Fighting Climate Change with FinTech*

Antonio Gargano† University of Houston

Alberto G. Rossi‡ Georgetown University

February 6, 2025

Abstract

We examine the sustainability of consumption choices using unique data from a FinTech app tracking spending and emissions. Using a randomized encouragement design, we show that carbon calculator services that provide transaction-level information on emissions do not change users' behavior. Instead, carbon-offsetting services, though less popular, are effective in reducing emissions. A survey of app users suggests the carbon calculator's ineffectiveness stems from users not prioritizing climate change over other economic issues. Limited attention instead explains the low adoption of carbon offsetting. These findings highlight the challenges and opportunities of sustainability tools that have been increasingly adopted by financial institutions.

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

JEL Classification: D14, G41, G51

*We are grateful to Anders Anderson, Brad Barber, Anastasia Buyalskaya, Carlo Chiarella, Isil Erel, Niklas Flamang, Sean Higgins, Ruidi Huang, Ryan Israelsen, Martina Jasova, Dominik Jurek, Roger Loh, Gonzalo Maturana, Rajesh Narayanan, Nagpurnanand Prabhala, Vesa Pursiainen, Dimuthu Ratnadiwakara, Varun Sharma, Johannes Stroebel, and Brian Wolfe for comments and suggestions. The paper has also benefited from comments made by participants at the 2024 European Finance Association (EFA) Meeting, 2024 Northern Finance Association (NFA) Meeting, 2024 Financial Intermediation Research Society Conference (FIRS), 2024 Midwest Finance Association Annual (MFA) Meeting, Asian Bureau of Finance and Economic Research (ABFER) 11th Annual Conference, 2024 Finance Down Under (FDU) Conference, 2024 Research in Behavioral Finance Conference, 6th Future of Financial Information Conference, Broo FinTech Workshop at the University of Delaware Fintech Innovation Hub, Clemson ESG and Policy Research Conference and 7th Shanghai-Edinburgh-UCL Fintech Conference, and seminar participants at NYU Stern School of Business, Ohio State University, UC Davis, Penn State, Temple University, UT San Antonio, McGill University, Florida State University, Brookings Institution, Luohan Academy, Louisiana State University, University of Illinois at Chicago, Vienna University of Economics and Business, Nova School of Business and Economics, Shanghai Advanced Institute of Finance, Development Bank of Japan and CUNEF. We acknowledge financial support from the University of Houston Behavioral Research Assistance Grants. All errors are our own.

†C.T. Bauer College of Business, University of Houston Email: agargano@bauer.uh.edu

‡McDonough School of Business, Georgetown University. Email: agr60@georgetown.edu.

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 suggest that households' direct emissions account for approximately one-third of global emissions. When indirect emissions are included, this share increases to as much as 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, Rossi and Utkus, 2020 and Gargano, Giacoletti, and Jarnecic, 2023). On the other hand, it is unclear to what extent the biases and frictions that hinder individuals from adopting more sustainable habits resemble those that impede optimal financial decision-making. This raises questions about the effectiveness of

[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.

FinTech app interventions in promoting sustainable behavior among consumers.

Our setting provides an ideal testing ground, as our industry partner was among the first banks to introduce these tools. Moreover, major traditional banks are now beginning to provide similar tools through their apps and online platforms.[5] Despite the potential exposure of millions of individuals to these tools, there is no evidence of their *causal* impact on 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 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, 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. This demographic is especially relevant for sustainability efforts and policymaking, given their personal stake in mitigating long-term climate impacts and openness to emerging technologies. 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 first validate our data by showing that app users' spending is widely distributed across consumption categories—suggesting that they use the card for a wide range of transactions—and document that the categories of consumption with

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

the highest emissions per euro are Utilities and Transportation.[6] We also show that the consumption patterns of our app users are in line with those published by the national statistical bureau.

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 category 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 the effectiveness of the tools aimed at helping individuals make more sustainable choices. To this end, we 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 emissions per euro spent.

Establishing causality is challenging because certain user characteristics, like education, may influence both consumption and the decision to subscribe to either service. While user fixed-effects

[6] In line with our findings, Goldstein, Gounaridis, and Newell (2020) finds that roughly 20% of US energy-related greenhouse gas (GHG) emissions stem from heating, cooling, and powering households.

can account for user time-invariant characteristics, sustainability preferences may change over time and impact the choice of adopting sustainability services as well as consumption. 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 encouraged group) are randomly assigned to receive encouragement to take it. The marketing campaigns took place in July 2022, targeting users with email and app notifications to encourage the adoption of Carbon Calculator and Carbon Offsetting tools as part of efforts 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 (see, e.g., Lee, 2023 and Carlin, Olafsson, and Pagel, 2023), it is difficult to predict whether providing a carbon footprint calculator would similarly reduce 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 individual consumption categories and 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 examine Carbon Offsetting. Upon enrollment, users receive a monthly allowance that mechanically reduces their emissions by up to 1,000 kg. Our instrumental variable (IV) analysis shows that adopting Carbon Offsetting results in nearly a 100% drop in emissions and emissions per euro. However, we detect no change in users' consumption behavior, indicating that the emissions reduction is solely due to the mechanical effect of the allowance. The large economic size of the effect is explained by the allowance being significantly larger than app users' average emissions, which are well below 1,000 kg. Also in this case, when we condition on consumption categories and user characteristics such as age, gender, and income, we find virtually no heterogeneity in our findings.

Our instrumental variable (IV) estimates represent Local Average Treatment Effects (LATE), that is, the causal effect of adopting the sustainability tools 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 based on administrative data 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 than Carbon Offsetting tools, the former does 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.

Since the transaction data do not provide insights into users' motivations and preferences, we follow emerging literature in finance and economics that employs surveys to understand the economic mechanisms driving individuals' behavior.[7] To this end, we deploy a survey on our app users. A first contribution of the survey is that it enables us to ask users whether they believe their behavior has changed—not only in the dimensions we can track but also in those we cannot measure within

[7] See Stantcheva (2023), Choi and Robertson (2020), D'Acunto et al. (2022), Giglio et al. (Forthcoming), Liu et al. (Forthcoming), Bauer, Ruof, and Smeets (2021), Brauer, Hackethal, and Hanspal (2022), Chinco, Hartzmark, and Sussman (2022), Gargano and Rossi (2023) and Gargano and Giacoletti (2024).

the app. This helps address concerns that users may be altering their behavior in ways that are not directly captured by the app.

We then evaluate why users do not respond to the carbon calculator information. Our results indicate that the ineffectiveness of the carbon calculator is unlikely due to its computation or delivery, as users find the information provided by the app to be easy to understand, accurate, novel, and accessible. Additionally, we do not find evidence to reject the hypothesis that individuals do not change their behavior because of constraints they face. Users express neutrality towards statements that: i) the cost of becoming more sustainable is high, and ii) they are already minimizing their emissions. Finally, we explore further the channels related to the adoption of sustainability services within the app, particularly in the context of the sacrifices individuals are willing to make—personally and collectively—to fight climate change. Our results show that our app users may not be willing to change their behavior because they do not perceive climate change as more important than the other socio-economic issues they face in society. In addition, they do not seem to be willing to bear the costs of the policies needed to combat climate change.

The reasons for the limited adoption of carbon offsetting tools are more straightforward. The primary drivers appear to be a lack of awareness and users' preference for direct benefits associated with carbon offsetting, such as having newly planted trees in their own country rather than abroad—as it is the default for the app. In contrast, high costs, the limited desire to be sustainable, and the belief that planting trees is not a successful carbon-offsetting tool, do not seem to be significant factors.

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,[8] 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.[9] 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. Chen, Lin, and Luo (2024) study how gamified social interactions on a payment

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

[9]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.

app can have a positive effect on green investment decisions. 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 comparison to information provisions and nudges.[10] 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)).[11] 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.

[10]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.

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

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 for this study were provided by an Italian Neobank. Like similar app-based financial institutions around the world—such as Chime in the US, Nubank in Brazil, and Revolut in the UK—it offers low-cost banking services through a streamlined, mobile-centric platform and no physical branches. Its services include checking accounts with associated debit cards, personal finance management tools, and peer-to-peer payments between its users, among others. The uniqueness of our setting is that our Neobank also offers its customers tools to monitor and manage the footprint/emissions associated with their spending.

More specifically, by paying a fee of €2.50, users can subscribe to the "Footprint Calculator" 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 transaction amount, carbon footprint information is updated in real-time once the transaction is approved, with the cumulative monthly total resetting to zero at the start of each month. The technology used to produce information on users' carbon footprint is provided by Doconomy—an industry leader in this space that provides this service to the majority of other banks and card providers.[12]

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.[13] Ideally, carbon footprints would be measured at the product level, but this is not yet feasible. Nonetheless, for our purposes, it is crucial to note that we employ state-of-the-art technology and the same metrics widely used by banks and credit card companies. Indeed,

[12] As reported at the following link: https://www.doconomy.com/products/impact-transactions, "Doconomy's world-leading Climate Transaction solution (Aland Index) is distributed to 90+ financial institutions in more than 40 countries to help their customers convert every transaction into its CO_2e footprint."

[13] As explained on Doconomy's website: "The Aland Index methodology is third party reviewed by EY and the data used for the calculations is based on the latest financial and environmental data from S&P Global."

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,[14] BNP Paribas,[15] Standard Chartered,[16] and Ålandsbanken[17]) 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,[18] which contains all carbon offset projects listed globally by four major voluntary offset project registries,[19] 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.[20] The €7 carbon offsetting price is also in line with the rest of the industry. Conte and Kotchen (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

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

[15] 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

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

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

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

[19] 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

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

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 resulting cross-sectional distribution. 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.[21] 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 Italy. This is partially expected, given the relatively young user base.

On the one hand, the relatively young age of the app's users limits the generalizability of our findings to the broader Italian population. On the other hand, this demographic is particularly relevant for sustainability efforts, as younger individuals will bear the brunt of climate change's long-term consequences, giving them a stronger personal incentive to engage with sustainability initiatives. As a result, this group is the one most likely to react to the carbon calculator and carbon offsetting

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

tools we study. Moreover, this cohort is of particular interest to policymakers. Younger individuals have a longer time horizon over which their financial behaviors and consumption patterns will shape environmental outcomes, making the early adoption of sustainable habits crucial for long-term emission reductions. Additionally, younger generations tend to be more receptive to new technologies, including those that promote sustainability—such as electric vehicles, digital payments (which reduce paper waste), and smart energy solutions.

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 several studies examine the factors that drive individuals' sustainable behaviors for specific products, like plastic cutlery, often within quasi-experimental settings (see e.g. Sachdeva and Zhao, 2021, Olson, 2013 and He et al., 2023), far less is known about 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.

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 this end, we study users' spending and emission habits across consumption categories. We first map merchant category codes (MCCs) from card transactions to the two-digit Classification of Individual Consumption According to Purpose (COICOP).[22,23] This is a classification developed by the United Nations Statistics Division to classify and analyze consumption expenditures incurred by households and comprises 13 categories.[24] We then compute, for each user, the fraction of spending and emission in each category using the entire sample, and report the average across users.

The results are reported in Figure 1. The red dots refer to the spending shares, while the 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.

To assess the validity of the data, we compare the spending shares in Figure 1 with data from the Istituto Nazionale di Statistica (ISTAT).[25] While the ISTAT data is at the household level (rather than the individual level) and covers all expenses (whereas Figure 1 is based solely on card transactions, the only type for which we can compute a footprint), there are striking similarities between the two sources. "Food & Beverages" and "Fast Food, Restaurant & Hotel" appear among the top consumption categories in both datasets, while "Alcohol & Tobacco" and "Education" rank among the lowest. The main difference arises from the "Home" and "Recreation" categories, which are the largest expenditure categories in the ISTAT and our app data, respectively. This discrepancy is likely explained by the fact that rent and mortgage payments are rarely made using cards. After removing these categories,

[22] In Section A of the Online Appendix, we similarly show that, even when we compute the analysis at the individual MCC codes, users' consumption is not concentrated in a few consumption categories.

[23] Note that this aggregation is not available to App users.

[24] 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.

[25] ISTAT is Italy's governmental body responsible for collecting, analyzing, and disseminating official data on demographics, the economy, society, and the environment. Data is available at this Link.

the correlation between the two series is 0.83.

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.[26] The top plot 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. While MCC codes typically classify the type of goods or services a business offers, some MCC codes can be company-specific for large corporations like United or American Airlines. As an example, the bottom plot 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

[26]Since the carbon emission associated with a transaction is equal to the product of the euros spent and the carbon emitted per euro associated with the MCC code of that transaction, we can retrieve the latter quantity by simply dividing emissions by euros spent.

transportation have the lowest carbon per Euro (0.2kg per €). Moving to the right, the graph is increasingly populated by ground transportation (with group transportation, like buses, having a lower footprint 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 €10,000 level of spending, individuals' emissions range from 500 to 8,000kg. At €45,000 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 €0 to €3,000), emissions per euro increase substantially from 0.4 to 0.45. The relationship then flattens for levels of spending between €3,000 to €8,000 only to become negative for levels of spending above €8,000.[27]

[27]When we formally test for this relation by regressing emissions per euro on squared spending and the level of spending

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 proportionally less on Utilities, which have relatively high emissions per euro, and more on Recreation, which has lower 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 could enable 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 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 €3,000), medium-spending (between €3,000 and €8,000), and high-spending (above €8,000) 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 individuals for all categories with the exception of Transportation, likely due to the more frequent use of cars and flights by high-spending individuals.

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

with obtain an estimate of $-.00041$ (t-stat of -13.42).

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 of these services and the changes in consumption.

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 the carbon calculator 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 it.

Unfortunately, we cannot employ such a strategy because the sustainability tools have been available to the entire 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 a marketing campaign 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 encouraged group) are randomly assigned to receive encouragement to take it. This design fits our setting because the marketing campaign promoted the adoption of these sustainability tools to certain users but not others in a random fashion. Imbens and Angrist (1994) and Angrist, Imbens, and Rubin (1996) show that this design allows for the estimation of the so-called local average treatment effect (LATE)—the effect of the sustainability tools for the compliers. 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. It was meant to understand the effectiveness of push and email notifications in enticing app users to subscribe to the bank's sustainability tools. To this end, the company ran an A/B test on the user population who did not yet subscribe to either the carbon calculator or carbon offsetting tools. The users were randomly split into two groups: an encouraged group and a control group. We confirmed with the marketing team that the company did not condition encouragement on users' characteristics because they wanted to assess the effectiveness of the promotional campaigns. Because the randomization was managed by the company, we verify that users' characteristics are balanced in Section 5.2.1 below.[28]

The encouraged group received both email and app push notifications to encourage signing up for either one of the sustainability tools, while the control group received no communication. The email and app notifications ranged in the type and content of the messages but either highlighted the carbon calculator 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. Starting from 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, policymakers aim to limit emissions not by reducing consumption but by shifting it towards more carbon-efficient alternatives. 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. Finally, $\mathbb{1}\{\widehat{Sus\_Tool}\}_{i,t}$ is the instrumented

[28]Discussions with the company revealed that the campaign was discontinued and not repeated due to the limited absolute number of users who subscribed to the carbon calculator and carbon offsetting tools as a result. However, as demonstrated below, we find a significant percentage increase in adoption due to the campaign despite a small absolute take-up.

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 estimates of β 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 encouraged group, compared to the control group. The exogeneity of the instrument is guaranteed by the fact that the assignment of the encouragement is random. As mentioned above, to provide evidence in this direction, Section 5.2.1 shows that users' characteristics are balanced across the encouraged 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 encouraged 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 to their income, it is harder for users to benchmark information on their emissions. Users may also perceive that adopting sustainable practices is too costly or may not view climate change as pressing enough to justify changes in their behavior. 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).

Displaying users' carbon footprints could even negatively impact their sustainable behavior (e.g., a positive β coefficient estimate) if users mistakenly believe that the displayed information represents their entire carbon footprint (rather than just the one derived from card transactions). This could lead them to conclude that they are acting 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 user 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 where 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.

These findings can be seen as lower-bound estimates of the carbon calculator's impact. This is because, after viewing the emissions linked to their transactions, users might feel compelled to switch some of their non-sustainable consumption to cash to alleviate concerns about their footprint. If such substitution occurs, we would observe a *d*ecrease in both total emissions and emissions per dollar for adopters of the carbon calculator. Note, however, that this potential bias should be small in our sample, given that ATM withdrawals account for only 3.5% of total spending both before and after the adoption of the carbon calculator.

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.

The estimates in Table 4 are based on total consumption and emissions, aggregated across all consumption categories. However, users' responsiveness to the information provided by the Carbon Calculator tool may vary across consumption categories due to external constraints or personal preferences.[29] To explore this, we estimate Equation 4 for *Emissions Per Euro* separately for each of

[29]For instance, users who need to travel long distances may find it impractical to switch from flights to lower-emission transportation options, as these alternatives may be too slow.

the thirteen COICOP consumption categories described in Section 4. The results, presented in Figure A.2, show that all t-statistics fall within the ±1.64 interval, indicating that the null effect observed in Table 4 is robust to disaggregating by category.

5.2.3 Second Stage: Carbon Offsetting

By subscribing to the carbon offsetting tool, users receive a monthly allowance that offsets their C02 emissions by up to 1,000Kg per month. While offsetting mechanically reduces users' footprint by the allowance amount, whether individuals' emissions change compared to before adopting carbon offsetting ultimately depends on how users change their behavior.

We start by describing the "positive" scenarios regarding the fight against climate change. First, users might not change their behavior. In this scenario, we would observe a drop in emissions, which is purely mechanical and driven by the allowance. Second, the subscription to the carbon offsetting service might motivate users to become more sustainable. In this scenario, the effect on emissions is driven by both the mechanical effect of the allowance and an active decision of the users to become more sustainable.

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 become less sustainable. 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. Drawing 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 the associated effort costs. 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 these two scenarios, we would expect the emissions to stay the same or even increase, depending on whether the change in behavior is fully or only partially offset by the allowance.

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—i.e., a drop in emissions. We could even have many users become net-zero emitters for allowance values close to their footprint prior to adopting offsetting.

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. Since we do not observe a significant change in consumption, these results are in line with the first scenario where the drop in emissions is purely mechanical and driven by the allowance rather than by an active decision of the user.[30] 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. This is because the allowance is very large compared to the emissions prior to the adoption of the service. Finally, the Kleibergen-Paap Wald F-statistics show that it is unlikely our procedure suffers from a weak instrument problem. Because of the mechanical effect of the allowance in reducing emissions, one would expect these results to carry over when disaggregating by category. We estimate Equation 4 for *Emissions Per Euro* separately for each of the thirteen COICOP consumption categories described in Section 4. The results, presented in Figure A.2, show that we obtain t-stats ranging from -1.69 to -18.84 for eleven out of the thirteen consumption categories.

[30]In the data, we only observe the emissions net of the allowance. However, we can reconstruct "gross" emissions for each transaction by multiplying the euro spent and the carbon-per-euro of the MCC code associated. The IV results are statistically insignificant for both gross carbon emissions and gross carbon emissions per euro, further confirming that adopting carbon offsetting *causes* a mechanical reduction in users' emissions but does not change their 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, 2022) 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 4, 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 4, 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, 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 4, 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 their carbon footprint dramatically.

5.4 Evidence In Support of the Exclusion Restriction

The validity of our IV strategy hinges on the exclusion restriction—that the marketing campaign affected users' behavior only through its effect on the adoption of the sustainability tools. To informally assess whether the treatment's encouragement 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. Naturally, our exclusion restriction also implies that the encouragement intervention does not directly influence behavior among users who adopt the sustainability tool; however, this assumption cannot be directly tested.

6 Economic Mechanism: Survey Evidence

The administrative data reveal two main findings. First, individuals are likely to purchase carbon calculator services but do not change their behavior after adopting them. Second, carbon offsetting services drastically reduce users' net emissions but have low uptake.

Since transaction data do not provide insights into users' motivations and preferences, we draw on emerging literature in finance and economics that uses surveys administered to agents whose actions are observed to understand the economic mechanisms driving individual behavior.[31] Understanding these economic channels is also crucial to informing the next generation of FinTech tools to combat climate change.

Section 6.1 describes the structure of the survey. Sections 6.2 and 6.3 contain the results of the carbon calculator and carbon offsetting tools. Finally, Section 6.4 presents results on users' knowledge about climate change and their opinion on the importance of this problem.

6.1 Structure of Survey

The survey was administered to a subset of 10,000 app users through email and app notifications over the two-week window between June 24th and July 8th, 2024. It was completed by 550 users, for a response rate of 5.5%. This response rate is within the typical range for unsolicited online surveys. McCahery, Sautner, and Starks (2016) achieve a response rate of 4.3% in their survey of institutional investors, while Giglio et al. (Forthcoming) obtain a response rate between 2.5%-4% when surveying retail investors.

The survey consists of three sections. The first starts by asking app users whether they ever subscribed to the carbon calculator tool. Depending on their answer, two different sets of questions are displayed. Those who have adopted the tool are asked whether they believe it has influenced their sustainability habits and to evaluate which factors are most important in driving their behavior. Non-adopters are instead asked to evaluate why they did not adopt the tool. Finally, both adopters and non-adopters are asked to select from a list of possible changes they would like to be implemented

[31] See Stantcheva (2023), Choi and Robertson (2020), Giglio et al. (Forthcoming), Liu et al. (Forthcoming), Bauer, Ruof, and Smeets (2021), Brauer, Hackethal, and Hanspal (2022), Chinco, Hartzmark, and Sussman (2022), Gargano and Rossi (2023) and Gargano and Giacoletti (2024).

in the app.

The second section follows a similar structure. It begins by asking whether the user has ever subscribed to the carbon offsetting program. Based on their response, users are then asked to rate various reasons for their decision. Finally, both adopters and non-adopters are asked to select from a list of potential changes they would like to see implemented in the app.

The final section of the survey includes questions designed to assess users' beliefs about the importance of climate change relative to other socioeconomic issues. The full list of questions is available in Online Appendix B.

6.2 Carbon Calculator: Why Don't Users Change Their Behavior?

Recall that our results based on administrative results show that adopting the carbon calculator services does not affect users' sustainability. Numerous potential economic channels could explain this lack of an effect. We start by evaluating the ones related to how the app is designed and the carbon calculator information delivered.

A natural concern is that users might not respond positively to the carbon calculator if they perceive the carbon footprint information to be inaccurate. Since carbon emissions are computed at the MCC code level, this method can at times lack precision. For instance, an app user who visits the same supermarket twice, buys very different items each time, but spends the same amount will see identical carbon footprints for both transactions. This may lead users to question the accuracy and credibility of the information provided. A related but distinct concern involves individuals' inability to comprehend how the information is calculated. A product's carbon footprint is the result of multiple supply chain steps, each contributing to the overall footprint. However, the calculations rely on proprietary technology from a third-party provider, introducing a layer of opaqueness. Consequently, users may disregard the information because they find it difficult to understand. A third possibility is that app users are sophisticated enough to know the approximate carbon footprint of their transactions before signing up for the service. As an analogy, this would be equivalent to individuals being able to accurately estimate the caloric intake of every item on their diet before using calorie-counting apps. In such cases, users may not change their behavior because the app provides information they already know. Finally, app users may not react to the information provided by the app if it is not salient enough, i.e., if visualizing it involves too many clicks.

To assess the relevance and potential importance of each channel, we ask carbon calculator adopters to express their agreement with the following statements: *"I understand how my emissions are calculated," "I think the information is accurate," "The information is new (I wasn't already aware of my emissions),"* and *"The information is easy to reach."* The scale ranges from 1 to 5, with 1 indicating complete disagreement with a statement, 5 indicating complete agreement, and 3 indicating neither agreement nor disagreement.

The top panels of Figure 5 display the distribution of the responses to each question, together with the average and the p-value of a test that the mean is equal to 3. Because of the ordinal nature of the data, we perform a Wilcoxon rank-sum test. For all four statements, more than 2/3 of the users respond with a 4 or 5, and we consistently reject the null that the mean is 3. This indicates that users find the information provided by the app to be easy to understand, accurate, new, and accessible. These results suggest that the way the carbon calculator information is computed and delivered may not be the primary reason users do not respond to it.

6.2.1 Conditioning on *Perceived* Effectiveness of the Carbon Calculator Tool

An appealing aspect of our setting is that the survey allows us to measure the extent to which individuals *perceive* the carbon calculator to be helpful. We show in Figure A.3 that, when asked, approximately half of the respondents believe their sustainability has improved since adopting the carbon calculator tool. This is true whether they are asked about dimensions measurable within the app, such as the emissions associated with their card transactions, as well as in areas the app cannot measure, such as the sustainability of their investments, their donations to pro-environment entities, and their meat consumption—this helps address concerns that the sustainability of consumption observed within the app may not accurately reflect sustainability in other domains that are not directly measured. Almost all the remaining users respond that their behavior has not changed. Finally, only a negligible percentage of the respondents say that the carbon calculator has negatively affected their sustainability. The disconnect between individuals' behavior and their perception further indicates that the lack of an effect we estimate in the administrative data is unlikely due to the app's shortcomings in processing and displaying the information.

Asking app users whether they perceive the carbon calculator helpful in improving their sustainability further allows us to explore alternative channels for its effectiveness or lack thereof. When we focus on those who respond that the app helps them be more sustainable, we consider two channels, i.e., that the tool helps the investors monitor their emissions and is motivating. To this end, we ask users whether they agree with the following statements: *"it [the carbon calculator] helps me monitor and achieve my target"* and *"It [the carbon calculator] is motivating."* The results, reported in the bottom left plots of Figure 5, show that the average responses are 3.53 and 3.80, respectively, both statistically different from 3. In Panel A of Table A.1, we show, using a Wilcoxon rank-sum test, that the average response to the second question is statistically higher than the one for the first question, suggesting the motivation channel has more bearing.

For those who respond that the tool is not helpful in improving their sustainability, we consider the role of constraints. In particular, some users may find it too costly to be more sustainable because substituting less sustainable consumption for more sustainable consumption may be prohibitively expensive. Another potential channel could be that some users may not react to the carbon calculator information if they are already minimizing their emissions and there is no additional room for them to be more sustainable. We ask the users to express their agreement with the following statements: *"It is too costly to be more sustainable (in terms of time and money)"* and *"I already minimize my emissions and can't do better."* As shown in the bottom right plots of Figure 5, both distributions are closely centered around 3, and we fail to reject the null that the average response is equal to 3, suggesting that neither economic channel is likely to drive the lack of response we document.

6.2.2 Understanding the Limitations of the Carbon Calculator Service by Focusing on non-Adopters and Users' Wishlist

Two additional approaches to identifying the limitations of the carbon calculator service are to analyze why a large fraction of users (74% as shown in Table 1) do not adopt it and to ask users which improvements they would like to be implemented in newer versions of the app.

Starting from the former, we ask non-adopters to express their agreement with the following statements about the carbon calculator: *"Cost is too high"*, *"I don't understand how my emissions are calculated," "I don't think the information is accurate," "The information is not new (I am already aware of my emissions)," "I didn't know this service existed," "I am not interested in being sustainable," "I do not use the card much."* The results, displayed in Figure A.4, show that the decision not to adopt the service is not related to the inherent limitations in how the carbon footprint information is processed and displayed by the app. We also find that only a small proportion of app users show no interest in sustainability. The two most common reasons for not adopting the service are a lack of awareness about its existence and a perception among some users that their infrequent use of the credit card linked to the app does not justify the cost.

To further understand whether the carbon calculator tool has fundamental flaws, we ask users to rate several proposed enhancements to the app based on the literature pointing to the effectiveness of gamification, peer benchmarking, goal setting, and nudges in motivating individuals.[32] As we show in Table 8, we do not find that users have a large appetite for any of the improvements we propose. First, 15% of the users think no improvements are necessary. Among those who choose at least one improvement, 26% would like to be compared and benchmarked to other users on the basis of their emissions; 24% would like to receive recommendations on how to become more sustainable; 20% would like to receive footprint information measured in the number of trees saved rather than CO2; 15% would like to receive reports associated with their emissions; and 15% would like to have the app to set personalized goals for their emissions. Note that the conclusions are similar, irrespective of whether we consider the responses of those who adopted the carbon calculator or those who did not.

Overall, the results in this section suggest it is difficult to precisely isolate distinct features that could increase the adoption and effectiveness of the carbon calculator tool.

6.3 Carbon Offsetting: Why Don't Users Adopt it?

Recall that our second key result from administrative data is that carbon offsetting services drastically reduce users' net emissions but have low uptake. To explore the underlying reasons for the limited adoption of the tool, we begin by asking app users why they did not adopt the carbon offsetting

[32] See Nisa et al. (2019) Dietz et al. (2009) and Stern (2020).

tool. We envision that three potential channels could be at play. First, users may not subscribe to carbon-offsetting services because of constraints, that is, because the cost is too high or because they cannot further reduce their emissions. Thus, we ask non-adopters to assign a score to the following motives: *"Cost is too high"* and *"My emissions are already low."* The distribution of responses is displayed in the top panels of Figure 6. Both distributions are centered at 3, and we fail to reject the null that the average response is equal to 3.

A second channel might be related to users' lack of trust in the effectiveness of carbon offsetting; that is, users may think that planting trees is an ineffective way to perform carbon offsetting, or they may think that carbon offsetting is not beneficial to them because the trees are planted in Guatemala and not in the country where they reside. To this end, we ask our app users to assign a score to these statements: *"I don't believe planting trees is effective"* and *"I would like the trees to be planted in my own country"*. The results, displayed in the top-right and bottom-left plots of Figure 6, indicate that users do not think that planting trees is ineffective (mean=2.59 and p-value=0.00). However, they have a strong preference for having them planted in their own country (mean=3.55 and p-value=0.00).

Finally, users might not subscribe simply because of a lack of interest or display limited attention. We ask to assign a score to these statements: *"I am not interested in being sustainable"* and *"I didn't know this service existed"*. Results are displayed in the bottom two plots. We reject the null that users are not interested in being more sustainable (mean=2.52 and p-value=0.00), and we find that limited attention is strongly significant (mean=3.29 and p-value=0.00).

Panel B of Table A.1 displays the results of pairwise comparisons between all the motives reported above. The most important motives are users' unawareness of the service's existence and the desire to plant trees in their own country. The latter has an average response statistically significantly larger than all the other motives, as shown by the second-to-last column labeled "N.Beat."[33] The former has an average response statistically significantly larger than four of the other motives and has an average response statistically significantly smaller than only one of the other motives, as shown by the last column labeled "N.Beaten."[34]

[33] For each motive, this column displays the number of tests resulting in a positive rejection of the null, i.e., the mean being significantly larger than the distribution of responses of an alternative motive.

[34] For each motive, this column displays the number of tests resulting in a negative rejection of the null, i.e., the mean being significantly larger than the distribution of responses of an alternative motive.

Overall, the results show that creating awareness through sensibilization campaigns and providing users with direct benefits deriving from newly planted trees could be promising avenues to increase the adoption of carbon-offsetting tools.

Understanding the drivers of enrollment decisions is also important, as it may help understand which features could lead to the broader adoption of carbon offsetting. The results, displayed in Figure A.5, show that adoption is mainly driven by the contained cost of the tool and users' limited price-sensitivity when it comes to climate change, as exemplified by the high score to the statement that every dollar spent on climate change is well-spent. Additionally, users responded they did not know how to limit their footprint on their own, so the tool was an efficient way for them to reduce their emissions. We find weaker support for the idea that users prefer to pay rather than change their behavior.

Finally, we enumerate a number of potential changes to the carbon offsetting services that could make the tool more appealing to consumers. As shown in Table 8, we do not find that users have a large appetite for any of the improvements we propose: 23% of the users state that the service does not require any improvement. Among those who choose at least one improvement, 26% would like to have more flexibility in offsetting their emissions (i.e., by gaining access to a wider range of projects beyond just reforestation), and 26% would like to see tangible evidence of the trees planted as a result of the carbon offsetting fees they pay. We do not detect much of a desire to have more flexibility in the type of carbon offsetting programs users have access to: only 20% of the users would like more carbon offsetting tiers; only 16% of the users would like to offset individual transactions; and only 12% of the users would like to be able to choose every month whether to continue with carbon offsetting or stop the service.

Overall, the results in this section suggest that the way the carbon offsetting is structured may not be the prime reason users do not sign up for it. Lack of awareness and the fact that app users do not directly benefit from the newly planted trees may play a larger role.

6.4 The Role of Literacy and Beliefs on Climate Change

In this final section, we explore further the channels related to the adoption of sustainability services within the app, particularly in the context of the sacrifices individuals are willing to make—personally and collectively—to fight climate change. Previous literature finds that individuals' knowledge and understanding of climate change, as well as their beliefs about its importance as a problem to resolve, are significant drivers of support for public policies promoting sustainability and interest in sustainable investments. Hence, it is possible that these factors could also explain our findings.

We start by eliciting investors' perceptions regarding climate change's importance and urgency. We report the results in the top-left plot of Figure 7. The plot highlights that the vast majority of respondents find climate change as an important and urgent issue as we reject the null that the average response is equal to 3 for both distributions. Between the two, it seems that respondents perceive climate as more urgent than important: 69% perceive it as urgent or very urgent, and 55% perceive it as important or very important.

Recognizing that climate change is an important problem is necessary but not sufficient for individuals to take action against it. This is particularly true for climate change, where individuals may not perceive their individual contribution as impactful. In the first bar of the top-right plot of Figure 7, we show that 69% believe that their actions are important, regardless of others' behavior, and only 20% of the respondents believe that their actions do not matter if others don't change their habits as well. Next, we ask respondents about the degree to which they perceive climate change to be caused by the actions of governments, society as a whole, private corporations, previous generations, or high-income individuals. As shown in the remaining bars in the top-right plot of Figure 7, our results show that individuals are aware that climate change is caused by society at large, and they are not ready to blame others for the issue.

However, a somewhat different picture emerges in the bottom-left plot, where we ask users if they perceive climate change to be more or less important than other common socio-economic issues, such as immigration, low economic growth, unemployment, income inequality, low birth rates, public debt, and the solvency of the public pension system. On average, only 30% of the users respond that climate is more important than other socio-economic problems (green segments). A non-negligible fraction (red segments) ranks it less important. Finally, the vast majority (blue segments) rank it equally important. Our results suggest that while individuals acknowledge the importance of climate change in isolation, they do not prioritize it over other pressing socioeconomic challenges they face.

Furthermore, when it comes to the policies needed to combat climate change, individuals don't seem to be willing to make the necessary sacrifices. In the bottom-right plot of Figure 7, we ask our respondents to choose whether they would be in favor of policies such as instituting taxes on flights and gas, banning polluting vehicles, subsidizing sustainable technologies and instituting carbon taxes for companies. Our app users are strongly against taxes on flights and gas, possibly because they believe such taxes would affect them directly and involve personal sacrifices. They are instead much more supportive of the other policies, possibly because they do not realize that they are ultimately the ones who would bear their costs.

A final concern could be that users' lack of environmental literacy could be a driver of our results. To this end, we first assess our app users' subjective knowledge of climate change by asking them, "*How do you rate your knowledge of climate change?*." About 84% of our respondents rate their knowledge to be normal, high, or very high. We then elicit users' objective knowledge on this matter by asking them, "*Which of these chemical elements contributes to climate change?*" Respondents can choose (one or more) of the following answers: "CO2" (correct answer), "Methane" (correct), "Hydrogen" (incorrect), and "Particulate Matter" (incorrect). We assign a point for each correct answer selected. The results, reported in the bottom-left plot of Figure A.6, show that the vast majority of users have a reasonable level of environmental literacy, as 90% of the respondents select at least one correct answer. Finally, the bottom right plot displays the score based on the question: "*Do you think cutting greenhouse gas emissions in half is enough to stop the rise in temperatures?*" Respondents can choose between "No" (correct answer) and "Yes" (incorrect): 68% of the users respond to the question correctly. Taken together, these results suggest that a lack of environmental literacy is likely not driving our main results.

All in all, this section suggests that the results from the administrative data may be driven by a subtle mechanism, i.e., that even environmentally conscious users like the ones we observe on this app may not be willing to change their behavior because they do not perceive climate change as more important than the other issues they face in society. In addition, they may not be willing to bear the costs of the policies needed to combat climate change. This rather discomforting result raises the issue of whether additional sensibilization campaigns may be needed to change individuals' perceptions regarding the climate change threat.

7 Conclusions

Climate change is one of the most pressing challenges modern society faces. While individual consumption accounts for up to 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.

A survey of app users indicates that the ineffectiveness of the carbon calculator arises from users not perceiving climate change as sufficiently important compared to other socioeconomic issues to warrant changes in their habits. The lack of adoption of carbon offsetting, on the other hand, is primarily driven by limited attention and a preference among users to see direct benefits from the externality associated with having trees planted in their country of origin.

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. Moreover, they suggest two complementary avenues for future research. 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 and for which survey respondents have shown a keen interest. The second question is whether the adoption and effectiveness of sustainability tools can be enhanced by increasing awareness of climate change, particularly in comparison to the economic challenges faced by countries.

References

Acharya, V., R. Berner, R. F. Engle, H. Jung, J. Stroebel, X. Zeng, and Y. Zhao. 2023. Climate stress testing. Working Paper.

Agarwal, S., W. Qian, and R. Tan. 2020. *Household finance*. Palgrave Macmillan.

Alekseev, G., S. Giglio, Q. Maingi, and J. Selgard. 2023. A quantity-based approach to constructing climate risk hedge portfolios. Working Paper.

Alok, S., N. Kumar, and R. Wermers. 2020. Do fund managers misestimate climatic disaster risk? *Review of Financial Studies* 33:1146–83.

Anderson, A., and D. T. Robinson. 2022. Financial literacy in the age of green investment. *Review of Finance* 26:1551–84.

Andersson, J. J. 2019. Carbon taxes and co2 emissions: Sweden as a case study. *American Economic Journal: Economic Policy* 11:1–30.

Angrist, J. D., G. W. Imbens, and D. B. Rubin. 1996. Identification of causal effects using instrumental variables. *Journal of the American Statistical Association* 91:444–55.

Baker, S. R., and L. Kueng. 2022. Household financial transaction data. *Annual Review of Economics* 14:47–67.

Barber, B. M., A. Morse, and A. Yasuda. 2021. Impact investing. *Journal of Financial Economics* 139:162–85.

Bauer, R., T. Ruof, and P. Smeets. 2021. Get real! individuals prefer more sustainable investments. *Review of Financial Studies* 34:3976–4043.

Becker, G. 2017. Does fintech affect household saving behavior? Findings from a natural field experiment. Working Paper.

Ben-David, D., I. Mintz, and O. Sade. 2021. Using ai and behavioral finance to cope with limited attention and reduce overdraft fees. Working Paper.

Bernard, R., P. Tzamourani, and M. Weber. 2023. Climate change and individual behavior. Working Paper.

Blanchard, O., C. Gollier, and J. Tirole. 2023. The portfolio of economic policies needed to fight climate change. *Annual Review of Economics* .

Bolton, P., and M. Kacperczyk. 2021. Do investors care about carbon risk? *Journal of Financial Economics* 142:517–49.

Brauer, K., A. Hackethal, and T. Hanspal. 2022. Consuming dividends. *Review of Financial Studies* .

Browning, M., T. F. Crossley, and W. Joachim. 2014. The measurement of household consumption expenditures. *Annual Review of Economics* 6:475–501.

Carlin, B., A. Olafsson, and M. Pagel. 2019. Fintech and financial fitness in the information age. Working Paper.

———. 2023. Mobile apps and financial decision making. *Review of Finance* 27:977–96.

Chen, C., T.-C. Lin, and X. Luo. 2024. Do gamified social interactions on a green fintech app nudge users' green investments? Working Paper.

Chinco, A., S. Hartzmark, and A. B. Sussman. 2022. A new test of risk factor relevance. *Journal of Finance* 77:2183–238.

Choi, D., Z. Gao, and W. Jian. 2020. Attetion to global warning. *Review of Financial Studies* 33:1112–45.

Choi, J. J., and A. Z. Robertson. 2020. What matters to individual investors? Evidence from the horse's mouth. *The Journal of Finance* 75:1965–2020.

Conte, M. N., and M. J. Kotchen. 2009. Explaining the price of voluntary carbon offsets. Working Paper.

D'Acunto, F., S. Mohrle, F. Neumeier, A. Peichl, and M. Weber. 2022. How to finance climate change policies? evidence from consumers' beliefs. Working Paper.

D'Acunto, F., N. Prabhala, and A. G. Rossi. 2019. The promises and pitfalls of robo-advising. *The Review of Financial Studies* 32:1983–2020.

D'Acunto, F., T. Rauter, C. K. Scheuch, and M. Weber. 2020. Perceived precautionary savings motives: Evidence from fintech. *National Bureau of Economic Research* .

D'Acunto, F., A. G. Rossi, and M. Weber. 2019. Crowdsourcing financial information to change spending behavior. Working Paper.

Das, S. R. 2019. The future of FinTech. Working Paper.

Dechezleprêtre, A., A. Faber, T. Kruse, B. Planterose, A. S. Chico, and S. Stantcheva. 2023. Fighiting climate change: International attitudes toward climate policies. Working Paper.

Dell, M., B. F. Jones, and B. A. Olken. 2014. What do we learn from the weather? the new climate–economy literature. *Journal of Economic Literature* 52:740–98.

Di Maggio, M., D. Ratnadiwakara, and D. Carmichael. 2022. Invisible primes: Fintech lending with alternative data. Working Paper.

Di Maggio, M., and V. Yao. 2020. Fintech borrowers: Lax-screening or cream-skimming? Working Paper.

Dietz, T., G. T. Gardner, J. Gilligan, and M. P. Vandenbergh. 2009. Household actions can provide a behavioral wedge to rapidly reduce us carbon emissions. *Proceedings of the National Academy of Sciences* 106:18452–6.

Druckman, A., and T. Jackson. 2016. Understanding households as drivers of carbon emissions. In R. Clift and A. Druckman, eds., *Taking Stock of Industrial Ecology*, chap. 9. Springer Open.

Duflo, E., and E. Saez. 2003. The role of information and social interactions in retirement plan decisions: Evidence from a randomized experiment. *Quarterly Journal of Economics* 118:815–42.

Eckles, D., R. F. Kizilcec, and E. Bakshy. 2016. Estimating peer effects in networks with peer encouragement designs. *PNAS* 113:7316–22.

Engle, R. F., S. Giglio, B. Kelly, H. Lee, and J. Stroebel. 2020. Hedging climate change news. *Review of Financial Studies* 33:1184–216.

Filippini, M., M. Leippold, and T. Wekhof. 2022. Sustainable finance literacy and the determinants of sustainable investing. Working Paper.

Fowlie, M., M. Greenstone, and C. Wolfram. 2018. Do energy efficiency investments deliver? evidence from the weatherization assistance. *Quarterly Journal of Economics* 5:1597–644.

Fuster, A., P. Godsmith-Pinkham, T. Ramadorai, and A. Walther. 2018. Predictably unequal? The effects of machine learning on credit markets. Working Paper.

Gargano, A., and M. Giacoletti. 2024. Reaching for income in the housing market. Working Paper.

Gargano, A., M. Giacoletti, and E. Jarnecic. 2023. Local experiences, attention and spillovers in the housing market. *Journal of Finance* 78:1015–53.

Gargano, A., and A. Rossi. 2023. Goal setting and saving in the fintech era. Journal of Finance (forthcoming).

Gargano, A., and A. G. Rossi. 2018. Does it pay to pay attention? *The Review of Financial Studies* 31:4595–649.

———. 2022. Goal setting and saving in the fintech era. Journal of Finance (Forthcoming).

Giglio, S., B. Kelly, and J. Stroebel. 2021. Climate finance. *Annual Review of Economics* 13:15–36.

Giglio, S., M. Maggiori, J. Stroebel, Z. Tan, S. Utkus, and X. Xu. 2023. Four facts about ESG beliefs and investor portfolios. Working Paper.

Giglio, S., M. Maggiori, J. Stroebel, and S. Utkus. Forthcoming. Five facts about beliefs and portfolios. *American Economic Review* .

Gillingham, K., A. Keyes, and K. Palmer. 2018. Advances in evaluating energy efficiency policies and programs. *Annual Review of Economics* 10:511–32.

Gneezy, U., and A. Rustichini. 2000. A fine is a price. *Journal of Legal Studies* 29:1–315.

Goldstein, B., D. Gounaridis, and J. Newell. 2020. The carbon footprint of houeshold energy use in the United States. *PNAS* 117:19122–30.

Harstad, B. 2012. Climate contracts: A game of emissions, investments, negotiations, and renegotiations. *Review of Economic Studies* 79:1527–55.

He, G., Y. Pan, A. Park, Y. Sawada, and E. S. Tan. 2023. Reducing single-use cutlery with green nudges: Evidence from china's food-delivery industry. *Science* 381:1–8.

Heeb, F., J. Kolbel, F. Paetzold, and S. Zeisberger. 2023. Do investors care about impact? *Review of Financial Studies* 36:1737–87.

Hong, H., G. A. Karolyi, and J. A. Sheinkmann. 2020. Climate finance. *Review of Financial Studies (forthcoming)* 33:1011–44.

Imbens, G. W., and J. D. Angrist. 1994. Identification and estimation of local average treatment effects. *Econometrica* 62:467–75.

IPCC. 2022. Climate change 2022: The physical science basis. contribution of working group ii to the sixth assessment report of the intergovernmental panel on climate change .

Kleibergen, F., and R. Paap. 2006. Generalized reduced rank tests using the singular value decomposition. *Journal of Econometrics* 113:97–126.

Korhonen, M., J. Pentti, J. Hartikainen, J. Ilomaki, S. Setoguchi, D. Liew, M. Kivimäki, and J. Vahtera. 2020. Lifestyle changes in relation to initiation of antihypertensive and lipid-lowering medication: A cohort study. *Journal of American Heart Association* 18:5–24.

Krueger, P., Z. Sautner, and L. T. Starks. 2020. The importance of climate risks for institutional investors. *Review of Financial Studies* 33:1067–111.

Laudenbach, C., J. Pirschel, and S. Siegel. 2018. Personal communication in a FinTech world: Personal communication in a fintech world: Evidence from loan payments. Working Paper.

Lee, S. K. 2023. Fintech nudges: Overspending messages and personal finance management. Working Paper.

Levi, Yaron nand Benartzi, S. 2023. Mind the app: Mobile access to financial information and consumer behavior. Working Paper.

List, J. A., and C. A. Gallet. 2001. What experimental protocol influence disparities between actual and hypothetical stated values? *Environmental and Resource Economics* 20:241–54.

Litterman, R., C. Anderson, N. Bullard, B. Cadecott, and M. Cheung. 2020. Managing climate risk in the u.s. financial system. *Rep., U.S. Commodity Futures Trading Comm* .

Liu, H., C. Peng, W. A. Xiong, and W. Xiong. Forthcoming. Taming the bias zoo. *Journal of Financial Economics* .

Loh, R. K., and H.-S. Choi. 2020. Physical frictions and digital banking adoption. Working Paper.

McCahery, J., Z. Sautner, and L. Starks. 2016. Behind the scenes: the corporate governance preferences of institutional investors. j. financ. 71,. *Journal of Finance* 71:2905–2932 .

Medina, P., and M. Pagel. 2021. Does saving cause borrowing? *Working Paper* .

Metcalf, G. E. 2021. Carbon taxes in theory and practice. *Annual Review of Economics* 13:245–65.

Metcalf, G. E., and J. H. Stock. 2023. The macroeconomic impact of europe's carbon taxes. *American Economic Journal: Macroeconomics* 15:265–86.

Misra, K., and P. Surico. 2014. Consumption, income changes, and heterogeneity: Evidence from two fiscal stimulus programs1. *American Economic Journal: Macroeconomics* 6:84–106.

Mullally, C., S. Boucher, and M. Carter. 2013. Encouraging development: Randomized encouragement designs in agriculture. *American Journal of Agricultural Economics* 95:1352–8.

Mulrow, J., K. Machaj, J. Deanes, and S. Derrible. 2019. The state of carbon footprint calculators: An evaluation of calculator design and user interaction features. *Sustainable Production and Consumption* 18:33–40.

Murphy, J. J., P. Allen, T. Stevens, and D. Weatherhead. 2005. A meta-analysis of hypothetical gap in stated preference valuation. *Environmental and Resource Economics* 30:313–25.

Nisa, C. F., J. J. Belanger, B. M. Shumpe, and D. G. Faller. 2019. Meta-analysis of randomised controlled trials testing behavioural interventions to promote household action on climate change. *Nature Communications* 10:4545–72.

Nordhaus, W. 1977. Economic growth and climate: the carbon dioxide problem. *American Economic Review* 67:341–6.

———. 1991. To slow or not to slow: the economics of the greenhouse effect. *Economic Journal* 101:920–37.

Olafsson, A., and M. Pagel. 2018. The liquid hand-to-mouth: Evidence from personal finance management software. *The Review of Financial Studies* 31:4398–446.

Olson, E. L. 2013. It's not easy being green: the effects of attribute tradeoffs on green product preference and choice. *Journal of the Academy of Marketing Science* 41:171–84.

Painter, M. 2020. An inconvenient cost: The effects of climate change on municipal bonds. *Journal of Financial Economics* 135:468–82.

Patnam, M., and W. Yao. 2020. The real effects of mobile money: Evidence from a large-scale fintech expansion. Working Paper.

Riedl, A., and P. Smeets. 2023. Why do investors hold socially responsible mutual funds? Journal of Finance (Forthcoming).

Rodemeier, M. 2023. Willingness to pay for carbon mitigation: Field evidence from the market for carbon offsets. Working Paper.

Rossi, A. G., and S. Utkus. 2020. Who benefits from robo-advising? Evidence from machine learning. Working Paper.

Sachdeva, S., and J. Zhao. 2021. Distinct impacts of financial scarcity and natural resource scarcity on sustainable choices and motivations. *Journal of Consumer Behaviour* 20:203–2017.

Stantcheva, S. 2023. How to run surveys: A guide to creating your own identifying variation and revealing the invisible. *Annual Review of Economics* 15:205–34.

Stern, P. C. 2020. A reexamination on how behavioral interventions can promote household action to limit climate change. *Nature Communications* 11:918–30.

Van Kooten, C. G., and C. M. T. Johnston. 2016. The economicsofforest carbon offsets. *Annual Review of Economics* 8:227–46.

West, S., N. Duan, W. Pequegnant, P. Gaist, D. Jarlais Des, and D. Holtgrave. 2008. Alternatives to the randomized controlled trial. *American Journal of Public Health* 23:18–27.

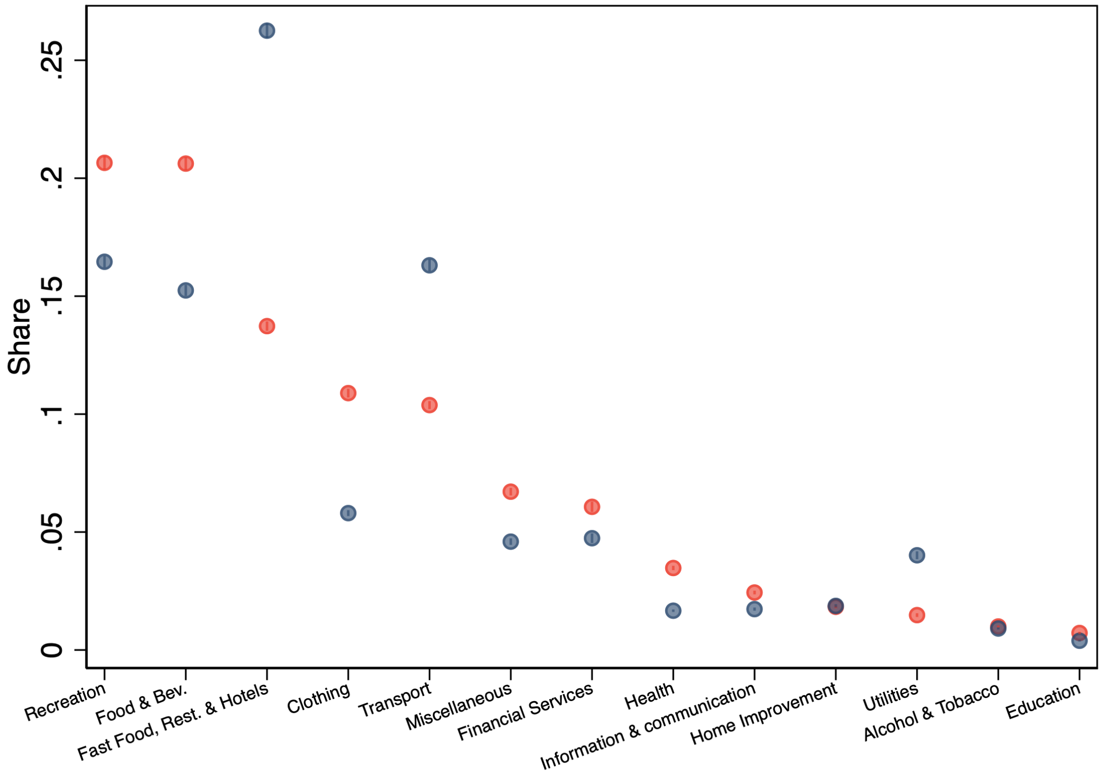

Figure 1: The Figure displays information on the distribution of spending (red dots) and emissions (blue dots) across consumption categories, displayed on the x-axis. For each user, we compute the share of spending and emissions in each category and display the across-users averages. Consumption categories are defined based on the first two digits of the Classification of Individual Consumption According to Purpose developed by the United Nations Statistics Division.

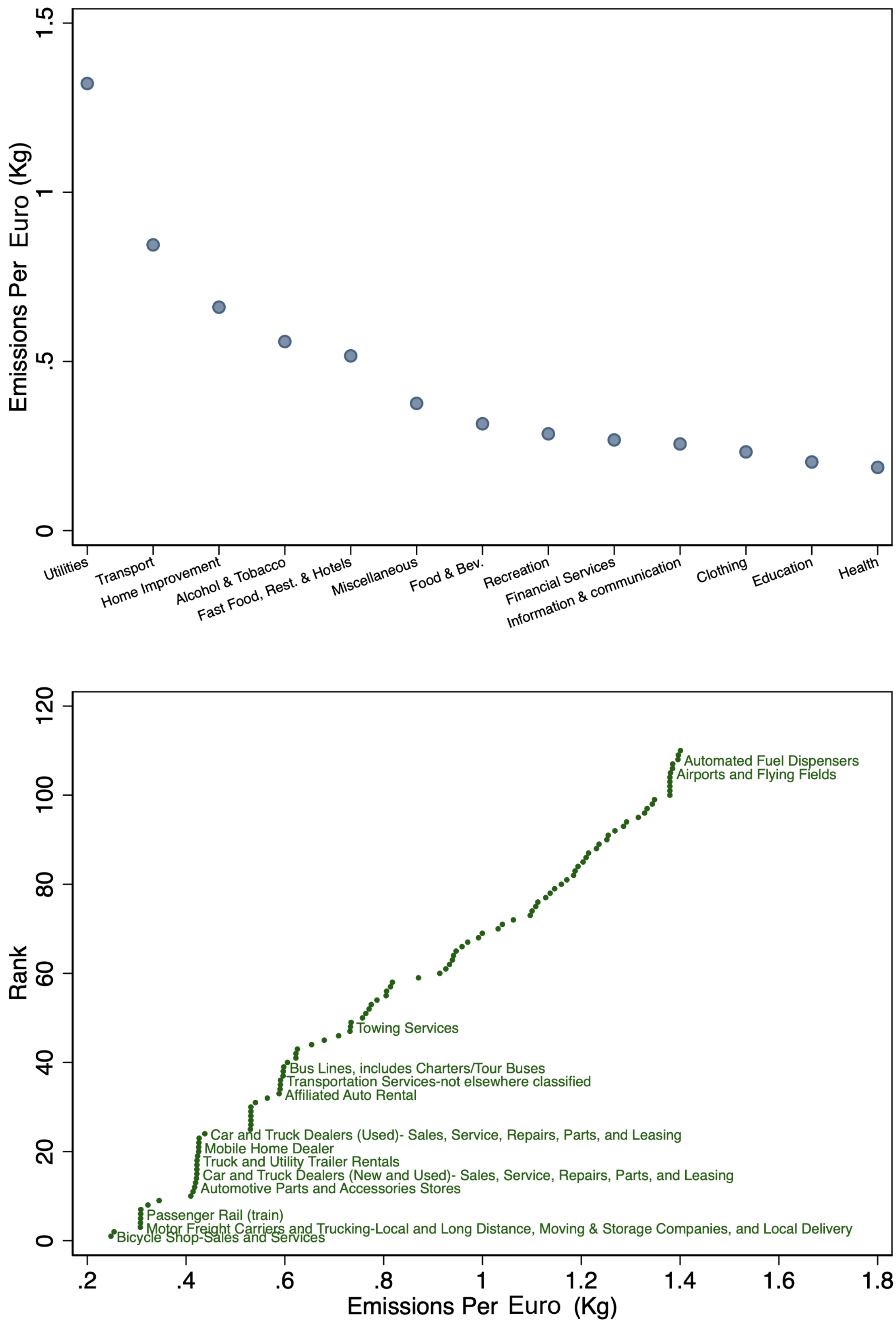

Figure 2: The Upper Figure displays the average emission per euro (in grams) across the Merchant Category Codes (MCC) in the consumption categories displayed on the x-axis. Consumption categories are defined based on the first two digits of the Classification of Individual Consumption According to Purpose 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.

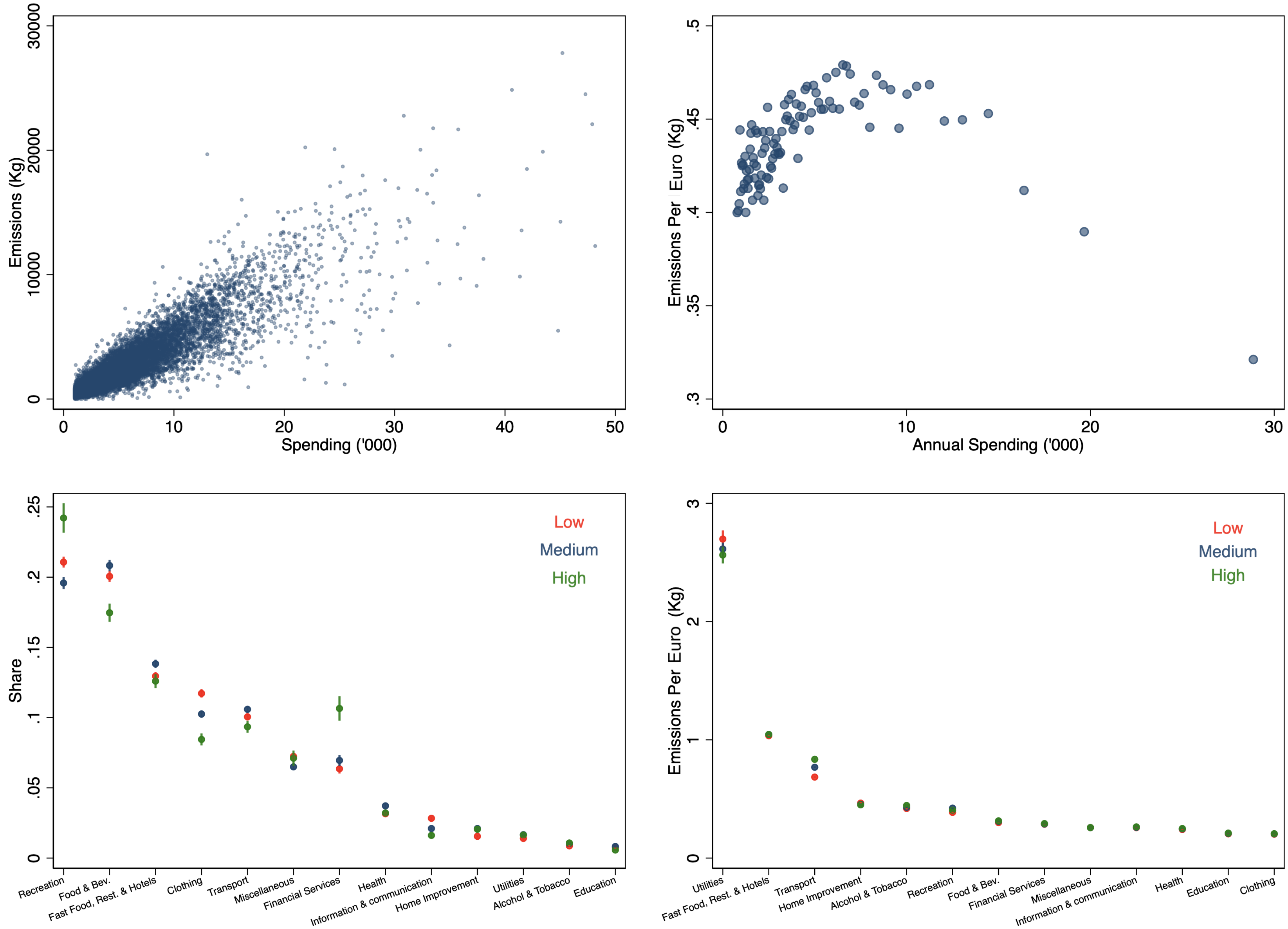

Figure 3: The Upper-left Figure displays the relation between total spending and emissions at the user level. The Upper-righ Figure displays the relation between annual spending and emissions per euro at the user level. The Lower-left (Lower-right) figures display the average across users of the share 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.

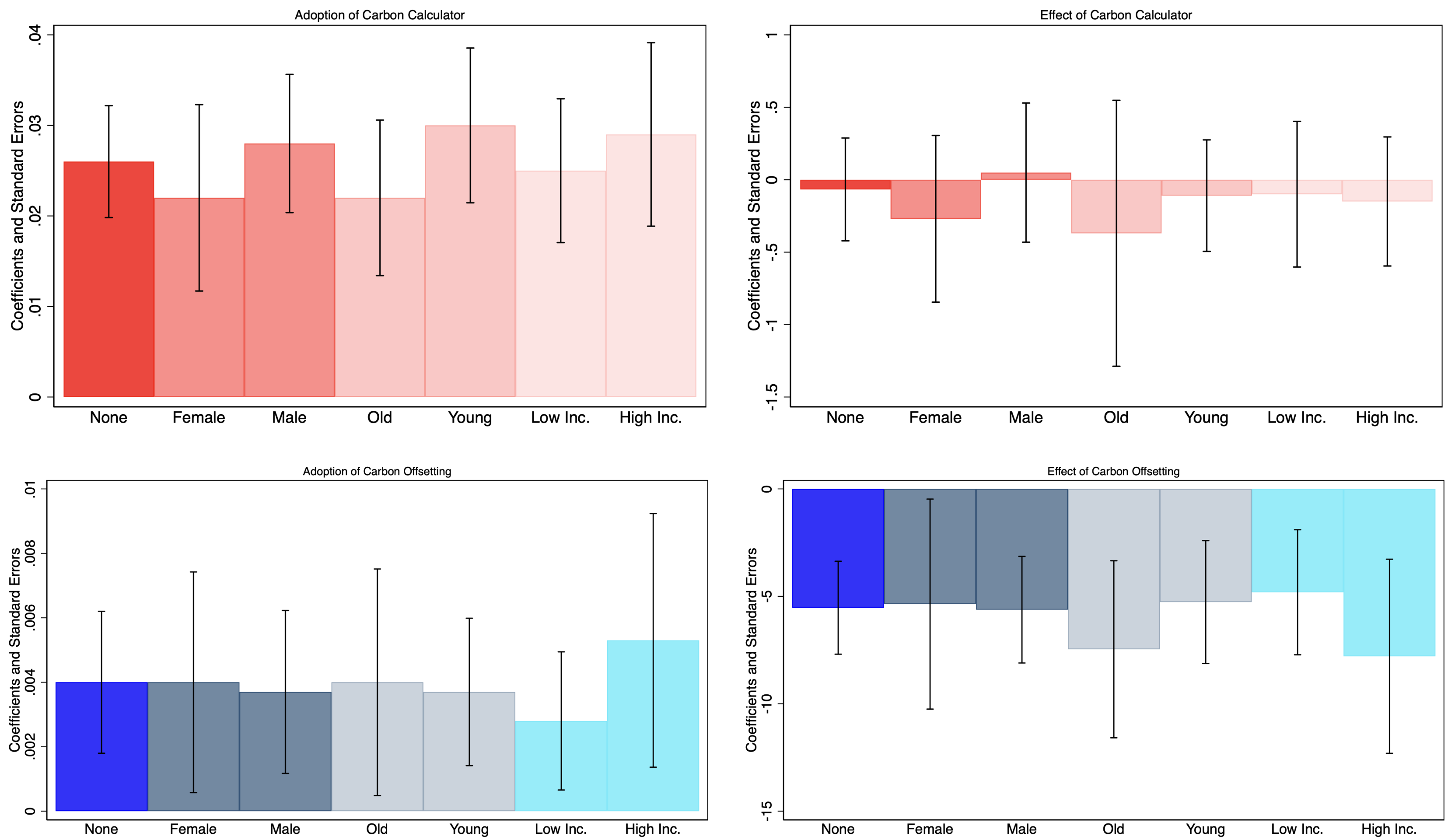

Figure 4: This Figure reports, in the left-hand-side plots, coefficient estimates, and associated 95% confidence intervals of the following regression model: $\mathbb{1}\{Sus\_Tool\}_{i,t} = \alpha_i + \alpha_t + \theta\ \mathbb{1}\{Encouraged\}_{i,t} + \epsilon_{i,t}$. In the right-hand-side plots, 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.

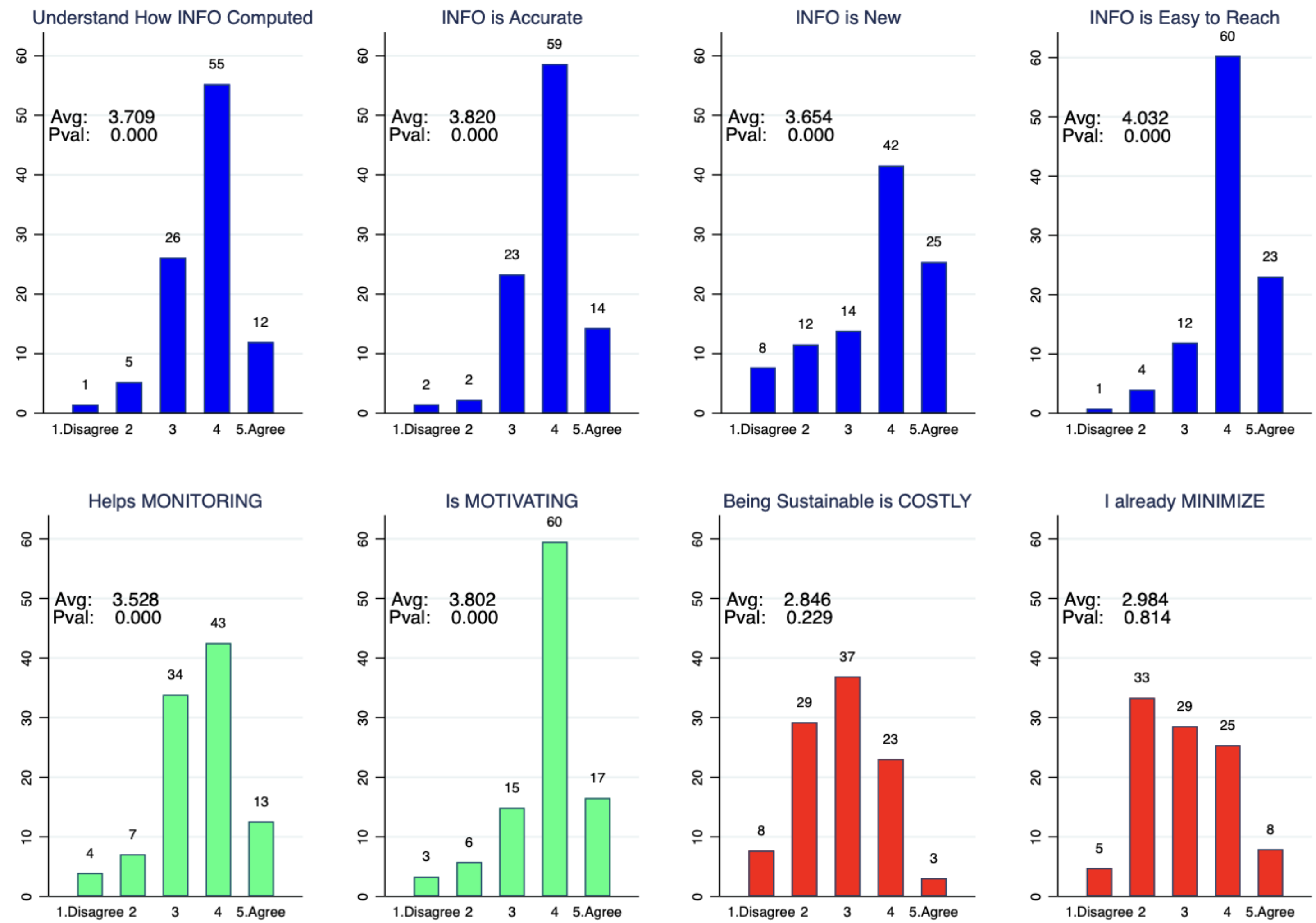

Figure 5: This Figure displays the distribution of responses (in percentages) to the Likert questions for the adopters of the Carbon Calculator. Respondents are asked to elicit how much they agree (on a scale from 1 to 5) with a series of statements. The top four plots report results for the following statements: *"The information is new (I wasn't already aware of my emissions)," "I understand how my emissions are calculated," "I think the information is accurate,"* and *"The information is easily accessible."* The bottom left plots report results for the following statements: *"It helps me monitor and achieve my target"* and *"It is motivating."* These statements are only shown to those respondents who claim they have not changed or claim they have improved their sustainability after adopting the Carbon Calculator. The bottom right plots report results for the following statements: *"It is too costly to be more sustainable (in terms of time and money)"* and *"I already minimize my emissions and can't do better."* These statements are only shown to those respondents who claim they either did not change or worsen their sustainability after adopting the Carbon Calculator. Each plot displays the average of the distribution and the p-value associated with the non-parametric Wilcoxon signed-rank test for the null that the distribution is centered at 3.

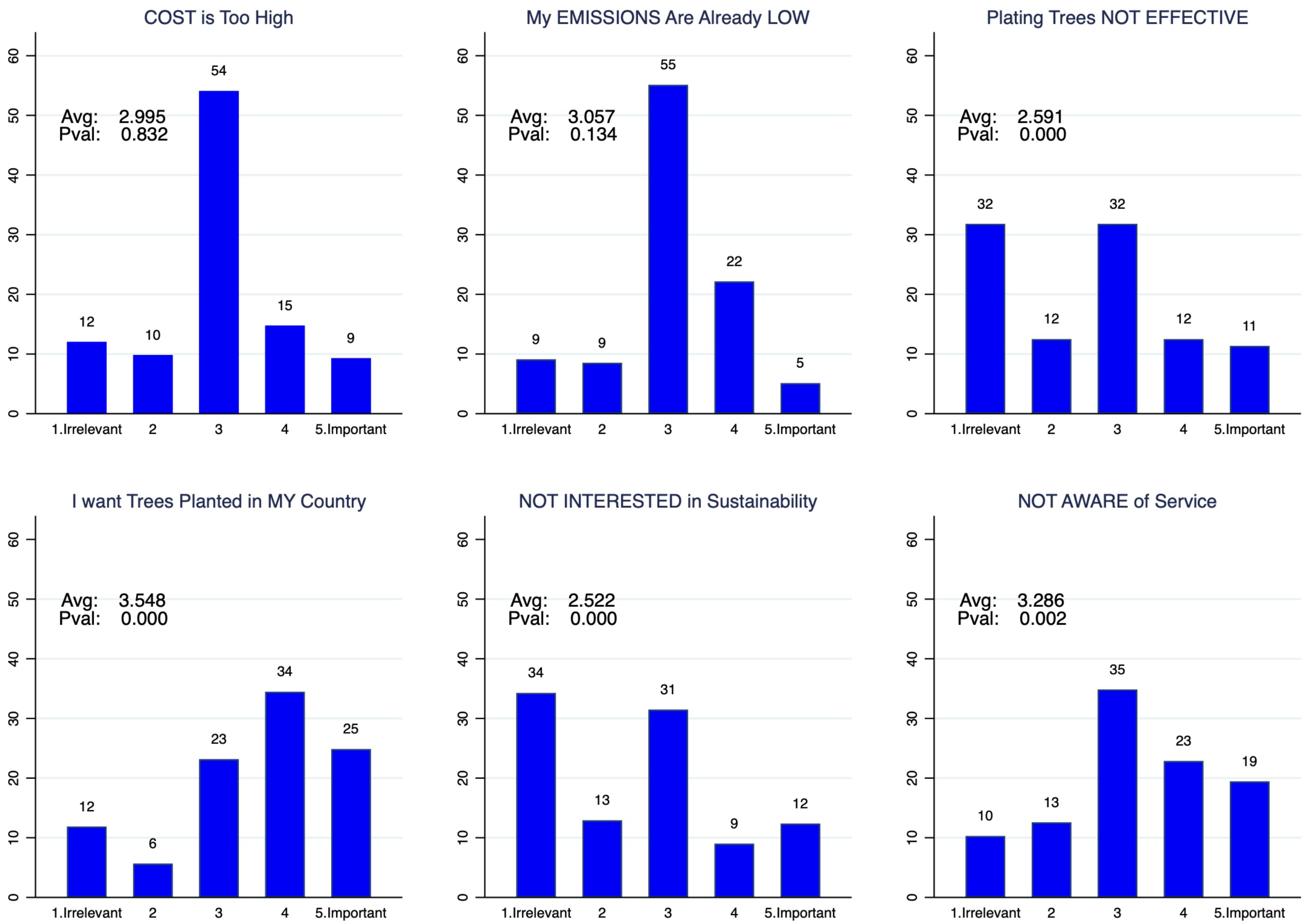

Figure 6: This Figure displays the distribution of responses (in percentages) to the Likert questions for the non-adopters of Carbon Offsetting. Respondents are asked to indicate their level of agreement with a series of statements on a scale from 1 to 5. The top-left plot report results for the *"cost is too high"* statement. The top-middle plot report results for the *"My emissions are already low"* statement. The top-right plot report results for the *"I don't believe planting trees is effective"* statement. The bottom-left plot report results for the *"I would like the trees to be planted in my own country"* statement. The bottom-middle plot report results for the *"I am not interested in being sustainable"* statement. The bottom-right plot report results for the *"I didn't know this service existed"* statement. Each plot displays the average of the distribution and the p-value associated with the non-parametric Wilcoxon signed-rank test for the null that the distribution is centered at 3.

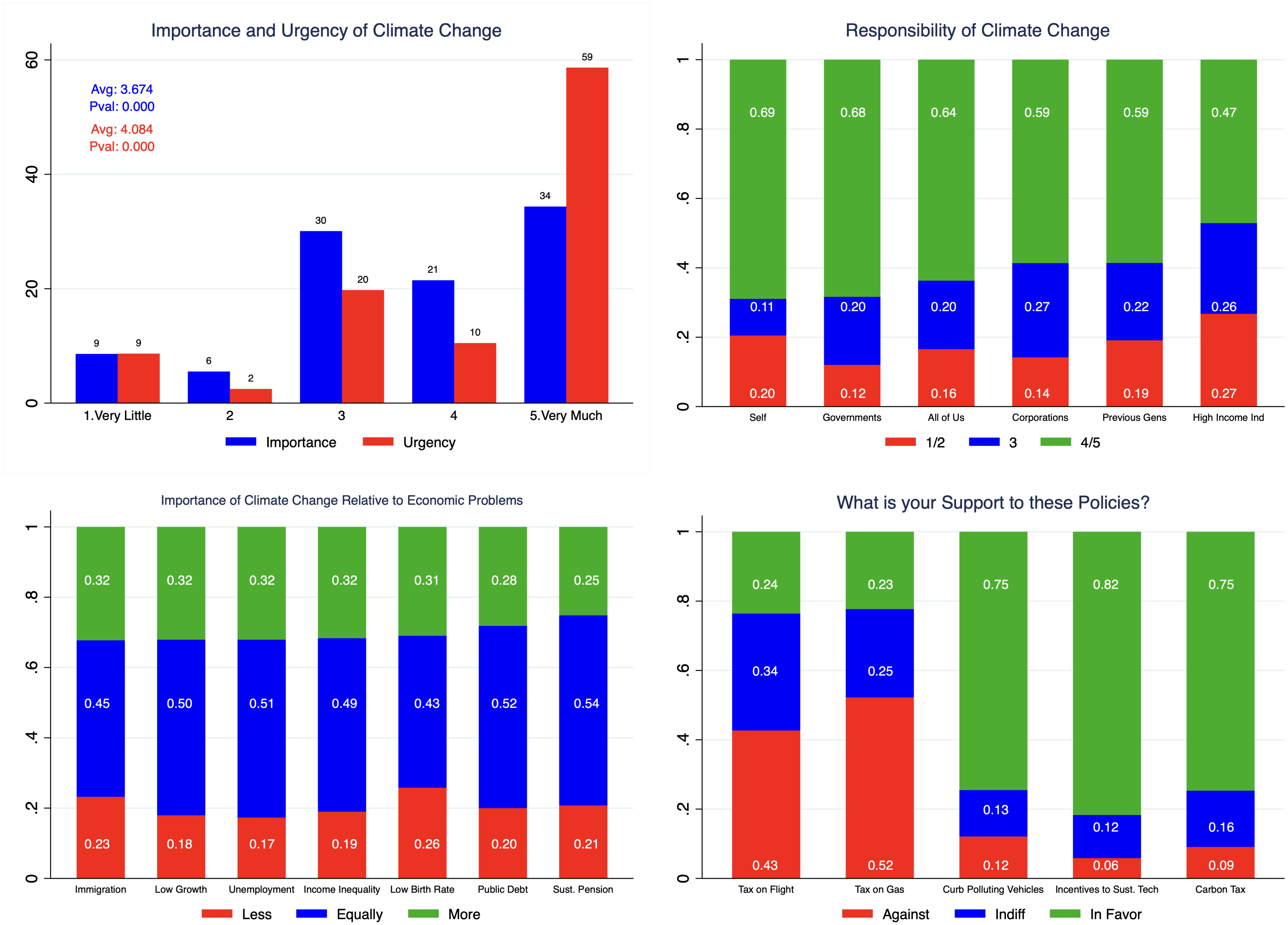

Figure 7: The top-left figure displays the distribution of responses (in percentages) to the questions *"On a scale from 1 to 5, how urgently do we need to intervene to tame climate change?"* (red bars) and *"On a scale from 1 to 5, do you think climate change has already (or will have) a negative effect on your life?"* (blue bars). The first bar of the top-right plot displays results for the question about respondents' perception of their contribution to fighting climate change. Green (blue) (red) segment denotes the *"Important regardless of others' behavior"* (*"Don't know"*) (*"Useless if others don't do the same"*) answer. The remaining bars refer to the question *"How much do you think the following entities negatively contribute to climate change?"*. The green (blue) (red) segment denotes the Very Little/Little (Fairly) (Much/Very Much) answers. The bottom-left plot refers to the question about respondents' perception of whether climate change is more, equally, or less important than other socioeconomic problems. The Green (blue) (red) segment denotes the *"More Important"* (*"Equally Important"*) (*"Less Important"*) answer. The bottom right plot refers to the question *"Do you support or oppose these policies to combat climate change?"*. Green (blue) (red) segment denotes the *"Support"* (*"Do not know"*) (*"Against"*) answer.

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 Encouraged and Non-Encouraged Users

		Panel A: Encouraged						
		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: Not Encouraged						
	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 5*th*, 25*th*, 50*th*, 75*th*, and 95*th* 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.

Table 8. Desired Changes To Sustainability Tools

Panel A: Carbon Calculator

	All	Non-Adopters	Adopters
Compare and reward users who perform better in terms of emissions	26.4	28.3	24.1
I would like to receive recommendations on how to minimize my emissions	23.9	21.6	26.8
I would like the information to be expressed in terms of trees	19.9	21.6	17.7
I would like to receive notifications and emails with reports on my emissions	15.1	14.8	15.5
I would like there to be an emission target for people with my characteristics	14.7	13.8	15.9

Panel B: Carbon Offsetting

	All	Non-Adopters	Adopters
I would like to decide how to compensate (not just by planting trees)	26.2	26.1	26.8
I would like to see tangible evidence of the trees planted.	25.8	26.1	25.0
I would like to choose from multiple plans with different costs and compensation	19.9	19.9	19.6
I prefer to choose which transactions to compensate for	15.7	15.6	16.1
I would like to decide each month whether to continue compensating	12.4	12.3	12.5

This Table displays the distribution of responses to the question *"Which of these changes you would like to be implemented?"* for carbon calculator (Panel A) and carbon offsetting (Panel B), excluding those who respond the app does not require any improvement. Results in column "All" are based on all users while results in columns "Non-Adopters" and "Adopters" are based only on non adopters and adopters, respectively.

Online Appendix for:
Fighting Climate Change with FinTech

A Distribution of Consumption Across Merchant Category Codes

To verify that users do not use the app only for a limited set of spending categories, we compute the Normalized Herfindahl–Hirschman Index (HHI) of users' spending and emissions shares across merchant category codes (MCCs) from card transactions. 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. 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. Figure A.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.[35]

[35] 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.

Additional Figures and Tables

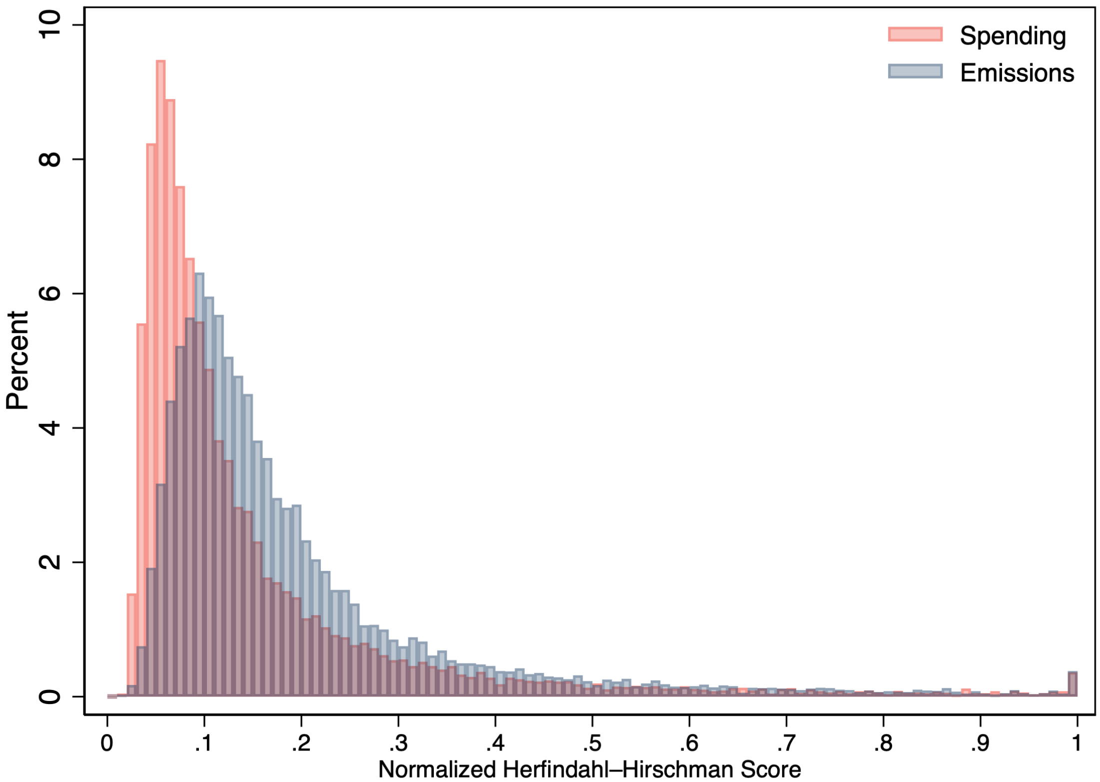

Figure A.1: This Figure displays information on the concentration of spending (red bars) and emissions (blue bars) across Merchant Category Codes. We first compute the Normalized Herfindahl–Hirschman Index for each user and display the resulting cross-sectional distribution.

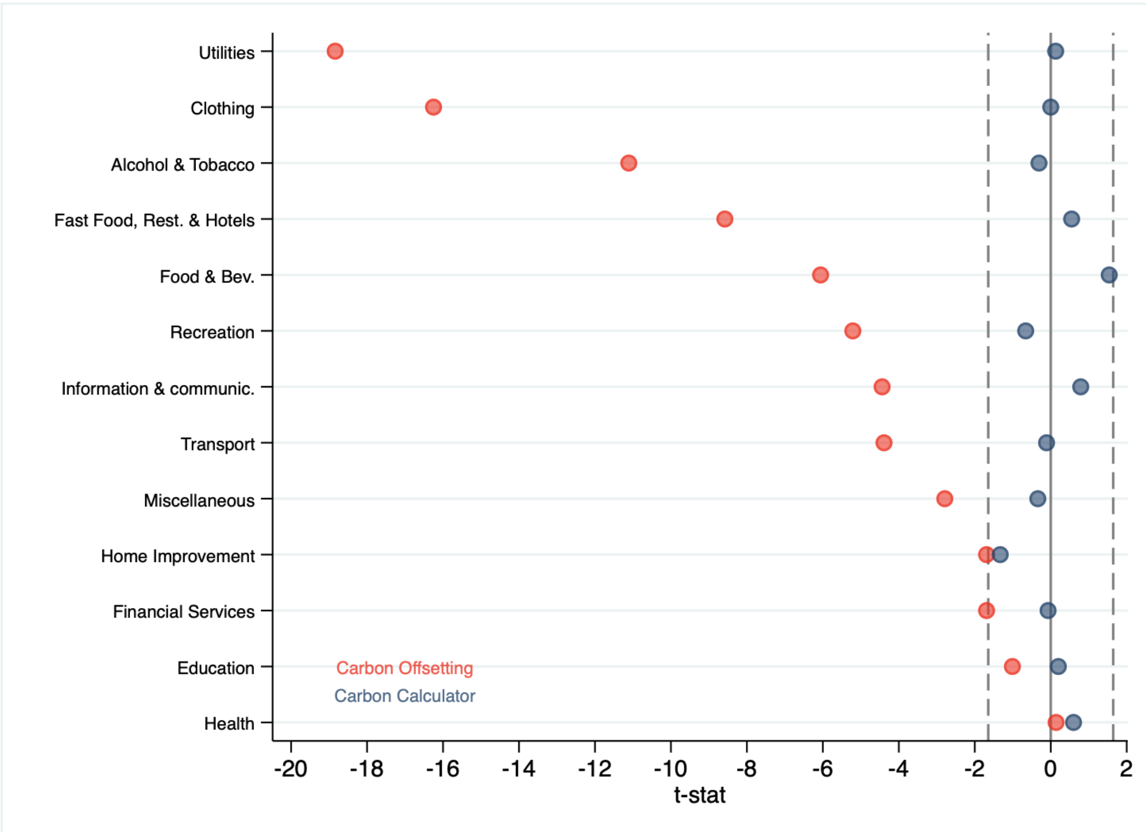

Figure A.2: This Figure displays the t-stats associated with the β coefficient estimates in the following regression model, estimated separately for each consumption category: $Emissions\ per\ Euro_{i,t} = \alpha_i + \alpha_t + \beta\ \mathbb{1}\{\widehat{Sus\_Tool}\}_{i,t} + \epsilon_{i,t}$, where $\mathbb{1}\{Sus\_Tool\}_{i,t}$ is a dummy variable equal to 1 if user i adopts the sustainability tool in week t, instrumented by $\mathbb{1}\{Encouraged\}_{i,t}$, an indicator variable for whether a user was encouraged to adopt the tool. The coefficients α_i and α_t denote user and time fixed-effects. Red and blue circles refer to the results for the Carbon Offsetting and the Carbon Calculator tool, respectively. The t-statistics are based on standard errors clustered at the user and week levels. Consumption categories (displayed on the y-axis) are defined based on the first two digits of the Classification of Individual Consumption According to Purpose (COICOP) developed by the United Nations Statistics Division and described in Section 4.1.

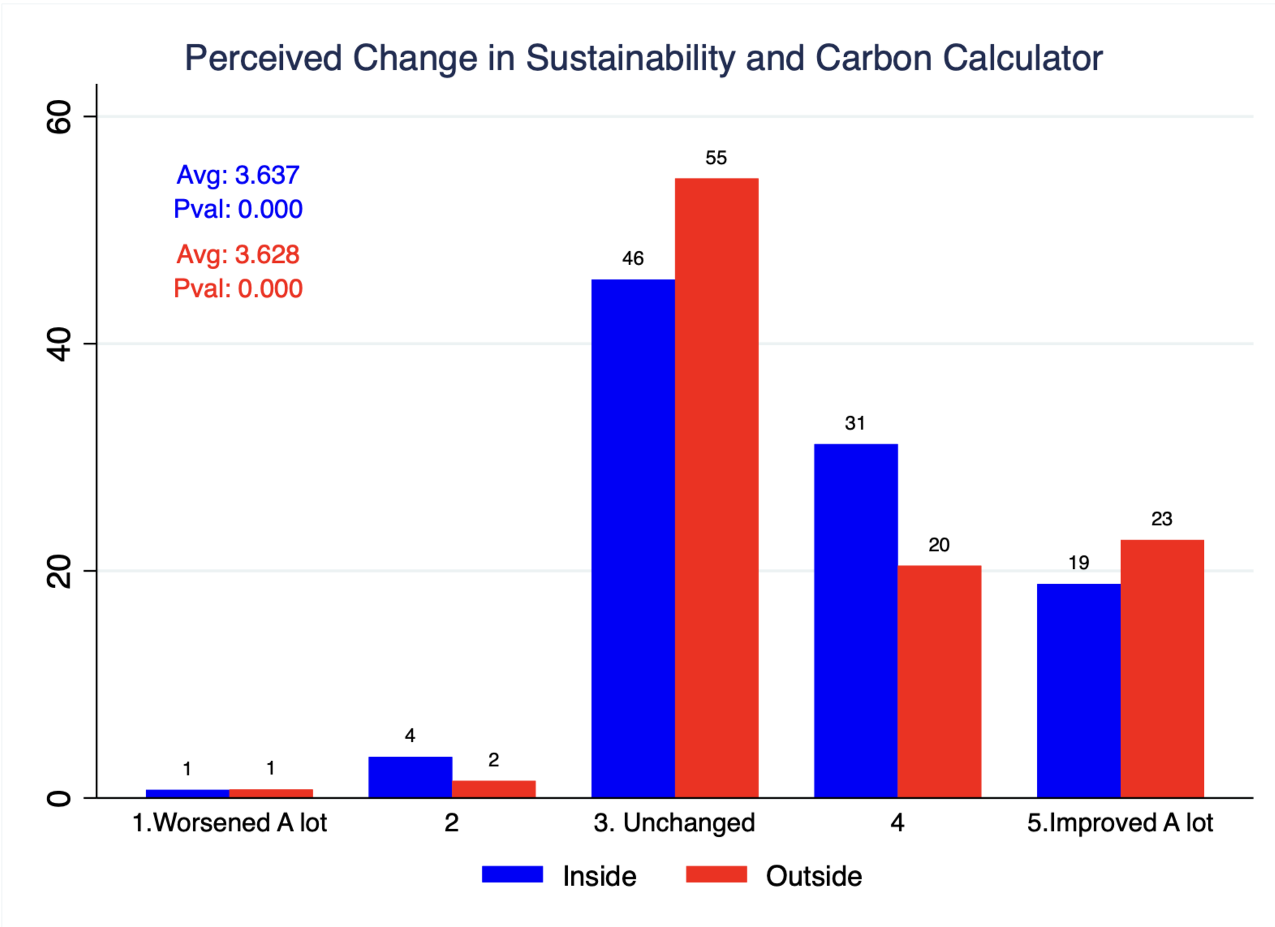

Figure A.3: This Figure displays the distribution of responses (in percentages) to the questions on users' perception of their sustainability after adopting the Carbon Calculator. Blue bars refer to the question *"On a scale from 1 to 5, how much do you think the sustainability of your consumption measured by the app has changed?"* while red bars refer to the question *"'On a scale from 1 to 5, how much has the sustainability of your consumption (not measured by the app) has changed? (Sustainable investments, donations to pro-environment entities, meat consumption, etc.)"*. We also display the average of the distribution and the p-value associated with the non-parametric Wilcoxon signed-rank test for the null that the distribution is centered at 3.

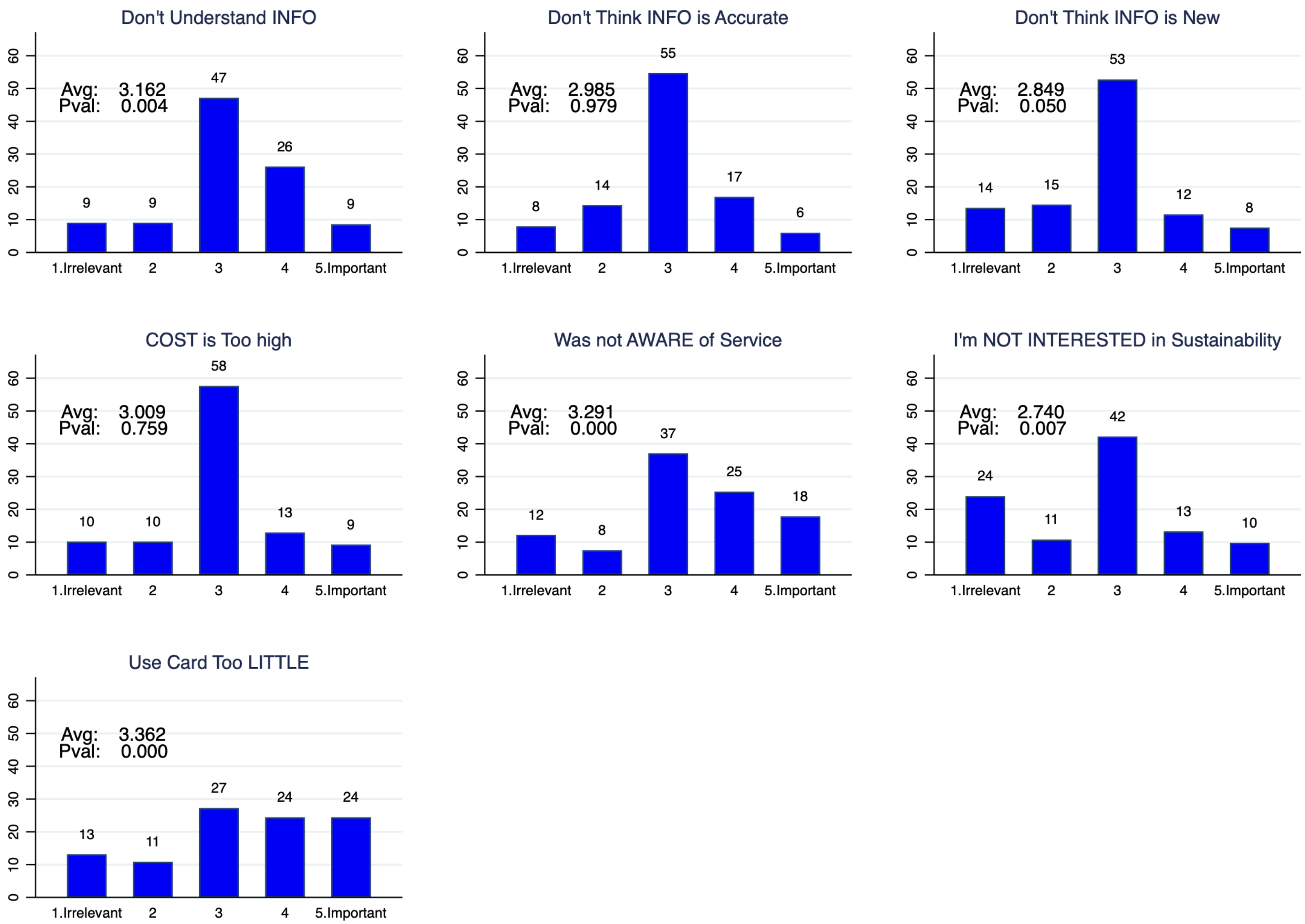

Figure A.4: This Figure displays the distribution of responses (in percentages) to the Likert questions for the non-adopters of the Carbon Calculator. Respondents are asked to indicate their level of agreement with a series of statements on a scale from 1 to 5. The top plots report results for the following statements: *"I don't understand how my emissions are calculated," "I don't think the information is accurate," "The information is not new (I am already aware of my emissions)."* The middle-left plot refers to the *"cost is too high"* statement. The middle plot refers to the *"I didn't know this service existed"* statement. The bottom right plot refers to the *"I am not interested in being sustainable"* statement. The bottom left plot refers to the *"I do not use the card much"* statement Each plot displays the average of the distribution and the p-value associated with the non-parametric Wilcoxon signed-rank test for the null that the distribution is centered at 3.

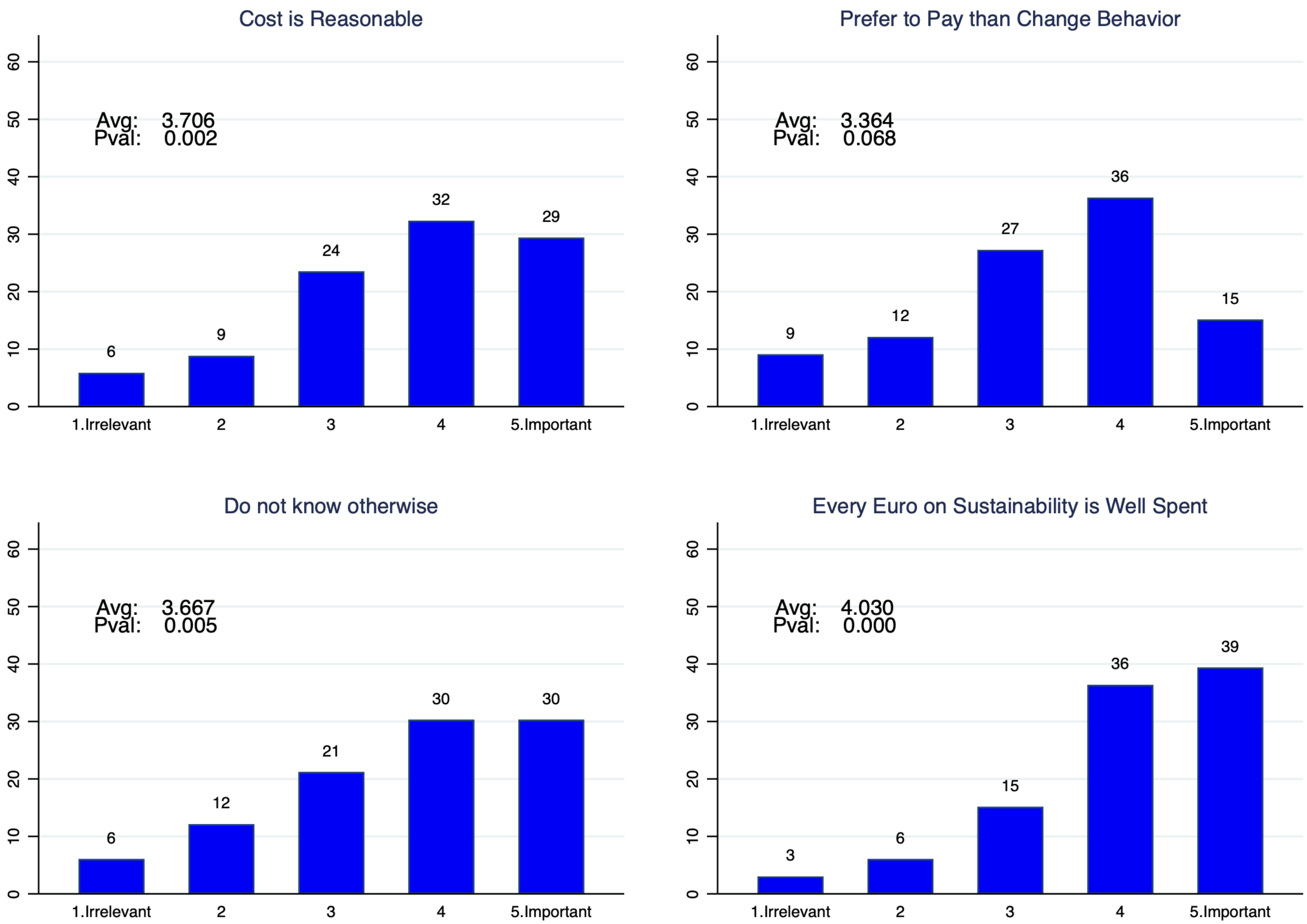

Figure A.5: This Figure displays the distribution of responses (in percentages) to the Likert questions for the adopters of Carbon Offsetting. Respondents are asked to indicate their level of agreement with a series of statements on a scale from 1 to 5. The top-left plot refers to the *"cost is reasonable"* statement. The top-right plot refers to the *"I prefer to pay for offsetting rather than change my consumption"* statement. The bottom left plot refers to the *"I didn't know how to be more sustainable"* statement. The bottom right plot refers to the *"Every euro spent on sustainability is well spent"* statement. Each plot displays the average of the distribution and the p-value associated with the non-parametric Wilcoxon signed-rank test for the null that the distribution is centered at 3.

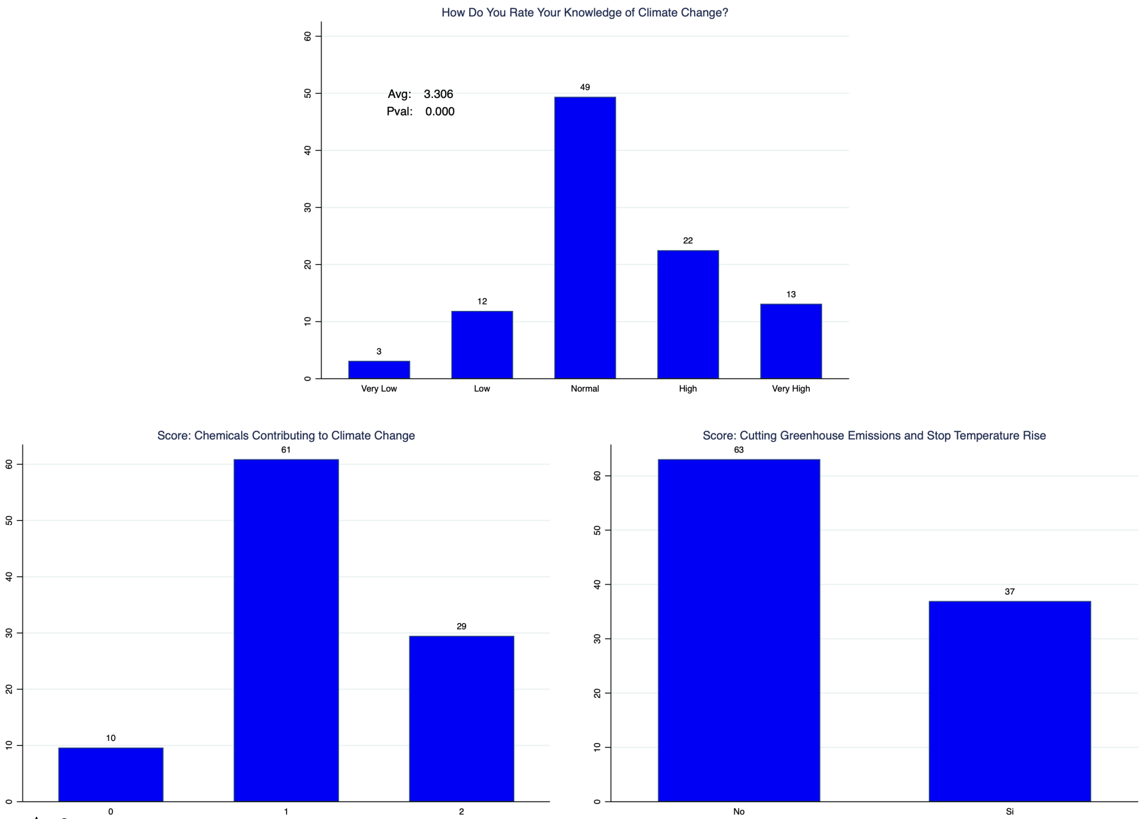

Figure A.6: This Figure displays the distribution of responses (in percentages) to the questions on climate change literacy. The top left plot displays the score based on the question: *"Which of these chemical elements contributes to climate change?"*. Respondents can choose (one or more) of the following answers, "CO2" (correct answer), "Methane" (correct), "Hydrogen" (incorrect), and "Particulate Matter" (incorrect). We assign (subtract) a point for each correct (incorrect) answer selected. The top right plot displays the score based on the question: *"Do you think cutting greenhouse gas emissions in half is enough to stop the rise in temperatures?"*. Respondents can choose between "No" (correct answer) and "Yes" (incorrect). The bottom left plot refers to the question *"How do you rate your knowledge of climate change?"*

Table A.1. Pairwise Tests of Mean Equality

Panel A: Carbon Calculators, Adopters

	Understand	Accurate	New	Reachable	Monitor	Motivating	Costly	Minimize	N.Beat	N.Beaten
Understand		-1.137	-0.676	-3.467***	1.643	-1.453	5.989***	4.851***	2	1
Accurate	1.137		0.154	-2.453**	2.697***	-0.427	6.750***	5.568***	3	1
New	0.676	-0.154		-1.996*	1.790*	-0.374	4.942***	4.024***	3	1
Reachable	3.467***	2.453**	1.996*		4.660***	1.905*	7.800***	6.639***	7	0
Monitor	-1.643	-2.697***	-1.790*	-4.660***		-2.803***	4.566***	3.567***	2	4
Motivating	1.453	0.427	0.374	-1.905*	2.803***		6.397***	5.273***	3	1
Costly	-5.989***	-6.750***	-4.942***	-7.800***	-4.566***	-6.397***		-0.599	0	6
Minimize	-4.851***	-5.568***	-4.024***	-6.639***	-3.567***	-5.273***	0.599		0	6

Panel B: Carbon Offsetting, Non-adopters

	Costly	My Emission Low	Trees Efficacy	Tress in Country	Not Interested	Not Aware	N.Beat	N.Beaten
Costly		-0.823	3.155***	-5.277***	3.832***	-2.544**	2	2
My Emission Low	0.823		3.745***	-5.056***	4.427***	-2.050**	2	2
Trees Efficacy	-3.155***	-3.745***		-6.614***	0.547	-4.864***	0	4
Trees in Country	5.277***	5.056***	6.614***		6.984***	2.395***	5	0
Not interested	-3.832***	-4.427***	-0.547	-6.984***		-5.372***	0	4
Not Aware	2.544**	2.050**	4.864***	-2.395**	5.372***		4	1

This Table displays the results from non-parametric two-sample mean equality tests. We display the z-score from the Wilcoxon rank-sum test and the associated level of significance (***, **, and * denote 1%, 5%, and 10% significance levels, respectively). Panel A refers to the Likert questions for the adopters of Carbon Calculator while Panel B refers to the Likert questions for the non-adopters of the Carbon Offsetting services. We test the null that the mean of the responses to the motive in each row is equal to the mean of the response to the motives in each column. In Panel A, the labels "Understand", "Accurate", "New", "Reachable", "Monitoring", "Motivating", "Costly" and "Minimize" refer to the following motives: *"I understand how my emissions are calculated"*, *"I think the information is accurate"*, *"The information is new (I wasn't already aware of my emissions)" "The information is easily accessible"*, *"It helps me monitor and achieve my target'*, *"It is motivating"*, *"It is too costly to be more sustainable (in terms of time and money)"* and *"I already minimize my emissions and can't do better"*. In Panel B, the labels "Costly", "My Emissions Low", "Trees Efficacy", "Trees in Country", "Not Interested", "Not Aware" refer to the following motives: *"cost is too high"*, *"My emissions are already low"*, *"I don't believe planting trees is effective"*, *"I would like the trees to be planted in my own country"*, *"I am not interested in being sustainable"*, and *"I didn't know this service existed"*. For the motive in each row, the column labeled as N.Beat displays the number of tests resulting in a positive rejection of the null (i.e., mean being significantly larger), while the column labeled as N.Beatean displays the number of tests resulting in a negative rejection of the null (i.e. mean being significantly smaller).

B Survey Questions

Section 1 of 3: Usage of CO2 Calculator

Q1) Have you ever used the CO2 calculator on the App?
- Yes
- No

Start of Block: IF ANSWER TO Q1 IS YES

Q) On a scale from 1 to 5, how much do you think the sustainability of your consumption measured by the App has changed?

1. It has worsened a lot
2.
3. It hasn't changed
4.
5. It has improved a lot

Q) What are the reasons for your answer to the previous question? (Specify below or leave blank)
____
____
____

Q) How much do you agree with each statement about the CO2 calculator? *[User can choose between 1.Strongly disagree/2.Disagree/3.Neither Agree Nor Disagree/4. Agree/5.Strongly agree]*

I UNDERSTAND how my emissions are calculated
I THINK the information is ACCURATE
The information is NEW (I wasn't already aware of my emissions)
The information is easily ACCESSIBLE

[These questions activate only if either 3,4,5 have been chosen in the first Q of the block]
It helps me MONITOR and achieve my TARGET
It is MOTIVATING

[These questions activate only if either 1,2,3 have been chosen in the first Q of the block]
It is too COSTLY to be more sustainable (in terms of time and money)
I already MINIMIZE my emissions and can't do better

Q) On a scale from 1 to 5, how much has the sustainability of your habits (not measured by the app) changed? (Sustainable investments, donations to pro-environment entities, meat consumption, etc.)
1. It has worsened a lot
2.
3. It hasn't changed
4.
5. It has improved a lot

Q) Do you have any suggestions on how to improve this service? (Specify below or leave blank)
____

Q) Select up to two changes you would like to be implemented from the list below:
I would like the information to be expressed in terms of TREES
Compare and reward users who perform better in terms of emissions
I would like there to be an EMISSION TARGET for people with my characteristics
I would like to receive RECOMMENDATIONS on how to minimize my emissions
I would like to receive NOTIFICATIONS and emails with REPORTS on my emissions

<u>### Start of Block: IF ANSWER TO Q1 IS NO</u>

Q) Why have you never used this service? (Specify below or leave blank)
____

Q) How important were the reasons listed below for your decision? *[Users can choose between 1.Very irrelevant/2.Irrelevant/3.Neither Irrelevant Nor Important/4.Important/5.Very important]*

COST is TOO HIGH
I DON'T UNDERSTAND how my emissions are calculated
I DON'T THINK the information is ACCURATE
The information is NOT NEW (I am already aware of my emissions)
I WAS NOT AWARE this service existed
I am NOT INTERESTED in being sustainable
I do not use the CARD much

Q) Do you have any suggestions on how to improve this service? (Specify below or leave blank)
____

Q) Select up to two changes you would like to be implemented from the list below:
I would like the information to be expressed in terms of TREES
Compare and reward users who perform better in terms of emissions
I would like there to be an EMISSION TARGET for people with my characteristics
I would like to receive RECOMMENDATIONS on how to minimize my emissions
I would like to receive NOTIFICATIONS and emails with REPORTS on my emissions

Section 2 of 3: Usage of CO2 Offset Services

Q1) Have you ever used the Emission Offset service on the App?
- Yes
- No

<u>### Start of Block: IF ANSWER TO Q1 IS YES</u>

Q) What are the reasons for your answer to the previous question? (Write below or leave blank)
____
____

Q) How important were the reasons listed below for your decision? *[Users can choose between 1.Strongly disagree/2.Disagree/3.Neither Agree Nor Disagree/ 4.Agree/5.Strongly Agree]*

COST is REASONABLE
I prefer to PAY for offsetting rather than CHANGE my consumption
I DIDN'T KNOW how to be more sustainable
Every euro spent on sustainability is WELL SPENT

Q) Do you have any suggestions on how to improve this service? (Write below or leave blank)

____
____

Q) Select up to two changes you would like to be implemented from the list below:
I prefer to CHOOSE which TRANSACTIONS to offset
I would like to CHOOSE between MORE PLANS with different costs and levels of offsetting
I would like to decide how to offset (NOT JUST PLANTING TREES)
I would like to decide EACH MONTH whether to CONTINUE offsetting
I would like to see TANGIBLE evidence of the TREES planted

Start of Block: IF ANSWER TO Q1 IS NO

Why have you never used this service? (Write below or leave blank)

____
____

Q) How important were the reasons listed below for your decision? *[Users can choose between 1.Strongly disagree/2.Disagree/3.Neither Agree Nor Disagree/4. Agree/5.Strongly agree]*

COST is TOO HIGH
My EMISSIONS are already LOW
I DON'T BELIEVE planting TREES is EFFECTIVE
I would like the TREES to be planted in my OWN COUNTRY
I am NOT INTERESTED in being sustainable
I DIDN'T KNOW this service existed

Q) Do you have any suggestions on how to improve this service? (Write below or leave blank)

____
____

Q) Select up to two changes you would like to be implemented from the list below:
I prefer to CHOOSE which TRANSACTIONS to offset
I would like to CHOOSE between MORE PLANS with different costs and levels of offsetting
I would like to decide how to offset (NOT JUST PLANTING TREES)
I would like to decide EACH MONTH whether to CONTINUE offsetting
I would like to see TANGIBLE evidence of the TREES planted

Section 3 of 3: Your Opinion on Climate Change

Q) Regarding the issues below for Italy, do you think climate change is: *[Users can choose between Less Important, Equally Important or More Important]*
- Public Debt
- Economic Inequality
- Sustainability of the Pension System
- Low Economic Growth
- Low Birth Rates
- Unemployment
- Immigration

Q) On a scale from 1 to 5, do you think climate change has already (or will have) a negative effect on your life?
1. Not at all
2.
3. Moderately
4.
5. Very much

Q) On a scale from 1 to 5, do you think climate change requires:
1. No intervention, it will resolve itself
2.
3. Medium-term intervention
4.
5. Immediate intervention

Q) Do you think your contribution to combating climate change is:
- Useless if others don't do the same
- Important regardless of others' behavior
- Don't know

Q) How much do you think the following entities contribute to climate change? *[Users can choose between Very Little/Little/Fairly/Much/Very Much]*
- Companies
- Governments
- Each of us
- Previous generations
- People with high incomes

Q) Which of these regions do you think contributes most to climate change?
- United States
- Europe
- India
- China

Q) Do you support or oppose these policies to combat climate change? *[Users can choose between Oppose/Don't Know/Support]*

- Flight tax (which increases ticket prices)
- Fuel tax (which increases gasoline prices)
- Limitation of polluting vehicles
- Subsidies for sustainable technologies
- A tax for polluting companies

Q) How do you consider your knowledge of climate change?
- Very Low
- Low
- Normal
- High
- Very High

Q) Which of these chemical elements contributes to climate change? (More than one answer is possible)
- CO_2
- Methane
- Hydrogen
- Particulate Matter

Q) Do you think cutting greenhouse gas emissions in half is enough to stop the rise in temperatures?
- Yes
- No

Q) What is your net monthly income?
- Less than €1,000
- Between €1,000 and €2,000
- Between €2,000 and €3,000
- Between €3,000 and €4,000
- More than €4,000
- Prefer Not to Answer