Journal of Accounting Research

DOI: 10.1111/1475-679X.12505
Journal of Accounting Research
Vol. 62 No. 1 March 2024
Printed in U.S.A.

CHICAGO BOOTH

How Does Carbon Footprint Information Affect Consumer Choice? A Field Experiment

BIANCA BEYER ,* RICO CHASKEL ,† SIMONE EULER ,† JOACHIM GASSEN ,† ANN-KRISTIN GROßKOPF ,‡ AND THORSTEN SELLHORN ‡

Received 1 August 2021; accepted 8 July 2023

ABSTRACT

This paper reports the results of a field experiment investigating how attributes of carbon footprint information affect consumer choice in a large

*Aalto University School of Business; †Humboldt-Universität zu Berlin; ‡Ludwig-Maximilians-Universität München

Accepted by Luzi Hail. We thank an anonymous associate editor, an anonymous reviewer, Jens Müller, Victor van Pelt, conference and workshop participants at the 2nd *JAR* Registered Reports Conference, LMU Munich, HU Berlin, Passau University, Aalto University, IESE Business School, University of Padova, and the European Accounting Association's Virtual Accounting Research Seminar (VARS), as well as members of the Accounting for Transparency collaborative research center for valuable comments. We also thank the head and several staff of canteen operations at Studentenwerk München for their support and insights, and Luise Engel for her valuable research assistance. We thank Sandra Denk, Andreas Oberhauser, Alexander Paulus, Julian Schneider, Victor Sehn, and Victor Wagner for their assistance in conducting the experiment. This study has received approval from the ethics board of HU Berlin. The authors acknowledge financial support from the German Research Foundation (Deutsche Forschungsgemeinschaft—DFG): project ID 403041268—TRR 266. Bianca Beyer acknowledges financial support from the Finnish Foundation for Economic Education (Liikesivistysrahasto). Data and code of the paper are accessible at https://github.com/trr266/carbonfood. This paper is the final registered report resulting from the Registration-Based Editorial Process (REP) implemented by JAR for its special 2021 Registered Reports Conference; details of the process are available here: https://www.chicagobooth.edu/research/chookaszian/journal-of-accounting-research/registered-reports. The accepted proposal and an online appendix for this report are available here: https://research.chicagobooth.edu/arc/journal-of-accounting-research/online-supplements.

dining facility. Our hypotheses and research methods were preregistered via the *Journal of Accounting Research*'s registration-based editorial process. Manipulating the measurement units and visualizations of carbon footprint information on food labels, we quantify effects on consumers' food choices. Treated consumers choose less carbon-intensive dishes, reducing their food-related carbon footprint by up to 9.2%, depending on the treatment. Effects are strongest for carbon footprint information expressed in monetary units ("environmental costs") and color-coded in the familiar traffic-light scheme. A postexperimental survey shows that these effects obtain although few respondents self-report concern for the environmental footprint of their meal choices. Our study contributes to the accounting literature by using an information-processing framework to shed light on the information usage and decision-making processes of an increasingly important user group of accounting information: consumers.

JEL codes: D83, M14, M41, Q56

Keywords: information processing; carbon footprint; consumers; decision making; field experiment

1. *Introduction*

We report on a field experiment that studies how attributes of carbon footprint information affect the choices of consumers in a food-service setting.[1] Our hypotheses and research methods underwent the *Journal of Accounting Research*'s registration-based editorial process. Climate change, environmental degradation, and related social conflicts are widely recognized global challenges. Against this background, information about environmental, social, and governance (ESG) issues increasingly shapes decisions in markets and society. For example, firms collect and monitor CO_2 emissions and other ESG data for internal decision making as well as in reports to external stakeholders (e.g., Kaplan and Ramanna [2021]). Key questions of accounting and disclosure research—the presentation of information by senders as well as its acquisition and evaluation by receiving decision makers—are at the core of this emerging research agenda.

Importantly, policy makers rely on the nudging effect of transparency regulation to foster firms' sustainable transformation. As catalysts of such nudging, noninvestor stakeholders are expected to impose pressure on firms (e.g., Hombach and Sellhorn [2019]). Consumers, in particular, exert influence on firms' product ranges and, thus, their environmental impact. In their reviews of corporate social responsibility (CSR) studies, Christensen et al. [2021] and Grewal and Serafeim [2020] identify consumers as a stakeholder group that could drive potential impacts of a CSR reporting mandate on the transition toward a more environmentally sustainable economy and society. For example, consumers' information

[1] Throughout this article, we use the terms "carbon footprint," "GHG emissions," and "CO_2 (equivalent) emissions" interchangeably to denote greenhouse gas (GHG) emissions.

processing and decision making potentially shape the efficacy of mandatory disclosures of CO_2 emissions. Featuring prominently in proposals by the SEC, the European Commission, the European Financial Reporting Advisory Group (EFRAG), and the new International Sustainability Standards Board (ISSB),[2] required disclosures of CO_2 emissions and carbon intensities are aimed not only at investors' information needs, but also, more broadly, seek to support climate change mitigation and adaptation.

In accounting and finance, investors' information processing, judgment, and decision making have been researched extensively (see Blankespoor et al. [2020] for a recent overview), but relatively little attention has, so far, been paid to consumers. Outside of accounting, however, there is an active debate about the effect of food labels on consumer decisions (see Bleich et al. [2017] and Rondoni and Grasso [2021] for reviews). Whereas this research focuses predominantly on the overall effects of labeling, as well as on the consumer attributes that moderate them, it devotes less attention to identifying how the representation and contextualization of numerical data shape these effects. Only recently, researchers have begun to evaluate the role of information contextualization in this regard (e.g., Camilleri et al. [2019], Hahnel et al. [2020]). The aim of our research is to contribute to this transdisciplinary debate with insights informed by, and relevant to, an accounting perspective.

To implement our study, we cooperated with *Studentenwerk München*, a large German student union (hereinafter: SWM), which operates lunch canteens for students, staff, and guests. This setting allows us to observe a large number of consumers, about 2,500 daily, going about an everyday task in their natural environment—while providing the conditions needed to administer treatments and measure outcomes of interest. These features combine the realism of naturally occurring consumer behavior with tight control over key aspects of the setting (e.g., Bloomfield et al. [2016], Floyd and List [2016]). During normal operations, the menu information is presented to diners on various displays that show the dish names, their main categories (such as "fish," "meat," "vegetarian," or "vegan"), as well as allergens and prices.

For our experiment, we add various alternating labels showing GHG emissions to these displays. Specifically, we manipulate three information presentation dimensions that relate to consumers' decision-making processes, and that we expect will affect how consumers process GHG data. First, we add a display of absolute CO_2-equivalent emissions in grams, depicted as a black-and-white leaf-shaped pictorial (*CO_2Neutral*). Second, we present this absolute GHG information as a leaf-shaped pictorial coded in traffic-light colors, with green (yellow, red) signaling low (medium, high) carbon footprints, respectively (*CO_2ColorCoded*). Third, we display this

[2] See European Commission (EC) [2022], ISSB [2022], Securities and Exchange Commission [2022], respectively.

color-coded GHG data in two different "translations" (Johnson [2021]), which contextualize the carbon footprint of dishes as (1) a percentage of a stylized individual's daily CO_2 budget only for food (*Budget*) and (2) a monetary estimate (in Euros) of the associated environmental costs (*Money*). These two translations, or contextualizations, should be more understandable than the "raw" GHG data, and, additionally, invoke mental budgets of varying fungibility. Hence, we expect each to render the GHG data more understandable while triggering differing mental accounting processes. Combined with a baseline condition (i.e., *no* numeric CO_2 footprint information), this experimental setup yields five distinct information conditions. Figure 1 shows their visualizations.

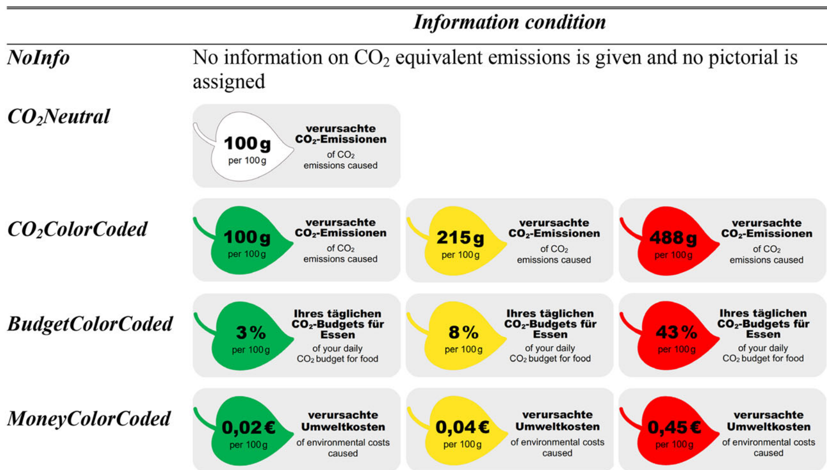
These information conditions are alternated pairwise over two treatment slots on each day of a 10-day experimental period, such that identification of treatment effects comes from within-day variation in information conditions, while the canteen menu and other factors are held constant. Our dependent variables are the binary choice between a (high-emissions) meat/fish option versus a (low-emissions) vegetarian/vegan option (*MeatFish*), as well as the quantity (*FoodWeight*) and carbon footprint (CO_2e) of the chosen food. This research design allows us to identify how carbon footprint information and its presentation attributes causally affect consumer choice.

Overall, providing any form of carbon footprint information causes diners to significantly reduce their food-related CO_2e emissions, in particular by purchasing significantly fewer meat/fish dishes.[3] Yet, given our research question, we are predominantly interested in the variation in effect sizes across information treatments. These are particularly pronounced when information labels are coded in traffic-light colors, and when the emissions information is displayed in monetary units as environmental costs caused (*MoneyColorCoded*). When subject to this information condition, participants purchase 2.3% less food, are 7.1 percentage points (PPs) less likely to select a meat or fish dish, and reduce their food-related CO_2e emissions by 9.2%—all relative to the baseline condition of no carbon footprint information.

We find varying effects of our two color-coded contextualizations relative to the color-coded raw CO_2e emissions information (CO_2*ColorCoded*). Contrary to our preregistered predictions, the effect of the food budget contextualization (*BudgetColorCoded*) is significantly smaller than that of the environmental cost contextualization (*MoneyColorCoded*), implying that the *nature* of numerical data contextualization is crucial for information processing. Whereas the food budget contextualization shows no clear effect on consumption choices, carbon footprint information expressed in monetary units causes economically significant effects. Finally, we find

[3] These effects, if observed on a large scale, would reduce meat and fish supply via lower demand, ceteris paribus.

Panel A: Stylized Visual Renderings



Panel B: Sample Visualizations of Disaggregated Dish-Level Treatments

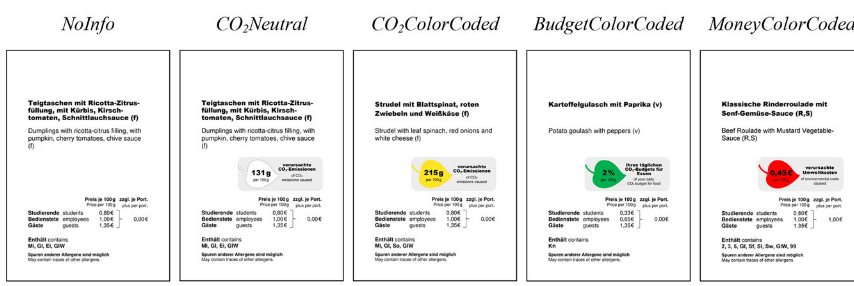


FIG. 1.—Visuals of the experimental treatments. This figure illustrates the visuals representing our information conditions (*NoInfo*, *CO_2Neutral*, *CO_2ColorCoded*, *BudgetColorCoded*, and *MoneyColorCoded*). Panel A visualizes our four information conditions. Panel B presents individual countertop information displays for these four information conditions and the baseline treatment (*NoInfo*). Over a 10-day experimental period, during two slots per day, we alternated these information treatments, augmenting the usual information about the dishes offered on various displays at the site. A detailed description of these information treatments and their measurement is provided in appendix A. For detail on the measurement of CO_2e variables based on *KlimaTeller* GHG data, see online appendix OA.B.

some evidence that color-coding per se positively influences treatment effect sizes. These results hold in direction and significance when reducing the sample to first-time diners only, when including additional control variables, and when measuring the unit of observation (main dishes purchased) in an alternative way. We provide an online platform that allows further exploration of our findings across various model specifications, including in the form of specification curves to assess overall robustness (https://trr266.de/carbonfood).

We seek to elucidate the experimental main findings using insights from our preregistered postexperimental survey. Based on 1,704 respondents (a 7.5% response rate), we provide suggestive evidence that treatment effects are not driven by our diners being particularly environmentally aware, or becoming more so over time. In particular, only 10.7% mention the ecological footprint of a dish as a relevant selection criterion, and this share is not affected significantly by our treatments. In addition, we find a small negative effect of our information treatments on the stated level of satisfaction with the chosen dish. We conclude with due caution that these results are more consistent with our information treatments triggering subconscious changes in dining behavior rather than causing fully aware rational decision-making processes based on updated information.

Our study makes three contributions to the literature. First, we contribute to the judgment and decision-making literature in accounting and behavioral economics by providing evidence on whether some of the theoretical mechanisms studied in laboratory settings, including information-processing strategies and mental accounting processes, have descriptive appeal in the field. In particular, our evidence complements lab experiments that show how information attributes affect decisions in accounting contexts (e.g., Cardinaels and van Veen-Dirks [2010]) by providing field evidence on the effects of color-coding and translations that invoke different mental budgeting frames. Our insights, in turn, can be further tested in accounting lab and field contexts.

Second, we contribute to the corporate reporting literature by being among the first to shed light on real-world consumers' information-processing and decision-making behavior related to the presentation of carbon footprint disclosures. For example, discussing the behavioral effects of such a reporting requirement, Christensen et al. [2021] observe that "we know little about the way firms' real responses differ depending on their ownership, customer, and supplier structures or about the precise causal chain from the release of CSR information to the firm response resulting from the (anticipated) reaction of certain stakeholders" (p. 92). By providing experimental evidence on consumers' use of, and responses to, carbon footprint information in a real-world setting, we help unpack this causal chain. Although it is not *firm-level* CSR reports that consumers use in our setting, individuals like our participants frequently rely on carbon footprint or other CSR information for their personal decisions—be it in their everyday roles as consumers, managers, employees, or as (retail) investors. For example, our findings imply that details may matter when it comes to how principals (e.g., compensation committees) present CO_2 information in contracts designed to incentivize agents (e.g., top managers) to exert effort toward achieving environmental goals.[4]

[4] Cohen et al. [2023] document the growing prevalence of executive compensation tied to ESG performance.

We also consider our insights on decision usefulness being affected by the presentation format of information to be relevant for the regulators and preparers of nonfinancial reporting. For example, whereas the Exposure Draft of IFRS S2 *Climate-Related Disclosures* proposed a choice of presentation formats for GHG emissions,[5] the final standard strictly prescribes the disclosure of absolute tons (ISSB [2023])—which, according to our results, may not be the most easily interpretable unit. Given our insights, preparers might opt to exploit their reporting discretion over using contextualizations—for example, presenting emissions information as relative intensities instead of absolute amounts—to strategically affect users' information-processing costs.

Third, we add to prior work in sustainability management on how carbon footprint food labeling affects consumer choice.[6] In their recent review, Rondoni and Grasso [2021] show that this literature stream has predominantly studied whether environmental disclosures per se affect consumer food choices, as well as the consumer-level drivers of this effect. For example, a recent study by Lohmann et al. [2022] finds, in a setting similar to ours, an average emissions reduction of 4.3% when using color-coded carbon footprint labels featuring the gram amount of CO_2 emissions. Relatively less is known about the effects of different presentation formats, measurement units, and framings. However, these attributes are important for designing information displays in ways that effectively nudge consumers toward more sustainable choices. For example, survey evidence shows that traffic-light color-coding is effective in shifting consumer choices toward lower-carbon products (e.g., Thøgersen and Nielsen [2016]). In experiments, traffic-light coding per se increased (decreased) the sales of low- (high-) emission dishes relative to the baseline (e.g., Spaargaren et al. [2013], Brunner et al. [2018]). However, from an accounting and disclosure perspective, it seems important to assess how this economically relevant color-coding "nudge" *compares* with neutral numerical information, as well as how different measurement units affect

[5] The choice proposed by the ISSB was between presenting GHG emissions either in absolute tons of CO_2e emissions or in CO_2e intensities scaled by some economic or technological denominator, such as sales or tons of product sold (ISSB [2022]).

[6] Our study is also related to the calorie labeling literature. Although this stream of literature is less relevant to our study than the carbon footprint labeling literature, both are similar in that they test what kind of labels most strongly affect consumer choices. Comparable to our treatments, we identify three types of labels: (1) uncontextualized, (2) contextualized, and (3) color-coded calorie information. Although Bollinger et al. [2011] indicate that uncontextualized labels decrease the average number of calories consumed, studies using different contextualizations yield mixed results (e.g., whereas Wisdom et al. [2010] find a negative effect of calorie labels, Downs et al. [2013] find an insignificant association). Ellison et al. [2013] suggest that color-coded calorie information reduces calorie intake. However, their results vary strongly with subjects' prior knowledge about health and nutrition. For reviews of the calorie labeling literature, please see Long et al. [2015] and Bleich et al. [2017].

decisions. Our experimental design allows us to investigate these questions in a highly powered field setting, in particular by holding consumers' choice sets (i.e., the range of dishes on offer) constant while presenting varying carbon footprint information treatments.

2. *Related Literature and Hypothesis Development*

2.1 INFORMATION ATTRIBUTES AND USER DECISION MAKING

To understand how information attributes affect users' decisions, accounting research has developed conceptual frameworks that structure information-processing tasks. For example, Maines and McDaniel's [2000] psychology-based framework evaluates how presentation format affects nonprofessional investors' information acquisition, evaluation, and weighting processes. Blankespoor et al. [2020] partition information-processing costs into costs of monitoring for, extracting, and analyzing information. These frameworks ultimately consider two key drivers linking information attributes to users' processing costs and ultimate decisions: first, noticing and acquiring information and, second, integrating it into one's decision-making process.

Both explain and predict the information usage and decision-making behavior of *investors*, the traditional focus of financial reporting. But emerging forms of corporate reporting increasingly target noninvestor stakeholders, such as consumers, employees, and nongovernmental organizations (NGOs) as information users. Relatively little is known about the information needs, processing capabilities, and decision-making processes of these noninvestor stakeholders, compared to those of investors. By applying the two categories that unite the Maines and McDaniel [2000] and Blankespoor et al. [2020] frameworks—information acquisition and information integration—to analyze the information usage and decision-making behavior of *consumers*, we contribute to the growing literature on nonfinancial, CSR-, ESG- and sustainability-related disclosure (e.g., Grewal and Serafeim [2020], Christensen et al. [2021]).

2.2 NUDGING AND INFORMATION PRESENTATION

In terms of information processing more broadly, our study also relates to the nudging literature in behavioral economics, marketing, and psychology, as well as to studies on judgment and decision making in accounting. By altering the choice architecture for an individual's decision without altering the choices or incentives themselves, nudging influences the individual's decision (e.g., Thaler et al. [2013]). It can encourage socially desirable behavior (e.g., "green nudging"; Thaler and Sunstein [2008]) or support individuals in making decisions that improve their personal welfare ("paternalistic nudging") by helping them overcome personal biases (Schubert

[2017]). Nudging is often achieved by varying *how* choices—such as the dishes in a canteen—are presented.[7]

In corporate reporting, regulators increasingly employ nudging to induce socially desirable change in business practices. Hombach and Sellhorn [2019] use the targeted transparency framework (Fung et al. [2007]) to show that such mandates often lead to public disclosure of previously nonpublic information. However, nudging can also involve designing and presenting already-public information in ways that target new user groups (e.g., Christensen et al. [2017]).

Related to the Maines and McDaniel [2000] and Blankespoor et al. [2020] information-processing frameworks, nudging can operate via users' information acquisition and/or information integration processes. First, nudging can facilitate users' information acquisition by making an item more salient. Since a salient item stands out, salience can focus users' limited perceptual and cognitive resources on a subset of available information. Eye-tracking studies show that users respond to guidance of attention. Sirois et al. [2018] find that key audit matters in an audit report attract users' attention. Similarly, Christensen et al. [2014] show that nonprofessional investors alter their decisions if key audit matters are visibly highlighted as important, whereas that same information, placed less visibly, has no such effect. In our field experiment, we investigate the extent to which color-coding will moderate the effect of carbon footprint information on consumer choice.

Second, nudging can link to users' information integration processes by enhancing understandability, in effect rendering the users' process of integrating an information item into their decision making less costly. For example, ESG scores are partitioned into discrete "grades" (e.g., ESG scores reported by Refinitiv), and credit analysts assign categorical ratings that summarize their complex judgments about firms' financial health. In accounting, earnings are a summary measure (e.g., Dechow [1994]) on which some users naively fixate to the near exclusion of other information (e.g., Sloan [1996]). Our experiment varies the understandability of carbon footprint information by providing different "translations" that we expect to make the information more compatible with users' familiar frames of reference and goals (Johnson [2021]), thus reducing processing costs compared to the absolute value of CO_2-equivalent emissions in grams.

Third, nudging can link to users' information integration processes by altering the "mental budgets" used when processing information. Mental accounting (Thaler [1985, 1999]) is a central concept in decision making. In the finance and accounting literature, it has extensively been linked to

[7] Lohmann et al. [2022] contrast choice architecture interventions via behavioral nudges (e.g., changing the order or salience of meal options on a menu) versus treatments that convey information (e.g., labels). Our study speaks to both types of intervention by combining CO_2 information (information) with color-coding (salience).

investors' decision making, for instance, to explain phenomena such as asset value premia and high volatility (Barberis and Huang [2001]), momentum (Grinblatt and Han [2005]), and arbitrage opportunities in option pricing (Rockenbach [2004]). Further, Bonner et al. [2014] show that investors use mental accounts when valuing a firm, and managers employ it when deciding about the aggregation of income statement items. This versatile concept has been shown to apply to decisions as heterogeneous as performance evaluation (Lipe [1993]) as well as tax planning and attitudes toward taxation (Lipe [1993], Olsen et al. [2019]). As argued by Hahnel et al. [2020], mental accounting should also apply to CO_2 emissions. By varying the contextualization of CO_2 information, we expect to invoke different mental budgets (i.e., a food-related versus an overall CO_2 budget), which should alter users' weighting of the information and, ultimately, their decisions.

2.3 FOOD LABELING AND CONSUMER CHOICE

Our study also links to the literature investigating the influence of carbon footprint labeling on consumers' food choices. These studies (reviewed in Rondoni and Grasso [2021]) are interested in how consumer-level factors (such as age, gender, or attitude) and product type moderate the impact of carbon footprint labeling on consumer choice. Specifically, we add to a recent line of work on the effects of carbon footprint label information attributes (e.g., Camilleri et al. [2019], Hahnel et al. [2020], Lohmann et al. [2022]) by varying the understandability and contextualization of numerical carbon footprint information for food items. Doing so follows Rondoni and Grasso's [2021, p. 8] call for more studies that occur in participants' natural environments and involve their natural tasks. This "in-the-wild" approach allows us to observe real consumption choices, thus combining "the most attractive elements of the experimental method and naturally occurring data: randomization and realism" (Floyd and List [2016, p. 444]). Ours is one of the highest powered field experiments in the carbon footprint food labeling literature, alongside Lohmann et al. [2022].

2.4 HYPOTHESIS DEVELOPMENT

As discussed above, prior research shows that carbon footprint information can affect consumer choice, and that incentives can amplify behavioral changes induced by environmental information. We use the carbon footprint labeling setting to explore whether conceptual frameworks developed to describe, explain, and predict the processing of *financial* information in the context of *investors'* decision making apply also to *consumers* and *nonfinancial* information. Specifically, we pursue four research questions: First, and similar to Lohmann et al. [2022], we establish the baseline effect of carbon footprint information (versus no such information) on diners' food choices in our field setting. Second, we investigate how contextualization, which affects understandability, moderates this effect. Third, we assess the impact of mental accounting by varying the scope of the mental budget invoked by the carbon footprint information. And finally, we test the effect of augmenting our carbon footprint information with the well-known traffic-light scheme color-coding.

In terms of outcomes, we capture the extensive and intensive margins of consumers' food consumption and related carbon footprint by measuring (1) the choice of one of the higher-carbon options (i.e., fish or meat; *MeatFish*), (2) the overall amount of food purchased (in grams; *FoodWeight*), and (3) the overall carbon footprint of the food purchased (i.e., the amount of food purchased, in grams, multiplied by each food item's CO_2-equivalent emissions value; CO_2e).

Since consumers systematically underestimate the carbon footprint of food (e.g., Grinstein et al. [2018], Camilleri et al. [2019]), we expect carbon footprint information for food items to induce lower CO_2 food choices relative to no such information being provided. Specifically, we expect the following:

H_1: Consumers provided with carbon footprint information exhibit lower food consumption and related carbon footprint compared to consumers receiving no carbon footprint information.

Next, we investigate whether contextualization of carbon footprint information moderates this baseline effect. Contextualization (i.e., comparing information to meaningful reference points) aids information integration by translating information into measurement units that are closer to the decision maker's objectives (Johnson [2021]).[8] "Raw" GHG emissions (in grams of CO_2 equivalents) do not relate intuitively to consumers' daily experience, and are, thus, particularly challenging to interpret (e.g., Hartikainen et al. [2014], Grinstein et al. [2018], Camilleri et al. [2019]).

To test the effect of contextualization, we provide the numeric carbon footprint information in two alternative units that correspond more closely to consumers' familiar frames of reference. First, behavioral research shows that individuals apply mental accounting to contextualize quantitative information, and to apply budgetary discipline (Thaler [1999], Capstick and Lewis [2010]). Hence, we contextualize the raw numeric information by allowing consumers to compare the carbon footprints of their food choices to a stylized person's daily CO_2-equivalent emissions budget for food under the UN's [2019] emissions reduction targets ("budget contextualization"). Second, we render the information in terms of monetary environmental costs ("money contextualization"). We predict that both contextualizations are more understandable than the raw CO_2 emissions. Thus, we state the following:

[8] For example, financial ratio analysis contextualizes absolute performance metrics such as earnings by relating them to denominators such as sales (profit margin), shareholders' equity (return on equity), or number of shares outstanding (earnings per share), or by conducting cross-sectional, intertemporal, and target-actual comparisons.

H2: Consumers provided with contextualized ("budget" or "money") carbon footprint information exhibit lower food consumption and related carbon footprints compared to consumers receiving noncontextualized ("raw") carbon footprint information.

Prior work (e.g., Henderson and Peterson [1992]) has shown that contextualization triggers mental accounting processes and can affect how individuals perceive and process abstract quantitative information. Hence, the mental budgeting frame triggered by a certain contextualization can influence the resulting decision. Hahnel et al. [2020] argue that mental accounting processes can be very influential in environmental decision making. Our contextualizations are designed to invoke two different mental accounting frames. We expect the "budget contextualization" to trigger a narrow, food-specific CO_2 budget frame, which should make customers more likely to choose with primarily their daily *food-related* carbon footprints in mind. In contrast, we expect the "money contextualization" to induce a much wider mental budget by implying general "fungibility" of CO_2 emissions between food and *any other source* (e.g., travel), all of which can be readily expressed in monetary units. As a wider frame allows for a greater set of "offsetting" considerations to rationalize a craving for CO_2-intensive foods, whereas a narrower mental budget does not, we predict the following:

H3: Consumers provided with carbon footprint information expressed as a percentage of a typical person's daily food-related CO_2-equivalent budget ("budget contextualization") exhibit lower food consumption and related carbon footprints compared to consumers receiving such information expressed as environmental costs of the CO_2-equivalent emission in Euros ("money contextualization").

Finally, we study the effect of greater salience by augmenting the neutral information treatment by color-coding our leaf-shaped pictorials using the familiar traffic-light scheme. We expect this prominent visual signal of the carbon footprint to enhance the effects of all information treatments. According to Elliot and Maier [2007], color affects psychological functioning and, thus, human behavior for several reasons. By carrying meanings grounded in evolutionarily ingrained responses to color stimuli reinforced by learned associations, color can carry specific information. It triggers fundamental evaluative processes, for example, to discern hostile from friendly stimuli, which lead to motivated behavior (e.g., "approach" or "avoidance"). These responses are context-specific, largely automatic, and happen instantaneously without conscious intention or awareness.

Color-coding has been shown to effectively aid consumer decision making among foods with complex attributes.[9] The familiar traffic-light scheme

[9] Thorndike et al. [2012, p. 532] state: "Reading and understanding nutrition labels is a complex task. Even highly literate consumers may have difficulty interpreting labels because of low numeracy skills."

reduces processing costs, facilitating interpretation of a given food item as "good," "medium," or "bad" (e.g., Hawley et al. [2013], Trudel et al. [2015]). We expect similar effects in our setting, in which the information of interest (CO_2 emissions) may be even less familiar to participants (and thus more difficult to interpret) than calorie information and other nutrition facts. We conclude that traffic-light color-coding can act via higher intensity of sensory input, merely directing attention to the color-coded CO_2 information, and/or as a heuristic that in itself conveys certain signals (e.g., red = "bad for you"; green = "good for you") via participants' automatic evaluative processes. The latter is related to Trudel et al.'s [2015] findings that color-coded information conveys information-processing cues triggering "stop" and "go" responses in consumers, similar to a traffic light. We test this joint attention and information effect of color-coding relative to the raw numerical treatment;[10] hence we state the following:

H_4: Consumers provided with color-coded carbon footprint information exhibit lower food consumption and related carbon footprints compared to consumers receiving neutral (i.e., black-on-white) carbon footprint information.

We note particular tension related to *FoodWeight*, the dependent variable capturing the overall *amount* of food purchased. Possibly, consumers reducing the carbon footprint of their food selection in response to a treatment will end up purchasing *higher*, rather than lower, but still *less* CO_2*-intensive* overall amounts. Consider, for example, a protein-hungry diner replacing, say, 100 g of (high-CO_2) beef steak with 300 g of (low-CO_2) chickpea salad.

3. *Research Design*

3.1 SETTING

SWM, our project partner, is a not-for-profit student union serving over 125,000 students in and around Munich, Germany. Its largest facility, *Mensa Leopoldstrasse*, caters to students, faculty, and staff, as well as other walk-in diners, serving over 2,500 lunches per day. As preregistered, our field experiment ran during a 10-day period in late 2022. Online appendix OA.A provides detailed explanation and visuals of our setting and method; key points are summarized below.

Diners choose their meals guided by information from several displays dispersed within the facility. They flexibly fill their plates with main and side dishes before proceeding to self-service checkouts. Prices are charged by weight plus a lump-sum surcharge for meat/fish dishes. Diners pay using an RFID chip card; however, its unique number is not linked to personal information.

[10] Unfortunately, our research design does not allow us to test apart these two possibilities.

During the experimental period, we alternatingly add four numeric carbon footprint information displays to the on-site menu displays. These information treatments, visualized in figure 1 and described in detail in the next section, vary at mid-day on each of the 10 experimental days, allowing us to observe treatment effects with menus and other factors held constant. We collect our outcome variables (*MeatFish*, *FoodWeight*, and *CO_2e*), a time stamp, diner status (student, employee, or guest), as well as transaction and chip card ID from the checkout register data.

Regarding potential Hawthorne-type effects (Adair [1984], Levitt and List [2009]), which could lead suspecting diners to behave differently from unsuspecting ones, we consider such behavioral shifts possible in our baseline effect (carbon footprint information versus none; H_1), but unlikely to vary systematically with our alternative information treatments (under H_2, H_3, and H_4). To address them, we conduct robustness tests excluding "repeat diners" (section 4.2.3).

3.2 TREATMENTS

3.2.1. Concepts and Measurement. To test our predictions, we first include a baseline condition of *no* numeric carbon footprint information. We then introduce four information treatments, visualized in figure 1 (details in online appendix OA.A.2), all of which use leaf-shaped pictorials labeled with the carbon footprint of the respective dish. The first (*CO_2Neutral*) depicts carbon footprint information as the absolute ("*raw*") number of grams of CO_2 equivalent emitted per 100 g of the dish. The second treatment (*CO_2ColorCoded*) augments this information with traffic-light color-coding, to test H_4 (color-coding) by contrasting the effects of the first two treatments. The third treatment (*BudgetColorCoded*) contextualizes carbon footprint as the relative share of a stylized person's daily CO_2e emission budget for food, whereas the fourth (*MoneyColorCoded*) uses environmental costs expressed in Euros. The third and fourth treatments test H_2 (contextualization) and H_3 (*Budget* versus *Money*), whereas all four combined relative to the baseline assess the main effect of carbon footprint information (H_1).

For our treatments we require CO_2-equivalent emission data for each dish. CO_2 equivalents, a common measure of overall GHG emissions, convert amounts of other GHGs into CO_2-equivalent amounts (Eurostat [2021]).[11] We use emissions in grams per CO_2 equivalent (gCO_2e) from *KlimaTeller*; these data are sufficiently granular to allow realistic emissions estimates for individual dishes.[12] The process is explained in online appendix OA.B.

[11] GHGs absorb and emit radiant energy in the thermal infrared range, causing the greenhouse effect. The primary GHGs in Earth's atmosphere are water vapor, carbon dioxide, nitrous oxide, methane, and ozone (IPCC [2018]).

[12] *KlimaTeller* is a German project offering a carbon footprint calculator for food. *KlimaTeller* uses the Eaternity database (EDB), which estimates emission based on life-cycle assessments published in peer-reviewed journals. EDB's life cycle concept includes four main stages: production, transportation, conservation, and processing.

3.2.2. Treatment Plan and Experimental Menu. A unique feature of our research design is that we vary treatments once during the day, controlling for dining choice set effects and other day-variant dish-choice determinants by including day and treatment-slot fixed effects. In contrast, prior field studies (e.g., Lohmann et al. [2022]) have regularly varied treatments over longer periods, implying that treatments apply to different dining choice sets, making it challenging to separate the treatment effect from choice set effects or other day-variant determinants. The treatment plan is presented in appendix B.

Designed in cooperation with SWM staff, our menu plan (shown in online appendix OA.A.3) has the following features: First, as is SWM policy, each daily menu offers two meat or fish dishes and four vegetarian or vegan dishes. Second, each day provides a balanced set of low-carbon (green), medium-carbon (yellow), and high-carbon (red) dishes.[13] Third, to avoid capturing consumer choices driven by health preferences, we ensure that carbon footprint is not correlated with calorie content for our dishes. Such correlations are generally insignificant (Pradhan et al. [2013], Drewnowski et al. [2015]), which is also true for our menu (see online appendix OA.A.4).

3.3 REGRESSION SPECIFICATIONS

As preregistered, we use two regression models to test our hypotheses related to the effects of carbon footprint information as well as its contextualization and presentation to participants:[14]

$$Pr\left(MeatFish_i = 1\right) = L\left(\beta_{1:4} Treatment_{1:4} + \lambda_{1:10} Day_{1:10} + \theta_{1:2} Slot_{1:2}\right) \quad (1)$$

$$Log(Choice_i) = \beta_{1:4} Treatment_{1:4} + \lambda_{1:10} Day_{1:10} + \theta_{1:2} Slot_{1:2} + \varepsilon_i \quad (2)$$

Our dependent variables measure diners' food choices at the extensive and intensive margins. For the extensive margin, *MeatFish* in equation (1) is a binary variable capturing a diner's choice of a more (meat/fish) or the less (vegan/vegetarian) CO_2e-intensive main dish. At the intensive margin, the dependent variable in equation (2), *Choice*, is either (1) the amount (*FoodWeight*) or (2) the estimated CO_2 equivalent emissions (*CO_2e*) caused by the chosen food. All variables are defined in appendix A. To measure these outcomes, we focus on the six treated meal options (for which participants indicate their choice at the checkout register) and ignore *separate* containers with only side dishes (which are untreated). Since diners may mix side dishes and main dishes also on their main plates, we assume

[13] We ensure that the vegetarian/vegan dishes have lower carbon footprints than the meat/fish dishes, since our *MeatFish* outcome variable depends on this to be the case.

[14] For the binary outcome variable, *MeatFish*, we employ a logistic regression model (equation (1)), and for the continuous outcome variables, *FoodWeight* and *CO_2e*, we estimate an OLS regression model (equation (2)).

that each plate contains equal amounts of main and side dishes. We approximate the carbon footprint of a side dish by multiplying the median per-gram CO_2e emissions across all main dishes in the experimental sample with half of the weight on the main plate. This conservative estimate leads to a somewhat muted variance of our *CO_2e* emissions measure, which reduces our treatment effects.

The index *i* indicates a purchased dish;[15] and *Treatment* identifies the four information treatments for carbon footprint: (1) the neutral CO_2 equivalent emissions in grams per 100 g of food (*CO_2Neutral*), (2) its color-coded counterpart (*CO_2ColorCoded*), (3) the color-coded food budget contextualization (*BudgetColorCoded)*, and (4) the color-coded environmental cost contextualization (*MoneyColorCoded)*; we test these against a baseline of no CO_2 information (*NoInfo*).

In equations (1) and (2), the coefficients of interest are β_1 through β_4, which capture the effects of the information conditions (1) through (4). We further include day ($\lambda_{1:10}$) and slot fixed effects ($\theta_{1:2}$) to ensure that it is neither the time of day (i.e., treatment slot) nor the day itself that drive the results. Standard errors are clustered at the day-slot-level to reflect the clustered treatment assignment (Abadie et al. [2013]). Note that the day fixed effects absorb all variance in diners' choices that stem from the menu offered on a particular day. Each day, diners are presented with a different choice set of dishes. Although, conceptually, this setting represents a discrete choice problem, we decided not to model it as such, since we are inherently unable to observe the relevant choice and diner characteristics. As we are predominantly interested in the effects of our information presentation treatments, we have thus decided to project the effects of the daily choice problems on our dependent variables by including daily fixed effects.[16]

[15] In the preregistered report proposal, we denoted individual *diners* as our level of analysis. Given the nature of the checkout data that was unavailable to us during the preregistration phase for data privacy reasons, we now base our main analysis on the dish level, allowing the option that one participant (unobserved by the data) buys multiple main dishes in a given treatment slot. We elaborate on this issue in more detail in section 4.2.4 where we present a robustness test using transactions, rather than dishes, as the unit of analysis, finding quantitatively and qualitatively very similar results.

[16] We acknowledge that this design choice does not address the question to what extent our treatment effects per se are moderated by characteristics of the choice sets and the potentially varying diner characteristics. We sought to balance this potential heterogeneity in our treatment effects by choosing a balanced menu for our treatment days. In addition, we provide diagnostic regressions as additional analyses, in which we interact our treatment effects with day-level differences across prominent choice set attributes, first and foremost the difference in carbon footprints across the two groups of dishes (meat/fish versus vegan/vegetarian).

4. Empirical Results

4.1 MAIN HYPOTHESIS TESTS

4.1.1. Sample Description. Table 1 describes our sample composition. The canteen sold 29,478 main dishes during the 10-day experimental period. We lose 6,765 observations due to one or more of the six daily main dishes running out before closing on eight of the days, thus altering participants' choice sets. Our main analyses are thus based on an experimental sample of 22,713 main dishes. The vast majority (20,165, or 89%) of dishes were purchased by students, who enjoy a deep price discount, whereas the remainder was purchased by nonstudent diners (i.e., 8% faculty and staff, and 3% guests). About 62% of main dishes ($N = 14{,}109$) were purchased by returning diners. Only a relatively small amount of 3,388 (15%) of main dishes was purchased by one-time visitors, whereas 43% (42%) were purchased by diners who visited the canteen between two and four times (more than four times) during the 10-day experimental period.

Additional insights emerge from our preregistered postexperimental survey described in online appendix OA.C.[17] Of the 1,704 responses (a

[17] Whereas the survey ran for the entire 10-day experimental period, we consider it "post-experimental" in the sense that diners were surveyed *after* being exposed to the experimental treatments and making their choices. To avoid Hawthorne-type awareness effects in repeat diners, we omitted manipulation checks from the survey questions.

TABLE 1
Composition of Experimental Sample

	N	%
Main dishes purchased	29,478	
− main dishes purchased after change in choice set	6,765	
= Experimental sample	22,713	100%
of which main dishes purchased by:		
students	20,165	89%
faculty or staff	1,861	8%
guests	687	3%
of which main dishes purchased by:		
first-time visitors	8,604	38%
returning visitors	14,109	62%
of which main dishes purchased by diners with:		
one total visit during the experimental period	3,388	15%
two to four total visits during the experimental period	9,682	43%
five or more total visits during the experimental period	9,643	42%

This table presents the composition of the experimental sample. The unit of observation is an individual main dish purchased by a diner.

7.5% response rate) described in online appendix OA.C.3, 1,325 could be uniquely matched to dish choices. Among the respondents, students are slightly overrepresented and guests not represented. Whereas fewer survey respondents chose a meat or fish dish (mean of *MeatFish* = 0.32) compared to the other experimental participants (0.40), their food choices were otherwise relatively similar to those of nonrespondents (panel A). The survey sample consists of 13.4% vegans and 21% vegetarians (panel B), which is considerably higher than in the wider population of Germany (3.1% and 6.9%, respectively) and the United States (0.7% and 7.0%, respectively; Veganz [2022], O'Malley et al. [2023]).[18] Respondents, who typically dined in groups of three, were on average highly satisfied with their canteen meals (panels C and F). Among the criteria that respondents usually apply for food selection, appearance (54.1%) and taste (35.1%) ranged far ahead of ecological footprint, which only 10.7% of respondents mentioned (panel D). Finally, respondents select canteen food under several dietary restrictions, most frequently meat avoidance (50.5%) (panel E). To the extent that the general population considers itself less constrained, our treatment effects would tend to understate population-wide effects.[19]

Table 2 presents sample sizes and summary statistics per treatment slot for our experimental outcome variables. Treatment slots lasted 72 minutes on average, with the reported variation reflecting dishes running out in several afternoons, which necessitated stopping the experiment for that day, and different peak times leading us to vary the timing of the switchover between treatment slots.[20] As anticipated in the preregistered proposal, Fridays (days 5 and 10) were slowest, with an average of about 1,620 main dishes sold, compared to roughly 2,435 on the other days; this corresponds to a churn rate of 66%. The average number of main dishes per experimental slot was 1,136, with a substantial range between 450 and 1,737 that owes in part to the variation in treatment slot length.

[18] Although it would be interesting to assess whether our treatment effects vary across these demographics, we abstain from doing so due to the small treatment cell sizes in our survey sample and the consequential lack of power.

[19] Since the survey was voluntary, respondents are a nonrandom draw from the experimental sample. To explore the extent of any self-selection bias, we show in online appendix OA.C.4 a determinant model of survey participation. In both an OLS specification and a logit specification, survey participation exhibits a statistically significant positive association with student status and *FoodWeight*, whereas our information treatments do not seem to be significant explanatory factors overall. Combined with the above, these insights suggest an overrepresentation of students and vegans/vegetarians compared to most populations.

[20] The fewest observations in our sample period are for slot 2 on day 4. Here, we stop recording data at around 12:30 p.m., when one of the dishes is sold out, altering the food choice set. However, according to our power analysis, the amount of day 4 slot 2 observations is still sufficient. Further, on experimental day 9, one of the six dishes runs out even sooner, leaving us with insufficient power for slot 2 of day 9. We successfully repeat this entire experimental day 9 on the Wednesday of the subsequent week and discard the original day 9 data. In our experimental analyses, we refer to that repeated experimental day as "day 9."

TABLE 2

Descriptive Statistics for Experimental Variables

Day	Slot	Information Condition	Span (minutes)	*N*	*MeatFish* (%)	*FoodWeight* (g)				CO_2e (g)			
						Mean	SD	Min	Max	Mean	SD	Min	Max
1	1	*NoInfo*	96	1,574	40.3	426	157	66	1,308	849	515	90	4,154
1	2	*CO_2Neutral*	44	756	37.4	425	163	90	1,382	824	501	116	4,389
2	1	*CO_2Neutral*	76	1,267	38.0	419	152	72	1,248	1,235	986	92	7,421
2	2	*CO_2ColorCoded*	64	1,265	31.6	424	160	32	1,338	1,172	959	59	7,957
3	1	*CO_2ColorCoded*	73	1,161	33.5	398	173	52	1,352	851	623	72	4,261
3	2	*MoneyColorCoded*	63	1,471	26.9	390	169	32	1,184	771	549	71	3,629
4	1	*NoInfo*	72	971	35.8	431	156	74	1,190	1,281	939	120	6,113
4	2	*BudgetColorCoded*	20	450	31.8	424	150	78	1,092	1,196	893	82	5,293
5	1	*BudgetColorCoded*	72	759	44.1	421	170	76	1,294	813	489	91	3,022
5	2	*MoneyColorCoded*	44	812	36.1	390	146	88	942	712	429	105	2,354
6	1	*MoneyColorCoded*	86	1,282	25.0	413	153	76	1,056	1,556	2,363	132	12,484
6	2	*NoInfo*	94	1,476	29.9	420	160	48	1,496	1,751	2,567	89	15,605
7	1	*CO_2Neutral*	76	1,234	38.7	424	165	60	1,404	759	390	97	3,438
7	2	*BudgetColorCoded*	104	1,737	37.5	418	156	20	1,446	738	358	27	2,438
8	1	*BudgetColorCoded*	73	1,114	31.3	379	172	36	1,434	1,157	1,262	53	7,926
8	2	*CO_2ColorCoded*	37	1,018	26.8	392	179	32	1,020	1,118	1,265	41	6,436
9	1	*CO_2ColorCoded*	76	1,079	27.4	473	184	60	1,312	1,105	847	68	4,878
9	2	*NoInfo*	102	1,621	30.8	474	183	32	1,378	1,138	846	35	6,085
10	1	*MoneyColorCoded*	72	616	41.1	447	167	80	1,416	1,181	889	90	4,651
10	2	*CO_2Neutral*	92	1,050	41.7	437	172	46	1,086	1,205	976	58	5,833
Total (experimental period)				22,713									
Average (experimental period)			72	1,136	33.9	421	167	20	1,496	1,072	1,177	27	15,605

This table presents descriptive statistics per experimental day and slot for the dependent variables employed in the experiment. It captures whether a diner chooses a meat or fish dish (*MeatFish* = 1) or a vegan or vegetarian dish (*MeatFish* = 0), the total weight of the dish purchased, in grams (*FoodWeight*), and the total CO_2 equivalent emissions of the dish purchased (*CO_2e*). The unit of observation is an individual main dish purchased by a diner. All variables are defined in appendix A. We marginally changed the design from the preregistered version to include all treatment slots and the length of the treatment windows.

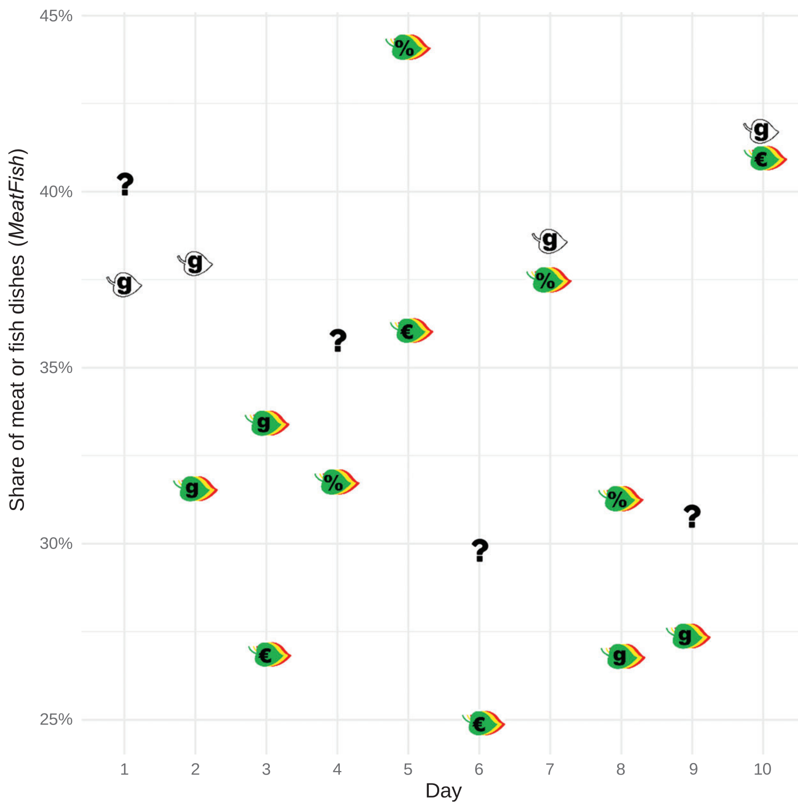


FIG. 2.—Mean values of *MeatFish* per experimental slot. This preregistered figure shows the mean values of the dependent variable *MeatFish*, which is equal to 1 if the diner chooses a nonvegetarian meal option. The *x*-axis shows the experimental days. All variables are defined in appendix A. The respective information conditions, visualized in figure 1, are indicated by the following symbols: ? = *NoInfo;* g = *CO_2Neutral;* g = *CO_2ColorCoded;* % = *BudgetColorCoded*; and € = *MoneyColorCoded*. The sample consists of 22,713 main dishes consumed by the diners during our 10-day experimental period.

Between 25% and 44.1% of diners per slot opted for a nonvegetarian dish (*MeatFish* = 1). The purchased main dishes weighed about 420 g (*FoodWeight*), on average, and ranged from as little as 20 g to as much as almost 1.5 kg. CO_2e emissions per dish (*CO_2e*) range from 27 g to more than 15.6 kg (the latter for beef roulade, an extremely carbon-heavy dish, offered on day 6; see online appendix OA.A.3), with an overall mean of 1.07 kg.

4.1.2. Experimental Results. As initial visual evidence on H_1 through H_4, figure 2 depicts daily means of *MeatFish*, the choice of a meat or fish dish, and figure 3 plots the values of *CO_2e* for our four information treatments and the baseline condition of no CO_2 information, per experimental slot.

Figure 2 shows that the share of meat or fish dishes varies across treatment days. This variation is likely driven by differences in menus; we pre-

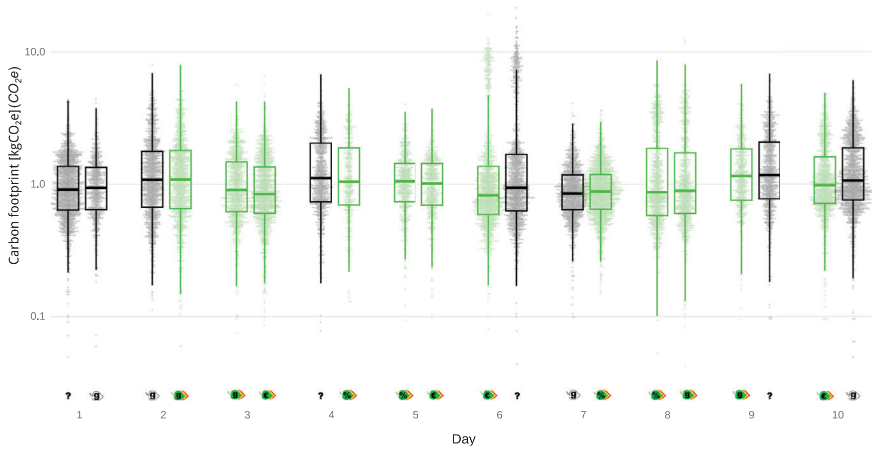


FIG. 3.—Distribution of CO_2e per experimental slot. This figure shows boxplots and bee swarm plots for the CO_2 equivalent emissions in grams (dependent variable: CO_2e) that diners purchased (y-axis), displayed by experimental treatment slot (*x*-axis), with color-coded information conditions (*CO_2ColorCoded*, *MoneyColorCoded*, *BudgetColorCoded*) in green and non–color-coded information conditions (*CO_2Neutral*, *NoInfo*) in black. All variables are defined in appendix A. The respective information conditions, visualized in figure 1, are indicated by the following symbols: ? = *NoInfo;* g = *CO_2Neutral;* g = *CO_2ColorCoded;* % = *BudgetColorCoded*; and € = *MoneyColorCoded*. The sample consists of 22,713 main dishes consumed by the diners in our two-week experimental period. We had preregistered density plots instead of boxplots and bee swarm plots but decided for the latter to more efficiently communicate the data distribution.

vent it from affecting our results by including day fixed effects in our regressions and hence exploiting only within-day variation across treatment slots. Visual inspection reveals that *MeatFish* is always lower when consumers receive any carbon footprint information at all, compared to the baseline information condition of *NoInfo* (days 1, 4, 6, and 9). Further, *MeatFish* is lower for color-coded and contextualized treatments, relative to the neutral treatment of *CO_2Neutral* (days 2, 7, and 10). Contrary to H_3, *MeatFish* is higher for *BudgetColorCoded* than *MoneyColorCoded* (day 5).

Turning to the other outcome variables, we find no substantial differences in the medians of the amount of food (*FoodWeight*) that participants purchased during the experimental period.[21] However, consistent with meat or fish dishes being higher in CO_2e emissions than vegetarian or vegan dishes, the differences shown in figure 2 also manifest in the overall carbon footprints of dishes (*CO_2e*), as figure 3 reveals. *CO_2e* varies visibly

[21] Recall from the discussion of H_4 in section 2.4 that predicting treatment effects for *FoodWeight* is complicated by participants possibly substituting greater amounts of lower CO_2 food for a given amount of higher CO_2 food. We hence consider *CO_2e* our main dependent variable of interest, as it combines the accurately measured qualitative choice inherent in *MeatFish* with the quantitative dimension of *FoodWeight*.

TABLE 3
Regression Results and Hypothesis Tests (Baseline Specification)

	Dependent Variable		
	MeatFish (1)	*Log(FoodWeight)* (2)	*Log(CO_2e)* (3)
Panel A: Regression results			
CO_2Neutral	−0.092***	−0.011	−0.031*
	(0.033)	(0.008)	(0.018)
CO_2ColorCoded	−0.216***	0.004	−0.052***
	(0.027)	(0.006)	(0.009)
MoneyColorCoded	−0.338***	−0.024***	−0.096***
	(0.026)	(0.007)	(0.012)
BudgetColorCoded	−0.074***	−0.010	−0.031***
	(0.022)	(0.008)	(0.010)
Num.Obs.	22,713	22,713	22,713
Adj. R^2/Pseudo R^2	0.010	0.021	0.036
Fixed effects: Day	Yes	Yes	Yes
Fixed effects: Slot	Yes	Yes	Yes
Panel B: Hypotheses tests			
H_1: Main Effect	−0.179***	−0.010**	−0.052***
H_2: Context	0.012	−0.020***	−0.012
H_3: Mental Budget	0.264***	0.014	0.065***
H_4: Color-Coding	−0.124***	0.015**	−0.020

This preregistered table presents the results of regressing diners' food choices on our information treatments (*CO_2Neutral, CO_2ColorCoded, BudgetColorCoded*, and *MoneyColorCoded*; panel A), along with the preregistered hypothesis tests based on these regression results (panel B). Column 1 presents the results for the probability of choosing a meat or fish dish (dependent variable: *MeatFish* = 1) or a vegan or vegetarian dish (dependent variable: *MeatFish* = 0), column 2 presents the results for total food weight per diner (dependent variable: *FoodWeight*), and column 3 presents the results for the total CO_2 equivalent emissions per dish (dependent variable: *CO_2e*). In panel A, we estimate column 1 by employing a logit-regression using equation (1), and columns 2 and 3 by employing an OLS regression using equation (2). In panel A, standard errors, clustered by day and slot, are presented in parentheses below the coefficient estimates. The R^2 in column 1 is a pseudo-R^2 obtained from the logit regression. In both panels, statistical two-sided significance of the coefficients is indicated at the 0.01 (***), 0.05 (**), and 0.10 (*) level, respectively. The unit of observation is an individual main dish purchased by a diner. In panel B, we use Wald tests to assess the respective average marginal effects. To test H_1, we estimate the average marginal effect of all information treatments (*CO_2Neutral, CO_2ColorCoded, BudgetColorCoded* and *MoneyColorCoded*) against the baseline (*NoInfo*). For H_2, we estimate the average marginal effect of the contextualized information treatments (*BudgetColorCoded* and *MoneyColorCoded*) minus the marginal effect of the noncontextualized treatment (*CO_2ColorCoded*). For H_3, we estimate the difference between the marginal effect of the *BudgetColorCoded* treatment and the *MoneyColorCoded* treatment. For H_4, we estimate the marginal effect of color coding the information treatment by testing *CO_2Neutral* against *CO_2ColorCoded*. All variables are defined in appendix A.

across information conditions; for example, the contextualized and color-coded treatments are associated with lower median *CO_2e* emissions than most of their daily counterparts.

We present the corresponding regression analyses in table 3. Panel A reports our main preregistered regression results and panel B reports our hypothesis tests. Overall, we document consistently negative treatment effects for *MeatFish* and *CO_2e*, resulting in support for our main effect hypothesis, H_1. For *CO_2e*, the treatment effect point estimates range from

3.0% (*BudgetColorCoded*) to 9.2% (*MoneyColorCoded*)[22] reductions in food-related carbon emissions. Including the 95% confidence intervals of the respective measures, the CO_2e treatment effect estimates range from about 0.6% (*BudgetColorCoded*) to −11.5% (*MoneyColorCoded*), which translates into a main effect estimate of H_1 (for all information treatments tested against the baseline condition of *NoInfo*) with a confidence interval ranging from −3.2% to −6.9% and a point estimate of −5.1%. This treatment effect is driven by our participants choosing fewer meat or fish dishes. Measured in PP differences relative to the sample average of a 33.9% likelihood of choosing a meat or fish dish (see table 2), treatment effects range from −1.6 PP (*BudgetColorCoded*) to −7.1 PP (*MoneyColorCoded*), resulting in a 95% confidence interval for H_1 ranging from −3.0 PP to −4.7 PP, with a point estimate of −3.9 PP. In comparison, the treatment effect on the intensive margin of food consumption (*FoodWeight*) is small and mostly insignificant. The overall main effect for *FoodWeight* for H_1 of −1.0% is statistically significant but economically negligible: for an average food choice, it translates into a reduction by about 4 g.

Turning to our hypotheses about the varying effects of different carbon footprint information treatments, we do not find consistent support for our expectation that contextualization per se increases the treatment effect (H_2). Although the *MoneyColorCoded* treatment causes strong effects, those of the *BudgetColorCoded* treatment are small. Consistently, and contrary to our expectations of a "wider" mental budget frame allowing consumers greater fungibility to offset their emissions (H_3), we find that the "narrower" *BudgetColorCoded* contextualization triggers a smaller change in diners' choices than the "wider" *MoneyColorCoded* contextualization. One could speculate that either the cognitive load of understanding a percentage carbon footprint budget is too high for the average participant, or that—maybe subconsciously—participants associate the monetary environmental cost information with direct personal financial losses. We have no evidence, however, that the diners mistakenly believe that the environmental costs displayed by the *MoneyColorCoded* treatment represent an actual surcharge.

Finally, we find partial support for H_4, which predicts that color-coding increases the treatment effect. Color-coding decreases the likelihood of participants choosing meat or fish dishes by 2.7 PP (95% confidence interval: 1.5 to 4.0 PP). Although the color-coding effect on CO_2e (−2.0%) is not

---

[22] Throughout this section, reported percentage effects for equation (2) and related hypothesis tests are calculated as $e^{coefficient} - 1$. So, for example, the coefficient for *MoneyColorCoded* of −0.096 (table 3, column 3) translates into $e^{-0.096} - 1 = -9.2\%$. PP effects for the *MeatFish* logit regressions (equation (1)) and related hypothesis tests are calculated based on the sample average of *MeatFish* (33.9%) and the corresponding intercept coefficient of $b = \log(0.339/(1 - 0.339)) = -0.667$ as $e^{b + coefficient} / (1 + e^{b + coefficient}) - 0.339$. This means, for example, that the coefficient for *MoneyColorCoded* of −0.338 (table 3, column 1) translates into a PP effect of $e^{0.667 + -0.338} / (1 + e^{0.667 + -0.338}) - 0.339 = -7.1$ PP.

significant at conventional levels (p-value = 0.13; 95% confidence interval: 0.6% to −4.5%), it is meaningful in economic terms and consistent with the significant *MeatFish* effect.

Taken together, our findings yield two main takeaways. First, providing carbon footprint information in *any form* helps consumers acquire, process, and integrate this information into their decisions. Second, the *presentation format* of carbon footprint labels matters for how well this information aids in decision making. Specifically, effects are particularly pronounced when the information's salience and understandability are increased by color-coding and money contextualization.

4.2 SUPPLEMENTARY ANALYSES

This section presents our (largely preregistered) supplementary analyses, which serve two purposes. First, to further explore the decision-making processes underlying our treatment effects, section 4.2.1 reassesses the main findings in the light of our postexperimental online survey. Second, to assess the sensitivity of our results to various research design choices, we then present selected robustness tests. Finally, in section 4.2.5, we introduce an online dashboard that allows readers to specify and explore a larger range of further regression specifications.

4.2.1. Mechanism Analysis. To further explore the decision-making process underlying participants' reactions to the information treatments, this section reassesses the main findings in light of our preregistered postexperimental online survey, which we show in appendix C and describe in detail in online appendix OA.C. We first consider participants' self-reported satisfaction with their chosen meals (*Happiness*), which, at 4.38 on a five-point Likert scale (median = 5), is high (online appendix OA.C.3, panel C), with some variation across information treatments (online appendix OA.C.3, panel F). In online appendix OA.C.5, we examine whether our treatments are associated with respondents' happiness with their meal choice.[23] First, we confirm that all our treatments, as well as an aggregate *Treatment* indicator variable capturing whether a participant received any information treatment, is negatively associated with the choice to select a *MeatFish* dish, indicating that our main effect of the experiment also manifests in the much smaller survey sample. Second, we find that being treated is negatively associated with *Happiness*, albeit only significantly so for the *CO_2Neutral* and *BudgetColorCoded* treatment conditions, as well as the composite *Treatment* indicator. This suggests that, on average, survey respondents exposed to carbon footprint information choose fewer meat or fish dishes and are somewhat less satisfied with their meals.[24] In economic terms, the negative effect

[23] Note that this test is subject to relatively low power, since the number of survey responses that could be matched to dish choices is less than 300 for each treatment window.

[24] Whereas better informed decisions should make strictly rational consumers better off and thus happier with their choices, our information treatments may have made diners feel

of *Treatment* on *Happiness* is very small, representing a little less than a tenth of one increment on a five-point Likert scale, ceteris paribus. There are several, at times competing explanations for this finding. In lack of a clear identification strategy to test any reasons apart, we leave the examination of reasons for this finding for future research.

Second, to further understand the role of peer pressure in participants' decisions, we explore the associations of whether respondents ate alone or in groups with their choice of *MeatFish* and their satisfaction (*Happiness*). Specifically, the notion that respondents' treatment-induced choice of fewer meat or fish dishes left them less happy with their meal may be driven by peer pressure. In that case, we would expect *MeatFish* and *Happiness* to be negatively associated with eating in a group. In online appendix OA.C.5, columns 5 through 8, we add several variables, namely *Group* (which indicates whether the respondent ate alone or not), as well as its interactions with our treatments and their composite measure, *Treatment.* Columns 5 and 7 document statistically significant negative associations of *Group* with *MeatFish.* However, its interactions with our treatments are mostly statistically insignificant. Columns 6 and 8 show little in the way of statistically significant associations of *Group* or its interactions with *Happiness.* Overall, and caveating the overall low power of these tests, we conclude that being in a group is associated with choosing fewer meat or fish dishes, but not with lower overall happiness with meal choice. Hence, whereas peer pressure may increase diners' propensity to opt for lower CO_2 food, we find no direct evidence that it moderates the effects of carbon footprint information.

Third and finally, we analyze how participants' food choice based on ecological criteria correlates with our treatments; 10.7% of survey respondents report that the ecological footprint is among the criteria they usually apply when selecting dishes in the canteen (online appendix OA.C.3, panel D). This preference does not appear to be driven by our information treatments, since regressions of the related indicator variable, *EcoSelection,* on our information treatments yield statistically insignificant coefficients (online appendix OA.C.6). Nor does it exhibit a clear time trend during the 10-day experiment, with overall low numbers and an increase that is statistically insignificant (online appendix OA.C.7).

4.2.2. Additional Control Variables. In this section, we augment equations (1) and (2) by including three dish-level indicator variables, which denote dishes purchased by a faculty/staff member (*FacultyStaff*), a nonuniversity guest (*Guests*), or a participant who visited the canteen more than once during the experimental period (*ReturningVisitor*). We further add *Visits,* the number of canteen visits by the buyer of the given dish during the experimental period. The results are presented in columns 1, 3, and 5 of table 4, which mirrors the table 3 structure.

---

less happy by making them understand their choices' ecological consequences better, or by inducing them to choose dishes they ended up liking less than expected.

TABLE 4

Regression Results and Hypothesis Tests (Additional Controls and First-Time-Only Diners)

	Dependent Variable					
	MeatFish		*Log(FoodWeight)*		*Log(CO_2e)*	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Regression results						
CO_2Neutral	−0.088***	−0.063*	−0.013*	−0.018***	−0.032**	−0.022**
	(0.024)	(0.035)	(0.008)	(0.006)	(0.015)	(0.008)
CO_2ColorCoded	−0.213***	−0.252***	0.002	−0.011	−0.052***	−0.057***
	(0.024)	(0.068)	(0.006)	(0.007)	(0.009)	(0.015)
MoneyColorCoded	−0.329***	−0.393***	−0.023***	−0.054***	−0.093***	−0.124***
	(0.022)	(0.085)	(0.007)	(0.011)	(0.011)	(0.015)
BudgetColorCoded	−0.077***	−0.092*	−0.010	−0.026**	−0.032***	−0.051***
	(0.018)	(0.049)	(0.009)	(0.011)	(0.009)	(0.012)
FacultyStaff	0.126		−0.025**		0.012	
	(0.080)		(0.010)		(0.021)	
Guests	0.684***		−0.061***		0.106**	
	(0.104)		(0.017)		(0.037)	
ReturningVisitor	−0.043		0.027**		0.027*	
	(0.045)		(0.010)		(0.015)	
Visits	0.033***		0.008***		0.013***	
	(0.010)		(0.002)		(0.004)	
Num.Obs.	22,713	8,604	22,713	8,604	22,713	8,604
Adj. R^2/Pseudo R^2	0.014	0.010	0.025	0.018	0.039	0.039
Fixed effects: Day	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects: Slot	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Hypothesis tests						
H_1: Main Effect	−0.175***	−0.178***	−0.011**	−0.024***	−0.052***	−0.056***
H_2: Context	0.012	0.030	−0.019***	−0.027***	−0.010	−0.026***
H_3: Mental Budget	0.252***	0.301***	0.013	0.028*	0.062***	0.072***
H_4: Color-Coding	−0.126***	−0.189***	0.015**	0.008	−0.020	−0.035***

This table presents the results of regressing the diners' food choices on the information treatments (*CO_2Neutral, CO_2ColorCoded, BudgetColorCoded*, and *MoneyColorCoded*) and control variables as stated, and the planned hypothesis tests based on these regression results (panel B). Columns 1 and 2 present the results for the probability of choosing a meat or fish dish (dependent variable: *MeatFish* = 1) or a vegan or vegetarian dish (dependent variable: *MeatFish* = 0), columns 3 and 4 present the results for total food weight per diner (dependent variable: *FoodWeight*), and columns 5 and 6 present the results for the total CO_2 equivalent emissions per dish (dependent variable: *CO_2e*). By including additional control variables, we conduct an unplanned supplementary analysis that was not preregistered as such (columns 1, 3, and 5). Reducing the sample to first-time diners only has been a planned supplementary analysis (columns 2, 4, 6). In panel A, we estimate columns 1 and 2 by employing a logit regression using equation (1), and columns 3 through 6 by employing an OLS regression using equation (2). In panel A, standard errors, clustered by day and slot, are presented in parentheses below the coefficient estimates. The R^2 in columns 1 and 2 is a pseudo-R^2 obtained from the logit regression. In both panels, statistical two-sided significance of the coefficients is indicated at the 0.01 (***), 0.05 (**), and 0.10 (*) level, respectively. The unit of observation is an individual main dish purchased by a diner. In panel B, we use Wald tests to assess the respective average marginal effects. To test H_1, we estimate the average marginal effect of all information treatments (*CO_2Neutral, CO_2ColorCoded, BudgetColorCoded* and *MoneyColorCoded*) against the baseline (*NoInfo*). For H_2, we estimate the average marginal effect of the contextualized information treatments (*BudgetColorCoded* and *MoneyColorCoded*) minus the marginal effect of the noncontextualized treatment (*CO_2ColorCoded*). For H_3, we estimate the difference between the marginal effect of the *BudgetColorCoded* treatment and the *MoneyColorCoded* treatment. For H_4, we estimate the marginal effect of color-coding the information treatment by testing *CO_2Neutral* against *CO_2ColorCoded*. All variables are defined in appendix A.

All hypothesis tests in panel B exhibit identical signs and significance levels, as well as quantitatively similar test statistics. Turning to the control variables, the coefficients on *Guests* across the three outcome variables indicate that this cohort tends to consume, on average, higher CO_2 dishes than students, albeit in smaller portions. A slightly different picture emerges for frequent canteen visitors (*Visits*), whose food choices as well as portion sizes and carbon footprints are all significantly increasing in their visiting frequency, ceteris paribus. Overall, since the sample attributes analyzed here do not influence the treatment effects, our conclusions remain unchanged compared to the main analysis in section 4.1.2 (table 3).

4.2.3. Excluding Repeat Visitors. Repeat visitors are more likely to notice and ponder our information treatments, which may make them aware of a field-experiment-in-progress and cause potential Hawthorne-type attention effects. To address these concerns, we repeat the main table 3 analysis restricting the sample to the first-time purchases of any dish during the experimental period with a given payment card.[25] Doing so effectively eliminates all dishes purchased by repeat visitors. Columns 2, 4, and 6 of table 4 present the results. Again, findings are directionally consistent with those reported for the main tests. Regarding *MeatFish*, hypothesis tests (panel B) exhibit identical signs and significance levels as the main tests for the full sample. For portion sizes (*FoodWeight*) and carbon footprints (CO_2e), test statistics are again qualitatively consistent, implying similar, if not somewhat stronger, marginal effects of our treatments compared to the full sample. We conclude that this analysis indicates no Hawthorne-type effects and is rather consistent with repeat visitors becoming marginally less reactive to the treatments.[26]

4.2.4. Transaction-Level Tests. As discussed previously, participants occasionally charge multiple main dishes to their cards during one visit, suggesting that they either are very hungry or (more likely) pay for multiple diners. Since this prevents us from unambiguously identifying individual diners, we decided to use main dishes bought as our main unit of analysis. To assess whether this research design choice, unforeseen and thus undiscussed during preregistration, affects our main inferences, we repeat our main analyses by using transactions (rather than dishes) as our unit of analysis. Doing

[25] These sample restrictions skew the temporal distribution of observations toward the earlier part of the experimental period, since later days naturally saw fewer and fewer first-time diners visiting the canteen. Notably, *N* drops from 22,713 to 8,604 dishes, consistent with the high degree of repeat business in the canteen shown in table 2.

[26] In principle, it would be feasible to estimate model variants with participant fixed effects to assess changes in treatment effects over time at the participant level. However, since repeat visitors are exposed to varying treatments and varying dining choice sets over the experimental period, our setting does not feature repeating treatment/choice set combinations over time, and is thus unable to render a meaningful comparison of effects over time at the participant level.

so also allows us to include additional side dishes on separate containers into the analysis. Online appendix OA.D provides details and presents a set of tables that are structured identically to our main tables 1 through 4. Transaction-level hypothesis tests yield virtually the same conclusions as those emerging from the dish-level tests and are thus not discussed here in detail. Overall, we conclude that the transaction-level tests are in line with, but statistically at times somewhat stronger than, our main inferences from the dish-level tests. Both specifications combined reflect the spirit of the preregistered diner-level analysis and give a coherent picture of the results.

4.2.5. Additional Robustness Tests. Our preregistered research plan limits the number of ex post research design choices. But even within these constraints we still faced several decisions, most of which are discussed in our preregistration, as well as tabulated herein and explained in the previous subsections. These selected supplementary analyses do not exhaust the set of plausible research design combinations available to us.

To address the robustness of our main insights to these choices, while avoiding the prohibitive cost of tabulating and discussing each permutation in detail, we prepared an online dashboard (https://trr266.de/carbonfood/) where interested readers can explore a multiverse of up to 61,440 regressions, which combine 12 research design choices that have between two and five options each.[27] To illustrate the range of choices and visualize the robustness of our results for H_1, figure 4 provides an exemplary specification curve (in the style of Simonsohn et al. [2020]) that plots 768 main effect estimates from estimating equation (2) for $Choice = CO_2e$, our most holistic outcome measure, reflecting eight design choices with a total of 19 options. Additionally, online appendix figures OA.E.1–3 visualize the robustness of the other three hypotheses tests for CO_2e, using the same set of choices and options.

5. Conclusion

With climate change a major societal issue, corporate GHG emissions reporting is on the rise. We conduct a preregistered field experiment that studies how carbon footprint information, presented in different measurement units and visualizations, affects consumer choice. Set in a large German student canteen, our 10-day-long experiment tests the effect of several different information treatments on the carbon footprints of more than 22,000 meals chosen by diners.

Three key insights emerge. First, although a postexperimental survey indicates low concern about food-related ecological footprint among diners,

[27] This approach has been suggested by scholars in psychology (Wicherts et al. [2016]) and information science (Gelman and Loken [2014]), to reduce the risk of p-hacking and to increase the transparency of research findings.

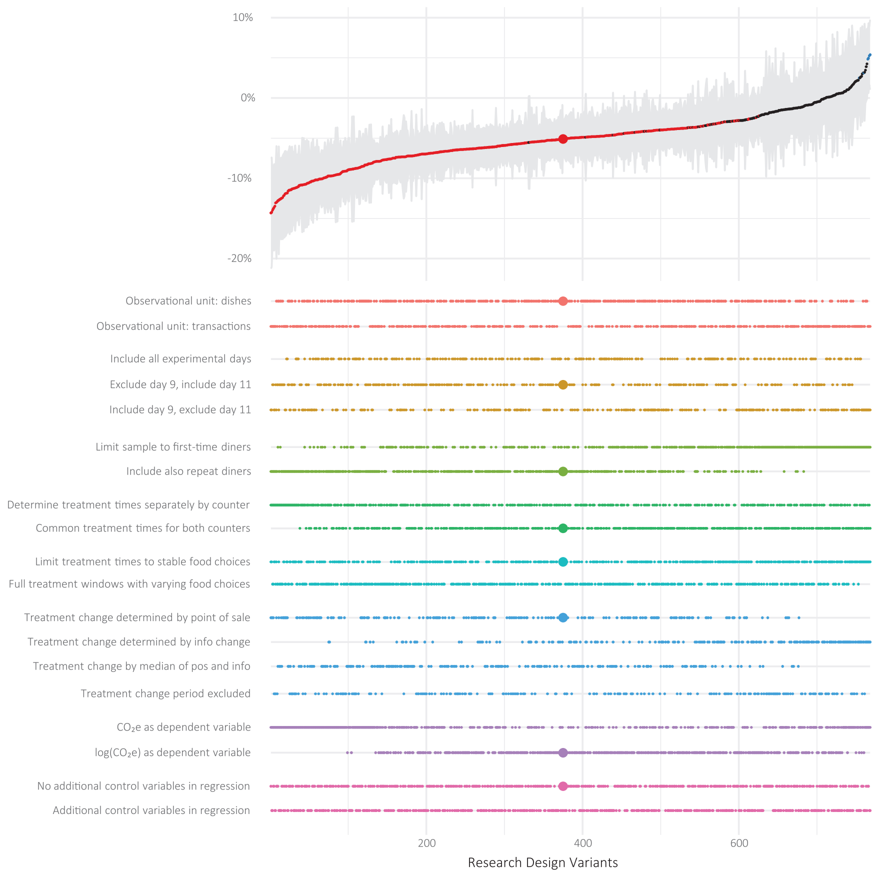


FIG. 4.—Specification curve for main effect on carbon footprint (H_1). This figure reports an unplanned supplementary analysis for H_1 based on 768 different research designs that incorporate various design choices. The upper half of the figure plots the coefficient estimates (solid line) and the corresponding 95% confidence intervals (gray area) for the designs characterized by the choices depicted in the lower half of the figure. The large dots indicate our preregistered research design and the corresponding effect estimate. The treatment effects are reported as percentage changes in food-related CO_2e (CO_2e) emissions caused by our four information treatments. They are estimated based on variants of the regression model in equation (2), with its data and specifications determined by the choices indicated. The average effect estimate is −5.1%, and 74.3% (0.8%) of the estimates are significantly negative (positive) ($|p| < 0.05$). The concept of the figure is based on Simonsohn et al. [2020], and it can be interactively created and explored using our online dashboard (https://trr266.de/carbonfood/).

participants significantly reduce food-related CO_2e emissions under *any* carbon footprint information treatment. Second, color-coding enhances this effect, but contextualization per se does not. Third, and contrary to expectations, a contextualization activating a *wider* mental budget frame of carbon footprint as environmental costs caused (displayed in monetary units) triggers lower CO_2 food choices relative to a *narrower* framing that presents food options as fractions of participants' carbon budget for food. Combining these two latter features, color-coded environmental-cost information elicits the strongest effect, with a 9.2% reduction in diners' carbon footprints. Our results are largely robust across several preregistered robustness tests and additional research design specifications.

Our study has several limitations. First, the decision-making process underlying participants' food choices under our information treatments is not observable. Drawing on insights from our preregistered postexperimental survey to discern whether participants decide rationally or respond to subconscious nudging, we find some (albeit weak) evidence of a decrease in consumers' self-reported satisfaction with their food choices under our four information treatments. We leave it for future work to establish whether this dampening effect on self-reported happiness is an artefact of our setting and data, reflects subconscious nudging toward low-utility outcomes, rational choices amidst gloomy thoughts of climate change evoked by the treatments, or some other mechanism. Similarly, future research could seek to disentangle whether the salience effect of color-coding in this carbon information context operates through a heightened attention-grabbing sensory stimulus, an aggregate information signal, or emotional affect. Second, our sample clearly does not represent the general populations of either Germany (our setting) or the United States. However, the vast overrepresentation of students and vegan/vegetarian participants need not necessarily undermine generalizability. After all, our main interest is not in the baseline effect of carbon footprint information per se (related to which our cohort may be more sensitive, but also more ex-ante aware), but in how different displays of essentially identical information are processed. Here, we have no strong priors about how our participants perform versus other demographics but leave this for subsequent studies to explore.

In addition to contributing to the transdisciplinary debate about the effect of carbon footprint labels on consumer choice, our findings also inform accounting research and practice by showing how information processing varies with the presentation format of numerical data. These insights seem particularly important for nonfinancial reporting, where diverse stakeholders process complex—and sometimes unfamiliar—numerical information. Whereas preparers and users of financial reports have adapted to monetary values and their interpretations for centuries, nonfinancial reporting presents users with new and unfamiliar measurement units and reference frames. Our work provides insights on how different ways of presenting this crucial information can affect users' decisions in contexts ranging from external reporting to management control.

Acknowledgments

Open access funding enabled and organized by Projekt DEAL.

APPENDIX A: VARIABLE DEFINITIONS

Variable	Description
Panel A: Dependent variables	
Choice	Any of the three outcome variables *FoodWeight*, *MeatFish*, or CO_2e
MeatFish	1 if the food purchased by the diner is a meat/fish option; 0 otherwise
FoodWeight	Food purchased by the diner, in grams
CO_2e	CO_2e emissions of food purchased by the diner, in grams, calculated as $\frac{(CO2e(main\ dish\ selected)\ +\ CO2e(median\ all\ dishes))}{2} \times \frac{FoodWeight}{100}$
SurveyParticipation	1 if a dish purchaser participates in the postexperimental survey
Happiness	Self-reported happiness of a survey participant with their food choice (Q1 in the survey instrument)
EcoSelection	1 if the survey participant lists ecological footprint among the criteria for selecting their canteen dishes (Q4 in the survey instrument)
Panel B: Independent variables	
Treatment	1 if any of the four information treatments CO_2*Neutral*, CO_2*ColorCoded*, *BudgetColorCoded*, or *MoneyColorCoded* is displayed
NoInfo	1 if no carbon footprint information is displayed; 0 otherwise
CO_2*Neutral*	1 if carbon footprint information is displayed in grams of CO_2e emissions, in a black-and-white pictorial; 0 otherwise
CO_2*ColorCoded*	1 if carbon footprint information is displayed in grams of CO_2e emissions, in a traffic-light-colored pictorial; 0 otherwise
BudgetColorCoded	1 if carbon footprint information is displayed in % of a stylized person's daily food-related CO_2e emissions budget, in a traffic-light-colored pictorial; 0 otherwise
MoneyColorCoded	1 if carbon footprint information is displayed in Euros of environmental costs caused, in traffic-light-colored pictorial; 0 otherwise
Panel C: Control variables	
FacultyStaff	1 if their ID card identifies the diner as university faculty or staff
Student	1 if their ID card identifies the diner as a student
Guests	1 if their ID card identifies the diner as a nonuniversity guest
Visits	Total number of days the diner visits the canteen over the sample period
ReturningVisitor	1 if *Visits* > 1
Group	1 if the survey participant visits with at least one other person

This table defines our variables. For details on the measurement of CO_2e variables based on *KlimaTeller* GHG data, see online appendix OA.B. For CO_2e, the median CO_2e of all main dishes over the entire experimental period is 154 g CO_2e per 100 g. For a visualization of the information treatments, see figure 1. For a detailed description of the postexperimental survey and its questions, see Appendix C and online appendix OA.C.

APPENDIX B: TREATMENT PLAN

	Information Condition	
Day	Slot 1	Slot 2
1	*NoInfo*	*CO_2Neutral*
2	*CO_2Neutral*	*CO_2ColorCoded*
3	*CO_2ColorCoded*	*MoneyColorCoded*
4	*NoInfo*	*BudgetColorCoded*
5	*BudgetColorCoded*	*MoneyColorCoded*
6	*MoneyColorCoded*	*NoInfo*
7	*CO_2Neutral*	*BudgetColorCoded*
8	*BudgetColorCoded*	*CO_2ColorCoded*
9	*CO_2ColorCoded*	*NoInfo*
10	*MoneyColorCoded*	*CO_2Neutral*

This table presents the assignments of our information conditions (*NoInfo*, *CO_2Neutral, CO_2ColorCoded, BudgetColorCoded*, and *MoneyColorCoded)* over the 10-day experimental period. In each slot, we provided carbon footprint information by adding leaf-shaped pictorials (visualized in figure 1) to the canteen's regular menu information displays. We allocated treatments across slots in a pattern that allows for day and slot fixed effects in our regression analyses. All variables are defined in appendix A.

APPENDIX C: POSTEXPERIMENTAL SURVEY

No.	Question	Alternative answers
1	How happy are you with your meal today?	Single choice (five options): Happy; somewhat happy; neither happy nor unhappy; somewhat unhappy; unhappy
2	With how many other people are you dining today?	Single choice (four options): I am dining by myself; We are two (three) [more than three] people.
3	Which food products do you USUALLY avoid?	Multiple choice (five options): Meat; Fish; Other animal products; Food causing allergies or intolerances (e.g., peanuts, histamine); Other (please specify below), max. 100 characters
4	What other criteria do you USUALLY apply to select your dishes in the canteen?	Multiple choice (randomized order, nine options): Animal welfare; Appearance; Ecological footprint; Health considerations; Length of the queue at the counter; Nutritional value (e.g., proteins, calories); Price; Taste; Other (please specify below), max. 100 characters
5	What other criteria did you apply TODAY to select your dishes at the canteen?	Multiple choice (randomized order, nine options): Animal welfare; Appearance; Ecological footprint; Health considerations; Length of the queue at the counter; Nutritional value (e.g., proteins, calories); Price; Taste; Other (please specify below), max. 100 characters

This table presents the postexperimental survey conducted. Survey participation is voluntary and thus endogenous. To maximize response rates, we kept the questions simple and the survey short. Furthermore, participation was incentivized via a raffle of one 100-Euro online shopping voucher. We handed out the vouchers after the experiment, to avoid drawing survey respondents' attention to who is handing them out, seeking to prevent Hawthorne-type effects. Survey participation was anonymous, and winners were identified via their checkout receipt IDs, which we collected in the survey. Respondents had the opportunity to enter multiple times but were restricted by the terms and conditions to participate at maximum once a day. The receipt IDs provide the opportunity to match survey participants' responses to our experimental data from the cash registers. Online appendix OA.C describes the survey in detail.

REFERENCES

Abadie, A.; S. Athey; G. W. Imbens; and J. Wooldridge. "When Should You Adjust Standard Errors for Clustering?" *The Quarterly Journal of Economics* 138 (2023): 1–35.

Adair, J. G. "The Hawthorne Effect: A Reconsideration of the Methodological Artifact." *Journal of Applied Psychology* 69 (1984): 334–45.

Barberis, N., and M. Huang "Mental Accounting, Loss Aversion, and Individual Stock Returns." *Journal of Finance* 56 (2001): 1247–92.

Blankespoor, E.; E. deHaan; and I. Marinovic. "Disclosure Processing Costs, Investors' Information Choice, and Equity Market Outcomes: A Review." *Journal of Accounting and Economics* 70 (2020): 101344.

Bleich, S. N.; C. D. Economos; M. L. Spiker; K. A. Vercammen; E. M. VanEpps; J. P. Block; B. Elbel; M. Story; and C. A. Roberto. "A Systematic Review of Calorie Labeling and Modified Calorie Labeling Interventions: Impact on Consumer and Restaurant Behavior." *obes* 25 (2017): 2018–44.

Bloomfield, R.; M. W. Nelson; and E. Soltes. "Gathering Data for Archival, Field, Survey, and Experimental Accounting Research." *Journal of Accounting Research* 54 (2016): 341–95.

Bollinger, B.; P. Leslie; and A. Sorensen. "Calorie Posting in Chain Restaurants." *American Economic Journal: Economic Policy* 3 (2011): 91–128.

Bonner, S. E.; S. M. Clor-Proell; and L. Koonce. "Mental Accounting and Disaggregation Based on the Sign and Relative Magnitude of Income Statement Items." *The Accounting Review* 89 (2014): 2087–114.

Brunner, F.; V. Kurz; D. Bryngelsson; and F. Hedenus. "Carbon Label at a University Restaurant—Label Implementation and Evaluation." *Ecological Economics* 146 (2018): 658–67.

Camilleri, A. R.; R. P. Larrick; S. Hossain; and D. Patino-Echeverri. "Consumers Underestimate the Emissions Associated with Food but Are Aided by Labels." *Nature Climate Change* 9 (2019): 53–59.

Capstick, S. B., and A. Lewis. "Effects of Personal Carbon Allowances on Decisionmaking: Evidence from an Experimental Simulation." *Climate Policy* 10 (2010): 369–84.

Cardinaels, E., and P. M. G. van Veen-Dirks. "Financial versus Non-Financial Information: The Impact of Information Organization and Presentation in a Balanced Scorecard." *Accounting, Organizations and Society* 35 (2010): 565–78.

Christensen, B. E.; S. M. Glover; and C. J. Wolfe. "Do Critical Audit Matter Paragraphs in the Audit Report Change Nonprofessional Investors' Decision to Invest?" *Auditing: A Journal of Practice & Theory* 33 (2014): 71–94.

Christensen, H. B.; E. Floyd; L. Y. Liu; and M. Maffett. "The Real Effects of Mandated Information on Social Responsibility in Financial Reports: Evidence from Mine-Safety Records." *Journal of Accounting and Economics* 64 (2017): 284–304.

Christensen, H. B.; L. Hail; and C. Leuz. "Mandatory CSR and Sustainability Reporting: Economic Analysis and Literature Review." *Review of Accounting Studies* 26 (2021): 1176–248.

Cohen, S.; I. Kadach; G. Ormazabal; and S. Reichelstein. "Executive Compensation Tied to ESG Performance: International Evidence." *Journal of Accounting Research* 61 (2023): 805–53.

Dechow, P. M. "Accounting Earnings and Cash Flows as Measures of Firm Performance: The Role of Accounting Accruals." *Journal of Accounting and Economics* 18 (1994): 3–42.

Downs, J. S.; J. Wisdom; B. Wansink; and G. Loewenstein. "Supplementing Menu Labeling with Calorie Recommendations to Test for Facilitation Effects." *American Journal of Public Health* 103 (2013): 1604–9.

Drewnowski, A.; C. D. Rehm; A. Martin; E. O. Verger; M. Voinnesson; and P. Imbert. "Energy and Nutrient Density of Foods in Relation to Their Carbon Footprint." *American Journal of Clinical Nutrition* 101 (2015): 184–91.

Elliot, A. J., and M. A. Maier. "Color and Psychological Functioning." *Current Directions in Psychological Science* 16 (2007): 250–54.

Ellison, B.; J. L. Lusk; and D. Davis. "Looking at the Label and beyond: The Effects of Calorie Labels, Health Consciousness, and Demographics on Caloric Intake in Restaurants." *International Journal of Behavioral Nutrition and Physical Activity* 10 (2013): 1–9.

European Commission (EC). "Directive (EU) 2022/2464 of the European Parliament and of the Council of 14 December 2022 Amending Regulation (EU) No 537/2014, Directive 2004/109/EC, Directive 2006/43/EC and Directive 2013/34/EU, as Regards Corporate Sustainability Reporting." *Official Journal of the European Union* 2016 (2022): 48–119.

Eurostat. "Eurostat Glossary: Carbon Dioxide Equivalent," 2021. Available at https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Carbon_dioxide_equivalent.

Floyd, E., and J. A. List. "Using Field Experiments in Accounting and Finance." *Journal of Accounting Research* 54 (2016): 437–75.

Fung, A.; M. Graham; and D. Weil. *Full Disclosure*. Cambridge: Cambridge University Press, 2007.

Gelman, A., and E. Loken. "The Statistical Crisis in Science." *American Scientist* 102 (2014): 460.

Grewal, J., and G. Serafeim. "Research on Corporate Sustainability: Review and Directions for Future Research." *Foundations and Trends in Accounting* 14 (2020): 73–127.

Grinblatt, M., and B. Han. "Prospect Theory, Mental Accounting, and Momentum." *Journal of Financial Economics* 78 (2005): 311–39.

Grinstein, A.; E. Kodra; S. Chen; S. Sheldon; and O. Zik. "Carbon Innumeracy." *PLoS ONE* 13 (2018): 1–14.

Hahnel, U. J. J.; G. Chatelain; B. Conte; V. Piana; and T. Brosch. "Mental Accounting Mechanisms in Energy Decision-Making and Behaviour." *Nature Energy* 5 (2020): 952–58.

Hartikainen, H.; T. Roininen; J. M. Katajajuuri; and H. Pulkkinen. "Finnish Consumer Perceptions of Carbon Footprints and Carbon Labelling of Food Products." *Journal of Cleaner Production* 73 (2014): 285–93.

Hawley, K. L.; C. A. Roberto; M. A. Bragg; P. J. Liu; M. B. Schwartz; and K. D. Brownell. "The Science on Front-of-Package Food Labels." *Public Health Nutrition* 16 (2013): 430–39.

Henderson, P. W., and R. A. Peterson. "Mental Accounting and Categorization." *Organizational Behavior and Human Decision Processes* 51 (1992): 92–117.

Hombach, K., and T. Sellhorn. "Shaping Corporate Actions Through Targeted Transparency Regulation: A Framework and Review of Extant Evidence." *Schmalenbach Business Review* 71 (2019): 137–68.

IPCC. IPCC "Annex I: Glossary [Matthews, J.B.R. (ed.)] Global Warming of 1.5°C. An IPCC Special Report on the Impacts of Global Warming of 1.5°C above Pre-Industrial Levels and Related Global Greenhouse Gas Emission Pathways, in the Context of Strengthening the Global Response to the Threat of Climate Change." 2018. Available at https://www.ipcc.ch/sr15/chapter/glossary/.

ISSB. "Exposure Draft - IFRS S2 Climate-related Disclosures." 2022. Available at https://www.ifrs.org/content/dam/ifrs/project/climate-related-disclosures/issb-exposure-draft-2022-2-climate-related-disclosures.pdf.

ISSB "IFRS S2: Climate-related Disclosures." 2023. Available at https://www.ifrs.org/issued-standards/ifrs-sustainability-standards-navigator/ifrs-s2-climate-related-disclosures.html/content/dam/ifrs/publications/html-standards-issb/english/2023/issued/issbs2/.

Johnson, E. J. *The Elements of Choice: Why the Way We Decide Matters*. New York: Riverhead Books, 2021.

Kaplan, R. S., and K. Ramanna. "Accounting for Climate Change." *Harvard Business Review* November-December (2021): 120–32.

Levitt, S. D., and J. A. List. "Was There Really a Hawthorne Effect at the Hawthorne Plant? An Analysis of the Original Illumination Experiments." NBER Working Paper Series (No. 15016; NBER Working Paper Series, Vol. 15016, Issue May) 2009. Available at http://www.nber.org/papers/w15016.

Lipe, M. G. "Analyzing the Variance Investigation Decision: The Effects of Outcomes, Mental Accounting, and Frmaing." *The Accounting Review* 68 (1993): 748–64.

LOHMANN, P. M.; E. GSOTTBAUER; A. DOHERTY; and A. KONTOLEON. "Do Carbon Footprint Labels Promote Climatarian Diets? Evidence from a Large-Scale Field Experiment." *Journal of Environmental Economics and Management* 114 (2022): 102693.

LONG, M. W.; D. K. TOBIAS; A. L. CRADOCK; H. BATCHELDER; and S. L. GORTMAKER. "Systematic Review and Meta-Analysis of the Impact of Restaurant Menu Calorie Labeling." *American Journal of Public Health* 105 (2015): e11–e24.

MAINES, L. A., and L. S. MCDANIEL. "Effects of Comprehensive-Income Characteristics on Nonprofessional Investors' Judgments: The Role of Financial-Statement Presentation Format." *The Accounting Review* 75 (2000): 179–207.

O'MALLEY, K.; A. WILLITS-SMITH; and D. ROSE. "Popular Diets as Selected by Adults in the United States Show Wide Variation in Carbon Footprints and Diet Quality." *The American Journal of Clinical Nutrition* 117 (2023): 701–8.

OLSEN, J.; M. KASPER; C. KOGLER; S. MUEHLBACHER; and E. KIRCHLER. "Mental Accounting of Income Tax and Value Added Tax among Self-Employed Business Owners." *Journal of Economic Psychology* 70 (2019): 125–39.

PRADHAN, P.; D. E. REUSSER; and J. P. KROPP. "Embodied Greenhouse Gas Emissions in Diets." *PLoS ONE* 8 (2013): 1–8.

ROCKENBACH, B. "The Behavioral Relevance of Mental Accounting for the Pricing of Financial Options." *Journal of Economic Behavior and Organization* 53 (2004): 513–27.

RONDONI, A., and S. GRASSO. "Consumers Behaviour Towards Carbon Footprint Labels on Food: A Review of the Literature and Discussion of Industry Implications." *Journal of Cleaner Production* 301 (2021): 127031.

SCHUBERT, C. "Green Nudges: Do They Work? Are They Ethical?" *Ecological Economics* 132 (2017): 329–42.

SECURITIES AND EXCHANGE COMMISSION. "The Enhancement and Standardization of Climate-Related Disclosures for Investors." 2022. Available at https://www.sec.gov/rules/proposed/2022/33-11042.pdf.

SIMONSOHN, U.; J. P. SIMMONS; and L. D. NELSON. "Specification Curve Analysis." *Nature Human Behaviour* 4 (2020): 1208–14.

SIROIS, L. P.; J. BÉDARD; and P. BERA. "The Informational Value of Key Audit Matters in the Auditor's Report: Evidence from an Eye-Tracking Study." *Accounting Horizons* 32 (2018): 141–62.

SLOAN, R. G. "Do Stock Prices Fully Reflect Information in Accruals and Cash Flows About Future Earnings?" *The Accounting Review* 71 (1996): 289–315.

SPAARGAREN, G.; C. S. A. van KOPPEN; A. M. JANSSEN; A. HENDRIKSEN; and C. J. KOLFSCHOTEN. "Consumer Responses to the Carbon Labelling of Food: A Real Life Experiment in a Canteen Practice." *Sociologia Ruralis* 53 (2013): 432–53.

THALER, R. H. "Mental Accounting and Consumer Choice." *Marketing Science* 4 (1985): 199–214.

THALER, R. H. "Mental Accounting Matters." *Journal of Behavioral Decision Making* 12 (1999): 183–206.

THALER, R. H., and C. R. SUNSTEIN. *Nudge: Improving Decisions About Health, Wealth, and Happiness.* New Haven, CT: Yale University Press, 2008.

THALER, R. H.; C. R. SUNSTEIN; and J. P. BALZ. "Choice Architecture." In *The Behavioral Foundations of Public Policy*, E. Shafir (Ed.). Princeton, NJ: Princeton University Press, 2013: 428–39.

THØGERSEN, J., and K. S. NIELSEN. "A Better Carbon Footprint Label." *Journal of Cleaner Production* 125 (2016): 86–94.

THORNDIKE, A. N., L. SONNENBERG, J. RIIS, S. BARRACLOUGH, and D. E. LEVY. "A 2-Phase Labeling and Choice Architecture Intervention to Improve Healthy Food and Beverage Choices." *American Journal of Public Health* 102 (2012): 527–33.

TRUDEL, R.; K. B. MURRAY; S. KIM; and S. CHEN. "The Impact of Traffic Light Color-Coding on Food Health Perceptions and Choice." *Journal of Experimental Psychology: Applied* 21 (2015): 255–75.

UN "Cut Global Emissions by 7.6 Percent Every Year for Next Decade to Meet 1.5°C Paris Target—UN Report." 2019. Available at https://www.unep.org/news-and-stories/press-release/cut-global-emissions-76-percent-every-year-next-decade-meet-15degc.

Veganz. "Veganz Ernährungsstudie." 2022. Available at https://veganz.de/blog/veganz-ernaehrungsstudie-2022/.

Wicherts, J. M.; C. L. S. Veldkamp; H. E. M. Augusteijn; M. Bakker; R. C. M. van Aert; and M. A. L. M. van Assen. "Degrees of Freedom in Planning, Running, Analyzing, and Reporting Psychological Studies: A Checklist to Avoid P-Hacking." *Frontiers in Psychology* 7 (2016): 1–12.

Wisdom, J.; J. S. Downs; and G. Loewenstein. "Promoting Healthy Choices: Information Versus Convenience." *American Economic Journal: Applied Economics* 2 (2010): 164–78.