Fighting Climate Change with FinTech*

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Abstract

We study the environmental sustainability of individuals' consumption choices using unique data from a FinTech App that tracks users' spending and emissions at the transaction level. Using a randomized encouragement design, we show that individuals are likely to purchase carbon calculator services that provide them with detailed transaction-level information about their emissions. However, such a tool does not cause significant changes in their consumption and emissions. On the other hand, services that offset individuals' emissions by planting trees are less likely to be adopted but prove effective in reducing users' net emissions. Conditioning on age, gender, and income does not alter our findings. Our results show the challenges and opportunities associated with the automated tools promoting sustainable behavior that were initially confined to specialized FinTech Apps and are now becoming widespread across large financial institutions.

Keywords: FinTech, Climate Change, Household Finance, Sustainable Behavior

JEL Classification: D14, G41, G51

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1 Introduction

Taming the risks of climate change represents one of humanity's most pressing challenges.[1] In response to this call, local and national governments from both developed and developing countries have implemented cap-and-trade and tax policies to reduce emissions from *corporations*.[2] These policies have received a lot of attention, and there is still much debate about their optimal design, effectiveness and unintended consequences (see Andersson, 2019, Metcalf, 2021, Blanchard, Gollier, and Tirole, 2023, and Metcalf and Stock, 2023).

On the other hand, much less is known about how to help *individuals* reduce their emissions. This is critical to fight climate change for at least two reasons. First, estimates from many developed countries indicate that households' direct emissions account for one-third, while including indirect emissions account for up to 70% of global emissions (see Druckman and Jackson, 2016 and Goldstein, Gounaridis, and Newell, 2020).[3] Second, the most recent projections from the Intergovernmental Panel on Climate Change (see IPCC, 2022) indicate that, with current policies and emission levels, the target of the 2015 Paris Agreement—i.e. to keep global warming well below 2 degrees Celsius and make a good-faith effort to stay at 1.5 degrees by 2100—will not be met.

FinTech Apps represent a promising tool to promote sustainable behavior among consumers. First, due to the high penetration of mobile phones worldwide, they can be deployed on a large scale.[4] Second, they have been shown to help overcome households' biases and improve spending (Ben-David, Mintz, and Sade, 2021, Lee, 2023 and Carlin, Olafsson, and Pagel, 2023), saving (Medina and Pagel, 2021 and Gargano and Rossi, 2022), and investment decisions (e.g., Gargano and Rossi, 2018 and Rossi and Utkus, 2020). On the other hand, it is not clear the extent to which the biases and frictions that prevent individuals from adopting more sustainable habits are similar in nature to those preventing optimal financial decision-making and can therefore be corrected with interventions through FinTech Apps.

[1] See Litterman et al. (2020) for an overview of the risks posed to the financial system and Dell, Jones, and Olken (2014) for an overview of the risks for the broader economy.

[2] See https://carbonpricingdashboard.worldbank.org for a complete list of carbon pricing initiatives.

[3] Direct emissions arise due to direct energy use in the home (heating, cooling, and powering) and due to burning personal transportation fuels (petrol and diesel) while indirect emissions are "embedded" in manufactured products or services through their supply chain).

[4] For example, Patnam and Yao (2020) study the effect of the adoption of mobile money services by 400 million users in India.

In this study, we partner with a digital bank that offers tools to help its customers monitor and reduce the environmental footprint associated with their consumption. The two services offered by the App are a "Footprint Calculator," which displays real-time carbon emissions associated with their transactions, and a "Carbon offsetting" program, pledging to offset individuals' emissions through reforestation projects.

Our setting represents a great laboratory because our industry partner was one of the first banks to introduce these tools. Large traditional banks are also starting to offer similar tools through their Apps and online interfaces.[5] While millions of individuals are therefore potentially exposed to these tools, there is no evidence on whether they have a *causal* impact on their consumption choices. Our dataset is extremely rich in that, for the universe of App users, we observe: the daily records of user deposits and expenditures, including monetary amounts, timestamps, and transaction channels (e.g., card, wire transfer, or ATM); the carbon footprint associated with card expenses, including CO2 emissions in grams and Merchant Category Codes for each transaction; daily updates on user activation of the carbon calculator and carbon offsetting features; information about App users, including profile creation dates, age, gender, enrollment date, residence location, birthplace, and other data relevant to Know Your Customer (KYC) compliance; and individual logins along with associated timestamps.

The App users are predominantly young, with an average age of 30, in line with similar studies that use FinTech App data. Consistent with their young age, 60% of our users have a monthly income of €1,250 or less, slightly below the national average of the country the App operates in, which equals €1,397. In terms of engagement and App usage, they log in 32% of the days, and transact 35% of the days, for an average transaction value of €59. Finally, the emissions tools offered by the company are relatively popular among its users: 26% of the users adopt the carbon calculator at some point; the corresponding value for the carbon offsetting tool is 7%.

While a number of studies assess which factors drive individuals' sustainable behavior for specific products, such as plastic cutlery, in quasi-experimental settings (see, e.g., Sachdeva and Zhao, 2021, Olson, 2013 and He et al., 2023), much less is known on how these decisions are made in the field across the full range of consumption categories. To this end, we provide stylized facts on how spending and emissions relate to each other, which also serves as a way to validate our data. We first present

[5]For example, Banco Santander, BNP Paribas, Standard Chartered, Nordea and Ålandsbanken.

results aggregating transactions at the merchant category code (MCC) level and show that spending is evenly spread across many categories. Second, we categorize spending and emissions into 13 categories according to the Classification of Individual Consumption According to Purpose (COICOP). For approximately half of the categories, the shares of spending and emissions are closely aligned. However, there are notable exceptions. Hotels and Restaurants, Transportation, and Utilities have a relatively high footprint compared to the monetary amount spent. At the other end of the spectrum, Recreation, Food and Beverage, and Clothing have a relatively small footprint. These deviations depend on certain spending categories, such as Utilities and Transport, having very high emissions per euro compared to the rest.

We then turn to study how spending and emissions vary at the individual level. As expected, we find a strong and positive correlation between total spending and carbon emissions. As spending levels increase, however, we also find an increase in the dispersion of emissions, indicating that individuals with higher spending have a broader range of consumption choices. When examining the relation between overall spending and the emissions per dollar, we find a non-monotonic relation: emissions per euro increase from low to medium spending levels, flatten for medium to high spending, and become negative thereafter. This pattern could be driven by two potential channels. First, it could be attributed to changes in consumption patterns as individuals' incomes increase, leading to differences in the types of products purchased. Second, it might be due to high-income individuals making more environmentally-friendly spending choices within each category. To distinguish between the two, we first analyze the share of spending across different consumption categories for low, medium, and high-spending individuals. In the second exercise, we examine average emissions per euro spent across these categories for individuals with different levels of spending. Our results suggest that differences in emissions per euro are primarily driven by variations in spending across consumption categories rather than by specific product choices within each category.

Whether FinTech can help in the fight against Climate Change, ultimately depends on whether tools aimed at helping individuals make more sustainable choices are effective. To this end, we proceed to study the causal effect of providing Carbon Calculator and Carbon Offsetting services on individuals' consumption choices. From a purely environmental perspective, reducing the risk of climate change entails reducing or offsetting emissions. Accordingly, we consider consumption and emissions as outcome variables. From an economic perspective, however, governments seek to limit emissions not by reducing consumption but by shifting it towards more carbon-efficient options. For this reason, we also consider the emissions per euro spent.

Establishing causality is challenging because certain user characteristics, like education, may influence both what people consume and whether they choose to subscribe to either service. While user fixed-effects can account for user time-invariant characteristics, people's sustainability preferences may change over time and impact their choice of adopting sustainability services as well as their consumption behavior. We overcome this identification challenge by exploiting the marketing campaigns run by the company to promote the adoption of its sustainability tools as a quasi-experimental encouragement design, whereby all subjects have access to the treatment, but some (the treated group) are randomly assigned to receive encouragement to take it. The marketing campaigns took place in July 2022, targeting specific users with email and app notifications to encourage them to adopt Carbon Calculator or Carbon Offsetting tools to combat climate change. We use this assignment to encouragement as an instrumental variable in our analysis.

In order to interpret our coefficient estimates causally, our instrument has to satisfy the relevance, exogeneity, and exclusion restriction conditions (Imbens and Angrist, 1994; Angrist, Imbens, and Rubin, 1996). We provide evidence of the instrument's relevance by showing that the marketing campaign significantly increased the adoption of the Carbon Calculator tool from 2.8% to 5.4% and the Carbon Offsetting tool from 0.4% to 0.8%. While the instrument's exogeneity is guaranteed by random assignment, we show that user characteristics are balanced between the treated and the control group. Finally, while the exclusion restriction that the encouragement to adopt the sustainability tools affects users' consumption behavior only through their adoption of such tools is inherently untestable, we provide formal tests that the encouragement does not change the behavior of those who do not adopt treatment.

We first assess the effectiveness of the Carbon Calculator tool in affecting individuals' sustainable behavior. While the previous literature suggests that offering tools to monitor consumption can reduce overspending, it is difficult to predict whether providing a carbon footprint calculator would similarly lead to reduced carbon emissions as the effectiveness of the carbon calculator likely depends on the reliability of the information it provides and users' ability to correctly interpret it. Empirically, we find that adopting the carbon calculator tool does not significantly impact users' behavior in terms of carbon emissions, spending, or emissions per euro. When we repeat the analysis conditioning on users' characteristics such as age, gender, and income, we find virtually no heterogeneity in our findings. Also note that our results are unlikely due to weak-instrument issues, as shown by standard Kleibergen-Paap (KP) Wald tests.

We then turn our attention to Carbon Offsetting. When they enroll in this service, users receive a monthly allowance, mechanically reducing their carbon footprint, but whether this leads to a decrease or increase in emissions relative to before adopting the tool depends on how users alter their consumption and associated gross emissions. We could envision four possible scenarios. In the first two "positive" scenarios, users may keep consumption and related gross emissions constant hence lowering their net emissions, or they could reduce their gross emissions, resulting in an even further reduction in their net emissions. A third possible scenario could be that users increase consumption and gross emissions up to the allowance amount. Drawing parallels with the medical literature, paying for carbon offsetting could be like taking medication without lifestyle changes, leading to positive estimates for consumption and gross emissions but no change in net emissions.[6] Finally, if users increase their gross emissions by more than the allowance, both gross and net emissions could rise after adopting carbon offsetting.

Our instrumental variable (IV) results show that adopting Carbon Offsetting does not alter consumption behavior but reduces users' net emissions and net emissions per euro to almost zero. When we repeat the analysis conditioning on user characteristics such as age, gender, and income, we find virtually no heterogeneity in our findings. These results rule out the third and fourth scenarios described above but are consistent with the first or second scenarios. That is, it could be that carbon offsetting causes users to decrease their gross emissions and their gross emissions per euro or that users do not change their behavior, and the whole difference derives from the carbon offsetting mechanical feature. To disentangle these two potential mechanisms, we recompute our results using gross emis-

[6] Korhonen et al. (2020) show that individuals continue with their unhealthy habits and are even more likely to engage in them after starting antihypertensive or statin pills treatment.

sions and gross emissions per euro and find that carbon offsetting does not cause changes in either one, suggesting that adopting carbon offsetting causes a mechanical reduction in users' emissions but does not change their behavior, so it does not affect their gross emissions behavior.

Our instrumental variable (IV) estimates represent Local Average Treatment Effects (LATE), that is, the causal effect of adopting the carbon calculator or the carbon offsetting tool after a random encouragement design. From a policy perspective, one could be interested in the Intent-To-Treat (ITT) estimate that is instead the causal effect of receiving a random notification regarding the carbon calculator or the carbon footprint tool, irrespective of whether the user ultimately signs up for the tool. In line with the IV results, we find no effect for Carbon Calculator but find a significant negative effect due to Carbon Offsetting for both emissions and emissions per Euro.

Our results show the challenges and opportunities associated with tools promoting sustainable behavior. While, on the one hand, users are more likely to subscribe to Carbon Calculator services, they do not have a significant effect on promoting sustainable behavior. Carbon Offsetting tools, on the other hand, have much lower adoption but are effective in reducing emissions.

2 Literature Review

This paper contributes to the literature on Financial Technology (FinTech) and household behavior. FinTech encompasses a broad range of new technologies that seek to improve and automate the delivery and use of financial services (see Das, 2019 for a review of the literature). A recent strand of the literature shows that FinTech can help households improve their investment and borrowing decisions (e.g. Gargano and Rossi, 2018, D'Acunto, Prabhala, and Rossi, 2019, Rossi and Utkus, 2020 and Di Maggio, Ratnadiwakara, and Carmichael (2022)), to reduce overspending (Ben-David, Mintz, and Sade, 2021, Lee, 2023, Levi, 2023 and D'Acunto, Rossi, and Weber, 2019), to better conduct house searches (Gargano, Giacoletti, and Jarnecic, 2023) and to save on bank fees (Carlin, Olafsson, and Pagel, 2019 and Loh and Choi, 2020). At the same time, another strand of the literature highlights the pitfalls generated by the introduction of new technologies. For example, Fuster et al. (2018) find that Black and Hispanic borrowers are disproportionately less likely to gain from the introduction of machine learning tools to predict creditworthiness, while Di Maggio and Yao (2020) find that FinTech borrowers are significantly more likely to default than their peers borrowing from traditional financial institutions. Laudenbach, Pirschel, and Siegel (2018) find that borrowers who speak directly with a bank agent are significantly less likely to default. We contribute to this literature by exploring the benefits and challenges of financial technology in promoting sustainable consumption, which remains largely unexplored.

Second, we contribute to the literature on climate finance (see Giglio, Kelly, and Stroebel (2021) and Hong, Karolyi, and Sheinkmann (2020) for a review of the literature). Since the seminal papers of Nordhaus (1977, 1991), the literature has mainly focused on quantifying the risks posed by climate change to the financial system (see, e.g., Litterman et al. (2020) and Acharya et al. (2023)), the extent to which they are priced,[7] and how to hedge them (Engle et al., 2020 and Alekseev et al., 2023). More recently, there has been an increasing interest in measuring awareness and attitudes toward climate change among consumers and retail investors.[8] This is crucial since the implementability and efficacy of policies aimed at curbing emissions depend on the support they have in public opinion. Moreover, risks are correctly incorporated into prices only to the extent that investors are able to evaluate them correctly. D'Acunto et al. (2022), Rodemeier (2023), Dechezleprêtre et al. (2023) and Bernard, Tzamourani, and Weber (2023) run information treatment experiments to study which factors affect consumers' support for policies aimed at reducing emissions and their willingness to pay for their implementation. Barber, Morse, and Yasuda (2021), Bauer, Ruof, and Smeets (2021), Heeb et al. (2023) and Giglio et al. (2023) study investors' preferences for sustainable investments and how they balance the trade-off between positive environmental impact and (possible) financial underperformance. We contribute to this literature by studying *actual consumption* choices. This is important because consumption decisions are a key driver of carbon emissions. Moreover, individuals frequently assert their commitment to sustainable behavior yet fail to substantiate their claims through corresponding actions (see List and Gallet, 2001 and Murphy et al., 2005).

Third, we contribute to the extensive body of research on (behavioral) interventions aimed at promoting sustainable behavior among households. Purely behavioral interventions range from social

[7]See Bolton and Kacperczyk (2021) for evidence on the stock markets, Painter (2020) for fixed-income markets and for the housing markets.

[8]Choi, Gao, and Jian (2020) study retail investors and find that they sell carbon-intensive firms when experiencing warmer than usual temperatures in their area. See Alok, Kumar, and Wermers (2020) and Krueger, Sautner, and Starks (2020) for evidence on professional investors.

comparison to information provisions and nudges.[9] Financial interventions offer instead monetary incentives through subsidies (when promoted by governments) or discounts. These studies typically focus on energy usage, since it is an outcome directly observable and represents the most important component of households' direct emissions, and have limited sample sizes of less than 500 subjects (Nisa et al. (2019)).[10] The evidence is highly mixed and context-specific. Nisa et al. (2019) review randomized field trials and find that behavioral interventions targeting frequently occurring behaviors (e.g., energy and water saving at home, recycling, food waste), taken alone, have very little effects on households' actions with no evidence of sustained positive effects once the intervention ends. Similarly, Gillingham, Keyes, and Palmer (2018) conclude that, while behavioral interventions are the most cost-effective, the magnitude of their savings potential is relatively small. On the contrary, Dietz et al. (2009) and Stern (2020) argue that interventions are effective when they target decisions with permanent effects, such as upgrading the energy efficiency of building shells or adopting more energy-efficient home power systems or vehicles. They also find that behavioral interventions are effective when combined with financial incentives or other interventions aimed at reducing non-behavioral barriers. We contribute to this literature by studying the effect of promoting sustainable behavior on overall consumption and by focusing on a large-scale intervention.

3 Data and Summary Statistics

In this section, we describe the App, illustrate the data used in the analysis and present summary statistics.

3.1 The App

The data used in this study were shared by a European FinTech app with deposit and payment features. What makes our setting unique is the fact that the App also offers its customers tools to monitor and manage the footprint/emissions resulting from their spending.

More specifically, by paying a fee of €2.50, users can subscribe to the "Footprint Calculator"

[9] Information provision interventions range from simple messages conveying tips on how to save energy to in-home displays, energy labels, or statistics about climate change.

[10] Other areas of intervention cover transportation choices, consumption of meat and recycling.

tool, which displays the carbon emissions from card transactions. Once activated, the information is displayed in the same section of the App where users can monitor their monthly total spending and individual transactions. Similarly to the monetary amount of a transaction, information on carbon footprint is updated in real-time once the transaction is approved, while the cumulated monthly figure resets to zero at the beginning of each month. The technology used to produce information on users' carbon footprint is provided by a third party—an industry leader in this space. The footprint of each transaction is obtained by multiplying its monetary amount by the emissions per euro of the associated Merchant Category Codes (MCCs), which in turn are constructed using proprietary technology. While the company we study was one of the first to establish this partnership, nowadays also large traditional banks in Europe (for example, Banco Santander,[11] BNP Paribas,[12] Standard Chartered,[13] and Ålandsbanken[14]) offer the same tool to its customers. More broadly, payment companies such as Mastercard and Klarna also offer this information to their customers.

With an additional fee of €7, users can also subscribe to the "Carbon offsetting" program, whereby the company pledges to offset up to 1,000kg of emissions per month by partnering with external entities that engage in reforestation projects. Note that reforestation is one of the most economically efficient ways to perform carbon offsetting (Van Kooten and Johnston, 2016). It is also the most widespread. As of May 2023, the data from the Berkeley Carbon Trading Project's Voluntary Registry Offsets Database,[15] which contains all carbon offset projects listed globally by four major voluntary offset project registries,[16] indicates that 40% of the projects are related to forestry and land use. Finally, other FinTech companies like AliPay reward their users' environmentally friendly decisions by planting trees.[17]

The €7 carbon offsetting price is also in line with the rest of the industry. Conte and Kotchen

[11] See https://www.santander.com/en/press-room/press-releases/2022/05/new-feature-on-santander-website-and-app-lets-customers-measure-carbon-footprint

[12] See https://www.prnewswire.com/news-releases/bank-of-the-west-bnp-paribas-first-us-bank-to-team-with-doconomy-to-enable-customers-to-track-co2-impact-of-purchases-300972553.html

[13] See https://www.sc.com/en/media/press-release/weve-partnered-with-doconomy-to-help-clients-manage-their-everyday-climate-impact-digitally/

[14] See https://www.alandsbanken.com/news/aland-index-nar-ut-till-40-miljoner-kunder-globalt

[15] Available here, https://gspp.berkeley.edu/research-and-impact/centers/cepp/projects/berkeley-carbon-trading-project/offsets-database

[16] American Carbon Registry (ACR), Climate Action Reserve (CAR), Gold Standard, and Verra (VCS). These four registries generate almost all of the world's voluntary market offsets

[17] See https://unfccc.int/climate-action/momentum-for-change/planetary-health/alipay-ant-forest

(2009) which factors explain the price variability of voluntary carbon offsets. They find that the price to offset 1,000kg of emissions ranges from a low of \$2.55 to a high of \$69.2, with the majority of the prices falling between \$10 and \$25.

3.2 The Dataset

The data is in the form of five SQL tables named *Transactions*, *Footprint*, *Subscription*, *Users*, and *Logins*. The company anonymized all information to guarantee user privacy. The sample covered by the data starts in January 2022 and ends in May 2023.

Transactions. This table contains information on all the deposits and expenditures associated with each user at the daily frequency. For each transaction, we have information on the monetary amount, time-stamp, and channel (e.g., card, wire transfer, or ATM).

Footprint. This table contains information on the footprint associated with card expenses. For each transaction, we observe the C02 emission (in grams), and the Merchant Category Code.

Subscription. This table contains daily information on whether a user has activated the carbon calculator and/or the carbon offsetting features.

Users. This table contains information on the users who created a profile on the App since its inception. The main variables contained in this table are the dates of opening and closing of a profile. Additional information includes users' age, gender, enrollment date, location of residence, place of birth, and other questions related to Know Your Customer (KYC) compliance.

Login. This table contains information on the individual logins (with associated time stamps).

3.3 Summary Statistics

Table 1 reports cross-sectional summary statistics computed in two steps. We first compute the value of each variable at the user level and then report the distribution of the variable across all users. For each variable, we report the number of observations used in the second step of the computations, the mean, standard deviation, and the 1st, 25th, 50th, 75th, and 99th percentiles.

Panel A shows that 70% of the users are males, suggesting that women are either less targeted by Financial Apps or are less interested in these tools in the country the App operates. Users are rather young, with an average age of 30 consistent with other studies using FinTech App data.[18] Finally, in terms of income, 60% of the respondents have a monthly income of €1,250 or less which is slightly lower than the average value of €1,397 in the Survey of Household Income and Wealth run by the Central Bank of the country where the App operates. This is partially expected given the relatively young age of the users.

Panel B reports results on App usage. The average user logs in 32% of the days, i.e., once every three days, and, conditional on logging in, they log in almost three times per day.

Panel C reports statistics on spending and emissions. Similar to the logging activity, the average user transacts on the App 35% of the days, and, conditional on spending, they perform almost two transactions per day for a total of €59. Finally, 26% of users adopt the carbon calculator at some point in time, while 7% of users adopt the carbon offsetting tool.

4 Spending and Emissions Patterns

In this section, we study the patterns of users' spending and emissions. This analysis serves two important purposes. First, because, to the best of our knowledge, we are the first to observe micro data on both spending and emissions, it is natural to explore the relation between the two. While a number of studies assess which factors drive individuals' sustainable behavior for specific products, such as plastic cutlery, in quasi-experimental settings (see e.g. Sachdeva and Zhao, 2021, Olson, 2013 and He et al., 2023), much less is known on how these decisions are made in the field across the full range of consumption categories. Second, because emissions are ultimately estimated from spending, it is important to validate our data.

Section 4.1 presents results on how users' consumption and emissions are distributed across consumption categories, while section 4.2 presents the results on the relation between consumption and emissions at the individual level.

[18]See D'Acunto et al. (2020), Becker (2017) and Olafsson and Pagel (2018)

4.1 Distribution of Spending and Emissions Across Consumption Categories

A first natural concern is that users might use the app only for a limited set of spending categories, making the data not representative of their overall consumption and emissions. To verify this is not the case, we compute the Normalized Herfindahl–Hirschman Index (HHI) of users' spending and emissions shares across merchant category codes (MCCs) from card transactions.[19] This measure is bounded between 0 and 1; a value of 1 indicates that a user uses the app only for a single category, while a value of 0 means that usage is uniformly distributed across multiple categories.

Panel A of Figure 1 reports the resulting cross-sectional distributions: red bars refer to spending, while blue bars refer to emissions. The mean and median values for the HHI of spending (emissions) are 0.15 and 0.09 (0.19 and 0.14), respectively. Moreover, less than 1% of users display an HHI equal to one. These results indicate that app usage is quite evenly spread across different categories.[20] While there is a high degree of correlation between the two distributions ($\rho = 0.72$), the overlap is not perfect. This is due to the fact that emissions in a given category depend on both the amount an individual spends and the carbon per euro of that category. The fact that the HHI distribution of emissions is shifted to the right indicates that some consumption categories have a relatively high footprint compared to others.

Next, we study users' spending and emission habits to shed further light on their distribution across consumption categories. We first map merchant category codes from card transactions to the two-digit Classification of Individual Consumption According to Purpose (COICOP). This is a classification developed by the United Nations Statistics Division to classify and analyze consumption expenditures incurred by households and comprises 13 categories.[21] We then compute, for each user, the fraction of spending and emission in each category using the entire sample, and report the average

[19] The Normalized HHI is equal to $\frac{HHI - \frac{1}{N_{MCC}}}{1 - \frac{1}{N_{MCC}}}$ where HHI is the standard Herfindahl–Hirschman Index (computed as the sum of the squared shares of emission/spending in each MCC code) and N_{MCC} is the number of categories a user spends in. For users who spend in only one category the Normalized HHI is set to 1. The normalization is necessary in our setting because the value of N_{MCC} differs across individuals, and the un-normalized HHI is bounded between $\frac{1}{N_{MCC}}$ and 1.

[20] We also compute results relative to the row number of consumption categories, and we find that the mean (median) user spends across 28 (25) codes.

[21] Food and non-alcoholic beverages; Alcoholic beverages and tobacco; Clothing and footwear; Housing, water, gas, electricity, and other fuels; Furnishings, household equipment, and routine maintenance of the house; Health; Transport; Communications; Recreation and culture; Education; Restaurants and hotels; Miscellaneous goods and services

across users.

Results are reported in Panel B of Figure 1, red dots refer to the spending shares, while blue dots refer to the emission shares. The consumption categories are sorted on the x-axis in decreasing order from left to right based on the spending shares. The top two consumption categories are Recreation and Food & Beverages, jointly accounting for close to 42% of expenditures. Next, we find Fast Food, Restaurants and Hotels, Clothing, and Transportation, each accounting for between 13% and 10% of total spending. The remaining categories account for approximately 5% or less. In terms of emissions, the most prominent categories are Restaurants and Hotels (27%), Recreation (17%), and Transportation (16%) which collectively account for 50% of the total.

For approximately half of the categories, the shares of spending and emissions are closely aligned. However, there are notable exceptions. Hotels and Restaurants, Transportation, and Utilities have a relatively high footprint compared to the monetary amount spent. For example, Hotels and Restaurants account for almost double the emissions (26%) compared to total spending (14%), and the same is true for Utilities (4% versus 2%). At the other end of the spectrum, Recreation, Food and Beverage, and Clothing have a relatively small footprint. For example, Clothing accounts for 12% of spending but only 6% of the emissions.

To shed further light on these patterns, we analyze the footprint of each category using the carbon emitted per euro spent, which we obtain by dividing information on spending and emissions from the transaction data. Panel A of Figure 2 displays the average across the merchant category codes in each COICOP consumption category, where labels are sorted on the x-axis in decreasing order from left to right. Consistent with other studies, Utilities is by far the category with the largest footprint, with close to 1.3 kg per euro spent. For example, Goldstein, Gounaridis, and Newell (2020) finds that roughly 20% of US energy-related greenhouse gas (GHG) emissions stem from heating, cooling, and powering households. This value is almost 90% larger than the second category, Transportation, which displays a footprint of 800 grams per euro spent. On the opposite side of the spectrum, we find that Health and Education with a footprint of less than 250 grams per euro spent.

It is important to note that there could be variation within each category as the MCC codes we use are so precise to the point of being company-specific for large corporations like United or

American Airlines. As an example, Panel B of Figure 2 displays the footprint of each of the 115 MCC codes mapped into the Transportation category. From the list, we remove company-specific labels. The x-axis displays the carbon per euro while the y-axis displays the ranking of each MCC (from the highest, appearing at the bottom, corresponding to more environmentally friendly codes). As expected, MCC codes associated with bike and green transportation have the lowest carbon per Euro (0.2Kg per €). Moving to the right, the graph is increasingly populated by ground transportations (with group transportation, like buses, having lower impact than individual transportation means, like cars). Finally, the area in the top right of the plot (corresponding to less environmentally friendly MCC codes) is populated by Airlines and related industries.

4.2 Spending and Emissions

Next, we turn to analyzing spending and emissions at the individual level. The top-left plot of Figure 3, displays a scatterplot relating total individual-level spending, expressed in thousands of euros, and emissions, expressed in Kilograms. As expected, the plot shows a strong positive relation between how much individuals consume and their carbon emissions, with a correlation coefficient of 0.9. The slope coefficient indicates that for each additional €10,000 of spending, emissions increase by 4,650kg. As we move from low- to high-spending levels, we also observe an increase in the dispersion in emissions for every level of spending, consistent with previous evidence that due to less binding budget constraints, these individuals can spend over a wider range of goods (see, e.g. Browning, Crossley, and Joachim, 2014, Baker and Kueng, 2022 and Agarwal, Qian, and Tan, 2020). For example, at the €10K level of spending, individuals' emissions range from 500 to 8,000kg. At €45K spending level, it ranges from 5,000kg to 28,000kg instead.

A natural question that could not be answered before the data we use in this study became available is whether there is a positive, negative, or non-monotonic relation between individuals' overall spending and their emissions per euro. That is, whether high-income—and hence high-spending—individuals produce proportionally more or less emissions compared to low-income individuals once we control for the different levels of spending. We tackle this question by relating users' annual spending to their emissions (in kg) per euro spent and reporting the results of these computations in the top-right plot of Figure 3. The data shows a clear non-monotonic pattern whereby, as we move from low- to medium-spending (from €0K to €3K), emissions per euro increase substantially from 0.4 to 0.45. The relationship then flattens for levels of spending between €3K to €8K only to become negative for levels of spending above €8K.[22]

The inverted U-shaped relation between emissions and spending could be due to two non-mutually exclusive potential channels. First, it could be that as individuals' incomes increase, their consumption bundles change. For example, Misra and Surico (2014) study the consumption response to positive income shocks induced by the U.S. tax rebates in 2001 and 2008, and find a high degree of heterogeneity across categories. Hence, the differences in emissions per euro could be due to differences in the categories of products high-spending individuals purchase. For example, they may spend relatively less on Utilities, which has relatively high emissions per euro, and relatively more on Recreation, which has relatively low emissions per euro. Alternatively, it could be that, as individuals' incomes increase, they may be interested in buying, within each spending category, the items with the lowest carbon emissions. Moreover, the bigger spending power allows them to make more environmentally-friendly spending choices.

To assess the relevance of these two possible mechanisms, we perform two exercises. First, in the spirit of the lower plot in Figure 1, in the lower-left plot of Figure 3 we compute the share of spending across the different COICOP consumption categories for low-spending (below €3K), medium-spending (between €3K and €8K), and high-spending (above €8K) individuals and report their averages and 95% confidence intervals in red, blue, and green, respectively. Second, in the lower-right plot of Figure 3, we report average emissions per euro and 95% confidence intervals for the different categories of spending across low-, medium-, and high-spending individuals in red, blue, and green, respectively.

Comparing medium-spending (blue) and high-spending (green) individuals in the lower-left plot of Figure 3 shows that the latter spend relatively more on Recreation and Financial Services, which have relatively low emissions per euro, and relatively less on Transportation and Fast Food, Restaurant, and Hotels, which have relatively high emissions per euro. Turning to the lower-right plot of Figure 3, we find instead that the emissions per euro are virtually identical for medium- and high-spending

[22]When we formally test for this relation by regressing emissions per euro on squared spending and the level of spending with obtain an estimate of $-.00041$ (t-stat of -13.42).

individuals for all categories with the exception of "Transportation", likely due to the more frequent use by high-spending individuals of cars and flights.

Comparing medium-spending (blue) to low-spending (red) individuals paints a similar picture. We observe relatively large differences in spending across categories (bottom-left plot of Figure 3), in that low-spending users allocate relatively more of their budget on Clothing and Recreation, which have relatively low emissions per euro and relatively less on Transportation and Fast Food, Restaurant, and Hotels, which have relatively high emissions per euro. At the same time, we find that with the exception of "Transportation", the emissions per euro in each category (bottom-right plot of Figure 3) are virtually identical for medium- and low-spending individuals.

Overall, the results in this section show that the differences in emissions per euro across individuals with different levels of spending are driven by differences in spending across consumption categories rather than by the products individuals choose within each category.

5 The Causal Effect of Sustainability Tools on Consumption Choices

In this section, we first provide the details of our identification strategy based on a quasi-experimental encouragement design. We then report our main empirical results.

5.1 Identification Strategy

Our main objective is to estimate the causal effects on individuals' consumption patterns of providing i) information regarding the carbon footprint of their transactions (i.e., the Carbon Calculator tool) and ii) carbon offsetting services. This task is challenging because time-invariant user characteristics, such as education, might drive both individuals' consumption decisions and their *endogenous* choice to subscribe to these services. Even though user fixed-effects can be used to absorb time-invariant unobservable characteristics, consumers' preferences for sustainability may be time-varying and explain both the decision to adopt either eco-balance or carbon-offsetting services and the changes in consumption behavior.

5.1.1 Ideal Experiment

In an ideal experiment, we would split users into a control and a treated group, and give access to the sustainability tools to the latter group for a certain period of time. This would allow us to estimate the causal effect of these sustainability tools using the following difference-in-differences specification:

$$Y_{i,t} = \alpha_i + \alpha_t + \beta \ \mathbb{1}\{Treated\_Sus\_Tool\}_{i,t} + \epsilon_{i,t} \tag{1}$$

where $\mathbb{1}\{Treated\_Sus\_Tool\}_{i,t}$ is a dummy variable that takes the value of 1 if user i has access to the sustainability tool—either eco-balance or carbon offsetting—after date t and zero otherwise; the variable $Y_{i,t}$ represents the value for user i on date t of one of the outcome variables we consider; and the coefficients α_i and α_t denote user and time fixed-effects. Equation 1 is a difference-in-differences estimator that compares the change in the outcome variable $Y_{i,t}$ after having access to the sustainability tool, relative to the change in $Y_{i,t}$ for those who did not have access to the sustainability tool.

Unfortunately, we cannot employ such a strategy because the sustainability tools have been available to the whole user base since the App's inception, and neither tool could be restricted to some users because of company policy and ethical considerations.

5.1.2 Encouragement Design

We overcome these identification challenges by exploiting the marketing campaigns run by the company to promote the adoption of its sustainability tools as a quasi-experimental encouragement design. In a standard encouragement design, all subjects have access to the treatment, but some (the treated group) are randomly assigned to receive encouragement to take it. This design is ideal in our setting because the marketing campaigns promoted the adoption of these sustainability tools (the treatments we are interested in) to certain users but not others in a random fashion. Imbens and Angrist (1994) and Angrist, Imbens, and Rubin (1996) show that this design estimates the so-called local average treatment effect (LATE)—the effect of the sustainability tools for the compliers. Moreover, this design has been used in a variety of settings ranging from social sciences to medicine (see, e.g., Duflo and Saez, 2003, West et al., 2008, Mullally, Boucher, and Carter, 2013, Eckles, Kizilcec, and Bakshy, 2016 and Fowlie, Greenstone, and Wolfram, 2018).

The marketing campaign was run in July 2022 and extended from July 6th to July 24th. The company divided the user population into a treatment group and a control group, and the treatment group received both email and App push notifications to encourage signing up for either one of the sustainability tools, while the control group was not contacted. The email and app notifications ranged in the type and content of the messages but either highlighted the eco-balance or carbon-offsetting tools available to the users to combat climate change.

We use the assignment to encouragement as an instrumental variable for the adoption of the tool in the following first-stage regressions:

$$\mathbb{1}\{Sus\_Tool\}_{i,t} = \alpha_i + \alpha_t + \theta\ \mathbb{1}\{Encouraged\}_{i,t} + \epsilon_{i,t} \tag{2}$$

where $\mathbb{1}\{Sus\_Tool\}_{i,t}$ is equal to 1 if the user has adopted a sustainability tool—either the carbon calculator or the carbon offsetting feature— and zero otherwise; and $\mathbb{1}\{Encouraged\}_{i,t}$ is set to 0 for all users prior to the encouragement intervention. After July 2022, this indicator switches to 1 for the households randomly assigned to receive the marketing campaign material.

The second stage regressions obtain causal estimates using the following specifications:

$$Y_{i,t} = \alpha_i + \alpha_t + \beta\ \mathbb{1}\{\widehat{Sus\_Tool}\}_{i,t} + \epsilon_{i,t}, \tag{3}$$

where $Y_{i,t}$ represents one of the outcome variables we consider. From a purely environmental perspective, reducing the risk of climate change entails reducing or offsetting emissions. Accordingly, we consider the following outcome variables: *Consumption*, the log total amount spent in Euros; and *Emissions*, the log total amount of CO2 emissions, which includes the offsetting allowance for those who adopt the Carbon Calculator. From an economic perspective, however, governments seek to limit emissions not by reducing consumption but by shifting it towards more carbon-efficient options. For this reason, we also consider *Emissions_Per_Euro*—the emissions per euro computed as the log of the ratio between total carbon emissions and euros spent-$\mathbb{1}\{\widehat{Sus\_Tool}\}_{i,t}$ is the instrumented endogenous regressor; the coefficients α_i and α_t denote user and time fixed-effects.

The parameter of interest is β, which measures the mean difference in the outcome variable after adopting the sustainability tool, adjusting for fixed effects. It is a difference-in-differences estimator that compares the change in consumption and carbon footprint after the adoption to before in the treated group, relative to the users that have either not yet adopted the tool or never adopted it during our sample period.

To interpret the β coefficient causally, the instrument should be relevant, exogenous, and satisfy the exclusion restriction. The relevance of the instrument hinges on the efficacy of the marketing campaign in encouraging its users to sign up for its sustainability tools. We provide evidence of this in Section 5.2.1, where we show that the marketing campaign increased the adoption of the sustainability tools by 100% for the treated group, compared to the control group. The exogeneity of the instrument is guaranteed by the fact that the assignment of the treatment is random. To provide evidence in this direction, Section 5.2.1 shows that users' characteristics are balanced across the treatment and control groups. Finally, the exclusion restriction requires that the encouragement to adopt the featured sustainability tools affects users' consumption behavior only through their adoption of such tools. This exclusion restriction is inherently untestable. Following Fowlie, Greenstone, and Wolfram (2018), in Section 5.4, however, we provide formal tests that the encouragement does not change the behavior of those who do not adopt treatment.

5.2 Empirical Results

5.2.1 First Stage

We start by comparing the characteristics of the treated users (i.e., those targeted by the marketing campaign) and the control group (i.e., those not targeted) in Panels A and B of Table 2. In both panels, we display the cross-sectional mean, median standard deviation, and representative percentiles for a number of variables capturing demographic characteristics, attention patterns, and consumption habits. Specifically, we consider: *Age*, user's age as of 2022; *Gender*, user's gender; *Frac. Logins*, the fraction of days with at least one login; *N. Logins*, the average number of logins per day; *Frac. Transactions*, the fraction of days with at least one transaction; *N. Transactions*, the average number of transactions per day; *Avg. Spending*, the average amount spent per day; and *Emissions*, the user's emissions. The attention and consumption variables are computed over the six months prior to the beginning of the marketing campaign.

Both the means and medians indicate that the differences across users are economically small. For example, the average age of the treated group is 29.8, and it equals 30.4 for the control group. The average percentage of days with at least one login is 31.6% in the treated group and 32.3% for the control group. The same is true for all the other covariates we consider. We also test the null of whether the means of the treated and control distributions are different from each other and find that none of the t-statistics are significant at the 10% level.

Turning to the relevance of our instrument, Table 3 reports the results from our first-stage regressions reported in Equation 2. Columns (1) and (2) display the results pertaining to the adoption of the carbon calculator and carbon offsetting tools, respectively. Starting from column (1), we find an estimate of θ equal to 2.6% (with a t-stat of 8.25). Given that 2.8% of the users not targeted by the campaign adopted the carbon footprint tool, the campaign increased adoption by 2.6/2.8=92.8%.

Moving to column (2), we find lower coefficient estimates of 0.4% (t-stat equal to 3.56). The much lower uptake of the carbon offsetting tool is not surprising, given that it comes at a higher price. Given that 0.4% of the users not targeted by the campaign adopted the carbon offsetting tool, the campaign increased adoption by 0.4/0.4=100%.

5.2.2 Second Stage: Carbon Calculator

The causal effect of providing individuals with information on their footprint by means of a carbon calculator is not obvious ex-ante. An extensive literature shows that offering individuals tools to monitor their consumption and saving helps them to reduce overspending (Lee, 2023; Carlin, Olafsson, and Pagel, 2023). Therefore, if users have the goal to be more sustainable by either reducing overall consumption or allocating it toward goods with a lower carbon footprint, one would expect a positive effect on overall carbon footprint and carbon footprint per euro spent (a negative β coefficient estimate from Equation 3) from providing such a tool.

However, these effects likely hinge on the information being reliable and the users being able to correctly process it. Unlike spending information, users' carbon footprint represents an *estimate*, because the footprint of every single product purchased is the result of many supply chain stages, ranging from the processing of the raw material to the shipping of the final product to the consumer. For example, Mulrow et al. (2019) compares 31 online calculators and finds a wide range of estimates across them. Moreover, while users might be able to easily assess whether they are overspending by comparing their expenses with their income, it is harder for users to benchmark information on their emissions. If these forces had a strong impact on users' behavior, one could expect a non-effect from providing carbon footprint information (a β not statistically different from zero).

Showing users their carbon footprint could even adversely affect the sustainability of their behavior (i.e., a positive β coefficient estimate) if users fail to realize that the displayed information might not necessarily cover their entire carbon footprint and reach the conclusion that they behave more sustainably than they previously thought.

We start by reporting the endogenous OLS results for the Carbon Calculator tool in Panel A of Table 4:

$$Y_{i,t} = \alpha_i + \alpha_t + \beta \ \mathbb{1}\{Sus\_Tool\}_{i,t} + \epsilon_{i,t}, \tag{4}$$

where α_i and α_t are user and week fixed-effects, and $\mathbb{1}\{Sus\_Tool\}_{i,t}$ is a dummy variable equal to 1 if users i has the sustainability tool activated in week t. The dependent variables are *Consumption*, *Emissions* and *Emissions Per Euro* in columns (1) through (3). Those who endogenously adopt the carbon calculator feature increase their spending by 1.4%, increase their emissions by 27.6%, and their emissions per euro by 2.9%. The reduced-form results hence suggest that, if anything, the effect of the carbon calculator has a negative impact on individuals' sustainable behavior both in terms of their overall polluting activity and in terms of the amount of carbon they create for every transaction they make.

The endogenous OLS results suffer from the serious concern that those who decide to sign up for the carbon calculator may decide to use the app more in the subsequent weeks/months as a result of adopting and testing the new feature, driving the bulk of the effects measured by the regression coefficients. For this reason, in Panel B of Table 4, we report the results from the second stage regression in Equation 3 when we instrument the adoption of the Carbon Calculator tool. The IV coefficient estimates paint a completely different picture in that none of the coefficients on consumption, gross emissions, or gross emissions per euro are statistically significant, suggesting that adopting the carbon calculator, on average, does not affect users' behavior in an economically or statistically significant way.

To assess whether our instrument is likely to be weak, we consider the Kleibergen-Paap (KP) Wald F-statistic, which is the version of the Cragg-Donald (CD) Wald F-statistic that allows for the adjustment of the clustering of standard errors. This statistic allows us to test the null hypothesis that our instrument is weak. For all IV specifications, we obtain Kleibergen-Paap Wald F-statistics of 68.22, 68.22, and 27.99, respectively. These values are substantially larger than those proposed by common rules of thumb, for example, an F-statistic above 10 is often suggested as indicative of unlikely weak instrument problems. Although these rules of thumb are not a definitive threshold for whether the issue of weak instrumentation is present or not, given the high values of our KP Wald-F statistics, we conclude that our IV procedure does not appear to face a weak instrument problem.

5.2.3 Second Stage: Carbon Offsetting

By subscribing to the carbon offsetting tool, users receive a monthly allowance which mechanically reduces their carbon footprint. While offsetting mechanically reduces users' footprint by the allowance amount, whether individuals' net emissions increase or decline compared to before adopting carbon offsetting ultimately depends on how users change their consumption and, in turn, the associated *gross* emissions.

To build intuition, Figure 4 depicts four scenarios for how gross (red bars) and net (blue bars) emissions could change after the adoption of carbon offsetting. Across all scenarios, we normalize to 100 (depicted by the horizontal dashed line) the gross emissions levels before adopting the tool and consider an allowance of 10 units.

We start by describing the "positive" scenarios regarding the fight against climate change. First, users might keep their consumption the same. In this scenario, gross emissions stay constant relative to their prior level, and net emissions drop by the amount set in the allowance (i.e., from 100 to 90). In terms of the coefficient estimates in Equation 3, we would then expect a non-significant β when using gross emissions and consumption and a negative β when using net emissions as outcome variables. Second, users might reduce their consumption and, in turn, gross emissions. This would be the case if the tool's adoption motivates users to become more sustainable and help the planet, further amplifying the effect of carbon offsetting. In this scenario, users' β estimates would be negative for both gross and net emissions variables.

We next consider scenarios where the adoption of the tool has a null or even a detrimental effect on reducing users' footprint. Individuals might incorporate the fact that their footprint is offset and might therefore increase consumption and gross emissions up to the allowance amount. In the context of Israeli daycares, Gneezy and Rustichini (2000) show that imposing a fine for being late increased parents' late pickups rather than decreasing them and conclude that imposing a price for the externalities generated by a set of actions may not act as a deterrent but could even increase their occurrence.

Using a parallel with the medical literature, paying for carbon offsetting might be akin to taking antihypertensive or statin pills in that they produce the positive effect of healthy habits without their cost in terms of effort. Korhonen et al. (2020) show evidence that individuals treat medications and healthy habits as substitutes and continue with their unhealthy habits—and are even more likely to engage in them—after starting medical treatment. In this scenario, estimates of β would be positive for consumptions and gross emissions and zero for net emissions. Finally, if the increase in gross emissions is larger than the allowance, we would estimate positive β coefficients for both the gross and net footprint measures.

From a policy perspective, the value of the fixed allowance amount is important. The larger the allowance amount relative to users' prior emission levels, the more likely we will find estimates in line with the first and second scenarios. We could even have many users become net-zero emitters for allowance values close to their footprint prior to adopting offsetting. Moreover, a higher allowance would also make the last two scenarios less likely.

In parallel with Section 5.2.2, we start by presenting in Panel A of Table 5 the OLS results, where we estimate an economically small (2.5%) but statistically significant increase in users' overall consumption. The effect on consumption is, however, dwarfed by the very large effects we estimate for *Emissions* and *Emissions Per Euro*. The coefficients imply a reduction of $1 - e^{-1.073} = 66\%$ for emissions and $1 - e^{-5.660} = 99\%$ for emissions per euro, suggesting that the offsetting allowances are enough to bring users' emissions to zero, after adopting carbon offsetting.

In Panel B of Table 5, we re-estimate the coefficients, instrumenting the adoption of carbon offsetting. Unlike the carbon calculator tool, we find that the IV results are broadly in line with the reduced OLS ones: the IV results suggest that carbon offsetting *causes* a reduction in emissions and emissions per euro. Economically, the magnitudes of the coefficients are in line with those of the OLS in that emissions are reduced to almost zero after adopting carbon offsetting. Finally, the Kleibergen-Paap Wald F-statistics show that it is unlikely our procedure suffers from a weak instrument problem.

The results reported so far exclude the third and fourth scenarios described above but are consistent with either the first or second scenarios. That is, it could be that carbon offsetting *causes* users to decrease their gross emissions and their gross emissions per euro or that users do not change their behavior, and the whole difference derives from the carbon offsetting mechanical feature. To disentangle these two potential mechanisms, we repeat the results in the last columns of Panel B of Table 5 but focus on gross rather than net emissions. The IV results are statistically insignificant for both gross carbon emissions and gross carbon emissions per euro, suggesting that adopting carbon offsetting *causes* a mechanical reduction in users' emissions but does not change their behavior, so it does not affect their gross emissions behavior.

5.2.4 Second Stage: Heterogenous Effects

The results reported so far do not condition on users' characteristics. However, an extensive literature studies how individual demographics are correlated with environmental literacy (i.e., knowledge of basic facts related to climate change, see e.g. Anderson and Robinson, 2022), preferences for and knowledge of socially responsible investments (see e.g. Bauer, Ruof, and Smeets, 2021 and Filippini, Leippold, and Wekhof) and support of policies addressing climate change (Dechezleprêtre et al., 2023). It is possible, therefore, that these variables might play a role in both the adoption of the sustainability tools and their effect. Moreover, one could even think of an extreme situation where carbon footprint information causes certain groups of users to increase their carbon footprint and others to decrease their carbon footprint, resulting in zero effects across all App users.

To estimate heterogeneity in the adoption of the sustainability tools, we explore alternative versions of our baseline results in Table 3 that condition on key user characteristics. The results of this exercise are reported in the left-hand-side plots of Figure 5, where the top plot focuses on the Carbon Calculator tool while the bottom plot focuses on the Carbon Offsetting tool.

To estimate heterogeneity in the effects of the sustainability tools on emissions, rather than reporting the full set of estimates reported in Tables 4 and 5, we focus on the coefficient on the *Carbon Per Euro* variable reported in the third column of Panel B of each Table. The results are reported in the right-hand-side plots of Figure 5, where the top plot focuses on the Carbon Calculator tool while the bottom plot focuses on the Carbon Offsetting tool. In each panel, the first bar—denoted by "none"—reports the results that do not condition on any user characteristic.

Starting from gender, Bauer, Ruof, and Smeets (2021) finds that women are more likely than men to choose pension plans aligned with United Nations' Sustainable Development Goals because they have stronger social preferences than men. However, when studying investments in socially responsible mutual Funds, Riedl and Smeets (2023) find no difference between males and females. On this front, we do not find major differences in either adoption or the effects of the sustainability tools. Females and males are equally likely to adopt carbon calculator (top-left plot) and carbon offsetting tools (bottom-left) plots. In terms of the effects, the carbon calculator tool (top-right plot) is equally ineffective for females and males in that neither coefficient estimate is statistically different from zero. While the carbon offsetting tool is effective in reducing the emissions of both females and males, the 95% confidence intervals show that the coefficient estimates are not statistically different from each other.

The second dimension we focus on is users' age. The rationale for this split is that younger users may react more to the carbon calculator information because more technologically savvy. Moreover, older people are less likely to support climate policies and invest in sustainable products (see Dechezleprêtre et al., 2023 and Bauer, Ruof, and Smeets, 2021). We take the median age of our App users (24 years), and we divide investors into young and old. Similar to the case for gender, we find that the coefficient estimates are similar across the two groups for most of the effects we study. The only exception regards the adoption of the carbon calculator tool, where younger users are more likely to respond to the encouragement (top-left plot).

Finally, the last two coefficient estimates split our sample into low- and high-income users. As we show in Figure 5, income is non-monotonically related to the *Carbon Per Euro* spent, in that low- and high-income individuals have a lower average carbon per euro compared to middle-income users, so we could expect the carbon calculator to have a heterogenous effect on users' behavior, depending on their income. In this case, we do not find differences in adoption and effects for the carbon calculator tool. Even though the estimates are noisy, we find that high-income users are more likely to adopt carbon offsetting, consistent with them having additional discretionary spending ability. We also find that the effects of carbon offsetting are larger for high-income individuals.

5.3 Intent-To-Treat Estimates

The results reported so far represent Local Average Treatment Effects (LATE), that is, the causal effect of adopting the carbon calculator or the carbon offsetting tool after a random encouragement design. From a policy perspective, one could be interested in the Intent-To-Treat (ITT) estimate that is instead the causal effect of receiving a random notification regarding the carbon calculator or the carbon footprint tool, irrespective of whether the user ultimately signs up for the tool. We estimate the following regression:

$$Y_{i,t} = \alpha_i + \alpha_t + \beta \; \mathbb{1}\{Encouraged\}_{i,t} + \epsilon_{i,t}, \tag{5}$$

where β provides the ITT estimate of interest.

Panel A of Table 6 reports the results for Carbon Calculator. In line with the IV results, we find that none of the coefficients are statistically different from zero. Panel B of Table 6 reports the results for the Carbon Offsetting tool. The estimates show no effect on overall consumption. They do, however, show a significant and negative effect on both *emissions* and *Emissions per Euro*. The coefficient magnitudes are much smaller than the ones reported in Table 5, consistent with the fact the vast majority of users do not sign up after receiving the notification and do not change their emissions behavior and the small percentage of users that sign up after receiving a notification decreasing dramatically their carbon footprint.

5.4 Evidence In Support of the Exclusion Restriction

Our IV strategy is predicated on an exclusion restriction, i.e. that the marketing campaign affected users' behavior only through its effect on the adoption of the sustainability tools. To informally test whether the treatment's encouragement activities had a direct effect on consumption and emissions, we test for an effect of the marketing campaign on the users in the encouraged group that did not adopt the tool. To conduct this test, we drop all users that adopt the tool over the sample. Using the remaining users, we estimate Equation (5) and report the results in Table 7. For both the carbon calculator (Panel A) and the carbon offsetting (Panel B) tools, we estimate coefficients non-statistically different from zero, irrespective of whether we focus on consumption, emissions, or emissions per euro, which suggests that our encouragement intervention had no effect on energy use in these households and supports the validity of the exclusion restriction. Of course, our exclusion restriction also implies that the encouragement intervention does not directly behavior among users adopting the sustainability tool, but we cannot test this assumption directly.

6 Conclusions

Climate change is one of the most pressing challenges modern society faces. While individual consumption accounts for 70% of global emissions, little is known regarding how to promote sustainable consumption behavior. In this paper, we study the effectiveness of Carbon Calculator and Carbon Offsetting services, delivered through a FinTech App, to help individuals monitor and reduce the environmental footprint associated with their consumption.

Using a randomized encouragement design, we show that individuals are likely to purchase Carbon Calculator services that provide detailed transaction-level information about their emissions. However, such a tool does not cause significant changes in their consumption and emissions. On the other hand, services that offset individuals' emissions by planting trees are less likely to be adopted but prove effective in reducing users' net emissions. We do not find differences in effects when we condition our estimates on individuals with different socio-demographic characteristics, such as age, gender, and income.

Our results show the challenges and opportunities associated with the automated tools promoting sustainable behavior that were initially confined to specialized FinTech Apps and are now becoming widespread across large financial institutions.

Future research should focus on two complementary avenues. The first is whether Carbon Calculator services could prove more effective when offered jointly with peer comparisons and commitment devices such as goals that have been shown effective in the FinTech literature. The second is whether the adoption of carbon-offsetting tools could be increased by educating the population about their costs and effectiveness.

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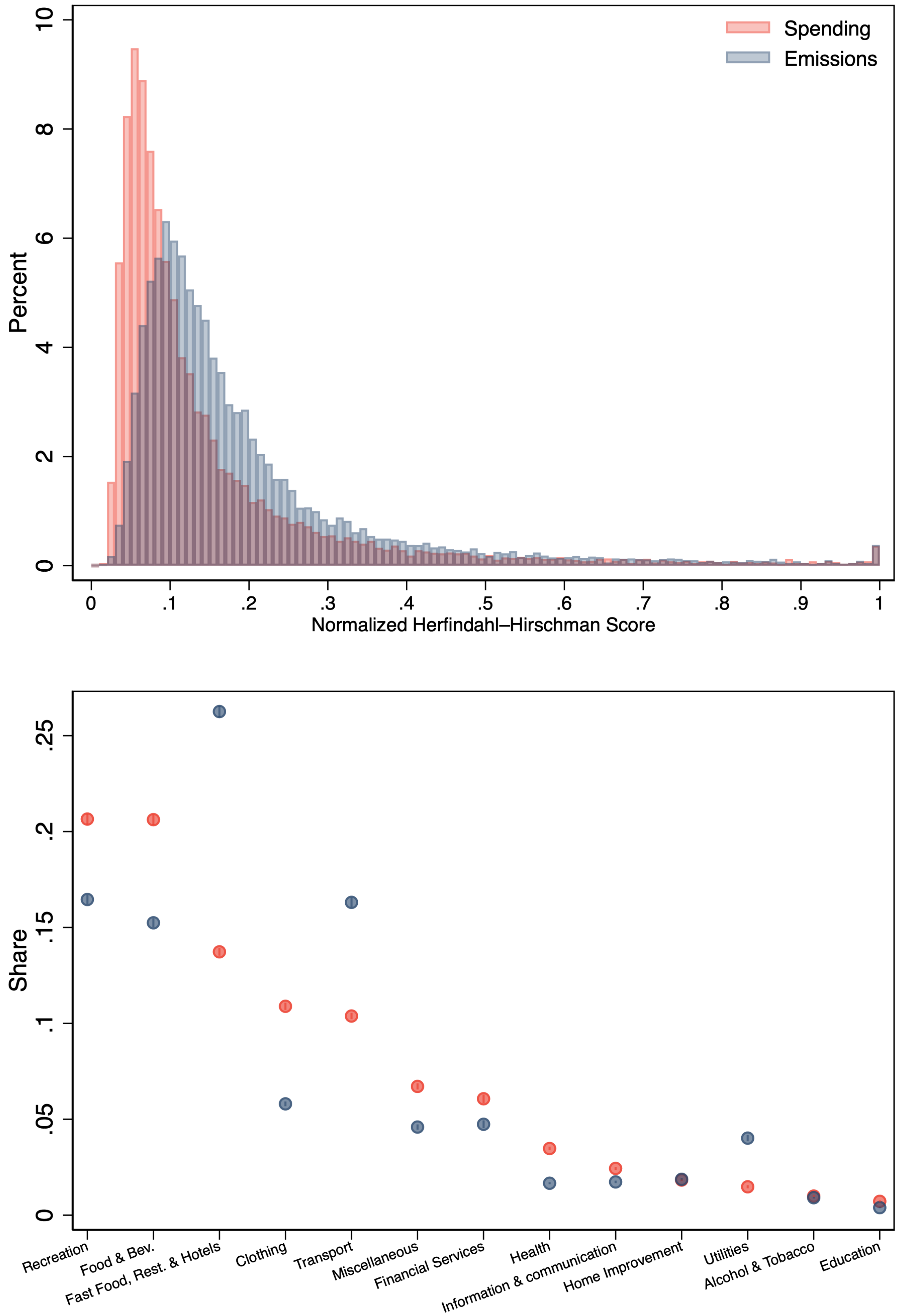

Figure 1: The Upper Figure displays information on the concentration of spending (red bars) and emissions (blue bars) across Merchant Category Codes. We first compute the Normalized Herfindahl–Hirschman Index for each user and display the resulting cross-section distribution. The Lower Figure displays information on the distribution of spending (red dots) and emissions (blue dots) across consumption categories, displayed on the x-axis. For each user, we compute the share of spending and emissions in each category and display the across-users averages. Consumption categories are defined based on the first two digits of the Classification of Individual Consumption According to Purpose developed by the United Nations Statistics Division.

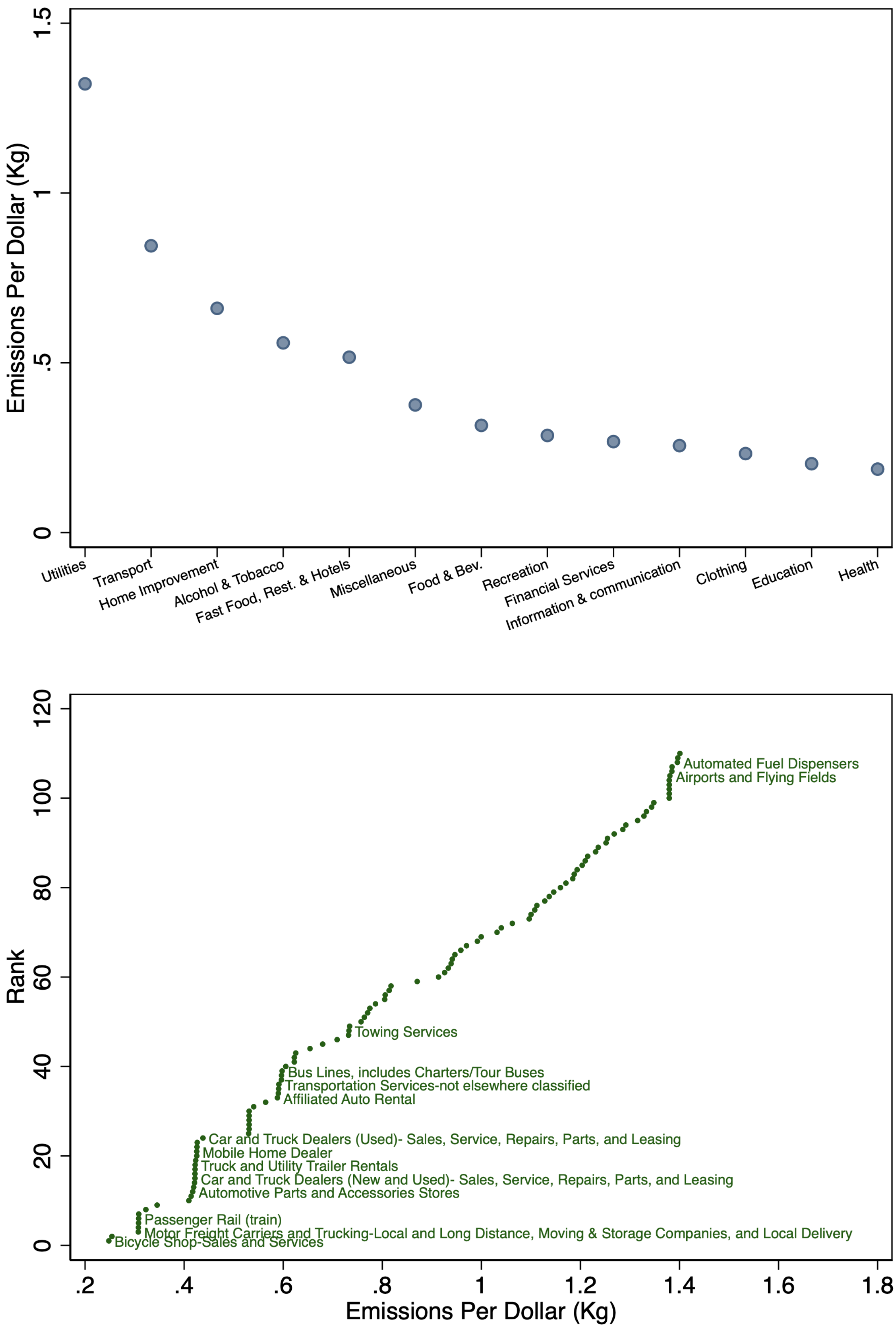

Figure 2: The Upper Figure displays the average emission per euro (in grams) across the Merchant Category Codes (MCC) in the consumption categories displayed on the x-axis. Consumption categories are defined based on the first two digits of the Classification of Individual Consumption According to Purpose developed by the United Nations Statistics Division. The Lower Figure displays the emission per euro (in grams) across the 115 individual MCCs in the "Transportation" category. MCCs are sorted in increasing order from left to right and their ranking is displayed on the y-axis. Labels are only displayed for MCCs that do not identify specific companies.

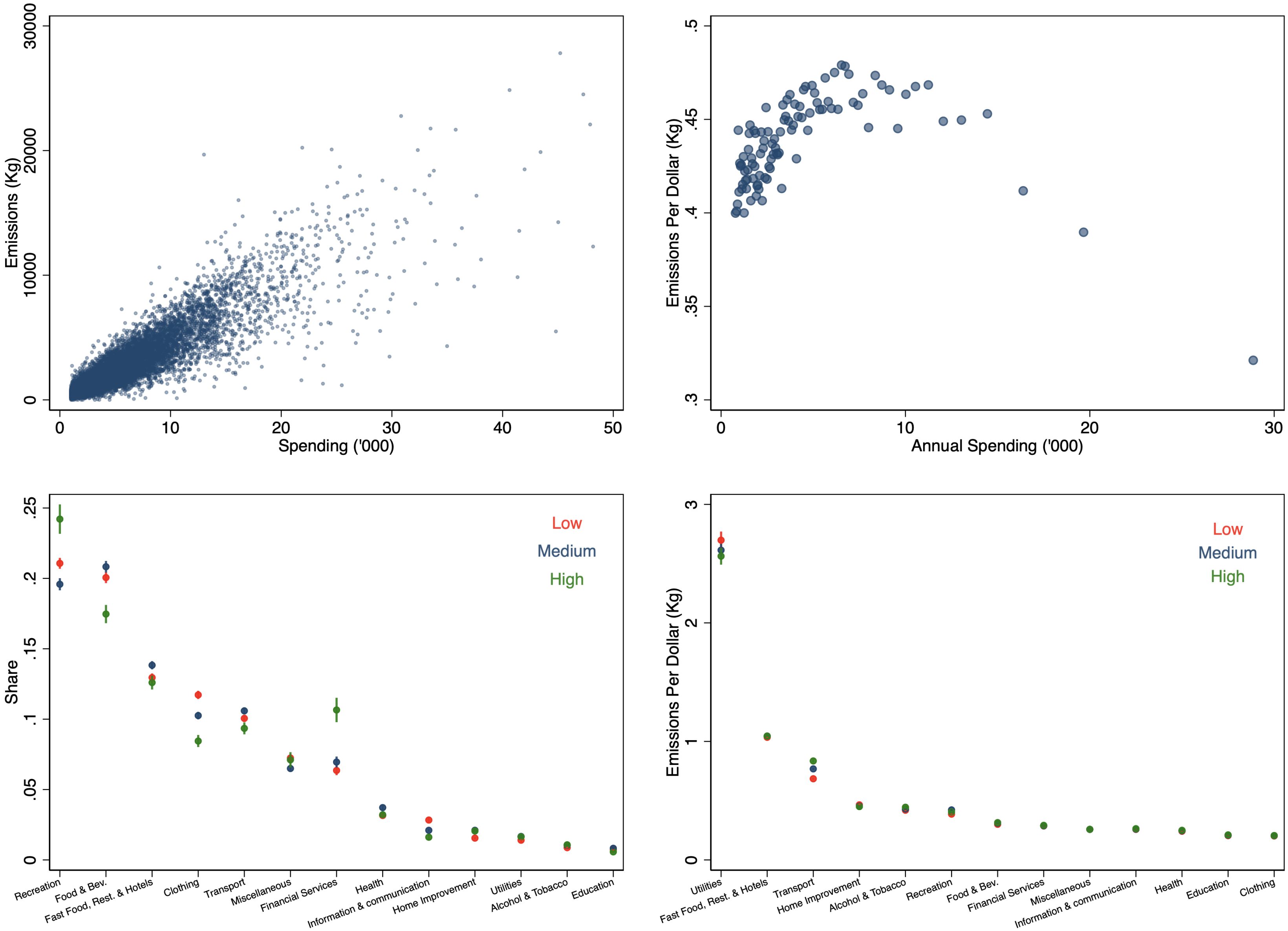

Figure 3: The Upper-left Figure displays the relation between total spending and emissions at the user level. The Upper-righ Figure displays the relation between annual spending and emissions per euro at the user level. The Lower-left (Lower-right) figures display the average across users of the share of spending (the average emissions per euro) in the consumption categories displayed on the x-axis. Consumption categories are defined based on the first two digits of the Classification of Individual Consumption According to Purpose developed by the United Nations Statistics Division. Red circles denote users with an annual spending less than €3,000 ("Low"); blue circles denote users with an annual spending between €3,000 and €8,000 ("Medium"); Green circles denote users with an annual spending higher than €8,000 ("High"). Categories are sorted in decreasing order from left to right based on the values of the "Low" group of users.

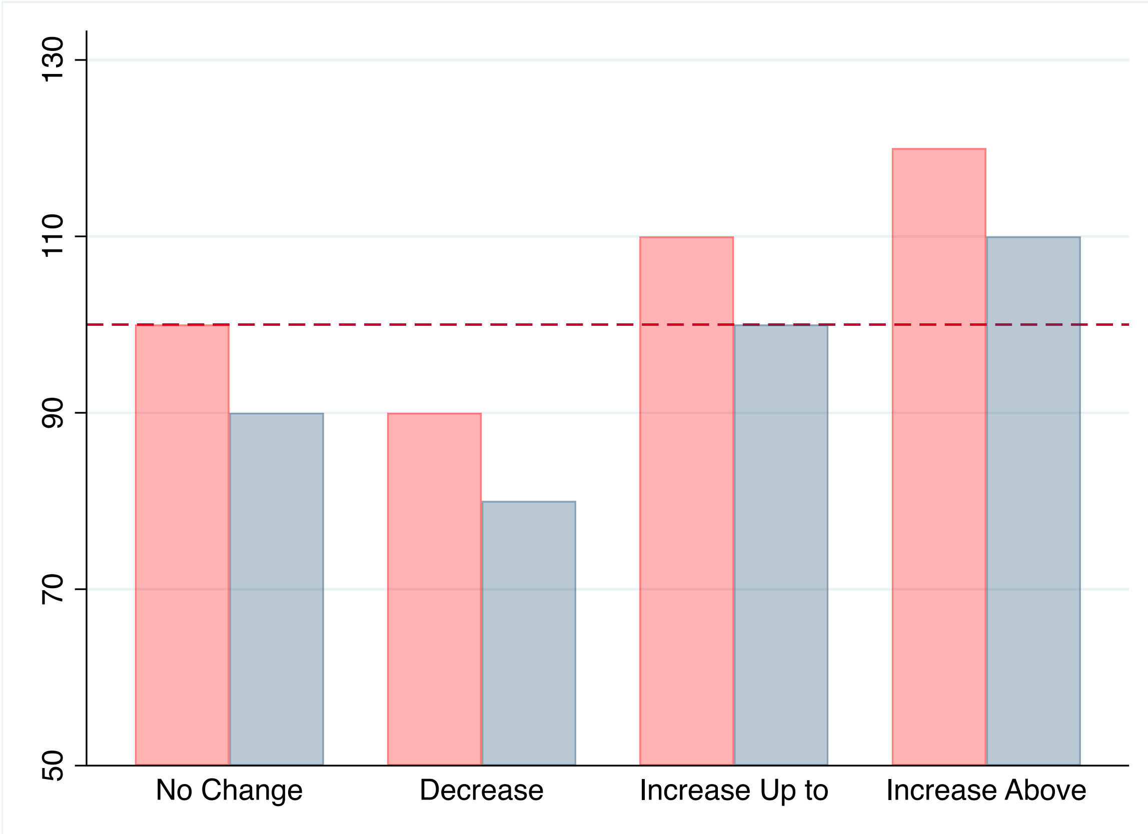

Figure 4: This figure displays four hypothetical scenarios on the effect of the adoption of Carbon Calculator on emissions. The level of emissions prior to the adoption is assumed to be 100, while the degree of offsetting is assumed to be 10 units. Red bars denote post-adoption consumption and associated gross emissions, while blue bars denote emissions net of the offsetting. "No Change" denotes the scenario where after the adoption, there is no change in consumption, "Decrease" denotes the scenario where there is a drop in consumption, "Increase Up To" denotes the scenario where there is an increase in consumption and gross emissions up to the allowance, while "Increase Above' denotes the scenario where there is a increase in consumption and gross emissions beyond the allowance

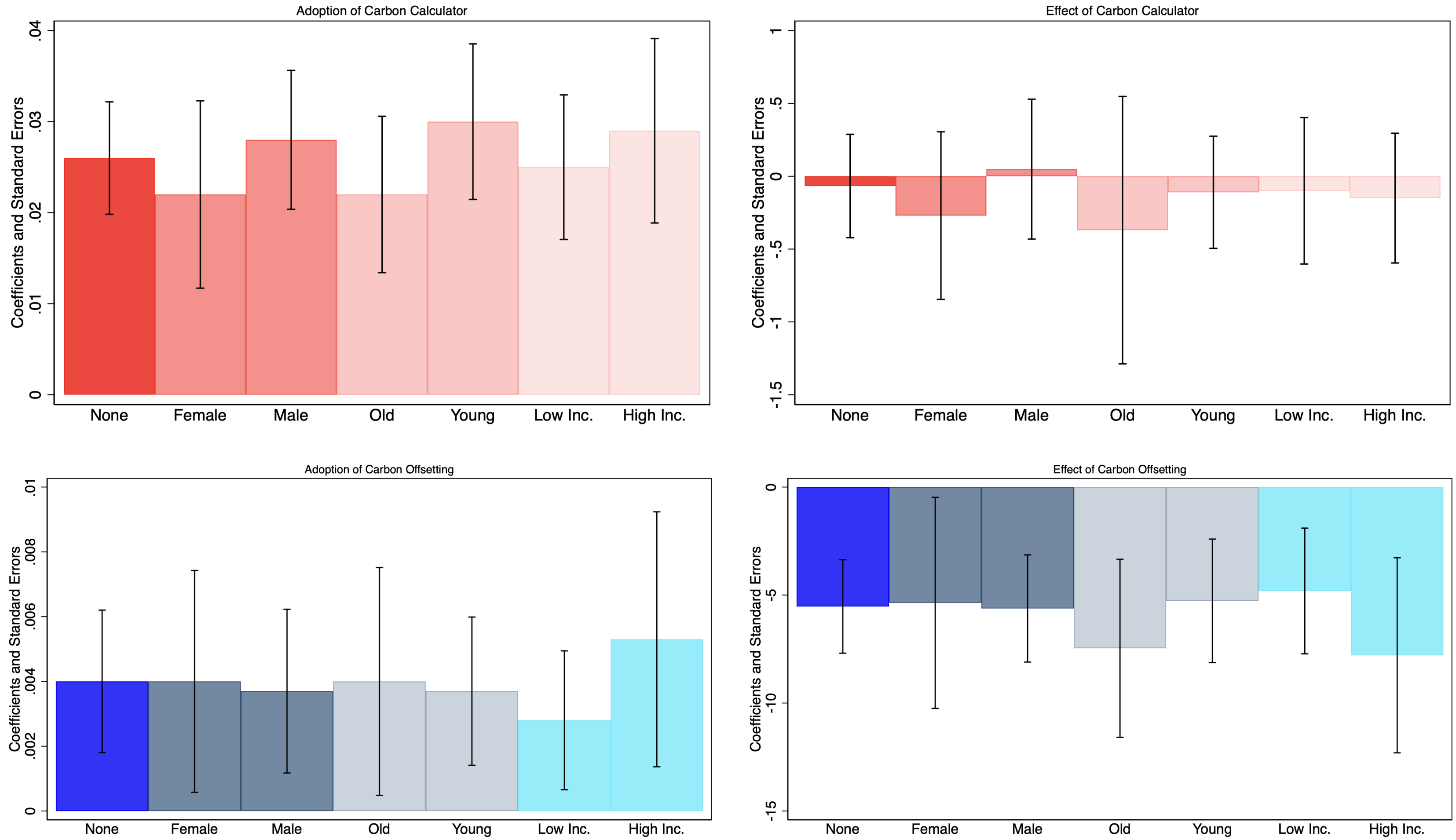

Figure 5: This Figure reports, in the left-hand-side plots, coefficient estimates, and associated 95% confidence intervals of the following regression model: $\mathbb{1}\{Sus\_Tool\}_{i,t} = \alpha_i + \alpha_t + \theta\ \mathbb{1}\{Encouraged\}_{i,t} + \epsilon_{i,t}$. In the right-hand-side plots, we estimate instead the following regression model: $Emissions\ per\ Euro_{i,t} = \alpha_i + \alpha_t + \beta\ \mathbb{1}\{\widehat{Sus\_Tool}\}_{i,t} + \epsilon_{i,t}$. In the Upper Figures, $\mathbb{1}\{Sus\_Tool\}_{i,t}$ is a dummy variable equal to 1 if user i adopts the Carbon Calculator in week t, while in the Lower Figures it is a dummy variable equal to 1 if user i adopts the Carbon Offsetting in week t. $\mathbb{1}\{Encouraged\}_{i,t}$ is an indicator variable for whether a user was encouraged to adopt either the carbon calculator (Upper Figures) or the carbon offsetting tool (Lower Figures); $Emissions\ per\ Euro$ is the ratio between the emissions and consumption by user i in week t. The coefficients α_i and α_t denote user and time fixed-effects. In right-hand-side Panels, $\mathbb{1}\{\widehat{Sus\_Tool}\}_{i,t}$ denote the regressor $\mathbb{1}\{Sus\_Tool\}_{i,t}$ instrumented with $\mathbb{1}\{Encouraged\}_{i,t}$, a dummy variable set to 0 for all users prior to the encouragement intervention and to 1 after July 2022 only for the users assigned to receive the marketing campaign material. In each plot, the first bar is based on the full sample. In the second and third bars, estimates are based on the sample of females and males, respectively. In the fourth and fifth bars, estimates are based on users above and below 24 years, respectively. In the sixth and seventh bars, estimates are based on users with an income below and above €15K. The t-statistics are based on standard errors clustered at the user and week level.

Table 1. Summary Statistics

Panel A. Demographic Characteristics

	Obs	Mean	Std	p1	p25	p50	p75	p99
Age	29,463	30.04	13.52	18.00	19.00	24.00	38.00	57.00
Gender	29,463	0.70	0.46	0.00	0.00	1.00	1.00	1.00
Income<€15K (Dummy)	29,589	0.66	0.47	0.00	0.00	1.00	1.00	1.00

Panel B. Login Activity

	Obs	Mean	Std	p1	p25	p50	p75	p99
Days Logins (%)	29,748	31.98	26.93	3.82	11.63	23.48	43.69	100.00
N. Logins per day	29,748	2.89	2.02	1.43	1.81	2.31	3.23	6.25

Panel C. Spending and Emissions

	Obs	Mean	Std	p1	p25	p50	p75	p99
Days Transactions (%)	29,615	35.95	30.90	3.08	10.00	25.15	59.92	100.00
N. Transactions per day	29,615	1.69	0.92	1.00	1.21	1.51	2.00	2.94
Avg. Spending (€)	29,615	58.88	269.52	0.00	2.45	16.90	46.76	195.68
Gross Emissions	29,615	928.75	3,202.06	0.00	5.94	126.23	820.80	4,220.38
Carbon Calculator (Dummy)	29,795	0.26	0.44	0.00	0.00	0.00	1.00	1.00
Carbon Offsetting (Dummy)	29,795	0.07	0.26	0.00	0.00	0.00	0.00	1.00

This Table reports cross-sectional summary statistics for the users in our sample. We first compute the value of each variable at the user level and then report the distribution of the variable across all users. For each variable, we report the number of observations used in the second step of the computations, the mean, standard deviation, as well as the $1st$, $25th$, $50th$, $75th$, and $99th$ percentiles. Panel A refers to the demographic characteristics: *Age*, the user age as of 2023; *Gender*, the user gender (1 for males and 0 for females); $Income <€15K$, a dummy equal to 1 if a user has an annual income of €15,000 or less. Panel B refers to the App usage: *Days Logins*, the fraction of days with at least one login between the first and the last login we observe; *N. Logins per day*, the average number of logins across the days with at least one login. Panel C refers to spending and emissions: *Days Transactions*, the fraction of days with at least one transaction between the first and the last transaction we observe; *N. Transcations per day*, the average number of transactions across the days with at least one transaction; *Avg. Spending*, the average transaction amount across the days with at least one transaction; *Emissions*, the annualized user emissions in kg; *Carbon Calculator*, a dummy equal to 1 if a user has ever activated the carbon calculator; *Carbon Offsetting*, a dummy equal to 1 if a user has ever activated the carbon offsetting.

Table 2. Balancing of Characteristics Across Treated and Non-Treated Users

		Panel A: Treated						
		Mean	Std	p5	p25	p50	p75	p95
Age		29.85	13.16	18.00	20.00	24.00	37.00	56.00
Gender		0.68	0.47	0.00	0.00	1.00	1.00	1.00
Days Logins		31.40	22.00	6.02	15.03	25.74	42.42	77.78
N. Logins		3.06	1.81	1.44	2.00	2.57	3.54	6.38
Days Transactions		37.39	29.42	5.38	13.64	27.43	57.58	100.00
N. Transcations		1.68	0.79	1.00	1.22	1.50	2.00	2.86
Avg. Spending		38.37	136.99	0.06	2.59	14.21	37.48	138.97
Emissions		920.08	4,210.73	0.00	8.06	136.87	689.64	3,884.81
		Panel B: Non Treated						
	t-test	Mean	Std	p5	p25	p50	p75	p95
Age	-1.45	30.38	12.87	18.00	20.00	25.00	37.00	57.00
Gender	-1.32	0.70	0.46	0.00	0.00	1.00	1.00	1.00
Days Logins	-1.57	32.36	22.19	6.29	15.56	26.87	43.75	79.01
N. Logins	-1.30	3.11	1.98	1.45	2.00	2.60	3.57	6.50
Days Transactions	-0.72	37.82	28.61	5.38	13.95	29.31	60.00	100.00
N. Transactions	-0.57	1.69	0.72	1.00	1.23	1.54	2.00	3.00
Avg. Spending	-1.31	43.70	217.58	0.03	1.67	13.46	38.52	155.20
Emissions	0.28	894.71	3,032.94	0.00	6.96	112.27	745.86	4,016.23

This Table presents cross-sectional summary statistics for the sample of the treated (Panel A) and the rest of the users (Panel B). We first compute the value of each variable at the user level and then report its distribution across all users. We report the mean, the standard deviation as well as the $5th$, $25th$, $50th$, $75th$, and $95th$ percentiles. *Age*, the user age as of June 2022, right before the beginning of the treatment; *Gender*, the user gender (1 for males and 0 for females); *Days Logins*, the fraction of days with at least one login; *N. Logins per day*, the average number of logins across the days with at least one login. *Days Transactions*, the fraction of days with at least one transaction; *N. Transcations per day*, the average number of transactions across the days with at least one transaction; *Avg. Spending*, the average transaction amount across the days with at least one transaction; *Emissions*, the user emissions in kg. The attention and consumption variables are computed over the six months prior to the beginning of the marketing campaign. In Panel B, we also report the t-stat associated with tests on the equality of means between treated and non-treated users.

Table 3. First Stage: Adoption of Sustainability Tools

	Sustainability Tool	
	Carbon Calculator (1)	*Carbon Offsetting* (2)
Encouragement	0.026***	0.004***
	(8.25)	(3.56)
User FE	✓	✓
Time FE	✓	✓
Adj-R^2	0.616	0.479
Obs	559,274	536,187

This Table reports coefficient estimates and associated t-statistics (in parentheses) of the following regression model:

$$\mathbb{1}\{Sus\_Tool\}_{i,t} = \alpha_i + \alpha_t + \theta\ \mathbb{1}\{Encouraged\}_{i,t} + \epsilon_{i,t}$$

where $\mathbb{1}\{Sus\_Tool\}_{i,t}$ is a dummy variable equal to 1 if the user i has adopted a sustainability tool in week t and zero otherwise; $\mathbb{1}\{Encouraged\}_{i,t}$ is set to 0 for all users prior to the encouragement intervention. After July 2022, this indicator switches to 1 for the users randomly assigned to receive the marketing campaign material. α_i and α_t denote user and time fixed-effect. Column (1) refers to the adoption of the Carbon Calculator, while Column (2) refers to the adoption of the Carbon Offsetting. The t-statistics are based on standard errors clustered at the user and week level. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels.

Table 4. Second Stage: Effect of Carbon Calculator

Panel A: Reduced-form OLS

	Consumption	*Emissions*	*Emissions Per Euro*
	(1)	(2)	(3)
Carbon Calculator	0.014***	0.276***	0.029**
	(6.04)	(6.80)	(2.26)
User FE	✓	✓	✓
Time FE	✓	✓	✓
Adj-R^2	0.35	0.54	0.27
Obs	559,274	559,274	112,595

Panel B: Instrumental Variable

	Consumption	*Emissions*	*Emissions Per Euro*
	(1)	(2)	(3)
Carbon Calculator	0.037*	0.014	-0.067
	(1.69)	(0.03)	(-0.37)
F-statistic	68.22	68.22	27.99
User FE	✓	✓	✓
Time FE	✓	✓	✓
Obs	559,274	559,274	112,595

This Table reports coefficient estimates and associated t-statistics (in parentheses) of the following regression models:

$$Y_{i,t} = \alpha_i + \alpha_t + \beta \ \mathbb{1}\{Sus\_Tool\}_{i,t} + \epsilon_{i,t} \quad \textit{Panel A}$$

$$Y_{i,t} = \alpha_i + \alpha_t + \beta \ \mathbb{1}\{\widehat{Sus\_Tool}\}_{i,t} + \epsilon_{i,t} \quad \textit{Panel B}$$

where $Y_{i,t}$ represents one of the three outcome variables of interest: *Consumption*, the log total amount spent by user i in week t; *Emissions*, the log amount of emissions by user i in week t; *Emissions per Euro*, the log of the ratio between the emissions and consumption by user i in week t. The coefficients α_i and α_t denote user and time fixed-effects. In Panel A, $\mathbb{1}\{Sus\_Tool\}_{i,t}$ is a dummy variable equal to 1 if user i adopts the Carbon Calculator in week t and coefficient estimates are based on OLS. In Panel B, we instrument this regressor with $\mathbb{1}\{Encouraged\}_{i,t}$ a dummy variable set to 0 for all users prior to the encouragement intervention and to 1 after July 2022 only for the users assigned to receive the marketing campaign material. The t-statistics are based on standard errors clustered at the user and week level. The F-statistic for the first-stage regression is calculated using the methodology developed by Kleibergen and Paap (2006). Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels.

Table 5. Second Stage: Effect of Carbon Offsetting

Panel A: Reduced-form OLS

	Consumption	*Emissions*	*Emissions Per Euro*
	(1)	(2)	(3)
Carbon Offsetting	0.025***	-1.073***	-5.660***
	(3.47)	(-9.98)	(-72.51)
User FE	✓	✓	✓
Time FE	✓	✓	✓
Adj-R^2	0.34	0.54	0.57
Obs	559,274	559,274	112,595

Panel B: Instrumental Variable

	Consumption	*Emissions*	*Emissions Per Euro*
	(1)	(2)	(3)
Carbon Offsetting	-0.071	-7.437**	-5.531***
	(-0.49)	(-2.05)	(-5.01)
F-statistic	12.69	12.69	8.25
User FE	✓	✓	✓
Time FE	✓	✓	✓
Obs	559,274	559,274	112,595

This Table reports coefficient estimates and associated t-statistics (in parentheses) of the following regression models:

$$Y_{i,t} = \alpha_i + \alpha_t + \beta \ \mathbb{1}\{Sus\_Tool\}_{i,t} + \epsilon_{i,t} \quad \textit{Panel A}$$
$$Y_{i,t} = \alpha_i + \alpha_t + \beta \ \mathbb{1}\{\widehat{Sus\_Tool}\}_{i,t} + \epsilon_{i,t} \quad \textit{Panel B}$$

where $Y_{i,t}$ represents one of the three outcome variables of interest: *Consumption*, the log total amount spent by user i in week t; *Emissions*, the log amount of emissions by user i in week t; *Emissions per Euro*, the log of the ratio between the emissions and consumption by user i in week t. The coefficients α_i and α_t denote user and time fixed-effects. In Panel A, $\mathbb{1}\{Sus\_Tool\}_{i,t}$ is a dummy variable equal to 1 if user i adopts the Carbon Offsetting in week t and coefficient estimates are based on OLS. In Panel B, we instrument this regressor with $\mathbb{1}\{Encouraged\}_{i,t}$ a dummy variable set to 0 for all users prior to the encouragement intervention and to 1 after July 2022 only for the users assigned to receive the marketing campaign material. The t-statistics are based on standard errors clustered at the user and week level. The F-statistic for the first-stage regression is calculated using the methodology developed by Kleibergen and Paap (2006). Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels.

Table 6. Second Stage: ITT Estimates

	Panel A: Carbon Calculator		
	Consumption	*Emissions*	*Emissions Per Euro*
	(1)	(2)	(3)
$\mathbb{1}\{Encouraged\}$	0.001	0.000	-0.004
	(1.47)	(0.03)	(-0.36)
User FE	✓	✓	✓
Time FE	✓	✓	✓
Adj-R^2	0.35	0.54	0.28
Obs	559,307	559,307	112,608

	Panel B: Carbon Offsetting		
	Consumption	*Emissions*	*Emissions Per Euro*
	(1)	(2)	(3)
$\mathbb{1}\{Encouraged\}$	-0.000	-0.028**	-0.047**
	(-0.49)	(-2.27)	(-2.42)
User FE	✓	✓	✓
Time FE	✓	✓	✓
Adj-R^2	0.34	0.54	0.35
Obs	536,220	536,220	103,840

This Table reports coefficient estimates and associated t-statistics (in parentheses) of the following regression models:

$$Y_{i,t} = \alpha_i + \alpha_t + \beta \ \mathbb{1}\{Encouraged\}_{i,t} + \epsilon_{i,t}$$

where $Y_{i,t}$ represents one of the three outcome variables of interest: *Consumption*, the log total amount spent by user i in week t; *Emissions*, the log amount of emissions by user i in week t; *Emissions per Euro*, the log of the ratio between the emissions and consumption by user i in week t. The coefficients α_i and α_t denote user and time fixed-effects while $\mathbb{1}\{Encouraged\}_{i,t}$ a dummy variable set to 0 for all users prior to the encouragement intervention and to 1 after July 2022 only for the users assigned to receive the marketing campaign material. The t-statistics are based on standard errors clustered at the user and week level. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels.

Table 7. Exclusion Restriction Test

Panel A: Carbon Calculator

	Consumption	*Emissions*	*Emissions Per Euro*
	(1)	(2)	(3)
$\mathbb{1}\{Encouraged\}$	0.001	-0.004	-0.002
	(1.08)	(-0.30)	(-0.21)
User FE	✓	✓	✓
Time FE	✓	✓	✓
Adj-R^2	0.35	0.54	0.28
Obs	524,519	524,519	96,602

Panel B: Carbon Offsetting

	Consumption	*Emissions*	*Emissions Per Euro*
	(1)	(2)	(3)
$\mathbb{1}\{Encouraged\}$	-0.000	-0.023*	0.004
	(-0.68)	(-1.90)	(0.40)
User FE	✓	✓	✓
Time FE	✓	✓	✓
Adj-R^2	0.34	0.54	0.28
Obs	530,586	530,586	101,314

This Table reports coefficient estimates and associated t-statistics (in parentheses) of the following regression models:

$$Y_{i,t} = \alpha_i + \alpha_t + \beta \ \mathbb{1}\{Encouraged\}_{i,t} + \epsilon_{i,t}$$

where $Y_{i,t}$ represents one of the three outcome variables of interest: *Consumption*, the log total amount spent by user i in week t; *Emissions*, the log amount of emissions by user i in week t; *Emissions per Euro*, the log of the ratio between the emissions and consumption by user i in week t. The coefficients α_i and α_t denote user and time fixed-effects while $\mathbb{1}\{Encouraged\}_{i,t}$ a dummy variable set to 0 for all users prior to the encouragement intervention and to 1 after July 2022 only for the users assigned to receive the marketing campaign material. The sample only includes users who never adopted the sustainability tool. The t-statistics are based on standard errors clustered at the user and week level. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels.