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Giving is a Question of Time: Response Times and Contributions to an Environmental Public Good

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Abstract Does it matter whether contribution decisions regarding environmental public goods are arrived at through intuition or reflection? Experimental research in behavioral economics has recently adopted dual-system theories of the mind from psychology in order to address this question. This research uses response time data in public good games to distinguish between the two distinct cognitive processes. We extend this literature towards environmental public goods by analyzing response time data from an online experiment in which over 3400 subjects from the general population faced a dichotomous choice between receiving a monetary payment or contributing to climate change mitigation efforts. Our evidence confirms a strong positive link between response times and contributions: The average response time of contributors is 40 % higher than that of non-contributors. This suggests that reflection, not intuition, is at the root of pro-environmental contributions. This result is robust to a comprehensive set of robustness checks, including a within-subjects analysis that controls for potentially unobserved confounds and recovers the relationship at the individual level.

Keywords Public goods · Cooperation · Dual-system theories · Response times · Climate change · Online experiment

JEL Classification C93 · H41 · D03

1 Introduction

Advances in behavioral economics have created new opportunities for expanding our understanding of pro-environmental preferences and decisions (Carlsson 2010; Croson and Treich 2014). One example is a renewed interest in the cognitive aspects of preference revelation,

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which has highlighted that choices in stated or revealed preference studies can reflect not just decision-makers' true preferences, but also their cognitive efforts and errors – even in the presence of non-trivial financial stakes (Kahneman et al. 1990; Hanley and Shogren 2005; Beshears et al. 2008). This interest in the role of cognitive aspects of preference revelation and choice has recently begun to extend towards public goods, setting off a series of experiments that find convergent evidence that decisions about contributions to public goods differ in cognitive style: while some decision-makers appear to base their choice on a first intuition (i.e. a simple heuristic) when resolving a trade-off between selfish and other-regarding motives, others appear to base their choice on reflection or, in other words, deliberate cognitive effort (e.g. Piovesan and Wengström 2009; Kocher et al. 2012; Rand et al. 2012, 2014; Nielsen et al. 2014; Kessler and Meier 2014; Ubeda 2014). The conceptualization of intuition and reflection as two principal types of cognitive styles mirrors the distinction drawn between System I and System II in the increasingly popular dual-system theories and their applications to economics (Fudenberg and Levine 2006; Loewenstein and O'Donoghue 2007; Kahneman 2011; Dreber et al. 2014): System I arrives at decisions through rapid intuitive processes. System II arrives at decisions through cognitively more demanding and hence slower reflective reasoning (Kahneman 2003; Evans 2003, 2008; Loewenstein et al. 2008). Together, these theories about cognitive style and the associated experiments raise the possibility that, everything else equal, individuals come to different choices about environmental public goods simply because they relied, in the decision situation, on intuition (System I) or reflection (System II).

The purpose of the present paper is to examine the question whether cognitive style matters systematically and substantially for individual decisions about a voluntary and costly contribution to a real-world environmental good. An affirmative answer, derived in an incentivized setting, would be of interest for environmental economists for at least two reasons. One is that it would lend additional support to the notion that the outcome of valuation exercises depends on whether a certain design choice, framing, or other aspect of the study favors intuition or reflection (Frör 2008; Menzel 2013).[1] Similarly, certain goods that invoke a strong emotional response (negative or positive) might lead to a higher fraction of impulsive choices (Fischer and Hanley 2007). Secondly, it would contribute to the debate among economists in general, and environmental economists in particular, on the relationship between individuals' elicited preferences for environmental goods and their 'true' or 'normative' preferences for these goods (Beshears et al. 2008).[2] Beyond methodological questions of preference elicitation, the question that motivates this paper also speaks to a more general discussion about whether one of the two cognitive systems, intuition or reflection, predisposes individuals towards more cooperative choices (Rand et al. 2012, 2014). The evidence so far, mostly derived in the context of abstract laboratory experiments, indicates the existence of an empirical link between the cognitive system and the choice to cooperate, but the direction of this link remains disputed.[3] In sum, the relationship between cognitive style and the decision to make

[1] In non-incentivized settings, for example, evidence from stated preference surveys has shown that giving respondents 'additional time to think' significantly reduces WTP estimates (Cook et al. 2012).

[2] In a non-incentivized CVM survey, Fischer and Hanley (2007) use the time subjects take for their decision (i.e. response time data) in order to classify responses as either carefully considered or impulsive. Depending on the framing of the environmental good in question, the authors conclude that 10–20 % of stated WTPs in their study were impulsive or habitualised and hence less likely to contain accurate information on the underlying preferences. Börger (2015) similarly finds that slower survey responses to a choice situation increase choice precision.

[3] Rand et al. (2012, 2014), for example, find that higher contributions in standard public good games are driven by intuitive decision making. In their series of studies, faster choices are associated with higher contributions

pro-environmental contributions is of relevance both in the context of preference elicitation and in the context of cooperative choice.

In an attempt to answer the motivating question, the present paper adds empirical evidence that—to our knowledge for the first time—originates from outside the laboratory. Specifically, it provides evidence on the link between cognitive systems and contribution behavior in the area of environmental decision making by exploring real contributions to voluntary climate change mitigation—the archetypal public good to environmental economists (e.g. Nordhaus 1993). Methodologically, it follows a growing body of the behavioral economics literature and identifies the essentially unobservable cognitive processes that govern the decision through response time (RT) data (Piovesan and Wengström 2009; Rand et al. 2012; Tinghög et al. 2013; Nielsen et al. 2014; Ubeda 2014; Cappelen et al. 2015).[4] This empirical strategy relies on the fact that on average, response times differ between intuition and reflection. When considering the consequences of a given choice or resolving a moral dilemma, faster decisions are more likely to be the result of intuitive processes while slower decisions are more likely to have involved reflection (Rubinstein 2007, 2013).

Our data are based on an extra-laboratory experiment[5] on voluntary individual climate action (Diederich and Goeschl 2014) that collected individual RT data of both contributors and non-contributors. In this experiment, subjects from the general population faced a dichotomous choice between receiving a monetary payment and contributing to voluntary mitigation efforts. Voluntary mitigation efforts took the form of a guaranteed and verifiable reduction of CO_2 emissions by one metric ton (Löschel et al. 2013; Diederich and Goeschl 2014). This unique dataset of choices and associated RT offers four distinct benefits: First, it is to our knowledge the first set of observations that allows a test of the link between cognitive system and contributions based on a real public good and the choice of the good (voluntary climate action) is of obvious interest to environmental economists. Second, with 3483 subjects, the number of independent observations is large compared to most datasets that examine this link. This is important in light of Rubinstein's (2007; 2013) dictum that the noisy approximation of mental processes through RT data is facilitated by large sample sizes. Third, observing a sample of subjects from the general population with a broad range of demographic backgrounds increases the representativeness of our results. Fourth, the dataset contains two RT observations per subject as each subject took two choices between different monetary rewards and mitigating one ton of CO_2. Hence, as in Piovesan and Wengström (2009), it is possible to analyze the within-subject relationship between RT and contributions while holding constant unobserved individual attributes or preferences. In contrast to prior studies based on one-shot games (i.e. cross sectional data), we can therefore exclude that the omission of unobserved variables leads to biased estimates of the relationship between response times and contributions.

Footnote 3 continued
and the application of time pressure shifts contributions towards the public good. Tinghög et al. (2013) and Verkoeijen and Bouwmeester (2014), however, fail to replicate the findings on the effects of time pressure, as do Duffy and Smith (2014) and Martinsson et al. (2014) when using cognitive load or priming designs in a public goods setting. In the closely related context of non-strategic distribution tasks, Piovesan and Wengström (2009) and Ubeda (2014) conclude that more generous allocations in dictator games are associated with reflection, not intuition. On the other hand, Schulz et al. (2014) find the opposite when analyzing the effects of cognitive load in a series of mini-dictator games. Similarly, Cappelen et al. (2015) find that participants sharing half of their endowment in a dictator game decide more quickly than those keeping their full endowment

4 In psychology response time data have been used for some time in order to distinguish between intuitive and reflective decision making (e.g. Luce 1986). For a recent overview over the use of response time data in behavioral economics see Spiliopoulos and Ortmann (2014).

5 Based on the categorization introduced by Charness et al. (2013).

Our results are threefold: First, we find a clear difference in response times between contributors and non-contributors in an extra-laboratory setting. This is evidence that the link between cognitive systems and contribution decisions detected in previous studies survives in a real choice situation outside the specific setting of an abstract lab task and when using subjects drawn from the general population. Secondly, we find that intuitive decisions are statistically associated with a choice not to contribute to climate change mitigation while a choice to contribute is more likely when the decision follows from reflection. This result on pro-environmental choice lends support to earlier findings (Piovesan and Wengström 2009; Ubeda 2014) that reflection favors pro-social choices. In our extra-laboratory setting with a large and diverse sample of subjects, we find that the average response time of contributors, controlling for other factors, is approximately 40 % longer than that of non-contributors. Thirdly, our finding carries over to the individual level: Subjects who switch from not contributing in their first decision to contributing in their second decision need significantly more time for their second decision and vice versa. In other words, our within-subjects analysis rules out that unobserved individual heterogeneity drives the positive relationship between response times and contributions. Jointly, these results contribute towards answering our motivating question in the following way: In our extra-laboratory experiment, it did matter whether decisions on environmental goods were based on intuition or reflection. One direct implication is that decision environments that are conducive to different cognitive styles are therefore likely to produce different outcomes. This reaffirms the presence of potentially challenging questions in environmental welfare economics (Croson and Treich 2014).

This paper is organized as follows: We summarize the experimental procedure in Sect. 2 and present the results in Sect. 3 before concluding with a discussion in Sect. 4.

2 Experimental Design

Our identification strategy for different cognitive processes rests on analyzing RT data (Piovesan and Wengström 2009; Rand et al. 2012; Tinghög et al. 2013; Nielsen et al. 2014; Ubeda 2014). These data have been collected alongside a previous experiment and exhibit several unique features that render them particularly suited for our purposes here. Among those are a large sample size, non-trivial financial stakes, and two consecutive observations per subjects that allow for a tight econometric control over unobserved individual factors that could otherwise bias the RT-contribution link. In the following paragraphs, we shall focus on the most important design features of the experiment. A more detailed description can be found in Diederich and Goeschl (2014).

2.1 Decision Task

In the experiment reported on in Diederich and Goeschl (2014), subjects made two consecutive dichotomous choices, deciding each time between receiving a monetary reward or providing a real public good.[6] The real public good took the form of a guaranteed and verifiable reduction of 1 metric ton of CO_2 emissions. Across all observations, there were slight

[6] Based on these choices, Diederich and Goeschl (2014) estimate a WTP for the voluntary contribution to emissions reductions and investigate determinants of the contribution decision while the present paper uses the RT data obtained by the same experiment to explore the underlying cognitive processes.

variations in the specific terms of the emissions reduction while retaining the basic design of receiving a personal monetary reward versus contributing to a public good.[7]

The treatment condition in the online experiment consisted of randomly assigning subjects to different monetary rewards. For each subject and each of the two choice situations, the reward was independently drawn from a uniform distribution of even integers between €2 and €100.[8] As a result, the data set contains significant between-subjects and within-subjects variation with respect to the trade-off between own interest (size of the monetary reward) and providing the public good. This variation forms the basis of robustness checks in our analysis, among them a check for the hypothesis that RT is determined by the degree of cognitive difficulty of the decision situation, rather than the cognitive system used (Krajbich et al. 2014; Evans et al. 2015; Krajbich et al. 2015). One potential issue with employing varying monetary rewards is that this could give rise to field price censoring (Harrison and List 2004): Participants who would otherwise have chosen to cooperate might choose the monetary reward instead, as they believe that they are able to provide an equivalent reduction of CO_2 emissions at a lower total cost. Based on different robustness checks discussed in Sect. 3.3 we conclude that our results are not affected by this potential confounding factor.

2.2 General Procedures

The experiment was conducted between May and July 2010 in collaboration with the large online polling organization 'YouGov'. Subjects were recruited from their existing panel of 65,000 members via e-mail. After following the invitation link participants reached an introduction screen. This screen explained, as common with the pollster's regular surveys, the thematic focus of the poll and the expected duration (10 min). Participants then faced a sequence of 10 to 13 computer screens, two of which were "decision screens" that required a choice between either a personal monetary payoff or a public good contribution. Each decision screen presented, through radio buttons, the binary choice between the public goods contribution ("reduction in CO_2 emissions of one metric ton") and the specific monetary reward (e.g."€46") that had been drawn for the subject in this decision, with the order of the cash and contribution button randomly assigned. There was no default and subjects clicked on the desired radio button and on a "proceed" button directly underneath. Before the first decision screen an information screen introduced the specifics of the choice situation.

The RT data for the present analysis contain, for each subject, a measure of the time they spent on each of the two "decision screens" that form the core of the experiment. For each decision screen, a subject's RT is defined as the time between entering that screen and clicking on the "proceed" button.

Participants' payoff at the end of the experiment was determined through a random incentive system (Grether and Plott 1979; Starmer and Sugden 1991; Lee 2008) with odds of one in fifty that the actual choice on each of the two decision screens was implemented.[9] This payment procedure was explained to subjects on the introduction screen as taking part in

[7] There were four variations in total. For example, in some conditions, a contribution decision was made public after the session. Session effects are therefore explicitly included when analyzing pooled data in Sect. 3. The main relationship between response times and contribution behavior is unaffected by the different variations.

[8] For each of the 50 reward categories, there are between 56 and 83 observations.

[9] Our design strived to present the experiment as indistinguishable from other YouGov polls as possible. These efforts included payment type and height (the polling company usually incentivizes panel members participating in a poll through either a piece-rate reward of approximately €1 for 20 min expected survey time or random lottery prizes, e.g. in the form of shopping vouchers), layout, and language of common questions on sociodemographics.

a lottery. This between-subjects random incentive system (Tversky and Kahneman 1981; Abdellaoui et al. 2011; Baltussen et al. 2012) decreases expected earnings, yet it is incentive compatible by ensuring that the conditional choice between the two options remains at face value.

2.3 Subject Pool

The sample of subjects was drawn from the representative subject pool of the online pollster 'YouGov'. This recruitment strategy provides two distinct advantages with regard to the research question, in particular vis-à-vis online labor markets (e.g. Amazon Mechanical Turk) that have become popular tools for running internet experiments (Paolacci et al. 2010; Buhrmester et al. 2011). First, as 'YouGov' is predominantly used for conducting surveys rather than experiments, the subject pool has little experience with standard experimental paradigms. This is important in light of evidence documenting the moderating effect of participants' experience on the relationship between RTs and cooperation (Rand et al. 2014). Second, there may be a concern that participants in online labor markets rush through a large number of consecutive surveys and tasks in order to increase their hourly compensation. Arguably, this could result in lower data quality by uninformed decision making. In case of 'YouGov', subjects can only take part in one survey at a time and only upon receiving an invitation by email message. The 3483 subjects analyzed here are a representative sample of the internet-using voting-age population of Germany.[10]

3 Results

3.1 Included Subjects

Panel A of Fig. 1 shows that RTs collected on the first decision screen follow a highly skewed distribution: 99 % of the study population decide within 115 s, yet among the remaining 1 % there are RT outliers of up to 75 min. These outliers likely result from subjects leaving the screen or the computer during the experiment to return to the decision screen later. Such RT outliers are not informative about the length of the decision process and potentially bias statistical results. Hence, for the results shown below, we exclude all participants that spent more than 300 s on the decision screen. The resulting RT distribution is displayed in panel B of Fig. 1. All core results we present below do not depend on the cutoff criterion, as tests for alternative cutoffs at 30, 60, 120, 180, 240, and 500 s and no cutoff demonstrate.

3.2 Response Times and Behavior

The recent experimental literature hypothesizes that a link exists between an observed contribution decision and the time it took to reach that decision, which is seen as an indicator for the decision system responsible. For a first look at the data, we follow Rubinstein (2007, 2013) and Piovesan and Wengström (2009) and classify each decision into one of four categories according to its percentile in the RT distributions: very fast (fastest 10 %), fast (10–50 %),

[10] We tested for difference to the general population of German voters: Using two-sided t tests, we reject the hypothesis that the means of socio-demographic characteristics coincide at the 1 % level. Our subjects are slightly more likely to be male, younger, and educated than the average German of voting age. Income is self-reported, and therefore the lower average income in the sample is unsurprising. Compared to the full set of subjects who finished the experiment, we exclude observations with missing values in one or more of the variables used in Sect. 3.

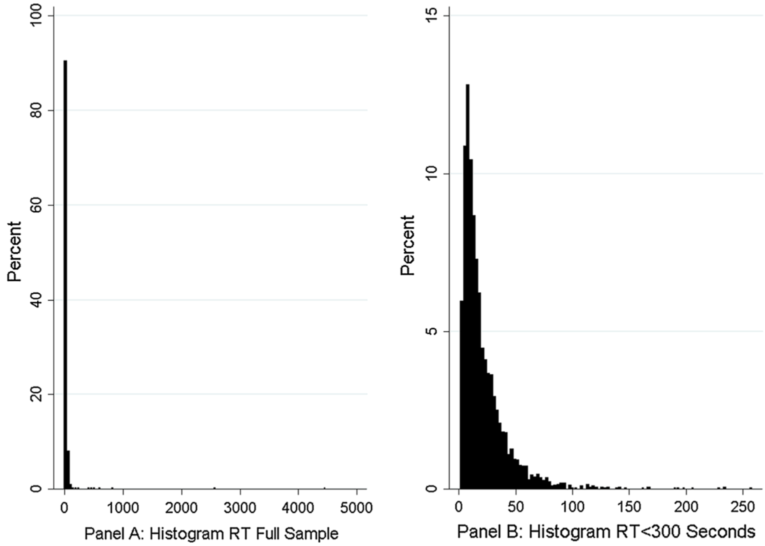

Fig. 1 Histogram of response times
Notes: This figure shows the distribution of the RT variable for Decision 1. RT from Decision 2 follow a comparable pattern. Panel A on the left shows the distribution for all participants. Panel B zooms in on a restricted sample of participants deciding within a]0; 300] s interval. Clearly data follow an exponential distribution and are hence log transformed for further analysis

Table 1 Categorization of response times

Category	N	Reaction time (s) Mean (SD)	Fraction of contributors Mean (SD)
Decision 1			
Very fast	349	4.17 (0.91)	0.088 (0.28)
Fast	1393	10.01 (2.70)	0.128 (0.33)
Slow	1393	26.06 (8.16)	0.203 (0.40)
Very slow	349	70.02 (31.95)	0.347 (0.48)
Decision 2			
Very fast	349	4.13 (1.07)	0.140 (0.35)
Fast	1393	10.36 (2.68)	0.234 (0.42)
Slow	1393	24.81 (7.52)	0.234 (0.42)
Very slow	349	65.67 (34.57)	0.300 (0.46)

This table shows mean RT and associated choices collected on both decision screens. Decision makers are categorized according to their relative decision speed

slow (50–90 %) and very slow (slowest 10 %). Table 1 summarizes, for each of the two subsequent decision screens, the descriptive statistics of the four RT categories and the associated contribution behavior. The average subject spends 21.84 (median = 15.09) s on the first and 21.05 (median = 15.16) s on the second decision screen.[11]

[11] Given these relatively small average RTs it seems unlikely that our observed effects are driven by subjects who leave the decision screen in order to search the internet for additional information on the public good.

Evidently, these RTs vary substantially between the four categories. At the first decision screen (Decision 1), subjects in the fastest category responded on average within 4 s (median = 4.28 s), while subjects in the slowest category took more than 1 min (median = 59.59 s). At the second decision screen (Decision 2), average RTs are similar, but hint at a slight acceleration of decision-making relative to Decision 1. Table 1 also reports the share of contributors for each RT category. Overall, 17 % of subjects chose to contribute in Decision 1, 23 % in Decision 2. Comparing, for each decision situation, the share of contributors across the four RT categories, we find a positive relationship between response time and contributions that is confirmed by statistical tests. In Decision 1, there are significant differences in contribution behavior between all RT categories (Chi^2-test: pairwise comparisons, $p < 0.05$). The difference is most pronounced between the fastest and the slowest group of subjects (Chi^2-test: $p < 0.001$, $\chi^2 = 68.48$): Among the fastest, only 8.8 % choose to contribute to the public good while among the slowest, a little more than 34 % of subjects do so. The relationship between RTs and contributions gets weaker in the second decision, as Table 1 shows. The difference between the fastest and the slowest group of subjects (14.0 % of contributors vs. 30.0 % of contributors) remains highly significant (Chi^2-test: $p < 0.001$, $\chi^2 = 26.12$). A pairwise comparison of the groups 'Fast' and 'Slow', however, does not yield a significant difference in contribution behavior (Chi^2-test: $p = 0.973$, $\chi^2 = 0.0012$).[12] To sum up, basic tests of correlation between RT categories and average contribution shares within each category are supportive of the hypothesis that faster, more intuitive decisions are associated with a lower probability of contributing while slower, more reflected decisions are associated with a higher probability. The correlation is strong when subjects encounter the choice for the first time and somewhat attenuated when the contribution choice is presented a second time. Before this result can stand, in the remainder of this section, we test and exclude several confounds and various alternative explanations for these substantial RT differences.

3.3 Robustness Checks

3.3.1 Categorization

Correlation tests that compare average contribution shares across categories can be sensitive to the method of categorization. The categorization in Sect. 3.2 relies on threshold values for the 10th, the 50th, and the 90th RT deciles as introduced by Rubinstein (2007, 2013) and Piovesan and Wengström (2009). Conceivably, a different choice of thresholds between categories could find different results.

To check for robustness to categorization choice, we examine the entire cumulative distribution function (CDF) of RTs for contributors and non-contributors (Rubinstein 2013) and find that the results do not depend on the specific categorization. For both decision screens, Fig. 2 shows two CDFs of deciding within t seconds, one for contributors $C(t)$ (grey dashed line) and one for those choosing the monetary reward $D(t)$ (black solid line). Inspecting the CDFs for Decision 1, $C(t)$ is consistently to the right of $D(t)$ over the full range of observed response times (t). This first-order stochastic dominance represents clear evidence that it takes longer for subjects to contribute than to behave selfishly (Rubinstein 2013).[13] Inspecting the CDFs for Decision 2, defecting again stochastically dominates contributing,

[12] We show below that part of this moderation can be attributed to those subjects who contribute in the first decision and do not change their behavior in the second decision.

[13] A CDF $C(t)$ of the action c is said to stochastically dominate a CDF $D(t)$ of the action d if $D(t) \geq C(t) \forall t$.

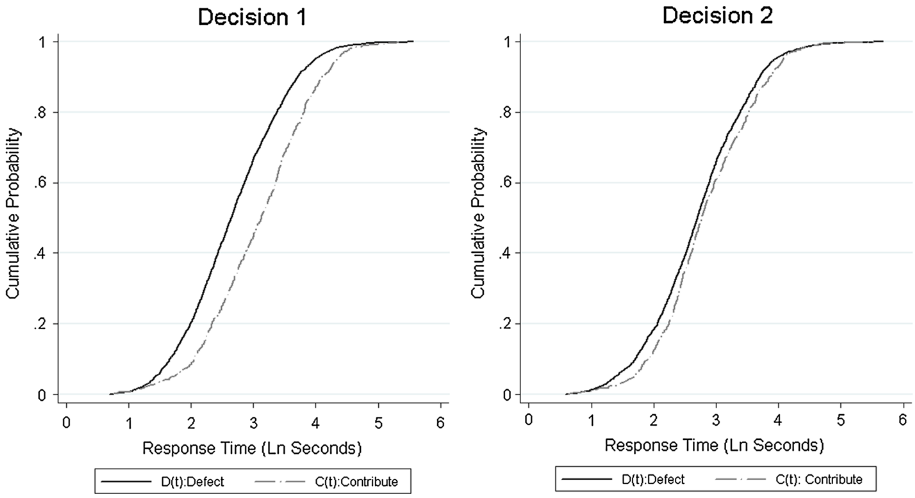

Fig. 2 CDF of response times separate for contributors and non-contributors
Notes: This figure shows the cumulative distribution function of response times separately for non-contributors (*black solid line*) and contributors (*gray dashed line*). The *left panel* shows data collected on the first decision screen and the *right panel* data collected on the second decision screen

but the difference between the CDFs is smaller. This indicates that the relationship between RTs and contributions, while still present, is weaker in the second decision and thus, supports the evidence in Sect. 3.2.

3.3.2 Individual Heterogeneity

RTs are a noisy proxy for identifying intuition or reflection (Rubinstein 2007, 2013). The present experiment responds to the resultant sample size requirement with observations from almost 3500 subjects. However, this large subject pool is highly diverse in terms of its demographic background and is exposed to variations in price and contribution characteristics within the experiment. Furthermore, RT collected on the decision screen might not only capture whether the decision was made intuitively but could also depend on participants' understanding of the task and their general swiftness in handling the survey software (Cappelen et al. 2015). This requires refining the simple analysis above in order to check whether differences in RTs are driven by differences in certain subject characteristics (such as age), by subjects' understanding and swiftness, or by treatment conditions (such as a high price) rather than differences in the use of decision systems. Table 2 reports the results of an OLS regression analysis of RT data in which we control for the presence of these potential confounding factors. Specifications (1)–(3) contain estimates for Decision 1 while specifications (4)–(6) report the corresponding estimates for Decision 2. Summarizing ahead of a more detailed discussion, the positive relationship between RT and contribution behavior turns out to be robust to the potential confounds examined here.

For the first decision, Table 2 reports the regression results for three different specifications. Specification (1) regresses the logarithm of RT as a function of the binary contribution decision and the monetary reward (price). An inspection of the coefficient for the contribution variable shows that a contributor took on average approximately 40 % more time to reach a decision than a non-contributor. The coefficient for the randomly allocated monetary reward

Table 2 Regression of reaction times

	Decision 1			Decision 2		
	(1) Ln(RT1)	(2) Ln(RT1)	(3) Ln(RT1)	(4) Ln(RT2)	(5) Ln(RT2)	(6) Ln(RT2)
Contributor (1 = yes; 0 = no)	0.393****	0.371****	0.306****	0.131****	0.124****	0.082***
	(11.02)	(10.16)	(8.56)	(4.38)	(4.00)	(2.71)
Price (euro)	0.00002	−0.0001	−0.0003	0.001**	0.001**	0.001**
	(0.04)	(−0.27)	(−0.80)	(2.32)	(2.33)	(2.23)
Age (years)		0.0063****	0.005****		0.009****	0.008****
		(6.50)	(5.47)		(9.90)	(9.09)
Education (cat. 1–11)		−0.0146**	−0.0123*		0.006	0.009
		(−2.14)	(−1.92)		(0.98)	(1.42)
Income (cat. 1–11)		−0.0204****	−0.017****		−0.022****	−0.019****
		(−3.75)	(−3.30)		(−4.02)	(−3.68)
Female (1 = yes; 0 = no)		−0.028	−0.027		−0.022	−0.019
		(−1.01)	(−1.05)		(−0.80)	(−0.76)
Time introduction screen (s)		0.00001	−0.0003**		−0.00005*	−0.0004***
		(0.35)	(−2.01)		(−1.66)	(−2.76)
Time information screen (s)		0.0004**	0.007****		0.0004***	0.006****
		(2.36)	(21.53)		(2.71)	(7.03)
Personal benefit (Cat. 1–4)		−0.0483***	−0.0327**		−0.125****	−0.112****
		(−2.73)	(−2.00)		(−7.38)	(−6.88)
Next generation benefit (cat. 1–4)		0.0768****	0.0550***		0.125****	0.110****
		(4.18)	(3.20)		(7.09)	(6.37)
Constant	2.617****	2.440****	2.294****	2.605****	2.136****	1.999****
	(83.37)	(28.04)	(26.13)	(135.64)	(26.98)	(25.56)

Table 2 continued

	Decision 1			Decision 2		
	(1) Ln(RT1)	(2) Ln(RT1)	(3) Ln(RT1)	(4) Ln(RT2)	(5) Ln(RT2)	(6) Ln(RT2)
Observations	3483	3483	3456	3483	3483	3458
R^2	0.053	0.081	0.185	0.04	0.09	0.1765
Prob> F	0.000	0.000	0.000	0.000	0.000	0.0000

OLS regression. t-statistics in parentheses. Robust standard errors. Session dummies included to control for the four conditions under which the contribution decision was taken. The dependent variable is RT on decision screen 1 [specifications (1)–(3)] or decision screen 2 [specifications (4)–(6)] in ln seconds. As the distribution of reaction times is close to an exponential distribution (see panel B of Fig. 1), a logarithmic transformation is applied to normalize the dependent variable. The results presented here hold also with untransformed RT. The last specification (3 or 6 respectively) serves as a robustness check for potential outliers, by excluding observations with a high leverage ($L > (2*k+2)/N$). All main results continue to hold when we jointly estimate Decision 1 and Decision 2 regressions in a SURE framework that accounts for potential correlation of the error terms

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$; **** $p < 0.001$

(price) is not significant: Subjects' RT is unrelated to the amount of money they have to give up for the environmental good, which argues against the idea that participants expend more cognitive effort when the stakes are higher.

Specification (2) adds demographic controls to the analysis, but finds little change in the fundamental relationship between RTs and contribution behavior. As expected, RT increases with age and decreases with education status and income. To proxy for individual variations in general reading and computer handling speed, we use the time spent on the relatively text-intensive introduction screen of the experiment, but find no evidence of a significant relationship with the RT at the decision screen. As a further control variable, we also use the time spent on the information screen. Since this screen contained some details that would become actionable on the decision screen, subjects could conceivably start the decision process before reaching the decision screen, resulting in a negative correlation with our RT measure. Testing this possibility, we indeed find a significant relationship, but it is both quantitatively small[14] and works in the opposite direction: Subjects who spent more time on the information screen tend to also spend more time on the actual decision screen.[15] Specification (2) also includes two variables from the post-experimental survey measuring subjects' attitudes regarding the benefits of CO_2 reductions for themselves and for future generations. We find that these variables relate to RT in a significant way. The relationship mirrors the observed relationship between RTs and the decision to contribute: RT decreases with the strength with which subjects believe that a contribution generates personal benefits, but increases with the strength with which subjects believe that a contribution generates benefits to the next generation. In other words, the more a subject believes that the consequences of the decision affect others, the more likely it is that reflection is involved in the decision.

Specification (3) checks how sensitive the coefficient estimates are to outliers. It excludes observations that display a high leverage when running regression diagnostics after specification (2). The high leverage is mainly driven by a few observations that stand out for the long time spent on the introduction or information screen. Overall 27 observations are discarded. The main relationship between RT and contributions is robust to this change, with an increase in contributors' response time of 31 %. The coefficients for time spent on introduction or information screen gain both in magnitude and significance.

Specifications (4)–(6) in Table 2 contain the corresponding analysis of RT data from Decision 2. Specification (4) reaffirms a highly significant and positive relationship between the contribution decision and RT. In contrast to the first decision, the RT differences are now smaller, but contributing still increases the RT by 13 %. Decisions are now also significantly slower when a higher monetary reward is at stake, even though this effect remains quantitatively small. In Table 3 we show that some of this effect could be driven by the difference between the monetary rewards subjects face in the first and the second decision. Specification (5) demonstrates that the link between RT and the second contribution decision is robust to the inclusion of the same controls considered in the first decision. Similarly, excluding potential outliers in specification (6) does not affect the significance of the main effect, albeit its size is slightly reduced.

The evidence on a positive relationship between RT and contributing in the second decision, as reported in Table 2, contains one obvious complication: since Decision 2 is taken

[14] One additional second spent on the information screen increases RT by an average of 0.04 %.

[15] As a further robustness check instead of controlling for the time spent on the information screen within the regression, we use the total time spent on both information and decision screen as a dependent variable. We still find a significant difference between contributors and defectors. One interpretation is that subjects who are more oriented towards pro-social goals spent more time acquiring information on how their decision could affect others. Fiedler et al. (2013) provide evidence along these lines.

Table 3 Regression of response times Decision 2 accounting for Decision 1 behavior

	(1) (LN RT 2)	(2) (LN RT 2)
Contributor Decision 2 (1 = yes; 0 = no)	0.265****	0.191***
	(5.74)	(3.02)
Contributor Decision 1 (1 = yes; 0 = no)	0.189**	−0.079*
	(2.57)	(−1.70)
Interaction (contrib1 × contrib2)	−0.407****	
	(−4.52)	
Negative difference price (p2 − p1 < 0)	−0.0006	−0.001*
	(−1.07)	(−1.74)
Positive difference price (p2 − p1 > 0)	0.003****	0.003****
	(3.57)	(3.38)
Interaction (Neg. price diff × contrib2)		0.001
		(1.03)
Interaction (positive price diff × contrib2)		0.0004
		(0.21)
Demographic controls	Yes	Yes
Constant	2.112****	2.111****
	(26.46)	(26.21)
Observations	3483	3483
R^2	0.10	0.09
Prob > F	0.000	0.000

OLS regression. t-statistics in parentheses. Robust standard errors. Session dummies included to control for the four conditions under which the contribution decision was taken. The dependent variable is RT on decision screen 2 in ln seconds. The same results emerge from an alternative specification in which we estimate separate regressions for Decision 1 contributors and non-contributors
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$; **** $p < 0.001$

subsequent to Decision 1, subjects have already taken a decision once, have therefore greater familiarity with the public good offered, and have seen a specific monetary reward. Table 3 takes these concerns into account and contains an additional robustness check for the link between RT and contributions in Decision 2 by explicitly including control variables for behavior and prices from Decision 1. Again, the main result is that the link between RT and contributions remains positive and significant, as we now explain in more detail.

Specification (1) in Table 3 contains the same demographic controls of specification (5) in Table 2. Furthermore, it includes variables capturing subjects' prior experience in Decision 1. One pair of variables captures the effect of having contributed in Decision 1 and of contributing in both decisions (through the interaction term), relative to a baseline of contributing in neither. A second pair measures by how much the cost of contributing has increased or decreased relative to the first decision, allowing for a possible asymmetry in the magnitude of the response. On the contribution decision, we find that average RT is 26 % higher for those who contribute in Decision 2 for the first time and 4.7 % higher for those who contribute in both decisions.[16] Subjects who do not change behavior between both decisions

[16] This estimate is the sum of coefficients from contribution decisions 1 and 2 minus the coefficient of the interaction term.

spend less time on the second decision screen and even more so, if their first choice was to defect. Among subjects who change their choice from Decision 1 to Decision 2, the average increase in RT is higher for those subjects that change from defecting to contributing than for those that change from contributing to defecting. This provides additional support for the general finding that the decision to defect requires less reflection. We will follow up on this result in Sect. 3.4. On the cost of contributing, we find that exogenously changing the contribution cost has an asymmetric effect on RT. While increases in contribution costs from Decision 1 to Decision 2 are associated with significantly higher RTs, decreasing costs are not significantly associated with lower RTs.

Specification (2) in Table 3 examines the possibility of an interaction between the change in price and contribution behavior in the second decision. The insignificant interaction terms show that the effects of a price increase or decrease affect contributors and non contributors in a uniform way. While the main effect of an increase in the announced price of the contribution does not change in size or significance, a falling price now results in a (weakly) significant negative effect on RT.

3.3.3 Field Price Censoring and Response Time Outliers

Two further factors could conceivably compromise the link between observed RTs and choices as correlates of cognitive processes and cooperation. One is the possible presence of field-price censoring (FPC): subjects with cooperative intentions may choose the cash option because they know that the public good can be provided more cheaply in the field than in the experiment. Their choices would be erroneously classified as non-cooperative. The other is the possible presence of subjects with a strong earning motive. If present, some of the very fast decisions might not be due to intuitive decision making, but due to subjects' objective to maximize their hourly compensation by rushing through the questionnaire without paying attention to any details of the task. In this section we show via different robustness checks that our results are not driven by these potentially biasing factors.

Potential candidates for FPC are subjects for whom the randomly drawn monetary reward was higher than the prevailing market price for contributing to the public good in the field. FPC requires that a significant share of subjects is familiar with the field price. Yet the follow-up questionnaire reveals that only 17 % of the subjects in our experiment state a price that is close (±10 €) to actual field prices. Using these price estimates and other items from the follow-up questionnaire, we employ three different methods for identifying potentially field price censored subjects[17] and define subsamples that exclude potential instances of FPC. Repeating the analysis conducted in Sect. 3.3.2 for the three subsamples, Table 4 shows that irrespective of the specific method of identification, excluding these subjects does not affect our previous results. As an additional check, we repeat the same analysis with the subsample of subjects that faced a monetary reward that was equal or lower than the field price, excluding FPC as a possibility. Again, the results remain unchanged. By excluding subjects that are well informed about specific characteristics of the public good, one of the tests for FPC (specifically Method 3) can be used to explore a different interpretation of the evidence. This is that differences in RT might be driven by differences in familiarity with the public good rather than differences in altruistic tendencies. A separate analysis of well informed subjects, however, shows that they do not differ quantitatively in the relationship between RT and contributing ($\beta = 0.345$) from other subjects.

[17] For a more detailed description of each method, refer to Diederich and Goeschl (2013) and the notes of Table 4.

Table 4 Regression coefficients for the contribution dummy accounting for FPC

Decision 1 coefficient (SE)	Decision 2 coefficient (SE)
Method 1	
0.390 (0.0383)	0.129 (0.0332)
N = 2735	N = 2874
Method 2	
0.350 (0.0443)	0.119 (0.0369)
N = 2051	N = 2263
Method 3	
0.354 (0.0400)	0.104 (0.0341)
N = 2866	N = 286

This table shows regression coefficients of the contribution dummy when controlling for the full set of demographics and when excluding field-price censored subjects based on three different methods. Method 1 excludes all subjects stating in the questionnaire that they did not contribute because they belief that there are cheaper ways of mitigating CO_2. Method 2 excludes all subjects whose field-price estimate is lower than the monetary reward offered. Method 3 excludes all subjects whose field price estimate is in close vicinity (±10 €) of the actual field price

We already excluded subjects with very long RTs from the analysis because their RT is likely not indicative for the underlying cognitive process. Similarly, very fast RTs could not only be the result of intuitive decision making but also be an expression of a subject's goal to finish the survey as fast as possible out of boredom or to maximize the hourly compensation. If true, such subjects would consistently try to spend as little time as possible on every screen of the experiment. Using additional RT data from the introduction and information screen we find that only 31 subjects out of 3483 are consistently among the fastest 10 % and 169 subjects are among the fastest 25 % on each screen. These numbers indicate that only a negligible fraction of the total study population was actually trying to speed through the questionnaire. In further analyses we find that our results are robust to excluding these subjects.

3.3.4 Indifference, Indecision, and Response Times

The result that RT and contribution behavior is linked lends support to the conjecture that cognitive style matters for choice outcomes. However, there is also an alternative interpretation of our results. Rather than reflecting the underlying decision process, RTs could simply reflect the cognitive difficulty of coming to a binary decision when the two options on offer are of similar value to the subject. In this interpretation, those that have a strong preference for one of the options should on average be able to make a faster decision for the preferred option than those subjects who are close to indifference between the two options (Krajbich et al. 2014; Evans et al. 2015; Krajbich et al. 2015).

In the context of the present experiment, the conjecture of "indecision by indifference" would imply that subjects that are quoted a monetary reward that is sufficiently close to their maximum willingness to pay would find the decision more difficult and therefore require more time for a decision. Those, on the other hand, for whom the reward and the reservation price of contributing are far apart would find it easier and be able to make a fast decision. Which decision is easy depends, under this conjecture, on the reward: If the reward offered is low, the decision to contribute is easy and vice versa. By implication, the RT for contributors is predicted to be low when offered a low price and high when offered a high price while the RT of defectors is predicted to be high for low prices and low for high prices.

Table 5 Contribution dummy coefficient for five ascending price ranges

Price range	N	Coefficient (SE)
EUR 2–20	607	0.224 (0.073)
EUR 20–40	713	0.409 (0.084)
EUR 40–60	668	0.350 (0.086)
EUR 60–80	739	0.351 (0.083)
EUR 80–100	690	0.404 (0.078)

To test this prediction, we exploit the fact that in Decision 1, each subject faced a randomly drawn contribution cost in the range of €2–100. Given this random assignment, the testable hypothesis is that all other things equal, contributors should be faster than non-contributors at the lower end of the range while non-contributors should be faster than contributors at the upper end of the range. We implement this test by running specification (2) of the OLS regression model (Table 2) separately for five equally spaced subsets of the reward range between €2 and 100. This provides, for each of the five reward bands, a coefficient estimate of how the decision to contribute influences RT. As we discuss below, the prediction that the RT coefficients of a positive contribution decision are negative at low prices and positive at high prices, is not fulfilled. Even a weaker prediction, namely that RT coefficients increase monotonically for higher monetary rewards, is not fulfilled. We therefore find no support for the conjecture of "indecision by indifference" (Table 5).

In each of the five reward bands, there is a significantly positive relationship between being a contributor and longer RTs. Strikingly, the effect is also quantitatively comparable across reward ranges. To add robustness, we re-run specification (2) (Table 2), including an interaction term between the contribution dummy and the reward variable. We find that the main effect of the contribution dummy remains highly significant (Coeff. = 0.347; $p = 0.000$). The interaction term, predicted to be negative, is not significantly different from zero ($\beta = 0.0004833$; $p = 0.673$). The alternative interpretation that the difficulty of the decision situation rather than the underlying cognitive processes generates the evidence therefore has little support in the data. The caveat applies that other forms of preference uncertainty that we cannot test for in this way could also play a role in determining RT in our experiment.

3.4 Within-Subject Differences

The cross-sectional evidence in Sects. 3.2 and 3.3 points towards a strong and robust relationship between the decision system employed and contribution behavior. On average, subjects that are more likely to be relying on intuitive processes choose the monetary reward while those that are more likely to be relying on reflection choose to contribute to the public good. This finding holds irrespective of RT categorization and controlling for a variety of confounds. The finding can also not be explained by variations in RT resulting from 'indecision by indifference'. Cross-sectional evidence, however, cannot rule out the possibility that the identified correlation is driven by unobserved individual characteristics (e.g. preferences, beliefs, and knowledge regarding climate change).

We address the possible role of unobserved individual characteristics in the link between decision system and contribution choice by exploiting the fact that the online experiment elicited two consecutive contribution decisions and the corresponding RTs for each subject. As all characteristics (observed and unobserved) can confidently be assumed constant for the same individual, a within-subject change in RT that is related to a within-subject

Table 6 Switching behavior and reaction times

Decision 1	Decision 2	RT2–RT1	Observations
Contributor	Defector	−4.20	117
Defector	Contributor	1.52	309
	No switch	−0.89	3057

Table 7 Decision times first difference equation

	(1) OLS	(2) IV
First diff. contrib. (contrib2–contrib1)	0.0822** (1.99)	0.423** (2.11)
First diff. price (p2 − p1)	0.0001 (0.23)	
Constant		−0.037** (−1.98)
Observations	3483	3483
R^2	0.10	–
Prob > F	0.000	0.0350
First stage F	–	28.60

t statistics in parentheses; session dummies included
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$; **** $p < 0.001$

change in contribution behavior would provide strong evidence for the existence of a true relationship.

As a first step, Table 6 compares the changes in decision times for those 426 subjects (12 %) who change their contribution decision from Decision 1 to Decision 2 with those subjects who do not.[18] The results shows that we can recover the cross-sectional correlation between contribution decision and RTs also at the individual level: Subjects who switch from contributing to free-riding require on average 4.20 s less time for their second choice. In contrast, subjects who switch from free-riding to contributing require on average 1.52 s more to come to that decision. The difference is (weakly) significant at the 10 % level (Mann–Whitney-test: $p = 0.072$).

Table 7 presents the results of an analysis with full controls for changes in the incentive structure at the subject level. There, we estimate the effect of changing contribution behavior on RT in a first-difference estimation framework. This within-subject framework captures the potential effects of all observable time varying factors during the experiment while differencing eliminates potential biases due to observed and unobserved individual time-constant characteristics. Specification (1) reports the coefficient estimates for regressing a change in RT on a change in contribution behavior and a change in price. Table 7 shows that on average, the same subject takes 8.2 % more time for a contribution decision than for a free-riding decision, compared to a baseline of subjects that do not change their contribution behavior. Changing the monetary reward does not affect a change in reaction times. Under the premise that this analysis includes all time-varying factors between the two decisions,[19] this evidence

[18] Note, that roughly three quarters of those who switch, change their behavior from being a non-contributor to being a contributor. This would be expected if defection truly followed from a (potentially error prone) first impulse.

[19] Potential candidates for unobserved time-varying factors could be boredom or fatigue by the subjects. Their role can be considered minor in light of the fact that the median subject completed the experiment within 6 min.

can be restated to say that on average, more reflective decision-making is associated with more cooperative behavior for the same individual.

As an additional robustness check, specification (2) accounts for the possible omission of unobserved time varying factors that conceivably bias the results of specification (1). The strategy is to employ an IV estimation framework in which the exogenous variation in the monetary rewards through random assignment is used as a instrument for changes in the contribution behavior. The randomly drawn rewards are uncorrelated with any unobserved time-varying factors and, under the validity of the exclusion restriction, valid instruments by design (Smith 2013).[20] In this framework, the coefficient estimate reports a positive within-subjects relationship between switching to cooperation and RT that confirms the previous results at the individual level.

4 Conclusion

In this paper we analyze RT data from an online experiment on the choice between a monetary reward and the provision of a carbon emissions reduction, in order to answer the questions whether and which cognitive processes are involved in the decision to contribute to a real environmental public good. We detect a positive relationship between RT and contributions, which survives various robustness checks and attempts to find alternative explanations consistent with our data. Our analysis benefits from a number of favorable features of the unique dataset available to us. These include a large sample size and two consecutive choices, which enables us to exclude confounds due to omitted variables. Based on our analysis, there is strong evidence that reflection rather than intuition is associated with individuals' choice to contribute towards voluntary climate action.

Our finding that the extent to which subjects reflect about their choice is positively associated with the likelihood that their choice is pro-environmental raises a few important implications. For environmental economists, such as ourselves, it underlines an ongoing methodological concern among the community that the design of preference elicitation procedures, including the decision environment, framing, and other features, may systematically affect subjects' cognitive style and thereby their choice. There are also normative concerns. It has been proposed that intuitive choices might reveal less information on the true underlying preferences (Fischer and Hanley 2007). One important reason for this, which is also reflected in current experimental evidence (Rubinstein 2013; Recalde et al. 2014), could be that intuitive and less considered choices are more prone to suffer from decision error. Welfare economics is only beginning to provide guidance to the environmental economist for cases when "decision utility" and "experienced utility" no longer coincide for behavioral reasons (Chetty 2015). But it is an obvious area for future research in environmental economics whether the gap between decision utility and experienced utility is indeed larger for intuitive than for reflective choices about environmental goods. Within our framework, comparing differences in subjective satisfaction with the initial choice between those who choose fast and those who reflected about their choice could be a fruitful first step (Chetty 2015). Similarly, subjects could be given a chance to revise their initial choice upon giving them an opportunity to deliberate (Kahneman and Thaler 2006; Gilboa 2009). Both approaches might be informative for future research.

Finally, our findings also add to the ongoing discussion about the cognitive underpinnings of cooperation. In the language of this literature, we find that cooperative behavior in an online

[20] The first stage regression F statistic returns $F = 28.60$. This indicates that the instruments are not weak.

experiment on contributions to a real environmental public good is associated with reflective processes, both at the cross-sectional level and at the individual level. This adds to the evidence base of papers (Tinghög et al. 2013; Duffy and Smith 2014; Verkoeijen and Bouwmeester 2014; Martinsson et al. 2014) that have failed to replicate earlier, opposite findings. These findings were that social dilemma situations in which the decision to cooperate is costly, individuals employing intuitive processes are more likely to cooperate while those employing reflective processes are more likely to act selfishly (e.g. Rand et al. 2012, 2014; Zaki and Mitchell, 2013; Nielsen et al. 2014). There are at least three possible explanations why our design might lead to different findings. Suter and Hertwig (2011) highlight that the decision context is essential for triggering different mental processes. Voluntary mitigation choices, as in the present experiment, differ from public good contributions in standard lab experiments along several important dimensions, among them the marginal per capita return (MPCR). The MPCR for climate protection is low on account of the large number of potential beneficiaries and the temporal structure of climate change. This means that the appropriate experimental paradigm among laboratory experiments to compare our results to may well turn out to be the standard dictator game experiment where the dictator's private return of contributing a token is zero. The proper comparison would then be evidence on cognitive style and giving in dictator games. This evidence shows that giving is typically associated with reflective reasoning, and selfish behavior with intuitive processes (Piovesan and Wengström 2009; Fiedler et al. 2013; Ubeda 2014; Corgnet et al. 2015).[21] A second candidate explanation is the absence of strategic uncertainty in our experiment. Subjects in a standard public goods game face strategic uncertainty (e.g. Gangadharan and Nemes, 2009) as their own payoff depends on the strategic behavior of others. Subjects in our experiment have complete control over their own monetary payoff. A third explanation are differences in the psychological distance between participants and thus the degree of empathy towards the potential beneficiaries of a contribution. Different cognitive processes are found to favor giving behavior depending on the psychological distance between the recipient and the potential contributor (Small and Loewenstein 2003; Loewenstein and Small 2007; Small et al. March 2007; Ein-Gar and Levontin 2013). Compared to lab experiments in which cooperation can emerge among a close group of fellow students, potential beneficiaries of climate change mitigation are a highly dispersed group that is temporally and spatially more distant from the participants in our experiment. All three reasons will require further experimental work in order to gauge their ability to reconcile these conflicting findings.

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Appendix: Instructions

Original in German available from the authors on request. Translated instructions for the relevant screens (screen-shots below) and treatments. Further information regarding the procedures available in Diederich and Goeschl (2013).

[21] This result is especially pronounces if no fifty-fifty split is possible. For deviating results, see Schulz et al. (2014) and Cappelen et al. (2015).

Introduction Screen

Dear participants,
We would like to invite you to participate in two lotteries and to answer some questions about CO_2-emissions and climate change. Your participation will take approximately 10 min. In the lotteries, you have the chance to win points worth up to a three-digit amount in Euros. As usual, all your information will be treated confidentially.

Information Screen

In the lotteries, you may choose between the following two prizes:

- A cash prize in points
  or
- the reduction of carbon (CO_2) emissions by 1 ton

How will the reduction of the CO_2 emissions take place? We will make use of a reliable opportunity provided by the EU emissions trading system: We will purchase and delete an EU emissions allowance for you. Emissions allowances are needed by power plants and other large installations within the EU in order to be allowed to emit CO_2. Since there is only a fixed overall amount of allowances in place, deleted ones are no longer available to facilitate emissions. Emissions in Germany and other EU countries decrease by exactly one ton through one deleted allowance. Because of the way in which CO_2 mixes in the air, it does not matter for the effect on the climate where CO_2 emissions are reduced. What counts is only total emissions worldwide. In the lotteries, 100 winners will be randomly selected out of about 5.000 participants. The following two lotteries may differ in the prizes offered as well as in the payoff procedures.

Decision Screen

Order of prizes randomized.

In this lottery, you have the choice between the two prizes listed below:

If you choose the cash amount and win, then the corresponding amount of points will be transferred to your points account within the next few days. All winners will receive a short notification email.

For every winner who chooses the emissions reduction one additional allowance will be deleted. Winners will receive a short notification email containing a hyperlink to Heidelberg University web pages where they can reliably verify the deletion.

Please choose now, which prize you prefer if drawn as winner:

- (*Radiobutton*) The reduction of CO_2 emissions by one ton through the deletion of one EU emissions allowance
- (*Radiobutton*) "Random Cash Price" Euro in bonus points.

Follow Up Questions Used

- Do you think that you will personally benefit from positive effects of reduced CO_2 emissions (for example from the mitigation of climate change)?
- Do you think that future generations in Germany (for instance your children and grand-children) will benefit if climate change mitigating CO_2 emissions reductions are undertaken in the present time?

Screenshots of German Version

See Figs. 3 and 4.

YouGov What the world thinks

18%

Bei den beiden folgenden Verlosungen dürfen Sie jeweils zwischen zwei verschiedenen Gewinnen wählen. Diese sind:

Ein Bargeldgewinn in Form von Punkten

oder

die Senkung der Kohlendioxid (CO2) – Emissionen um 1 Tonne

Wie funktioniert die Senkung der CO2-Emissionen? Wir verwenden dazu eine zuverlässige Möglichkeit mit Hilfe des EU Emissionshandelssystems: Wir kaufen und löschen für Sie eine *EU Emissionsberechtigung*.
Emissionsberechtigungen werden in der EU von Kraftwerken und anderen großen Industrieanlagen benötigt, um CO2 ausstoßen zu dürfen. Da es nur eine feste Anzahl von Berechtigungen gibt, stehen gelöschte Berechtigungen nicht mehr zum Ausstoß von CO2 zur Verfügung.
Die Emissionen in Deutschland und den anderen EU-Ländern sinken durch eine gelöschte Berechtigung um genau 1 Tonne!

Durch die Art und Weise, wie sich CO2 in der Luft verteilt, macht es dabei für die Wirkung auf das Klima keinen Unterschied, wo auf der Welt CO2-Emissionen gesenkt werden. Es zählen nur die Gesamtemissionen weltweit.
Bei den Verlosungen werden 100 Gewinner auf etwa 5.000 Teilnehmern zufällig ausgewählt. Die beiden folgenden Verlosungen können sich in den Gewinnen sowie im Auszahlungsverfahren unterscheiden.

Fig. 3 Information screen

YouGov What the world thinks

20%

In dieser Verlosung haben Sie die Wahl zwischen den beiden unten stehenden Gewinnmöglichkeiten.

- Falls Sie den Geldbetrag wählen und gewinnen, erhalten Sie in den nächsten Tagen die entsprechenden Punkte automatisch auf Ihrem Punktekonto gutgeschrieben. Alle Gewinner erhalten dazu eine kurze Benachrichtigungs-E-Mail.

- Die Löschung der Emissionsberechtigungen erfolgt in dieser Verlosung für alle Gewinner in einem Sammelauftrag: Für jeden Gewinner, der die Senkung der Emissionen gewählt hat, wird eine Emissionsberechtigung mehr gelöscht. Die Gewinner erhalten eine Benachrichtigungs-E-Mail mit einem Weblink, über den sie die Löschung auf den Internetseiten der Universität Heidelberg zuverlässig nachvollziehen können.

Bitte wählen Sie nun aus, welchen Preis Sie in dieser Verlosung möchten, falls Sie als Gewinner gezogen werden:

○ Die Senkung der CO2-Emissionen um 1 Tonne durch Löschen einer EU Emissionsberechtigung

○ 46 Euro in Form von Bonuspunkten

Fig. 4 Decision screen

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