Individual Carbon Footprint Reduction: Evidence from Pro-environmental Users of a Carbon Calculator

Citation for the original published paper (version of record):
Enlund, J., Andersson, D., Carlsson, F. (2023). Individual Carbon Footprint Reduction: Evidence from Pro-environmental Users of a Carbon
Calculator. Environmental and Resource Economics, 86(3): 433-467.
http://dx.doi.org/10.1007/s10640-023-00800-7

Environmental and Resource Economics
https://doi.org/10.1007/s10640-023-00800-7

Individual Carbon Footprint Reduction: Evidence from Pro-environmental Users of a Carbon Calculator

Jakob Enlund[1] · David Andersson[2] · Fredrik Carlsson[3]

Accepted: 1 August 2023

Abstract
We provide the first estimates of how pro-environmental consumers reduce their total carbon footprint using a carbon calculator that covers all financial transactions. We use data from Swedish users of a carbon calculator that includes weekly estimates of users' consumption-based carbon-equivalent emissions based on detailed financial statements, official registers, and self-reported lifestyle factors. The calculator is designed to induce behavioral change and gives users detailed information about their footprint. By using a robust difference-in-differences analysis with staggered adoption of the calculator, we estimate that users decrease their carbon footprint by around 10% in the first few weeks, but over the next few weeks, the reduction fades. Further analysis suggests that the carbon footprint reduction is driven by a combination of a shift from high- to low-emitting consumption categories and a temporary decrease in overall spending, and not by changes in any specific consumption category.

Keywords Pro-environmental behavior · Carbon footprint · Consumer behavior

JEL Classification D12 · D91 · Q5

✉ Jakob Enlund
jakob.enlund@lnu.se

David Andersson
david.andersson@chalmers.se

Fredrik Carlsson
fredrik.carlsson@economics.gu.se

1 Department of Economics and Statistics, Linnaeus University, Växjö, Sweden

2 Department of Space, Earth and Environment, Physical Resource Theory, Chalmers University of Technology, Gothenburg, Sweden

3 Department of Economics, University of Gothenburg, Gothenburg, Sweden

Published online: 18 August 2023

1 Introduction

Most large-scale environmental problems, such as climate change, are the aggregate result of consumption and production decisions made by many actors in numerous countries. To achieve national and multinational goals, such as the Paris Agreement or Agenda 2030, extensive changes in behavior are needed. In a first-best world, most of these changes would result from economic policies, such as carbon taxes coupled with technological development. However, standard policies are often not stringent enough to reach ambitious and necessary goals. Therefore, attention has been given to alternative approaches to influence consumer behavior. These approaches often rely on the assumption that consumers have pro-social or pro-environmental preferences (Andreoni 1990; Kotchen and Moore 2007), and are willing to make costly sacrifices to reduce the environmental impact of their consumption.

One challenge associated with complex environmental problems is that consumers often lack sufficient information on their contribution to these problems and their extent. Therefore, a first step toward influencing consumers is to provide them with this information coupled with information on how to reduce these problems (Jessoe and Rapson 2014). Combining this information with a comparison of one's own and others' performance and information on appropriate behavior, or moral suasion, has been shown to reduce resource use by around 1–5% in various domains (Carlsson et al. 2021). The most prominent example of such an attempt is the use of so-called home energy reports (Allcott 2011), but similar interventions have been evaluated for water use (Brent et al. 2020; Ferraro and Price 2013; Torres and Carlsson 2018), non-residential energy use (Klege et al. 2022), food waste (Kallbekken and Sælen 2013), and household waste (Ek and Söderberg 2021). At the same time, there is evidence that the effect of information on behavior decreases over time (Ferraro et al. 2011), and there are examples of zero effects in some settings (e.g., Gravert and Collentine 2021).

Product labels are another way to inform consumers about the environmental impact of their consumption and facilitate their choices. When it comes to product labels related to greenhouse gas (GHG) emissions, they have primarily been evaluated in the food domain, where the findings suggest that consumers are indeed affected by the provision of information (see, e.g., Kurz 2018; Vanclay et al. 2011; Kažukauskas et al. 2021). Indirectly related to carbon labels is the use of energy efficiency labels, which also have a sizeable impact on consumer behavior (see, e.g., Newell and Siikamäki 2014; Allcott and Taubinsky 2015).

A key characteristic of the information provisions and product labels discussed above is that they focus on one domain or even one product category. First, this means that by definition they have a limited impact, since each domain represents only a small fraction of the total environmental impact of consumption. Second, a comprehensive evaluation of information provisions in one domain requires information about potential spillover effects on other domains to understand the total effect (Carlsson et al. 2021).[1] Third, it is unclear what scaling up these interventions into several domains would mean and result in.

[1] Note that the direction of such spillover effects is ambiguous. There could be motivational spillovers between different domains (Andersson and Nässén 2023; Frey 1993; Thøgersen and Ölander 2003) such that consumers act more environmentally friendly in other domains than the one targeted. However, there could also be a negative spillover because environmentally friendly behavior in one domain may make people feel like they have an implicit license to not have to act environmentally friendly in others (Mazar and Zhong 2010).

For example, an information intervention that includes all consumption domains should increase the chances of identifying behavioral adjustments that are deemed feasible for the consumer, in which case the mitigation potential should be higher compared to more narrowly targeted interventions.

Apart from the approaches of individual information provision or product labels mentioned above, alternative approaches that target behavior at a larger scale have also been explored. One such approach is a system of personal carbon trading, in which each individual receives carbon allowances to cover emissions from energy use and transport (see, e.g., Fawcett 2010; Fuso Nerini et al. 2021; Fawcett and Parag 2010). However, this approach has not been implemented on a large scale, and consequently there is no empirical evaluation of its effectiveness. Another potential large-scale approach is the formation of carbon communities, where coordination and cooperation among community members facilitate a reduction of emissions. There are several case studies indicating an effect on individual behavior (Heiskanen et al. 2010). However, formally evaluating the impact is challenging in this case since it involves a large-scale implementation, and for natural reasons, there is a selection of what type of communities strive to become a carbon community.

What is the potential for individuals to reduce their total carbon footprint? Previous research has estimated the technical potential for households to reduce total emissions. The analysis by Ivanova et al. (2020) implies a mitigation potential for the US population of roughly 55%.[2] Bjelle et al. (2018) estimated the direct mitigation potential for Norwegian households to be 24–35%. Carlsson Kanyama et al. (2021) analyzed the mitigation potential for Swedish households to be roughly 40% when considering potential consumption adjustments from food, transport, and housing to less carbon-intensive products and services.

In this paper, we provide the first empirical examination of the potential to reduce people's total carbon footprints using a carbon calculator App. Specifically, we investigate how motivated and pro-environmental Swedish users of a carbon calculator App change their behavior after App installation. The App provides information about users' carbon footprints based on financial transactions paired with an environmentally extended input–output analysis, data from official registers, and data entered by the users themselves (Andersson 2020). The App provides detailed information on carbon footprints, both in total and for different categories and individual purchases. In addition, the App provides suggestions on how to reduce the carbon footprint, and social comparison with groups. Compared with the interventions previously described, the detailed information provided across all consumption domains increases the chances that the App pinpoints feasible areas of improvement also for low-emitting individuals. Users who connect their bank to the App receive 2–216 weeks of past transaction data, which provides a baseline estimate of their carbon footprint. To identify the behavioral response after App installation, we use a difference-in-differences design with staggered treatment adoption (Sun and Abraham 2021). Hence, the identification comes from comparing emission levels in a particular week between those who have installed the App and those who have not yet installed it, controlling for individual fixed effects.

[2] Ivanova et al. (2020) synthesized the emission mitigation potential of a large set of consumption adjustments found in the literature and estimated the reduction potential of the top 10 consumption options to 9.2 tons per capita per year. From the supplementary material in Ivanova et al. (2020), the average U.S. GHG emissions per capita per year is 16.6 tons, which indicates a reduction potential of at least 55%.

The increased use of smartphones has resulted in a wide variety of Apps intended to help people make better decisions, ranging from eating healthier and losing weight (Semper et al. 2016) to exercising more (Kennelly et al. 2018). One important area where the role of Apps has been evaluated is medication adherence, i.e., ensuring that patients take the medications they have been prescribed (Al-Ubaydli et al. 2017). There is, for example, evidence that reminders through Apps or simple text messages improve medication adherence (Vervloet et al. 2012).

Online carbon calculators have also become more common, but there have been few rigorous evaluations of their role and effect on behavior (Salo et al. 2019). Recently, Fosgaard et al. (2021) evaluated the impact of providing information on GHG emissions of grocery purchases in a randomized experiment. They found that the provision of information had a substantial impact in the short run (a 27% reduction in emissions in the first month). This suggests that the provision of information could play a non-negligible role. At the same time, they also found that this effect did not persist over time. Over the whole period of four months, the reduction in emissions was not statistically significant.

Our data contains 173,246 week-by-user observations from 2517 self-selected Swedish users of the App, spanning from 2016 to early 2020 (the beginning of the COVID-19 pandemic). Five hundred thirty users in our unbalanced panel provided emissions data after App installation, and we use them to estimate the behavioral response. These were highly active and engaged App users who held pro-environmental attitudes. We find that the users decreased their carbon footprint by around 10% in the first few weeks after App installation, but over the subsequent weeks, this reduction fades. Additional analysis suggests that the carbon footprint reduction was not driven by any specific consumption category, but rather by a combination of a shift from high- to low-emitting consumption categories, and a temporary decrease in overall transactions. The results were not driven by self-reported changes in lifestyle factors that affected users' estimated carbon footprints, suggesting that the estimates do not suffer from any of the biases associated with self-reported data, such as social desirability bias (Lopez-Becerra and Alcon 2021). We find no evidence that users started to decrease their footprint before App installation, but that there was a strong and immediate drop directly after.

Was the reduction driven by the App or some other underlying factor that induced both carbon footprint reduction and App installation? Several factors support the interpretation that the effect was driven by the content of the App. First, the App is designed to induce and facilitate carbon footprint reduction and, as will be explained in Sect. 2, has features similar to behavioral interventions that have been shown in experimental studies to induce behavioral change. Second, we find no anticipating behavioral adjustment before App installation, i.e., we find parallel pre-treatment trends, implying that alternative explanations are confined to a triggering event concurrent to App installation. Hence, the results are inconsistent with motivated pro-environmental consumers decreasing their footprint and then installing the App some weeks later to see how they are progressing. Third, the immediate reduction and then gradual reversal is consistent with the behavioral responses documented in several experimental studies using similar treatments (e.g., Allcott and Rogers 2014; Bonan et al. 2021; Fosgaard et al. 2021). Fourth, our users were highly active in the App, showing that they were interested and engaged in its content. The experimental study by Fosgaard et al. (2021) found particularly strong and persistent effects among those engaged in their App with similar features as Svalna, but with a focus on food consumption. Fifth, our users hold particularly pro-environmental attitudes and values. Previous research suggests that individuals with sufficient room for improvement respond more strongly to similar pro-environmental behavioral interventions if they have strong environmental values (Bonan et al. 2021). Finally, we see no indication that users installed the App in response to any obvious pro-environmental events, such as Earth Day or large climate manifestations. Instead, there was a gradual influx of users during our study period. For these reasons, it is plausible that the estimated effect was caused by the content of the App, at least partly. However, since this is not an experiment, we cannot rule out the possibility that the effects were partly driven by some other underlying factor that concurrently triggered both App installation and behavioral adjustment. In either case, our results indicate the potential for motivated consumers to reduce their total carbon footprint—motivated in the sense that they are willing to change, as indicated by their choice to install and engage with the App, as well as by their pro-environmental attitudes.

The rest of the paper is organized as follows. Section 2 describes the carbon calculator, and how and why its content can induce behavioral change. Section 3 presents and discusses the data used. Section 4 describes the empirical strategy, Sect. 5 the results, and Sect. 6 concludes.

2 The Carbon Calculator

The carbon calculator used in this study is provided by Svalna Inc. The mobile application, called Svalna, estimates each user's carbon footprint associated with purchases made.[3] By connecting their bank account(s) and/or credit cards to the App, users can get an overview of the carbon footprint of their spending in different consumption categories. Since its launch in 2016, the App has gained users through media coverage in the national press and a community intervention campaign developed in collaboration with Uppsala Municipality.

2.1 Estimating the Carbon Footprint

The App uses a hybrid approach that relies on data from three primary sources to calculate the GHG emissions related to the user's consumption behavior: (1) financial transaction data from the user's bank coupled with data on GHG emissions per monetary unit for different categories, (2) data from official databases, and (3) profile data entered by the user.

First, each transaction is automatically categorized and assigned an estimated carbon footprint. Additional data is received when users manually connect their bank again within the App. Users are asked to classify transactions that the system does not automatically identify, and the algorithm improves with each piece of additional information.[4] Users can also indicate whether they bought a specific item second-hand and receive a lower carbon footprint for that purchase. For some consumption categories, such as food and heating,

[3] The App can be downloaded for free from App Store/Google Play (currently only available in Sweden). The App had approximately 19,000 registered users in January 2022. A large share of this group uses the App without connecting a bank account and/or are no longer active users.

[4] All transactions (credit/debit card transactions, invoices, internal/external bank account transactions, cash withdrawals, etc.) are classified according to a modified version of the Classification of Individual Consumption According to Purpose (COICOP) scheme developed by the UN Statistics Division. This means that the GHG emissions associated with the vast majority of purchases are estimated as the product of the expenditure and the GHG intensity (g CO_2eq/monetary unit) of the associated COICOP consumption category. GWP100 is used for all estimates.

other data sources are used in combination with transaction data to estimate the carbon footprint of those specific purchases.

Second, the App uses data from official registers where financial information is not provided. Users living in multi-dwelling houses are typically connected to the local district heating network and pay for heating as part of their rent, which means financial data are not sufficient. Instead, the App collects data on the energy performance of the users' homes (as identified via their home addresses) from the energy performance database maintained by the National Board of Housing, Building and Planning.[5] For vehicles, data on fuel type, fuel efficiency, and distance traveled are automatically collected from the Swedish Transport Agency database if the user fills in their vehicle's registration number.[6] This information is then used to estimate an individual GHG intensity for fuel purchases.

Third, users are asked to answer some questions in a user profile when generating their account. The questionnaire contains questions on, e.g., dietary habits, the number of household members, and information on air travel (departure/arrival destination) in the past two years. Users are free to specify lifestyle changes at any time, and when this is done, the carbon footprints from associated consumption categories are adjusted by the calculator for future purchases. For example, if a user switches from a mixed to a vegetarian diet, the carbon-equivalent footprint from each food-related purchase will be adjusted downwards; see Andersson (2020) for a comprehensive description.

2.2 Features in the App

There are four sections of the App, all illustrated in Fig. 1: (i) an Overview (ii) an Emissions section, (iii) a Goals section, and (iv) a Groups and comparison section. Here, we only briefly describe how they work and are designed, and refer to Andersson (2020) for a more detailed description.

The *overview* section provides information on the current estimated yearly carbon footprint, a trend line describing the variation over time, and an indicator of the percentage change over the last few months. It also includes a breakdown of the estimated yearly carbon footprint, and a list of the most recent purchases, their categorization, and their carbon footprint.

The *emissions* section of the application enables users to explore how their carbon footprint has evolved over time and learn how consumption activities are connected to GHG emissions. The carbon footprint calculated by the App is divided into four main categories: (1) transportation, (2) goods and services, (3) food and beverages, and (4) residential energy (with several sub-categories). It is also possible to examine sub-categories and individual transactions and their respective GHG emissions to gain a more detailed understanding of the impact related to different activities and transactions.

In the *goals* section, the user can set a goal to reduce their annual carbon footprint. Given the difficulties of setting a reasonable goal, the App suggests a goal that the user can then change. In addition, the section illustrates how different behavioral changes would affect a user's future carbon footprint. The system currently includes 15 suggested adjustments that describe large-scale lifestyle changes. The suggested actions are based on the user's data, and users are only exposed to suggested adjustments that will reduce their

[5] Internet resource. Retrieved from: Boverket, sök energideklaration, Accessed Jan. 3, 2022.

[6] Internet resource. Retrieved from: Transportstyrelsen, Accessed Jan. 3, 2022.

carbon footprint. For instance, while a meat-eater might be suggested to become vegetarian, a vegan will not. This means that users who already maintain a more sustainable lifestyle might not receive any suggested actions from the App.

The *groups* section comprises both automatically generated geographical groups and user-generated groups. All users are by default assigned to a municipality group. In these groups, users can compare their carbon footprint with the average in the four sub-domains and see their ranking compared with other users in the municipality. Users are also free to form their own groups or join existing groups. The users organize themselves into these groups by sending invites or requests. Group functionality involves the same functionality as the geographical groups and in addition, the users can set a joint goal. It is also possible for workplaces to form a group and organize their staff into competing sub-groups with a leaderboard.

2.3 How Can Users Reduce Their Carbon Footprint?

There are primarily three ways in which users can reduce their carbon footprint, as measured by the calculator. First, users can reduce the carbon intensity of their financial transactions. This is achieved by reducing spending in a category that has a high emission coefficient (e.g., electricity, household appliances, clothing, furniture, and fuels for transport and heating) and instead increasing spending in a category that has a lower emission coefficient (e.g., various services, cultural and sporting events, and entertainment). The same effect occurs if users increase financial transactions to charity or savings accounts (deferred consumption). In addition, by indicating that something was bought second-hand, the carbon footprint of that purchase is reduced. Second, users can decrease overall spending, at least temporarily. Third, users can change lifestyle factors such as car ownership, the number of household members, and dietary habits, which affects the emission coefficient of many consumption categories. For example, the App uses reported dietary habits to determine the carbon footprint of food consumption. Changing one's dietary habit status from meat-eater to vegetarian reduces the carbon footprint from all food consumption.

2.4 How Can the App Influence Behavior?

The information provided in the emissions section can influence consumption behavior in at least three ways. First, individuals who care about the environmental impact of their consumption might receive new or better information about the carbon footprint of various consumption activities and adjust their behavior accordingly. One feature of the carbon calculator is that the informational feedback is tailored and personalized, enabling the user to identify key areas where the carbon footprint can be reduced. The information feedback is vast and highly detailed since users can get feedback on emission levels for all individual transactions. This enables users to easily infer emission-reducing consumption adjustments across a vast array of consumption categories and domains. In this regard, efforts to reduce the carbon footprint can be directed toward the "low-hanging fruit" for everyone, be it transportation habits, household energy conservation, a reduced rate of replacement of clothing/furniture/appliances, or diet habits. A similar argument has been underlined by Buchanan et al. (2015) and Tiefenbeck et al. (2018) regarding feedback on household energy consumption. Furthermore, in a study on electricity use with a feedback system that breaks electricity consumption down into household appliances, electricity use was reduced by around 8% (Asensio and Delmas 2015), compared to the around 2% reduction

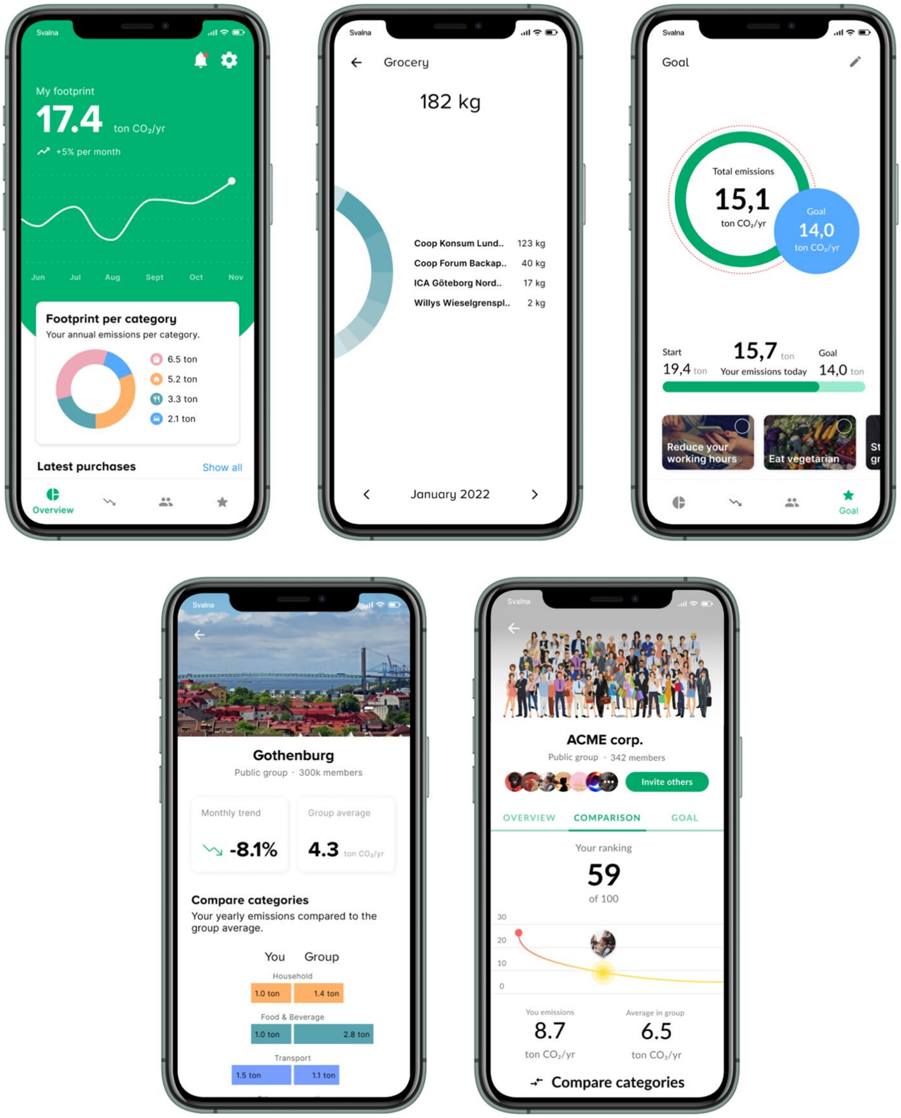


Fig. 1 Main sections and features of the mobile application. *Note* The figure illustrates the App's sections for the general overview (top left), emissions from individual purchases (top middle), goal-setting and tailored suggestions (top right), and group functions and comparisons (bottom two)

induced by 'home energy reports' that give aggregated feedback on past electricity usage (Allcott 2011; Allcott and Taubinsky 2015; Costa and Kahn 2013).

Second, the behavior might also be affected by the fact that information on the carbon footprint is made more salient. For example, the empirical literature has documented that consumers pay attention to the price before tax and hence ignore the sales tax (Chetty et al. 2009), or that they ignore the fuel and electricity costs of cars and light bulbs compared to the sales prices of such products (Allcott 2011; Allcott and Taubinsky 2015). Moreover, a key role of product labels is to make certain characteristics more salient. For example, energy labels have been introduced to increase the attention to energy use in the purchase of durable goods (Andor et al. 2020). In the case of choices involving a moral dimension, such as climate change, it could be important to influence individuals to make attentive choices (Löfgren and Nordblom 2020), through for example, a carbon calculator.

Third, the information from the App also illustrates how the carbon footprint to a large extent is related to the level of consumption. This can have a direct effect on the overall level of consumption, not only due to concerns about the environmental impact of the consumption, but also because of concerns about one's financial situation.

In addition to this, the carbon calculator App has two behavioral features that might play a role. In the App, users can set goals. By encouraging people to set non-binding goals or commit to certain actions, the likelihood of behavioral change can be increased. This is because people dislike being inconsistent and not following through with their plans and promises (Festinger 1962). Voluntary goal setting has been found to affect behavior in areas such as energy saving (Harding and Hsiaw 2014) and vehicle use (Kormos et al. 2015). Commitment, which is presumably a stronger level of engagement than merely setting a goal, has been found to affect behavior in areas such as smoking cessation (Giné et al. 2010) and environmentally friendly behavior (Baca-Motes et al. 2013). Since users of the carbon calculator App are not obligated to set goals, and the goals are not formulated as commitments to a certain behaviors, we do not expect any sizeable overall effects of these App features.

The App also provides information about how the user compares with other users. In particular, the user can compare their footprint with that of an average Swede and with the average in their municipality. Mounting empirical evidence suggests that an individual's behavior is influenced both by information about what other people do, so-called *descriptive norms*, and by what other people Approve of, so-called *injunctive norms* (Allcott 2011; Cialdini 2003; Carlsson et al. 2021; Czajkowski et al. 2017; Ferraro and Price 2013; Goeschl et al. 2018; Nyborg et al. 2016).[7] Social influence is likely to be more effective when the behavior is observable by others and easily scrutinized. As emphasized by Nyborg et al. (2016), individual GHG emissions originate from a wide array of behaviors, many of which are barely observable. In the App, users interact in groups, and can compare themselves with others in much more detail. This is expected to strengthen the effect of social information on the users' behavior.

[7] Thus, the user is provided with a descriptive norm. Descriptive normative feedback could affect behavior through at least three mechanisms. First, consistent with theories that people tend to conform to the behavior of others (e.g. Cialdini 2003), those who learn that they behave differently might conform to the norm. Second, when considering pro-environmental behavior, they are also learning to what degree they are contributing to a public good, i.e., to what degree they are free-riding or doing more than their fair share (Miller and Prentice 2016). The prediction is then that particularly high emitters will reduce their footprint, but that low emitters will increase their footprint towards the norm, referred to in social psychology as a boomerang effect. Third, as underlined by for example Miller and Prentice (2016), normative feedback might have informational influence. For example, information on neighbors' lower energy usage might convey to high energy users that energy conservation is feasible. One could imagine that normative feedback on certain low-emitting lifestyle choices could induce behavioral change through this mechanism, for example regarding transportation alternatives to and from work.

3 Data

The data provided by Svalna Inc. includes weekly estimates of total carbon-equivalent emissions based on detailed purchasing data, survey questions, and register data, as described in Sect. 2. The total carbon footprint is divided into four main categories: (1) transportation, (2) goods and services, (3) food and beverages, and (4) residential energy. Each of these in turn consists of several sub-categories, but we will restrict our analysis to total emissions and these four categories, which correspond to the categories users see in the App. We use pre-pandemic data, as purchasing behavior was severely affected thereafter, making it difficult to identify the effect of the App and to generalize the results. The availability of transaction data for each user depends on when and how often the user decides to connect to their bank. With each manual bank connection, the App downloads and analyzes historic transactions. This means that we have data both before and after App installation for those who connected to their bank at least twice, and data before installation for those who connected to their bank exactly once.

To identify the behavioral response after App installation, we use a difference-in-differences design with staggered treatment adoption. We follow the method recently proposed by Sun and Abraham (2021) which is robust to heterogeneous treatment effects, whereby units adopting treatment last are used as control. Hence, in our setting, the *control* group consists of all users who installed the calculator at the end of our sample period, i.e. in early 2020 before the pandemic.[8] Thus, the control group provides data only on purchase behavior before App installation. The exact length of these historical data depends on the bank, but the average number of weeks is 68. The *treatment* group consists of users who installed the App before 2020. These users are considered treated from the point in time they install the App.[9] Following the method of Sun and Abraham (2021), we exclude in the empirical analysis the period after which control users install the App[10] Therefore, and as explained in Sect. 4, identification comes from comparing consumption in a particular week between those who have installed the App and those who have not yet installed it, controlling for individual fixed effects. The main identifying assumption is that, in the absence of treatment, carbon footprints in the control group have parallel trends to those in the treatment group.

Column (1) of Table 1 presents data on all users in our sample who provide the identifying variation and therefore allows us to estimate behavioral change after App installation. Column (2) presents data for the treatment group, i.e. users who adopted the calculator before 2020 and provided post-treatment data. Column (3) presents data for the control group, i.e. users who adopted the calculator in early 2020. Column (4) indicates the difference in means between these two groups. While there is no statistically significant difference in pre-treatment carbon footprints between the groups, there are some differences in mean characteristics, such as gender, commuting distance, and household size.

[8] In the main analysis, users who installed the App between 1 January 2020 and the start of the pandemic, 1 March 2020, are used as controls. In the appendix, we show that the main results are not dependent on exactly when these arbitrary cut-off dates are set.

[9] Hence, readers should keep in mind that treatment in our setting consists of being exposed to the content of the App and/or a concurrently triggering unobserved factor inducing App installation and behavioral adjustment.

[10] This is why the number of observations will always be lower in our empirical analysis compared to the full dataset.

Table 1 User characteristics

	(1)				(2)		(3)		(4)	(5)
	Identifying sample				Treatment		Control		Difference (3)−(2)	National population
	Mean	Sd	Min	Max	Mean	Sd	Mean	Sd		Mean
Gender										
Female	0.390	0.488	0	1	0.349	0.477	0.419	0.494	0.070*	0.47
Male	0.252	0.434	0	1	0.269	0.444	0.24	0.427	− 0.029	0.53
Not specified	0.358	0.480	0	1	0.382	0.486	0.341	0.474	− 0.041	0
Age	32.4	11.8	15	78	33.3	11.4	31.8	12	− 1.53	48
Region										
Big City (Stockholm, Gothenburg, Malmö)	0.270	0.444	0	1	0.282	0.451	0.262	0.440	− 0.021	0.18
Large town	0.379	0.485	0	1	0.420	0.494	0.351	0.478	− 0.069*	0.24
Commuting town	0.165	0.371	0	1	0.131	0.338	0.188	0.391	0.056*	0.33
Rural town	0.186	0.389	0	1	0.167	0.373	0.200	0.400	0.033	0.25
Dwelling										
Apartment	0.751	0.433	0	1	0.718	0.451	0.774	0.419	0.056*	0.55
House	0.249	0.433	0	1	0.282	0.451	0.226	0.419	− 0.056*	0.45
Adults in household	1.83	0.853	1	10	1.93	0.994	1.76	0.731	− 0.168***	1.59
Children in household	0.593	0.954	0	5	0.639	0.956	0.560	0.951	− 0.079	0.57
Number of cars	0.461	0.573	0	3	0.522	0.590	0.419	0.556	− 0.102**	0.479
Commuting distance (km)	15.7	27.6	0	236	18.5	31.8	13.7	24	− 4.81**	N/A
Diet										
Mixed	0.527	0.499	0	1	0.504	0.500	0.544	0.498	0.040	N/A
Vegan	0.129	0.335	0	1	0.124	0.329	0.133	0.340	0.009	N/A
Vegetarian	0.170	0.376	0	1	0.178	0.383	0.164	0.371	− 0.014	N/A
Pescatarian	0.173	0.379	0	1	0.194	0.396	0.159	0.366	− 0.035	N/A
Uses mobile App	0.943	0.232	0	1	0.937	0.243	0.947	0.225	0.009	

Table 1 (continued)

	(1)				(2)		(3)		(4)	(5)
	Identifying sample				Treatment		Control		Difference (3)−(2)	National population
	Mean	Sd	Min	Max	Mean	Sd	Mean	Sd		Mean
Number of profile updates	1.45	1.44	1	33	2.01	2.1	1.06	0.276	− 0.948***	
Pre-treatment weeks available	68.1	57.3	2	216	67.3	58.5	68.7	56.5	1.42	
Post-treatment weeks available	16.1	16.7	0	92	19.6	17.3	3.61	2.59	− 16***	
Mean pre-treatment footprint/week (kg CO_2e)	140	122	0.049	2016	137	108	142	131	5.81	
Mean pre-treatment spending/week (000s SEK)	12.7	21.7	0.050	455	11.7	15.8	13.4	24.9	1.65	
Observations	1240				510		730		1240	

Column 1 presents characteristics and data from all users who provide identifying variation to estimate behavioral change after App installation. *Treatment* in column 2 are users who adopted the calculator before 2020 and connected to their bank at least twice, thus providing post-treatment data. *Control* in column 3 are users who adopted the calculator in early 2020 before the pandemic and whose' pre-treatment data provide the control observations in our empirical analysis. Column 4 presents the difference in means between the treatment and control groups, with asterisk indicating any statistically significant difference from a simple t-test, unadjusted for multiple hypotheses testing, with * $p < 0.1$, ** $p < 0.5$, *** $p < 0.01$. Column 5 presents, for comparison, the mean values for the Swedish adult population from Statistics Sweden (2022)

Although balanced characteristics between these two groups are not necessary for our empirical strategy, one might worry that these differences would indicate that the parallel trends assumption is violated.[11] The most common way to evaluate whether the parallel trends assumption is plausible in a setting with staggered treatment adoption is by estimating pre-treatment effects in a regression framework (Cunningham 2021). In Sect. 4, we will demonstrate that pre-treatment effects are small and generally insignificant, offering support for the identifying assumption. To complement this, Appendix Fig. 5 plots the raw unconditional carbon footprint pre-treatment trends for the treatment and control groups separately. The figure demonstrates that carbon footprints in pre-treatment weeks have very similar trends prior to App installation.

The identifying sample consists of 1240 users in total, of whom 730 and 510 are in the control and treatment groups, respectively.[12] The mean age is around 32–33, and most people live in apartments with one other person and no children, own zero cars, and eat a mixed diet. Ninety-five percent of the users use the mobile version of the calculator, while the rest use the web page version. Before the adoption of the calculator, users had a mean weekly footprint of 140 kg CO_2eq and spent, on average, 12,700 SEK per week.[13] The large variation in the availability of pre-treatment data is due to differences in data availability between different banks, while the variation in the availability of post-treatment data is due to between-user differences in the number of days between the first and last bank connection.

There are some notable differences between the typical user and the Swedish population. Users are younger, with an average age of around 32 compared to around 48 among adults in Sweden overall. They are also more likely to live in a big city (28% compared to 18%) and in an apartment (73% compared to 55%). There are no official statistics on the number of vegetarians and vegans, but the share among the users (around 30%) is higher than what other studies have shown, where the share is often around 10%. There is also survey evidence that the users of the App are more pro-environmental.[14] In sum, users in both the treatment and control groups differ somewhat from the general Swedish population, and it's important to keep this in mind when interpreting the external validity of the results of this study.

In Appendix Table 6, and Appendix Figs. 6 and 7, we present and illustrate data on App usage in the treatment group. On average, users engage with the App 10 times after App installation and explore all sections of the App. A third of the users set an emission reduction target. Appendix Fig. 6 shows how users gradually drop out of our sample as they stop updating their bank data (solid black line). While the number of users active in the App in a particular week drops quickly after App installation (grey solid line), the share of

[11] For an overview of the identifying assumptions of difference-in-differences designs and how to test them, including designs with staggered adoption of treatment, see e.g., Angrist and Pischke (2008) or Cunningham (2021).

[12] An additional 1303 users, discussed below, are included in the empirical analysis but do not provide identifying variation post-treatment. They are, therefore, not of primary interest, which is why we present and discuss their characteristics separately below.

[13] Note that this figure includes all outgoing transactions.

[14] In a survey answered by 2151 users of the App, around 80% stated that they were very worried about changes in the earth's climate, deterioration of the ocean environment, and environmental degradation in general. Identical survey questions were used in a study sent out to a random sample of the Swedish population, where around 50% were very worried about these environmental problems: SOM Miljö- och klimatopinion i Sverige 2020, Accessed March 9, 2022.

users in the sample that engages with the App *each week* is at least 20% (dashed line). In a review of carbon calculators, Salo et al. (2019) emphasized that engaging people more than once is a particular challenge for most calculators. Compared to this, users in our treatment group are highly active.

Although comprehensive and detailed, the purchasing data and thus emission estimates come with measurement errors. First, emissions are based on which of the 65 consumption sub-categories each transaction belongs to, which most often is determined by the calculator's algorithm based on a small descriptive text for each transaction. Because incorrect categorizations occur, we manually identify transactions that are obviously incorrect categorizations by the App. For such expenses up to a threshold of 50,000 SEK/week/sub-category, we set the emissions at the user-average emission intensity. Expenses higher than this threshold are classified as financial transactions with a zero carbon-equivalent intensity. As we will show in Sect. 5, the results are not sensitive to where this arbitrary threshold is set.

Second, users can manually re-categorize transactions that are erroneously categorized by the App. Twenty percent of the users in our sample have made such re-categorizations. Half of the re-categorizations concern transactions smaller than 1000 SEK, and around 5% concern transactions larger than 20,000 SEK. Re-categorizations might be done incorrectly and in a manner that systematically reduces the user's reported carbon footprint. Some users might want to reduce their overall carbon footprint by re-categorizing transactions from categories with high carbon intensity to categories with low carbon intensity, for example, to improve relative to peers also using the calculator. Note that in the App, users can re-categorize transactions that occurred before the App was installed. If users systematically re-categorize transactions occurring before or after App installation differently, this would bias our results. However, there is no obvious reason why users would differentiate between transactions before and after App installation when making re-categorizations. Nevertheless, since we have data on the total expenditures re-categorized each week by each user, we can formally test this.[15] Table 2 presents the results from regressing the logged total weekly amount re-categorized on a dummy for post-treatment periods, controlling for user and time fixed effects. We cannot reject the null hypothesis of no difference between the amounts re-categorized for the weeks before and after the App installation, suggesting that manual re-categorizations will unlikely bias our results.

Third, as described in Sect. 2, the carbon intensity of many consumption categories is partly based on self-reported lifestyle factors, such as dietary habits and household size. To the extent that users systematically report lifestyle changes inaccurately, for example, to manipulate the footprint downwards, this could bias our results. However, we will show that our main results are not driven by those who self-report lifestyle changes after treatment.[16] It is also important to understand that one important role of the carbon calculator is to induce lifestyle changes. Thus, users reporting such changes should not be seen as a problem in itself.

Fourth, to fine-tune the estimated long-term footprint, the calculator sometimes automatically assigns emission values to weeks without corresponding financial transactions.

[15] Unfortunately, we do not have data on original consumption categories for re-categorized transactions, and therefore cannot control or correct for users' re-categorizations.

[16] Closely related is the possibility in the App to manually report flights. To avoid our results being affected by biased reporting of flights, we calculate emissions from aviation using the transaction data only and ignore any self-reported information on aviation.

This is done when official databases and self-reported lifestyle factors imply that there should be regular emissions from a certain category, but the algorithm is unable to detect any corresponding transaction.[17] While this improves the precision of the emission estimates in the longer run, it decreases the temporal precision of the calculator because immediate changes in consumption behavior will not be detected. Furthermore, it also makes it difficult to measure the carbon intensity (CO_2eq/SEK) of purchases. To address this, we recalculate emissions in these categories from observed transactions only, to increase the temporal precision of consumer behavior.[18]

Fifth, although there is a consensus among scholars that multi-regional input–output databases currently represent the preferred approach to calculating carbon footprints (Tukker et al. 2018), putting this data to use to provide carbon estimates for specific consumer goods will inevitably lead to results that deviate from the most accurate estimate for certain products. Hence, using price as a proxy for emissions will, on average, overestimate the emissions associated with the purchases of expensive and high-quality products and underestimate the emissions related to the production of the cheapest products. Since high-income households are more likely to buy expensive products and services, this means that we are likely to overestimate the carbon footprint of high-income households (Girod and De Haan 2010).

Sixth, users of the App may change their behavior in ways that may not be completely noticeable through their spending patterns. For example, the App does not take into consideration the potential emission reductions from altered waste management practices. Also related, if users live in households with more than one member (around half of the users in our sample) and some expenditures are shared, the App would naturally only partly capture altered consumption.[19] Some consumption categories are, however, very well captured by the transaction data, in particular, those with relatively homogeneous products within them and/or those where product heterogeneity is well captured by official registers (e.g., gas purchases combined with registered information on car ownership).

In addition to the 1240 users presented in Table 1, we also include in our estimation users who adopted the calculator before 2020, but only connected their bank once and thus only provide pre-treatment data. Unlike our control group, these users will not provide any variation enabling us to estimate post-treatment effects, which is of primary interest. However, we still include them to increase statistical power to detect any behavioral change before App installation, i.e. an anticipation effect. These additional 1303 users are presented in Appendix Table 7 and compared to the treatment group previously presented.

[17] This is done for seven sub-categories within residential energy, as well as for groceries when such expenditures reach unrealistically low levels. For example, the calculator can infer a reasonable range of emissions from heating based on self-reported information on household size, dwelling type, and dwelling size, combined with official information on the heating source for the user's address. If no transactions can be identified as relating to heating, the calculator assigns an average emission value for that user every week.

[18] Because most users have some kind of extrapolation in their data, mainly from district heating and electricity, this adjustment decreases the estimated footprint somewhat for the majority of users. Our main estimates without this adjustment, which are discussed in Sect. 5 and presented in the Appendix, are therefore somewhat attenuated, but remain statistically significant and are furthermore not statistically different from our main results.

[19] See further Andersson (2020) on how shared expenditures and households with more than one member are handled.

Table 2 Manually re-categorized transactions before and after treatment

	(1) ln(Recat+1)
Treatment	0.085
	(0.086)
User FE	Yes
Week-by-year FE	Yes
Observations	167,798

The table presents results from a regression using the user-by-week panel and controlling for user and time fixed effects. The dependent variable is the total number of SEK re-categorized in the App by each user each week, as further explained in Sect. 3. The independent variable is a dummy for having installed the App. Standard errors are presented in parentheses and clustered on users

* $p < 0.1$, ** $p < 0.5$, *** $p < 0.01$

Figure 2 illustrates data availability before 2020 from the three user groups used in the empirical analysis.[20]

Table 3 reports summary statistics for all users active in our sample period, including those in early 2020. The mean weekly carbon footprint is 149 kg CO_2eq, which corresponds to a yearly footprint of 7.7 tons CO_2eq. The average carbon footprint of the adult population in Sweden is roughly 178 kg CO_2eq per week corresponding, to 9.3 tons CO_2eq per year, if estimated similarly as in the App.

There is substantial variation in the carbon footprint, and the median weekly footprint is 78 kg CO_2eq. The subsequent rows break this down into the four main consumption categories: transportation, goods and services, food and beverages, and residential energy. The categories with the highest average footprint are goods and services, and food and beverages. However, the largest variation in carbon footprint is found in the transportation group, suggesting that some users have a substantial carbon footprint from transportation.

4 Empirical Strategy

To evaluate whether users alter their purchasing behavior after App installation, we estimate various versions of a standard difference-in-differences model with staggered treatment adoption:

$$y_{it} = \tau_{it} App_{it} + \eta_t + \rho_i + \epsilon_{it} \tag{1}$$

where y_{it} is a measure of purchasing behavior of individual i in week t. Our main outcome variable is weekly carbon-equivalent emissions from total consumption, but we also examine emissions from the four sub-categories of consumption. In addition, we consider the emission intensity of weekly spending (CO_2eq/SEK), and total weekly spending. We log-transform the dependent variable in our main specifications for primarily two reasons.

[20] Note that our user panel is highly unbalanced, where the median post-treatment week length is around 15 weeks. This explains the fact that the total number of post-treatment data points never reaches more than 300 in a given week, although the total number of users providing post-treatment data is 530.

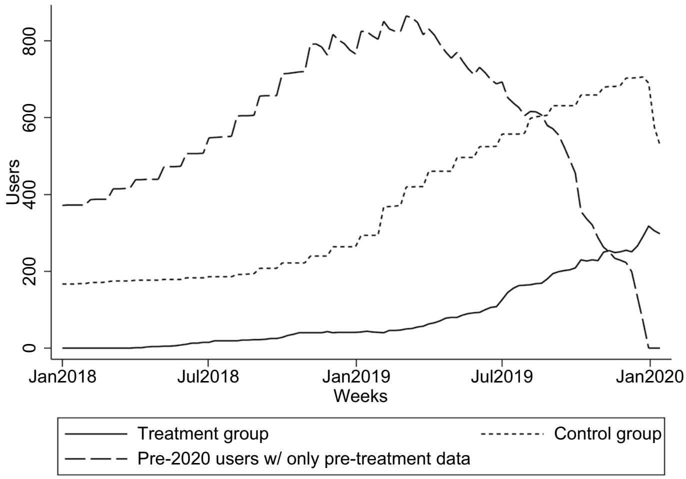


Fig. 2 Data availability by user group. *Note* The figure shows data availability for each week in our sample from the three user groups used in the empirical analysis. *Treatment group* indicates the number of users with available post-treatment data. *Control group* are users who adopted the calculator in early 2020 and who provide pre-treatment emissions data. The long-dashed line indicates pre-treatment data available from users who adopted the calculator before 2020 but only provide pre-treatment data, i.e., they only connected to their bank once. Note that pre-treatment data from the treatment group are not included in the figure

Table 3 Summary statistics

	Mean	SD	Median	Min	Max
Total footprint	148.57	360.10	78	0	25,338
Transportation	37.53	284.62	0	0	25,327
Goods and services	44.03	98.68	15	0	8883
Food and beverages	45.11	93.84	24	0	4214
Residential energy	21.90	137.99	1	0	19,504
Observations	173,246				

The table presents summary statistics for the entire week-by-user panel dataset on the total consumption-based carbon footprint and the four main subcategories of consumption

First, because the main dependent variable is based on individual consumption, it is highly skewed and sensitive to outliers. The log transformation reduces this problem. Second, we find it more plausible that the consumption response is proportional to the individuals' own consumption level rather than absolute.[21]

App_{it} is the treatment indicator of individual i in week t and is equal to one after App installation. Thus, this is the point in time after which the user receives information about the consumption-based carbon footprint and experiences the associated features of the carbon calculator App. η_t is week fixed effects and controls for any time-variant shocks or

[21] We handle the zeros in the dependent variable by adding 1 to each observation before log-transforming. Less than 2% of the observations have zeros in the dependent variable.

trends that affect all users similarly, such as inflation, economic shocks, and seasonality in income or spending. For example, if there are general trends in environmental awareness or the supply of climate-friendly products, they will be accounted for by the time fixed effects. ρ_i is individual fixed effects and controls for any time-invariant observed or unobserved individual characteristics that affect individuals' purchasing behavior. ϵ_{it} is an idiosyncratic error term. The behavioral response before and after treatment is thus captured by τ_{it}. To account for within-user serial correlation in the error term, we cluster standard errors at the user level.

Estimating Eq. (1) using the commonly used two-way fixed effects estimator and OLS can lead to severely biased results when the treatment effect is heterogeneous, either within-unit over time or between groups of units treated at different times, as shown in a number of recent studies (e.g., Borusyak et al. 2021; De Chaisemartin and d'Haultfoeuille 2020; Callaway and Sant'Anna 2021; Goodman-Bacon 2021; Sun and Abraham 2021). This is because the usual two-way fixed effects estimation procedure provides a weighted average of many 2-by-2 difference-in-differences treatment effects. If estimated with a two-way fixed effects regression, some of these weights can be negative or incorrect due to heterogeneous treatment effects.[22] To address this, we use the approach suggested by Sun and Abraham (2021), where separate event studies are estimated for each treatment cohort, defined as the week of App installation in our setting. The average leads and lags across treatment cohorts are then calculated, weighted by the number of users in each treatment cohort. This procedure ensures correct and non-negative weights and accounts for possible heterogeneous treatment effects. As proposed by Sun and Abraham (2021), we use as our control group the last treated units in our sample, which in our setting are users who installed the App in early 2020.

What is the interpretation of τ_{it}? A key underlying assumption for a standard difference-in-differences model such as Eq. (1) is that, in the absence of treatment, baseline outcomes follow parallel trends in the treatment and control groups, so that control users provide a plausible counterfactual to the treated users (Angrist and Pischke 2008; Sun and Abraham 2021; Roth et al. 2022). Note that this assumption does not require baseline characteristics or even outcomes to be balanced across the treated and control groups, as these are absorbed by the user fixed effects ρ_i, but merely that they follow parallel trends. As is standard in the difference-in-differences literature, we test this by estimating individual pre-treatment effects, where no effects would support the assumption of parallel trends. Roth et al. (2022) and others have recently raised the concern that such tests may fail to reject no pre-treatment effects due to low statistical power. This may be a particular concern in our study given the small number of users and identifying observations. To address this, as mentioned in Sect. 3, we include in all our analyses users who installed the App before 2020 and only connected their bank once and therefore only provide pre-treatment data. While these users do not provide any identifying variation to estimate treatment effects after App installation, they increase the power to detect any effect prior to treatment. This test will also detect any anticipation effect. Individuals might start reducing their footprint for reasons unrelated to the calculator, and then start using the calculator later, perhaps after a couple of weeks of consumption adjustment to see how they are progressing. In this case, we expect to detect gradual decreases in footprints prior to treatment.

[22] One possible source of treatment effect heterogeneity in our setting is some minor updates and improvements of the App during the sample period, which theoretically could induce a stronger effect for later adopters.

Given parallel trends and no anticipation effects, and given that the calculator App induces individuals to adjust their consumption behavior, τ_{it} can be interpreted as the causal effect of the carbon calculator for the type of subjects who install the App. However, since we are using self-selected users of the carbon calculator and have no information on why users start using it, we cannot entirely rule out the possibility that τ_{it} partly captures an underlying factor or event that immediately triggers both App installation and behavioral adjustment. Thus, in the absence of pre-treatment effects, we can interpret τ_{it} as the consumption response after App installation for individuals motivated to reduce their footprint, where this motivation is induced by the calculator App or some other underlying cause (such as a climate campaign), or a combination of the two.

Finally, note that the treatment indicator is an intent to treat. Although all users in the treatment group have made at least two manual bank connections, we know that some users are very inactive in the App, and we furthermore have limited information on how they process the information. Additionally, the small number of users and identifying observations make it difficult to identify differences in behavior between different types of users, such as in level of App activity.

5 Results

We begin with the results from a flexible version of Eq. (1), an event study model with week-specific treatment effects for up to 8 weeks before App installation and 30 weeks after. Using 8 weeks before should allow us to detect any anticipation effect and evaluate the plausibility of the parallel trends assumption. We bin all weeks outside of this time frame into two variables and use the week before App installation as the reference period. The results, illustrated in Fig. 3, show that users reduce their consumption-based carbon emissions by around 11% directly after App installation. The figure reports main estimates for the initial 20 weeks after App installation together with 90% confidence intervals; full results are presented in Appendix Table 8. Coefficient estimates for the weeks following the initial periods indicate a gradual slide back to footprint levels prior to App installation, but caution is warranted because the statistical precision is low and decreases as we move further away from the time of App installation. Moreover, we observe no effects on emissions before App installation, indicating no anticipation effect and offering support to the parallel trends assumption. This supports the interpretation that we are catching the immediate behavioral response for individuals who have decided to reduce their footprint, either due to the content of the calculator and/or some underlying shift in preferences occurring at the same time.

Figure 4 reports estimates from the same model specification but for each of the main consumption categories: (1) transportation, (2) goods and services, (3) food and beverages, and (4) residential energy. There is less precision in the estimates for the separate categories, which not the least is indicated by the wide confidence intervals, mostly because they are based on fewer transactions. Although it varies from week to week, the pattern is by and large that the carbon footprint is reduced directly after App installation, but that emission levels revert to pre-installation levels after a few weeks.

Next, we focus on a specification where we bin the effects for weeks 0–4, 5–12, and after 12 weeks, respectively. The main reasons for doing this are to increase the precision of our estimates and that many household costs are paid monthly and not weekly. Thus, the immediate effect is one month after App installation, and then we allow for a medium-term effect of two additional months, and finally an effect beyond the three first months. We also include a binned effect for four weeks prior to App installation, i.e., a similar length as the immediate effect, making all weeks before that the reference period. Column (1) in Table 4 presents the effect on total carbon-equivalent emissions using this specification, hence analogous to the results in Fig. 3. We see a highly statistically significant average decrease of almost 10% in weekly carbon footprint in the first five weeks after App installation. This negative effect decreases to around 6.5% for weeks 5–12. For the weeks beyond the first 12 weeks, the coefficient estimate suggests an average decrease of around 4.5%, but the statistical precision is low, and the coefficient estimate is not statistically significant at the conventional level.[23] Subsequent columns in Table 4 split the outcome variable into the four sub-categories of consumption. By doing so, we can investigate whether there are negative spillover effects between categories, whereby decreases in one consumption category are counterbalanced by increases in other categories. The results indicate that carbon footprints decreased in all four consumption domains in the first five weeks, although the statistical precision decreases substantially when splitting the data. As such, this suggests that there are, on average, no negative spillover effects between the four consumption categories. Short-run emission decreases are statistically significant at the five percent level for goods and services, while they are significant at the 10% level for transportation, residential energy, and food and beverages. Beyond the first 12 weeks, none of the estimated coefficients are statistically significant.

Table 5 investigates the mechanisms underlying the above results. As discussed in Sect. 2, users can reduce their footprint in primarily three ways: (i) shifting consumption from high intensity (CO_2eq/SEK) to lower intensity categories, (ii) decreasing overall spending, and (iii) changing lifestyle factors (e.g., address, car ownership, or dietary habits) by manually reporting the change in the App.

Column (1) in Table 5 examines the first mechanism by estimating the effect on the logged carbon-equivalent intensity of consumption, i.e., the logged weekly average emission per SEK spent. We find suggestive evidence that consumption is shifted towards consumption with lower carbon-equivalent intensity in the first 12 weeks, although some caution is warranted as the coefficients are only statistically significant at the 10% level. Column (2) examines whether overall spending is reduced or not. The results suggest that this is the case for the first five weeks. This means, consequently, that the users increase their savings in the short-run, which at some later point in time will be used for consumption and/or investments, resulting in a carbon footprint.

In Columns (3) and (4), we also investigate whether the results are driven by changes in lifestyle factors self-reported by the user. We do this by splitting the sample of users into those who do not have any lifestyle factor changes during the sample period (column 3) and those who do (column 4). Out of the 510 users in the treatment group, a majority (n

[23] In Appendix Table 9, we report several sensitivity checks. First, we show alternative thresholds at which uncategorized expenditures are treated as equivalent to savings and thus are assigned zero emissions. As explained in Sect. 3, this threshold is set to 50,000 SEK in the main estimations. Columns (1)–(3) instead set it to 100,000, 500,000, and 1,000,000, respectively. Second, columns (4)–(5) present alternative definitions of the exact treatment and control groups. Third, column (6) presents estimates using a hyperbolic sine transformation of the dependent variable instead of a log-transformation. The results are only marginally affected by any of these sensitivity checks. Finally, column (7) presents a linear version of Eq. (1), where the dependent variable is in kg CO_2eq. The coefficient estimates in this version suggest a decrease of around 10 kg CO_2eq after App installation, although precision is low for the short-term effect.

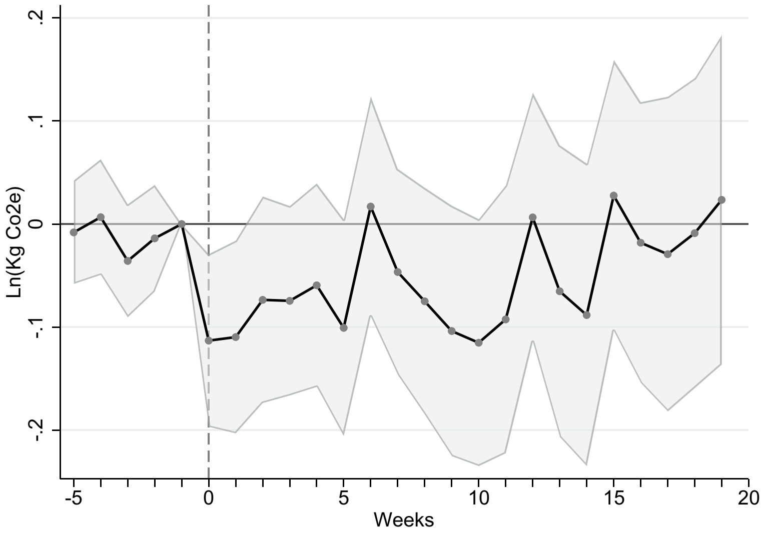


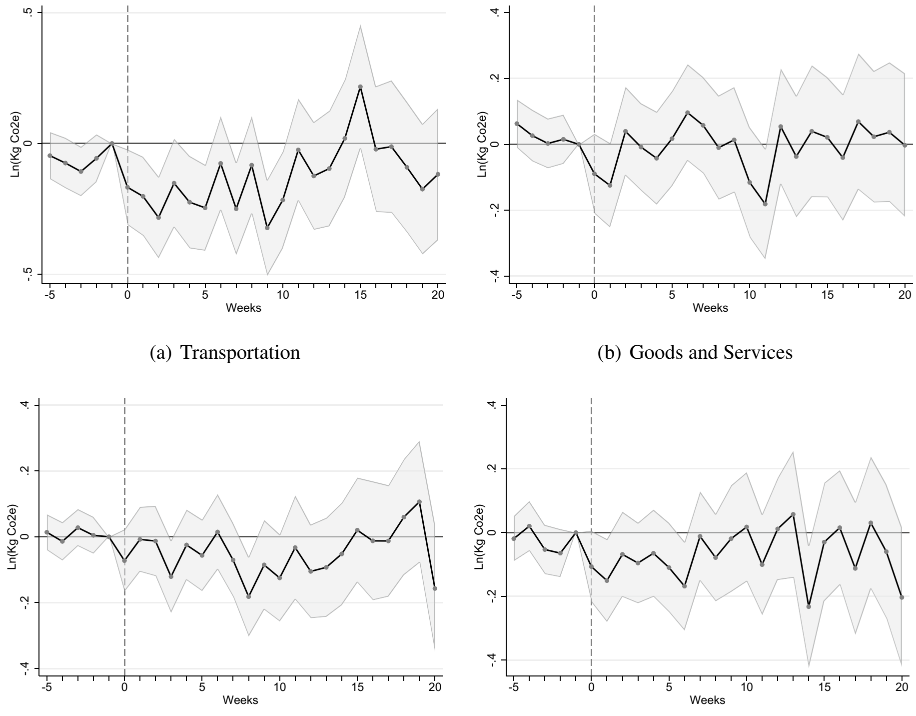
Fig. 3 App installation and carbon footprints. *Note* The figure illustrates estimated coefficients and 90% confidence intervals from the model in Eq. (1), using as dependent variable total weekly CO_2eq emissions. Week zero is the week of App installation. Full results are available in Appendix Table 8

= 352) do not have any reported lifestyle changes.[24] The results indicate that reported lifestyle changes do not explain the results. Those with lifestyle changes do not have a larger reduction in their carbon footprint compared to those who do not have any lifestyle changes reported.

Taken together, the results in Table 5 suggest that the overall decrease in carbon footprint is driven by a combination of a shift towards expenditures with lower carbon intensity and a temporary decrease in overall expenditures.

Since this is not an experiment, we cannot rule out the possibility that the effects are partly driven by some underlying factor, unrelated to the App, that concurrently triggers both App installation and behavioral adjustment. However, taking a holistic view of the empirical analysis—including the descriptive statistics, user characteristics and behavior, content of the App, and past experimental research on related interventions—the overall results suggest that the content of the App induces carbon footprint reduction, at least partly. In particular (i) the App has features similar to those that are known to induce pro-environmental behavioral change, (ii) there is no anticipating effect, confining alternative explanations to concurrent triggering events, (iii) our users are highly engaged, likely have room for improvement, and hold pro-environmental attitudes, suggesting they are particularly likely to respond to the App's content (e.g., Fosgaard et al. 2021; Bonan et al. 2021), (iv) the immediate reduction and gradual reversal is consistent with previous experimental findings (e.g., Allcott and Rogers 2014; Fosgaard et al. 2021; Bonan et al. 2021), and (v) the gradual influx of users suggests that the result is not driven by a few single obvious pro-environmental events, such as Earth Day or climate manifestations.

[24] In column (3), we analyze 352 users in the treatment group, 679 in the control group, and 1330 pre-2020 users who only provide pre-treatment data. The analogous figures for column (4) are 158, 28, and 678.



(a) Transportation

(b) Goods and Services

(c) Residential Energy

(d) Food and Beverages

Fig. 4 App installation and carbon footprints in four consumption categories. *Note* The figures illustrate estimated coefficients and 90% confidence intervals from the model in Eq. (1), using as dependent variable CO_2eq emissions from one of four consumption categories. Week zero is the week of App installation. Full results are available in Appendix Table 8

6 Conclusions

Reducing the carbon footprint at the individual level is not as straightforward as it seems at first glance. Reducing the overall level of consumption and using less energy from carbon sources are the most straightforward options, but beyond that, it is more complex for motivated individuals to reduce their footprint. Using carbon calculators to facilitate pro-environmental choices is consequently an interesting alternative, in particular if the provision of information can be coupled with behavioral nudges, such as social information or moral suasion.

As far as we are aware, there have been no evaluations of a comprehensive carbon calculator and its role in reducing people's carbon footprint. Using data on pro-environmental consumers who adopt and actively use a carbon calculator, we investigate their efforts to reduce their carbon footprint. The reduction in carbon footprint is substantial in the first month, with around a 10% decrease. This reduction is driven by a combination of a shift towards expenditures with lower carbon intensity and a temporary decrease in overall expenditures. This effect size is large compared to those found in other studies on resource use, which typically report a reduction of between 2 and 5% from recieving so-called home-energy reports (Carlsson et al. 2021). However, this is an effect on energy use and

Table 4 App installation and carbon footprints: main results

	(1) Total	(2) Transportation	(3) Goods and services	(4) Food and beverages	(5) Residential energy
4 weeks before treatment	− 0.013	0.024	− 0.031	0.014	0.0046
	(0.015)	(0.024)	(0.020)	(0.019)	(0.017)
Week 0–4	− 0.096***	− 0.079*	− 0.088**	− 0.055*	− 0.058*
	(0.028)	(0.042)	(0.035)	(0.033)	(0.030)
Week 5–12	− 0.067**	− 0.037	− 0.030	− 0.075*	− 0.019
	(0.031)	(0.043)	(0.039)	(0.039)	(0.032)
> 12 weeks	− 0.045	0.037	− 0.027	− 0.053	0.034
	(0.035)	(0.041)	(0.041)	(0.055)	(0.034)
User FE	Yes	Yes	Yes	Yes	Yes
Week-by-year FE	Yes	Yes	Yes	Yes	Yes
Observations	167,798	167,798	167,798	167,798	167,798
Mean dependent var.	4.21	1.48	2.64	2.92	1.44
Sd. of dependent var.	1.39	1.81	1.65	1.52	1.61
Users	2519	2519	2519	2519	2519

The table presents results from estimating the event study model specified in Eq. (1), but with relative times around treatment adoption binned into four variables that are used as independent variables: 4 weeks before treatment, 0–4 weeks after treatment, 5–12 weeks after treatment, and all subsequent weeks. The dependent variable is log(CO_2e+1), where CO_2e is consumption-based carbon-equivalent emissions. Column 1 uses total emissions, while subsequent columns use emissions from the four main consumption categories further specified in Sect. 3. All models are estimated using the approach suggested by Sun and Abraham (2021), which accounts for possible heterogeneous treatment effects depending on when users install the App. All models control for user and time fixed effects. Standard errors are presented in parentheses and clustered on users

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

not the carbon footprint. The effect on carbon footprint depends on the energy mix and type of marginal energy source. Let us illustrate with two studies. In Allcott (2011), the average effect size on electricity use is 2%. Back-of-the-envelope estimates suggest that this would result in a reduction of around 0.8% in CO_2eq emissions. The study in Germany by Andor et al. (2020) finds a considerably smaller effect size of 0.7%, which would result in an estimated reduction of around 0.1% in CO_2eq emissions.[25] Compared to these studies, our estimated effect in the short run is huge. Furthermore, for a country like Sweden, the average CO_2eq emissions per individual are very low, which means that the effect on the carbon footprint from reducing electricity use is only relatively minor.[26] However, after the first month, the effect in our study fades, although still statistically significant in the first

[25] We use the carbon intensities and electricity uses reported in Andor et al. (2020), and an average of 1250 kg CO_2eq per month for the U.S. and 720 kg for Germany.

[26] Using the carbon intensity of 13 g/kWh and the average electricity use of 8025 kWh reported in (Andor et al. 2020), a 10% reduction in electricity use results in about 1 kg less of CO_2eq emissions per household. With an average of 607 kg CO_2eq per month among our users, this corresponds to a reduction of 0.15% of CO_2eq per month.

Table 5 App installation and carbon footprints: mechanisms and robustness

	(1) ln(CO_2e/SEK)	(2) ln(SEK+1)	(3) ln(CO_2e+1)	(4) ln(CO_2e+1)
4 weeks before treatment	– 0.017	– 0.005	– 0.014	0.016
	(0.013)	(0.017)	(0.016)	(0.043)
Week 0–4	– 0.045*	– 0.061**	– 0.090***	– 0.076*
	(0.023)	(0.031)	(0.032)	(0.044)
Week 5–12	– 0.041*	– 0.031	– 0.066*	– 0.036
	(0.024)	(0.034)	(0.037)	(0.041)
> 12 weeks	0.006	– 0.053	– 0.115***	0.039
	(0.028)	(0.043)	(0.035)	(0.053)
User FE	Yes	Yes	Yes	Yes
Week-by-year FE	Yes	Yes	Yes	Yes
Observations	164,440	167,798	152,464	62,820
Mean dependent var.	– 4.16	8.31	4.21	4.14
Sd. of dependent var.	1.08	1.64	1.4	1.38
Users	2517	2519	2361	864

The table presents results from estimating the event study model specified in Eq. (1), but with relative times around treatment adoption binned into four variables that are used as independent variables: 4 weeks before treatment, 0–4 weeks after treatment, 5–12 weeks after treatment, and all subsequent weeks. CO_2e is consumption-based carbon-equivalent emissions. Column (3) restricts the sample to users that have not reported any lifestyle changes in the App, and column (4) to those that have. All models are estimated using the approach suggested by Sun and Abraham (2021) and control for user and time fixed effects. Standard errors are presented in parentheses and clustered on users

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

subsequent weeks. Similar patterns of effects of information have been found in other studies (Allcott and Rogers 2014; Ferraro et al. 2011; Fosgaard et al. 2021). In particular, there is even evidence of "action and backsliding" of home-energy reports, i.e. that users reduce their electricity use directly after receiving the information but that these efforts decay over time. This suggests that the information treatment should be repeated to have a consistent effect. The long-run effects of home-energy reports, after they have stopped being received, are indeed decaying but are still statistically significant after a few years (Allcott and Rogers 2014).

As we have indicated, the sample size in this study is not very large, and conducting a more large-scale study would be necessary to more precisely estimate carbon footprint reduction efforts and the App's effect, especially beyond the short-run. In addition, we are not able to explore the individual effects of the various features of the App. Moreover, the users of the carbon calculator App are not a random sample of the population. On the contrary, because users have self-selected into the App and are reported to hold particularly pro-environmental attitudes, it's likely that they are motivated to change. To know if the use of this type of carbon calculator could spur behavioral changes in a larger population and to understand the mechanisms, a proper experiment with randomization would need to be conducted.

Even if the use of carbon calculators would result in emission reductions, how could such solutions scale to a larger share of the population? One answer is that banks around the world are currently taking steps to integrate carbon footprint calculators into their digital platforms (see, for example, BNP Paribas,[27], NatWest,[28], Nordea[29], and Klarna[30]). Banking platforms are already trusted and used by a majority of the population in most countries in the world, so offering carbon footprint information to customers might provide a competitive advantage and also relate to other green revenue streams such as green funds and loans. Therefore, carbon footprint information could potentially scale through banking platforms. However, since banks have no strong incentive to help customers reduce their footprint or make such information very salient on their platforms, understanding how this information could affect people likely determines the effectiveness of this solution.

Assuming that the carbon calculator App drives the observed effect, the fact that there is only a short-run impact may not be surprising when considering the features of the App. There is little in it that encourages the user to return and use it repeatedly, and there are essentially no reminders sent to users to check their progress. The possibilities to scale a carbon calculator would require a design where the user is exposed to the App content repeatedly. Our results are also in line with a similar study on information provision relating to food consumption, where only an initial statistically significant effect was found (Fosgaard et al. 2021). Again, a proper evaluation using an experiment would be important in order to learn what could keep users at a lower level of their carbon footprint.

Appendix

See Figs. (5, 6 and 7)

See Tables (6, 7, 8 and 9)

[27] Internet resource. Retrieved from: Bank of the West Accessed Mar. 1, 2022.

[28] Internet resource. Retrieved from: NatWest Accessed Mar. 1, 2022.

[29] Internet resource. Retrieved from: Nordea, Accessed Mar. 1, 2022.

[30] Internet resource. Retrieved from: Klarna, Accessed Mar. 1, 2022.

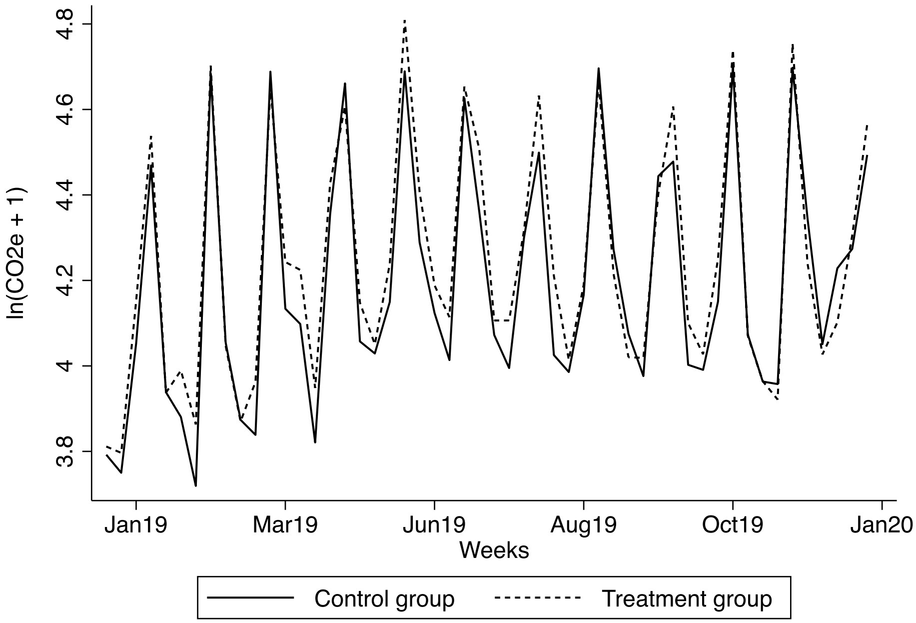


Fig. 5 Pre-treatment trends in carbon footprint. *Note* The figure shows the weekly means of logged carbon footprints in the treatment and control groups before App installation. The treatment group consists of users who installed the App during 2019 and the control group comprises users who installed it in early 2020

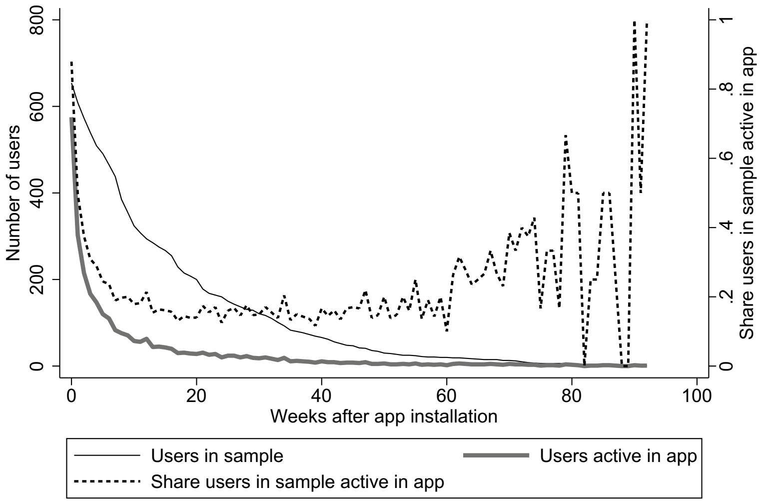


Fig. 6 App activity among post-treatment users in sample. *Note* The figure shows App activity among the post-treatment users in the panel, in relation to weeks after App installation. The solid black line shows the number of users left in the unbalanced panel. The solid grey line shows the number of users who are active in the App at least once a particular week. The dashed line shows the ratio between the two solid lines, i.e., the share of users left in the panel who are active at least once a particular week

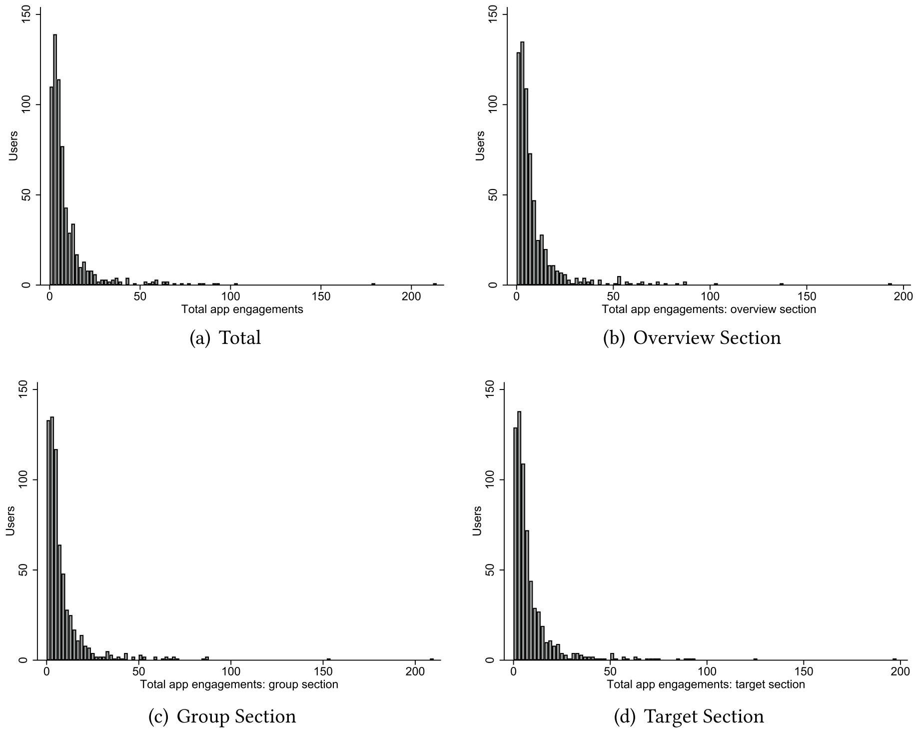


Fig. 7 Number of App engagements among post-treatment users in sample. *Note* The figures shows the distribution of total App engagements after App installation for users in the treatment group, i.e., those who connected to their bank at least twice. Figure 4a shows total engagements, while Fig. 4b–d shows total engagements in specific sections of the App

Table 6 activity in treatment group

	Mean	SD	Median	Min	Max
engagements					
Total	10.8	18.8	5	0	214
Overview section	10.3	17.4	5	0	194
Target section	10.2	17.1	5	0	197
Group section	9.95	17.3	5	0	210
Reduction target set	0.29	0.45	0	0	1
Number of profile updates	2.01	2.1	1	1	33
Observations	510				

The table shows App activity after App installation for users in the treatment group, i.e., users who connected to their bank at least twice. *App engagement* is the number of times the user engaged with the App in total, or with specific sections of the App. *Reduction target set* is a dummy indicating whether the user had set an emission reduction target in the target section of the App. *Number of profile updates* indicates how many times a user had updated any part of their profile

Table 7 User characteristics: treatment group and pre-2020 users without post-treatment data

	(1) Treatment		(2) No treatment data		(3) Difference (2)−(1)
	Mean	Sd	Mean	Sd	
Gender					
Female	0.349	0.477	0.387	0.487	0.038
Male	0.269	0.444	0.231	0.422	− 0.038
Not specified	0.382	0.486	0.382	0.486	− 0.0002
Age	33.3	11.4	32	11.4	− 1.26
Region					
Big city (Stockholm, Gothenburg, Malmö)	0.282	0.451	0.260	0.439	− 0.022
Large town	0.420	0.494	0.322	0.467	− 0.098***
Commuting town	0.131	0.338	0.167	0.373	0.035
Rural town	0.167	0.373	0.252	0.434	0.085***
Dwelling					
Apartment	0.718	0.451	0.738	0.440	0.021
House	0.282	0.451	0.262	0.440	− 0.021
Adults in household	1.93	0.994	1.81	0.759	− 0.122**
Children in household	0.639	0.956	0.631	1.02	− 0.008
Number of cars	0.522	0.590	0.420	0.578	− 0.102***
Commuting distance (km)	18.5	31.8	15	27.8	− 3.55*
Diet					
Mixed	0.504	0.500	0.573	0.495	0.069**
Vegan	0.124	0.329	0.103	0.304	− 0.021
Vegetarian	0.178	0.383	0.140	0.348	− 0.038*
Pescatarian	0.194	0.396	0.184	0.388	− 0.010
Uses mobile App	0.937	0.243	0.782	0.413	− 0.155***
Number of profile updates	2.01	2.1	1	0	− 1.01***
Pre-treatment weeks available	67.3	58.5	59.7	47.6	− 7.55**
Mean pre-treatment footprint/week (kg CO_2e)	137	108	172	165	35.1***
Mean pre-treatment spending/week (000 s SEK)	11.7	15.8	14.6	39.5	2.81
Observations	510		1303		1813

The table presents characteristics and data from two users groups. Column 1 presents users that adopts the calculator before 2020 and connects their bank at least twice, thus providing post-treatment data. Column 2 presents users that adopt the calculator before 2020 and connects their bank exactly once, thus only providing pre-treatment data. Column 3 presents the difference in means between the two groups, with asterisks indicating any statistically significant difference from a simple t-test, with * $p < 0.1$, ** $p < 0.5$, *** $p < 0.01$

Table 8 App installation and carbon footprint: total footprint and four sub-categories

	(1) Total	(2) Transportation	(3) Goods and services	(4) Food and beverages	(5) Residential energy
< − 8	0.012	− 0.065	0.054	0.002	− 0.040
	(0.027)	(0.044)	(0.037)	(0.031)	(0.035)
− 8	0.021	− 0.034	0.031	0.021	0.018
	(0.035)	(0.059)	(0.049)	(0.037)	(0.048)
− 7	− 0.003	− 0.172***	0.066	− 0.022	− 0.020
	(0.034)	(0.058)	(0.047)	(0.037)	(0.047)
− 6	− 0.067**	− 0.090	− 0.106**	− 0.038	− 0.045
	(0.033)	(0.056)	(0.048)	(0.035)	(0.045)
− 5	− 0.008	− 0.047	0.063	0.014	− 0.019
	(0.031)	(0.055)	(0.045)	(0.033)	(0.043)
− 4	0.007	− 0.075	0.027	− 0.014	0.020
	(0.034)	(0.059)	(0.048)	(0.036)	(0.048)
− 3	− 0.036	− 0.107*	0.003	0.028	− 0.053
	(0.033)	(0.058)	(0.046)	(0.034)	(0.047)
− 2	− 0.014	− 0.057	0.015	0.005	− 0.065
	(0.031)	(0.056)	(0.045)	(0.034)	(0.046)
− 1	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
0	− 0.113**	− 0.167*	− 0.089	− 0.072	− 0.107
	(0.051)	(0.088)	(0.074)	(0.058)	(0.068)
1	− 0.110*	− 0.202**	− 0.124	− 0.008	− 0.151*
	(0.057)	(0.092)	(0.078)	(0.060)	(0.079)
2	− 0.074	− 0.283***	0.040	− 0.013	− 0.068
	(0.061)	(0.095)	(0.082)	(0.065)	(0.081)
3	− 0.075	− 0.152	− 0.008	− 0.121*	− 0.096
	(0.056)	(0.104)	(0.081)	(0.067)	(0.077)
4	− 0.059	− 0.225**	− 0.042	− 0.025	− 0.065
	(0.060)	(0.107)	(0.086)	(0.065)	(0.083)
5	− 0.101	− 0.246**	0.017	− 0.056	− 0.110
	(0.064)	(0.100)	(0.088)	(0.066)	(0.085)
6	0.017	− 0.076	0.096	0.015	− 0.168**
	(0.065)	(0.110)	(0.089)	(0.070)	(0.085)
7	− 0.047	− 0.250**	0.058	− 0.071	− 0.012
	(0.061)	(0.108)	(0.089)	(0.068)	(0.086)
8	− 0.075	− 0.083	− 0.010	− 0.182**	− 0.079
	(0.067)	(0.114)	(0.096)	(0.074)	(0.084)
9	− 0.104	− 0.323***	0.014	− 0.085	− 0.019
	(0.074)	(0.112)	(0.097)	(0.083)	(0.102)
10	− 0.115	− 0.216*	− 0.115	− 0.125	0.017
	(0.073)	(0.113)	(0.102)	(0.081)	(0.104)
11	− 0.093	− 0.025	− 0.181*	− 0.033	− 0.101
	(0.079)	(0.119)	(0.103)	(0.096)	(0.097)

Table 8 (continued)

	(1) Total	(2) Transportation	(3) Goods and services	(4) Food and beverages	(5) Residential energy
12	0.006	− 0.124	0.054	− 0.105	0.011
	(0.074)	(0.125)	(0.107)	(0.087)	(0.098)
13	− 0.065	− 0.096	− 0.037	− 0.093	0.057
	(0.086)	(0.134)	(0.113)	(0.092)	(0.121)
14	− 0.088	0.019	0.040	− 0.052	− 0.233**
	(0.089)	(0.137)	(0.122)	(0.095)	(0.118)
15	0.028	0.217	0.021	0.020	− 0.030
	(0.080)	(0.145)	(0.111)	(0.097)	(0.113)
16	− 0.018	− 0.022	− 0.040	− 0.012	0.015
	(0.083)	(0.146)	(0.117)	(0.110)	(0.110)
17	− 0.029	− 0.012	0.069	− 0.013	− 0.112
	(0.093)	(0.154)	(0.126)	(0.103)	(0.127)
18	− 0.009	− 0.091	0.023	0.060	0.030
	(0.091)	(0.152)	(0.122)	(0.107)	(0.127)
19	0.023	− 0.175	0.037	0.106	− 0.060
	(0.097)	(0.152)	(0.129)	(0.113)	(0.128)
20	− 0.137	− 0.118	− 0.003	− 0.157	− 0.204
	(0.096)	(0.153)	(0.133)	(0.119)	(0.134)
21	0.028	0.034	0.083	− 0.053	0.072
	(0.102)	(0.158)	(0.141)	(0.115)	(0.142)
22	0.013	0.183	− 0.103	0.048	− 0.202
	(0.106)	(0.185)	(0.134)	(0.115)	(0.131)
23	− 0.015	− 0.066	0.074	0.078	− 0.159
	(0.122)	(0.174)	(0.152)	(0.139)	(0.156)
24	− 0.011	0.104	0.031	0.038	0.006
	(0.107)	(0.191)	(0.140)	(0.136)	(0.132)
25	− 0.206*	− 0.159	− 0.206	− 0.137	− 0.111
	(0.114)	(0.166)	(0.149)	(0.135)	(0.146)
26	0.013	− 0.022	0.015	0.125	0.082
	(0.130)	(0.184)	(0.167)	(0.156)	(0.179)
27	− 0.246*	− 0.162	− 0.199	− 0.053	− 0.097
	(0.140)	(0.191)	(0.176)	(0.157)	(0.184)
28	0.050	0.184	− 0.020	0.052	− 0.051
	(0.139)	(0.210)	(0.184)	(0.157)	(0.193)
29	0.026	0.128	0.072	− 0.063	− 0.245
	(0.129)	(0.232)	(0.170)	(0.166)	(0.175)
30	− 0.015	− 0.164	0.300	− 0.204	− 0.044
	(0.156)	(0.225)	(0.203)	(0.180)	(0.202)
> 30	− 0.033	0.102	− 0.033	− 0.005	− 0.087
	(0.087)	(0.127)	(0.103)	(0.141)	(0.131)
User FE	Yes	Yes	Yes	Yes	Yes
Week-by-year FE	Yes	Yes	Yes	Yes	Yes

Table 8 (continued)

	(1) Total	(2) Transportation	(3) Goods and services	(4) Food and beverages	(5) Residential energy
Observations	167,798	167,798	167,798	167,798	167,798
Mean dependent var	4.208	1.477	2.639	2.915	1.438
Sd. of dependent var	1.386	1.815	1.650	1.522	1.606
Users	2519	2519	2519	2519	2519

The table presents results from estimating the event study model specified in Eq. (1) and illustrated in Figs. 3 and 4. The dependent variable is log(CO_2e+1), where CO_2e is consumption-based carbon-equivalent emissions. Column 1 uses total emissions, while subsequent columns use emissions from the four main consumption categories further specified in Sect. 3. All models are estimated using the approach suggested by Sun and Abraham (2021), which accounts for possible heterogenous treatment effects depending on when users install the App. All models control for user and time fixed effects. Standard errors are presented in parentheses and clustered on users

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

Table 9 The carbon calculator and carbon footprints: sensitivity

	(1) Ln(CO_2e+1)	(2) Ln(CO_2e+1)	(3) Ln(CO_2e+1)	(4) CO_2e	(5) asinh(CO_2e)	(6) Ln(CO_2e+1)	(7) Ln(CO_2e+1)	(8) Ln(CO_2e+1)
4 weeks before treatment	− 0.014	− 0.014	− 0.015	− 0.494	− 0.014	− 0.011	− 0.010	− 0.003
	(0.015)	(0.015)	(0.015)	(4.237)	(0.016)	(0.015)	(0.017)	(0.011)
Week 0–4	− 0.089***	− 0.092***	− 0.091***	− 9.236	− 0.101***	− 0.089***	− 0.091***	− 0.067***
	(0.028)	(0.028)	(0.028)	(5.797)	(0.030)	(0.026)	(0.029)	(0.020)
Week 5–12	− 0.067**	− 0.070**	− 0.071**	− 12.284**	− 0.071**	− 0.064**	− 0.062*	− 0.053**
	(0.031)	(0.032)	(0.032)	(5.562)	(0.034)	(0.030)	(0.033)	(0.022)
> 12 weeks	− 0.043	− 0.045	− 0.044	− 11.325	− 0.046	− 0.044	− 0.051	− 0.036
	(0.035)	(0.035)	(0.035)	(7.098)	(0.038)	(0.035)	(0.035)	(0.022)
User FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	167,798	167,798	167,798	167,798	167,728	170,930	163,194	167,728
Mean dependent var	4.213	4.219	4.220	149.122	4.852	4.207	4.206	4.499
Sd. of dependent var	1.391	1.399	1.402	361.208	1.479	1.384	1.389	0.958
Users	2519.000	2519.000	2519.000	2519.000	2518.000	2536.000	2490.000	2518.000

The table presents results from estimating the event study model specified in Eq. (1), but with relative times around treatment adoption binned into four variables that are used as independent variables: 4 weeks before treatment, 0–4 weeks after treatment, 5–12 weeks after treatment, and all subsequent weeks. CO_2e is consumption-based carbon-equivalent emissions. Columns 1–3 vary the threshold over which uncategorized expenditures are counted as savings-equivalent with zero emissions, as further explained in Sect. 3. Column 5 uses the hyperbolic sine transformation of CO_2e as the dependent variable. Column 6 and 7 use alternative control groups compared to the main analyses, which use as control those that adopt the App in 2020 before the pandemic in early March. Column 6 uses as control those that adopt the App after November 2019 and before the pandemic, and column 7 uses as control those that adopt the App after January 2020 and before the pandemic. Column 8 is the same as the main analyses in column 1 of Table 4, but includes emissions from extrapolated consumption data, as further explained in Sect. 3. All models are estimated using the approach suggested by Sun and Abraham (2021), which accounts for possible heterogeneous treatment effects depending on when users install the App. All models control for user and time fixed effects. Standard errors are presented in parentheses and are clustered on users

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

Acknowledgements We are grateful to two anonymous reviewers, Christina Gravert, Johannes Haushofer, Randi Hjalmarsson, Katarina Nordblom, Abhijeet Singh, David Strömberg, and Måns Söderbom for extensive feedback, as well as participants at seminars held at the University of Gothenburg and the Center for Collective Action Research (CeCAR) for helpful comments and suggestions. We are grateful to the Swedish Research Council for Sustainable Development (Formas, Grant Number 2019-02011) and the Swedish Foundation for Strategic Environmental Research (Mistra, Grant Number 2016/3) for grant funding. Raw user data has been provided by Ross Linscott at Svalna inc. Enlund and Carlsson have done additional data processing and are solely responsible for the empirical analysis and all conclusions from it, since Andersson is also CEO and founder of Svalna Inc.

Funding Open access funding provided by Linnaeus University.

References

Al-Ubaydli O, List JA, LoRe D, Suskind D (2017) Scaling for economists: lessons from the non-adherence problem in the medical literature. J Econ Perspect 31(4):125–144

Allcott H (2011) Social norms and energy conservation. J Public Econ 95(9–10):1082–1095

Allcott H, Rogers T (2014) The short-run and long-run effects of behavioral interventions: experimental evidence from energy conservation. Am Econ Rev 104(10):3003–3037

Allcott H, Taubinsky D (2015) Evaluating behaviorally motivated policy: experimental evidence from the lightbulb market. Am Econ Rev 105(8):2501–2538

Andersson D (2020) A novel approach to calculate individuals' carbon footprints using financial transaction data-app development and design. J Clean Prod 256:120396

Andersson D, Nässén J (2023) Measuring the direct and indirect effects of low-carbon lifestyles using financial transactions. J Clean Prod 386:135739

Andor MA, Gerster A, Sommer S (2020) Consumer inattention, heuristic thinking and the role of energy labels. Energy J 41(1)

Andreoni J (1990) Impure altruism and donations to public goods: a theory of warm-glow giving. Econ J 100(401):464–477

Angrist JD, Pischke J-S (2008) Mostly harmless econometrics: an empiricist's companion. Princeton University Press, Princeton

Asensio OI, Delmas MA (2015) Nonprice incentives and energy conservation. Proc Natl Acad Sci 112(6):E510–E515

Baca-Motes K, Brown A, Gneezy A, Keenan EA, Nelson LD (2013) Commitment and behavior change: evidence from the field. J Consum Res 39(5):1070–1084

Bjelle EL, Steen-Olsen K, Wood R (2018) Climate change mitigation potential of Norwegian households and the rebound effect. J Clean Prod 172:208–217

Bonan J, Cattaneo C, d'Adda G, Tavoni M (2021) Can social information programs be more effective? The role of environmental identity for energy conservation. J Environ Econ Manag 108:102467

Borusyak K, Jaravel X, Spiess J (2021) Revisiting event study designs: robust and efficient estimation. arXiv preprint arXiv:2108.12419

Brent DA, Lott C, Taylor M, Cook J, Rollins K, Stoddard S (2020) What causes heterogeneous responses to social comparison messages for water conservation? Environ Resour Econ 77(3):503–537

Buchanan K, Russo R, Anderson B (2015) The question of energy reduction: the problem (s) with feedback. Energy Policy 77:89–96

Callaway B, Sant'Anna PH (2021) Difference-in-differences with multiple time periods. J Econom 225(2):200–230

Carlsson F, Gravert C, Johansson-Stenman O, Kurz V (2021) The use of green nudges as an environmental policy instrument. Rev Environ Econ Policy 15(2):216–237

Carlsson Kanyama A, Nässén J, Benders R (2021) Shifting expenditure on food, holidays, and furnishings could lower greenhouse gas emissions by almost 40%. J Ind Ecol 25(6):1602–1616
Chetty R, Looney A, Kroft K (2009) Salience and taxation: theory and evidence. Am Econ Rev 99(4):1145–1177
Cialdini RB (2003) Crafting normative messages to protect the environment. Curr Dir Psychol Sci 12(4):105–109
Costa DL, Kahn ME (2013) Energy conservation "nudges'' and environmentalist ideology: evidence from a randomized residential electricity field experiment. J Eur Econ Assoc 11(3):680–702
Cunningham S (2021) Causal inference: the mixtape. Yale University Press, New Haven
Czajkowski M, Hanley N, Nyborg K (2017) Social norms, morals and self-interest as determinants of pro-environment behaviours: the case of household recycling. Environ Resour Econ 66(4):647–670
De Chaisemartin C, d'Haultfoeuille X (2020) Two-way fixed effects estimators with heterogeneous treatment effects. Am Econ Rev 110(9):2964–2996
Ek C, Söderberg M (2021) Norm-based feedback on household waste: large-scale field experiments in two Swedish municipalities
Fawcett T (2010) Personal carbon trading: a policy ahead of its time? Energy Policy 38(11):6868–6876
Fawcett T, Parag Y (2010) An introduction to personal carbon trading
Ferraro PJ, Miranda JJ, Price MK (2011) The persistence of treatment effects with norm-based policy instruments: evidence from a randomized environmental policy experiment. Am Econ Rev 101(3):318–322
Ferraro PJ, Price MK (2013) Using nonpecuniary strategies to influence behavior: evidence from a large-scale field experiment. Rev Econ Stat 95(1):64–73
Festinger L (1962) A theory of cognitive dissonance, vol 2. Stanford University Press, Redwood City
Fosgaard TR, Pizzo A, Sadoff S (2021) Do people respond to the climate impact of their behavior? The effect of carbon footprint information on grocery purchases. Technical report, IFRO Working Paper
Frey BS (1993) Motivation as a limit to pricing. J Econ Psychol 14(4):635–664
Fuso Nerini F, Fawcett T, Parag Y, Ekins P (2021) Personal carbon allowances revisited. Nat Sustain 4(12):1025–1031
Giné X, Karlan D, Zinman J (2010) Put your money where your butt is: a commitment contract for smoking cessation. Am Econ J Appl Econ 2(4):213–235
Girod B, De Haan P (2010) More or better? a model for changes in household greenhouse gas emissions due to higher income. J Ind Ecol 14(1):31–49
Goeschl T, Kettner SE, Lohse J, Schwieren C (2018) From social information to social norms: evidence from two experiments on donation behaviour. Games 9(4):91
Goodman-Bacon A (2021) Difference-in-differences with variation in treatment timing. J Econom 225:254–277
Gravert C, Collentine LO (2021) When nudges aren't enough: norms, incentives and habit formation in public transport usage. J Econ Behav Organ 190:1–14
Harding M, Hsiaw A (2014) Goal setting and energy conservation. J Econ Behav Organ 107:209–227
Heiskanen E, Johnson M, Robinson S, Vadovics E, Saastamoinen M (2010) Low-carbon communities as a context for individual behavioural change. Energy Policy 38(12):7586–7595
Ivanova D, Barrett J, Wiedenhofer D, Macura B, Callaghan M, Creutzig F (2020) Quantifying the potential for climate change mitigation of consumption options. Environ Res Lett 15(9):093001
Jessoe K, Rapson D (2014) Knowledge is (less) power: experimental evidence from residential energy use. Am Econ Rev 104(4):1417–1438
Kallbekken S, Sælen H (2013) 'Nudging'hotel guests to reduce food waste as a win-win environmental measure. Econ Lett 119(3):325–327
Kažukauskas A, Broberg T, Jaraitė J (2021) Social comparisons in real time: a field experiment of residential electricity and water use. Scand J Econ 123(2):558–592
Kennelly MA, Ainscough K, Lindsay KL, O'Sullivan E, Gibney ER, McCarthy M, Segurado R, DeVito G, Maguire O, Smith T et al (2018) Pregnancy exercise and nutrition with smartphone application support: a randomized controlled trial. Obstet Gynecol 131(5):818–826
Klege RA, Visser M, Datta S, Darling M (2022) The power of nudging: using feedback, competition, and responsibility assignment to save electricity in a non-residential setting. Environ Resour Econ 81(3):573–589
Kormos C, Gifford R, Brown E (2015) The influence of descriptive social norm information on sustainable transportation behavior: a field experiment. Environ Behav 47(5):479–501
Kotchen MJ, Moore MR (2007) Private provision of environmental public goods: household participation in green-electricity programs. J Environ Econ Manag 53(1):1–16

Kurz V (2018) Nudging to reduce meat consumption: immediate and persistent effects of an intervention at a university restaurant. J Environ Econ Manag 90:317–341
Löfgren Å, Nordblom K (2020) A theoretical framework of decision making explaining the mechanisms of nudging. J Econ Behav Organ 174:1–12
Lopez-Becerra E, Alcon F (2021) Social desirability bias in the environmental economic valuation: an inferred valuation approach. Ecol Econ 184:106988
Mazar N, Zhong C-B (2010) Do green products make us better people? Psychol Sci 21(4):494–498
Miller DT, Prentice DA (2016) Changing norms to change behavior. Annu Rev Psychol 67:339–361
Newell RG, Siikamäki J (2014) Nudging energy efficiency behavior: the role of information labels. J Assoc Environ Resour Econ 1(4):555–598
Nyborg K, Anderies JM, Dannenberg A, Lindahl T, Schill C, Schlüter M, Adger WN, Arrow KJ, Barrett S, Carpenter S et al (2016) Social norms as solutions. Science 354(6308):42–43
Roth J, Sant'Anna PH, Bilinski A, Poe J (2022) What's trending in difference-in-differences? A synthesis of the recent econometrics literature. arXiv preprint arXiv:2201.01194
Salo M, Mattinen-Yuryev M, Nissinen A (2019) Opportunities and limitations of carbon footprint calculators to steer sustainable household consumption-analysis of Nordic calculator features. J Clean Prod 207:658–666
Semper H, Povey R, Clark-Carter D (2016) A systematic review of the effectiveness of smartphone applications that encourage dietary self-regulatory strategies for weight loss in overweight and obese adults. Obes Rev 17(9):895–906
Statistics Sweden (2022) Statistical database at statistics Sweden. Available at https://www.statistikdatabasen.scb.se/pxweb/en/ssd/ Accessed 9 Mar 2022
Sun L, Abraham S (2021) Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. J Econom 225(2):175–199
Thøgersen J, Ölander F (2003) Spillover of environment-friendly consumer behaviour. J Environ Psychol 23(3):225–236
Tiefenbeck V, Goette L, Degen K, Tasic V, Fleisch E, Lalive R, Staake T (2018) Overcoming salience bias: how real-time feedback fosters resource conservation. Manag Sci 64(3):1458–1476
Torres MMJ, Carlsson F (2018) Direct and spillover effects of a social information campaign on residential water-savings. J Environ Econ Manag 92:222–243
Tukker A, de Koning A, Owen A, Lutter S, Bruckner M, Giljum S, Stadler K, Wood R, Hoekstra R (2018) Towards robust, authoritative assessments of environmental impacts embodied in trade: current state and recommendations. J Ind Ecol 22(3):585–598
Vanclay JK, Shortiss J, Aulsebrook S, Gillespie AM, Howell BC, Johanni R, Maher MJ, Mitchell KM, Stewart MD, Yates J (2011) Customer response to carbon labelling of groceries. J Consum Policy 34(1):153–160
Vervloet M, Linn AJ, van Weert JC, De Bakker DH, Bouvy ML, Van Dijk L (2012) The effectiveness of interventions using electronic reminders to improve adherence to chronic medication: a systematic review of the literature. J Am Med Inform Assoc 19(5):696–704