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Social influence and carbon dioxide mitigation☆

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HIGHLIGHTS

- Having social influence increases people's willingness to mitigate their carbon impact.
- However it is difficult to scale up these effects.
- People tend to overestimate how much influence they have.

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ABSTRACT

We investigate the potential of social influence to increase people's willingness to mitigate their carbon impact. In a large-scale online experiment consisting of two waves of data collection participants are given the choice to spend any share of a 10 GBP endowment on mitigation. If a wave-1 participant is told that their (anonymized) choice will be observed by a wave-2 participant *before* that participant makes their choice, then the wave-1 participant's willingness to mitigate (WTM) increases by about 17 %. This is not the case if their choice is observed by the wave-2 participant *after* that participant has already made their choice, which demonstrates that it is indeed the possibility of influence and not only observability that matters. Increasing influence at the extensive margin, i.e. increasing the number of wave-2 participants observing the choice, does not increase WTM. We also elicit beliefs and find that most participants overestimate how much influence they have.

1. Introduction

Climate change is one of the greatest threats facing humanity today. Social and economic implications range from increased mortality and violence to reduced human productivity and economic growth (Auffhammer, 2018; Carleton and Hsiang, 2016; IPCC, 2023). Because of these and other impacts there is understandable widespread concern about the environment. At the same time there is a gap between concern about climate change and effective action taken against the forces that drive environmental degradation. Why do some people not act on their concerns, while others do? Some research suggests that many people feel powerless to combat climate change in that they perceive that their individual actions will not have any meaningful overall impact on climate change. Sociologists and social psychologists have argued that such feelings of helplessness can act as a barrier between climate concern and effective climate action (Gifford, 2011; Gunderson, 2022; Keller et al., 2022; Nielsen et al., 2021). Given that the marginal impact any individual can have on the global fight against climate collapse is negligible one might indeed be tempted to ask: why do some people act at all? Anecdotal evidence from e.g. the "Fridays for Future" or "No Fly" movements suggests that one of the ways in which individuals can have an impact is via their social influence, both direct and indirect, on others.

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Indeed there is evidence that people copy climate-friendly behaviours from their neighbours and friends (Wolske et al., 2020).[1]

In this paper we ask whether giving people the possibility of social influence increases their willingness to mitigate. We also ask how economically meaningful such "influence effects" are and what are the limitations of such effects. In our large scale online experiment comprising over 4500 participants, across various treatments and two waves of data collection, each participant is given the choice to spend any share of a 10 GBP endowment on mitigation. In our main treatments, if a wave-1 participant is told that their anonymized choice will be observed by one wave-2 participant *before* the wave-2 participant, in turn, makes their choice, then the wave-1 participant's willingness to mitigate (WTM) increases by about 17 %. This is not the case if the wave-1 participant's choice is observed by the wave-2 participant *after* the wave-2 participant has already made their choice, which demonstrates that it is influence and not just observability that matters. We also find that influence is real. Participants (in wave 2) who are shown someone else's choice before making their own choice are indeed influenced. However, influence is not as significant as assumed by the observed wave-1 participants, who on average overestimate it.

Participants who are more optimistic about the effectiveness of social influence tend to mitigate more suggesting some potential to leverage influence effects for policy. At the same time our study shows that it is important to be cautious about the policy relevance of such influence effects as we find that influence cannot easily be scaled up. Increasing influence at the extensive margin, which we define as increasing the number of participants who observe the choice, does not increase WTM. This finding is reminiscent of scope insensitivity documented in previous research on charitable giving (Heeb et al., 2023; Kahneman and Knetsch, 1992; Karlan and Wood, 2017; Metzger and Guenther, 2019) as well as carbon mitigation in other contexts (Rodemeier, 2025). By contrast decreasing social influence at the intensive margin, which we define as increasing the number of participants whose choices are observed, decreases WTM. This is in line with evidence on the diffusion of social responsibility (Campos-Mercade, 2022; Falk et al., 2020; Latane and Nidda, 1981; Offerman et al., 2024).[2] These results show that while influence has the potential to increase WTM this effect is not easily scalable in possible policy interventions. Taken together these results highlight the potential as well as the limits of social influence to motivate people into acting to solve a difficult collective action problem.

Our findings contribute to an active and growing literature on how behavioural insights can be used to motivate people to act against environmental degradation. On a more general level our research belongs to an enormous literature on peer effects and spillovers summarized e.g. in Sacerdote (2014) or Bramoulle et al. (2020). From our perspective the most relevant among these are applications to climate action (Wolske et al., 2020). A widely used intervention studied with respect to climate friendly behaviour is to provide households with feedback about their own as well as other's past consumption, such as periodic "home energy reports". These reports contain historical electricity consumption data, convey social norms through comparisons with homes in the neighborhood, and provide energy conservation tips (Allcott and Mullainathan, 2010). Home energy reports have been shown to reduce electricity consumption (Allcott and Kessler, 2019; Allcott and Mullainathan, 2010; Allcott and Rogers, 2014; Costa and Kahn, 2013) or household water use (Bernedo et al., 2014; Buchanan et al., 2015; Ferraro and Price, 2013). Fang et al. (2023) combined home energy reports containing information about CO_2 emissions of shower use with immediate real-time feedback and showed that each intervention became more effective when implemented jointly rather than in isolation. Tiefenbeck et al. (2018) also show that real-time feedback can foster resource conservation. Some of the research in this area is summarized by Abrahamse and Steg (2013).[3]

While there is a substantial amount of research documenting spillovers or social influence, there is much less research on influence motives, i.e. the question of the extent to which the possibility of having social influence motivates people to act. In the context of charitable donations, Reinstein and Riener (2012) found that giving people influence in public good games by revealing first-mover choices increases contributions, but only when anonymity is lifted. Karlan and McConnell (2014) found (i) that offering public recognition does increase giving in a field experiment with US alumni and (ii) that in a lab experiment with undergraduates there is no significant change in giving from students when their contributions in a previous round are publicly (non-anonymously) revealed before rather than after other participants make their contributions in a subsequent round. Taken together these studies suggest that social image concerns play a more important role in charitable giving than influence motives. Our work contributes to this literature by showing that influence motives matter in contexts, such as the global fight against climate change, where there are virtually no strategic complementarities of direct influence. Like Esguerra et al. (2023) we find that influence motives are relevant in a context where participants are anonymous and hence social pressure and social image concerns are likely of little importance.[4] To our knowledge there is no prior work studying how influence motives impact people's willingness to mitigate their carbon impact.

One novelty in our study is that we examine the scalability of influence motives. Our work highlights that it is important not to be overly optimistic about what influence interventions could achieve. When we tried to scale up influence by giving people the chance to influence more individuals, we did not see a (further) increase in willingness to mitigate. A second novelty of our work compared to the literature is that we are able to assess to what extent people over- or under-estimate the possibility of social influence. Some work in this direction has been done by Andre et al. (2024). In line with evidence from psychology and political science (Geiger and Swim, 2016; Mildenberger and Tingley, 2019; Pearson et al., 2018) they find that respondents in a large online survey vastly underestimate the prevalence of climate-friendly attitudes and behaviours among their fellow citizens. Andre et al. (2024) show that correcting these misperceptions in an experiment causally raises the individual willingness to act against climate change as well as individual support for climate policies. The difference in our study is that,

[1] First, separate from any social concern, an individual can obtain private benefits from mitigating as it affects how they view themselves. However, since a lot of the benefit of mitigation in terms of improved environmental conditions comes from the overall amount of mitigation in society, this is where the marginal impact of individual mitigation is usually thought to be small or even negligible. There can then be additional private benefits from conforming to a social norm (Akerlof, 1980; Bicchieri, 2006; Fehr and Schurtenberger, 2018; Lindbeck et al., 1999; Mengel, 2008). There can be both consequentialist as well as possible norm-based motives to increase one's mitigation in order to influence others. A consequentialist motive would be present when the convex nature of the overall mitigation benefit, such as due to tipping points (IPCC, 2023; Lenton et al., 2019), means that a higher amount of mitigation by others makes mitigation more beneficial. But there can also be social norm based motives stemming from a desire to fit in or be part of a movement.

[2] Diffusion of responsibility is, however, not the only possible explanation of this finding and it can occur for different motives. There can be free-riding motives, if others believe that other Wave 1 participants will mitigate enough to influence the Wave 2 participant or participants could worry that the impact of their own choice is too marginal among twenty others (a dilution problem).

[3] There is also a somewhat less related literature focused on whether people can be influenced by "green default nudges" (Berger et al., 2022) or by receiving information or feedback on sustainable choices more generally, not necessarily information about the behaviour of others (Bain, 2015; Bilen, 2022; Loeschel et al., 2023; Pace et al., 2025).

[4] Sherif and Simon (2024) also find that social image concerns are important to motivate climate-friendly behaviours but can co-exist with role-model aspirations.

Table 1
Top Panel: Sample Characteristics. Mean Age, Share of Female respondents (self reported gender), share self-identifying as working, middle and upper class as well as self-reported ethnicity. Political (Orientation) ranges from −5 (extreme left) to 5 (extreme right). Shares missing to 100 percent are "Other". Middle and Bottom Panel: Summary Statistics and variable labels for attitudes towards climate change and own climate impact. Questions are abbreviated to fit the table. Full questions can be found in screenshots in the Online Appendix. Answer options for "Thought" are (i) "Not at all" or "Very little", (ii) "Some", (iii) "A lot" or "A great deal". For the variable "Belief" it is (i) "Entirely caused by natural processes or (ii) Mainly caused by natural processes", (ii) "Equally caused by human activity and natural processes", (iii) "Mainly caused by human activity" or "Entirely caused by human activity". For the variable "Worry" they are "Not all" or "Not very", (ii) "Somewhat worried", (iii) "Very worried" or "Extremely Worried". For Attitudes II the answers were given using sliders ranging from 0 to 10.

Wave 1 Demographics			
Mean Age	40.50		
Share Female	50		
Mean Political	−0.308		
Share Working Class	55.37		
Share Middle Class	44.36		
Share Upper Class	0.27		
Share White British	80.10		
Share Other White	8.04		
Share South Asian	4.18		
Attitudes I			
How much have you thought about climate change before today? (`Thought`)			
	Very little	Some	A lot
	0.14	0.43	0.43
Is climate change caused by natural processes, human behaviour or both? (`Belief`)			
	Natural	Equal	Human
	0.06	0.19	0.75
How worried are you about climate change? (`Worry`)			
	Not	Somewhat	Very
	0.15	0.48	0.37
Attitudes II			
	Mean	Median	SD
Do you feel personal responsibility to reduce climate change? (`Responsibility`)			
	4.75	5	2.49
How likely is it that limiting your own energy use ...? (`Indiv Effect`)			
	3.54	3	2.54
How likely is it that a large number of people limiting ...? (`Coll Effect`)			
	5.98	6	2.53
How likely is it that you limiting your own energy use will inspire ...? (`Inspire`)			
	3.28	3	2.43

while they document misperceptions about the prevalence of climate-friendly attitudes and behaviours, we document misperceptions about the possibility of influencing others to act in a more climate-friendly manner.

The paper is organized as follows. In Section 2 we describe the design of the experiment and some properties of our sample. Section 3 contains the main results and Section 4 concludes.

2. Experiment

In this section we outline the design of the experiment (Section 2.1) and discuss some descriptive statistics regarding our sample of respondents (Section 2.2).

2.1. Design

Our experiment consists of two waves of data collection. Our main hypotheses will be addressed using data from Wave 1. The three key treatments in Wave 1 are the baseline, an influence, and an observability treatment.

In the baseline treatment (**BASE**) participants are given an endowment of 10 GBP and asked how much of this endowment they would like to donate to a carbon offsetting scheme, specifically the tree planting offset at https://www.mycarbonplan.org. We call the amount donated a participant's willingness to mitigate or WTM in this paper.[5] After indicating their willingness to mitigate, participants answer a series of questions regarding their attitudes towards climate change and climate action. We then elicited beliefs regarding social influence. We first elicit general beliefs about the effectiveness of individual and collective action as well as social influence. See Table 1 for the exact questions used. We then ask participants, specifically, how much they believe a Wave 2 participant will mitigate if they observe a single Wave 1 mitigation decision of 2 or 5 or 8 GBP, respectively. We did not incentivize these beliefs.[6] Last, we elicited some demographics. The order of these different modules was fixed and did not change across treatments. Demographics

[5] For clarity we use WTM to refer to the amount donated to the tree planting scheme during the experiment. We note, though, that this is only a coarse measure of participants' overall willingness to mitigate. In principle it is possible for a participant to keep the 10 GBP and then use it after the experiment to mitigate in a way they deem more effective than the tree-planting scheme. The measure also does not include other mitigation activities a participant may engage in outside the lab.

[6] There is evidence that unless there are specific reasons for participants to misstate their beliefs, it can be better not to incentivize belief elicitation. See e.g. Danz et al. (2022).

and climate attitudes are summarized in Tables 1 and Online Appendix Table D.2 below.

In the influence treatment **INF-(1,1)** participants are told - before making their choice - that there is a second wave of data collection and that their (anonymized) WTM will be shown to a randomly selected participant in Wave 2 *before* that participant makes their choice. Hence participants know that their choice can influence someone else. Other than that this treatment is identical to the baseline.

The observability treatment **OBS-(1,1)** is identical to **INF-(1,1)** except for the fact that the randomly selected participant in Wave 2 will see the Wave 1 participant's WTM *after* they make their choice. Hence, while there is observability in both treatments, there is no possibility to influence the Wave 2 participant's choice in treatment **OBS-(1,1)**.[7] Comparing the baseline and **INF-(1,1)** will help us test whether having social influence increases efforts to mitigate, while the comparison with **OBS-(1,1)** allows us to test whether any such increase is purely driven by observability or whether the possibility to influence matters in itself. Hence the purpose of the **OBS** treatments is not to study observability *per se* but merely to eliminate a potential confound for the study of influence.

The remaining treatments then vary influence and observability at both the extensive and intensive margins, i.e., by varying the number of observing participants and the number of observed participants respectively. In treatments **INF-(20,1)** and **OBS-(20,1)** each Wave 1 participant is observed by twenty Wave 2 participants instead of just one. Each of these twenty Wave 2 participants still sees only one decision from Wave 1. In treatments **INF-(1,20)** and **OBS-(1,20)** each Wave 1 participant is observed only by one Wave 2 participant as in our main treatments, but now each Wave 2 participant observes twenty Wave 1 decisions. Lastly, in **INF-(20,20)** and **OBS-(20,20)** Wave 1 participants are observed by twenty Wave 2 participants who each observe twenty Wave 1 decisions.

We pre-registered our experiment at the AEA trial registry with number AEARCTR-0010768 (see Online Appendix B for details). Ethical approval was obtained by the University of Essex Social Sciences Faculty Ethics Committee with number ETH2223-0583.

2.2. Sample and data collection

We implemented our survey experiment using a sample of 4701 adults (across Waves 1 and 2) from the UK.[8] Sample sizes per treatment can be found in Online Appendix Table D.1. We collected the data in collaboration with the survey company Prolific. The sample is broadly representative of the adult UK population (see Table 1) in terms of age, gender and social class in Wave 1. In Wave 2 women are somewhat overrepresented (see Online Appendix Table D.2). Online Appendix Tables D.3 and D.4 show balancing tests for Wave 1 and Wave 2, respectively. Online Appendix Table D.3 shows that the Wave 1 sample is balanced across treatments with respect to age, gender, social class, birth country, ethnicity, first language, and religion. In Wave 2 older people and those not born in the UK, not being white and not speaking English as a first language are somewhat more likely to be assigned to the **INF** condition.[9] We are not concerned by this, though, as we are not interested in comparing **INF** and **OBS** conditions in Wave 2.

Table 1 summarizes the attitudes and beliefs our participants express regarding climate change as well as regarding the impact of their own choices on the climate. In line with other literature as well as with responses in general social surveys (Bouman et al., 2020; Lange and Dewitte, 2019) about an equal proportion of participants indicate that they think some or a lot about climate change and are somewhat or very worried about it. Only a minority are not worried. Most participants believe that climate change is largely caused by human behaviour.

When we ask participants about the impact of their own choices we see that there is substantial variation in how much personal responsibility people feel to act to combat climate change. Unsurprisingly, most participants express more optimism in the effectiveness of collective as opposed to individual action.

Online Appendix Table D.7 analyzes determinants of these attitudes. The table shows that women worry more about climate change than men, feel more responsibility for mitigation and have a stronger belief in the effectiveness of both individual and collective action. People who describe themselves as middle class have thought more about climate change, worry more about it and are more likely to believe that it is human-caused compared to both the self-described working class and upper class. Christians and Muslims (as opposed to non-religious respondents) think less about climate change and worry less about it. They are also less likely to believe that it is human caused. By contrast they have a greater belief in the effectiveness of individual action and in their ability to inspire others.

The experiment was computerized using the Qualtrics online survey tool and fielded in February and March 2023 as well as June 2024.[10] The vast majority of participants spent between 2–6 minutes answering the survey. Based on our participants' decisions we offset 2037 tonnes of CO_2 emissions via My Carbon Plan Ltd's tree planting scheme at the end of our experiment.[11]

3. Results

We start by presenting our main results including our pre-registered test (Section 3.1), then explore how influence changes at the extensive and intensive margins (Section 3.2) by varying the number of observing (Wave 2) and observed (Wave 1) participants respectively and compare perceived with actual influence (Section 3.3).

3.1. Main test

The right-hand figure in Table 2 shows the distribution of WTM choices in the baseline treatment and treatment **INF-(1,1)**. The first thing to note is that choices 0, 5 and 10 are much more frequent than other choices. This is partly because of truncation (anyone with a WTM$\geq$ 10 will presumably choose 10) and partly because a choice of 5 could be salient to many as it means splitting the windfall gain equally between mitigation and personal consumption. See also the discussion in footnote 5.

Comparing the two treatments we clearly see a decrease in the percentage of participants choosing zero mitigation in **INF-(1,1)** compared to the baseline, while there are visible increases in the percentage of participants choosing WTM $\in \{5, 10\}$. When people perceive that they have social influence they seem to be willing to mitigate more.

To investigate this point more formally we use regression analysis. Table 2 shows the results for our main pre-registered test. Compared to the baseline, mean WTM increases by about 17 % (from 2.83 GBP to 3.30 GBP on average) when (Wave 1) participants know they have social influence, i.e. when they know that their mitigation decision will be seen by someone else (in Wave 2) *before* that person in turn makes their decision. This effect is highly statistically significant and robust

[7] Of course it is possible that in treatment **OBS-(1,1)** the observed Wave 1 WTM motivates Wave 2 participants to increase their efforts to mitigate *outside of the experiment*. There is no immediate influence within the experiment, though, in these treatments. In that sense, while treatments **INF-(1,1)** and **OBS-(1,1)** have equal observability, **INF-(1,1)** has strictly higher influence.

[8] This is somewhat less than what we originally planned as some Wave 2 data were not collected due to a software error. Wave 1 was unaffected by this.

[9] We do not have "political orientation" for Wave 2 participants. Due to a coding error in the survey software this variable was not collected in Wave 2.

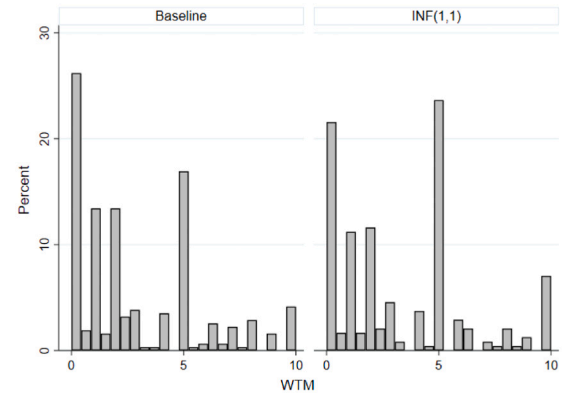
[10] See Online Appendix B for details.

[11] It should be noted that My Carbon Plan's price for carbon offsets (via tree planting) is relatively low compared to other providers. It is possible that this created some trust issues among participants depressing the level of WTM's we observe (Rodemeier, 2025). This should not affect the internal validity of our study, though.

Table 2
Left Panel: Main pre-registered comparison (column (1)). Willingness to mitigate (WTM) regressed on treatment dummies (OLS regression). Demographic controls are gender, age, social class, political orientation, ethnicity, country of origin, first language and religion. Age and political orientation (− 5 to 5) are included linearly and other controls are fixed effects. Attitudes I and Attitudes II are the questions summarized in Table 1. Right Panel: Histogram of WTM in Baseline and treatment **INF-(1,1).**

	Willingness to Mitigate			
	(1)	(2)	(3)	(4)
INF-(1,1)	0.477**	0.491**	0.440**	0.443**
	(0.209)	(0.209)	(0.200)	(0.191)
OBS-(1,1)	-0.014	0.000	0.000	-0.008
	(0.211)	(0.212)	(0.203)	(0.194)
Constant	2.830***	1.405***	-0.439	-0.669
	(0.142)	(0.487)	(0.542)	(0.535)
Demographics	-	✓	✓	✓
Attitudes I	-	-	✓	✓
Attitudes II	-	-	-	✓
Observations	1,093	1,092	1,092	1,076
R-squared	0.006	0.025	0.109	0.206

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1



towards including demographic controls as well as attitudes towards climate change and climate action across specifications (2)–(4). The table also shows that just being observed without having influence (**OBS-(1,1)** treatment) does not change WTM substantially compared to the baseline.[12] Comparison of the R^2 across columns (1)–(4) shows that, maybe unsurprisingly, demographics and especially climate attitudes are more important in explaining WTM than the possibility of having social influence, which nevertheless explains 0.6 % of the variation in our online experiment.

Last, we can also compare the WTM in the **INF-(1,1)** treatment with the **OBS-(1,1)** treatment instead of with the baseline. The hypothesis that the WTM are equal is rejected at the 5 % level (*t*-test based on column (1) in Table 2, $p = 0.0248$). In sum, our main test unambiguously shows that when participants are given social influence they are willing to mitigate more on average compared to both a baseline condition and a condition where they are being observed, but cannot actually influence another participants' decision.

Online Appendix Table D.8 considers several dimensions of heterogeneity in the treatment effect. Unsurprisingly WTM is higher for those who have thought more about climate change, worry more about it, feel more responsibility to act and believe in higher individual as well as collective effectiveness of climate action and have a stronger belief that their actions will inspire others. Interestingly, while baseline WTM increases in all these variables (when considered separately) the treatment effect does not. Online Appendix Table D.6 studies the heterogeneity of the treatment effect by basic demographic variables. None of the demographic covariates seems to significantly affect the size of the treatment effect. Lastly, Online Appendix Tables D.9 and D.10 show that the main results are robust to dropping exceptionally fast respondents.

3.2. Changing the intensive and extensive margins of influence

In the previous subsection we have seen that WTM can be increased by about 17 % when participants know that their mitigation decision will be seen by one other person *before* that person, in turn, makes their decision. A natural question is to which extent this can be scaled up. Are people willing to mitigate even more if they could potentially influence many others? In this subsection we ask what happens if we increase influence at the extensive margin, defined as increasing the number of Wave 2 participants who observe a Wave 1 participant's choice as well as what happens when we decrease influence at the intensive margin, defined as increasing the number of Wave 1 participants whose choices are observed by a Wave 2 participant.

Table 3
Changing influence at the intensive and extensive margin. Willingness to mitigate (WTM) regressed on treatment dummies (OLS regression). The baseline is treatment **INF-(1,1)**. Demographic controls include gender, age, social class, political orientation, ethnicity, country of origin, first language and religion. Age and political orientation (− 5 to 5) are included linearly and other controls are fixed effects. Attitudes I and Attitudes II are the questions summarized in Table 1.

	Willingness to Mitigate			
	(1)	(2)	(3)	(4)
INF-(1,20)	− 0.496**	− 0.512**	− 0.482**	− 0.485**
	(0.244)	(0.243)	(0.232)	(0.227)
INF-(20,1)	0.131	0.126	0.105	0.162
	(0.414)	(0.409)	(0.393)	(0.387)
INF-(20,20)	− 0.411*	− 0.448*	− 0.384*	− 0.400*
	(0.235)	(0.232)	(0.222)	(0.217)
Constant	3.307***	1.536***	− 0.234	0.018
	(0.153)	(0.534)	(0.605)	(0.607)
Demographics	–	✓	✓	✓
Attitudes I	–	–	✓	✓
Attitudes II	–	–	–	✓
Observations	901	897	897	888
R-squared	0.007	0.041	0.126	0.176

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 3 reports the results of regressions where WTM in **INF-(1,1)** (which is used as the baseline for Table 3) is compared with other treatments where influence is either scaled up or down. In treatment **INF-(20,1)** a Wave 1 participant's WTM is shown to twenty Wave 2 participants instead of just one as in our main treatment **INF-(1,1)**. Table 3 shows that this increase in the number of people influenced has a small positive, but not statistically significant impact on WTM. It should be noted that we do not have a lot of power in this treatment. Since for every Wave 1 participant twenty Wave 2 participants are required in this condition, collecting a large sample was prohibitive. Still, the point estimates are fairly small and we conclude that influence does not easily scale up. One might wonder whether this small effect is due to ceiling effects, i.e. participants wanting to increase their donation beyond the maximum possible 10 GBP but not being able to. To check for this we

[12] As mentioned above, it is not clear that treatments **OBS** imply no social influence at all, as it is possible that the observed choice(s) motivates Wave 2 participants to increase their efforts to mitigate *outside of the experiment*. There is no immediate influence within the experiment, though, in these treatments. In that sense, while treatments **INF** and **OBS** have equal observability, **INF** has strictly higher influence.

Table 4
Willingness to Mitigate (WTM) in influence conditions in Wave 2 depending on the amount of Wave 1 mitigation observed. Cases where only one Wave-1 WTM is observed. Demographic controls are gender, age, social class, political orientation, ethnicity, country of origin, first language and religion. Attitudes I and Attitudes II are the questions summarized in Table 1.

	Willingness to Mitigate Wave 2			
	(1)	(2)	(3)	(4)
Amount Observed	0.075***	0.082***	0.087***	0.095***
	(0.026)	(0.026)	(0.024)	(0.023)
Constant	2.536***	1.387***	−0.448	−0.431
	(0.120)	(0.306)	(0.378)	(0.372)
Demographics	–	✓	✓	✓
Attitudes I	–	–	✓	✓
Attitudes II	–	–	–	✓
Observations	1,252	1,250	1,250	1,249
R-squared	0.006	0.040	0.139	0.209

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

drop in a sequence of regressions (using specification (1) in Table 3) all participants with a WTM of 10, bigger than 9, 8, 7,6 or 5. The effect sizes we find across these six regressions range from −0.086 to 0.072. While we cannot fully rule out ceiling effects, this analysis shows that there is no significant effect also among the part of the sample that is unconstrained, which is the vast majority of our participants.

Treatment **INF-(1,20)** decreases influence at the intensive margin. Here, as in **INF-(1,1)** each Wave 1 participant can only influence one Wave 2 person, but that Wave 2 person sees the WTM of twenty Wave 1 participants. Table 3 shows that this produces a substantial decrease in WTM compared to **INF-(1,1)**. In fact, WTM is no higher in this condition than in the baseline treatment without influence (**BASE**). Increasing the extensive margin of influence (as in treatment **INF-(20,20)**) produces only a slight increase again in WTM compared to **INF-(1,20)**.[13] In sum, while social influence increases participants' WTM compared to a baseline (Table 2), increasing the number of people influenced at best increases the WTM slowly. By contrast, changing the intensive margin, i.e. reducing the amount of influence participants have on any given person does lead to a marked decrease in WTM. In fact, in our treatments where participants are only one of twenty others observed the WTM is barely above that of the baseline treatment. Perhaps unsurprisingly, social influence works only if participants feel that their choice might actually make a difference. We have also seen that while having social influence motivates people to mitigate more, increasing influence at the extensive margin does not seem to increase mitigation further.

3.3. Actual vs perceived influence

Last, we can ask how significant the influence actually is in the experiment and whether Wave 1 participants have accurate expectations regarding their influence. Influence could be either positive or negative. It is conceivable that Wave 2 participants imitate Wave 1 decisions (Apesteguia et al., 2007), try to learn from Wave 1 decisions in other ways (Kovarik et al., 2018), or feel pressure to conform due to e.g., social norms (Bicchieri, 2006; Young, 2015). In all these cases we would expect a positive influence of Wave 1 decisions on Wave 2 decisions. However it is also conceivable that higher Wave 1 choices have a negative impact on Wave 2 WTM. Wave 2 participants might for example trade-off their mitigation levels with what others have done and if the latter is above their expectations, they may mitigate less themselves (Fellner et al., 2013).

Table 4 shows that on average observing higher prior donations increases mitigation in Wave 2, but the effects are relatively modest. For example observing a prior donation of 10 GBP as opposed to a prior donation of 0 GBP raises the amount mitigated by 75 pence (0.75 GBP). Online Appendix Table D.11 shows regressions for the case where more than one WTM is observed and asks whether it is the mean, mode or median WTM that matters in this case. The coefficients for mean, median and modal amounts observed are not pairwise statistically different (t-test, $p > 0.1664$).

In our experiment, while Wave 1 participants can influence others, Wave 2 participants cannot influence others. For the more general case where influence can propagate to N others, we can compute the social multiplier of a 1 GBP increase in WTM as N gets large (Glaeser et al., 2003). Based on the magnitudes estimated above, this social multiplier is around 1.1.[14]

If we contrast the actual social influence with the beliefs participants expressed in Wave 1, we can see that - at least according to this measure - participants overestimate influence. For an increase in the observed amount from 2 to 5 GBP Wave 1 participants on average expect an increase in Wave 2 mitigation of 1.62 GBP when the actual increase is only 0.27 GBP. Similarly, for a further increase in the observed amount from 5 to 8 GBP Wave 1 participants expect an increase in Wave 2 mitigation of 1.16 GBP when the actual increase is only 0.68 GBP. These averages, however, hide a substantial amount of heterogeneity.

We broadly identify four types: Those who underestimate social influence (type I), those who mildly overestimate it (type II) and those who substantially overestimate it (type III). A fourth type (type ACC) contains the respondents who accurately estimate influence i.e. whose guesses are within 10 % of the actual influence.[15] Fig. 1 shows the distribution of these types across all our different treatment conditions.[16] The figure shows that, irrespective of the treatment, only about 10 percent of Wave 1 participants anticipate the amount of influence a Wave 1 decision will exert on a Wave 2 participant accurately. Most people over-estimate influence. There is, however, substantial heterogeneity with around 15–20 % of respondents strictly under-estimating influence. There is arguably some room for researcher demand with this elicitation, as participants may not want to enter the same answer to questions about different amounts. In this case the amount of accurate estimates should be underestimated.

We then ask whether there are demographic or other co-variates which are robustly associated with over- or under-estimation (Online Appendix Table D.12). There are no statistically significant demographic covariates of underestimation. However, we do find that those who mildly overestimate social influence (type II) are more likely to be middle class and those who substantially overestimate social influence (type III) are more likely to be from the UK and self-identify as “White British” and less likely to be Muslim than others. In terms of climate attitudes we find that those who claim to have thought more about climate change are less likely to substantially over-estimate (but more likely to mildly overestimate), while those who worry more substantially overestimate more often.

Last, we find that those who tend to mildly or substantially overestimate social influence are also willing to mitigate more. The pairwise correlation between WTM and influence beliefs is 0.1452^{***}. Online

[13] In **INF-(20,20)** each Wave 2 participant observes 20 Wave 1 decisions before the former makes their own WTM decision and each Wave 1 participant's decision is observed by 20 Wave 2 participants before the latter make their WTM decisions.

[14] This is based on a back of the envelope calculation for N large where the social multiplier approaches $\frac{1}{1-y}$, where y is our estimated effect size. There is a more general question to what extent people take into account indirect influence - this question is addressed in Friedman et al. (2024) in a lab experiment with a sequential collective action game.

[15] Online Appendix Figure C.2 shows the overall distribution of the estimated influence by all Wave 1 participants as well as the cutoffs for the different types.

[16] In all treatments participants were asked to estimate how much a Wave 2 participant would mitigate who sees exactly one other donation (of differing amounts) before they make their choice.

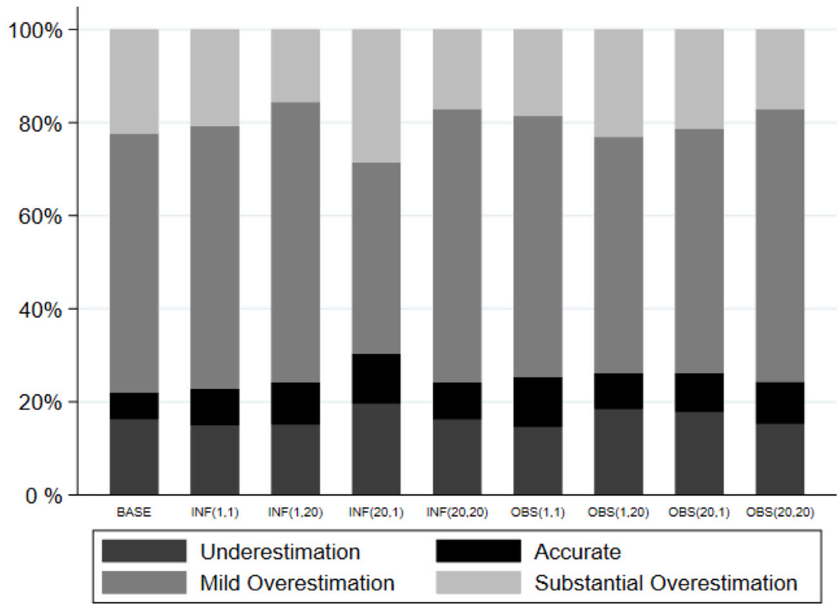


Fig. 1. Distribution of types among Wave 1 participants (accurate estimation of influence, over- or under-estimation).

Appendix Figure C.3 shows kernel density estimates of WTM for different levels of influence beliefs by Wave 1 participants. The figure shows a positive association mainly driven by those who mildly overestimate influence.[17] This suggests that over-estimation can potentially have positive effects on climate change mitigation.

Apart from asking whether people over- or under-estimate social influence, we can also ask how good an idea they have of the baseline WTM of others. Here we find that people on average slightly underestimate other's willingness to pay. While in the baseline treatment the average WTM is 2.87, participants estimate this to be 2.42 (t-test, $p < 0.01$). Sixteen percent of respondents are accurate (within 10 percent of 2.87), 67 percent underestimate and the remainder overestimate. This underestimation of baseline WTM could contribute to the overestimation of social influence and indeed, the two are mildly correlated.

4. Conclusions

We investigated the potential of social influence to increase people's willingness to mitigate their carbon impact. In a large-scale online experiment ($N = 4701$) participants were given the choice to spend any share of a 10 GBP endowment on mitigation. If participants are told that their choice will be observed by one other participant *before* that participant, in turn, makes their choice, then willingness to mitigate (WTM) increases by about 17 %. The fact that this is not the case if their choice is observed by the other participant *after* that participant has already made their choice, documents that influence and not only observability matters. This shows that indeed the possibility of having influence and not merely observability matters.

It is important to note that we are not claiming that observability or social image concerns do not have effects on WTM. In fact, previous literature has found that they do and such social image concerns are likely attenuated by the anonymity in our setting. What our setting shows is that there are influence motives *over and above* any possible effects created by observability.

Our results also caution against a naive belief in the power of social influence. While the possibility of social influence increases participants' willingness to mitigate increasing influence at the extensive margin does not increase WTM further in our study. This is in line with findings on scope insensitivity by (Rodemeier, 2025) and others discussed in the Introduction. The findings of Rodemeier (2025) also suggest that individual WTP for carbon mitigation – in a setting where there is no social influence – is susceptible to scope insensitivity, possibly due to inattention. By contrast participants are sensitive to when their influence is diluted at the intensive margin and they decrease their WTM compared to the undiluted case. This sensitivity can occur for different, though closely related reasons. Diffusion of responsibility can be closely related to free-riding motives, if others believe that other Wave 1 participants will mitigate enough to influence the Wave 2 participant. Alternatively participants could worry that the impact of their own choice is too marginal among twenty others (a dilution problem) even or especially if others do not mitigate a lot.

While our study points to limits in leveraging social influence, it can nevertheless be useful as part of a policy mix to encourage people to act to combat climate collapse. Our heterogeneity analysis suggests some useful guidance for targeting and could be combined with e.g. network-based targeting strategies (Drago et al., 2020; Friedman et al., 2024; Galeotti et al., 2020). An important direction for future research is to assess the welfare implications of such interventions. These can be nuanced because both those who influence as well as those who are influenced by others might feel pride or shame, derive warm-glow, or feel social or moral pressure (Allcott and Kessler, 2019; Butera et al., 2022; Loeschel et al., 2023; Rodemeier, 2025).[18]

Last, we found that, while there is substantial heterogeneity, most participants tend to overestimate how much influence they have. This suggests that social influence is most effective in the short run. Is overestimation welfare-enhancing? Overestimation of social influence can have some benefits to the extent that it motivates people to act against climate collapse. Its welfare effects however, will generally depend on a number of factors, whose study is beyond the scope of this paper. For

[17] Online Appendix Table D.13 contains regressions showing that those who mildly or substantially overestimate do indeed have higher WTM.

[18] Recent literature documents subtle issues that should be accounted for in relation to welfare when considering non-price and price based policy tools. For instance, Rodemeier and Löschel (2025) document that information nudges can crowd out the effectiveness of Pigouvian subsidies, while List et al. (2023) and Hahn et al. (2024) provide general frameworks and methods to assess the effectiveness of price and non-price policies in relation to welfare.

instance, if such overestimation leads to the pursuit of suboptimal avenues and to the abandonment of more effective alternative routes to address the climate crisis, then overestimation could be detrimental.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Friederike Mengel reports financial support was provided by Leverhulme Trust. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Online Appendix

Supplementary data to this article can be found online at doi:10.1016/j.jpubeco.2025.105558.

Data availability

Data will be made available on request.

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