DEPARTMENT OF FOOD AND RESOURCE ECONOMICS
UNIVERSITY OF COPENHAGEN

IFRO Working Paper

# Do People Respond to the Climate Impact of their Behavior? The Effect of Carbon Footprint Information on Grocery Purchases

*Toke R. Fosgaard*
*Alice Pizzo*
*Sally Sadoff*

**2021 / 05**

**IFRO Working Paper 2021 / 05**

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Published: June 2021

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Department of Food and Resource Economics (IFRO)
University of Copenhagen
Rolighedsvej 23
DK 1958 Frederiksberg  DENMARK
www.ifro.ku.dk/english/

# Do People Respond to the Climate Impact of their Behavior?
# The Effect of Carbon Footprint Information on Grocery Purchases

Toke R. Fosgaard[1], Alice Pizzo[1], Sally Sadoff[2]

June 2021

**Abstract**

Food production is a primary contributor to climate change with greenhouse gas (GHG) emissions varying widely across food groups. In a randomized experiment, we examine the impact of providing individualized information on the GHG emissions of grocery purchases via a smartphone app, compared to providing information on spending. Carbon footprint information decreases GHG emissions from groceries by an estimated 27% in the first month of treatment, with an estimated 45% reduction in emissions from beef, the highest emissions food group. Treatment effects fade in the longer-run along with app engagement. However, we find evidence of persistent effects among those who remain engaged with the app. Our results suggest that individualized carbon footprint information can reduce the climate impact of food consumption but requires sustained engagement.

**Key words:** Field Experiment, Pro-environmental Behavior, Carbon Footprint, Food Consumption, Consumer Behavior.

**JEL codes:** C93, D11, D91, Q5

[1] University of Copenhagen, Department of Food and Resources Economics
[2] University of California, San Diego, Rady School of Management

## Introduction

There is an urgent need to reduce greenhouse gas (GHG) emissions that contribute to climate change. Because political constraints limit the extent to which GHG emissions can be addressed using price mechanisms, there is growing interest in informational interventions aimed at shifting individual behavior. Prior work has examined informational interventions to reduce energy usage and increase demand for more energy efficient technologies, such as cars, appliances, and lightbulbs.

A behavior that has received surprisingly little attention in this area of research is food consumption. An estimated 20-30% of all GHG emissions originate from food production, making it a critical target for GHG reductions (European Commission, 2006; Vermeulen et al, 2012). It is also an area where informational interventions could potentially be effective. First, while there is growing awareness that the food production process contributes to climate change, information on the carbon footprint of particular food groups is not readily available and people generally underestimate the impacts (Camilleri et al., 2019; Macdiarmid et al., 2016). For example, despite recent attention to beef as a high emissions food group, many may not be aware of the magnitude: producing a single serving of beef (100 grams, 3.53 ounces, or 0.22 pounds) generates GHG emissions equivalent to driving 49.86 kilometers (30.98 miles), about the average daily commute in the U.S. (BTS, 2017).

Second, because emissions vary greatly by food group, shifts in composition can have a large impact (Garnett, 2011). For example, emissions related to the production of ground beef are ten times higher than those for chicken (Poore & Nemecek, 2018). More generally, eating fewer animal products can reduce individuals' total carbon footprint by an estimated 22% (Lacroix, 2018). However, food consumption behaviors are very difficult to shift and so may not be responsive to light-touch informational interventions.

In this study, we implement a randomized field experiment among a national sample of the Danish population to examine the impact of providing individuals with information about the GHG emissions of their grocery purchases. We provide the information through a smartphone application (app) that collects data on an individual's grocery purchases both prior to and during the 19-week intervention. We compare the impact of a "Carbon" app that provides item-level carbon-equivalent emissions of individuals' grocery purchases to a "Spending" app that provides item-level cost information. Similar to smart meters for home energy usage, the apps provide real time individualized feedback. Both apps also provide social comparisons – comparing individual behavior to similar users – as has been done previously in the context of energy and water usage. To measure revealed preferences for the two types of information, we also include a treatment group that makes both apps available to participants.[3]

We make several contributions to the existing literature. Our study is the first to test the impact of an individualized intervention aimed at decreasing the environmental impact of regular grocery purchases. Previous studies have tested the impact of carbon labels on a limited set of products or a one-time purchase at an experimental food market or in the laboratory (Vanclay et al ., 2010; Elofsson et al., 2016; Vlaeminck et al., 2014; Camilleri, 2019). In related work, Jalil et al. (2020) find that informing undergraduates about the environmental and health consequences of meat consumption reduced demand for meat at the institution[4]

We are also the first to estimate the effect of providing individuals with information about the climate impacts of their behavior. While interventions aimed at changing environmental behaviors are motivated by the externalities of energy usage, prior work has not provided direct information on how individual behavior translates into environmental impact. Instead, prior interventions have largely provided information about individuals' direct costs (Allcott & Knittel, 2019; Allcott & Taubinsky, 2015; Davis & Metcalf, 2016; Jessoe & Rapson, 2014). Or, has provided individualized feedback in terms of usage rather than environmental impact or carbon emissions (Brandon et al., 2019; Hahn & Metcalfe, 2016 and List & Price, 2016 provide reviews).[5] Related work tests general messages about the need for conservation but does not provide individualized information (e.g., Ferraro & Price, 2013; Ito et al., 2018). Our study examines whether people are responsive to individualized feedback about the externalities of their behavior. We measure the effect of providing emissions information relative to providing the type of cost/spending information that has been typical of the literature to date.

Third, we directly measure engagement with the informational interventions. Participants can only receive the information if they open the app, which we track throughout the treatment

[3] We were not able to include a group that receives no information because we could only collect outcome data via the app.
[4] A related literature examines behavioral interventions aimed at improving the healthfulness of food consumption (see e.g., Bauer & Reisch (2019) for a recent review).
[5] Tiefenbeck et al. (2018) couple individualized feedback on water usage with a picture of a polar bear on an ice cap that shrinks as water usage increases.

period. Prior studies that provide individualized feedback over time – for example through smart meters, home energy reports or robocalls – are not able to measure whether people actually hear or read the information (e.g., Allcott & Rogers, 2014; Brandon et al., 2019; Ferraro & Price, 2013).[6] Related work measures willingness to pay for receiving information but does not measure subsequent engagement (Allcott & Kessler, 2019). We measure revealed preferences for the emissions information by comparing engagement with the Carbon app to engagement with the Spending app over time.

We observe 175,146 item-level grocery purchases for 258 participants over a 19-week baseline period and a 19-week treatment period. Our primary outcome of interest is the carbon-equivalent emissions of participants' weekly grocery purchases. In the first month of treatment, participants who receive the Carbon app significantly reduce carbon emissions from groceries relative to participants who receive the Spending app. We estimate a 5.8kg decrease in weekly carbon emissions ($p$=0.003), a 27% decline compared to baseline. The magnitude is equivalent to reducing driving by 49 kilometers (30 miles) per week. During this period, the Carbon app decreases both overall purchases and emissions per purchase, with an estimated 45% decrease in emissions from beef ($p$=0.019), which has been the focus of prior work (Camilleri et al., 2019). However, over the full 19-week treatment period, the impact of the Carbon app is smaller – an estimated 2.4 kg per week decrease – and not statistically significant.

The pattern of treatment effects over time mirrors the pattern of app usage over time. Engagement in the app is concentrated in the first four weeks of treatment with over half of total app usage taking place in the first month. App usage is similar in the first four weeks for the Carbon and Spending treatments with participants in both groups checking the app on average a little over once a week. Over the full treatment period, app usage is lower in the Carbon treatment than the Spending treatment, though the differences are not statistically significant. We find similar results for the treatment group that received access to both apps. Providing both apps increases total app usage but crowds out usage of the individual apps, particularly longer term usage of the Carbon app. Over the 19-week treatment period, usage of the Spending app is almost 40% higher than the Carbon app ($p$=0.074). These results suggest a weak preference for spending information compared to emissions information over the longer term.

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[6] Allcott & Rogers (2014) examine how behavior relates to the timing of when home energy reports are sent.

Taken together, our findings demonstrate that providing people with personalized emissions information can affect their food purchasing behavior. However, our results also suggest that the impact of the informational intervention requires sustained engagement. In periods with regular app usage, we find meaningful treatment effects on carbon emissions, which decline along with app engagement. We also find suggestive evidence that the impact on emissions is sustained over the longer term for users who remain engaged with the app. These results inform the design of policies seeking to use low cost, highly scalable informational interventions to shift food purchasing behavior.

The rest of the paper is organized as follows. The second section describes the experimental design. The third section discusses the results, and the fourth section concludes.

## Experimental Design and Methods

We recruited a national Danish sample to participate in the study.[7] To do so, we worked with Statistics Denmark, which is the Danish governmental organization that creates statistics on the Danish society. On our behalf, Statistics Denmark selected a representative sample of 100,000 Danish adults. In two waves, mid-January 2020 and mid-June 2020, we sent an invitation to participate in our study through the mandatory public electronic mail system in Denmark (only 96,324 were effectively reached). The invitation letters included a description of the research project and the requirements for participation, which consisted in answering a brief survey, download an app and set-up a profile to use it. We varied the framing of the language describing the purpose of the study (the title and one sentence in the description changed) across letters using: an environmental frame, an economical frame or a neutral frame (see Appendix Figure A.1 for letters). No significant difference in study participation was found across the invitation framings. In order to participate in the study, participants clicked on a link at the bottom of the letter. The link took them to a survey about perceptions and attitudes towards food in relation to health, the environment and money. We also asked participants to rank five food items (potatoes, beef, chicken, cheese and orange) on three dimensions: pollution, cost and health.

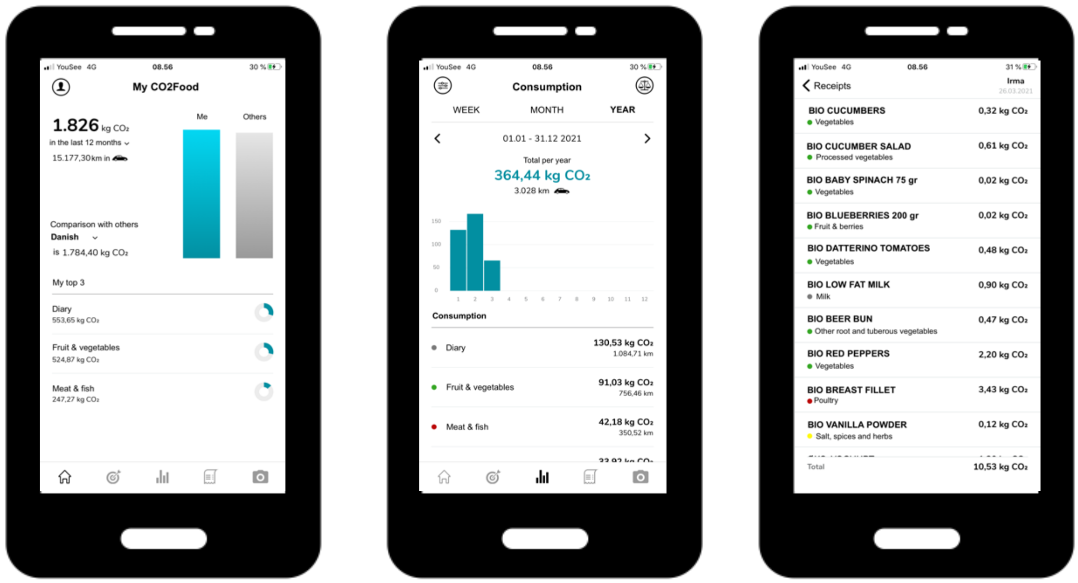
[7] We registered our study at the American Economic Association's registry (AEARCTR-0005291) for randomized controlled trials.

Upon survey completion, we randomly assigned participants to receive the Carbon app, the Spending app or both apps. Respondents downloaded the assigned app(s) to their smartphone, activated an app-user profile that included optional demographic questions, and connected the app to an e-receipt system of widespread use in Denmark. The e-receipt system collects data from the most common supermarkets in the country using individual payment card data. Participants who did not have the e-receipt system set up yet, they could easily sign up; a quick guide to do so was provided in the online survey platform. The automatic e-receipt system registers all food purchases at the individual level without the need for any manual entries. Moreover, it provides historic data on grocery purchases prior to the intervention. The app platforms therefore both served as the data collection device and the information provider. As noted above, because the app was required to collect the outcome data on grocery purchases, we were not able to include a group that received no app and no information.

Respondents in the *Carbon* treatment received the Carbon app, which provides an overview of the $CO_2$ emission associated with their food purchases. In the *Spending* treatment, participants received the Spending app, which provides an overview of the expenditures related to own food consumption. In the *Both* treatment, respondents received both apps. The two apps were developed by the same company (Spenderlog) and share structural visual design. In both apps, the overview is organized by food groups (e.g., dairy, meat and fish, fruit and vegetables), individual foods (e.g., cheese, fresh milk, beef, chicken, apples), and item-level purchases. Users can see weekly, monthly or yearly summaries. The apps also show comparisons of the user with other households active in the app for all of Denmark (default), as well as by region, household income, household type (e.g., apartment, house) and family type (e.g., single, couple, couple with kids). One additional app feature allows users to set any kind of quantitative goal in relation to their groceries (e.g., reduction in candy consumption).[8] Figure 1 shows examples of the app layout from the Carbon app. The analogous screenshots for the Spending app are in Appendix Figure A.3.

[8] Only about 6% of participants use this feature and set a goal.

**Figure 1:** Carbon app screenshots




Within this framework, the Spending app provides cost information about participants' grocery purchases and the Carbon app shows the carbon footprint linked to each item. In the Carbon app, the emissions information is shown both in terms of kilograms of $CO_2$ and kilometers driven by an average passenger vehicle, which is a common measure to ensure that non-experts can relate to the data.[9] The calculations are based on the methodology developed by the International Organization for Standardization (ISO, 2006), which estimates the greenhouse gas (GHG) emissions of the full food production process and supply chain. This includes the environmental impact of land use change, farming, inputs (e.g., imported feed and fertilizer), outputs (e.g., livestock manure sold to another holding), processing, and transportation. To provide a summary measure, the GHG emissions are converted into kilograms of Carbon Dioxide equivalents (kg of $CO_2$-e). Major greenhouse gases such as methane and nitrous oxide are expressed in terms of their effect relative to one kg of $CO_2$. For example, since methane is 25 times more efficient at retaining heat in the atmosphere than $CO_2$, one kg of methane corresponds to 25 kg of $CO_2$-equivalents. Similarly, one kg of nitrous oxide equals 298 kg of $CO_2$-equivalents (Boardman, 2008; Fødevarernes klimaaftryk, 2009; ISO, 2006).

[9] Interestingly, Allcott & Knittel (2019)benchmark cost information about vehicle fuel efficiency against the cost of groceries (e.g., in terms of gallons of milk).

Of the 100,000 invited participants, 96,324 received the email invitation, 2713 completed the enrollment survey, 332 downloaded their randomly assigned app(s) and 258 created a profile and connected it to their e-receipt system. We randomized participants on a rolling basis using the survey software (Qualtrics). Because randomization occurred before participants downloaded the app, we were not able to block the randomization on demographic characteristics or baseline behavior. We tracked participants for at least 19 weeks after they initially enrolled and installed the app(s). We also include 19 weeks of pre-intervention grocery purchases as the baseline comparison in our analysis.

## Results

### 1. Descriptive Statistics

Our experimental sample includes the full distribution of the national adult population of Denmark in terms of geography (drawing from all regions of the country), age (ranging from 20-72), household income and composition. As shown in columns (1) and (2) of Table 1, compared to the overall population, our participants are on average more likely to be female, older, more likely to be employed, higher income, more likely to have children in the household and more heavily drawn from the capital region (Copenhagen). We also note that the demographic data are not fully complete for all respondents, since they were provided in the app set-up of their profile. As shown in Appendix Table A.4, reweighting our sample to match the national population does not change our results (columns (5) & (10)).

Columns (3)-(5) reports baseline characteristics for each treatment group. For the Carbon treatment and the Both treatment groups, we report *p*-values from t-tests of binary differences with the Spending treatment in parentheses. While the Carbon treatment does not show any significant difference on the distribution of demographics and demographic groups compared to the reference group, the proportion of the age groups 50-59 and 70-79 significantly differs between the Both treatment and the Spending treatment.

The middle panel reports baseline grocery purchases for the experimental sample. We focus our experimental analysis at the weekly level in an effort to find a unit that includes at least one grocery shopping trip per individual and is not driven by heterogeneity in how people spread their shopping throughout the week (e.g., many small trips vs. one large trip). In the 19 weeks prior to study enrollment, participants averaged about 2.5 grocery trips per week with average weekly spending of \$56 (USD) and weekly carbon equivalent ($CO_2$-e) emissions of 20.7 kg. The weekly emissions are equivalent to driving 172 kilometers (107 miles), which is about two-thirds of the estimated 252 kilometers that the average Dane drives per week (Christiansen & Baescu, 2020).

**Table 1:** Descriptive statistics

| | **National Population** | **Experimental Sample** | **Spending Treatment** | **Carbon Treatment** | **Both Treatment** |
|---|---|---|---|---|---|
| Sample size *(N)* | -- | 258 | 94 | 73 | 91 |
| ***Demographics*** | | | | | |
| Female | 50.3% | 63% | 66% | 58% [0.299] | 64% [0.777] |
| Age | 42 | 46.9 | 45.8 | 46.8 [0.560] | 47.9 [0.287] |
| 20-29 | 13% | 11% | 13% | 9% [0.460] | 11% [0.692] |
| 30-39 | 12% | 21.4% | 22.6% | 23.5% [0.788] | 18% [0.513] |
| 40-49 | 13% | 25% | 28.6% | 25% [0.738] | 22% [0.350] |
| 50-59 | 14% | 22.6% | 16.6% | 23.5% [0.241] | 28% [0.078] |
| 60-69 | 11% | 16% | 12% | 17.6% [0.272] | 19.5% [0.174] |
| 70-79 | 10% | 3.4% | 7% | 1.5% [0.109] | 1% [0.060] |
| Employed | 66% | 75% | 73% | 80% [0.160] | 73% [0.764] |
| Household Income (\$) | | | | | |
| <47.4k | 34% | 18% | 19.4% | 19.6% [0.785] | 14.6% [0.577] |
| 48-79k | 26% | 23% | 29% | 18% [0.236] | 21% [0.419] |
| >80k | 39% | 59% | 51.4% | 62% [0.441] | 64% [0.276] |
| Household Type | | | | | |
| Single | 24% | 22% | 28% | 17.5% [0.180] | 20% [0.327] |
| Single + children | 4% | 8% | 9% | 8% [0.882] | 6% [0.590] |
| Couple | 33% | 32.6% | 29% | 32% [0.668] | 37% [0.263] |
| Couple + children | 24% | 34% | 30% | 40% [0.220] | 33% [0.642] |
| 3 or more adults | 15% | 4% | 4% | 3% [0.865] | 4% [0.968] |
| Capital Region (Copenhagen) | 23% | 39% | 37.5% | 40.6% [0.615] | 39% [0.756] |

**Table 1 Continued:** Descriptive statistics

| | National Population | Experimental Sample | Spending Treatment | Carbon Treatment | Both Treatment |
|---|---|---|---|---|---|
| ***Baseline grocery purchase (19 weeks)*** | | | | | |
| Weekly trips | -- | 2.32 | 2.19 | 2.54 | 2.25 |
| | | | | [0.153] | [0.473] |
| Weekly spending ($) | -- | 56 | 53 | 62 | 55 |
| | | | | [0.051] | [0.226) |
| Weekly C0$_2$-e emissions (kg) | -- | 20.7 | 19.8 | 23.1 | 19.8 |
| | | | | [0.073] | [0.372] |
| ***Baseline survey responses*** | | | | | |
| Climate attitude index (1-5) | -- | 4.15 | 4.14 | 4.19 | 4.12 |
| | | | | [0.7455] | [0.7654] |
| Food emissions awareness index (1-5) | -- | 3.02 | 2.83 | 3.17 | 3.09 |
| | | | | [0.043] | [0.138] |
| Environmental ranking mistakes (0-5) | -- | 2.19 | 2.29 | 2.17 | 2.09 |
| | | | | [0.488] | [0.261] |

*Notes*: The first column of the table reports demographics for the national adult population of Denmark using StatBank.dk. Columns 2-5 report demographics, baseline grocery purchases and baseline survey responses for the full experimental sample and by treatment group. We report demographics based on non-missing responses. In columns (4) and (5), we report *p*-values in brackets from *Ranksum* and *Chi-squared* tests (for percentages) of equality compared to the Spending treatment. Conversion rate Danish kroner to U.S. dollars (6.33DKK=$1) as on March 30$^{th}$, 2021.

In the bottom panel of Table 1, we report average responses from the baseline survey participants completed prior to receiving the app. We report average responses on a climate attitude index and a food emissions awareness index with responses on a 1-5 Likert scale.[10] Participants score highly on climate attitude with average scores of 4.15, indicating high willingness to address $CO_2$ emissions. Scores are lower, an average of 3.02, for the food emissions awareness index. Consistent with their self-reported lack of food emissions awareness, fewer than 20% of participants correctly rank the emissions impact of five food items (potatoes, beef, chicken, cheese and orange). Taken together, these results suggest that participants want to address climate change through their personal behavior but are not fully informed on how to do so through their food purchases.

[10] The climate attitude index is an average of the response to: "It is important that we all do our part to reduce $CO_2$ emissions and take care of the environment," and "If the majority does nothing to reduce $CO_2$ emissions and take care of the environment, it does not help that I do anything." The responses are scaled so that higher scores indicate more desire to help reduce emissions. The food emissions awareness index averages: "I think about how much $CO_2$ has been spent on producing and transporting foods I buy," and "I'm in doubt about how to eat to eat climate friendly." The responses are scaled so that higher scores indicate more awareness of food emissions. See Appendix Table A.1 for responses to each of the survey questions.

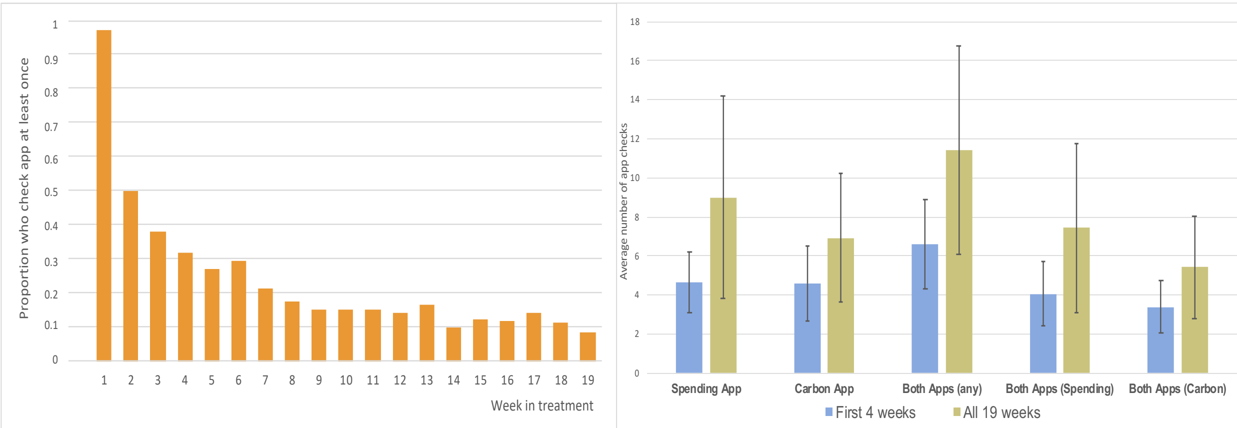
There is some baseline imbalance between the Carbon treatment and the Spending treatment. Participants in the Carbon treatment have higher self-reported food emissions awareness scores ($p$=0.043), higher weekly spending ($p$=0.051) and higher carbon emissions ($p$=0.073). As discussed above, because we had to randomize participants into the assigned app before we could receive their demographic information or baseline grocery purchases, we were not able to block the randomization on baseline characteristics. As shown in Appendix Table A.4, when we include demographic controls in the analysis the baseline difference in emissions between the Carbon treatment and the Spending treatment is small and not statistically significant (columns (1) and (6)).

## 2. App Engagement

Figure 1 Panel A displays the share of people in each week of the experiment who check the app at least once, pooling all treatment groups (Appendix Figure A.2 shows app usage over time by treatment group). App checking is concentrated in the first month of the experiment with more than 90% of participants checking the app at least once in the first week after they set-up their profile in the app, about half of participants checking the app at least once in the second week, almost 40% checking in the third week and a little over a third checking in the fourth week. App usage steadily declines in the second month of the study with an average of 23% checking at least once in a given week and then plateaus at about 10-15% for the remainder of the study through week 19. Given this pattern of app usage, our analysis focus on both the first month, when there is greater engagement, and the longer run outcomes (through 19 weeks) with lower average engagement.

To examine revealed preferences for spending information compared to emissions information, Figure 2 Panel B shows the average number of total app checks in the first 4 weeks and the full 19 weeks of the intervention by treatment group. Across all groups, over half of total app checks for the 19-week treatment period take place in the first month. Comparing the Spending treatment and the Carbon treatment, there is little difference in average app engagement in the short term. App usage in both groups averages a little over once a week during the first month of treatment, 1.15 ($p$=0.57 from a *Ranksum* test of differences across treatments). Over the longer term, however, there is greater engagement with the Spending app than the Carbon app. In the full 19-week treatment period, usage of the Spending app averages about 0.47 times per week compared to 0.36 checks per week for the Carbon app, though the differences are not statistically significant ($p$=0.25).

**Figure 2:** App Engagement




*Notes:* Panel A shows the proportion of participants who check the app at least once in a given week based on an individual participants' date of enrollment. The figure pools all treatments. For the Both treatment group, we measure whether a participant checks either app at least once. Panel B shows the average number of app checks by treatment group in the first 4 weeks of treatment and all 19 weeks of treatment. Bars indicate 95% Confidence Intervals.

A similar pattern emerges for participants who have access to both apps. Usage of the Carbon and Spending apps are similar in the first month of treatment, averaging about once per week ($p$=0.31) but engagement with the Spending app is almost 40% higher than the Carbon app over the 19-week treatment period, averaging 0.39 and 0.28 checks per week respectively ($p$=0.074). These results suggest a weak preference for cost information compared to emissions information over the longer term.

Providing both apps increases overall app usage compared to providing either of the apps alone ($p$<0.01 for all comparisons in the both the short and longer term). However, it crowds out the usage of the individual apps. In particular, usage of the Carbon app is about 30% lower in the short term and about 25% lower over the full treatment period, when participants receive both apps compared to receiving the Carbon app alone ($p$=0.016 in the short term and $p$=0.082 in the longer term).

When participants do check the app, it is generally within a few days of a shopping trip. The average app check is 1.02 days after the previous shopping trip and 4.4 days before the next one. 41.5% of app checks are on the same day as a shopping trip. Of these 41.5% occur before the shopping trip and 58.5% occur after the shopping trip in the overall period. These patterns are similar for the Spending app and the Carbon app, both in the short and longer term.

## 3. Treatment effects on carbon emissions

Our main analysis estimates the impact of providing participants with the Carbon app compared to providing them with the Spending App. As discussed above, these groups have similar engagement levels in the first month of the experiment. Table 2 reports the results from difference-in-differences fixed effects regressions estimating the impact on weekly $CO_2$-equivalent ($CO_2$-$_e$) emissions of the Carbon app treatment compared to the Spending app treatment. Each participant-week is an observation, and we cluster standard errors at the individual level. The first three columns restrict the sample to the first month of treatment. The last three columns include the full 19-week treatment period. Columns (1) and (4) include all participants. Columns (2-3) and columns (5-6) split the sample based on app engagement, measured as being above or below median app usage during the relevant period. All regressions include 19 weeks of pre-intervention observations.[11]

In the Appendix, we report estimates from random effects (RE) regressions and the results do not change (Appendix Table A.4, Column (1) & (6)). In the RE models, we include controls for the demographic characteristics reported in Table 1, the recruitment wave and the Likert-scale responses to the baseline survey questions (we transform all non-continuous variables into dummies, and we use an indicator variable for missing covariates). Excluding these covariates does not affect the results (Appendix Table A.4, Column (2) & (7)).

Column 1 reports the estimated effects of providing the Carbon app for the first month. Our coefficient of interest is the interaction term of After X Treatment which estimates the effect of the Carbon app during the intervention period. We estimate that providing information about $CO_2$-e emissions via the app reduces the subsequent $CO_2$-e emissions of weekly food purchases by about 5.8 kg ($p$=0.003), a 27% decrease compared to pre-treatment baseline emissions of 21.25 kg. However, the impact of the Carbon app does not persist over time. As shown in column 4, over the 19-week experiment period, we estimate a decline in emissions of about 2.4 kg, a 11.3% decrease that is not statistically significant ($p$=0.177).

[11] Appendix Table A.2 presents correlates of above-median app usage.

**Table 2.** Effect of Carbon App on Weekly Emissions

| | First four weeks | | | Overall treatment period | | |
|---|---|---|---|---|---|---|
| | **Overall** (1) | **Lower engagement** (2) | **Higher engagement** (3) | **Overall** (4) | **Lower engagement** (5) | **Higher engagement** (6) |
| After | 5.171*** | 3.403** | 6.938*** | 3.447*** | 2.686** | 4.349* |
| | (1.510) | (1.656) | (2.511) | (1.291) | (1.334) | (2.342) |
| After X Carbon Treatment | -5.837*** | -3.192 | -8.558*** | -2.438 | -0.164 | -5.635* |
| | (1.977) | (2.341) | (3.186) | (1.800) | (2.013) | (3.160) |
| Constant | 21.247*** | 20.829*** | 21.681*** | 21.247*** | 20.429*** | 22.327*** |
| | (0.177) | (0.205) | (0.290) | (0.455) | (0.500) | (0.819) |
| *Baseline weekly emissions* | *21.247* | *20.828* | *21.681* | *21.247* | *20.428* | *22.327* |
| *Average app checks* | *1.16* | *0.59* | *1.77* | *0.43* | *0.18* | *0.84* |
| *Observations* | 3841 | 1955 | 1886 | 6346 | 3610 | 2736 |
| *Participants* | 167 | 85 | 82 | 167 | 95 | 72 |

** p<0.1, ** p<0.05, *** p<0.01*

*Notes:* Fixed effects regressions with weekly carbon-equivalent emissions as the dependent variable. Observations at the weekly level. Standard errors clustered at the participant level in parentheses.

We also present estimates of providing both apps compared to the Spending app alone, as well as estimates pooling the Carbon app and the Both app treatment groups (Appendix Table A.4, Columns (3),(4), (8) and (9)). The pattern of results is similar, though the effect sizes are smaller and not statistically significant for the Both treatment. The larger impact of the Carbon treatment compared to providing both apps may be due to the higher engagement with the Carbon app when it is provided alone. Or there may be effects of providing the Spending app to participants that interacts with the impact of the Carbon app.

Relatedly, we note that across all regressions, there is a positive and significant coefficient for "After," which suggests that weekly $CO_2$-e emissions are increasing during our study period. We implemented the study during the onset of the COVID-19 pandemic when grocery purchases increased (Chenarides et al., 2021), which mechanically increases $CO_2$-e emissions from groceries. An alternative interpretation is that providing the Spending app to participants affects grocery purchases. We cannot clearly disentangle the effect of the Spending app and seasonality (including perhaps the COVID-19 effect) since, as we discuss above, we do not have a participant group that receives no information and no app.

To examine whether assignment to the Spending app affects behavior, we use a synthetic control group that is made up of participants who enroll in the second wave of the study. We use their pre-intervention purchases (when they were not yet participants in our study) that occur in the same period as the post-intervention purchases for the first wave. We compare the synthetic control group (i.e., second wave pre-intervention period) to the Spending treatment in the first wave and find no significant differences (Appendix Table A.3).

Taken together, our results suggest that the Carbon app has meaningful effects in the short run, but the impact tends to fade out over time. The fade out in treatment effects corresponds with a fade out in engagement discussed in the section above. To further examine the role of engagement, we split the sample by above and below median app usage. In the first month, above median and below median users check the app on average 1.77 times and 0.59 time per week, respectively. Over the full treatment period, above-median users sustain their usage at 0.84 times per week compared to below median users who check on average 0.18 times per week during 19-week intervention.

We estimate that among highly engaged (above-median) participants, providing information about $CO_2$-e emissions reduces weekly $CO_2$-e emissions by about 8.5 kg ($p$=0.008) in the first month of treatment, a 38% decrease compared to pre-treatment baseline weekly emissions of 22.3 kg (column 3). That compares to the insignificant 3.2 kg reduction in $CO_{2-e}$ emission for those who are below the median app usage, corresponding to a 16% decrease (column 2). When we examine the longer-term effects of the Carbon app, we find suggestive evidence that the most-engaged participants who sustain their engagement also sustain meaningful treatment effects. As shown in column 6, we estimate that above-median users reduce their $CO_2$-e emissions by an average of 5.6 kg ($p$=0.076) per week over the 19-week intervention, which is similar to the short-term effect estimated for the full sample. For the least-engaged, the long run reduction in $CO_2$-e emissions is smaller than for the whole sample and non-significant (0.16 kg; $p$=0.935). These results suggest that most-engaged are driving the treatment impact of the Carbon app, though we caution that the estimated treatment effects are statistically indistinguishable across subgroups.

To address the concern that above median users of the Carbon app may not be comparable to above-median users of the Spending app, we also split the sample based on predicted engagement with the Carbon app. We regress our models' covariates on usage among those who received the Carbon app and then use the coefficients to create a predicted Carbon app usage score for all participants. We then split the sample by those predicted to be above- or below- median users. Among the predicted engaged compliers, the Carbon app reduces $CO_2$-e emissions by an estimated

9.7 kg ($p$=0.002), which corresponds to a 45% reduction in the first month of treatment. In the long run, those predicted to be above-median users show a reduction of 4.7 kg in $CO_2$ emissions ($p$=0.095). For the less-engaged, the reductions are not significant in either the short or long-run.

Taken together, our results suggest that for time periods and people with high app engagement, providing emissions information can have a meaningful and sustained impact on the carbon footprint of grocery purchases.

## 4. Mechanisms

Finally, we explore the mechanisms leading to our observed reduction in weekly $CO_2$-e emissions when providing the Carbon app. Table 3 has the same structure has Table 2 except that we examine different outcomes, which are reported for each column. As shown in columns 1 and 2, we find that overall purchase quantities and money spent are significantly lower among participants who receive the Carbon app. Purchases decline by about 28% in the first month of the experiment, while smaller and insignificant reductions are observed over the full 19-week intervention (columns 6 and 7). We note that lower emissions foods also tend to be less expensive and so the reduced spending could reflect both changes in quantity and changes in basket composition. Indeed, when decoupling the carbon emissions from the total quantities, we find suggestive evidence that net of total quantities the Carbon app also reduces carbon emissions per item and per dollar spent (columns 3 and 4). In particular, we find a large and significant decrease in emissions from beef consumption in both the short and longer run (columns 5 and 10). We estimate a 1.2 kg per week reduction in $CO_2$-e emissions from beef in the first month of treatment ($p$=0.019), a 45% decrease that is equivalent to over 21% of the treatment impact on overall emissions. The Carbon app does not directly highlight beef as a high emissions food group – as prior informational interventions have done (Camilleri et al., 2019; Jalil et al., 2020) – and yet has a large impact on this critical target for reducing the carbon footprint of food production and consumption. Achieving such effects through price changes would require an over 30 percent increase in price, based on estimated price elasticities for beef consumption (Taylor & Tonsor, 2013).

**Table 3.** Mechanisms

| | First four weeks of treatment | | | | | Overall treatment period | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| *Dep. Var.:* | Quantity<br>(1) | Money<br>(2) | CO2 per item<br>(3) | CO2 per dollar<br>(4) | CO2 by beef<br>(5) | Quantity<br>(6) | Money<br>(7) | CO2 per item<br>(8) | CO2 per dollar<br>(9) | CO2 by beef<br>(10) |
| After | 5.246*** | 13.754*** | 0.091* | 0.070*** | 0.416 | 3.206*** | 8.232** | 0.059 | 0.046** | 0.561* |
| | (1.234) | (3.772) | (0.047) | (0.022) | (0.348) | (1.185) | (3.194) | (0.037) | (0.019) | (0.291) |
| After X Carbon Treatment | -5.579*** | -16.515*** | -0.105* | -0.055* | -1.197** | -2.269 | -5.085 | -0.059 | -0.030 | -0.789* |
| | (1.658) | (5.150) | (0.063) | (0.033) | (0.506) | (1.619) | (4.414) | (0.053) | (0.024) | (0.418) |
| Constant | 19.016*** | 56.955*** | 0.891*** | 0.315*** | 2.628*** | 19.016*** | 56.955*** | 0.891*** | 0.315*** | 2.628*** |
| | (0.147) | (0.455) | (0.006) | (0.003) | (0.044) | (0.412) | (1.119) | (0.013) | (0.006) | (0.105) |
| *Baseline weekly value* | *19.016* | *56.954* | *0.891* | *0.315* | *2.628* | *19.016* | *56.954* | *0.891* | *0.315* | *2.628* |
| *Observations* | 3841 | 3841 | 3841 | 3841 | 3841 | 6346 | 6346 | 6346 | 6346 | 6346 |

** p<0.1, ** p<0.05, *** p<0.01*

*Notes*: Fixed effects regressions. The dependent variable is reported for each column. Observations at the week level. Standard errors clustered at the participant level in parentheses.

# Conclusion

Our study demonstrates that providing access to personalized emissions information can have a meaningful impact on grocery purchases. The estimated 5.8 kg decrease in weekly $CO_2$ equivalent emissions is equivalent to switching from a beef burger to a plant-based burger (e.g. pea-based burger) or reducing driving by 49 kilometers (30.44 miles) per week (Poore & Nemecek, 2018). The magnitude of the short-run effect is similar to the effect of adding a social comparison to a monthly home energy report. Allcott (2011) estimates that the average treatment effects translate into 0.62 kWh per day, or 10.4 hours of lightbulb use per day for a standard 60-watt incandescent lightbulb. Our estimated 5.8 kg decrease in $CO_2$-e emission per week for the Carbon treatment corresponds to 1.172 kWh per day, or 19.53 lightbulb hours (EPA, 2019).

Our study also highlights the challenges of sustaining the impact of the emissions intervention. Our results suggest that in periods and among people who remain engaged with the app, the emissions information has meaningful effects. However, the impacts fade quickly along with engagement. This differs somewhat from evidence in the home energy context suggesting that decreases in energy usage may be sustained after people stop receiving home energy reports (Allcott & Rogers, 2014; Brandon et al., 2019). This may be in part because they received reports for a longer period and built-up habits during this time. It may also be in part due to the nature of the technology. People can reduce their home energy, for example by one-time installations of energy efficient light bulbs and appliances that have a persistent impact (Brandon et al., 2019). In contrast, grocery purchase decisions are largely made in real time. Future work could examine integrating personalized feedback on climate footprint on grocery receipts or newly implemented scan-and-go tools which allow you to scan and purchase items with your smartphone in the grocery store. As our work demonstrates, it is critical to understand how engagement with these interventions affects their impact.

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## Appendix

**Figure A.1:** Invitation letter translated to English from the original language. The treatment variation includes the logo, the last words of the title and the second period of the second paragraph ("You can therefore learn which foods you buy the most and where you can save on your purchases" for the economic version; absent in the neutral version of the letter).

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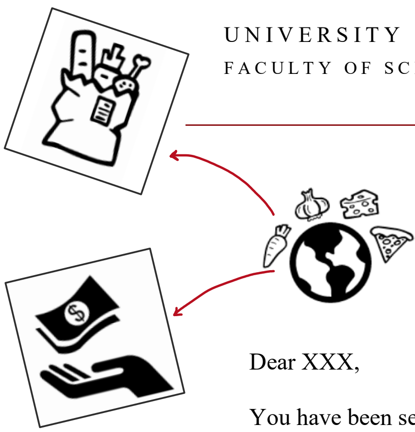


**Become wiser about your food purchases through participation in the University of Copenhagen's Food Survey and help the climate.**

Dear XXX,

You have been selected by Statistics Denmark to receive an invitation to a food survey conducted by the Department of Food and Resource Economics at the University of Copenhagen.

**What is the study about?**
The survey uses a free smartphone app, which gives you information about your food purchases and, among other things, the ability to compare your purchases with others' purchases. You can therefore learn which foods you buy the most and where you can reduce your impact on the climate. We use the information from the app about food purchasing to map the development in ordinary Danes' shopping habits. We therefore need your participation so that we can draw solid conclusions based on as many answers as possible.

**What about data security?**
You will remain anonymous, and you may withdraw and have your data deleted from the survey at any time by contacting us at the email or telephone number below. The data collection respects the rules of the Personal Data Regulation (GDPR).

**How do I participate?**
1. Click on the link below. Then you come to our project page where we ask you to answer 11 short questions and register with your e-mail.
2. Download the app on your smartphone and register as a user.
3. Give us consent to use your information for research under profile settings. Activate the collection of your e-receipts so that the information in the app is updated automatically (more information about e-receipts follows).

It typically only takes 15 mins to get started, after which you do not need to spend any more time.
You will only be fully included in the study when all 4 steps have been completed.
We greatly appreciate if you take the time to attend.

**Click here to participate** (preferably use a smartphone - this makes it easier to download the app): https://link_to_survey

You can read more about the survey: https://ifro.ku.dk//research_website/

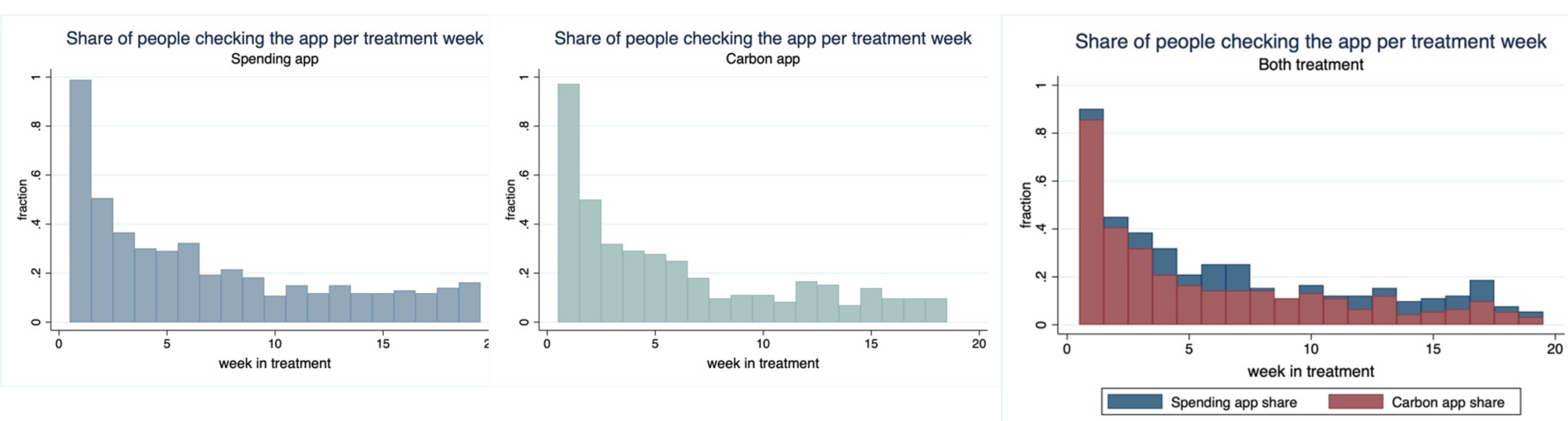
If you have any questions, please feel free to contact the research team behind the study at projekt@ifro.ku.dk or 35XXXXXX

**Table A.1:** Baseline survey responses

| | Experimental Sample | Spending Treatment | Carbon Treatment | Both Treatment |
|---|---|---|---|---|
| *It is important that we all do our part to reduce $CO_2$ emissions and take care of the environment* | 4.5 | 4.41 | 4.63<br>[0.054] | 4.5<br>[0.336] |
| *I think about how much $CO_2$ has been spent to produce and transport the foods I buy* | 3.07 | 2.82 | 3.12<br>[0.131] | 3.28<br>[0.017] |
| *I'm in doubt about how to eat to eat climate friendly (reverse)* | 2.96 | 2.84 | 3.21<br>[0.042] | 2.9<br>[0.759] |
| *If the majority does nothing to reduce $CO_2$ emissions and take care of the environment, it does not help that I do anything (reverse)* | 3.79 | 3.87 | 3.75<br>[0.593] | 3.73<br>[0.320] |
| *I keep a close eye on how much money I spend on food* | 3.22 | 3.21 | 3.30<br>[0.631] | 3.16<br>[0.816] |
| *At the end of the month, I often change my food purchases to have enough money* | 2.0 | 2.05 | 2.08<br>[0.984] | 1.89<br>[0.496] |
| *It is important to me that my food is healthy* | 4.25 | 4.25 | 4.21<br>[0.778] | 4.27<br>[0.572] |
| *I'm in doubt about how to eat to eat healthy* | 1.84 | 1.95 | 1.68<br>[0.108] | 1.85<br>[0.742] |

*Notes:* Average on 1-5 Likert-scale of each baseline survey question for the experimental sample and by treatment. We report *p*-values in brackets from *Ranksum* tests compared to the Spending treatment.

**Figure A.2:** Share of people checking the app per treatment week by treatment



## **Table A.2:** Predicting engagement

| | All treatments | Carbon & Spending | Spending | Carbon | Both (Spending app) | Both (Carbon App) |
|---|---|---|---|---|---|---|
| Baseline emissions | 0.003** | 0.005*** | 0.003 | -0.002 | 0.029*** | 0.016*** |
| | (0.001) | (0.002) | (0.004) | (0.004) | (0.005) | (0.004) |
| Climate Attitude | -0.029 | -0.164*** | 0.030 | -1.272*** | 0.075 | 0.344*** |
| | (0.031) | (0.045) | (0.065) | *(0.133)* | *(0.072)* | *(0.084)* |
| Food Awareness | 0.039** | 0.043* | -0.114*** | *0.812**** | *-0.349**** | *-0.220**** |
| | (0.018) | (0.025) | (0.041) | (0.073) | (0.061) | (0.058) |
| Eye on money | -0.026 | 0.058** | -0.100*** | 0.346*** | -0.080** | -0.140*** |
| | (0.016) | (0.023) | (0.036) | (0.056) | (0.040) | (0.043) |
| End of month | -0.035* | -0.081*** | -0.228*** | -0.290*** | -0.064 | -0.043 |
| | (0.018) | (0.023) | (0.041) | (0.056) | (0.050) | (0.058) |
| Health Attitude | 0.223*** | 0.199*** | 0.116* | 0.822*** | 0.554*** | 0.429*** |
| | (0.026) | (0.036) | *(0.060)* | *(0.100)* | *(0.077)* | *(0.076)* |
| Health Doubt | -0.081*** | -0.015 | -0.237*** | 0.432*** | -0.162*** | 0.002 |
| | (0.023) | (0.030) | (0.047) | (0.081) | (0.059) | (0.063) |
| Climate Doubt | 0.042** | 0.075*** | 0.124*** | 0.298*** | -0.344*** | -0.236*** |
| | (0.019) | (0.027) | (0.045) | (0.069) | (0.049) | (0.050) |
| Free riding | 0.042** | -0.042* | -0.068* | -0.214*** | 0.489*** | 0.567*** |
| | (0.017) | (0.022) | (0.041) | (0.056) | (0.050) | (0.056) |
| Female | -0.030 | 0.003 | 0.488*** | -0.844*** | 0.138 | 0.356*** |
| | (0.049) | (0.063) | (0.106) | (0.136) | (0.119) | (0.130) |
| Female(missing) | 6.141 | 10.490 | 9.641 | 5.774 | 8.444 | 8.861 |
| | (65.674) | (554.233) | (133.738) | (161.566) | (214.102) | (169.167) |
| Age | -0.002 | 0.003 | 0.045*** | -0.002 | 0.001 | -0.018*** |
| | (0.002) | (0.003) | (0.006) | (0.006) | (0.006) | (0.006) |
| Income2 | 0.508*** | 0.418*** | 2.251*** | -1.635*** | 2.618*** | 1.608*** |
| | (0.116) | (0.155) | (0.328) | (0.477) | (0.452) | (0.400) |
| Income3 | 0.717*** | 0.539*** | 0.515* | 1.106*** | 3.015*** | 1.483*** |
| | (0.121) | (0.148) | (0.287) | (0.388) | (0.438) | (0.378) |
| Income4 | 1.054*** | 0.999*** | 0.715** | 1.390*** | 2.718*** | 0.749* |
| | (0.129) | (0.160) | (0.320) | (0.384) | (0.454) | (0.397) |
| Income5 | 0.952*** | 0.920*** | 0.788** | 0.656 | 1.980*** | 0.050 |
| | (0.134) | (0.170) | (0.320) | (0.420) | (0.453) | (0.406) |
| Income(missing) | 0.667*** | 1.117*** | 1.154*** | 1.595*** | -0.001 | -1.560*** |
| | (0.131) | (0.160) | (0.291) | (0.486) | (0.436) | (0.452) |
| Family2 | 0.069 | 0.196 | 1.034*** | 0.136 | -0.091 | 0.716*** |
| | (0.095) | (0.122) | (0.209) | (0.315) | (0.241) | (0.243) |
| Family3 | -0.125* | -0.167* | 0.547*** | -1.426*** | 0.061 | 0.836*** |
| | (0.066) | (0.087) | (0.150) | (0.199) | (0.190) | (0.199) |
| Family4 | -0.800*** | -0.798*** | -0.407** | -1.530*** | -0.560** | 0.001 |
| | (0.078) | (0.105) | (0.177) | (0.229) | (0.254) | (0.272) |
| Family5 | -0.763*** | -0.634*** | 0.000 | -0.244 | -1.599*** | -0.176 |
| | (0.142) | (0.202) | (.) | (0.449) | (0.317) | (0.305) |
| Family(missing) | -5.434 | -5.872 | -6.240 | -6.614 | -10.344 | -13.021 |
| | (65.674) | (357.300) | (88.504) | (161.566) | (302.510) | (239.241) |
| Employment2 | 0.914*** | 0.226 | -0.234 | 5.175 | 2.825*** | 2.596*** |
| | (0.133) | (0.186) | (0.245) | (161.565) | (0.311) | (0.322) |
| Employment3 | 1.079*** | 0.847*** | 1.135** | 6.812 | 1.940*** | 1.816*** |
| | (0.170) | (0.232) | (0.471) | (161.566) | (0.448) | (0.430) |
| Employment4 | 0.827*** | -0.173 | -0.644* | 0.000 | 4.218*** | 1.860*** |
| | (0.162) | (0.234) | (0.343) | (.) | (0.481) | (0.421) |
| Employment5 | 1.053*** | 0.443** | -1.024*** | 3.921 | 1.691*** | 1.915*** |
| | (0.151) | (0.219) | (0.313) | (161.565) | (0.322) | (0.337) |
| Employment(missing) | 0.612*** | 0.164 | 0.633 | 4.350 | 1.684*** | 0.940** |
| | (0.167) | (0.241) | (0.401) | (161.566) | (0.413) | (0.424) |
| Region2 | 0.045 | -0.402*** | 0.066 | -1.065*** | 0.634*** | 0.790*** |
| | (0.066) | (0.094) | (0.163) | (0.211) | (0.213) | (0.218) |
| Region3 | 0.785*** | 0.858*** | 1.706*** | 1.467*** | 0.142 | 0.704*** |
| | (0.064) | (0.081) | (0.157) | (0.188) | (0.165) | (0.180) |
| Region4 | -0.221*** | -0.284*** | -0.371*** | 0.112 | -0.532*** | -0.807*** |
| | (0.061) | (0.083) | (0.134) | (0.195) | (0.142) | (0.141) |
| Region5 | 0.698*** | 1.223*** | 0.000 | 1.656*** | -0.074 | 0.684*** |
| | (0.087) | (0.122) | (.) | (0.221) | (0.222) | (0.245) |
| Region(missing) | -0.536* | -4.796 | -3.590 | 0.000 | 3.873 | 7.326 |
| | (0.301) | (423.687) | (100.265) | (.) | (213.712) | (169.172) |
| Recruitment wave | 0.030 | 0.312*** | 0.435*** | 1.209*** | -1.169*** | -0.901*** |
| | (0.042) | (0.057) | (0.097) | (0.136) | (0.120) | (0.116) |
| Constant | -2.308*** | -1.769*** | -3.096*** | -7.306 | -5.178*** | -4.558*** |
| | (0.259) | (0.352) | (0.544) | (161.568) | (0.673) | (0.685) |
| *Observations* | 4902 | 3173 | 1653 | 1349 | 1672 | 1634 |

d.v. app activity "above-median" dummy
* p<0.1, ** p<0.05, *** p<0.01

*Notes*: The Probit model regressions include controls for: demographics (gender, age, income, household type, employment, region) and recruitment wave as dummy variables (with one category omitted for each demographic), and baseline survey answers as categorical variables.
Income1 (omitted) = "<150,000 DKK a year"; Income2 = "150,000 – 299,000 DKK"; Income3 = "300,000 – 499,000 DKK"; Income4 = "500,000 – 799,000 DKK"; Income5 = ">800,000 DKK". Family1 (omitted) = "Single"; Family2 = "Single with kids"; Family3 = "Couple"; Family4 = "Couple with kids"; Family5 = "3 or more adults". Employment1 (omitted) = "Self-employed"; Employment2 = "Employed"; Employment3 = "Unemployed"; Employment4 = "Student"; Employment5 = "Senior Citizen". Region1 (omitted) = "Capital Region"; Region2 = "Zealand": Region3 = "Southern Denmark"; Region4 = "Mid Jutland": Region5 = "North Jutland".

## **Table A.3:** Synthetic control

| | First four weeks | Overall treatment period |
|---|---|---|
| After | 2.106 | 5.343*** |
| | (1.943) | (1.770) |
| After X Synthetic group | -0.287 | -1.124 |
| | (5.192) | (2.055) |
| Constant | 26.669*** | 18.770*** |
| | (2.744) | (0.457) |
| *Observations* | 2086 | 5624 |

** p<0.1, ** p<0.05, *** p<0.01*

*Notes:* Fixed effects regressions with weekly carbon-equivalent emissions as the dependent variable. Observations at the weekly level. Standard errors clustered at the participant level in parentheses. The weeks' structure is "artificial" in order to match the Spending treatment period of the first recruitment with the pre-intervention period of the overall second recruitment. Thus, the synthetic group taken as the treatment of the F.E. interaction is composed by all participants of all three treatments recruited in the second wave. The control group is the Spending treatment from the first recruitment wave.

## **Figure A.3:** Spending app screenshots

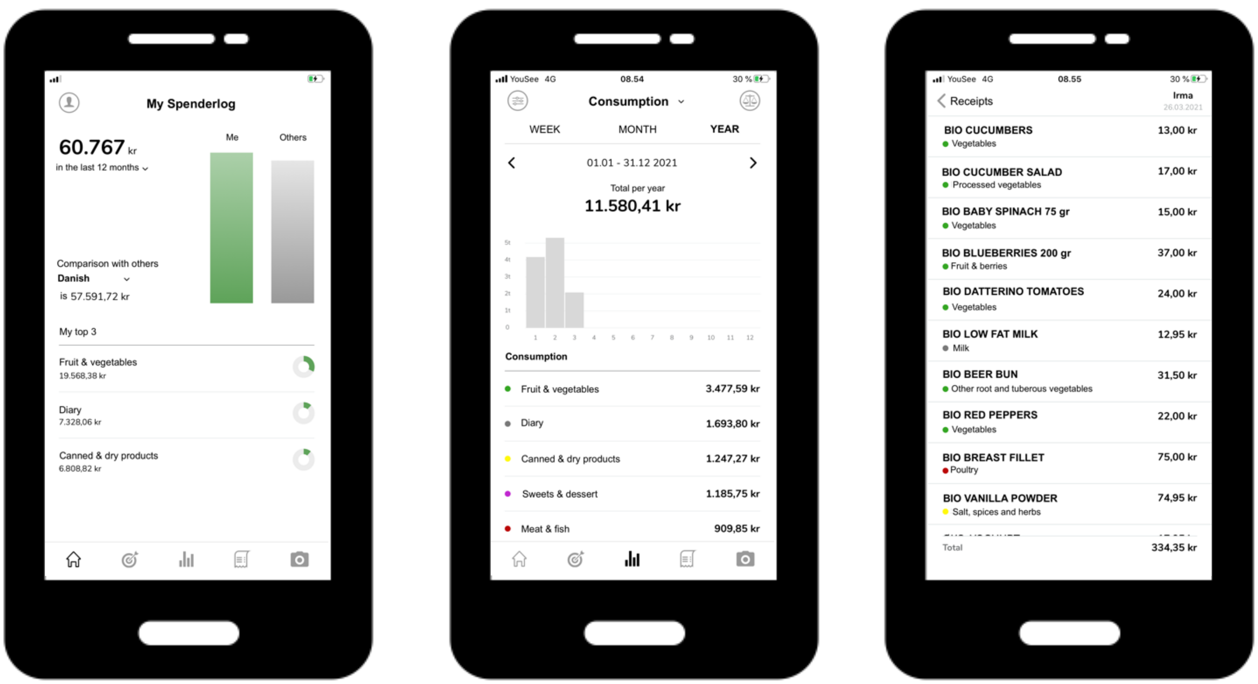


**Table A.4:** Sensitivity checks

| | First four weeks of treatment | | | | | Overall treatment period | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Random Effects | R.E. no covariates | Pooled Treatment | Both Treatment | Averaged weight (IPW) | Random Effects | R.E. no covariates | Pooled Treatment | Both Treatment | Averaged weight (IPW) |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| After | 5.171*** | 5.171*** | 5.171*** | 5.171*** | 4.967*** | 3.447*** | 3.447*** | 3.447*** | 3.447*** | 3.488*** |
| | (1.517) | (1.510) | (1.508) | (1.510) | (1.501) | (1.294) | (1.291) | (1.290) | (1.291) | (1.255) |
| Treatment ^ | 0.521 | 3.272 | | | 0.820 | 0.992 | 3.272 | | | 1.284 |
| | (2.544) | (2.724) | | | (2.512) | (2.558) | (2.724) | | | (2.523) |
| After X Treatment | -5.837*** | -5.837*** | -3.698** | -1.982 | -5.461*** | -2.438 | -2.438 | -1.296 | -0.380 | -2.494 |
| | (1.985) | (1.977) | (1.767) | (1.979) | (2.001) | (1.805) | (1.800) | (1.552) | (1.750) | (1.783) |
| Climate Attitude | 1.098 | | | | 0.927 | 0.954 | | | | 0.827 |
| | (1.598) | | | | (1.564) | (1.472) | | | | (1.436) |
| Food Awareness | 1.054 | | | | 0.992 | 0.567 | | | | 0.548 |
| | (1.072) | | | | (1.048) | (0.975) | | | | (0.949) |
| Eye on money | 2.008** | | | | 1.898** | 2.178** | | | | 2.008** |
| | (0.868) | | | | (0.848) | (0.849) | | | | (0.828) |
| End of month | -0.358 | | | | -0.393 | -0.543 | | | | -0.602 |
| | (0.961) | | | | (0.926) | (0.897) | | | | (0.873) |
| Health Attitude | -1.600 | | | | -1.432 | -1.135 | | | | -1.026 |
| | (1.273) | | | | (1.285) | (1.196) | | | | (1.191) |
| Health Doubt | 2.064* | | | | 1.928 | 1.819* | | | | 1.686 |
| | (1.196) | | | | (1.194) | (1.074) | | | | (1.073) |
| Climate Doubt | 1.930* | | | | 1.729 | 1.694 | | | | 1.477 |
| | (1.146) | | | | (1.111) | (1.095) | | | | (1.066) |
| Free riding | 0.350 | | | | 0.310 | 0.397 | | | | 0.357 |
| | (0.887) | | | | (0.887) | (0.864) | | | | (0.854) |
| Female | 4.456* | | | | 4.316 | 5.214** | | | | 4.947** |
| | (2.652) | | | | (2.625) | (2.408) | | | | (2.360) |
| Female(missing) | 6.157 | | | | 7.357 | 9.963 | | | | 11.336 |
| | (8.259) | | | | (8.663) | (9.265) | | | | (9.691) |
| Age | 0.261** | | | | 0.247** | 0.223** | | | | 0.206** |
| | (0.110) | | | | (0.106) | (0.105) | | | | (0.100) |
| Income2 | 1.988 | | | | 2.085 | 5.183 | | | | 5.249 |
| | (4.259) | | | | (4.139) | (4.089) | | | | (3.943) |
| Income3 | 5.727 | | | | 6.028 | 7.983* | | | | 8.416** |
| | (4.198) | | | | (4.026) | (4.193) | | | | (3.996) |
| Income4 | 9.274* | | | | 9.903* | 10.203** | | | | 10.826** |
| | (5.335) | | | | (5.146) | (5.144) | | | | (4.942) |
| Income5 | 3.672 | | | | 4.211 | 5.217 | | | | 5.775 |
| | (5.731) | | | | (5.572) | (5.608) | | | | (5.403) |
| Income(missing) | 5.076 | | | | 5.194 | 5.981 | | | | 6.195 |
| | (4.960) | | | | (4.811) | (4.653) | | | | (4.488) |
| Family2 | 10.010** | | | | 10.104** | 7.958** | | | | 8.172** |
| | (4.060) | | | | (4.161) | (3.567) | | | | (3.654) |
| Family3 | 10.115*** | | | | 9.664*** | 9.211*** | | | | 8.955*** |
| | (3.052) | | | | (2.973) | (2.795) | | | | (2.700) |
| Family4 | 21.187*** | | | | 20.383*** | 20.195*** | | | | 19.615*** |
| | (4.099) | | | | (4.010) | (3.794) | | | | (3.692) |
| Family5 | 33.303** | | | | 31.618** | 33.187** | | | | 31.660** |
| | (15.262) | | | | (15.208) | (14.550) | | | | (14.522) |
| Family(missing) | 10.294* | | | | 8.953 | 12.993** | | | | 11.669** |
| | (6.031) | | | | (6.004) | (5.319) | | | | (5.131) |
| Employment2 | -2.262 | | | | -0.622 | -7.079 | | | | -4.918 |
| | (11.014) | | | | (9.855) | (9.545) | | | | (8.751) |
| Employment3 | 2.127 | | | | 3.494 | -6.171 | | | | -4.010 |
| | (12.465) | | | | (11.392) | (10.872) | | | | (10.104) |
| Employment4 | 1.198 | | | | 3.150 | -4.106 | | | | -1.746 |
| | (11.473) | | | | (10.382) | (10.035) | | | | (9.269) |
| Employment5 | -2.698 | | | | -0.561 | -7.797 | | | | -5.158 |
| | (12.491) | | | | (11.556) | (10.888) | | | | (10.254) |
| Employment(missin | -2.291 | | | | -0.441 | -10.142 | | | | -7.670 |
| | (12.268) | | | | (11.142) | (10.706) | | | | (9.920) |
| Region2 | 1.941 | | | | 2.300 | 1.379 | | | | 1.794 |
| | (4.144) | | | | (4.027) | (3.813) | | | | (3.721) |
| Region3 | -4.193 | | | | -4.254 | -4.739 | | | | -4.607 |
| | (3.260) | | | | (3.217) | (3.120) | | | | (3.071) |
| Region4 | -0.434 | | | | -0.004 | -0.258 | | | | 0.228 |
| | (3.482) | | | | (3.460) | (3.241) | | | | (3.192) |
| Region5 | 3.040 | | | | 1.325 | 1.592 | | | | 0.058 |
| | (6.220) | | | | (5.769) | (5.461) | | | | (5.057) |
| Region(missing) | -8.506 | | | | -8.824 | -9.768 | | | | -10.313 |
| | (8.025) | | | | (8.247) | (9.019) | | | | (9.253) |
| Recruitment wave | 2.298 | | | | 1.831 | -1.217 | | | | -1.518 |
| | (2.325) | | | | (2.260) | (2.145) | | | | (2.089) |
| Constant | -27.622* | 19.817*** | 20.756*** | 19.836*** | -26.784* | -19.782 | 19.817*** | 19.836*** | 19.836*** | -19.299 |
| | (15.418) | (1.921) | (0.140) | (0.173) | (14.485) | (13.843) | (1.920) | (0.173) | (0.438) | (13.134) |
| *Observations* | 3841 | 3841 | 5934 | 4255 | 3841 | 6346 | 6346 | 4255 | 7030 | 6346 |
| ^ treatment: | *Carbon* | *Carbon* | *Pooled* | *Both* | *Carbon* | *Carbon* | *Carbon* | *Pooled* | *Both* | *Carbon* |

* p<0.1, ** p<0.05, *** p<0.01

*Notes:* Regression table for the short run and the overall treatment period, which includes the following models: (1,6) full version of random effects regression with weekly carbon-equivalent emissions as the dependent variable as in Table 2; (2,7) random effects regression results excluding control variables; (3,8) for the Pooled treatment (Carbon and Both treatments together); (4,9) for the Both treatment; (5,10) IPW estimations. Standard errors clustered at the participant level in parentheses. The random effects and IPW regressions include controls for: demographics (gender, age, income, household type, employment, region) and recruitment wave as dummy variables (with one category omitted), and baseline survey answers as categorical variables. See notes of Table A.2 for more details on demographics.