Peer-to-peer solar and social rewards:

Evidence from a field experiment*

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Abstract

Observability has been demonstrated to influence the adoption of pro-social behavior in a variety of contexts. This study implements a field experiment to examine the influence of observability in the context of a novel pro-social behavior: peer-to-peer solar. Peer-to-peer solar offers an opportunity to households who cannot have solar on their homes to access solar energy from their neighbors. However, unlike solar installations, peer-to-peer solar is an invisible form of pro-environmental behavior. We implemented a set of randomized campaigns using Facebook ads in the Massachusetts cities of Cambridge and Somerville, in partnership with a peer-to-peer company. In the campaigns, treated customers were informed that they could share "green reports" online, providing information to others about their greenness. We find that interest in peer-to-peer solar increases by up to 30% when "green reports," which would make otherwise invisible behavior visible, are mentioned in the ads.

Keywords Peer to peer solar; pro-environmental behavior; social rewards; visibility; Facebook

JEL codes C93; D91; Q20

1 Introduction

Observability has been known for decades to be an important driver of human behavior in different realms, including the adoption of new technologies (Rogers and Shoemaker 1971; Rogers 1983). Social approval, which observability makes possible, is a feature of many economic models, including Akerlof (1980), Holländer (1990), Ellingsen and Johannesson (2008; 2011). Observability is also an important ingredient for indirect reciprocity and norm enforcement to work (see Kraft-Todd et al. 2015 for a review). Observability implies that people may be more likely to undertake a given behavior, especially if considered pro-social, when others around them see them doing so. Observability is especially important in the adoption of green behaviors and technologies, along with the role of visibility in leading late adopters to follow early adopters (see Carattini et al. 2019 for a review).

However, several types of pro-environmental behaviors are not visible to others, such as carbon offsetting, the use of renewable energy tariffs, or avoiding carbon-intensive transport. Interestingly, some of these behaviors also tend to have relatively low levels of uptake. A large literature has used social interventions to spur the adoption of pro-environmental behaviors, often relying, following Cialdini (2003), on a combination of descriptive norms, i.e. the perception of how people actually behave, if sufficiently positive, and injunctive norms, i.e. what people generally consider the "right thing to do" in a given context. In general, these interventions tend to reduce energy consumption by about 2-4%, with smaller effects in the long run (Buckley 2020). The real frontier for social interventions, however, leverages social interactions to encourage people to adopt new behaviors, especially non-normative behaviors that are adopted by only a small fraction of the population. In the context of climate-friendly behaviors, we should ideally target decisions that can notably and durably reduce emissions.

In this paper, we are interested in investigating whether making otherwise invisible pro-social behavior visible can generate interest in the behavior among prospective customers. That is, we implement a new type of intervention around observability, assessing whether even knowing that a climate-friendly behavior will be observable can generate interest among prospective customers. Our context is one with a non-normative behavior with the potential to substantially reduce a household's carbon footprint. In particular, we address the following question: Are households more likely to start engaging in invisible climate-friendly behavior if they are informed that they will be receiving shareable reports on their greenness, which would make their climate-friendly behavior observable by peers?

Our study focuses on what is known as "peer-to-peer solar." Peer-to-peer solar refers to a contract between two households, where one household has a rooftop solar photovoltaic (PV) system and sells electricity to the grid to cover the equivalent amount of electricity consumed by the other household (usually a close neighbor). This contract allows a household that has a rooftop that is not suitable for solar, is a renter, or is too financially constrained to install solar to still purchase electricity generated from a solar system. The household with the solar system will often put in a larger solar installation than they would have otherwise done in order to cover the electricity of the neighbor, often making the solar investment more profitable due to economies of scale. On the margin, access to peer-to-peer solar would be expected to lead to more solar panels installed than otherwise. As a result, peer-to-peer solar contributes to the economy's decarbonization, and as such, participation in a peer-to-peer solar contract can be viewed as a pro-environmental behavior.

However, unlike actually installing solar, signing a contract for peer-to-peer solar is an invisible form of pro- environmental behavior for the households that do not have solar on their rooftop. Hence, households may be, everything else equal, less attracted to engage in peer-to-peer solar compared to other forms of pro-environmental or pro-social behavior that are directly observable by peers. But there may be ways to improve observability, such as through social media. Thus, peer-to-peer solar provides an ideal context to test the role of observability in the adoption of climate-friendly behaviors in the field.

To this end, we partnered with a startup company in the United States active in peer-to-peer solar, MySunBuddy, and realized a field experiment under the form of several randomized Facebook campaigns promoting MySunBuddy with different messaging. In particular, MySunBuddy agreed to offer to a subsample of customers the possibility to receive and share "green reports" online with their friends and network, which would document one's contribution to solar energy. Hence, our experimental design included a frame informing prospective customers that they will have the possibility to share their greenness with like-minded individuals on online social networks.

The campaigns were run in 2018 and 2020 in the Massachusetts cities of Cambridge and Somerville, in collaboration with the local authorities. Because of the collaboration with the municipalities, we further tested whether people were more likely to show interest in peer-to-peer solar in the presence of frames emphasizing the fact that both cities were active in transitioning towards a cleaner economy. These frames introduce a second public good focused on the local community, in addition to global climate mitigation (community-led action or simply "community frame"). Alternatively, we deployed frames emphasizing the importance of being a frontrunner (individual-led action, or simply "individual frame"). Thus, we implemented a 2x2 design, leveraging the combination of shareable green reports versus no green reports and community frames versus individual frames. Overall, this led to four different ads per campaign running on Facebook, and four landing pages per campaign on MySun-

Buddy.com. Our ads were seen by several tens of thousands of people in Cambridge and Somerville.

In line with our hypotheses, we find that social media users are more likely to show interest in peer-to-peer solar and respond to the ads when informed that they would be receiving shareable green reports displaying their greenness, while community and individual frames are found to lead to similar engagement to one another. Hence our data confirm our main hypothesis about the importance of creating social rewards for otherwise invisible climate-friendly behavior. The effect that we find is sizable. Social media users are about 30% more likely to show interest in peer-to-peer solar when they are informed that they can make their behavior socially visible. The green reports appear to be most effective in combination with the community frame, which confirms the importance of local social norms and visible behavior for spurring cooperation (as highlighted in Carattini et al. 2019). When comparing community frames and individual frames alone, there is some evidence that individual frames may be more effective than community frames, which would be in line with Bollinger et al. (2020).

We find that heterogeneity matters in important ways in our empirical setting, which uses Facebook advertisements. We find that when Facebook campaigns last relatively long, the algorithm starts reaching out to a less relevant audience and demographics, which are less responsive to our messaging. Hence, our study also provides a methodological contribution related to the running of field experiments through Facebook ads in presence of a heterogeneous audience and an optimizing algorithm. In particular, we show that the effectiveness of a behavioral intervention using Facebook ads can vary over its duration, such that its ability to lead to behavioral change decreases once the most relevant audience is exhausted.

Three implications follow from this finding about Facebook ads. First, without accounting for the role of heterogeneity in the audience and the optimizing approach of Facebook algorithms, one may underestimate the effectiveness of a given campaign on its most relevant audience. Second, cost-effectiveness and power analyses (see Duflo et al. 2006) would be biased unless they account for such features of Facebook ads. Increasing sample size with Facebook ads is costly and may also introduce noise from less relevant audiences, potentially overweighing the direct effect on standard errors. Third, from an external validity perspective, the effectiveness of a campaign on a potentially small portion of the potential audience should not be used as a proxy for its effectiveness at large, given that Facebook ads intentionally start reaching out to the most relevant audience first.

Our paper has important implications for policymakers and practitioners. It shows evidence from a real-world context that people care about the ability to share their pro-social behavior with their online social networks, as this possibility increases the attractiveness of contributing to the pro-social behavior. It also shows that online visibility can serve as a substitute for physical visibility, when the latter is not an option – as is the case for peer-to-peer solar. Therefore, online reports describing one's contribution to the environment can mimic, at least to some extent, the virtue signaling of installing solar panels on one's rooftop.

Hence, our paper adds to a series of findings from the study of charitable giving, building on the behavior of organizations of several types that provide to donors the opportunity to take credit for their donation, from bumper stickers to names on buildings. For instance, donations to Dutch churches increase with observability, if only for a limited period (Soetevent 2005). Similar evidence has been provided in lab experiments, showing that players substantially increase their intrinsic generosity if their behavior is observable (Andreoni and Petrie 2004; Rege and Telle 2004; Milinski et al. 2006; Ariely et al. 2009). That is, in the lab, people do not want only to be fair, but also want to be perceived as fair (Andreoni and Bernheim 2009). Our paper shows that social rewards can be created by making otherwise invisible behavior visible, which may be relatively inexpensive if done online as in our context, and that they can lead to greater interest in pro-social behavior. Hence, our findings may have implications for a wide range of pro-social behaviors, for which organizations could provide donors and supporters with shareable progress reports, leveraging indirect reciprocity.

Moreover, our paper adds to a recent literature showing that local social norms tend to drive climate-friendly behaviors, regardless of the global public good property of climate change mitigation, and that visible local social norms are in particular more likely to influence people's behavior (as covered in Carattini et al. 2019). People are more likely to purchase a hybrid car or solar panel if they see others around them doing so in an especially visible way, which sends a signal that the local community is going green (Narayanan and Nair 2013; Baranzini et al. 2017; Bollinger et al. 2022). Further, in line with our findings, people are more likely to engage in climate-friendly behaviors if others see them doing so, as visibility may be conducive to social rewards. Sexton and Sexton (2014), for instance, find that households in Democratic-leaning areas are willing to pay a substantial premium to drive a Toyota Prius rather than another hybrid car with similar characteristics but without the unique "halo" of greenness that the Prius provides. Making otherwise invisible behavior visible may contribute to increase the number of potential adopters, as our paper shows. It may also be valued by existing customers, who could appreciate the opportunity to show their greenness and leadership as frontrunners (see for instance Gosnell et al. 2021).

To summarize, our paper contributes to five strands of literature. First, we contribute to an established literature in behavioral economics and social psychology examining the role of observability in the context of indirect reciprocity and the provision of local public goods (e.g. Nowak and Sigmund 1998; Wedekind and Milinski 2000; Andreoni and Petrie 2004; Rege and Telle 2004; Haley and Fessler 2005; Milinski et al. 2006; Andreoni and Bernheim 2009; Ariely et al. 2009; Rand et al. 2009; Yoeli et al. 2013). We not only provide additional evidence that observability increases contributions to public goods, but also try a new type of observability intervention – one that simply informs people of the presence of observability. When there is already observability, for instance via social media, simply telling people about it is often simple and practically free. Our work thus suggests that doing so is a useful policy prescription.

Second, a growing literature is aimed at identifying the role of social spillovers in the adoption of solar energy, including through the effect of visibility (Bollinger and Gillingham 2012; Richter 2013; Graziano and Gillingham 2015; Rode and Weber 2016; Baranzini et al. 2017; Carattini et al. 2018; Bollinger et al. 2022; see also Carattini et al. 2019 and Wolske et al. 2020 for reviews of the literature).

Third, a very recent research agenda aimed at bringing non-normative pro-social behaviors from non-normative to normative, leveraging forerunners and using social norms in innovative ways to avoid that they backfire (see Sparkman and Walton 2017; Kraft-Todd et al. 2018; Bicchieri and Dimant 2019; Mortensen et al. 2019; Andreoni et al. 2020; Carattini and Blasch 2020; Gosnell et al. 2021; and Spencer et al. 2019 for a theoretical social network analysis).

Fourth, a recent literature aimed at identifying new opportunities in the solar market, including to address the distributional effects of the current subsidy systems and to identify ways to reach out to lower income households (Rai and Sigrin 2013; Borenstein and Davis 2016; Borenstein 2017; Glachant and Rossetto 2021).

Fifth, a nascent literature using Facebook ads to address a wide range of research questions while uncovering new insights on the methodological aspects of this relatively new tool for experimental research (e.g. Celebi 2015; Dehghani and Tumer 2015; Blanco and Rodriguez 2020; Levy 2021).

The remainder of the paper is as follows. Section 2 provides background information on peer-to-peer solar and describes our experimental design. Section 3 presents our data and empirical approach. Section 4 reports our main empirical results. Section 5 concludes.

2 Background and experimental design

2.1 Peer-to-peer solar

In the United States, electricity generation has seen substantial changes over the past 20 years. Electricity generation from coal decreased rapidly from 2008 to 2019. Over the same time period, electricity generation from natural gas doubled in terms of magnitude, mainly due to an increase in natural gas availability from the shale gas revolution. The magnitude and share of electricity generated by renewable sources also increased steadily since 2008. According to the Energy Information Administration, by 2019, the share of electricity generation from renewables had reached approximately 17%, with solar energy representing about 10% of that.[1] The market for solar energy has been helped by state and federal policies aimed at encouraging the adoption of renewable energy as well as a (related) decrease in the cost of producing solar panels (Borenstein 2017; Crago and Chernyakhovskiy 2017; Creutzig et al. 2017). The price of an average-sized residential system has gone from around $40,000 in 2010 to roughly $18,000 by 2020.[2]

[1] https://www.eia.gov/energyexplained/electricity/electricity-in-the-us.php (last accessed on September 17, 2020).

[2] https://www.seia.org/solar-industry-research-data (last accessed on September 17, 2020).

Though the adoption of solar energy has been increasing over time, its expansion has been limited by several factors. First, only 22 to 28% of residential buildings in the United States are suitable for a rooftop solar photovoltaic (PV) system (Denholm et al. 2008). Second, despite decreasing production and installation costs and the presence of subsidies, solar remains expensive for some households, who may not be able to afford the fixed cost or be eligible for a loan. Peer-to-peer solar opens the solar market to a new customer base. This customer base is composed of homeowners who may not be able to afford a solar installation in the current circumstances, whose roof may not be suitable to host a solar PV system, and renters, who have been largely excluded by the recent expansion in the solar market (Krishnamurthy and Kristrom 2015). In peer-to-peer solar markets, anyone with a solar PV system can sell their excess electricity back to the grid and cover the equivalent amount of electricity consumed by another neighbor (Parag and Sovacool 2016; Sousa et al. 2019; Hahnel et al. 2020). For homeowners with a solar PV system, peer-to-peer solar can be attractive because all excess solar electricity generated above the houshold's consumption is compensated at a value lower than they would be receiving from selling it to the local utility. For buyers, peer-to-peer solar can be attractive because all net metering credits are sold at a value lower than the retail rate of electricity, in the order of about 15%. The biggest challenge to peer-to-peer solar is often coordinating the contracts.

The peer-to-peer solar company with which we partner in this study is MySunBuddy. MySunBuddy was founded at a hackathon in 2015 and incorporated one year later.[3] MySunBuddy's innovative peer-to-peer solar online marketplace leverages the Virtual Net Energy Metering (VNEM) system. VNEM is a system used in states such

[3]See https://www.masscec.com/blog/2015/04/16/innovation-wins-big-boston-cleanweb-hackathon (last accessed on September 17, 2020).

as California, Maine, and Massachusetts for distributing economic benefits in shared solar energy markets (Oliver 2013). VNEM can be thought of an expansion of the standard "net metering" system. "Net metering" means that utility customers with solar PV can reduce their electricity bills by offsetting their consumption with their energy generation through the calculation of the net consumption at the monthly or yearly level (Rose et al. 2009). Households that generate more than they use will earn net metering credits. Any extra credits at the end of a true-up period (usually a year) are often valued by utilities at a level below the standard electricity tariff rates.

States with VNEM, such as Massachusetts, allow solar customers to transfer excess credits to other customers within the same distribution company, thus allowing those credits to be valued at the full retail rate (Oliver 2013). This enables larger solar systems to be financially attractive. MySunBuddy aims to facilitate the contracting by helping sellers of credits find a buyer, and vice-versa. This matching of sellers and buyers for net metering credits allows both sellers and buyers to enjoy a financial profit, while MySunBuddy takes a cut. At the same time, it allows people without renewable generation to join the market for renewables and, at the margin, increases the total number of solar panels installed by making larger solar systems more profitable, possibly making some solar systems on the margin worth pursuing.

2.2 Experimental design

We conducted two experimental campaigns in 2018 and 2020 in the Massachusetts cities of Cambridge and Somerville. In both cases we partnered with the city administrations, whose programs endorsed our campaigns. The campaigns in Somerville were supported by Somerville Green Tech. The campaign in Cambridge was supported by the Cambridge Energy Alliance. The timing of the campaigns reflects the process of receiving such endorsements. The 2018 campaign was conducted only in the city of Somerville. Somerville gave its endorsement first and the first campaign ran from October 11, 2018 to November 23, 2018. The 2020 campaign was conducted in both the city of Cambridge and the city of Somerville, from December 6, 2019 to February 10, 2020, following the endorsement from the city of Cambridge and with the inclusion of Somerville for comparability purposes. The experiment was conducted by purchasing ad space on Facebook's ads market. Facebook ads run on both Facebook and Instagram platforms. Given that both platforms share the same parent company, which was Facebook Inc. (now Meta Platforms Inc.), in this paper we generally refer to "Facebook ads".[4] The potential audience of Facebook ads is 120,000 for Cambridge and 67,000 for Somerville, based on the number of Facebook users who registered as residents of either city.

The experiment follows a 2×2 treatment design, which is summarized in Table 1. The 2×2 treatment design is the result of the combination of two specific messages: "community frame" (as opposed to an "individual frame") and the provision of "green reports" (compared to no provision). The community frame leverages community feelings related with community-led action, reminding residents of Cambridge and Somerville of the initiatives that their respective cities are undertaking to transition towards a cleaner economy. It aims at leveraging conditional cooperation by individuals responsive to the action of others in the community, in line with Carattini et al. (2019). Specifically, the community frame is worded as "Somerville (Cambridge) is racing to go green, and you can help this exciting movement." In contrast, the individual frame refers to frontrunner-led action and is worded as "Private citizens like you are racing to go green, and you can lead this exciting movement." Further, at

[4] In our experiment, ads were run on both platforms, but the majority ran on Instagram, and mostly on mobile phones.

the very bottom of the ads, the individual frame states “lead the pack!” while the community frame, for instance in the case of Somerville, states “help Somerville lead the pack!”.

The green reports are introduced to create the possibility of social rewards through online sharing of one’s greenness and to inform prospective customers of this possibility. Green reports are introduced at the end of the ads along the following lines: “share your progress with friends through Twitter, Facebook and LinkedIn to connect with like-minded neighbors”.[5] Hence, the green reports allow testing whether introducing potential observability makes an otherwise socially invisible climate-friendly behavior more appealing.

Summarizing, we have the following four treatment arms: individual frame (IF), individual frame with reports (IFR), community frame (CF), and community frame with reports (CFR). IF is the baseline treatment group of the experiment. It does not include either the community frame or a mention of the green reports (Figure 1a). “Individual frame with reports” is a treatment arm that includes green reports but not the community frame (Figure 1b). “Community frame” includes the community frame but not green reports (Figure 1c). “Community frame with reports” is a treatment with both community frame and green reports (Figure 1d). Figures 1a to 1d are based on the 2020 Somerville campaign. Figures A.1a-A.2d in Appendix A show the ads that were used in the 2018 Somerville campaign and the 2020 Cambridge campaign.

Every user clicking on one of the four ad types is directed to the MySunbuddy website. Further, each treatment arm has its own customized landing page, reflecting

[5] The 2018 campaign has the same community and individual framing as the 2020 campaign. However, it has a slightly different framing of the green reports, which is as follows: “our social media tools help connect you with like-minded neighbors and friends.” Figures A.1a-A.1d show the details of the 2018 campaign ads. Slight differences in messaging between the 2018 and 2020 campaigns are due to feedback from the city of Cambridge, which, as mentioned, joined the experiment at a later stage with respect to the city of Somerville.

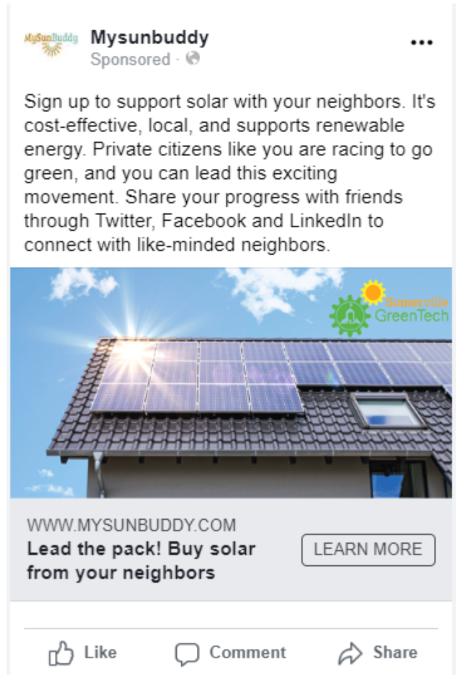
the message(s) present on the ads, on top of the standard website content. Figures B.1 to B.4 in Appendix B present the landing pages for the different treatment arms in the Somerville 2020 campaign. Similar landing pages were used for the 2018 Somerville campaign as well as for the 2020 Cambridge campaign.

In this experiment, we explore four key aspects of behavior. First, we are interested in the effect of the green reports, which inform prospective customers that they will be able to make their otherwise invisible pro-social behavior visible by sharing progress reports online with like-minded friends and peers. Second, we are interested in the combination of green reports and individual or community frames. We posit that green reports are most effective in combination with the community frame, building on evidence suggesting that combining local social norms and visible behavior can be effective in spurring cooperation also in global social dilemmas (see again Carattini et al. 2019 for a review). Third, we are interested in the effect, in isolation, of individual and community frames. Bollinger et al. (2020) find that individual-based messaging is more effective in the uptake of rooftop solar systems, and we are interested to see if the same occurs in our context. Finally, we would like to understand how interest in peer to peer solar, and the effect of our treatment and treatment combinations, varies as we expand the scope of the campaigns. The motivation for this analysis is that the optimizing procedures within Facebook may mechanically introduce heterogeneity in the sample as the audience to which we reach out expands. We expect lower interest in the later phases of the campaigns to lead to more noise in the estimation of the treatment effects.

Figure 1: 2020 Somerville campaign Facebook ads

(a) IF treatment arm

(b) IFR treatment arm



(c) CF treatment arm

(d) CFR treatment arm

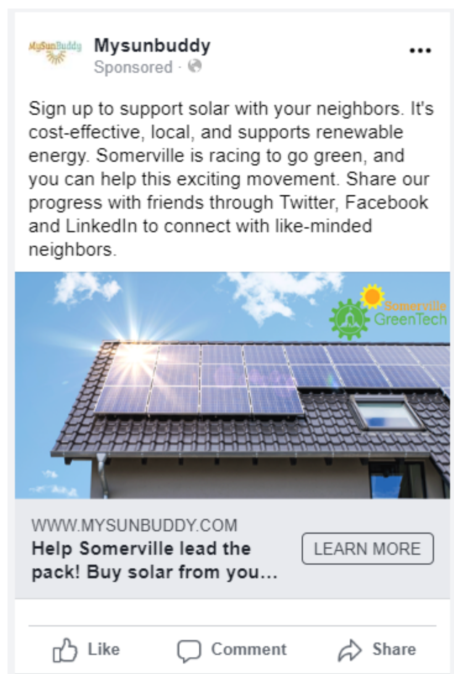


Table 1: 2×2 Treatment Assignment

	No Community Frame	Community Frame
No Green Reports	IF	CF
Green Reports	IFR	CFR

3 Data and empirical approach

3.1 Data and descriptive statistics

Facebook provides daily values for three main variables: clicks, impressions, and reach. Clicks represent the number of times an ad gets clicked on. Impressions represent the number of times that an ad appears online. Reach represents the number of users who see an ad at least once, over the duration of the campaign. Such values are also provided by age categories and by gender.

Our main outcome variable is the number of clicks on each Facebook ad. Recall that our 2×2 treatment design gives us four different ads. Facebook randomly allocates ad space across ads, in principle ensuring that one user (i.e. one Facebook account) in the target population is only exposed to one treatment arm.[6] Hence, ad space is relatively uniformly distributed across ads, as shown in Table 2. In the context of our campaigns, we instructed Facebook's algorithm to maximize clicks. Hence, the same individual may be exposed to the same ad more than once, leading impressions to exceed reach.

To perform our empirical analyses, we expand the original dataset provided by Facebook to build a dataset in which each individual (or Facebook account) who sees

[6]Potentially, contamination may still occur, especially if Facebook and Instagram accounts are not linked. That is, if anything, we provide lower-bound estimates of the effectiveness of our intervention.

the ads (as measured by the variable "reach") represents one observation. For each observation, the outcome variable can take either value 0 or 1, depending on whether that specific individual clicked on the ad or not. Hence, our approach accounts for slight differences in reach across treatment arms. In our regression model, described in Section 3.2, we control for year- and city-specific fixed effects as well as the individuals' characteristics provided by Facebook, namely reported gender and age groups.

Such socioeconomic characteristics also allow us to compare our samples with the underlying populations of Cambridge and Somerville, respectively. Table 3 shows the demographic statistics of the experimental sample, by campaign. Table C.3 in Appendix C presents the same statistics for the underlying populations, from the American Community Survey (ACS). The demographics for the 2018 campaign in Somerville are similar to those of the underlying population, as provided by the ACS, with gender as slight exception.

In 2018, we ran an extensive campaign, reaching out to a much larger fraction of the potential audience. An extensive campaign implies that Facebook ends up reaching out to a broader population than compared to the groups of individuals that the algorithm would approach first. We leverage this feature in the analyses realized in Section 3.2. In particular, the narrower campaigns of 2020 reached out to a younger, and more female crowd.

3.2 Empirical approach

We are interested in the treatment effect of the community frame (versus individual frame) and green reports (versus no green reports) on the proclivity of individuals to click on the ads and thus visit MySunBuddy's landing page. To this end, we use logit given the binary outcome variable, while estimates from a linear probability model

Table 2: Reaches and impressions for each treatment arm

	Somerville (2018)	Somerville (2020)	Cambridge (2020)	Pooled
Panel A: reaches for each treatment arm				
Individual frame (IF)	10,952	3,112	2,521	16,044
Individual frame and green reports (IFR)	11,333	3,863	3,149	17,697
Community frame (CF)	10,761	4,140	2,752	16,737
Community frame and green reports (CFR)	11,147	4,307	2,797	17,531
Panel B: impressions for each treatment arm				
Individual frame (IF)	41,185	9,824	7,514	58,533
Individual frame and green reports (IFR)	45,254	11,061	11,821	68,136
Community frame (CF)	43,246	11,859	9,520	64,625
Community frame and green reports (CFR)	44,471	12,447	8,389	65,307

Table 3: Socioeconomic characteristics of the experimental sample

	Somerville (2018)	Somerville (2020)	Cambridge (2020)	Pooled
Share of females	44.28%	51.30%	61.66%	49.14%
Share of 18-24	26.56%	41.86%	53.90%	35.14%
Share of 25-34	28.20%	40.18%	36.54%	32.44%
Share of 35-44	12.08%	8.88%	5.64%	10.15%
Share of 45-54	9.63%	3.35%	1.16%	6.63%
Share of 55-64	11.00%	2.43%	0.84%	7.17%
Share of 65+	12.53%	3.29%	1.92%	8.47%

are provided as robustness tests.

Equation (1) provides our empirical specification. $Click_i$ is the outcome variable for individual i, taking value 1 if the individual clicked on the ad.

$$Click_i = \alpha + \beta_1 C_i + \beta_2 R_i + \gamma_1 City_i + \gamma_2 Year_i + X_i + \epsilon_i \tag{1}$$

where β_1 provides the average treatment effect of the community frame, β_2 provides the average treatment effect of the green reports, γ_1 represents the city fixed effect, γ_2 represents the year fixed effects, X_i represents a matrix of control variables (gender or age), and ϵ_i is the heteroskedasticity-consistent error term.[7] As mentioned, we estimate this specification with both a logit model (in the main body of text) and a linear probability model (in the Appendix).

At the end of Section 3.2 we also run a specification distinguishing between all

[7] In our main tables, we cluster by year whenever analyzing campaigns over multiple years, but our findings are generally unaffected when using standard heteroskedasticity-consistent standard errors instead.

treatment arms, i.e. individual frame (IF), individual frame with reports (IFR), community frame (CF), and community frame with reports (CFR), with one of them, individual frame (IF), serving as reference category. Running all treatment arms separately may slightly reduce our power.

Table C.1 provides balance of covariates when considering two main treatment arms. Given small yet statistically significant differences across treatments for several variables, we account for these differences by including covariates in our main specifications. Further, as a robustness test, we also estimate average treatment effects on the treated using a matching approach, with a logit model.[8] Matching based on covariates provides balanced samples.

4 Empirical results

4.1 Average treatment effects for the green reports over the entire campaigns

Table 4 shows the estimates for the average treatment effects based on a logit model over the entire duration of the campaigns. Column (1) provides estimates for the 2018 and 2020 campaigns in Somerville. Column (2) provides estimates for the 2020 campaign in Cambridge. Column (3) provides estimates over all campaigns, controlling for city- and year-specific fixed effects and thus estimating the full model provided by equation (1). Matching estimates are provided in Table D.1. Linear probability model estimates are provided in Table E.1. Estimates obtained when relaxing the assumption of clustered standard errors are provided in Tables F.2 and F.6 for logit and linear probability models, respectively. Estimates for all covariates are provided

[8] Very similar results would be obtained when using a linear probability model after matching.

in Appendix F.

We first focus on the green reports. Point estimates are relatively consistent across specifications, generally indicating a stronger propensity to click on the ads if green reports are mentioned. Estimates for Cambridge are somehow larger but noisier (Table 4). A similar pattern emerges when looking at the matching approach (Table D.1), the linear probability estimates (Table E.1), or the estimates where standard errors are not clustered (Tables F.2 and F.6), although precision may vary slightly.

The coefficient for column (1), for the 2018 Somerville campaign, is 0.0004. Since the probability of clicking on the ads for the 2018 Somerville campaign is 0.0054 (as reported in Table F.1), the effect of the green reports is, on average, around 7%. Similarly, the coefficient for column (3), pooling data over both campaigns, is 0.0006. Since the probability of clicking on the ads for all the campaigns is around 0.0141 (as reported in Table F.1), the effect of the green reports is, on average, around 4%. This average effect is very much in the same order of magnitude of other social interventions aiming at changing energy-related behaviors (see again Buckley 2020 for a review). In our context, however, we target a one-off behavioral change that would lead a given household to buy solar energy for many future periods, potentially reducing to virtually zero its energy-related greenhouse gas emissions.

4.2 Heterogeneity and other hypotheses

Past research has shown the importance of considering heterogeneity among individuals when examining the effectiveness of a given social intervention. For instance, in a related context Andor et al. (2020) find that "home energy reports" as in Allcott (2011) may not be particularly (cost-)effective with the average German household, who tend to have baseline energy consumption levels and carbon footprints below

Table 4: Estimates from logit: average treatment effects on the treated over the entire campaigns

Campaign	Somerville	Cambridge	Somerville+Cambridge
Community frame (CF)	-0.0003***	-0.0007	-0.0003***
	(0.000)	(0.002)	(0.001)
Green reports (R)	0.0004***	0.0014	0.0006***
	(0.000)	(0.002)	(0.000)
Controls			
Gender & age	YES	YES	YES
Year FE	YES		YES
City FE			YES
N	143,040	33,506	176,546

Note: Standard errors in parentheses are clustered by year in column (1) and (3).
Heteroskedasticity-consistent standard errors are used otherwise.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

those of their American counterparts. Yet, there are categories of households within German society for which home energy reports can be especially cost-effective. In sum, considering heterogeneity may change how a social intervention is evaluated, and the corresponding policy recommendations.

In this study, one observation that follows from Section 4.1 is that, while the estimates for Cambridge are larger than the ones for Somerville or all the campaigns taken together, the estimates for Cambridge are noisy. As a result, one could conclude that the sample size for the Cambridge campaign was too small and that, in turn, this particular campaign should have been expanded further, or additional campaigns run, to provide more power. However, such a conclusion assumes that the response to the treatment is the same across individuals and that Facebook's algorithm selects individuals from the audience pool at random.

Our experiment invalidates both assumptions. Table 3 already showed that Facebook's algorithm starts with a younger crowd, and if the campaign continues is then extended to accounts belonging to older individuals. If Facebook's algorithm is correct, individuals exposed to the ads in the earlier phases should be more likely to click on the ads. That is, individuals exposed to the ads in a later phase are more likely to ignore the ads that we were running. Hence, expanding the size of an experiment using Facebook ads may or may not improve power, as the increase in sample size may be countered by noise from individuals ignoring the ads. Figure 2 provides evidence suggesting that this might be the case. Figure 2 shows with pooled data over all campaigns that our experiment went through two phases, one in which our ads received a fair amount of attention, and one in which they received much less. As a result, we proceed by identifying these two phases for each campaign and estimating treatment effects for each of them. As displayed in Table 5, for each campaign we observe that, in the first phase the treatment effect for the green reports is strong and statistically significant, while in the second phase the effect is virtually (and statistically) zero. Phases seem to vary slightly across cities and campaigns, depending on the characteristics of the audience as well as the average spending per day in each of the campaigns.[9]

In the case of the Somerville 2018 campaign, as mentioned, one in about 185 Facebook users clicked on the ads. This ratio is driven upward by the first phase, when the probability of clicking is about 1/160. In the second phase, this probability drops substantially. In the 2020 campaigns, the probability of clicking on the ads decreases by about 50% in the second phase. A similar pattern applies to the other campaigns, as shown in Figure 2 with pooled data.

The coefficients for the first phase are relatively large in magnitude for the green reports. In the case of the Somerville 2018 campaign, the coefficient for the green reports in the first phase is 0.00204. Hence, it represents about a third of the average probability of clicking of 0.00600 (1/160). That is, the green reports increase the probability of engaging with the ads by about a third. Similar estimates can be retrieved for the 2020 campaigns. For the Somerville 2020 campaign, the relevant ratio is 0.0117 (effect of the green reports) over 0.0366 (average probability of clicking on the ads). For the Cambridge 2020 campaign, the relevant ratio is 0.0111 over 0.0486. Hence, we conclude that the effect of the green reports is to lead the most-relevant audience of Facebook users to be about 30% more likely to engage with peer-to-peer solar. Had we focused on the entire campaign, we would have concluded that the effect of the green reports is in the order of 4%, which is already important for a social intervention, but vastly lower than the 30% effect that we can identify

[9] We selected the phases for this discussion following visual inspection. Our results are robust to the inclusion of an initial phase, in which the algorithm learns and tries to optimize its targeting efforts, as suggested in Figure 2. However, since having three phases rather than two phases does not add much in terms of key lessons, we prefer to stick to only two phases in the analyses. This is a conservative approach, which should lead, if anything, to lower-bound estimates for the first phase.

when Facebook targets the most responsive audience. Table F.1 in the Appendix provides details for all these calculations.

In the columns displaying the coefficients for phase 2, we observe that as soon as the best audience was exhausted, the ads reached less responsive Facebook users, thus leading to very noisy estimates. As shown in Figure 2, after a short learning period, the number of clicks per reach rapidly reaches its peak, for then gradually declining. Table C.4 in the Appendix shows the socioeconomic characteristics for the two phases, for each of the campaigns. In particular for the case of Cambridge, we observe strong differences between the two phases, with a much higher proportion of younger and female Facebook users targeted in the first phase. Similar findings can be derived when using a matching approach or a linear probability model, as shown in Tables D.2 and E.2, respectively.

Hence, we derive the following two main findings from our campaigns. First, social platform users are much more likely to engage with peer-to-peer solar if they are informed that they will be able to make their otherwise invisible consumption of solar energy visible. That is, they value the possibility to share green reports with their peers, making them more likely to consider MySunBuddy's offering. The effect can be even in the order of 30%.

Second, the effectiveness of a behavioral intervention using Facebook ads may vary over its duration. In particular, it seems that the ability of a campaign to lead to behavioral change decreases once the most relevant audience is exhausted. From a methodological perspective, this is an important finding, as not accounting for such effect may potentially lead researchers to underestimate the effectiveness of their treatment. This finding also has implications for the cost-effectiveness and power considerations of behavioral interventions, which also need to account for Facebook optimization and learning processes, as well as for external validity purposes, as the

Table 5: Estimates from logit: average marginal effects by phase

Campaigns	Somerville 2018		Somerville 2020		Cambridge 2020	
Phases	(1)	(2)	(1)	(2)	(1)	(2)
Time period	Oct 11-Oct 23	Oct 24-Nov 23	Dec 6-Dec 25	Dec 26-Feb 10	Dec 6-Jan 7	Jan 8-Feb 10
Community frame (CF)	-0.0004	-0.0000	0.0040	-0.0007	0.0089	0.0001
	(0.001)	(0.001)	(0.007)	(0.001)	(0.006)	(0.002)
Green reports (R)	0.0020**	-0.0003	0.0117*	-0.0008	0.0111*	-0.0017
	(0.001)	(0.001)	(0.007)	(0.001)	(0.006)	(0.002)
Controls						
Gender & age	YES	YES	YES	YES	YES	YES
N	24,656	79,234	3,295	35,788	8,506	25,000

Note: Heteroskedasticity-consistent standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

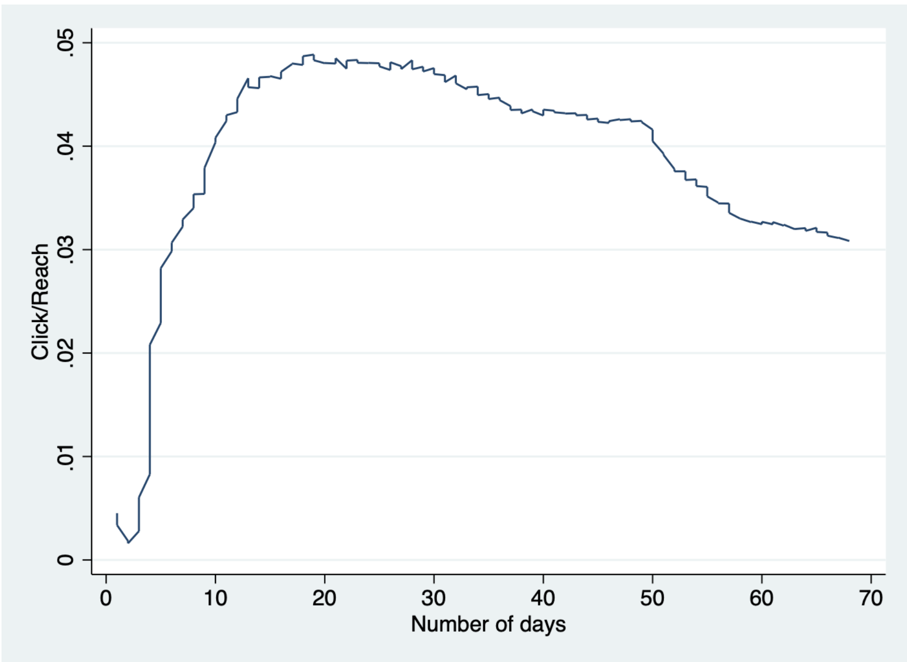
effectiveness of a short campaign may not persist over a larger campaign reaching out to a suboptimal audience. In this respect, Table F.2 in the Appendix provides estimates of the cost per click for our campaigns, as provided by Facebook.

We perform a robustness check in the Appendix with estimates from a linear probability model using the different phases (Table E.2). We find similar effects as in our primary analysis. Our analyses also show that in the first phase, the effect of the green reports can be seen also when considering all frames (IF, IFR, CF, and CFR) separately, although not with the same precision. The green reports seem to be most effective in combination with the community frame, which is intuitive, but additional research would be needed to measure such interactions with more power. Indeed, Table 6 shows positive effects of the community frame with reports over the individual frame (the reference category) in all campaigns, but the effect in the 2018 Somerville campaign tends to be smaller and its effect harder to be detected in a statistically significant way. The effect of the community frame with reports dominates that of the individual frame with reports in all but one campaign. The effect of the individual frame with reports is positive in both 2020 campaigns and virtually zero in the 2018 Somerville campaign.

Finally, we discuss whether individual or community frames are the most effective, when examining each in isolation. As shown in Table 4, we observe a consistent negative coefficient for the community frames over the entire campaign, suggesting that the individual frames tend to be more effective at generating interest in peer to peer solar, a result consistent with for instance Bollinger et al. (2020), but shown in a quite different context here. This effect can be detected in a statistically significant way, at the 1% level, in the Somerville campaigns as well as when pooling the data over all campaigns. The estimate for the Cambridge campaign is larger in absolute value, but the standard errors are also larger, so that in this case the coefficient turns out to be marginally non-significant, as in the case of the green reports. In contrast with the green reports, the effects tend to be noisier again when looking at the two phases separately.

Future research may also examine the effect of this type of intervention on other outcome variables and in other contexts. Concerning the latter point, it may be interesting to know how the effect of observability varies depending on the local context. For instance, based on Sexton and Sexton (2014), one may expect the effect of green reports to be weaker in more politically conservative areas. However, online visibility is different from local, physical visibility. Hence, people with strong pro-environmental preferences living in conservative areas may still want to share their behavior with like-minded peers, and possibly even more so than people with similar preferences living in more progressive areas. Moreover, the interaction between online visibility and community frame may also depend on the local context, for instance depending on the degrees of community feelings experienced in a given community. Further, our intervention intentionally targeted users of Facebook and Instagram, who may be especially prone to online sharing and to seeking social approval. Targeting interventions can greatly improve their cost-effectiveness (Allcott 2011; Ferraro and Miranda 2013; Andor et al. 2020), yet from a theoretical perspective it may be interesting to analyze how different population groups may react to an intervention giving the possibility to share one's greenness online. Finally, it could also be useful to determine how fast one may exhaust the most relevant audience, depending on the size of the Facebook population that is targeted in the campaign.

Figure 2: Clicks per reach over time



Note: The line indicates the average click per reach over the 2020 campaigns in Cambridge and Somerville.

Table 6: Estimates from logit: marginal effects for all treatment arms in the first phase

Campaigns	Somerville 2018	Somerville 2020	Cambridge 2020
Phases	(1)	(1)	(1)
Individual frame and green reports (IFR)	-0.0006	0.0208*	0.0049
	(0.001)	(0.011)	(0.009)
Community frame (CF)	-0.0039**	0.0133	0.0020
	(0.002)	(0.011)	(0.009)
Community frame and green reports (CFR)	0.0013	0.0186*	0.0178*
	(0.001)	(0.010)	(0.010)
Controls			
Gender & age	YES	YES	YES
N	24,656	3,295	8,506

Note: Heteroskedasticity-consistent standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

5 Conclusions

Transitioning to a cleaner economy requires the adoption of a new set of technologies and behaviors. Some of these behaviors currently have relatively low levels of adoption. Hence, the challenge is to identify ways to bring them from non-normative to normative. Peer-to-peer solar is one of these non-normative behaviors. Further, many behaviors with relatively low levels of adoption are not observable to others. Hence, people adopting them may not enjoy social rewards from behaving pro-environmentally. Again, peer-to-peer solar is one of these behaviors that is difficult to observe.

However, there are ways to make otherwise invisible climate-friendly behavior visible, with the aim of creating social rewards and making such behavior more appealing to prospective customers. We implement such a solution in the context of peer-to-peer solar, partnering with a startup company active in the United States. We use Facebook ads to inform prospective customers that they will have the possibility to receive green reports and share them online to display their greenness with their network. We do so in the context of a field experiment, randomizing the information about green reports to allow for causal inference.

We find that the people Facebook considers to be the most relevant audience are more likely to show interest in peer-to-peer solar when they are informed that they could share their greenness with others. That is, consumers anticipate the effects of future observability, and react to it in a positive manner. The effect can be up to a 30% increase in engagement with peer-to-peer solar when greenness is shareable. Hence, our experiment paves the way for new interventions, potentially on a larger scale and targeting other non-normative, socially invisible behaviors, aimed at introducing ways to make them observable to peers, while informing prospective customers of such observability. Such interventions could be combined with other treatments leveraging the intrinsic proclivity of green frontrunners to display their greenness, with the aim of leading others to follow them.

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Appendix

A Facebook ads

As mentioned in Section 3, this Appendix section provides the layout of the Facebook ads for the campaigns not included in the main body of text, namely the 2018 campaign in Somerville (in Figure A.1) and the 2020 Cambridge campaign (in Figure A.2).

Figure A.1: 2018 Somerville campaign Facebook ads

(a) Individual frame (IF) treatment arm

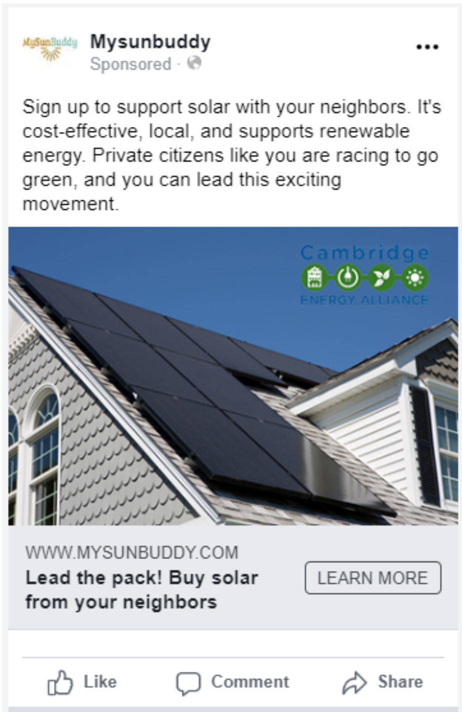
(b) Individual frame and green reports (IFR) treatment arm

(c) Community frame (CF) treatment arm

(d) Community frame and green reports (CFR) treatment arm

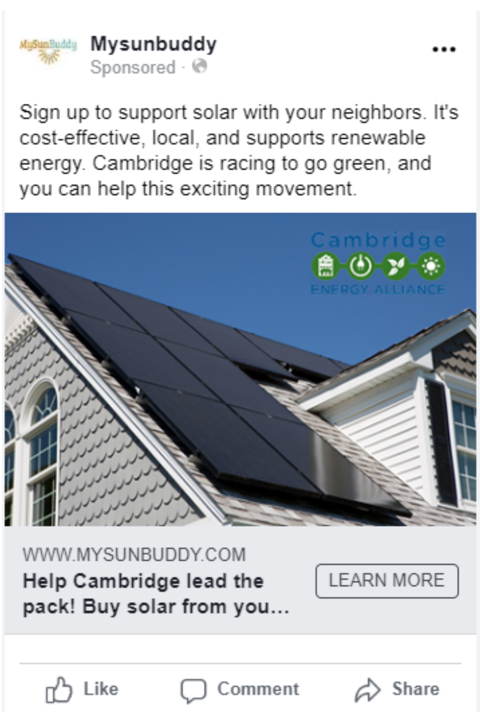
Figure A.2: 2020 Cambridge campaign Facebook ads

(a) Individual frame (IF) treatment arm



(b) Individual frame and green reports (IFR) treatment arm

(c) Community frame (CF) treatment arm



(d) Community frame and green reports (CFR) treatment arm

B Landing pages

Complementing the layout of the Facebook ads, as presented in Section 2 and in Appendix Section A, in this section we provide the layout of the landing pages corresponding to each treatment arm for the 2020 Somerville campaign. Landing pages are provided in Figure B.1 for the individual frame, in Figure B.2 for the individual frame with green reports, in Figure B.3 for the community frame, and in Figure B.4 for the community frame with green reports.

Figure B.1: 2020 Somerville campaign landing pages: individual frame (IF) treatment arm

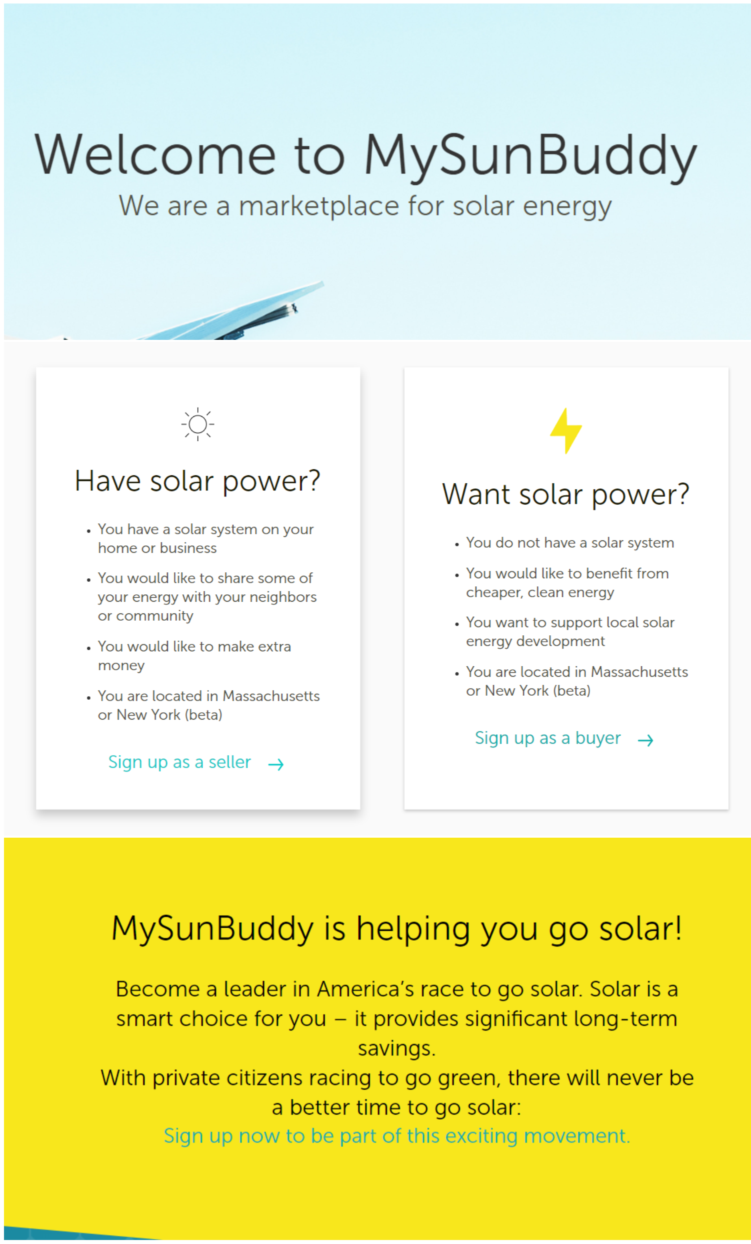


Figure B.2: 2020 Somerville campaign landing pages: individual frame and green reports (IFR) treatment arm

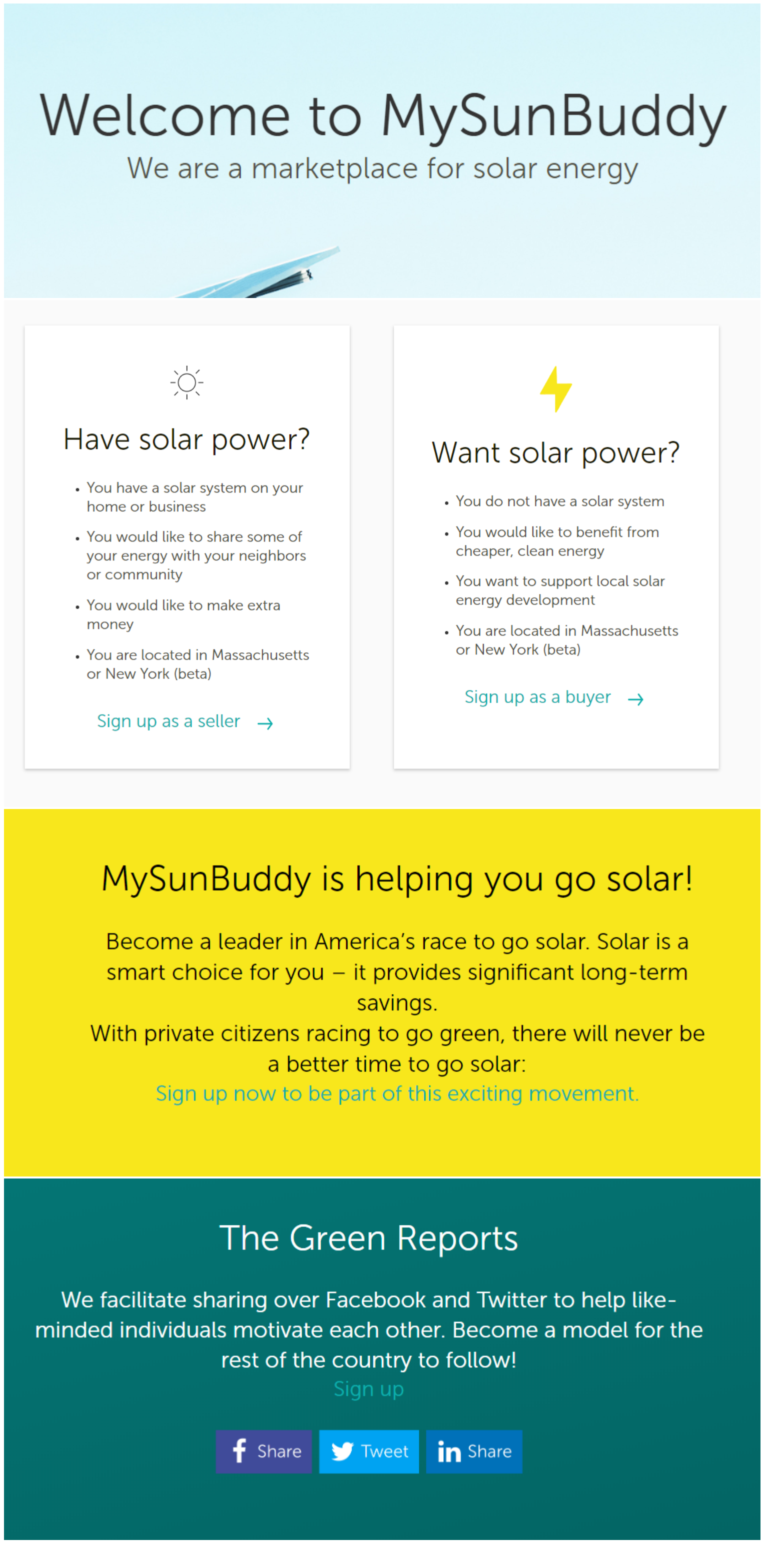


Figure B.3: 2020 Somerville campaign landing pages: community frame (CF) treatment arm

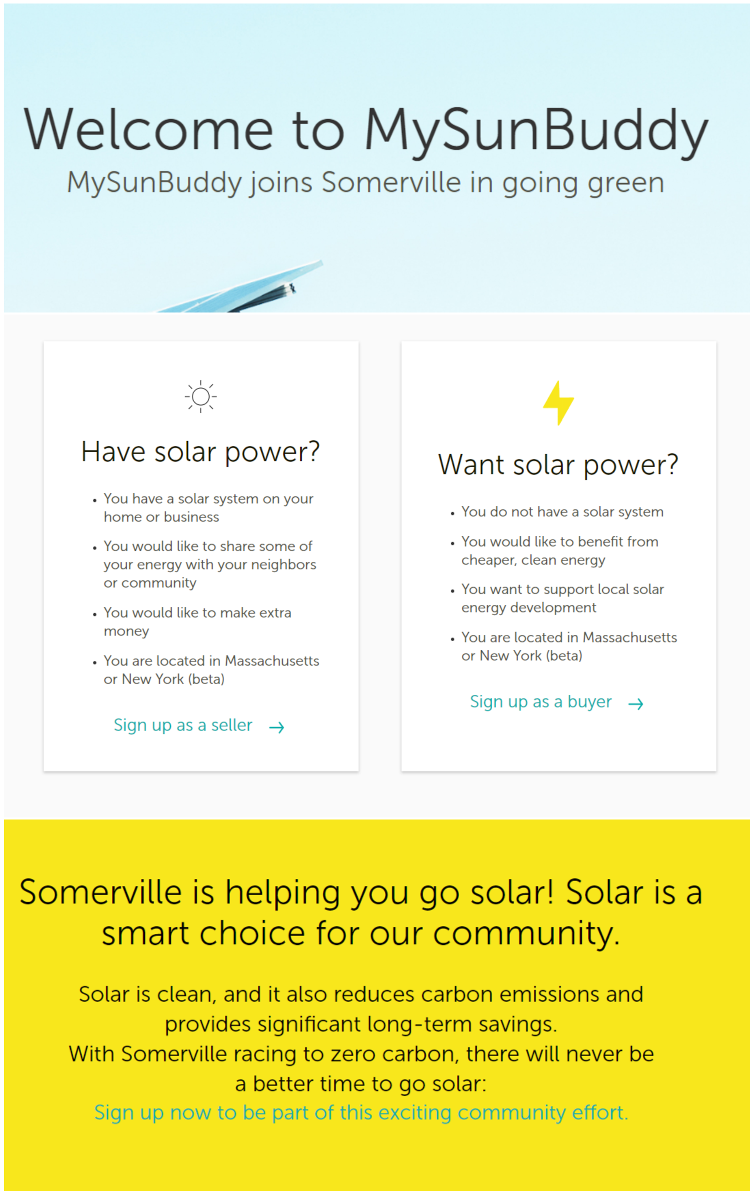
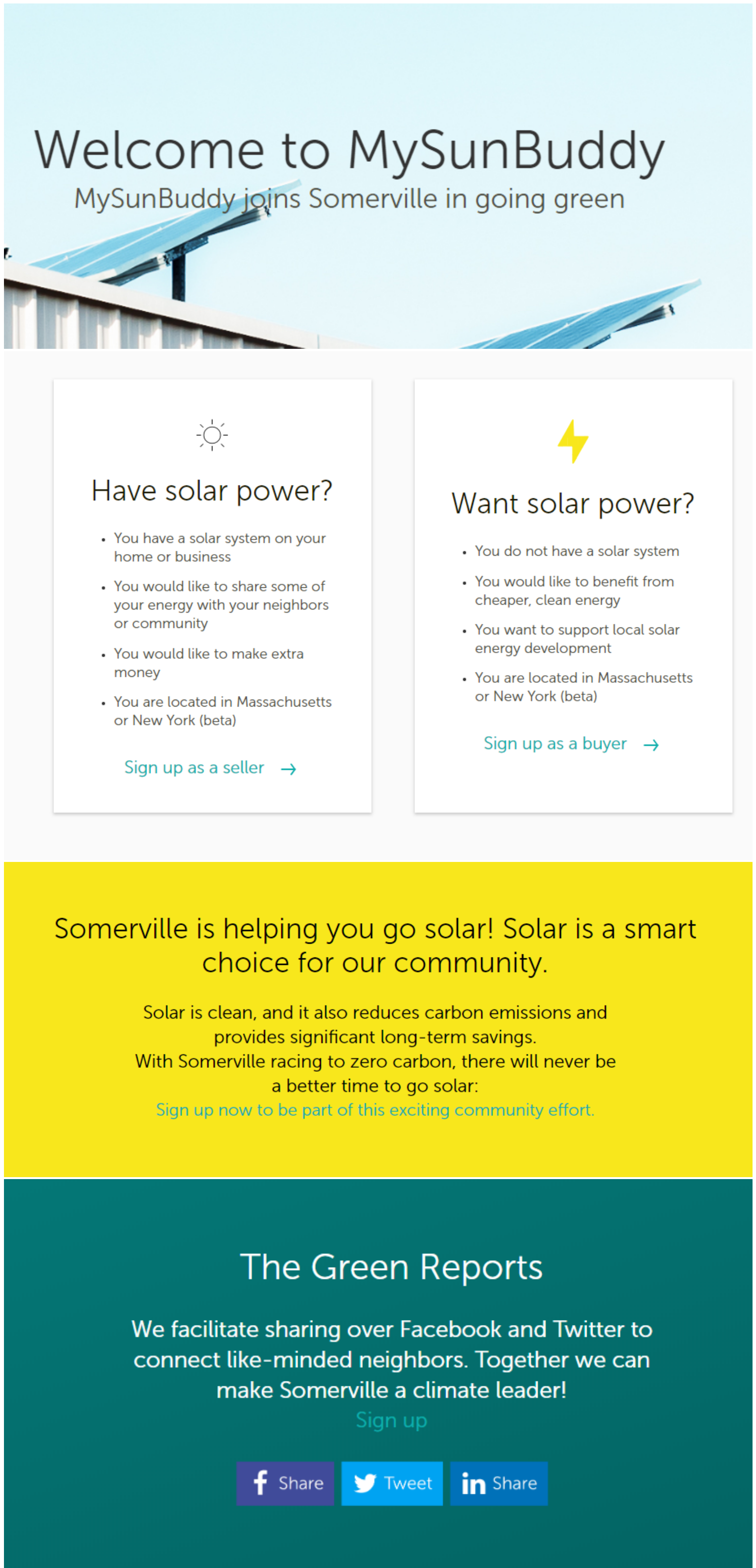


Figure B.4: 2020 Somerville campaign landing pages: community frame and green reports (CFR) treatment arm



C Socioeconomic characteristics and comparison with the underlying population

Complementing the summary statistics provided in Section 3, in this section we provide additional tables describing our sample and the underlying population to which it compares. Table C.1 provides the balance of covariates, before matching. Table C.3 provides summary statistics for the underlying populations of Cambridge and Somerville along the dimensions that we observe for our sample. Table C.4 provides summary statistics for our sample, between the two phases.

Table C.1: Balance of covariates before matching with two treatment arms

Campaign	Somerville		Cambridge		Somerville+Cambridge	
Treatment	Community frame (CF)	Green reports (R)	Community frame (CF)	Green reports (R)	Community frame (CF)	Green reports (R)
Female	-0.010***	0.025***	0.020***	-0.010*	-0.006**	0.020***
Gender unknown	-0.001*	0.000	-0.002	-0.001	-0.001*	0.000
Age 18-24	-0.002	0.005*	-0.018***	0.030***	-0.009***	0.013***
Age 25-34	-0.002	0.013***	0.022***	-0.020***	0.002	0.008***
Age 35-44	0.001	-0.001	0.003	-0.004	0.002	-0.003*
Age 45-54	-0.004**	-0.002	0.000	-0.001	-0.002	-0.003**
Age 55-64	0.002	0.006***	-0.005***	-0.002	0.002	-0.006***
Age 65+	0.005***	0.009***	-0.002	-0.003**	0.005***	-0.009***
N	143,040	143,040	33,506	33,506	176,546	176,546

Note: Numbers in the table are differences in unmatched data between treatment arms.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table C.3: Socioeconomic characteristics of the underlying population

	Somerville city	Cambridge city
Total population	80,434	115,665
Population of 18+ years	71,266	101,358
Share of female	49.99%	50.98%
Share of age 18-24	16.24%	23.03%
Share of age 25-34	37.78%	32.03%
Share of age 35-44	15.87%	13.88%
Share of age 45-54	10.31%	9.34%
Share of age 55-64	9.49%	8.85%
Share of age 65+	10.31%	12.87%

Note: All data come from the American Community Survey 2018 5-year estimates. All shares are calculated over the population above 18.

Table C.4: Socioeconomic characteristics across the two phases

Campaign	Somerville 2018			Somerville 2020			Cambridge 2020		
Phase	(1)	(2)	(1) - (2)	(1)	(2)	(1) - (2)	(1)	(2)	(1) - (2)
Time period	Oct 11- Oct 23	Oct 24- Nov 23		Dec 6- Dec 25	Dec 26- Feb 10		Dec 6- Jan 7	Jan 8- Feb 10	
Share of females (%)	40.15	45.57	-5.42***	62.17	50.28	11.9***	63.04	61.19	1.85***
Share of 18-24 (%)	24.04	27.34	-3.30***	58.6	40.29	18.3***	58.7	52.27	6.43***
Share of 25-34 (%)	29.39	27.83	1.56***	32.57	40.90	-8.33***	33.46	37.59	-4.13***
Share of 35-44 (%)	13.03	11.79	1.24***	5.29	9.25	-3.92***	4.19	6.14	-1.95***
Share of 45-54 (%)	9.92	9.54	0.38*	1.55	3.52	-1.98***	0.98	1.22	-0.24*
Share of 55-64 (%)	11.11	10.97	0.15	0.86	2.58	-1.71***	0.85	0.84	0.0025
Share of 65+ (%)	12.51	12.53	-0.26	1.13	3.49	-2.36***	1.83	1.94	-0.11

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

D Matching estimates

Complementing the main estimates displayed in Section 4, this section provides estimates from regression adjustment (matching based on covariates). Table D.1 provides them for the entire campaigns. Table D.2 provides them by phase. Table D.3 provides estimates for each individual treatment arm for the first phase, where the individual frame is the treatment of reference to which all other treatments are compared.

Table D.1: Estimates from regression adjustment (matching based on covariates): average treatment effect on the treated over entire campaigns

Campaign	Somerville	Cambridge	Somerville+Cambridge
Community frame (CF)	-0.0001***	-0.0009	-0.0002**
	(0.000)	(0.002)	(0.000)
Green reports (R)	0.0002***	0.0014	0.0004***
	(0.000)	(0.002)	(0.000)
N	143,040	33,506	176,546

Note: Standard errors in parentheses are clustered by year in column (1) and (3). Heteroskedasticity-consistent standard errors are used otherwise.
*** p<0.01, ** p<0.05, * p<0.1.

Table D.2: Estimates from regression adjustment (matching based on covariates): average treatment effect on the treated by phase

Campaign	Somerville 2018		Somerville 2020		Cambridge 2020	
Phase	(1)	(2)	(1)	(2)	(1)	(2)
Time period	Oct 11-Oct 23	Oct 24-Nov 23	Dec 6-Dec 25	Dec 26-Feb 10	Dec 6-Jan 7	Jan 8-Feb 10
Community frame (CF)	-0.0004	0.0000	0.0046	-0.0010	0.0030	-0.0001
	(0.001)	(0.001)	(0.006)	(0.001)	(0.005)	(0.002)
Green reports (R)	0.0020**	-0.0003	0.0129*	-0.0008	0.0057	-0.0021
	(0.001)	(0.001)	(0.007)	(0.001)	(0.005)	(0.002)
N	24,656	79,234	3,176	34,284	8,324	24,427

Note: Heteroskedasticity-consistent standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table D.3: Estimates from regression adjustment (matching based on covariates): average treatment effect on the treated for all treatment arms in the first phase

Campaign	Somerville 2018	Somerville 2020	Cambridge 2020
Phase	(1)	(1)	(1)
Time period	Oct 11-Oct 23	Dec 6-Dec 25	Dec 6-Jan 7
Individual frame and green reports (IFR)	-0.0001	0.0082	-0.0008
	(0.001)	(0.008)	(0.005)
Community frame (CF)	-0.0035***	-0.0021	-0.0042
	(0.001)	(0.008)	(0.005)
Community frame and green reports (CFR)	0.0028**	0.0071	0.0181**
	(0.001)	(0.008)	(0.009)
N	24,656	3,176	8,324

Note: Heteroskedasticity-consistent standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

E Linear probability model estimates

Complementing the main estimates displayed in Section 4, this section provides estimates from a linear probability model. Table E.1 provides them for the entire campaigns. Table E.2 provides them by phase. Table E.3 provides estimates for each individual treatment arm for the first phase, where the individual frame is the treatment of reference to which all other treatments are compared.

Table E.1: Linear probability model estimates: Average treatment effects over the entire campaigns

Campaign	Somerville	Cambridge	Somerville+Cambridge
Community frame (CF)	-0.0003	-0.0007	-0.0004
	(0.000)	(0.002)	(0.000)
Green reports (R)	0.0004	0.0013	0.0006
	(0.000)	(0.002)	(0.000)
Controls			
Gender & age	YES	YES	YES
Year FE	YES		YES
City FE			YES
N	143,040	33,506	176,546

Note: Standard errors in parentheses are clustered by year in column (1) and (3).
Heteroskedasticity-consistent standard errors are used otherwise.
*** p<0.01, ** p<0.05, * p<0.1.

Table E.2: Linear probability model estimates: Average treatment effect by phase

Campaign	Somerville 2018		Somerville 2020		Cambridge 2020	
Phase	(1)	(2)	(1)	(2)	(1)	(2)
Time Period	Oct 11- Oct 23	Oct 24- Nov 23	Dec 6- Dec 25	Dec 26- Feb 10	Dec 6- Jan 7	Jan 8- Feb 10
Community frame (CF)	-0.0003	-0.0000	0.0041	-0.0008	0.0091	0.0001
	(0.001)	(0.001)	(0.007)	(0.001)	(0.006)	(0.002)
Green reports (R)	0.0020**	-0.0003	0.0116*	-0.0008	0.0112*	-0.0018
	(0.001)	(0.001)	(0.007)	(0.001)	(0.006)	(0.002)
Controls						
Gender & age	YES	YES	YES	YES	YES	YES
N	24,656	79,234	3,362	35,788	8,506	25,000

Note: Heteroskedasticity-consistent standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table E.3: Linear probability model estimates: average treatment effects for all treatment arms in the first phase

Campaign	Somerville 2018	Somerville 2020	Cambridge 2020
Phase	(1)	(1)	(1)
Individual frame and green reports (IFR)	-0.0006	0.0189**	0.0046
	(0.001)	(0.009)	(0.008)
Community frame (CF)	-0.0031**	0.0108	0.0018
	(0.001)	(0.008)	(0.008)
Community frame and green reports (CFR)	0.0016	0.0165*	0.0196*
	(0.002)	(0.009)	(0.011)
Controls			
Gender & age	YES	YES	YES
N	24,656	3,362	8,506

Note: Heteroskedasticity-consistent standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

F All tables displaying estimates for control variables

Complementing the main estimates displayed in Section 4, this section provides estimates for all variables used in the estimations whose main coefficients are presented in the tables in the main body of text as well as additional estimations varying the specification of our standard errors, also including estimates for all variables used in the estimation. Table F.1 does so for a specification using logit and clustered standard errors, measuring average marginal effects over the entire campaigns. Table F.2 does so for the exact same specification, this time with heteroskedasticity-consistent standard errors. Table F.3 provides estimates for all variables when the estimation is done by phases and Table F.4 when all individual treatments are included for the first phase. Tables F.5 and F.7 provide estimates for all variables when the estimation uses a linear probability model, over the entire campaign and by phases, respectively.

Table F.1: Estimates from logit displaying all control variables with clustered standard errors: Average marginal effects over the entire campaigns

Campaign	Somerville	Cambridge	Somerville+Cambridge
Community frame (CF)	-0.0003***	-0.0007	-0.0003***
	(0.000)	(0.002)	(0.000)
Green reports (R)	0.0004***	0.0014	0.0006***
	(0.000)	(0.000)	(0.000)
Male	-0.0024*	-0.0066***	-0.0034***
	(0.001)	(0.002)	(0.001)
Gender unknown	0.0001	-0.0027	-0.0010
	(0.001)	(0.009)	(0.001)
Age 25-34	-0.0007*	-0.0000	-0.0006***
	(0.000)	(0.002)	(0.000)
Age 35-44	-0.0014	-0.0149***	-0.0036
	(0.002)	(0.004)	(0.002)
Age 45-54	0.0008	-0.0268***	-0.0008
	(0.004)	(0.006)	(0.007)
Age 55-64	0.0008	-0.0230**	-0.0003
	(0.005)	(0.007)	(0.008)
Age 65+	0.0012	-0.0111*	0.0004
	(0.005)	(0.007)	(0.008)
Year dummy	0.0130***		0.0149***
	(0.002)		(0.002)
City dummy			-0.0099***
			(0.001)
N	143,040	33,506	176,546

Note: Standard errors in parentheses are clustered by year in column (1) and (3). Heteroskedasticity-consistent standard errors are used otherwise. *** p<0.01, ** p<0.05, * p<0.1. "Male" is a dummy variable that captures if the Facebook user is male. "Unknown" is a dummy variable identifying users whose gender is unknown. "Age ##-##"s are dummies that represent whether the user belongs to that age group. "Year dummy" is a dummy variable for the 2020 campaign. "City dummy" is a dummy variable for the city of Somerville.

Table F.2: Estimates from logit displaying all control variables with heteroskedasticity-consistent standard errors: Average marginal effects over the entire campaigns

Campaign	Somerville	Cambridge	Somerville+Cambridge
Community frame (CF)	-0.0003	-0.0007	-0.0003
	(0.000)	(0.002)	(0.001)
Green reports (R)	0.0004	0.0014	0.0006
	(0.000)	(0.002)	(0.001)
Male	-0.0024***	-0.0066***	-0.0034***
	(0.001)	(0.002)	(0.001)
Gender unknown	0.0001	-0.0027	-0.0010
	(0.002)	(0.009)	(0.002)
Age 25-34	-0.0007	-0.0000	-0.0006
	(0.001)	(0.002)	(0.001)
Age 35-44	-0.0014*	-0.0149***	-0.0036***
	(0.001)	(0.004)	(0.001)
Age 45-54	0.0008	-0.0268***	-0.0008
	(0.001)	(0.006)	(0.002)
Age 55-64	0.0008	-0.0230**	-0.0003
	(0.004)	(0.007)	(0.002)
Age 65+	0.0012	-0.0111*	0.0004
	(0.005)	(0.007)	(0.001)
Year dummy	0.0130***		0.0149***
	(0.001)		(0.001)
City dummy			-0.0099***
			(0.001)
N	143,040	33,506	176,546

Note: Heteroskedasticity-consistent standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. "Male" is a dummy variable that captures if the Facebook user is male. "Unknown" is a dummy variable identifying users whose gender is unknown. "Age ##-##"s are dummies that represent whether the user belongs to that age group. "Year dummy" is a dummy variable for the 2020 campaign. "City dummy" is a dummy variable for the city of Somerville.

Table F.3: Estimates from logit displaying all control variables: Average marginal effects by phases

Campaign	Somerville 2018		Somerville 2020		Cambridge 2020	
Phase	(1)	(2)	(1)	(2)	(1)	(2)
Time Period	Oct 11- Oct 23	Oct 24- Nov 23	Dec 6- Dec 25	Dec 26- Feb 10	Dec 6- Jan 7	Jan 8- Feb 10
Community frame (CF)	-0.0004	-0.0000	0.0040	-0.0007	0.0089	0.0001
	(0.001)	(0.001)	(0.007)	(0.001)	(0.006)	(0.002)
Green reports (R)	0.0020**	-0.0003	0.0117*	-0.0008	0.0111*	-0.0017
	(0.001)	(0.001)	(0.007)	(0.001)	(0.006)	(0.002)
Male	-0.0004	-0.0005	-0.0131**	-0.0055***	-0.0068	-0.0063***
	(0.001)	(0.001)	(0.007)	(0.001)	(0.005)	(0.002)
Gender unknown	0.0081*	-0.0019	0.0008	0.0009	-0.0076	-0.0015
	(0.005)	(0.002)	(0.042)	(0.007)	(0.020)	(0.010)
Age 25-34	0.0005	-0.0003	0.0102	-0.0022	0.0031	-0.0002
	(0.001)	(0.001)	(0.007)	(0.002)	(0.005)	(0.002)
Age 35-44	0.0005	0.0002	0.0134	-0.0054**	-0.0133	-0.0135***
	(0.002)	(0.001)	(0.016)	(0.002)	(0.011)	(0.004)
Age 45-54	0.0016	0.0030**	0.0109	-0.0088***	-0.0358**	-0.0232***
	(0.002)	(0.001)	(0.031)	(0.003)	(0.013)	(0.006)
Age 55-64	0.0043*	0.0024*		-0.0146***	-0.0344*	-0.0189*
	(0.002)	(0.001)		(0.002)	(0.014)	(0.008)
Age 65+	0.0038*	0.0032***		-0.0125***	-0.0017	-0.0140*
	(0.002)	(0.001)		(0.003)	(0.018)	(0.007)
N	24,656	79,234	3,295	35,788	8,506	25,000

Note: Heteroskedasticity-consistent standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. "Male" is a dummy variable that captures if the Facebook user is male. "Unknown" is a dummy variable identifying users whose gender is unknown. "Age ##-##"s are dummies that represent whether the user belongs to that age group. "Year dummy" is a dummy variable for the 2020 campaign. "City dummy" is a dummy variable for the city of Somerville. Unsurprisingly, there are very few observations for users in the age 55-64 and age 65+ groups in the first phase of the Somerville 2020 campaign. As a result, the two variables are dropped automatically in the logit model, as it happens when a variable perfectly predicts the outcome.

Table F.4: Estimates from logit displaying all control variables: Marginal effects for all treatment arms in the first phase

Campaign	Somerville 2018	Somerville 2020	Cambridge 2020
Phase	(1)	(1)	(1)
Individual frame and green reports (IFR)	-0.0006	0.0208*	0.0049
	(0.001)	(0.011)	(0.009)
Community frame (CF)	-0.0039**	0.0133	0.0020
	(0.002)	(0.011)	(0.009)
Community frame and green reports (CFR)	0.0013	0.0186*	0.0178*
	(0.001)	(0.010)	(0.010)
Male	-0.0004	-0.0138**	-0.0066
	(0.001)	(0.007)	(0.005)
Gender unknown	0.0082*	0.0009	-0.0072
	(0.005)	(0.043)	(0.020)
Age 25-34	0.0005	0.0101	0.0031
	(0.001)	(0.007)	(0.005)
Age 35-44	0.0005	0.0135	-0.0132
	(0.002)	(0.017)	(0.011)
Age 45-54	0.0016	0.0113	-0.0357***
	(0.002)	(0.031)	(0.013)
Age 55-64	0.0042**		-0.0342**
	(0.002)		(0.015)
Age 65+	0.0038**		-0.0016
	(0.002)		(0.018)
N	24,656	3,295	8,506

Note: Heteroskedasticity-consistent standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Unsurprisingly, there are very few observations for users in the age 55-64 and age 65+ groups in the first phase of the Somerville 2020 campaign. As a result, the two variables are dropped automatically in the logit model, as it happens when a variable perfectly predicts the outcome.

Table F.5: Linear probability model estimates displaying all control variables with clustered standard errors: Average treatment effects over the entire campaigns

Campaign	Somerville	Cambridge	Somerville+Cambridge
Community frame (CF)	-0.0003	-0.0007	-0.0004
	(0.000)	(0.002)	(0.000)
Green reports (R)	0.0004	0.0013	0.0006
	(0.000)	(0.002)	(0.000)
Male	-0.0024	-0.0066***	-0.0033
	(0.003)	(0.002)	(0.003)
Gender unknown	-0.0002	-0.0028	-0.0015
	(0.001)	(0.008)	(0.002)
Age 25-34	-0.0008	-0.0000	-0.0008
	(0.001)	(0.002)	(0.001)
Age 35-44	-0.0014	-0.0146***	-0.0031
	(0.002)	(0.005)	(0.004)
Age 45-54	0.0004	-0.0259***	-0.0009
	(0.003)	(0.010)	(0.005)
Age 55-64	0.0003	-0.0224***	-0.0007
	(0.004)	(0.011)	(0.005)
Age 65+	0.0006	-0.0106	-0.0005
	(0.004)	(0.006)	(0.006)
Year dummy	0.0128*		0.0124*
	(0.001)		(0.002)
City dummy			-0.0173**
			(0.001)
N	143,040	33,506	176,546

Note: Standard errors in parentheses are clustered by year in column (1) and (3). Heteroskedasticity-consistent standard errors are used otherwise. *** p<0.01, ** p<0.05, * p<0.1. "Male" is a dummy variable that captures if the Facebook user is male. "Unknown" is a dummy variable identifying users whose gender is unknown. "Age ##-##"s are dummies that represent whether the user belongs to that age group. "Year dummy" is a dummy variable for the 2020 campaign. "City dummy" is a dummy variable for the city of Somerville.

Table F.6: Linear probability model estimates displaying all control variables with heteroskedasticity-consistent standard errors: Average treatment effects on the treated over the entire campaigns

	(1) Somerville	(2) Cambridge	(3) Somerville+Cambridge
Community frame (CF)	-0.0003	-0.0007	-0.0004
	(0.000)	(0.002)	(0.001)
Green reports (R)	0.0004	0.0013	0.0006
	(0.000)	(0.002)	(0.001)
Male	-0.0024***	-0.0066***	-0.0033***
	(0.001)	(0.002)	(0.001)
Gender unknown	-0.0002	-0.0028	-0.0015
	(0.002)	(0.008)	(0.002)
Age 25-34	-0.0008	-0.0000	-0.0008
	(0.001)	(0.002)	(0.001)
Age 35-44	-0.0014*	-0.0146***	-0.0031***
	(0.001)	(0.004)	(0.001)
Age 45-54	0.0004	-0.0259***	-0.0009
	(0.001)	(0.005)	(0.001)
Age 55-64	0.0003	-0.0224***	-0.0007
	(0.001)	(0.007)	(0.001)
Age 65+	0.0006	-0.0106*	-0.0005
	(0.001)	(0.006)	(0.001)
Year dummy	0.0128***		0.0124***
	(0.001)		(0.001)
City dummy			-0.0173***
			(0.001)
N	143,040	33,506	176,546

Note: Heteroskedasticity-consistent standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. "Male" is a dummy variable that captures if the Facebook user is male. "Unknown" is a dummy for the unknown gender agents. "Age ##-##"s are dummies that represent whether the agent belongs to that age group. "Year dummy" is a variable that indicates whether the agent is the 2020 campaign. "City dummy" is a variable that indicates whether the agent is in the city of Somerville.

Table F.7: Linear probability model estimates displaying all control variables: Average treatment effects by phase

Campaign	Somerville 2018		Somerville 2020		Cambridge 2020	
Phase	(1)	(2)	(1)	(2)	(1)	(2)
Time period	Oct 11- Oct 23	Oct 24- Nov 23	Dec 6- Dec 25	Dec 26- Feb 10	Dec 6- Jan 7	Jan 8- Feb 10
Community frame (CF)	-0.0003	-0.0000	0.0041	-0.0008	0.0091	0.0001
	(0.001)	(0.001)	(0.007)	(0.001)	(0.006)	(0.002)
Green reports (R)	0.0020**	-0.0003	0.0116*	-0.0008	0.0112*	-0.0018
	(0.001)	(0.001)	(0.007)	(0.001)	(0.006)	(0.002)
Male	-0.0004	-0.0005	-0.0129**	-0.0055***	-0.0068	-0.0063***
	(0.001)	(0.001)	(0.006)	(0.001)	(0.005)	(0.002)
Gender unknown	0.0074*	-0.0017	0.0004	0.0008	-0.0072	-0.0018
	(0.004)	(0.001)	(0.038)	(0.007)	(0.018)	(0.009)
Age 25-34	0.0005	-0.0002	0.0102	-0.0022	0.0031	-0.0002
	(0.001)	(0.001)	(0.007)	(0.002)	(0.005)	(0.002)
Age 35-44	0.0005	0.0002	0.0131	-0.0054**	-0.0128	-0.0132***
	(0.002)	(0.001)	(0.016)	(0.002)	(0.011)	(0.004)
Age 45-54	0.0016	0.0030**	0.0101	-0.0084**	-0.0335**	-0.0226***
	(0.002)	(0.001)	(0.027)	(0.003)	(0.012)	(0.006)
Age 55-64	0.0042**	0.0024**	-0.0291***	-0.0148***	-0.0338*	-0.0186**
	(0.002)	(0.001)	(0.005)	(0.002)	(0.014)	(0.008)
Age 65+	0.0038**	0.0033***	-0.0281***	-0.0126***	-0.0018	-0.0134*
	(0.002)	(0.001)	(0.005)	(0.003)	(0.017)	(0.006)
N	24,656	79,234	3,362	35,788	8,506	25,000

Note: Heteroskedasticity-consistent standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. “Male” is a dummy variable that captures if the Facebook user is male. “Unknown” is a dummy variable identifying users whose gender is unknown. “Age ##-##”s are dummies that represent whether the user belongs to that age group. “Year dummy” is a dummy variable for the 2020 campaign. “City dummy” is a dummy variable for the city of Somerville.

G Magnitude of the treatment effects and cost estimates

Complementing the discussion in Section 4, this section provides details about the average probability of clicking on the ads, effect of the green reports, and ratio between the two (Table F.1) and about the cost per click for every campaign and phase (Table F.2).

Table F.1: Average probability of clicking on the ads, effect of the green reports, and ratio between the two

	Somerville 2018			Somerville 2020			Somerville	Cambridge 2020			All campaigns
Phase	Pooled	(1)	(2)	Pooled	(1)	(2)	Pooled	Pooled	(1)	(2)	Pooled
Average click	0.0054	0.0060	0.0052	0.0182	0.0366	0.0165	0.0089	0.036	0.0486	0.0318	0.0141
Treatment effect for the green reports	0.0002	0.0020	-0.0003	About 0	0.0117	-0.0008	0.0004	0.0014	0.0111	-0.0017	0.0006
Ratio	0.04	0.34	-0.06	0.00	0.32	-0.05	0.05	0.04	0.23	-0.05	0.04

Note: The table provides average probability of click over the ads and treatment effects for the green reports for all phases of all campaigns as well as their averages pooled over each entire campaign. The ratio between average probability of clicking over the ads and the treatment effect for the green reports is provided for the first phase as discussed in Section 4.

Table F.2: Cost per click

	Somerville 2018			Somerville 2020			Cambridge 2020		
Phase	Pooled	(1)	(2)	Pooled	(1)	(2)	Pooled	(1)	(2)
Cost per click	1.41	1.26	1.46	0.76	0.50	0.80	0.45	0.33	0.52

Note: The table provides estimates from Facebook of the cost per click for all phases of all campaigns as well as their averages pooled over each entire campaign.