_x_program	Yes	Yes	Yes	Yes
Fit statistics				
Controls	Yes	Yes	Yes	Yes
Cluster S.E.: Acad. Day	Yes	Yes	Yes	Yes
Cluster S.E.: Person	Yes	Yes	Yes	Yes
Observations	13,284	13,284	13,284	13,284
R^2	0.37424	0.40082	0.37456	0.40121
Within R^2	0.01248	0.00570	0.01298	0.00635

Clustered (person_id & academ.day_id) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 16: Test of hypothesis 1.2

Note: This table reports estimates from the following regression:

$$CO2_{i,y,t} = \sum_{w \neq -1} \theta_w InfoTreatWeek(w)_{y,t} + \sum_{w \neq -1} \kappa_w InfoTreatWeek(w)_{y,t} \times Noticed\_CO2\_Info_i + FE + \epsilon_{i,y,t} \tag{15}$$

$CO2_{i,y,t}$ is the carbon footprint of the meal purchased by individual i on academic day t of academic year y (we define academic day as academic week × weekday, e.g. Friday of academic week #3). Dummy $InfoTreatWeek(w)_{y,t}$ is always equal to 0 in the control academic year of 2021-2022, and is equal to 1 when the academic day in 2022-2023 academic year corresponds to the week w pre-/post-information treatment. Dummy $Perceived\_Reliability_i$ is a variable ranging from 1 to 5 depending on individual i's answer in the follow-up survey about whether they consider carbon footprint-related information provided on the posters in HEC canteen reliable or not (1 = "Not reliable at all", 5 = "Very reliable").

Dependent Variables:	CO2	log(CO2)	CO2	log(CO2)
Model:	(1)	(2)	(3)	(4)
Variables				
Info.Week1.PostTreat	-0.2843	0.0201	-0.0877	0.0140
	(-0.9579)	(0.1409)	(-0.2302)	(0.0609)
Info.Week2.PostTreat	-0.3124	-0.0525	-0.6839*	-0.2649
	(-1.065)	(-0.3440)	(-1.791)	(-1.139)
Info.Week3.PostTreat	-0.1309	0.0287	-0.4389	-0.1892
	(-0.4680)	(0.2048)	(-1.059)	(-1.074)
Info.Week4.PostTreat	-0.2373	0.1188	-0.7797	-0.0118
	(-0.7178)	(0.7228)	(-1.259)	(-0.0455)
Info.Week5p.PostTreat	-0.4420	-0.0396	-0.6155	-0.1699
	(-1.406)	(-0.2532)	(-1.558)	(-0.8650)
Info.Week1.PostTreat × discount			-0.1895	0.0421
			(-0.3559)	(0.1507)
Info.Week2.PostTreat × discount			0.5348*	0.2785
			(1.955)	(1.098)
Info.Week3.PostTreat × discount			0.3763	0.2644
			(1.175)	(1.414)
Info.Week4.PostTreat × discount			0.6069	0.1137
			(0.9307)	(0.5221)
Info.Week5p.PostTreat × discount			0.1458	0.1193
			(0.5775)	(0.9062)
Fixed-effects				
person_id-academ.year	Yes	Yes	Yes	Yes
academ.year-weekday	Yes	Yes	Yes	Yes
academ.week_id-type_x_program	Yes	Yes	Yes	Yes
Fit statistics				
Controls	Yes	Yes	Yes	Yes
Cluster S.E.: Acad. Day	Yes	Yes	Yes	Yes
Cluster S.E.: Person	Yes	Yes	Yes	Yes
Observations	13,284	13,284	12,603	12,603
R^2	0.37424	0.40082	0.37054	0.39918
Within R^2	0.01248	0.00570	0.01286	0.00627

Clustered (person_id & academ.day_id) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 17: Test of hypothesis 1.3: Discount

Note: This table reports estimates from the following regression:

$$CO2_{i,y,t} = \sum_{w \neq -1} \theta_w InfoTreatWeek(w)_{y,t} + \sum_{w \neq -1} \kappa_w InfoTreatWeek(w)_{y,t} \times Discount_i + FE + \epsilon_{i,y,t} \tag{16}$$

$CO2_{i,y,t}$ is the carbon footprint of the meal purchased by individual i on academic day t of academic year y (we define academic day as academic week × weekday, e.g. Friday of academic week #3). Dummy $InfoTreatWeek(w)_{y,t}$ is always equal to 0 in the control academic year of 2021-2022, and is equal to 1 when the academic day in 2022-2023 academic year corresponds to the week w pre-/post-information treatment. Variable *discount* is based on the follow-up survey and measures how patient individual i is (higher discount = more patient).

Dependent Variables:	CO2	log(CO2)	CO2	log(CO2)
Model:	(1)	(2)	(3)	(4)
Variables				
Info.Week1.PostTreat	-0.2843	0.0201	-0.3062	0.0041
	(-0.9579)	(0.1409)	(-1.049)	(0.0286)
Info.Week2.PostTreat	-0.3124	-0.0525	-0.3135	-0.0534
	(-1.065)	(-0.3440)	(-1.100)	(-0.3483)
Info.Week3.PostTreat	-0.1309	0.0287	-0.1065	0.0425
	(-0.4680)	(0.2048)	(-0.3750)	(0.2944)
Info.Week4.PostTreat	-0.2373	0.1188	-0.2497	0.1229
	(-0.7178)	(0.7228)	(-0.7388)	(0.7208)
Info.Week5p.PostTreat	-0.4420	-0.0396	-0.4785	-0.0574
	(-1.406)	(-0.2532)	(-1.496)	(-0.3621)
Info.Week1.PostTreat × immediacy			0.1719	0.1251
			(0.5646)	(0.7652)
Info.Week2.PostTreat × immediacy			0.0144	0.0095
			(0.0525)	(0.0543)
Info.Week3.PostTreat × immediacy			-0.2375	-0.1307
			(-1.064)	(-1.100)
Info.Week4.PostTreat × immediacy			0.0871	-0.0428
			(0.2869)	(-0.2992)
Info.Week5p.PostTreat × immediacy			0.2123	0.1028
			(1.123)	(1.146)
Fixed-effects				
person_id-academ.year	Yes	Yes	Yes	Yes
academ.year-weekday	Yes	Yes	Yes	Yes
academ.week_id-type_x_program	Yes	Yes	Yes	Yes
Fit statistics				
Controls	Yes	Yes	Yes	Yes
Cluster S.E.: Acad. Day	Yes	Yes	Yes	Yes
Cluster S.E.: Person	Yes	Yes	Yes	Yes
Observations	13,284	13,284	13,284	13,284
R^2	0.37424	0.40082	0.37437	0.40097
Within R^2	0.01248	0.00570	0.01269	0.00595

Clustered (person_id & academ.day_id) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 18: Test of hypothesis 1.3: Immediacy

Note: This table reports estimates from the following regression:

$$CO2_{i,y,t} = \sum_{w \neq -1} \theta_w InfoTreatWeek(w)_{y,t} + \sum_{w \neq -1} \kappa_w InfoTreatWeek(w)_{y,t} \times Immediacy_i + FE + \epsilon_{i,y,t} \tag{17}$$

$CO2_{i,y,t}$ is the carbon footprint of the meal purchased by individual i on academic day t of academic year y (we define academic day as academic week × weekday, e.g. Friday of academic week #3). Dummy $InfoTreatWeek(w)_{y,t}$ is always equal to 0 in the control academic year of 2021-2022, and is equal to 1 when the academic day in 2022-2023 academic year corresponds to the week w pre-/post-information treatment. Variable *immediacy* stands for the preference for the immediacy of individual i and is measured based on the follow-up survey.

Dependent Variables:	CO2	log(CO2)	CO2	log(CO2)
Model:	(1)	(2)	(3)	(4)
Variables				
Info.Week1.PostTreat	-0.2843	0.0201	-1.300	-0.2939
	(-0.9579)	(0.1409)	(-1.451)	(-0.7660)
Info.Week2.PostTreat	-0.3124	-0.0525	-0.0408	0.0440
	(-1.065)	(-0.3440)	(-0.0419)	(0.0824)
Info.Week3.PostTreat	-0.1309	0.0287	-1.264***	-0.5605**
	(-0.4680)	(0.2048)	(-2.710)	(-2.042)
Info.Week4.PostTreat	-0.2373	0.1188	-1.099	-0.1801
	(-0.7178)	(0.7228)	(-1.510)	(-0.5800)
Info.Week5p.PostTreat	-0.4420	-0.0396	-1.054**	-0.1925
	(-1.406)	(-0.2532)	(-2.238)	(-0.8578)
Info.Week1.PostTreat × care_environm			0.3396	0.1049
			(1.416)	(1.011)
Info.Week2.PostTreat × care_environm			-0.0927	-0.0329
			(-0.2933)	(-0.1776)
Info.Week3.PostTreat × care_environm			0.3771***	0.1962***
			(3.719)	(2.702)
Info.Week4.PostTreat × care_environm			0.2898	0.1005
			(1.429)	(1.086)
Info.Week5p.PostTreat × care_environm			0.2036*	0.0508
			(1.681)	(0.9081)
Fixed-effects				
person_id-academ.year	Yes	Yes	Yes	Yes
academ.year-weekday	Yes	Yes	Yes	Yes
academ.week_id-type_x_program	Yes	Yes	Yes	Yes
Fit statistics				
Controls	Yes	Yes	Yes	Yes
Cluster S.E.: Acad. Day	Yes	Yes	Yes	Yes
Cluster S.E.: Person	Yes	Yes	Yes	Yes
Observations	13,284	13,284	13,284	13,284
R^2	0.37424	0.40082	0.37487	0.40119
Within R^2	0.01248	0.00570	0.01347	0.00632

Clustered (person_id & academ.day_id) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 19: Test of hypothesis 1.4

Note: This table reports estimates from the following regression:

$$CO2_{i,y,t} = \sum_{w \neq -1} \theta_w InfoTreatWeek(w)_{y,t} + \sum_{w \neq -1} \kappa_w InfoTreatWeek(w)_{y,t} \times Care\_Environment_i + FE + \epsilon_{i,y,t} \quad (18)$$

$CO2_{i,y,t}$ is the carbon footprint of the meal purchased by individual i on academic day t of academic year y (we define academic day as academic week × weekday, e.g. Friday of academic week #3). Dummy $InfoTreatWeek(w)_{y,t}$ is always equal to 0 in the control academic year of 2021-2022, and is equal to 1 when the academic day in 2022-2023 academic year corresponds to the week w pre-/post-information treatment. Variable $Care\_Environment_i$ measures the degree to which individual i cares about environment, and it ranges from 1 ("I don't care") to 4 ("I care a lot, and it dramatically influences my habits").

Dependent Variable:	Q11_with_info			
Model:	(1)	(2)	(3)	(4)
Variables				
Constant	5.240***	3.903***		
	(3.591)	(3.849)		
mean_CO2_habit	-0.4735**		-0.5406**	
	(-2.129)		(-2.522)	
age	-0.0410*	-0.0322	-0.0376	-0.0341
	(-1.732)	(-1.390)	(-0.9318)	(-0.8032)
female	-0.0464	0.1436	0.2446	0.4283
	(-0.0989)	(0.3327)	(0.4801)	(0.8663)
median_CO2_habit		-0.1665		-0.1918
		(-1.568)		(-1.548)
Fixed-effects				
type_x_program			Yes	Yes
Fit statistics				
Observations	356	356	308	308
Squared Correlation	0.03968	0.01364	0.06837	0.04957
Pseudo R^2	0.04828	0.02274	0.11158	0.07974
BIC	195.76	200.39	205.69	211.21

Heteroskedasticity-robust co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 20: Test of hypothesis 2.2: Logistic regression

Note: The table reports OLS estimates of the logistic regression:

$$PostersWithInfo_i = \alpha + \beta CO2\_habit_i + \gamma Controls_i + \epsilon_i$$

where $PostersWithInfo_i$ is equal to 1 if individual i chose that she/he prefers posting carbon footprint-related information in HEC canteen, and zero otherwise. Consumption habits of the individual i, $CO2\_habit_i$ are measured as the within-individual mean (median) pre-info treatment carbon footprint of dishes, measured in *kg* $CO2$/meal. Standard errors are heteroskedasticity-robust.

Dependent Variable:	Q11_with_info			
Model:	(1)	(2)	(3)	(4)
Variables				
Constant	1.085***	1.008***		
	(13.03)	(17.09)		
mean_CO2_habit	-0.0288**		-0.0323**	
	(-2.157)		(-2.325)	
age	-0.0027	-0.0020	-0.0020	-0.0020
	(-1.473)	(-1.221)	(-0.5919)	(-0.5955)
female	-0.0024	0.0086	0.0090	0.0217
	(-0.0832)	(0.3147)	(0.2972)	(0.7446)
median_CO2_habit		-0.0104		-0.0110
		(-1.567)		(-1.527)
Fixed-effects				
type_x_program			Yes	Yes
Fit statistics				
Observations	356	356	356	356
R^2	0.02381	0.01133	0.08229	0.06731
Within R^2			0.03044	0.01462

Heteroskedasticity-robust co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 21: Test of hypothesis 2.2: Linear probability regression

Note: The table reports OLS estimates of the linear probability model:

$$PostersWithInfo_i = \alpha + \beta CO2\_habit_i + \gamma Controls_i + \epsilon_i$$

where $PostersWithInfo_i$ is equal to 1 if individual i chose that she/he prefers posting carbon footprint-related information in HEC canteen, and zero otherwise. Consumption habits of the individual i, $CO2\_habit_i$ are measured as the within-individual mean (median) pre-info treatment carbon footprint of dishes, measured in kg $CO2$/meal. Standard errors are heteroskedasticity-robust.

Dependent Variables:	do_nothing	only_info	ban	pricing
Model:	(1)	(2)	(3)	(4)
Variables				
Constant	0.0263***	0.0492***	0.2918***	0.6327***
	(4.856)	(6.719)	(18.96)	(38.77)
manager	-0.0160***	-0.0206***	0.0412***	-0.0046
	(-3.522)	(-3.421)	(3.056)	(-0.3354)
Fit statistics				
Cluster S.E.: Person	Yes	Yes	Yes	Yes
Observations	1,748	1,748	1,748	1,748
R^2	0.00357	0.00284	0.00197	2.25×10^{-5}
Adjusted R^2	0.00300	0.00227	0.00140	-0.00055

Clustered (person_id) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 22: Test of hypothesis 2.5 and 2.6

Note: The table reports OLS estimates of the following regression:

$$vote_{i,s} = \alpha + \beta manager_{i,s} + \epsilon_{i,s}$$

where $manager_{i,s}$ is the dummy variable equal to 1 if the vote outcome of individual i corresponds to the "dean" treatment and zero if it corresponds to "referendum" treatment. Variable $vote_{i,s}$ is a binary outcome of the individual i's vote. In column 1, the $vote_{i,s}$ is equal to 1 if individual i voted for "do nothing" in a given treatment s, and zero otherwise. Variable *vote* in columns 2, 3 and 4 is defined analogously. Standard errors are heteroskedasticity-robust.

A Additional results

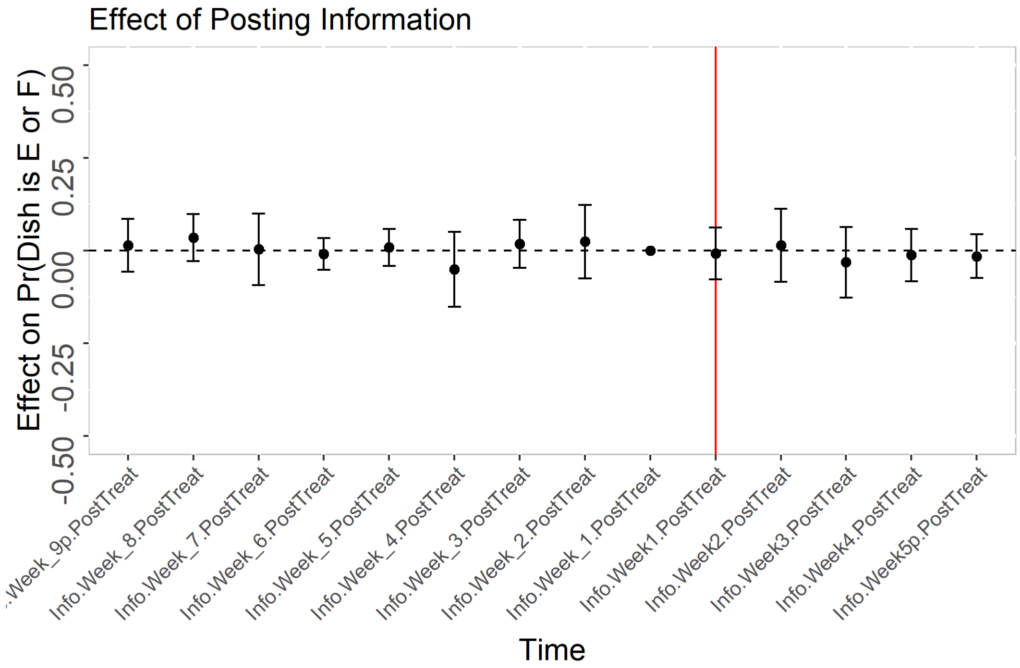


Figure 14: Effect of Posting Information: Linear probability model

Note: The estimated equation is:

$$CO2\_rank\_EF_{i,y,t} = \sum_{w\neq 1} \theta_w InfoPostTreat(w)_{y,t} + \zeta Controls_{y,t} + Person \times AcademYearFE_{i,y}$$
$$+AcademWeek \times ProgamFE_{i,t} + AcademYear \times WeekdayFE_{y,t} + \epsilon_{i,y,t}$$

95% confidence intervals are based on standard errors clustered by person ID and academic day.

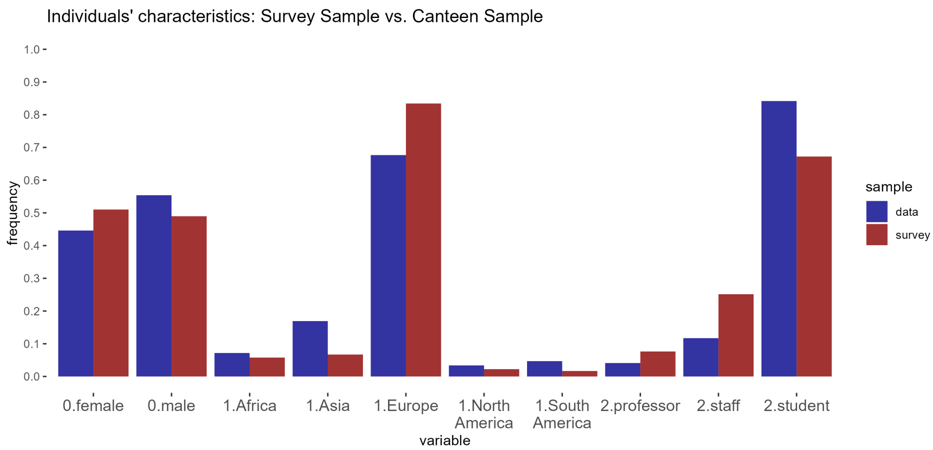


Figure 15: Demographic characteristic of subjects in in the field experiment and survey respondents.

B Claimed vs Actual behavior

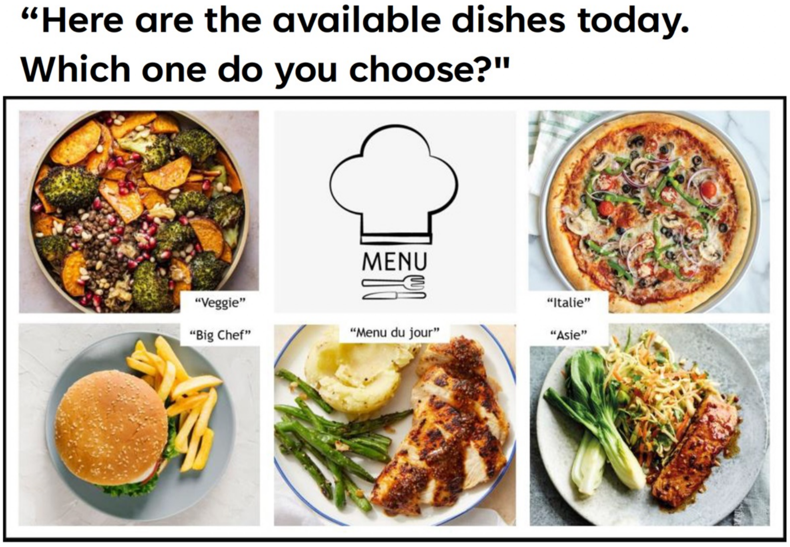
By comparing our data to the data from a survey run in the HEC community by Malaingre (2022), we can measure the difference between users' attitudes toward food carbon footprint and users' behavior. In the period between March and April 2022, an internet survey was run among HEC students, staff, and faculty. The survey format somewhat parallels the field experiment we ran the following academic year. After providing some key demographic data such as age, gender, and occupation (student, staff, or faculty), subjects were asked to choose one among five dishes (See Figure 16). Then, a survey participant had to choose again among the same five dishes when a measure of the carbon footprint of each dish was provided, either in terms of a letter grade or in terms of kg CO_2 eq. per portion. In the following question, subjects were asked to choose among the same dishes but with modified prices in the same spirit of the bonus-malus pricing.[30]. Two levels of value were considered for the value of CO_2: 1 $Euro$/kg CO_2 eq. and 0.1 $Euros$/kg CO_2 eq.. Answers in Malaingre (2022) survey suggest that the mere fact of providing information, with no financial incentives, reduced the average dish CF by about one-third (see Table 23) This is in sharp discrepancy with how users reacted to information in our field experiment. This difference could have various causes. First, it could be a difference in the two samples' demographic characteristics. Second, whereas in real conditions of HEC canteen dishes differ in prices, in the survey it was stated that the five dishes would have the same prices. Therefore, the outcome of the survey would rather represent what people would have done in counterfactual reality with flat prices. Third, it could be that the survey itself disclosed the order of magnitude of dishes' CF, and this information propagated within HEC community, thus leading us to find little reaction to the information treatment because users were aware of dishes CF before the introduction of CF labels. Fifth, the difference between the survey findings and the experiment findings could reflect the gap between claimed vs actual behavior, well documented in the marketing literature (Morwitz (2012)).

Figure 17 shows that the demographic characteristics of the survey sample (642 subjects) are comparable to those in our experiment. For 328 out of the 642 subjects who answered the survey, we could link answers in the survey to the actual behavior. We test whether individuals who participated in Malaingre (2022) survey changed their real-world behavior after receiving

[30] Whereas in our experiment the price-neutral threshold was a 3 kg CO_2 eq. per dish, in Malaingre (2022) it was of 2 kg CO_2 eq.

the carbon footprint information from the survey.[31] We find that while there seems to be a self-selection into Malaingre (2022) survey based on lower levels of pre-survey carbon footprint, the survey itself has no effect on the behavior of participants. Table 24 demonstrates the results.

Panel A: Menu in Malaingre (2022)



Panel B: Menu in Malaingre (2022) with carbon footprint information

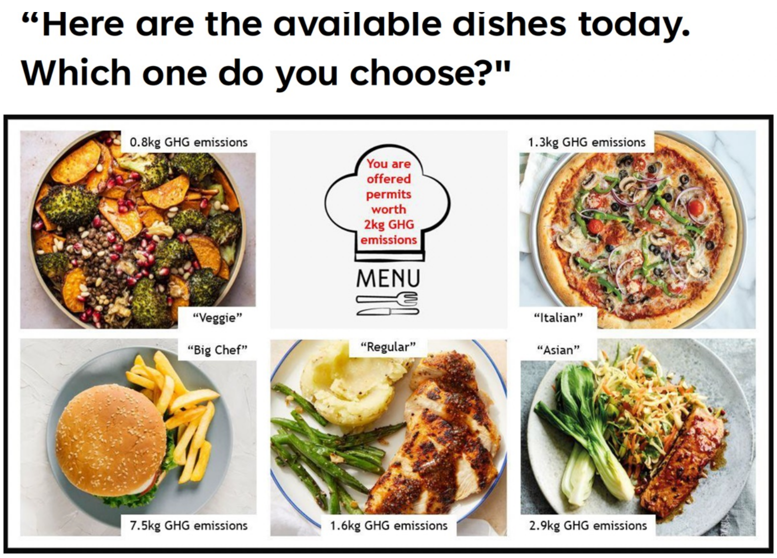
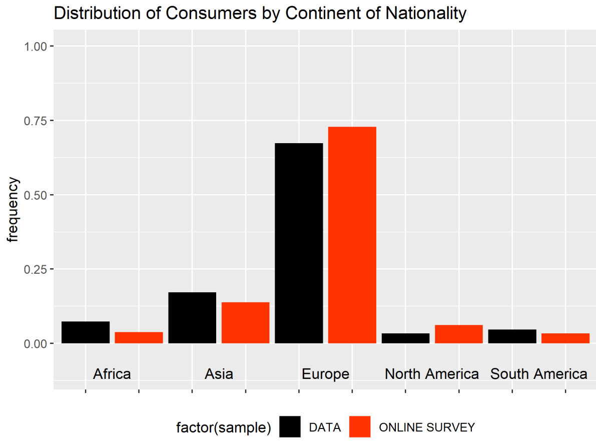


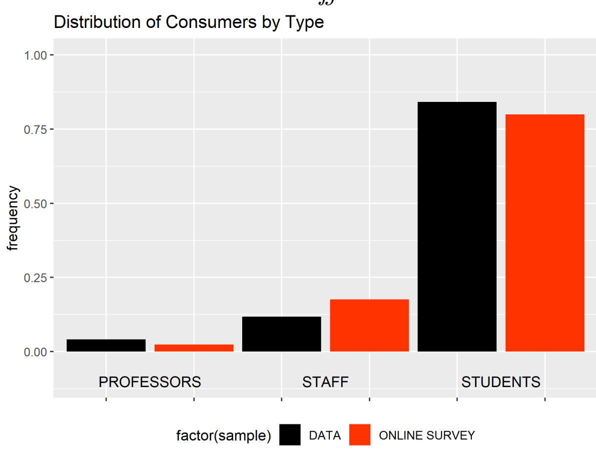
Figure 16: A set of dishes offered in Malaingre (2022) online survey

[31] Out of 328 individuals who were successfully matched to the canteen data, only 176 satisfied the regular customer sample criteria.

Panel A: Continents



Panel B: Affiliation



Panel C: Gender

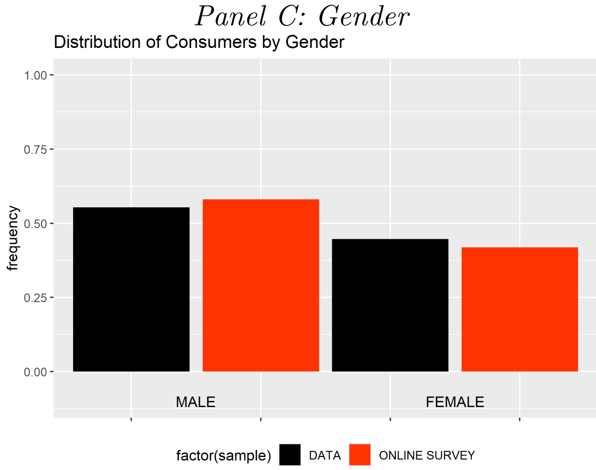


Figure 17: Comparison of the population of in Malaingre (2022) survey vs overall population of HEC canteen users

Dependent Variables:	CO2	log(CO2)
Model:	(1)	(2)
Variables		
(Intercept)	2.452***	0.6655***
	(33.69)	(25.35)
Info.PostTreat	-0.8539***	-0.3965***
	(-8.663)	(-10.49)
Fit statistics		
Observations	1,075	1,075
R^2	0.05852	0.08736
Adjusted R^2	0.05764	0.08650

Heteroskedasticity-robust co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 23: Survey-based information effect in Malaingre (2022)

Note: The table reports panel regression:

$$CO2_{i,t} = \lambda_0 + \lambda_1 Info.PostTreat_t + \epsilon_{i,t}$$

Where $t \in \{PreInfo, PostInfo\}$. $CO2_{i,t}$ is the carbon footprint of the dish chosen by survey participant i in the online survey of Malaingre (2022). The sample is the original sample of online survey respondents in Malaingre (2022).

Dependent Variables:		CO2			log(CO2)	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Survey.Treat	-0.2256*	-0.2283*		-0.1075*	-0.1112*	
	(-1.792)	(-1.852)		(-1.806)	(-1.897)	
Survey.PostTreat	0.1558	0.1530	0.1009	0.0494	0.0544	0.0400
	(1.267)	(1.386)	(1.069)	(0.9291)	(1.086)	(0.9411)
CO2.EW	1.135***			0.2871***		
	(9.511)			(7.986)		
age	-0.0131*	-0.0130*		-0.0017	-0.0017	
	(-1.941)	(-1.934)		(-0.5476)	(-0.5497)	
female	-0.5633***	-0.5639***		-0.2859***	-0.2869***	
	(-7.350)	(-7.339)		(-8.193)	(-8.241)	
temp.stdz	0.0459			0.0407**		
	(0.8336)			(2.002)		
cloudcover.stdz	0.0334			0.0253		
	(0.7985)			(1.609)		
precip.stdz	0.0258			0.0176**		
	(1.011)			(2.402)		
Fixed-effects						
weekday	Yes			Yes		
type_x_program	Yes	Yes		Yes	Yes	
continent	Yes	Yes		Yes	Yes	
date		Yes	Yes		Yes	Yes
person_id			Yes			Yes
Fit statistics						
Cluster S.E.: Date	Yes	Yes	Yes	Yes	Yes	Yes
Cluster S.E.: Person	Yes	Yes	Yes	Yes	Yes	Yes
Observations	40,055	40,055	40,409	40,055	40,055	40,409
R^2	0.07849	0.10582	0.31591	0.06696	0.08526	0.34797
Within R^2	0.03860	0.00983	3.61×10^{-5}	0.02618	0.01383	3.5×10^{-5}

Clustered (person_id & date) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 24: Test of the effect of Malaingre (2022) online survey on behavior of survey participants

Note: *Survey.Treat* is a dummy variable equal to one if HEC canteen user participated in Malaingre (2022) online survey, and zero otherwise. *Survey.PostTreat* is a dummy variable equal to 1 *after* the participant of the above-mentioned survey participated in the survey and zero otherwise. The sample includes all HEC canteen users who purchased at least 10 meals in our sample.

C Follow-up Survey: Questions and Summary

C.1 Attention check

To ensure the quality of the responses used for our analysis, we require that a survey participant has spent at least 5 minutes on their response. We also drop observations of responses that took more than 7 days to complete. These two filters have led to 13.3% decrease in the sample size. Further, we require that both attention checks embedded in our survey design have been passed successfully. Specifically, in the first attention check, we presented respondents with 4 posters containing information about 4 different dishes and asked which dish has the highest carbon footprint. As expected, a vast majority of 98% of the responses have completed this question successfully. In the second attention check, we verify whether survey respondents understood correctly the results of the prior HEC canteen experiment by asking to indicate on a continuous scale between 0% and 100% the magnitude of the carbon footprint reduction – according to the results of the HEC canteen experiment presented on the previous slide – triggered by each of the three treatments in our experiment (information provision, red meat supply restriction, and bonus-malus system). We treated as correct those responses that indicated effect of information treatment below 10%, the effects of supply restriction between 20% and 30%, and the effects of bonus-malus system between 20% and 30%.

C.2 Questions and Distribution of Answers

Question 1: How frequently do you expect to have lunches at the HEC canteen (HEC's main restaurant) between January 2024 and June 2024? (Note that this question concerns your future use of the HEC canteen, not how often you had lunch in the past)

Category	Percentage
frequently (more than twice per week)	40.78
not at all	31.56
rarely (less than once per week)	6.03
somewhat frequently (between once and twice per week)	21.63

Table 25: Distribution of Answers to Question 1

Question 1: Did you notice any experiments with dishes' carbon footprint information and carbon pricing at the HEC canteen during the last academic year 2022-23? (Multiple answers possible) (1) No, I did not have lunch at the HEC canteen during the academic year 2022-23. (2) No, I didn't notice. (3) Yes, I noticed that carbon footprint information was provided. (4) Yes, I noticed changes in prices related to carbon footprint. (5) Yes, I noticed that red meat was not offered on Thursdays.

Category	Percentage
(1)	2.84
(2)	2.13
(4)	3.19
(4),(5)	1.42
(3)	8.16
(3),(4)	17.02
(3),(4),(5)	59.93
(3),(5)	3.55
(5)	1.77

Table 26: Distribution of Answers to Question 1

Question 2: What dish in the above list has the highest carbon footprint

Category	Percentage
Roasted beef	100.00

Table 27: Distribution of Answers to Question 2

Question 3: The estimates of the carbon footprint of dishes posted in the HEC canteen research study were based on data provided by the ADEME (French Environment and Energy Management Agency) on the website www.agribalyse.ademe.fr. In your opinion, are these estimates of carbon footprint reliable?

Category	Percentage
1 = Not reliable at all	0.71
2	2.48
3	15.25
4	48.94
5 = Very reliable	32.62

Table 28: Distribution of Answers to Question 3

Question 5: Considering that currently at the HEC canteen, low-CO_2 dishes are approximately 20% MORE expensive than high-CO_2 dishes, in your opinion, how effective would each of the following three policies be in reducing the average carbon footprint of the dishes purchased at the HEC canteen?

1 = Not effective at all, 5 = Very effective

	1	2	3	4	5
Displaying carbon footprint information on dish posters	7.09	35.11	33.69	14.89	9.22
Introducing 2 days per week without high CO2 dishes (such as red meat)	8.16	9.22	16.31	23.40	42.91
Making low-CO2 dishes 10% LESS expensive than high-CO2 dishes by simultaneously decreasing the price of low-CO2 dishes AND increasing the price of high-CO2 dishes	2.84	6.38	12.06	28.72	50

Table 29: Distribution of Answers to Question 5

Question 6: Which of the following two information designs would you prefer to be displayed at the main dishes' stands in the HEC canteen?

Category	Percentage
With information about the carbon footprint of the dish	93.26
Without information about the carbon footprint of the dish	6.74

Table 30: Distribution of Answers to Question 6

Before answering the following three questions, subjects were provided information on the first findings of this paper:

"In the academic year 2022-23, a team of HEC researchers conducted an experiment at the HEC canteen (referred to as the HEC canteen research study henceforth).

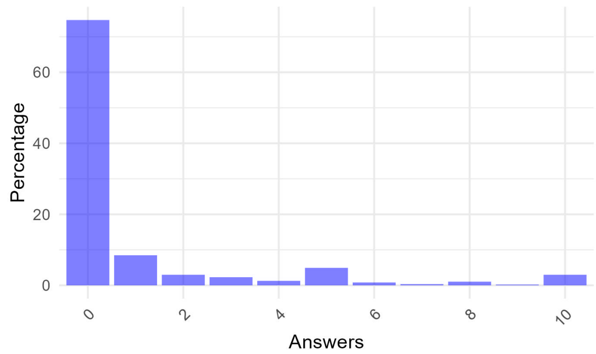
The research has shown that:

- The mere posting of information about the carbon footprint of dishes **had no significant impact** on the average carbon footprint of dishes chosen at the canteen.
- The elimination of red meat from the menu for **two days per week** could reduce the average carbon footprint of dishes chosen at the canteen **by about 25**%.
- Make **low-CO2 dishes 10% LESS expensive** than high-CO2 dishes (by **simultaneously** decreasing the price of low-CO2 dishes **AND** increasing the price of high-CO2

dishes) reduced the average carbon footprint of dishes chosen at the canteen **by about 25%**.

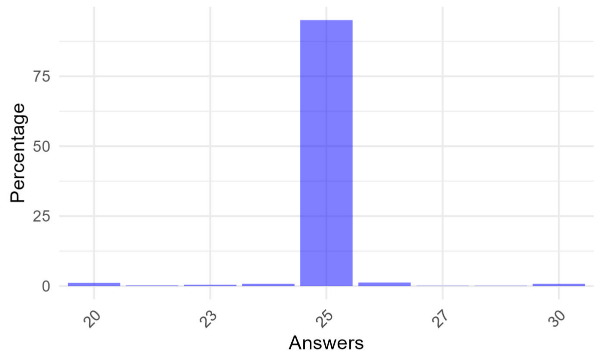
The next question will be about the findings of this research."

Prompt for questions 7.1 to 7.3: **According to the HEC canteen research study, by which percentage each of the following three policies could reduce the average carbon footprint of dishes purchased at the HEC canteen?**



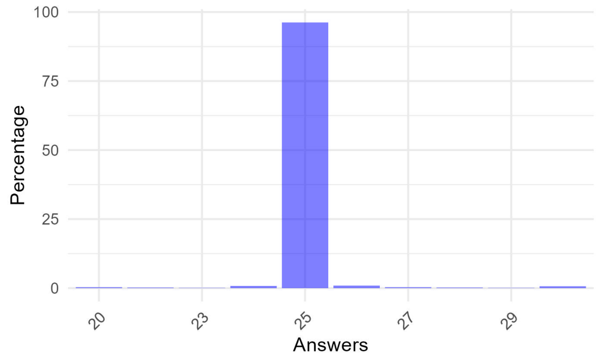
Policy: Displaying carbon footprint information on dish posters

Figure 18: Distribution of Answers to Question 7.1



Policy: Introducing **2 days per week without high-CO2 dishes** (such as red meat)

Figure 19: Distribution of Answers to Question 7.2



Policy: Making **low-CO2 dishes 10% LESS expensive** than high-CO2 dishes by **simultaneously** decreasing the price of low-CO2 dishes **AND** increasing the price of high-CO2 dishes

Figure 20: Distribution of Answers to Question 7.3

Question 8: After learning about the results of the HEC canteen research study, in your opinion, how effective would each of the following three policies be in reducing the average carbon footprint of dishes purchased at the HEC canteen?

1 = Not effective at all, 5 = Very effective

	1	2	3	4	5
Displaying carbon footprint information on dish posters	54.26	29.79	10.99	3.19	1.77
Introducing 2 days per week without high CO2 dishes (such as red meat)	3.90	6.03	16.67	42.20	31.21
Making low-CO2 dishes 10% LESS expensive than high-CO2 dishes by simultaneously decreasing the price of low-CO2 dishes AND increasing the price of high-CO2 dishes	1.42	4.61	14.89	41.84	37.2

Table 31: Distribution of Answers to Question 8

Question 9: Suppose HEC Paris has a target of reducing the HEC canteen's carbon footprint by approximately 25%. Suppose this target can be achieved with either of the following two policies without increasing the spending of an average HEC canteen user. Which policy would you prefer?

Category	Percentage
Do not offer red meat 2 days per week BUT maintain low-CO2 footprint dishes 20% MORE expensive than high-CO2 footprint dishes.	28.01
Make low-CO2 dishes 10% LESS expensive than high-CO2 dishes (by simultaneously decreasing the price of low-CO2 dishes AND increasing the price of high-CO2 dishes) BUT offer red meat every day	71.99

Table 32: Distribution of Answers to Question 9

Question 10.A: For this question only, imagine that you are the Dean of HEC Paris. As the Dean, your responsibilities include setting the strategic direction and vision of HEC Paris. Additionally, in line with recent trends emphasizing more sustainable practices in organizations, you are tasked with defining the sustainability policy of HEC Paris. Considering that in 2022, provision of food and catering on the HEC campus accounted for 39% of greenhouse gas emissions from the internal operations, you are now in charge of defining the policy to be implemented at the HEC canteen for the next 6 months. Which one of the following four policies would you choose to implement?

Category	Percentage
Policy 2: Just display carbon footprint information on dish posters	5.11
Policy 3: Do not offer red meat 2 days per week	27.74
Policy 4: Make low-CO2 dishes 10% LESS expensive than high-CO2 dishes by simultaneously decreasing the price of low-CO2 dishes AND increasing the price of high-CO2 dishes	67.15

Table 33: Distribution of Answers to Question 10.A

Question 11.A: Now, suppose a referendum is conducted among the HEC community to determine the HEC canteen policy for the next 6 months

Category	Percentage
Policy 1: Do nothing	1.38
Policy 2: Just display carbon footprint information on dish posters	2.07
Policy 3: Do not offer red meat 2 days per week	33.79
Policy 4: Make low-CO2 dishes 10% LESS expensive than high-CO2 dishes by simultaneously decreasing the price of low-CO2 dishes AND increasing the price of high-CO2 dishes	62.76

Table 34: Distribution of Answers to Question 11.A

Question 10.B: Suppose a referendum is conducted among the HEC community to determine the HEC canteen policy for the next 6 months [Table presenting each policy]

Category	Percentage
Policy 1: Do nothing	2.92
Policy 2: Just display carbon footprint information on dish posters	8.03
Policy 3: Do not offer red meat 2 days per week	18.25
Policy 4: Make low-CO2 dishes 10% LESS expensive than high-CO2 dishes by simultaneously decreasing the price of low-CO2 dishes AND increasing the price of high-CO2 dishes	70.80

Table 35: Distribution of Answers to Question 10.B

Question 11.B: For this question only, imagine that you are the Dean of HEC Paris. As the Dean, your responsibilities include setting the strategic direction and vision of HEC Paris. Additionally, in line with recent trends emphasizing more sustainable practices in organizations, you are tasked with defining the sustainability policy of HEC Paris. Considering that in 2022, provision of food and catering on the HEC campus accounted for 39% of greenhouse gas emissions from the internal operations, you are now in charge of defining the policy to be implemented at the HEC canteen for the next 6 months. Which one of the following four policies would you choose to implement?

Category	Percentage
Policy 1: Do nothing	2.07
Policy 2: Just display carbon footprint information on dish posters	4.14
Policy 3: Do not offer red meat 2 days per week	27.59
Policy 4: Make low-CO2 dishes 10% LESS expensive than high-CO2 dishes by simultaneously decreasing the price of low-CO2 dishes AND increasing the price of high-CO2 dishes	66.21

Table 36: Distribution of Answers to Question 11.B

Question 12: Which one of the following sentences would best reflect your attitude toward climate change?

Category	Percentage
I care a lot, and it dramatically influences my habits	18.79
I care and take some 'sustainable' actions (e.g., car-sharing, changes in diet...)	61.70
I care about climate change, but currently, I don't take any 'sustainable' actions (e.g., to help reduce emissions or conserve energy)	18.44
I don't care	1.06

Table 37: Distribution of Answers to Question 12

Question 13: On a scale of 1 (strongly disagree) to 10 (strongly agree), please indicate your degree of agreement with the following statements:

1 = Strongly disagree, 10 = Strongly agree

	1	2	3	4	5	6	7	8	9	10
Compassion for those who are suffering is the most crucial moral value	1.77	1.42	4.61	4.26	14.18	12.06	17.02	22.34	9.57	12.77
Respect for authority is something all children need to learn	0.35	2.84	6.38	5.67	13.48	12.06	18.79	17.73	7.45	15.25
Loyalty to one's group is more important than one's individual concerns	3.19	6.03	6.74	7.09	18.79	14.54	19.50	14.18	5.32	4.61
People shouldn't do disgusting things, even if it doesn't harm anyone	12.41	9.57	9.22	5.32	12.41	8.16	9.57	13.12	6.03	14.18
Justice, fairness and equality are the most important requirements for a society	1.06	0.71	1.77	2.48	5.67	4.26	11.70	27.30	21.28	23.76

Table 38: Distribution of Answers to Question 13

Question 14: Imagine your absolutely favorite dish among all dishes you've ever experienced in your life. If you were given the two following options, what would you choose?

Category	Percentage
Have a full portion of your favorite dish tomorrow	84.75
Have half a portion of your favorite dish now	15.25

Table 39: Distribution of Answers to Question 14

Question 15: Again, imagine your absolutely favorite dish. If you were given the two following options, what would you choose?

Category	Percentage
Have a full portfion of your favorite dish in 3 months + 1 day	96.45
Have half a portion of your favorite dish in 3 months	3.55

Table 40: Distribution of Answers to Question 15

Question 16: Again, imagine your absolutely favorite dish. How much are you willing to pay **today** (in EUR) to have **one full portion** of your favorite dish **tomorrow**?

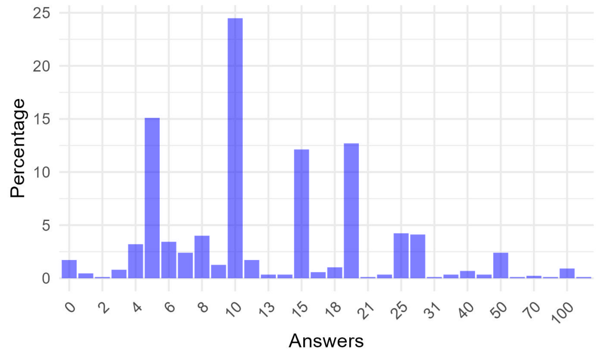


Figure 21: Distribution of Answers to Question 16

Question 17: Again, imagine your absolutely favorite dish. How much are you willing to pay **today** (in EUR) to have **one full portion** of your favorite dish **in 3 months + 1 day?**

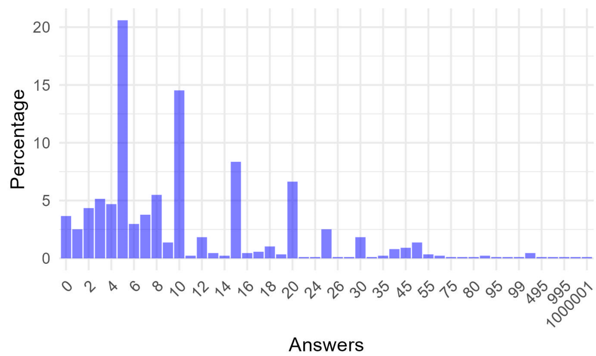


Figure 22: Distribution of Answers to Question 17