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 natural 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, to study social media users' interest in peer-to-peer solar through clicks on the ads. 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 also helps to facilitate indirect reciprocity and norm enforcement (see Kraft-Todd et al. 2015 and Yoeli et al. 2017 for reviews). 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 and injunctive norms. 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 consider new behaviors, especially non-normative behaviors that are currently adopted by only a small fraction of the population. In the context of climate-friendly behaviors, we should ideally target interest in decisions that can notably and durably reduce emissions.

In this paper, we investigate 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 just 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 considering invisible climate-friendly behavior if they are informed that they will be receiving shareable reports making 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.

While peer-to-peer solar may save the individual some money, it requires effort to set up and contributes to decarbonization. As such, participation in a peer-to-peer solar contract can be seen as a pro-environmental behavior. 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. Households may be, all else equal, less attracted to engage in peer-to-peer solar compared to other forms of pro-social behavior that are directly observable by peers, but there may be ways to improve observability, such as through social media. Peer-to-peer solar provides an ideal context to test the role of observability in leading individuals to consider the adoption of climate-friendly behaviors in the field.

We partnered with a startup company in the United States active in peer-to-peer solar, MySunBuddy, and realized a natural field experiment under the form of several randomized Facebook campaigns. 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 (community-led action or simply “community frame”). In addition, we deployed frames emphasizing the importance of being a frontrunner (individual-led action, or simply “individual frame”). 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 MySunBuddy.com. Our ads were seen by several tens of thousands of people in Cambridge and Somerville.

We explore social media users’ interest in peer-to-peer solar, as measured by clicks on our different ads. We believe that for a very non-normative behavior such as peer-to-peer solar, the act of actively considering the behavior is informative. We implemented our intervention at an early stage when MySunBuddy was still experimenting with the registration process and with getting contracts with both potential peer-to-peer solar buyers and peer-to-peer solar sellers – a crucial early period for the company. In another study on the adoption of solar energy, the conversion rate was one solar installation every 8 to 24 leads (Bollinger et al. 2019). While the exact conversion ratio may vary across contexts, we consider clicks to be a strong signal of interest, especially given how exposed to ads social media users are. In the marketing literature conversion rates from clicks vary depending on the product, such as vitamins and supplements (Moe et al. 2002), books (Montgomery et al. 2004), cars (Sismeiro and Bucklin 2004), electronics (Ghose and Yang 2009; Xu et al. 2014), clothing (Agarwal et al. 2011), software (Yao and Mela 2011), hotel rooms (Ghose et al. 2014), jewels (Li et al. 2016), banking services (Schwartz et al. 2017), as well as the wide range of products offered by e-commerce platforms and online retailers (Moe et al. 2002; Van den Poel and Buckinx 2005; Park and Park 2016). Yet, they most often share the same order of magnitude and are generally similar to those from the case of solar installations in Bollinger et al. (2019), and overall support the relevance of our exercise.

We find that social media users are more likely to show interest in peer-to-peer solar when informed that they would be receiving shareable green reports displaying their greenness, while community and individual frames are found to lead to similar levels of engagement. 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 up to 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. When comparing community frames and individual frames alone, we find evidence that individual frames may be more effective than community frames.

We find that heterogeneity matters in important ways in our empirical setting. When Facebook campaigns last relatively long, the algorithm starts reaching out to a less relevant audience, which is 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 once the most relevant audience is exhausted, 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. As a result, claims about scalability may need to account for such potential "voltage drop" as one moves from the most relevant audience to further audiences.

Our paper contributes to six strands of literature. First, 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; Soetevent 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. Second, a very recent research agenda aimed at bringing pro-social behaviors from non-normative to normative, leveraging forerunners and using social preferences in innovative ways to avoid that they backfire (e.g. Sparkman and Walton 2017; Kraft-Todd et al. 2018; Bicchieri and Dimant 2019; Mortensen et al. 2019; Spencer et al. 2019; Andreoni et al. 2020; Carattini and Blasch 2020; Gosnell et al. 2021). In the context of climate-friendly behaviors, it has been shown that individuals tend to care about what their neighbors do or think, despite the global properties of the social dilemma (Carattini et al. 2019).

Third, a growing literature 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), as well as 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). Fourth, a nascent literature using Facebook ads to address a wide range of research questions while uncovering new methodological insights (e.g. Celebi 2015; Dehghani and Tumer 2015; Blanco and Rodriguez 2020; Levy 2021). Fifth, an influential literature assessing the ability of behavioral interventions to scale and be effective when implemented over a large population (Al-Ubaydli et al. 2017; Davis et al. 2017; Al-Ubaydli et al. 2020; List 2022).

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]

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,

[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).

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 household's consumption is compensated at a value higher 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%. Thus there is a pecuniary incentive as well as a pro-social incentive for buyers and sellers. The biggest challenge to peer-to-peer solar is often coordinating the contracts.

The peer-to-peer solar startup 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 Virtual Net Energy Metering (VNEM). VNEM is a system used in states such as California, Maine, and Massachusetts for distributing economic benefits in shared solar energy markets (Oliver 2013). VNEM can be thought of as 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

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

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. When we implemented our intervention, MySunBuddy was at a critical early stage, and had just begun matching buyers and sellers of solar energy and working out the contracting process.

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. We ran the 2020 campaign 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. Our motivation was to leverage conditional cooperation by individuals responsive to the action of others in the community, in line with Carattini et al. (2019). The rationale for this approach is described in more detail in Section 2.3. In our context, 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 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!".

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

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, as discussed more in detail in Section 2.3. 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. The progress to which the ads refer relates to the amount of solar energy used instead of the default energy mix, which is more carbon-intensive than solar energy in Massachusetts as well as in the rest of the United States.

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). "Individual frame" 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.

All ads also included the following language, which is common across treatments:

[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.

"Sign up to support solar with your neighbors. It's cost-effective, local, and supports renewable energy." With the individual frame, the rest of the Facebook ad goes as follows: "private citizens like you are racing to go green, and you can lead this exciting movement." With the community frame, the rest of the Facebook ad, for instance in the case of Somerville, goes as follows: "Somerville is racing to go green, and you can lead this exciting movement." With either frame, when the green reports are mentioned, the Facebook ad continues as follows: "share your progress with friends through Twitter, Facebook and LinkedIn to connect with like-minded neighbors."

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 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, as social media users may be more inclined, when primed and made aware of the potential visibility of their behavior, to contribute to a global public good such as climate change mitigation in presence of and when contributing to efforts to make one's city greener. While theoretically one may be concerned about crowding out as well, with social media users being less inclined in showing interest in peer-to-peer solar when informed of other initiatives that the city in which they live

Table 1: 2×2 Treatment Assignment

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

is undertaking to become greener, we consider it unlikely that social media users who would not consider free riding on the world population on climate change mitigation would free ride on their fellow city members or the city government on local efforts at turning their city greener. We recall that our intervention targets a particular subsample of the population, also because of Facebook's optimizing algorithm, that may have an inclination in contributing to local and global public goods.

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.

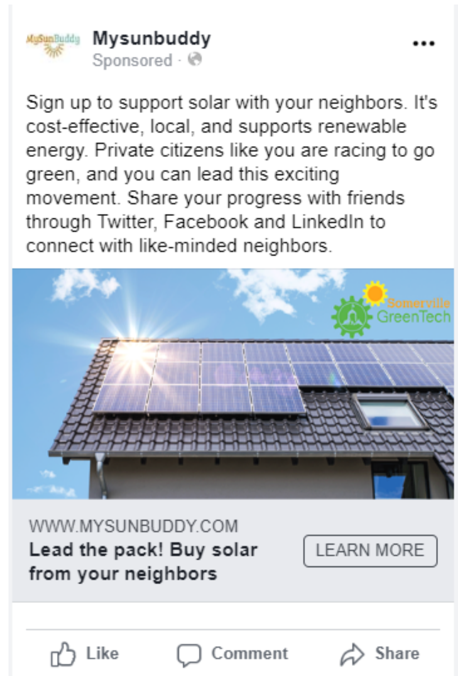
2.3 Theoretical foundations for our intervention

We now briefly discuss the theoretical motivation for our observability and framing treatments more in detail, starting with observability.

Figure 1: 2020 Somerville campaign Facebook ads

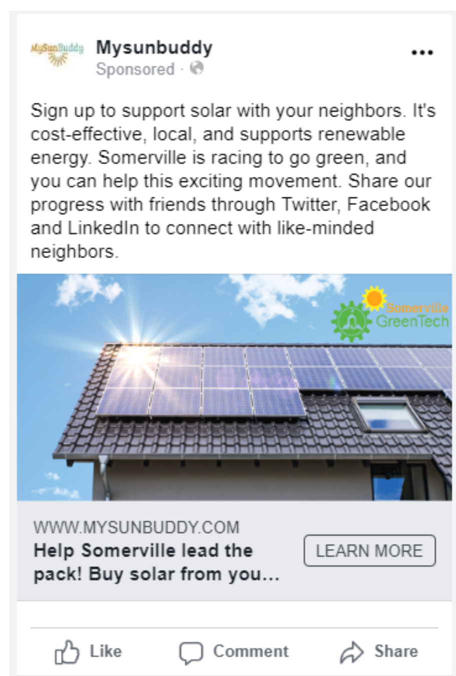
(a) IF treatment arm

(b) IFR treatment arm



(c) CF treatment arm

(d) CFR treatment arm



Observability is thought to promote pro-social behavior by engaging a pro-social psychology that has been shaped by reputational concerns, such as those generated by norm enforcement (Bicchieri 2005; Boyd 2018). Norm enforcement can not only shape people's behavior, but also corresponding preferences and beliefs (Bicchieri 2005; Bicchieri and Mercier 2014). Internalization can also lead to such phenomena as self-signaling (Akerlof and Kranton 2000; Bénabou and Tirole 2006). We note that this process of internalization can occur without conscious awareness: individuals having conscious access to so-called "proximate" preferences and beliefs, but not the underlying ("ultimate" or "functional") forces that shaped them. In the case of observability, this could mean that people may simply be more aware of pro-social asks, or get a stronger "warm glow" (Andreoni 1990) when observed, but they likely do not realize this is because their pro-social psychology was shaped by forces such as norm enforcement.

Our community frame is intended to motivate individuals to act pro-socially, but instead of emphasizing individual's contributions to climate change mitigation, it emphasizes cooperative efforts at the city level, to which an individual could add. That is, both the individual and community frames are intended as framing interventions, but of different types. It is worth emphasizing that the community frame may affect behavior in various ways, including beyond the channels that we intended the frame to leverage, and our intervention is not designed to isolate the effects of local social norms, signals of the local community's greenness or community approval for (visible) climate-friendly behavior, community leadership, or making one's city greener being a local public good on top of the global public good that is climate change mitigation. Hence, our community frame captures the combined effect of all those channels, when opposed to the individual frame.

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. For privacy reasons, we do not observe any information on the users themselves.

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 impressions 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, impressions are relatively uniformly distributed across ads, as shown in Table 2, which provides counts for impressions for each treatment arm.[7] 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. As mentioned, we do not observe multiple interactions with the same individual and can only compare impressions with reaches at the treatment arm level.

Clicks are also our variable of interest, as a measure of interest in peer-to-peer solar. For a very non-normative behavior such as peer-to-peer solar, we deem the

[6]Potentially, contamination may still occur, especially if Facebook and Instagram accounts are not linked, or if family members or friends share information about the ads that they see on social media. That is, if anything, we provide lower-bound estimates of the effectiveness of our intervention.

[7]Facebook argues that their A/B testing feature, which is what we used to randomize the assignment of Facebook ads, "helps ensure your audiences will be evenly split and statistically comparable" as reported on their website: https://www.facebook.com/business/help/1738164643098669 (last accessed, August 15, 2023). Randomization is further explained in Facebook's introduction to A/B testing: https://www.facebook.com/gpa/blog/introduction-to-split-testing (last accessed, August 15, 2023).

act of actively considering the behavior already very informative. Hence, we implemented our intervention at a time when MySunBuddy was still experimenting with the registration process and with getting contracts with both potential peer-to-peer solar buyers and peer-to-peer solar sellers. Exact conversion rates from leads, including clicks, to final decisions may vary across contexts, but, as mentioned above, in another study on the adoption of solar energy, on average one adoption resulted from every 8 to 24 leads (Bollinger et al. 2019). The study focused on the purchase of solar systems, which implies higher stakes than engaging in peer-to-peer solar, the latter being reversible as well.

To perform our empirical analyses, we expand the original dataset provided by Facebook to build a dataset in which each time an individual (or Facebook account) sees the ads (as measured by the variable "reach") represents one observation. We expand the dataset by treating each reach as a distinct observation, so that our data are organized by individual and not by date as originally provided by Facebook. 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, which are to be expected even with randomization, as Facebook may not have perfect control on their users' scrolling behavior. 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. In robustness tests, we also control for impressions as well as for day of the week, weekly time trends, and daily time trends.

Such socioeconomic characteristics also allow us to compare our samples with the underlying populations of Cambridge and Somerville, respectively. Table C.2 in Appendix C presents the demographic statistics of the experimental sample, by campaign, the same statistics for the underlying populations, from the American Community Survey (ACS), as well as for the entire United States, also from the same source. 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. Unsurprisingly, the population of both Cambridge and Somerville is notably younger than that of the entire United States, a point to which we return in Section 5 when discussing avenues for future research.

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 the groups of targeted individuals the algorithm approaches 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 visit MySunBuddy's landing page. We use logit given the binary outcome variable, while estimates from a linear probability model are provided for completeness.

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 pro-

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

vides 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.[8] 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 4, we also run a specification distinguishing between all 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 the balance of covariates when considering the two main treatment arms. Given small yet statistically significant differences across treatments for several variables resulting from the randomization process, 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.[9] Matching based on covariates provides balanced samples. The matching approach that we use follows from exact matching by cell, which is feasible in presence of a limited number of control variables, as famously illustrated by Angrist (1998), among others.

In what follows, we first start by examining the effect of the green reports, our main variable of interest. Then we proceed by analyzing heterogeneity over the duration of the campaigns as well as the effect of community frames versus individual frames and the interaction between the latter and the green reports.

[8] In our main tables, we cluster by year whenever analyzing campaigns over multiple years, but our findings are generally unaffected when using clustering by year and city. Among our additional results, we also show specifications with standard heteroskedasticity-consistent standard errors instead.

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

4 Empirical results

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

As mentioned, we first start by analyzing the effect of the green reports. Table 3 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). Coefficients for the control variables are provided in Table F.1. Point estimates for the green reports are relatively consistent across specifications, generally indicating a stronger propensity to click on the ads if green reports are mentioned, but estimates for Cambridge are statistically insignificant, even if somewhat larger. Table F.2 in the Appendix rules out a statistically significant interaction between the city of Cambridge and the green reports.

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 H.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 H.1), the effect of the green reports is, on average, around 4%.

A similar pattern emerges when looking at the matching approach (Table D.1), the estimates where standard errors are clustered by city and year (Table F.3), or the estimates controlling for impressions (Table F.5), day of the week (Table F.6), weekly

Table 3: 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.
Reported estimates are average marginal effects.
*** p<0.01, ** p<0.05, * p<0.1.

time trends (Table F.7), and daily time trends (Table F.8), although precision may vary slightly. If anything, controlling for impressions leads to larger point estimates for the green reports. Even though we consider a logit model with clustered standard errors the most appropriate specification in our context, linear probability estimates or estimates where the assumption of clustered standard errors is relaxed are still provided, in Tables E.1 and F.4, respectively. We also provide, in Table G.1, estimates in scientific notation, although we still prefer the standard notation in decimal form and apply it to the remaining tables.

4.2 Heterogeneity

We now turn to the analysis of heterogeneity over the duration of the campaigns. 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 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. 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. 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 C.2 already showed that Facebook's algorithm starts with a younger crowd, and if the campaign continues, the sample 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, consistent with the negative coefficients for impressions in some columns of Table F.5 or for the weekly and daily time trends in Tables F.7 and F.8, respectively. 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. For descriptive purposes, we proceed by identifying these two phases for each campaign and estimating treatment effects for each of them. As displayed in Table 4, 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.[10]

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, to 1/192. In the 2020 campaigns, the probability of clicking on the ads decreases by about 50% in the second phase. Figure 2 displays this pattern with pooled data for all campaigns.

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

[10]We selected the phases for this discussion following visual inspection, for descriptive purposes. 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. Unfortunately, no more information is available concerning the functioning of Facebook's algorithm to help distinguishing the various phases.

reports in the first phase is 0.002. It represents about a third of the average probability of clicking of 0.006 (1/160). That is, the green reports increase the probability of engaging with the ads by about a third, or 34%, as calculated by dividing the relevant coefficient by the average across all treatment arms, given the 2x2 design employed in this study. 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). In this case, we would obtain that the green reports increase the probability of engaging with the ads by 32%. For the Cambridge 2020 campaign, the relevant ratio is 0.0111 over 0.0486. In this case, we would obtain that the green reports increase the probability of engaging with the ads by 23%, a lower yet still large effect. We conclude that the effect of the green reports is to lead the most-relevant audience of Facebook users to be up to 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 still important for a social intervention, but vastly lower than the 20-30% effect that we identify when Facebook targets the most responsive audience. Table H.1 in the Appendix provides background information for all these calculations.

While it is theoretically possible that some of the interest that social media users show is driven by their curiosity about the green reports, which were not described in detail on the Facebook ads, it seems rather unlikely that the abovementioned effect of around 20-30% is driven by such curiosity, especially given how often social media users are exposed to advertisement as well as to news feeds stimulating their curiosity. Given the effects that we identify, conversion rates would need to be dramatically lower than in Bollinger et al. (2019), and in the rest of the marketing literature, to challenge the meaningfulness of our findings.

In the columns displaying the coefficients for phase 2, we observe that as soon

Table 4: Estimates from logit: 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.
Reported estimates are average marginal effects.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

as the best audience was exhausted, the ads reached less responsive Facebook users, 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.3 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.

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 on the order of 30%.

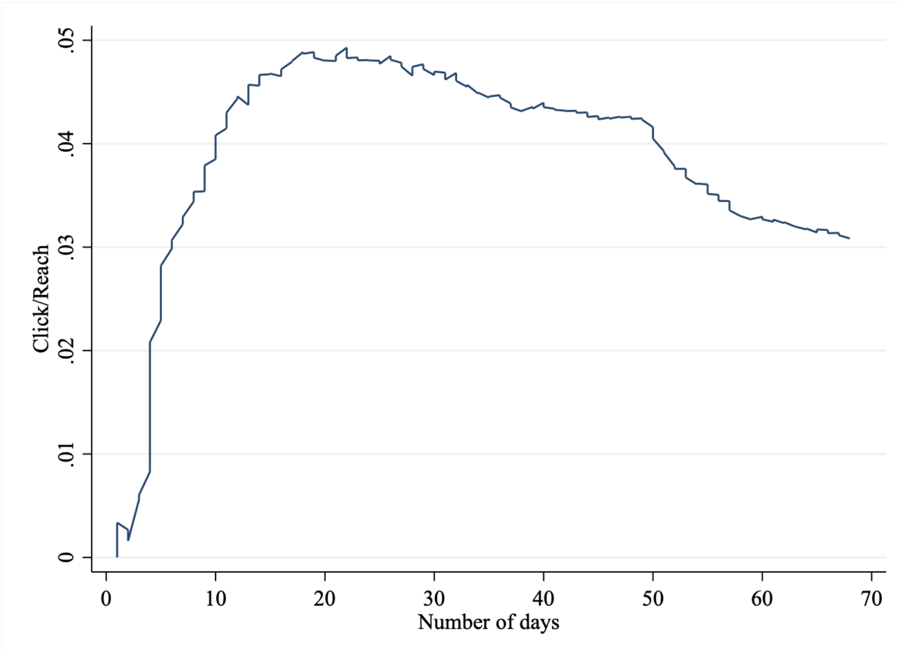
Second, the effectiveness of a behavioral intervention using Facebook ads may vary over its duration. In particular, it seems that the ability of a campaign to lead to behavioral change decreases once the most relevant audience is exhausted. From a methodological perspective, this is an important finding, 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 and scalability purposes, as the effectiveness of a short campaign may not persist over a larger campaign reaching out to a suboptimal audience. Table H.2 in the Appendix provides estimates of the cost per click for our campaigns, as provided by Facebook. Cost per click is a measure of the cost-effectiveness of running ads, as it takes into account both the cost of running ads and the clicks that they may generate. Cost per click can be interpreted, generally speaking, as the mirror image of clicks per reach. In Table H.2, we observe that for the Somerville 2018 campaign, cost per click increases from \$1.26 in the first phase to \$1.46 in the second phase. For the Somerville 2020 campaign, cost per click increases from \$0.50 in the first phase to \$0.80 in the second phase. For the Cambridge 2020 campaign, cost per click increases from \$0.33 in the first phase to \$0.52 in the second phase.

We perform a robustness check in the Appendix with estimates from a matching approach and a linear probability model using the different phases, in Tables D.2 and E.2, respectively. We find similar effects as in our primary analysis. Note that in Table D.2, the coefficient for the green reports in the Cambridge campaign is statistically non-significant.

4.3 Community frame versus individual frame and interactions

We continue our examination by assessing the effect of the community and individual frames and their interaction with the green reports. 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 5 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 is smaller and statistically insignificant. 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

Figure 2: Clicks per reach over time



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

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 3, we observe a consistent negative coefficient for the community frames over the entire campaign, which is statistically significant at the 1% level in the Somerville campaigns, but not for the Cambridge campaign, despite the larger point estimate. The evidence from Somerville suggesting that the individual frames tend to be more effective at generating interest in peer-to-peer solar would be consistent with Bollinger et al. (2020), but shown in a quite different context here.

Table 5: 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.
Reported estimates are average marginal effects.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

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.

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. 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. When there is already observability, for instance via social media, simply telling people about it is often simple and practically free. Our work suggests that doing so is a useful policy prescription, at least in the context of our study. 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, potentially in combination with other community-based efforts.

Future research could 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 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.

Further, a research frontier in behavioral economics involves examining who the observers are and how that may matter in determining one's pro-sociality in presence of observability, with multiple studies bringing participants in the lab and making their behavior observable to their fellow lab participants pointing to negligible or even detrimental effects of observability for pro-sociality (Noussair and Tucker 2007; Chaudhuri and Paichayontvijit 2010; Khadjavi et al. 2014; Cason et al. 2016; Brent et al. 2019; see also Bradley et al. 2018 for a meta-analysis). In this respect, we note that social observability in the lab is usually not targeted at the same social circle with whom one would share information on social media as in our field experiment and may also have different implications in terms of social learning. The extent to which making otherwise invisible pro-social behavior visible depends on the degree of control that people have in determining who observes their behavior is an important question that future research could pursue. Moreover, the interaction between online visibility and community frame may also depend on the degrees of community feelings experienced in a given community. Additionally, 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.

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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

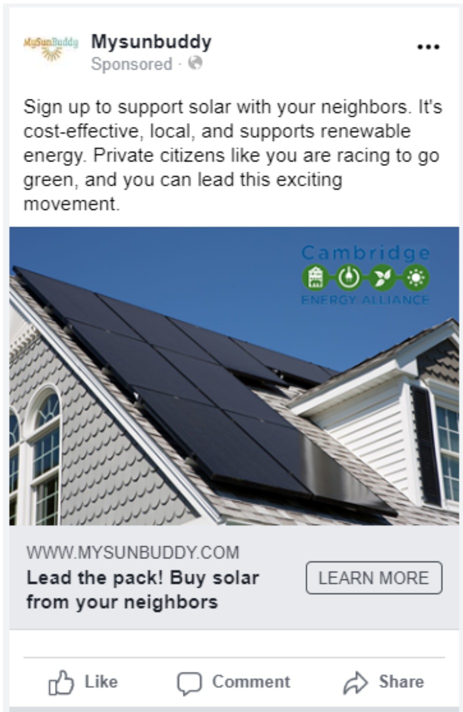
(b) Individual frame and green reports (IFR) treatment arm

(c) Community frame (CF) treatment arm

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

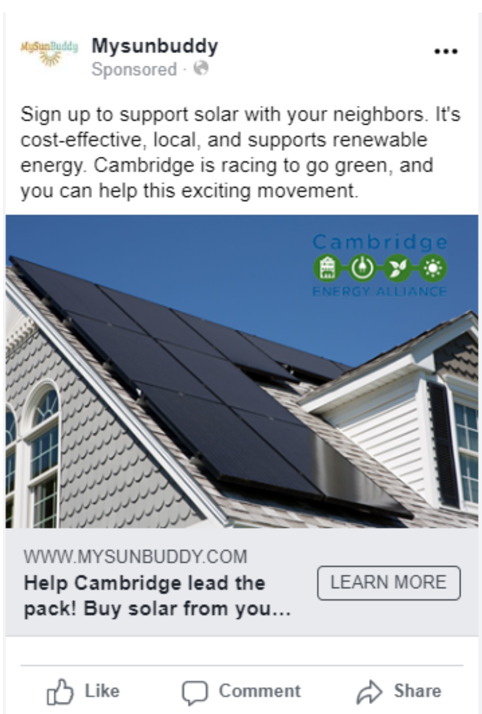
Figure A.2: 2020 Cambridge campaign Facebook ads

(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

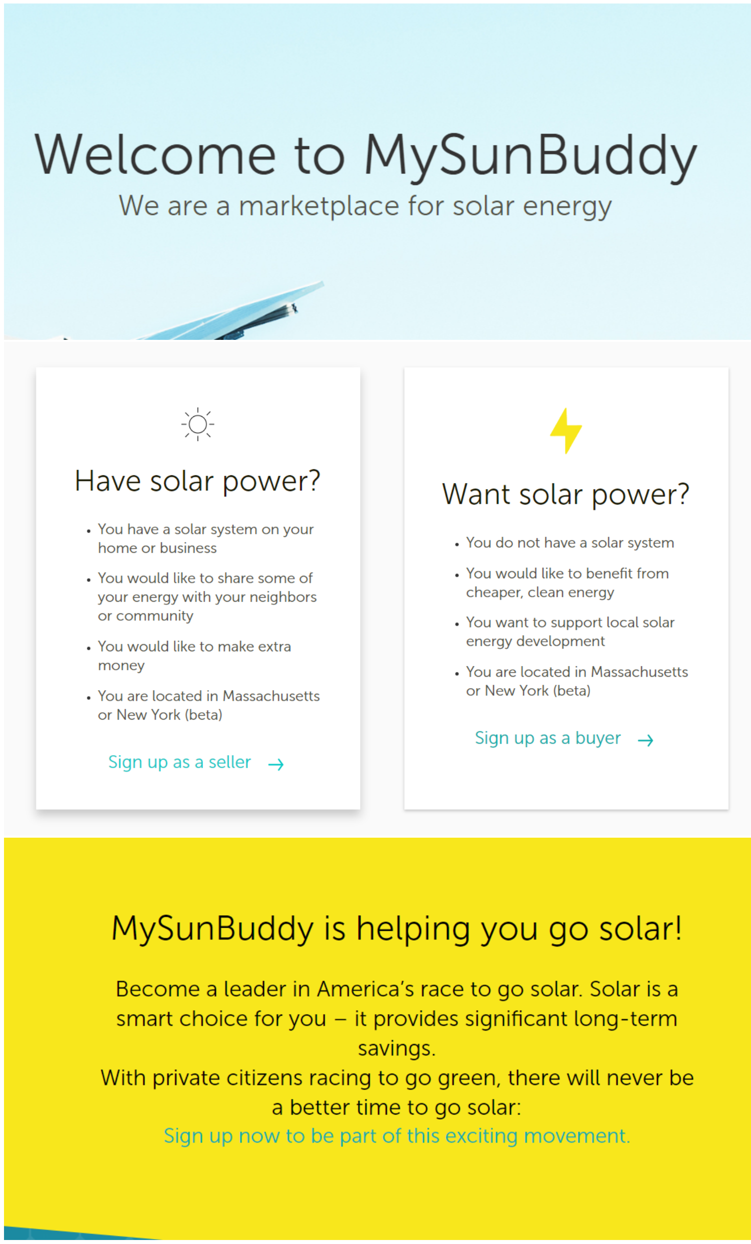


Figure B.2: 2020 Somerville campaign landing pages: individual frame and green reports (IFR) treatment arm

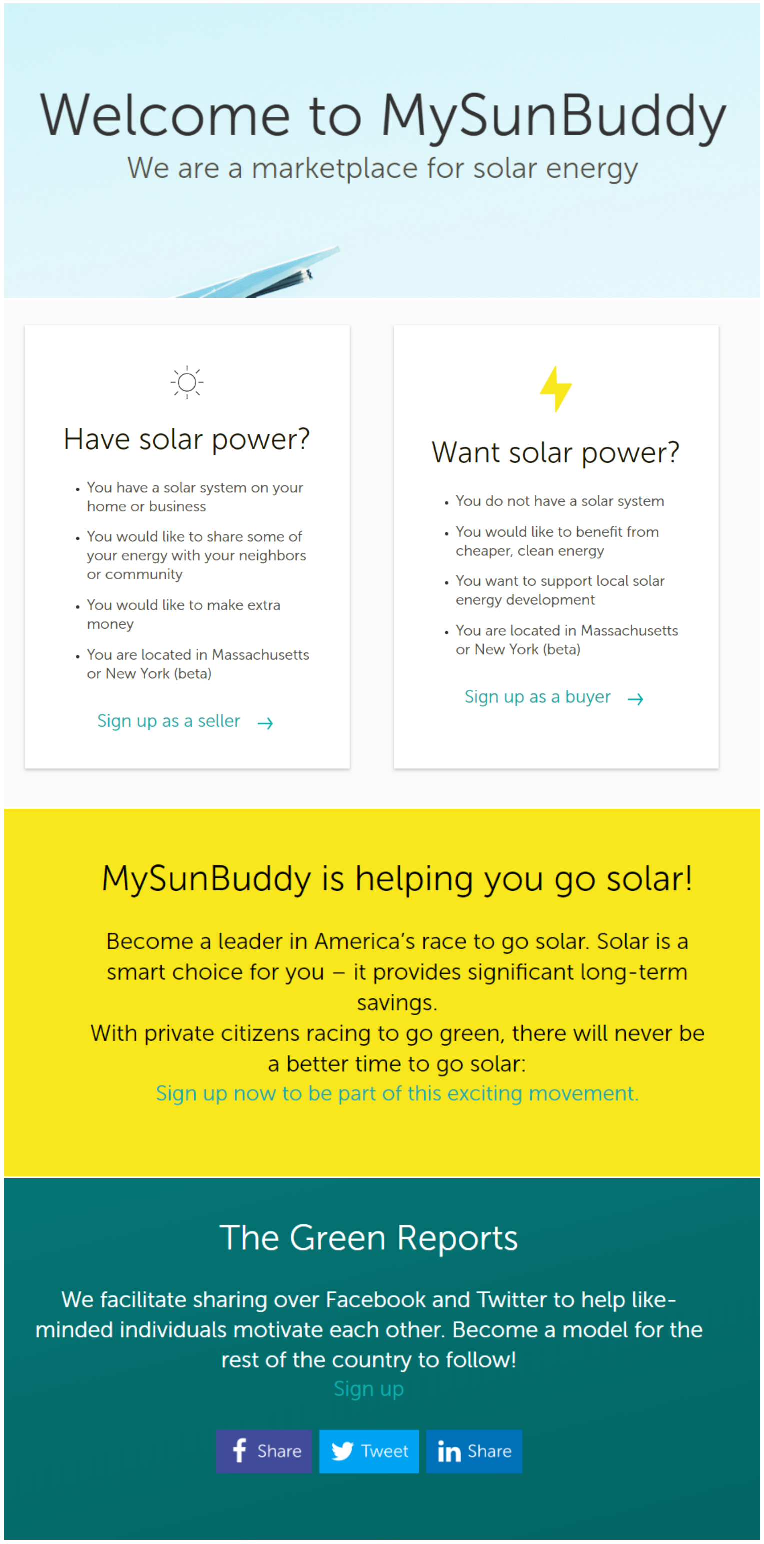


Figure B.3: 2020 Somerville campaign landing pages: community frame (CF) treatment arm

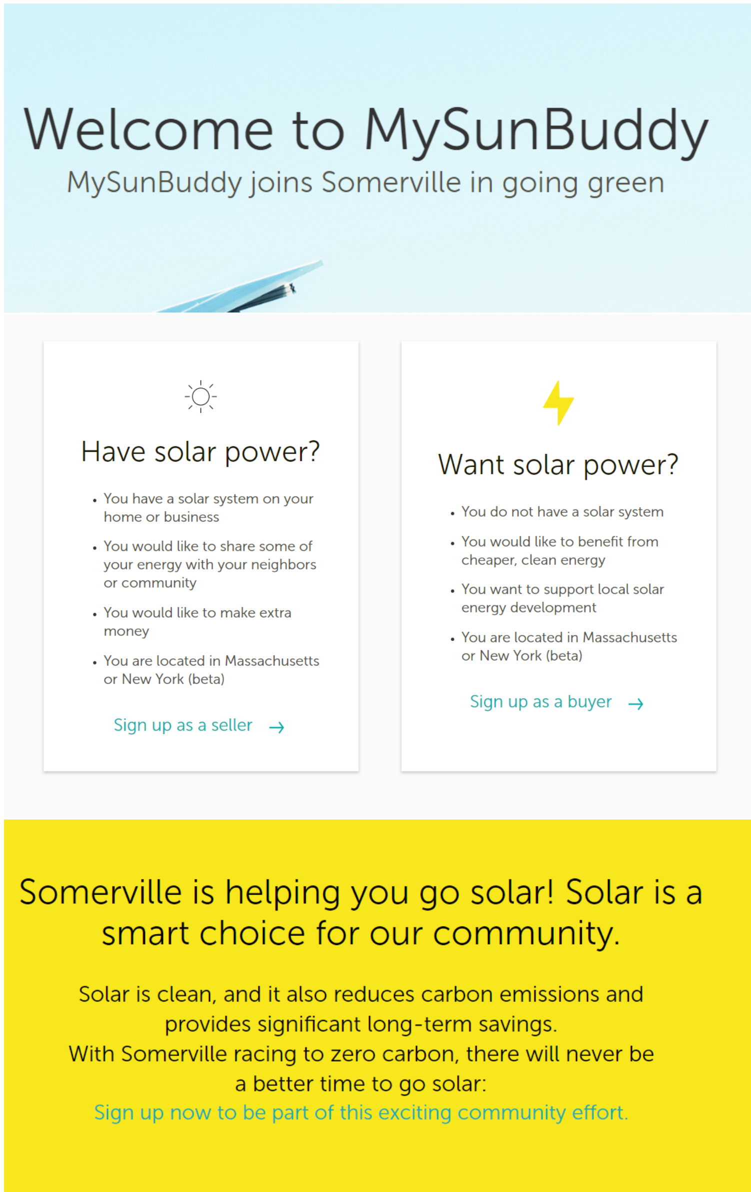
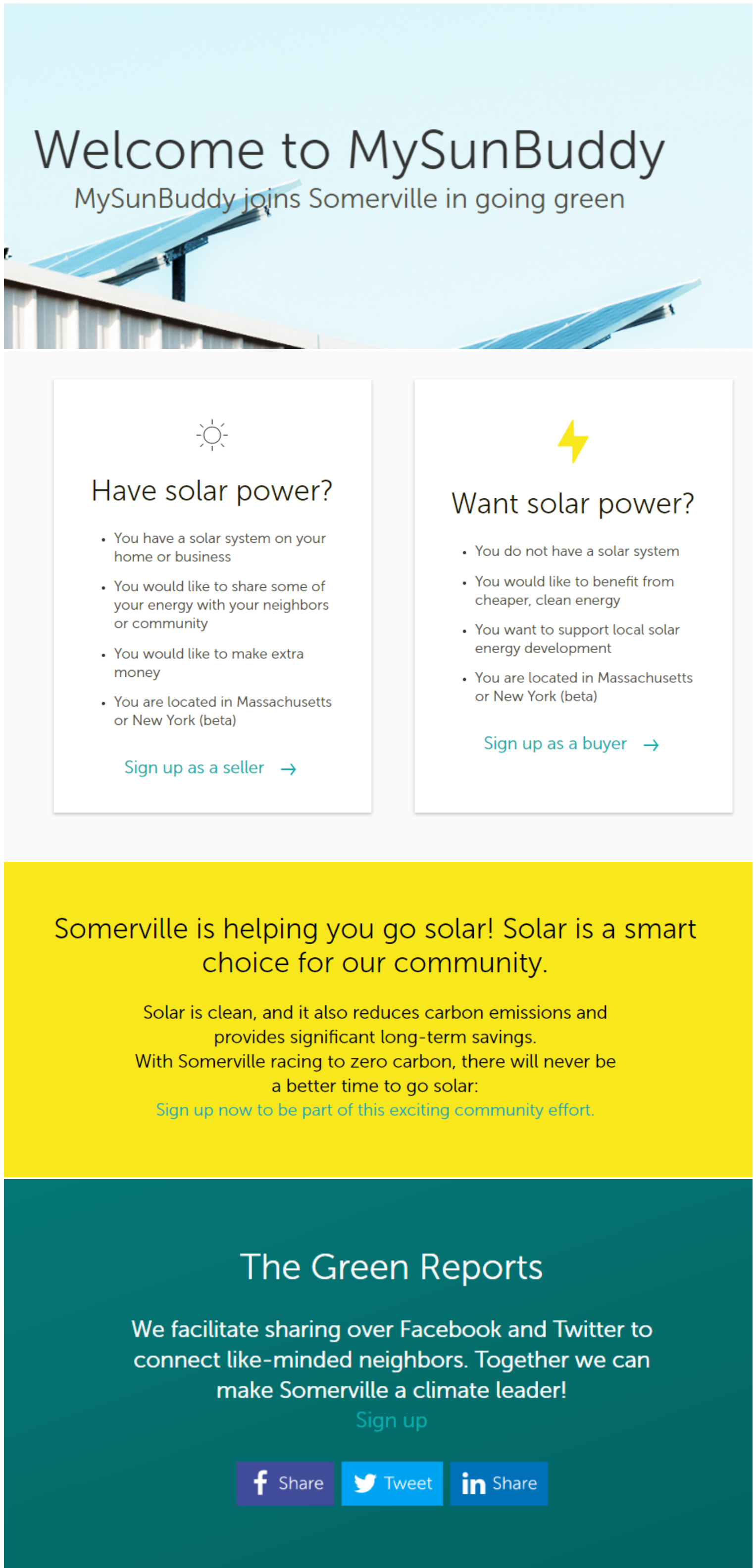


Figure B.4: 2020 Somerville campaign landing pages: community frame and green reports (CFR) treatment arm



C Socioeconomic characteristics and comparison with the underlying population

In this section, we provide summary statistics describing our sample and the underlying population to which it compares. Table C.1 provides the balance of covariates, before matching. Table C.2 provides summary statistics for the sample and for underlying populations of Cambridge and Somerville as well as the entire United States along the dimensions that we observe for our sample. Table C.3 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.2: Socioeconomic characteristics of the sample, the underlying population, and the entire United States

	Sample					Population		
	Somerville		Cambridge	Pooled		Somerville	Cambridge	United States
	2018	2020	2020					
Share of females	44.28%	51.30%	61.66%	49.14%	Total population	80,434	115,665	322,903,030
Share of 18-24	26.56%	41.86%	53.90%	35.14%	Population of 18+ years	71,266	101,358	249,349,790
Share of 25-34	28.20%	40.18%	36.54%	32.44%	Share of female	49.99%	50.98%	51.31%
Share of 35-44	12.08%	8.88%	5.64%	10.15%	Share of age 18-24	16.24%	23.03%	12.39%
Share of 45-54	9.63%	3.35%	1.16%	6.63%	Share of age 25-34	37.78%	32.03%	17.87%
Share of 55-64	11.00%	2.43%	0.84%	7.17%	Share of age 35-44	15.87%	13.88%	16.35%
Share of 65+	12.53%	3.29%	1.92%	8.47%	Share of age 45-54	10.31%	9.34%	17.08%
					Share of age 55-64	9.49%	8.85%	16.56%
					Share of age 65+	10.31%	12.87%	19.75%

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

Table C.3: 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 or considering additional control variables, also including estimates for all variables used in the estimation, except, for a more compact presentation, when controlling for days of the week. Table F.1 shows all estimates for our baseline estimation using logit and clustered standard errors by year, measuring average marginal effects over the entire campaigns. Table F.2 adds city interactions to our baseline model with clustered standard errors by year. Table F.3 extends our baseline estimation to clustered standard errors by city and year. Table F.4 uses heteroskedasticity-consistent standard errors. Table F.5 adds impressions as control variable to our baseline model with clustered standard errors by year. Tables F.6, F.7, and F.8 consider various time dimensions as additional control variables, namely day of the week, a weekly time trend, and a daily time trend, respectively. Table F.9 provides estimates for all variables when the estimation is done by phases and Table F.10 when all individual treatments are included for the first phase. Tables F.11, F.12, and F.13 provide estimates for all variables when the estimation uses a linear probability model, over the entire campaign (including with heteroskedasticity-consistent standard errors in Table F.12) and by phases, respectively.

Table F.1: Estimates from logit displaying all control variables with clustering standard errors by year: 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. Reported estimates are average marginal effects. “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. *** p<0.01, ** p<0.05, * p<0.1.

Table F.2: Estimates from logit with city interactions and clustering standard errors by year: Marginal effects over the entire campaigns

Campaign	Somerville+Cambridge
Somerville * CF	-0.0002
	(0.000)
Somerville * R	0.00005
	(0.0002)
Somerville	-0.0090***
	(0.001)
Community frame (CF)	-0.0002***
	(0.000)
Green reports (R)	0.0006***
	(0.000)
Male	-0.0034***
	(0.001)
Gender unknown	-0.0010
	(0.001)
Age 25-34	-0.0006***
	(0.000)
Age 35-44	-0.0036
	(0.002)
Age 45-54	-0.0008
	(0.007)
Age 55-64	-0.0003
	(0.008)
Age 65+	0.0004
	(0.008)
Year dummy	0.0149***
	(0.002)
N	176,546

Note: Standard errors in parentheses are clustered by year. *** 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 with clustering standard errors by city and year: 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)	(0.000)
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)	(0.006)
Age 55-64	0.0008	-0.0230**	-0.0003
	(0.005)	(0.007)	(0.006)
Age 65+	0.0012	-0.0111*	0.0004
	(0.005)	(0.007)	(0.006)
Year dummy	0.0130***		0.0149***
	(0.002)		(0.002)
City dummy			-0.0099***
			(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. Reported estimates are average marginal effects. “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. *** p<0.01, ** p<0.05, * p<0.1.

Table F.4: Estimates from logit displaying all control variables with heteroskedasticity-consistent standard errors: 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. Reported estimates are average marginal effects. "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. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table F.5: Estimates from logit controlling also for impressions with clustering standard errors by year: Marginal effects over the entire campaigns

Campaign	Somerville	Cambridge	Somerville+Cambridge
Community frame (CF)	-0.0003***	-0.0002	-0.0003***
	(0.000)	(0.002)	(0.000)
Green reports (R)	0.0006***	0.0023	0.0009***
	(0.000)	(0.002)	(0.000)
Impressions	-0.0000	-0.0002***	-0.0001*
	(0.000)	(0.000)	(0.000)
Male	-0.0023*	-0.0113***	-0.0038***
	-0.001	-0.002	-0.001
Gender unknown	-0.0024	-0.0129	-0.0048***
	-0.003	-0.009	-0.002
Age 25-34	-0.0007***	-0.0032	-0.0012***
	0.000	-0.002	0.000
Age 35-44	-0.0033	-0.0278***	-0.0065**
	-0.003	-0.006	-0.003
Age 45-54	-0.0015	-0.0553***	-0.0049
	-0.005	-0.018	-0.007
Age 55-64	-0.0012	-0.0444**	-0.0041
	-0.006	-0.018	-0.008
Age 65+	-0.0004	-0.0227**	-0.0028
	-0.006	-0.009	-0.008
Year dummy	0.0089***		0.0109***
	(0.003)		(0.004)
City dummy			-0.0094***
			(0.001)
N	143040	33506	176546

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

Table F.6: Estimates from logit controlling also for day of the week with clustering standard errors by year: Marginal effects over the entire campaigns

Campaign	Somerville	Cambridge	Somerville+Cambridge
Community frame (CF)	-0.0003***	-0.0002	-0.0003***
	(0.000)	(0.002)	(0.000)
Green reports (R)	0.0006***	0.0022	0.0009***
	(0.000)	(0.002)	(0.000)
Monday	0.0006	0.0095***	0.0025*
	(0.001)	(0.004)	(0.0014)
Tuesday	0.0013***	0.0114***	0.0036***
	(0.000)	(0.004)	(0.000)
Wednesday	0.0003	0.0030	0.0009
	(0.001)	(0.004)	(0.001)
Thursday	-0.0013	0.0026	-0.0004
	(0.0013)	(0.004)	(0.0014)
Friday	-0.0005	0.0002	-0.0004
	(0.001)	(0.004)	(0.001)
Saturday	-0.0012***	0.0028	-0.0004
	(0.000)	(0.004)	(0.0008)
Controls			
Gender & age	YES	YES	YES
Year FE	YES		YES
City FE			YES
N	143040	33506	176546

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

Table F.7: Estimates from logit controlling also for a weekly time trend with clustering standard errors by year: Marginal effects over the entire campaigns

Campaign	Somerville	Cambridge	Somerville+Cambridge
Community frame (CF)	-0.0005**	0.0008	-0.0001
	(0.0003)	(0.002)	(0.000)
Green reports (R)	0.0004***	0.0009	0.0004**
	(0.0002)	(0.002)	(0.000)
Weekly time trend	-0.0008***	-0.0019***	-0.0010***
	(0.0001)	(0.000)	(0.000)
Male	-0.0021**	-0.0093***	-0.0034***
	(0.001)	(0.002)	(0.001)
Gender unknown	-0.0007	-0.0083	-0.0031***
	(0.001)	(0.009)	(0.001)
Age 25-34	-0.0004***	-0.0013	-0.0005***
	(0.0001)	(0.002)	(0.000)
Age 35-44	-0.0017	-0.0223***	-0.0047**
	(0.0012)	(0.006)	(0.002)
Age 45-54	0.0005	-0.0499***	-0.0027
	(0.0034)	(0.018)	(0.0069)
Age 55-64	0.0006	-0.0403**	-0.0020
	(0.004)	(0.017)	(0.008)
Age 65+	0.0011	-0.0183**	-0.0010
	(0.004)	(0.009)	(0.008)
Year dummy	0.0187***		0.0232***
	(0.000)		(0.005)
City dummy			-0.0092***
			(0.001)
N	143040	33506	176546

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

Table F.8: Estimates from logit controlling also for a daily time trend with clustering standard errors by year: Marginal effects over the entire campaigns

Campaign	Somerville	Cambridge	Somerville+Cambridge
Community frame (CF)	-0.0005**	0.0009	-0.0001
	(0.000)	(0.002)	(0.000)
Green reports (R)	0.0004***	0.0008	0.0004**
	(0.000)	(0.002)	(0.000)
Daily time trend	-0.0001***	-0.0003***	-0.0001***
	(0.000)	(0.000)	(0.000)
Male	-0.0021**	-0.0091***	-0.0034***
	(0.001)	(0.002)	(0.001)
Gender unknown	-0.0006	-0.008	-0.0030***
	(0.001)	(0.009)	(0.001)
Age 25-34	-0.00040***	-0.0012	-0.0005***
	(0.000)	(0.002)	(0.000)
Age 35-44	-0.0017	-0.0220***	-0.0047**
	(0.001)	(0.006)	(0.002)
Age 45-54	0.0005	-0.0495***	-0.0027
	(0.003)	(0.018)	(0.007)
Age 55-64	0.0006	-0.040**	-0.0019
	(0.004)	(0.018)	(0.008)
Age 65+	0.00113	-0.0180**	-0.0009
	(0.004)	(0.009)	(0.00766)
Year dummy	0.0188***		0.0236***
	(0.000)		(0.005)
City dummy			-0.009***
			(0.001)
N	143040	33506	176546

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

Table F.9: Estimates from logit displaying all control variables: 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. Reported estimates are average marginal effects. "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. *** p<0.01, ** p<0.05, * p<0.1.

Table F.10: 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. Reported estimates are average marginal effects. 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. *** p<0.01, ** p<0.05, * p<0.1.

Table F.11: 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. “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. *** p<0.01, ** p<0.05, * p<0.1.

Table F.12: 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. "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. *** p<0.01, ** p<0.05, * p<0.1.

Table F.13: 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. "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. *** p<0.01, ** p<0.05, * p<0.1.

G Scientific notation

In this section, we provide our main estimates from Table 3 in scientific notation, for the reader who may be interested in assessing the effect of our treatments at a very fine level. We do so in Table G.1.

Table G.1: Estimates from logit in scientific notation: average treatment effects on the treated over the entire campaigns

Campaign	Somerville	Cambridge	Somerville+Cambridge
Community frame (CF)	-3.2122e-04***	-6.7490e-04	-3.4658e-04***
	(0.492e-04)	(20.463e-04)	(0.642e-04)
Green reports (R)	4.4102e-04***	13.5992e-04	6.0133e-04***
	(1.303e-04)	(20.551e-04)	(1.442e-04)
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. Reported estimates are average marginal effects. In scientific notation, e-04 stands for 10 to the power of 4, consistently with the estimates provided in Table 3.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

H 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 H.1) and about the cost per click for every campaign and phase (Table H.2).

Table H.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	(1)+(2)	(1)	(2)	(1)+(2)	(1)	(2)	Pooled	(1)+(2)	(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 H.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.