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Nudging when the descriptive norm is low: Evidence from a carbon offsetting field experiment[*]

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Abstract

Nudges and behavioral interventions have become a popular tool to stimulate pro-social behavior. Little is known, however, on how to design effective social interventions in contexts in which the descriptive norm is low, i.e. when a desirable behavior is only practiced by a minority within the respective reference group. Bringing climate-friendly behaviors from non-normative to normative is, however, crucial to tackle the climate crisis. We take up this challenge, devise a new strategy for social interventions, and test it with an especially sophisticated target group. In particular, we implemented a field experiment at two subsequent conferences in environmental economics, with which we examine the conference participants' proclivity to offset their carbon emissions as part of the standard registration process. We introduced two randomized treatment conditions, one relying on social norms and one on social identity, to be compared with a neutral control group. The social norm treatment leverages past contributions to voluntary carbon emissions at those conferences. The social identity treatment primes participants' social identity as environmental economists. We provide two main insights. First, if properly adjusted to the context, interventions leveraging social norms can be effective in changing behavior also when the descriptive norm is low and when the target group is composed of experts, if targeted individuals feel socially close to the referenced peer group. Second, the effectiveness of such interventions increases as individuals are exposed to multiple "doses" of treatment, although with decreasing marginal returns. Hence, our paper provides novel insights to policymakers and practitioners on the use of social interventions when the descriptive norm is low as well as on the ability of nudges to affect experts.

Keywords Carbon offsets; Social norms; Social identity; Nudge; Field experiment
JEL codes A11; C93; D12; D91; H23; H41; Q54

1 Introduction

Behavioral economics is nowadays mainstream economics and the use of nudges has become widespread (Thaler and Sunstein, 2008). The Nobel prize in economics to Richard Thaler is only one manifestation of the importance of social interventions in guiding current operations by policymakers and practitioners alike in sustaining pro-social behavior. Following Cialdini (2003), many studies combine descriptive norms, i.e. how many people are undertaking a given behavior in a given local context, and injunctive norms, i.e. what people generally consider the “right thing to do” in a given local context, to drive pro-social behavior. The power of descriptive norms leads less pro-social individuals to adjust their behavior, while injunctive norms remind the more pro-social individuals that they should not change theirs, preventing in this way a possible boomerang effect and leading to a convergence towards more pro-sociality (Schultz et al., 2007).

However, the literature is largely silent on how to use social interventions when the descriptive norm is low, i.e. when a desirable behavior is only practiced by a minority within the respective reference group. It is known, however, that the standard use of descriptive norms may backfire, for instance if it suggests alarmingly high rates of an undesirable behavior, which signal that many people are undertaking it, so that the undesirable behavior may be perceived as socially accepted (Cialdini, 2003). Yet, bringing behaviors from non-normative to normative, or from uncommon to common, may be precisely where social interventions can be very effective. Tackling climate change, one of the most important challenges of this century, requires for instance a transition towards greener technologies and behaviors, some of which currently experience very low levels of uptake, such as carbon offsetting or the use of renewable energy tariffs. Leading people to start undertaking these new behaviors may have particularly important implications in terms of emissions savings, while most social interventions promoting more effort in energy conservation have only led to energy savings in the order of 5% or less (Buckley, 2020). Hence, fully exploiting the power of local social norms to address global social dilemmas such as climate change can be considered crucial in the current context (Carattini et al., 2019), especially as top-down approaches such as carbon pricing are only gradually implemented.

In this paper, we take up the challenge and devise a new way to implement a social intervention in a context in which the descriptive norm is low. To set the bar sufficiently high, we implement our social intervention with experts, as sophisticated agents are notoriously known to be less influenced by nudges (List, 2003; Harrison and List, 2004). Hence, we implement a field experiment and, with the support of the conference organizers, introduce two treatment conditions to the registration process of the main European scientific conference in environmental and resource economics, the annual conference of the European Association of Environmental and Resource Economics (EAERE), which is attended every year by about 700 participants. At EAERE conferences, at the end of the online registration process, participants are invited, every year and regardless of our intervention, to voluntarily offset the greenhouse gas emissions generated during their traveling to the conference venue. EAERE has offered for many years this option to its participants, most likely making it the first association to offer carbon offsetting directly as part of the registration process. In 2015, one year before our intervention was first implemented, about 20% of conference participants purchased a carbon offset to compensate for their emissions when traveling to Helsinki, Finland, the conference venue (Carattini and Tavoni, 2016). The fact that environmental and resource economists are experts in the study of externalities and are highly aware of the detrimental effects of carbon emissions, as well as the concept of carbon offsetting, offers a particularly interesting context for these interventions, given that the same group has been shown in the past to be unresponsive to carbon offsetting defaults (Löfgren et al., 2012).

From a theoretical perspective, carbon offsetting represents the ideal example of private provision of a global public good. Even leaving aside possible ethical and practical reservations to the use of carbon offsetting (Carattini and Tavoni, 2016), from a narrowly rational perspective individuals have no incentive to engage in costly climate change mitigation. To explain such behavior, one needs to account for behavioral features such as possible guilt (Kotchen, 2009) or the warm glow of contributing to a public good (Andreoni, 1990). Consistently with other climate-friendly behaviors in which the local social norm has been shown to drive cooperation in the climate commons (Carattini et al., 2019), a corresponding social norm within an individual's peer group has been found to stimulate the uptake of voluntary carbon offsets (Blasch and Ohndorf, 2015).

Our experiment proceeded as follows. With it, we were interested in adapting the standard descriptive norm approach to non-normative behaviors. Further, we explored an alternative approach to social norms, which relied on social identity. Previous research has shown that priming social identities, which can be defined as identities emanating from group membership (Tajfel and Turner, 2004; Goldstein et al., 2008), can also lead to behavioral changes (Akerlof and Kranton, 2000; LeBoeuf et al., 2010; Bartels and Onwezen, 2014). Finally, we aimed to test whether the effectiveness of a social intervention may intensify when individuals are repeatedly exposed to a given treatment.

Hence, we designed one treatment around social norms, leveraging the efforts done by past conference attendees to offset their greenhouse gas emissions, and one treatment around social identity, priming participants' social identity as environmental and resource economists, and implemented both of them in two subsequent conferences, in 2016, when the conference venue was Zurich, Switzerland, and in 2017, when the conference venue was Athens, Greece. Since a substantial proportion of participants attended both conferences (around 40%), we have a suitable degree of variation to observe the effect of multiple "doses" of treatment for either treatment. In both conferences, participants are randomly assigned to one treatment, the other treatment, or a neutrally-framed control group.

For the social norm (SN) treatment, the registration website reminded people of the pioneering role of EAERE in offering carbon offsetting options at its conference, and the important contributions to reduce the association's carbon footprint that resulted from attendees' past participation in the program. Hence, the SN treatment sought to crowd in the motivation of environmental and resource economists to voluntarily offset the CO_2 emissions of their flight to the conference by using, implicitly, a combination of descriptive and injunctive norms. However, given the relatively low descriptive norm (20% in the previous year), no explicit figure was used to communicate the norm. Rather, the treatment emphasized the importance of carbon offsets in contributing to EAERE's commitment to sustainability and the successful offsetting that took place in previous years. The following text was used: "For many years EAERE has given to participants the possibility to offset the carbon emissions related with their traveling to the conference venue and thereby successfully contributed to decrease the conference's carbon footprint."

The social identity (SI) treatment focused on priming participants' social identity as environmental and resource economists. This second treatment sought to crowd in the motivation of environmental and resource economists to voluntarily offset the CO_2 emissions of their flights to the conference by priming their identity as a member of a "green" group. Participants were primed with questions about the benefits that they may enjoy as members of EAERE. In particular, they were asked about the following services that the association offers to its members, and how frequently they made use of them: access to the association's flagship journal (*Environmental and Resource Economics*, ERE), preferential access to other journals and books, participation at workshops and conferences, use of the job market platform for candidates and recruiters. Concerning the annual conference, participants were not only asked to report the frequency of attendance, but also to rank its importance compared to other conferences in the discipline.

We find that our intervention, and in particular the SN treatment, can effectively increase carbon offsetting rates among experienced subjects, in particular if they relate to the peer group that is referenced in the treatment, i.e. past conference attendees contributing to the same global public good. In our context, we distinguish between members of the association, and non-members, with members driving the effect of the SN treatment. This treatment effect is amplified when a second dose of treatment is administered in a consecutive year, albeit with diminishing marginal returns. The effects that we find for the intervention correspond to an up to 200% increase in the provision of the global public good. The costs of implementing the treatment are minimal, given that the treatment is administered through a a pre-existing online platform. Hence, we provide a novel, feasible approach to contribute to bring non-normative behaviors to normative, by adjusting social norms to the context and target group. Our field experiment thus paves the way to additional fieldwork by researchers and practitioners, expanding our findings to other groups of buyers, other contexts in which carbon offsets are sold, for instance at the time of purchasing a flight or renting a car, or to other non-normative climate-friendly behaviors, such as the use of renewable energy tariffs, batteries storing electricity, or the purchase of electric cars.

This paper makes three important contributions to the literature. First, while many studies demonstrated the power of social norms, evidence lacks on whether interventions can stimulate pro-social behaviors when baseline pro-sociality is low, without resorting to deception (as in Lindman et al., 2013, for instance). Leveraging norms while baseline-free, our novel intervention stimulates behavioral change, especially in individuals relating strongly to the referenced peer group. Hence, we join a recent strand of literature tackling non-normative behaviors (e.g. Jacobsen et al., 2013; Andreoni et al., 2020), to which we provide evidence from a field experiment. Second, we demonstrate that our intervention is effective with experienced subjects, on whose susceptibility to social interventions the literature has cast doubts. Hence, we contribute to literature analyzing the behavior of experts in various realms (e.g. List, 2003; Harrison and List, 2004), to literature analyzing the behavior and preferences of economists (Löfgren et al., 2012; Fourcade et al., 2015; Carattini and Tavoni, 2016; DellaVigna and Pope, 2018), as well as to a strand of research examining the determinants of the private contributions to pure and impure public goods, including global public goods such as climate change mitigation (Kotchen, 2006; Kotchen and Moore, 2007; Kotchen, 2009; Jacobsen et al., 2013). Third, few studies have considered the effect of repeated exposure (e.g. Allcott and Rogers 2014). We find that effectiveness increases with exposure, with diminishing returns. Hence, we show that, if well designed, social interventions can be effective even if the descriptive norm is low and individuals are sophisticated, especially so if exposed repeatedly. In this way, we contribute to a large and growing literature on social interventions spurring pro-social and pro-environmental behaviors, which has mostly focused on normative behaviors (see the review by Buckley, 2020), and largely neglected non-normative ones.

The remainder of this paper is organized as follows. Section 2 introduces the experimental design. Section 3 describes the data and empirical approach. Section 4 provides the empirical results. Section 5 concludes.

2 Experimental design

2.1 The European Association of Environmental and Resource Economics

The European Association of Environmental and Resource Economists (EAERE) is an international association representing European environmental and resource economists and its mission is "to contribute to the development and application of environmental, climate and resource economics as a science in Europe".

Each summer, EAERE organizes an annual conference, bringing together, according to the association, about 700 scholars. Every four years, the annual conference is organized jointly with its American counterpart, the Association of Environmental and Resource Economists (AERE), under the name of "World Congress of Environmental and Resource Economists" (WCERE). EAERE was a forerunner in offering conference participants the option to offset the CO_2 emissions generated by attending the annual conference by air travel.

2.2 Experimental setting

We conducted our field experiment in June 2016, when the EAERE annual conference took place in Zurich, Switzerland, and in June 2017, when the EAERE annual conference took place in Athens, Greece. The experiment was implemented as part of the online registration process for the conference participants. Every year, participants are asked whether to purchase carbon offsets with their conference registration to compensate for the CO_2 emissions created by their air traveling to the conference. The purchase is completely voluntary and is part of EAERE's menu approach, which also includes specific fees for the conference dinner and other side activities.

We introduced two treatments in the online registration form of the conference. The first treatment intended to leverage descriptive and injunctive norms for conference carbon offsetting, while not providing any baseline numbers for the descriptive norm (SN treatment). The second treatment intended to prime environmental and resource economists' social identity (SI treatment). A control group saw the regular registration form as it had been used in the years prior to the implementation of our intervention. Allocation to the two treatments, or to the neutrally-framed control group, was done randomly by an algorithm introduced by the conference organizers. The propensity to offset in the two treatment groups can thus be compared with the outcome from the neutrally-framed control group for causal inference on the effect of the treatments. The exact wording of each treatment is provided in what follows.

2.3 Treatment implementation

The text shown to respondents in the control group before the offset decision took place was as follows:

"You are offered the option of purchasing CO_2 offset compensation fee of 10 EUR for flights within Europe and 40 EUR for flights coming from outside of Europe. Information on how the money collected from the CO_2 offsets will be used will be available soon."

The text shown to respondents in the social norm treatment before the offset decision took place was as follows:

"For many years EAERE has given to participants the possibility to offset the carbon emissions related with their traveling to the conference venue and thereby successfully contributed to decrease the conference's carbon footprint. You are thus

offered the option of purchasing CO_2 offset compensation fee of 10 EUR for flights within Europe and 40 EUR for flights coming from outside of Europe.
Information on how the money collected from the CO_2 offsets will be used will be available soon."

The text and questions shown to respondents in the social identity treatment before the offset decision took place were as follows:

- "(How frequently) Do you use the following services for EAERE members?
  - job market (either as employer or candidate)
  - workshops and summer schools
  - free access to electronic version of ERE journal
  - discount on paper version of ERE journal
  - discount on subscription to other related journals
  - 33.3% discount on books published by Springer
- How many EAERE/WCERE conferences have you attended in the last 5 years?
- How important do you consider the yearly EAERE/WCERE conference compared to other economics conferences you regularly attend (important in terms of interacting with 'your community')?
  - Very important
  - Fairly important
  - Less important
  - Not at all important

You are offered the option of purchasing CO_2 offset compensation fee of 10 EUR for flights within Europe and 40 EUR for flights coming from outside of Europe. Information on how the money collected from the CO_2 offsets will be used will be available soon."

2.4 Intent to treat versus treatment effect

For the Social Identity (SI) intervention, our data revealed that not all participants subject to this condition complied with the treatment. Within the target group of those who took a flight to the conference and had not offset travel emissions on their own, only about half of the participants in this treatment group (56% in 2016 and 49% in 2017) replied to the two questions asking them about previous attendance or about the importance of the association. Hence, these figures suggest a relatively high level of "non-compliance" with the treatment, where, as in the standard jargon, "compliers" are those who replied to those two questions and "non-compliers" those who did not.

This is a common case of exogenous treatment and endogenous compliance. In this case, considering as treated only those who answered the abovementioned questions (OLS based on treatment received) would provide an estimate that is biased by selection. Using treatment assigned (intent to treat) would provide diluted estimates, potentially underestimating the effectiveness of the treatment, as it would not account for the fact that not everybody in the SI treatment group was actually subject to the treatment. Correcting intent to treat (or ITT) by the share of compliers provides the causal effect of interest (Imbens and Angrist, 1994). This is equivalent to using treatment assignment as instrumental variable (IV) for treatment received. The instrumented coefficient measures the Local Average Treatment Effect (LATE).

Eventually, when comparing the ITT and IV regressions (see Table 2 and the discussion in section 4), we see only minor differences between the two. The same would be true if we were to use alternative definitions of "compliance", including using the entire list of questions.

3 Empirical approach

3.1 Data and descriptive statistics

A total of 680 participants registered for the annual 2016 EAERE conference in Zurich, and 792 participants registered for the 2017 conference in Athens. Table A.1 provides the summary statistics for the main variables used in this paper, for the two years in our sample. Most of the participants were academics (affiliated to either a university or research institute as compared to representatives from industry, public administration, or other organizations). Most participants were based in European institutions (73% in 2016 and 76% in 2017, respectively). Participants from all academic levels were attending the conference. In 2016 (2017), 22% (25%) of them held the title of professor and 47% (44%) had a doctoral degree. The remaining participants did not hold an academic title. 74% (70%) of the participants registered before the cutoff date for the early-bird rate. 35% (27%) were already EAERE members when they registered. Almost two thirds (64%) of the participants took a flight to travel to the conference in 2016, while almost all participants (92%) took a flight to travel to the conference in 2017. This can be explained by the geographical location of the two conference venues (Zurich in 2016 and Athens in 2017). On average among all participants, regardless of treatment assignment and traveling mode, 11% (20%) decided to offset their flight emissions through EAERE as part of the registration process. Participants were given two options: 10 euros worth of carbon credits, more or less equivalent to a flight within Europe as indicated by EAERE, or a 40 euros worth of carbon credits, more or less equivalent to an international flight to Europe as indicated by EAERE. 10% (19%) of the sample opted for the 10-euro offset, 1 % for the 40-euro offset. These figures reflect in part the choice of the venue as well as the ratio between European and international participants. 13% (20%) of the sample reported to have offset their emissions through a third-party service. Participants that did not fly or declared that they had already offset their travel emissions elsewhere were excluded from our analyses and considered outside the target group. Hence, Table A.1 provides descriptive statistics for both the full sample and the"target group. Note that the control characteristics of several participants in our panel changed between 2016 and 2017: 14 participants changed academic status, 7 obtained the title of professor, 24 earned a doctoral degree, 79 switched either on or off their EAERE membership, 6 moved their primary affiliation to a non-European institution, and 63 switched from early bird registration to late registration, or vice versa.

Following our randomization process, 31% (34%) of the participants were assigned to the SN treatment and 39% (33%) to the SI treatment. Tables 1, A.2, and A.3 show the balance of covariates between the SN and SI treatment groups and the control group for the full sample over both years (Table 1) and for the target group in each of the two years (Tables A.2 and A.3). No striking differences are identified between the control group and treatment groups as assigned. For the pooled sample, slight differences, statistically significant at the 10% level, can be found between the SN treatment and the control group for the share of EAERE members, a variable on which we run separate regressions. In 2017, some differences arise in the academic variables between the SN treatment and the control group. In a conservative vein, we control in all of our specifications for our entire set of covariates.

When splitting the data into separate datasets for the two years while distinguishing between compliers and non-compliers (Tables A.2 and A.3), several imbalances arise, suggesting that compliers and non-compliers differ. Compliers and non-compliers within the SI group show significant differences to the control and SN groups in terms of the shares of academics, participants with a doctoral degree, EAERE membership as well as in the fraction of participants registering early. In our empirical analyses, we account for non-compliance as described above, even though, as already mentioned, our empirical results are not sensitive to any specification change.

3.2 Empirical specifications

As a baseline specification, we use a linear probability model to estimate the influence of the two treatments on the probability that participants offset their conference carbon emissions. For all panel data specifications, the Hausman test consistently fails to reject the null hypothesis that the preferred model is a random effects specification ($p = 0.66$ and higher). Hence, we present the random effects specification for all panel models in the paper. Fixed effects models are presented as robustness tests. The Breusch Pagan Lagrange Multiplier test provides further evidence that the intent to treat random effects specification is more appropriate than a pooled OLS specification ($p<0.01$). Our specifications also account for treatment intensity and imperfect compliance with the SI treatment, as reported above. They also include control variables as described above. Tables including the full list of coefficients are provided in the Appendix.

Table 1: Balance of covariates for years 2016 and 2017 (all participants)

Variable	**Control**			**Treatment**					
				SN			**SI**		
	Mean	SD	N	Mean	SD	N	Mean	SD	N
Socioeconomic characteristics									
Based outside Europe	0.25	0.43	463	0.28	0.45	478	0.25	0.43	531
Academic	0.92	0.28	463	0.90	0.31	478	0.90	0.28	531
Prof.	0.22	0.41	463	0.26	0.44	478	0.25	0.43	531
Dr.	0.47	0.50	463	0.45	0.50	478	0.45	0.50	531
Conference variables									
Early bird	0.70	0.46	463	0.73	0.45	478	0.72	0.45	531
EAERE member	0.27	0.47	463	0.33*	0.47	478	0.32	0.47	531
Flying to the conference	0.77	0.42	463	0.79	0.41	478	0.80	0.40	531
Self-reported offset	0.15	0.36	463	0.17	0.38	478	0.18	0.38	531

Note: *, **, and *** indicate statistically significant differences from the control group, respectively.

4 Empirical results

4.1 Average and heterogeneous treatment effects

We start presenting empirical results based on data from both years, since our intervention was implemented exactly in the same way in 2016 and 2017. This allows us to analyze a panel dataset. We decompose our data later in the section, to examine the effect of repeated exposure to the intervention. Our analysis excludes participants who had not taken a flight to the respective conferences and a minority of respondents who declared to be offsetting on their own. Our baseline results from the panel data are presented in the top panel of Table 2, which uses all observations over the two years (unbalanced panel) and a linear probability model. Based on the top panel, it seems that, on average, neither of our interventions was successful in increasing the proclivity of environmental economists to engage in carbon offsetting. This finding is consistent between columns (1) and (2), where we use two different specifications to account for the fact that not all individuals offered the social identity treatment actually took the time to respond to the priming questions. As per standard procedure with "voluntary compliance" to a treatment (Imbens and Angrist, 1994), we provide estimates for both the case in which we use treatment assignment as variable of interest (intent to treat, ITT) and the case in which we use treatment assignment as instrumental variable to instrument treatment received (whether the participant responded to our questions, IV), which allows uncovering the causal effect of the treatment. The two estimates are very similar and confirm that there is no statistically significant average treatment effect for either treatment. Unless otherwise specified, in all the estimations that follow, we only provide the IV (causal) estimate.

Average treatment effects, however, often do not allow uncovering the differences in individual behavior. Heterogeneity needs to be analyzed to better understand the

Table 2: Experimental data for 2016 and 2017: average and heterogeneous treatment effects

Average treatment effects		
	ITT	IV
Social norm	0.019 (0.033)	0.019 (0.033)
Social identity	-0.029 (0.032)	-0.054 (0.059)
Constant	0.162*** (0.056)	0.156*** (0.055)
Control variables	Yes	Yes
N	912	912
Overall-R^2	0.078	0.072
Treatment effects by subgroup		
	Members	Non-members
Social norm	0.115* (0.069)	-0.024 (0.035)
Social identity	-0.012 (0.105)	-0.077 (0.067)
Constant	0.222* (0.134)	0.154*** (0.059)
Control variables	Yes	Yes
N	282	630
Overall-R^2	0.117	0.045

Note: heteroskedasticity-consistent standard errors in parentheses.

Significance levels are indicated as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Social identity is instrumented in all IV models.

Table A.4 displays coefficients for control variables.

effects of an experiment and the mechanisms underlying behavioral change (Deaton, 2010). Hence, in the bottom panel of Table 2 we show heterogeneous treatment effects along a particularly relevant dimension in this context: social proximity to the referenced peer group, which we proxy by membership in the association organizing the conference (EAERE). Indeed, we can expect the treatments to affect members and non-members in different ways. The SN treatment, for instance, leverages the cooperativeness of past conference attendees to incite current attendees to offset their emissions as well. Thus, it makes sense to assume that how the latter respond may depend on their social proximity to the association and to past cohorts of conference attendees, and we can expect such social proximity to be stronger for members. Hence, we would expect a stronger reaction to the treatment among members. Similarly, the SI treatment aims at increasing the feeling of identity in the environmental and resource economics community. Thus, it makes sense to assume that how participants respond depends on their previous level of identity, which we can expect to be stronger for members. However, unlike the SN treatment, our prediction for the SI treatment is ambiguous. Members with already a strong identity may not be affected by the treatment, but at the same time non-members with very little attachment to the association may also be unaffected. Which effect may dominate is ultimately an empirical question.

The bottom panel of Table 2 shows large treatment effects for members who have been exposed to the SN treatment during the conference registration process. Table 2 also shows that adoption among members is higher than among non-members also in the baseline case, i.e. the control group. This makes sense, as we would expect members to care more about the external effects of their traveling to the conference venue and be more supportive of the solutions offered by the association to internalize them. It makes, however, the reaction to our SN treatment even more interesting.

Members are more affected by the treatment despite the higher level from which they start.

To estimate the magnitude and statistical siginificance of such effects, we turn again to Table 2. The coefficient in Table 2 measures the treatment effect among members at 11.5 percentage points. In percent, this is an increase of about 30% compared to baseline levels. Hence, heterogeneous treatment effects confirm our priors on the effect of social norms on members and non-members. As Table 2 shows, no heterogeneous treatment effects can be detected for the SI treatment. This result tends to imply that participants of either group are not significantly affected by the SI treatment, on average. That is, it seems that the SI treatment was much weaker than the SN treatment, and, if anything, our battery of questions led to a very small and statistically insignificant negative effect on carbon offsetting.

Heterogeneous treatment effects for the SN treatment are even more significant in Table 3, in which we use an interaction term capturing whether participants are members or non-members and infer on the magnitude of the heterogeneous treatment effect from the entire sample of observations. The heterogeneous treatment effect is statistically significant at 5% in Table 3.

Next, we restrict the panel to only those individuals who attended both conferences (balanced panel). About 37% of the participants in the 2016 conference also participated to the 2017 conference, although not all of them took a flight to reach both venues. The relevant estimates for the entire sample (ITT and IV) and for the subsamples of members and non-members are provided in Table 4. The results from Table 4 are entirely consistent with the findings from Tables 2 and 3.

Table 3: Experimental data for 2016 and 2017: heterogeneous treatment effects with interaction

Average treatment effects	IV
Social norm	-0.019 (0.037)
Social norm-member interaction	0.120** (0.060)
Social identity	-0.047 (0.059)
Constant	0.166*** (0.055)
Control variables	Yes
N	912
Overall-R^2	0.077

Note: heteroskedasticity-consistent standard errors in parentheses.

Significance levels are indicated as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The interaction term is estimated only for the SN treatment,

as it is the only treatment that changed participants' behavior in our context.

Social identity is instrumented in the IV model.

Table A.5 displays coefficients for control variables.

Table 4: Experimental data for 2016 and 2017: average and heterogeneous treatment effects (balanced panel)

Average treatment effects		
	ITT	IV
Social norm	0.031 (0.058)	0.032 (0.057)
Social identity	-0.061 (0.055)	-0.088 (0.080)
Constant	-0.074 (0.132)	-0.091 (0.129)
Control variables	Yes	Yes
N	214	214
Overall-R^2	0.162	0.157
Treatment effects by subgroup		
	Members	Non-members
Social norm	0.176* (0.103)	-0.057 (0.059)
Social identity	-0.048 (0.132)	-0.149 (0.092)
Constant	-0.095 (0.225)	0.047 (0.147)
Control variables	Yes	Yes
N	104	110
Overall-R^2	0.268	0.060

Note: heteroskedasticity-consistent standard errors in parentheses.

Significance levels are indicated as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Social identity is instrumented in the IV model.

Table A.6 displays coefficients for control variables.

4.2 Treatment intensity

The "strength" of a treatment may also depend on how many "doses" of treatment a participant is exposed to. To address this question, we take advantage of the panel format of our data. Recall that a substantial portion of the participants in the 2017 conference also participated to the 2016 conference. Given that in both years treatments were randomized independently from previous treatment assignment, in the balanced panel we have 23% of participants in the 2017 conference who were repeatedly exposed to a treatment, of which 32% were exposed twice to the SN treatment and 28% exposed twice to the SI treatment. Table 5 focuses only on the SN treatment, since it is the only treatment that changed participants' behavior in our context. The first column in Table 5 shows clearly that people exposed to the SN treatment in both 2016 and 2017 are more likely to offset in 2017 than their fellow participants who were exposed to the SN treatment only in either 2016 or 2017, and to control in the other year. For reasons of statistical power, we do not account in this analysis for the order of treatment exposure, i.e. if participants were exposed to control in 2016 and the SN treatment in 2017 or vice versa. Table 5 also does not show the coefficients involving the SI treatment. Our analysis shows that no significant effect can be detected for multiple doses of the SI treatment. That is, when the treatment is weak, even multiple doses do not affect behavior.

In this context, the baseline is represented by the conference participants who were assigned to the control group in both 2016 and 2017. About 1 over 5 conference participants decided to offset in 2017. Using the exact coefficients provided by the first column of Table 5, offsetting is 15 percentage points higher with one dose of the SN treatment. A second dose increases offsetting further, although with diminishing marginal returns, in line with previous evidence on the effectiveness of multiple treat-

Table 5: Experimental data for 2017: accounting for repeated treatment exposure

	Overall	Members	Non-members
Social norm-social norm	0.210* (0.117)	0.371** (0.165)	0.126 (0.156)
Control-social norm	0.150* (0.080)	0.265** (0.125)	0.095 (0.107)
Constant	0.116* (0.068)	0.171 (0.152)	0.113 (0.079)
All other treatment combinations	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
N	565	150	415
R^2	0.083	0.184	0.040

Note: heteroskedasticity-consistent standard errors in parentheses.

Significance levels are indicated as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.7 displays coefficients for control variables.

ments for the provision of effort contibuting to lower greenhouse gas emissions.(Allcott and Rogers, 2014) The coefficient of Table 5 suggests a 21 percentage point higher propensity to offset when conference participants are exposed to two doses of treatment. Hence, some of our participants need a double dose of the treatment to be eventually nudged towards the pro-social behavior.

When considering the results for EAERE members and non-members separately, it becomes apparent that, consistently with our previous results, mainly the members of the association react to the repetition of the treatment. Heterogeneity between members and non-members is analyzed in the second and third columns of Table 5. Consistently with our previous results, we observe that only members react in a statistically significant way to the treatment. For both members and non-members, we observe a larger propensity to offset for conference participants subject to two treatment doses. The effect of each dose is, however, much stronger among members.

One dose of SN treatment leads members to be 26.5 percentage points more likely to offset, two doses 37.1 percentage points more likely. In percent, behavioral change exceeds 200% with two doses of treatment.

4.3 Robustness tests

Finally, we provide in Table 6 a battery of robustness tests for our baseline results from Tables 2 and 4. The robustness table includes linear models with fixed effects as well as non-linear models such as probit, for which we provide average marginal effects. The top panel focuses on the entire sample, whereas the following two panels separate members and non-members. Our main results are robust to all these different specifications. Our analyses show that this is true for all the other findings provided in this section.

5 Conclusions

Tackling climate change requires a multiplicity of approaches, in particular until ambitious climate policies will be implemented by all countries. Social interventions have a particularly important role to play. While a large literature uses social interventions to curb greenhouse gas emissions, these usually rely on relatively high descriptive norms to trigger cooperation, thus neglecting behaviors with relatively low descriptive norms. Such omission may be rather consequential, as some of these behaviors may allow saving a substantial amount of greenhouse gas emissions. This paper aims at filling this gap. It focuses on carbon offsetting, a climate-friendly behavior that is still very far from being mainstream. We implement an original intervention that stimulates the private provision of carbon offsetting, a global public good. Our intervention leverages social norms and past contributions by some of the individuals in

Table 6: Robustness tests

	Average treatment effects									
	Baseline				Robustness					
	Linear models								Non-linear models	
	Unbalanced		Balanced		Unbalanced		Balanced		Unbalanced	Balanced
	ITT	IV	ITT	IV	ITT FE	IV FE	ITT FE	IV FE	ITT probit	ITT probit
Social norm	0.0190 (0.0330)	0.019 (0.033)	0.031 (0.058)	0.032 (0.057)	0.002 (0.067)	0.005 (0.065)	0.002 (0.067)	0.005 (0.065)	0.024 (0.038)	0.047 (0.093)
Social identity	-0.0292 (0.0316)	-0.054 (0.059)	-0.061 (0.055)	-0.088 (0.080)	-0.046 (0.060)	-0.068 (0.088)	-0.046 (0.060)	-0.068 (0.088)	-0.028 (0.038)	-0.097 (0.091)
Constant	0.162*** (0.056)	0.156*** (0.055)	-0.074 (0.132)	-0.091 (0.129)	-0.004 (0.198)	-0.016 (0.195)	-0.008 (0.212)	-0.015 (0.210)		
Control variables	Yes									
N	912	912	214	214	912	912	214	214	912	199
Within R^2					0.074	0.078	0.074	0.078		
Overall R^2	0.078	0.072	0.162	0.157	0.960	0.960	0.838	0.838		
Pseudo R^2									0.075	0.090
	Treatment effects by subgroup: members									
Social norm	0.118* (0.067)	0.115* (0.069)	0.180* (0.099)	0.177* (0.102)	0.231* (0.135)	0.240* (0.145)	0.231* (0.135)	0.240* (0.145)	0.201* (0.113)	0.280** (0.126)
Social identity	-0.002 (0.063)	-0.012 (0.105)	-0.020 (0.090)	-0.044 (0.131)	0.113 (0.116)	0.178 (0.189)	0.113 (0.116)	0.178 (0.189)	0.012 (0.105)	-0.017 (0.140)
Constant	0.220 (0.136)	0.222* (0.134)	-0.087 (0.229)	-0.094 (0.225)	0.290 (0.443)	0.268 (0.464)	0.337 (0.477)	0.299 (0.503)		
Control variables	Yes									
N	282	282	104	104	282	282	104	104	282	100
Within R^2					0.112	0.044	0.112	0.044		
Overall R^2	0.116	0.117	0.263	0.267	0.957	0.954	0.888	0.880		
Pseudo R^2									0.091	0.206
	Treatment effects by subgroup: non-members									
Social norm	-0.024 (0.034)	-0.024 (0.035)	-0.053 (0.053)	-0.057 (0.059)	-0.058 (0.058)	-0.062 (0.064)	-0.058 (0.058)	-0.062 (0.064)	-0.001 (0.001)	-0.072 (0.494)
Social identity	-0.041 (0.033)	-0.077 (0.067)	-0.088* (0.050)	-0.149 (0.092)	-0.078 (0.053)	-0.134 (0.100)	-0.078 (0.053)	-0.134 (0.100)	-0.001 (0.001)	-0.077 (0.362)
Constant	0.163*** (0.060)	0.154*** (0.059)	0.084 (0.142)	0.049 (0.146)	0.307* (0.176)	0.295 (0.190)	0.280 (0.183)	0.270 (0.198)		
Control variables	Yes									
N	630	630	110	110	630	630	110	110	630	99
Within R^2					0.356	0.237	0.356	0.237		
Overall R^2	0.057	0.045	0.074	0.059	0.994	0.993	0.963	0.960	0.043	0.102

Heteroskedasticity-consistent standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Social identity is instrumented in all IV models. Probit models show average marginal effects. As standard in probit models, some observations are not used when variables perfectly predict the outcome. By construction, the fixed effects model provide the same coefficients with both balanced and unbalanced panels. Tables A.8, A.9, and A.10 display coefficients for control variables.

the target group, while remaining baseline-free.

We implement this intervention with a large group of experts over two annual conferences. The goal of involving experts is threefold. First, to set the bar high, since experienced subjects tend to be less susceptible to change behavior with social interventions. Second, to exploit the fact that this specific group of experts allows us to test whether the effectiveness of our intervention relates to how close individuals are to the peer group of reference. Third, implementing our intervention over two yearly conferences with partly overlapping attendees allows us to test the effect of repeated exposure to our treatments.

We find that our intervention can be effective among those experts who relate to the peer group of reference, which in the setting of this field experiment is represented by members of the association who relate to past conference attendees that contributed to the global public good of climate change mitigation through carbon offsetting. In this context, a second dose of treatment substantially increases the effectiveness of our intervention, albeit with diminishing marginal returns.

While the intervention based on priming social identity appeared ineffective, we observe an increase of up to 200% in the provision of the global public good for the social norms intervention. The intervention that we devised therefore offers a novel, promising, and relatively low-cost approach contributing to bring non-normative behaviors to normative, by adjusting social norms to the context and target group. Hence, our findings open new opportunities to apply norm-based nudging for prosocial and pro-environmental behaviors that are currently not prevalent, without the need to resort to deception to avoid backfiring.

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Appendix

A Balance of covariates

Table A.1: Summary statistics for the 2016 and 2017 conferences

	2016						**2017**					
	Full sample			**Target group**			**Full sample**			**Target group**		
	Mean	Std. Dev.	N	Mean	Std. Dev.	N	Mean	Std. Dev.	N	Mean	Std. Dev.	N
Academic title												
Academic	0.87	0.33	680	0.86	0.35	347	0.93	0.25	792	0.93	0.25	565
Prof.	0.22	0.42	680	0.25	0.43	347	0.25	0.43	792	0.23	0.42	565
Dr.	0.47	0.50	680	0.48	0.50	347	0.44	0.50	792	0.46	0.50	565
Conference variables												
Early bird	0.74	0.44	680	0.75	0.43	347	0.70	0.46	792	0.73	0.44	565
EAERE member	0.35	0.48	680	0.38	0.49	347	0.27	0.44	792	0.27	0.44	565
Flying to the conference	0.64	0.48	680	1.00	0.00	347	0.92	0.27	792	1.00	0.00	565
Based outside Europe	0.27	0.45	680	0.37	0.48	347	0.24	0.43	792	0.25	0.44	565
European offset (EAERE)	0.10	0.30	680	0.20	0.40	347	0.19	0.39	792	0.26	0.44	565
World offset (EAERE)	0.01	0.11	680	0.02	0.15	347	0.01	0.11	792	0.02	0.13	565
Self-reported offset	0.13	0.34	680	0.00	0.00	347	0.20	0.40	792	0.00	0.00	565
Treatment groups												
Control group	0.30	0.46	680	0.28	0.45	347	0.33	0.47	792	0.33	0.47	565
SN treatment	0.31	0.46	680	0.32	0.47	347	0.34	0.47	792	0.33	0.47	565
SI treatment (total)	0.39	0.49	680	0.40	0.49	347	0.33	0.47	792	0.34	0.47	565
SI treatment (compliers)	0.20	0.40	680	0.22	0.42	347	0.15	0.35	792	0.17	0.37	565

Table A.2: Balance of covariates for year 2016 (target group only)

Variable	**Control**			**Treatment**								
				SN			**SI (compliers)**			**SI (non-compliers)**		
	Mean	SD	N	Mean	SD	N	Mean	SD	N	Mean	SD	N
Socioeconomic characteristics												
Based outside Europe	0.38	0.49	97	0.41	0.49	111	0.35	0.48	78	0.30	0.46	61
Academic	0.87	0.34	97	0.80	0.40	111	$0.94^{\circ\circ\circ}$	0.25	78	0.85	0.36	61
Prof.	0.26	0.44	97	0.20	0.40	111	$0.36^{\circ\circ}$	0.48	78	0.20^{++}	0.40	61
Dr.	0.45	0.50	97	0.53	0.40	111	0.51	0.50	78	0.38°	0.49	61
Conference variables												
Early bird	0.71	0.46	97	0.78	0.42	111	0.86**	0.35	78	$0.64^{\circ,+++}$	0.48	61
EAERE member	0.30	0.46	97	0.39	0.49	111	0.47**	0.50	78	0.38	0.49	61

Note: *, **, and *** indicate statistically significant differences from the control group, respectively; $^{\circ}$, $^{\circ\circ}$, and $^{\circ\circ\circ}$ indicate statistically significant differences between the SN and the two SI treatment (sub)groups; $^{+}$, $^{++}$ and $^{+++}$ indicate statistically significant differences between the two SI treatment (sub)groups.

Table A.3: Balance of covariates for year 2017 (target group only)

Variable	**Control**			**Treatment**								
				SN			**SI (compliers)**			**SI (non-compliers)**		
	Mean	SD	N	Mean	SD	N	Mean	SD	N	Mean	SD	N
Socioeconomic characteristics												
Non European	0.25	0.44	189	0.24	0.43	185	0.28	0.45	94	0.25	0.43	97
Academic	0.94	0.24	189	0.96	0.20	185	0.89°	0.31	94	0.92	0.28	97
Prof.	0.18	0.38	189	0.28**	0.45	185	0.31**	0.46	94	$0.19^{\circ,++}$	0.39	97
Dr.	0.53	0.50	189	0.40***	0.49	185	$0.53^{\circ\circ}$	0.50	94	$0.38^{**,++}$	0.49	97
Conference variables												
Early bird	0.74	0.44	189	0.74	0.44	185	0.69	0.46	94	0.73	0.45	97
EAERE member	0.23	0.42	189	0.28	0.49	185	0.37**	0.49	94	0.22^{++}	0.41	97

Note: *, **, and *** indicate statistically significant differences from the control group, respectively; $^{\circ}$, $^{\circ\circ}$, and $^{\circ\circ\circ}$ indicate statistically significant differences between the SN and the two SI treatment (sub)groups; $^{+}$,$^{++}$ and $^{+++}$ indicate statistically significant differences between the two SI treatment (sub)groups.

B Main models including coefficients for the control variables

Table A.4: Experimental data for 2016 and 2017: average and heterogeneous treatment effects including coefficients for the control variables

Average treatment effects		
	ITT	IV
Social norm	0.019 (0.033)	0.019 (0.033)
Social identity	-0.029 (0.032)	-0.054 (0.059)
Academic	0.089* (0.048)	0.0884* (0.048)
Prof.	0.042 (0.042)	0.049 (0.043)
Dr.	0.012 (0.034)	0.018 (0.036)
EAERE member	0.081*** (0.030)	0.082*** (0.031)
Based outside Europe	-0.219*** (0.032)	-0.219*** (0.036)
Early bird	0.060* (0.031)	0.062** (0.031)
Constant	0.162*** (0.056)	0.156*** (0.055)
N	912	912
Overall-R^2	0.078	0.072
Treatment effects by subgroup		
	Members	Non-members
Social norm	0.115* (0.069)	-0.024 (0.035)
Social identity	-0.012 (0.105)	-0.077 (0.067)
Academic	0.095 (0.119)	0.108** (0.051)
Prof.	0.039 (0.085)	0.069 (0.052)
Dr.	0.080 (0.081)	-0.019 (0.038)
Based outside Europe	-0.307*** (0.062)	-0.186*** (0.038)
Early bird	0.026 (0.064)	0.0725** (0.034)
Constant	0.222* (0.134)	0.154*** (0.059)
N	282	630
Overall-R^2	0.117	0.0452

Note: heteroskedasticity-consistent standard errors in parentheses.

Significance levels are indicated as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Social identity is instrumented in all IV models.

Table A.5: Experimental data for 2016 and 2017: heterogeneous treatment effects with interaction including coefficients for the control variables

Average treatment effects	
	IV
Social norm	-0.019 (0.037)
Social norm-member interaction	0.120** (0.060)
Social identity	-0.047 (0.059)
Constant	0.166*** (0.055)
Academic	0.0882* (0.048)
Prof.	0.0471 (0.043)
Dr.	0.012 (0.035)
EAERE member	0.0401 (0.037)
Based outside Europe	-0.217*** (0.032)
Early bird	0.0659** (0.031)
Control variables	Yes
N	912
R^2	0.077

Note: heteroskedasticity-consistent standard errors in parentheses.

Significance levels are indicated as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.6: Experimental data for 2016 and 2017: average and heterogeneous treatment effects including coefficients for the control variables (balanced panel)

Average treatment effects		
	ITT	IV
Social norm	0.031 (0.058)	0.032 (0.057)
Social identity	-0.061 (0.055)	-0.088 (0.080)
Academic	0.287*** (0.111)	0.295*** (0.110)
Prof.	0.129 (0.094)	0.137 (0.096)
Dr.	0.164* (0.085)	0.170** (0.086)
EAERE member	0.117** (0.054)	0.116** (0.053)
Based outside Europe	-0.245*** (0.083)	-0.242*** (0.084)
Early bird	-0.026 (0.061)	-0.022 (0.061)
Constant	-0.074 (0.132)	-0.091 (0.129)
N	214	214
R^2	0.162	0.157
Treatment effects by subgroup		
	Members	Non-members
Social norm	0.176* (0.103)	-0.057 (0.059)
Social identity	-0.048 (0.132)	-0.149 (0.092)
Academic	0.272 (0.231)	0.276** (0.110)
Prof.	0.178 (0.148)	0.186 (0.119)
Dr.	0.331** (0.156)	-0.034 (0.100)
Based outside Europe	-0.351*** (0.111)	-0.113 (0.119)
Early bird	0.041 (0.108)	-0.040 (0.065)
Constant	-0.095 (0.225)	0.047 (0.147)
N	104	110
R^2	0.268	0.060

Note: heteroskedasticity-consistent standard errors in parentheses.

Significance levels are indicated as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Social identity is instrumented in all IV models.

Table A.7: Experimental data for 2017: accounting for repeated treatment exposure including coefficients for the control variables

	Overall	Members	Non-members
Social norm-social norm	0.210* (0.117)	0.371** (0.165)	0.126 (0.156)
Control-social norm	0.150* (0.080)	0.265** (0.125)	0.095 (0.107)
Academic	0.134** (0.056)	0.190 (0.170)	0.125** (0.059)
Prof.	0.039 (0.059)	-0.159 (0.130)	0.123* (0.073)
Dr.	-0.017 (0.044)	-0.113 (0.115)	-0.003 (0.048)
EAERE member	0.063 (0.046)		
Based outside Europe	-0.223*** (0.037)	-0.345*** (0.073)	-0.173*** (0.045)
Early bird	0.070* (0.039)	0.031 (0.101)	0.089** (0.045)
Constant	0.116* (0.068)	0.171 (0.152)	0.113 (0.079)
All other treatment combinations	Yes	Yes	Yes
N	565	150	415
R^2	0.083	0.184	0.040

Note: heteroskedasticity-consistent standard errors in parentheses.

Significance levels are indicated as * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.8: Robustness tests: average treatment effects including coefficients for the control variables

	Average treatment effects					
	Robustness					
	Linear models				Non-linear models	
	Unbalanced		Balanced		Unbalanced	Balanced
	ITT FE	IV FE	ITT FE	IV FE	ITT probit	ITT probit
Social norm	0.002 (0.067)	0.005 (0.065)	0.002 (0.067)	0.005 (0.065)	0.024 (0.038)	0.047 (0.093)
Social identity	-0.046 (0.060)	-0.068 (0.088)	-0.046 (0.060)	-0.068 (0.088)	-0.028 (0.038)	-0.097 (0.091)
Academic	0.262* (0.147)	0.264* (0.147)	0.262* (0.147)	0.264* (0.147)	0.120 (0.088)	
Prof.	0.000 (0.265)	0.000 (0.264)	-1.33e-18 (0.265)	-2.01e-18 (0.264)	0.049 (0.056)	0.343* (0.198)
Dr.	-0.128 (0.164)	-0.120 (0.163)	-0.128 (0.164)	-0.120 (0.163)	0.008 (0.039)	0.393** (0.193)
EAERE member	0.098 (0.067)	0.096 (0.067)	0.098 (0.067)	0.010 (0.067)	0.086 (0.057)	0.134 (0.092)
Based outside Europe	0.181 (0.296)	0.178 (0.295)	0.181 (0.296)	0.178 (0.295)	-0.274 (0.176)	-0.406** (0.169)
Early bird	0.020 (0.073)	0.024 (0.072)	0.020 (0.073)	0.024 (0.072)	0.079 (0.056)	-0.021 (0.100)
Constant	-0.004 (0.198)	-0.016 (0.195)	-0.008 (0.212)	-0.015 (0.210)		
N	912	912	214	214	912	199
Within R^2	0.074	0.078	0.074	0.078		
Overall R^2	0.960	0.960	0.838	0.838		
Pseudo R^2					0.075	0.090

Heteroskedasticity-consistent standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Social identity is instrumented in all IV models.

Probit models show average marginal effects. As standard in probit models, some observations are not used when variables perfectly predict the outcome.

By construction, the fixed effects model provide the same coefficients with both balanced and unbalanced panels.

Table A.9: Robustness tests: treatment effects on members including coefficients for the control variables

	Members					
	Robustness					
	Linear models				Non-linear models	
	Unbalanced		Balanced		Unbalanced	Balanced
	ITT FE	IV FE	ITT FE	IV FE	ITT probit	ITT probit
Social norm	0.231* (0.135)	0.240* (0.145)	0.231* (0.135)	0.240* (0.145)	0.201* (0.113)	0.280** (0.126)
Social identity	0.113 (0.116)	0.178 (0.189)	0.113 (0.116)	-0.178 (0.189)	0.012 (0.105)	-0.017 (0.140)
Academic	-0.208 (0.453)	-0.228 (0.472)	-0.208 (0.453)	-0.228 (0.472)	0.153 (0.240)	0.331 (0.258)
Prof.	-0.118 (0.440)	-0.062 (0.467)	-0.118 (0.440)	-0.062 (0.467)	0.046 (0.134)	0.510** (0.252)
Dr.					0.104 (0.131)	-0.561*** (0.194)
Based outside Europe					-0.535*** (0.174)	0.043 (0.131)
Early bird	0.208 (0.166)	0.228 (0.178)	0.208 (0.166)	0.228 (0.178)	0.034 (0.105)	
Constant	0.290 (0.443)	0.268 (0.464)	0.337 (0.477)	0.299 (0.503)		
N	282	282	104	104	282	100
Within R^2	0.112	0.044	0.112	0.044		
Overall R^2	0.957	0.954	0.888	0.880		
Pseudo R^2					0.091	0.206

Heteroskedasticity-consistent standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Social identity is instrumented in all IV models.

Probit models show average marginal effects. As standard in probit models, some observations are not used when variables perfectly predict the outcome.

By construction, the fixed effects model provide the same coefficients with both balanced and unbalanced panels.

Table A.10: Robustness tests: treatment effects on non-members including coefficients for the control variables

	Non-members					
	Robustness					
	Linear models				Non-linear models	
	Unbalanced		Balanced		Unbalanced	Balanced
	ITT FE	IV FE	ITT FE	IV FE	ITT probit	ITT probit
Social norm	-0.058 (0.058)	-0.062 (0.064)	-0.058 (0.058)	-0.062 (0.064)	-0.001 (0.001)	-0.072 (0.494)
Social identity	-0.078 (0.053)	-0.134 (0.100)	-0.078 (0.053)	-0.134 (0.100)	-0.001 (0.001)	-0.077 (0.362)
Academic	0.183 (0.128)	0.181 (0.139)	0.183 (0.128)	0.181 (0.139)	0.003 (0.006)	
Prof.	0.020 (0.210)	0.072 (0.237)	0.020 (0.210)	0.072 (0.237)	0.002 (0.004)	0.198 (1.556)
Dr.	-0.450*** (0.163)	-0.457** (0.178)	-0.450*** (0.163)	-0.457** (0.178)	-0.000 (0.000)	0.032 (0.224)
Based outside Europe					-0.004 (0.011)	-0.118 (0.876)
Early bird	0.026 (0.067)	0.033 (0.072)	0.026 (0.067)	0.033 (0.072)	0.002 (0.004)	-0.074 (0.622)
Constant	0.307* (0.176)	0.295 (0.190)	0.280 (0.183)	0.270 (0.198)		
N	630	630	110	110	630	99
Within R^2	0.356	0.237	0.356	0.237		
Overall R^2	0.994	0.993	0.963	0.960	0.043	0.102
Pseudo R^2					0.091	0.206

Heteroskedasticity-consistent standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Social identity is instrumented in all IV models.

Probit models show average marginal effects. As standard in probit models, some observations are not used when variables perfectly predict the outcome.

By construction, the fixed effects model provide the same coefficients with both balanced and unbalanced panels.