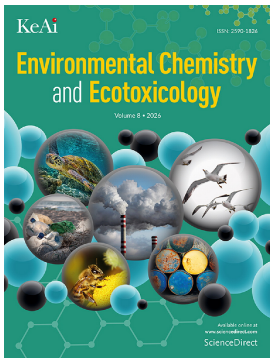
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Risk, time and social preferences shape cross-country support for carbon dioxide removal technologies

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Abstract

Technical innovations that remove carbon dioxide from the atmosphere are gaining attention to compensate for the insufficient pace of emissions reductions. Given the scale of carbon dioxide removal (CDR) deployment envisioned, there is a notable deficit in our understanding of the underlying predictors of public support of CDR, particularly in the global South. In economic theory, risk, time and social preferences serve as fundamental predictors of judgment and decision making. The current article thus undertakes a systematic examination of economic preferences and how they predict support for three CDR technologies (direct air capture, enhanced rock weathering, afforestation and reforestation). We employ experimentally validated instruments to examine how fundamental differences in individual tendencies to take risks, be patient or act pro-socially affect CDR support. Drawing on nationally representative surveys in five countries (n = 4,000 respondents from Brazil, China, Germany, Kenya, USA), we first establish how CDR support varies between technologies and countries, with support lower for novel CDR technologies and broadly higher for global South publics. To explain such differences, we reveal the relevance of economic preferences for CDR support, notably the positive predictive effects of risk-taking, altruism, and trust. We also indicate how the relevance of economic preferences varies across technologies and countries. Risk-taking, altruism and trust have stronger effects on novel, engineered CDR support, but positive reciprocity matters more for afforestation. The results stress the importance of economic preferences as core, under-explored predictors of

individual and cross-country variation in public support of CDR technologies.

Keywords: Economic preferences; Carbon dioxide removal; Public perceptions; Altruism; Risk; Climate change, Global South.

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1. Introduction

Technical innovations to remove carbon dioxide from the atmosphere, known as carbon dioxide removal (CDR), have become imperative as humanity's carbon budget dwindles (Riahi et al. 2022; IPCC 2023; Smith et al. 2024). Estimates from the IPCC (2023) suggest that upwards of 400 Gt of CO2 will need to be sequestered by the end of the century to limit warming to 1.5 degrees C – and to compensate for the insufficient pace of emissions reductions. Given the extent of climate damage already evident (Bastien-Olvera et al. 2024; Lenton et al. 2023), there is growing discussion about the need to be able to sequester annually as much as 10 Gt CO2 in the coming decades (IPCC 2023; Edenhofer et al. 2025a). Such scales vastly exceed what is now achievable (Lamb et al. 2024; Desport et al. 2024). Scale-up to such levels will moreover inevitably have to confront fundamental constraints regarding geologic storage potential, land use impacts, policy tradeoffs and integration challenges, patterns of social opposition, among others (Giddens et al. 2025; Yao et al. 2020; Mace et al. 2021; Sovacool et al. 2023; Stuart-Smith et al. 2023; Kazlou et al. 2024; Nawaz et al. 2025; Shindell and Rogelj 2025; Jia et al. 2025; Verbist et al. 2025).

Unlike the oft-nuanced level of discussion in academic research and climate and energy policy circles, CDR is hypothetical and widely unfamiliar to the public (Cox et al. 2020; Wolske et al. 2019; Baum et al. 2024). There are also substantive questions about the potential for backlash and controversy, especially for more novel engineered CDR methods (Low et al. 2022; Waller et al. 2025a, 2025b). Developing and implementing CDR at the scale envisioned requires the public to be engaged at an early stage and in an ongoing fashion (Fritz et al. 2024a, 2026; Hilser et al. 2024; Nawaz et al. 2024; Malakar et al. 2025; Smith et al. 2025; Scott-Buechler and Wang 2025).

Surveys are a useful tool to better understand how publics perceive and the extent to which they support such technologies, given that they offer large-scale, representative insights. Prior studies, crucially complemented by more qualitative, nuanced analysis (Fritz et al. 2024a; Low et al. 2024; Cox et al. 2022), illustrates how level of support varies between CDR technologies. Notably, there appears to be a level of provisional support for most CDR technologies (Wolske et al. 2019; Cox et al. 2020; Jobin and Siegrist 2020; Wenger et al. 2021; Bellamy 2022; Baum et al. 2024; Lee et al. 2025). At the same time, support is typically higher for conventional approaches, such as afforestation – or nature protection – instead of novel ones like direct air capture (Wolske et al. 2019; Jobin and Siegrist 2020; Wenger et al. 2021; Bellamy 2022; Merk

et al. 2023; Nawaz et al. 2023; Baum et al. 2024; Lee et al. 2025). Reasons for varying levels of support across individuals and countries, and differences in support across technologies, however, are not well understood.

To better understand CDR support, one can map public reactions to different CDR technologies directly onto risk, time, and social preferences, which are core dimensions of economic theory. First, CDR technologies differ in their perceived technological and environmental-related risks (Edenhofer et al. 2025b). Approaches like direct air capture and enhanced rock weathering are characterized by high technological uncertainty and potential environmental side-effects, while nature-based options like afforestation are broadly less risky. Risk-averse individuals might be less supportive of the novel CDR technologies. Second, CDR involves intertemporal trade-offs with costs incurred in the present and any climate benefits accruing only in the distant future (van der Spek et al. 2025; Desport et al. 2024). Individuals with higher discount rates who place less weight on future benefits may be less willing to support CDR. Third, most CDR technologies generate climate benefits that are globally shared (Smith et al. 2024; Edenhofer et al. 2025b). This can create a free-rider problem where each actor prefers others to bear any costs. Social preferences such as altruism and reciprocity can explain why individuals nevertheless support policies that support public goods whose benefits are shared. Individuals with strong pro-social preferences may thus be more supportive of CDR, despite its diffuse and globally shared benefits. In total, economic preferences might explain variation in CDR support across technologies. Moreover, there is also variation in economic preferences across the globe (Falk et al., 2018) which may be able to explain cross-country variation in support for CDR.

To date, however, no study has systematically investigated the role of economic preferences for CDR support while only a handful of survey studies have employed a cross-country design to examine and explain differences between countries and CDR technologies (Cox et al. 2020; Spence et al. 2021; Nawaz et al. 2023; Atris et al. 2025; Baum et al. 2024; Lee et al. 2025). Of these, only one study (Baum et al. 2024) includes countries from the global North and South – indeed, at the time of writing, only three studies explore CDR perceptions in the global South: two for Malaysia (Aziz et al. 2025; Cox et al. 2025), one for Japan, Taiwan, China (Atris et al. 2025). As such, there is a notable deficit in our understanding of public perceptions and support of CDR technologies in the global South and how they contrast with the better-studied global North. What emerges so far is that publics in the global South may be more supportive of CDR (Baum et al. 2024; Low et al. 2024, for counterpart focus groups). As such, more investigation

is needed into how perceptions of CDR may differ globally, including better understanding of the reasons underlying any such differences.

Here we use the experimentally validated instruments from Falk et al. (2018; 2023) to measure risk, time, and pro-social preferences (in the form of positive reciprocity, negative reciprocity, altruism, and trust), while drawing on cross-country, nationally representative surveys in five countries (n = 4,000, about 800 in: Brazil, China, Germany, Kenya, USA). We thereby highlight how economic preferences predict CDR support, and how these relationships vary between technologies and countries.

The results suggest that higher levels of risk-taking, altruism, and trust predict greater support for novel CDR (enhanced rock weathering, direct air capture), but positive reciprocity matters more for afforestation and reforestation. Risk-taking also predicts lower support for afforestation. Also, risk-taking, altruism, trust, and to a weaker extent negative reciprocity all explain cross-country differences in support for novel CDR, amounting to on average around 18% of such differences. Risk-taking, altruism, and positive reciprocity explain only about 9% of cross-country differences in support for afforestation.

In total, stable, fundamental economic preferences can provide key insights into CDR support, especially for novel CDR technologies, notably those more willing to take risks are more supportive of novel CDR in countries such as China, Brazil, and Germany, while altruistic and trusting respondents are generally more supportive of novel CDR across countries.

2. Background

2.1. Literature and research gaps

Regarding why some individuals are more supportive of CDR than others, several factors have been identified, such as climate change beliefs (Baum et al. 2024; Fritz et al. 2024b; Brutschin et al. 2024; Wolske et al. 2019; Merk et al. 2023; Satterfield et al. 2023; Scott-Buechler et al. 2024; Atris et al. 2025), concerns over messing with nature and negative environmental impacts (Cox et al. 2020, 2022; Wolske et al. 2019; Bellamy 2022; Merk et al. 2023; Nawaz et al. 2023; Baum et al. 2024); trust in scientists and responsible institutions (Brutschin et al. 2024; Jobin and Siegrist 2020; Wenger et al. 2021; Aziz et al. 2024; Scott-Buechler and Wang 2025); belief in science and technology as a climate solution (Baum et al. 2024; Brutschin et al. 2024; Spence et al. 2021; Atris et al. 2025; Aziz et al. 2024); and the importance of justice concerns (Cox et al. 2022; Scott-Buechler et al. 2024; Scott-Buechler and Wang 2025; Fritz et al. 2026).

Nonetheless, the understanding of what drives public support of CDR remains nascent, notably given the limited geographic focus of such research. So far, it is mostly climate-relevant factors which have received attention, though their importance tends to vary depending on the context and (technology) focus of the study (Fritz et al. 2024b; Brutschin et al. 2024). Meanwhile, the relevance of more stable, fundamental differences in individuals' tendencies to take risks, delay outcomes, and act pro-socially – often collectively referred to as economic preferences – have received little attention. Such a neglect of economic preferences represents a notable gap for several reasons.

First, there is rich evidence economic preferences can broadly predict behavior across multiple economic contexts (Falk et al. 2018, 2023) and pro-environmental and climate-related behavior (Schmitt et al. 2018; Schleich et al. 2019; Lades et al. 2021; Haverkamp et al. 2023; Andre et al. 2024; Engler et al. 2024; Qian et al. 2024; Baum et al. 2026; Nichols et al. 2026). Lades et al. (2021), for example, revealed that altruism predicts everyday pro-environmental behavior, while risk preferences, time preferences, and other types of social preferences do not. Similarly, a recent meta-analysis (Nichols et al. 2026) finds limited evidence for significant associations between economic preferences and sustainable behaviors.

There is also an emerging literature on associations between economic preferences and public support for environmental policies. For example, Goerg et al. (2025) found positive associations between public support for more ambitious climate policies and negative reciprocity, trust and, in some experimental treatments, altruism, patience, and risk-taking attitudes. Meanwhile, positive reciprocity and policy support are negatively correlated in their study. To better understand public support for CDR and how it may evolve in the future, we therefore argue that these deep-rooted preferences for risk, time and pro-sociality are a potential source of rich insight.

Second, there are obvious, though implicit, connections to the extant literature on the potential importance of risk, time, and social preferences for public perceptions and support of CDR. In general, decisions related to CDR are characterized by various types of intertemporal tradeoffs. For one, there is the question of how much to invest in climate mitigation, and bear the costs of doing so today, to avoid the ultimately greater costs in the future of not doing so. Concerning CDR, there is also the question of how much funding should be devoted from limited public budgets to such methods, potentially to the detriment of mitigation efforts. However, the role of time preferences in CDR support has not yet been investigated.

To the extent that economic preferences have been considered in the literature on CDR support, this has entailed looking at the perceived risks that are specific to CDR (Gregory et al. 2016; Wolske et al. 2019; Cox et al. 2020; Jobin and Siegrist 2020; Spence et al. 2021; Satterfield et al. 2023; Baum et al. 2024). In addition, the issue of "mitigation deterrence" or "moral hazard" has also received strong attention, namely in the limited experimental research undertaken (Austin and Converse 2021; Campbell-Arvai et al. 2017; Sol Hart et al. 2022; Sloot and Bostrom 2024). The importance of the individual tolerance of risk, however, has not yet been examined. The same is also true of altruism, reciprocity, and other kinds of social preferences – excepting the narrow version of trust that has been employed, i.e. in scientists and responsible institutions, not in other people and their intentions more broadly. Evidence for the importance of economic preferences (risk aversion, altruism, trust) on attitude formation has been revealed, however, for solar geoengineering (Merk and Pönitzsch 2017) and nuclear energy (Whitfield et al. 2009; De Groot et al. 2013).

Third, although some studies have shown that support for CDR differs across countries (Cox et al. 2020; Baum et al. 2024; Fritz et al. 2026), there is little understanding of the reasons for these differences. Thus, we argue that it is crucial to better understand cross-country differences in CDR support, given that such differences will inform which regions are more conducive and amenable to deployment. Furthermore, as detailed above, there is clear evidence that economic preferences differ across countries (Falk et al., 2018) and are relevant to CDR-related decisions. Economic preferences represent relatively stable individual characteristics that could influence both CDR support and other attitudes and beliefs – notably the climate-related beliefs that have received the most consideration in the literature.

Unlike such beliefs, or CDR support itself, economic preferences are less likely to be influenced by the ongoing policy debates in a country, thus positioning them as more structural or ultimate factors of decision-making which inform and help make sense of individual-level and cross-country differences in CDR support. Accordingly, we systematically investigate how much economic preferences measures explain cross-country differences in CDR support as well as whether there are meaningful differences regarding the importance of the various economic preferences.

2.2. Hypotheses

Based on the above literature, the current article undertakes a systematic examination of how six economic preferences (risk-taking, patience, altruism, positive and negative reciprocity, and

trust) predict support for three carbon removal technologies (direct air capture, enhanced rock weathering, afforestation and reforestation). It tests three pre-registered hypotheses:[1]

H1: Economic preferences predict support for carbon removal technologies.

H2: The associations between the six economic preference measures and the support variable differ across the three CDR technologies.

H3: Differences in support for carbon removal technologies across the five countries can be (partly) explained by the six economic preference measures.

3. Methods

3.1. Procedure and sample

The survey was designed to investigate the relationship between economic risk, time and social preferences and the support of Carbon Dioxide Removal (CDR) technologies. After some initial background about the focus of the survey, participants were asked either a question block on economic preferences, which was adapted from Falk et al. (2018), or about their and others' support for three CDR technologies (the order was randomly chosen). The CDR technologies were direct air capture, enhanced rock weathering, and afforestation and reforestation, and the order in which the three CDR technologies appeared was also randomized.

After these two question blocks, participants were asked about support for a set of twelve environmental policies, several questions about climate change beliefs and perceptions, and questions about socio-demographic characteristics (questions related to filling the quotas for age, gender, education, income, geographic area, and region in the country were asked at the start of survey). Questions within blocks with multiple items were generally randomized. The survey concluded with a final debriefing about the purposes of the survey, including an

[1] As can be seen in the pre-registration (hyperlink), we initially planned to also test whether differences in support for carbon removal technologies across the three technologies can (partly) be explained by the six economic preference measures. However, we ultimately determined that our data structure was not optimal to conduct this test, i.e. since expressed CDR support differs for individuals across the three technologies, while the six economic preference measures are stable for each individual. Moreover, due to space constraints we do not include a formal test of whether the associations between the six economic preference measures and the support variable differ across the five countries. This analysis is provided in SI.3. Finally, again owing to space constraints, we do not investigate differences in the measurement of CDR support in this article.

invitation for final comments. The full English version of the survey is available in the Supplementary Information.

To script and administer the survey, provide the sample of participants, and remunerate those who took part we contracted a professional survey firm, Norstat. Full and informed consent was provided by all participants before beginning the study. Upon successful survey completion, participants received their monetary compensation directly from Norstat. The survey was approved by the XXX. Pre-registration of the survey in the Open Science Foundation registry (XXX) was completed on August 23, 2025.

Nationally representative samples from five countries (Brazil, China, Germany, Kenya, United States of America) were collected from August 20th to September 12th, 2025, with the survey conducted in five languages (Portuguese in Brazil; simplified Mandarin in China; German in Germany; Swahili and English in Kenya; English in United States). Countries were selected to ensure that there is broad geographic representation with members from both the global North and global South, including emerging economies (Brazil, China) and developing economies (Kenya). Countries were also identified with heterogeneous profiles in terms of economic preferences, according to the results of Falk et al. (2018). We established quotas for each of the country samples to promote nationally representative data regarding age (at least 18), gender, geographic region, and geographic area (e.g. urban versus rural), with broad quotas for income and education (i.e. above and below median levels for the relevant country).

We have data from 4015 participants (after conducting quality checks). However, we dropped 15 participants due to missing data of the dependent variable; they answered three times with "don't know" when asked whether they support the three CDR technologies (see below). Hence, the final sample which is used for analyses consisted of 4000 participants, with 800 from Brazil, 799 from China, 802 from Germany, 804 from Kenya, and 795 from USA. Note that some participants did not answer all three support questions and hence some analyses are based on a subset of these 4000 participants.

We conducted several types of quality-control checks during fieldwork, which are explained in Supplementary Information SI.6. They included attention checks, comprehension checks after reading about each of the technologies, speeder and flatlining checks (providing the same response across several sequential items), and a verbatim check of open-ended responses and for (some) socio-demographic questions. By applying the checks, a total of 3,302 respondents were removed to attain the final sample (see Tables SI.16 and SI.17).

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3.2. Measures

Given that the current research focuses on associations between economic preferences and support for three CDR technologies (while controlling for numeracy and socio-demographic covariates), we provide further information on these variables and omit the discussion of others that are not relevant for the current analysis.

3.2.1. Support for CDR technologies

After having presented information about each of the CDR technologies (consisting of text and pictures, see Supplementary Information), the survey asked participants a series of questions related to CDR support. Here we focus on questions that asked participants how much they supported or opposed the CDR being developed and deployed in their country, using the actual name of the country (e.g. China or Brazil). They could answer on a scale from -50 (= Strongly oppose) to +50 (= Strongly support). There was also a mid-point (0, Neither oppose nor support), which was the set default before clicking, and a "Don't know" option for any wishing to opt out. Participants were required to click a value on the scale, even if to leave the value at 0; if they did not click at least once on the scale, an error message appeared to remind them to answer the question. Answers to this question are the main dependent variable in our survey.[2]

3.2.2. Economic preferences

Economic preferences of participants for risk-taking, patience, positive reciprocity, negative reciprocity, altruism, and trust were measured following Falk et al. (2018). Employing a mix of interdependent binary choice questions and Likert-scale response questions, their approach is designed to predict behavior in incentivized choice experiments. Falk et al. (2023) validated this approach by establishing how answers to the hypothetical questions correspond to choices from incentivized experimental behaviors. As in Falk et al. (2018), our survey asked respondents to answer as if the choices were paid out for real. The risk-taking measure, for instance, combines a sequence of hypothetical lottery choices, where people are asked to

[2] The survey also asked participants to indicate how much of a role the respective CDR technology should play in addressing climate change, how much they supported or opposed the CDR being developed and deployed *within their own community*, and whether they thought people in their community would support or oppose the CDR technology being developed and deployed *in their country/in their community*. The current paper does not analyse answers to these questions.

choose five times between a definite payment of a specified amount and a riskier (50% chance) but higher-paying option, and a self-assessment of their general willingness to take risks. Depending on how participants answered the first lottery choice, the next question would adjust the amount of this risker pay-off either upwards (if the risker option was chosen previously) or downwards (if the option of a definite payment was chosen). Participants also indicated their willingness to take risks in general on a Likert scale.

For time preferences (or "patience"), the participants were asked to choose between a definite payment and a higher amount (of different values) to be paid out in 12 months. As for risk preferences, the next choice in the sequence would have a higher amount for the delayed option if the definite payment was selected in the prior round, or a lower amount if not. Participants were also asked a single-item question about their general willingness to give up something beneficial today to benefit more in the future.

Both positive reciprocity and altruism were also examined using hypothetical choice situations, one in which participants were asked how valuable of a "thank you" gift they would give to a stranger who had helped them (for positive reciprocity), and the other about how much they would donate to a good cause if they unexpectedly received a certain amount of money (for altruism). Both measures also included a single-item counterpart about their broad willingness to return a favor (for positive reciprocity) or donate to good causes without expecting anything in return (for altruism). Negative reciprocity was assessed through three questions about their willingness to take revenge or punish unfair behavior from others; trust was assessed by a single-item question about the belief that people only have the best intentions.

The monetary values employed for the hypothetical choice situations, crucially, were adjusted to be in line with the median income level in the given country. For instance, the definite payment today for the hypothetical choice sequence for time preferences was set as: €100 in Germany; ¥100 in China; $150 in the United States; R$ 100 in Brazil; and KES 300 in Kenya. The values were adjusted, where necessary, with reference to data for median income or consumption per day from World Bank and Our World in Data (Hasell et al. 2022). All other values employed throughout the choice tasks were adjusted to a similar extent so that the nature of choices would remain comparable between countries but also similar valuable to participants irrespective of their country. Otherwise, there would be a risk that differences in the perceived values of the amounts may influence the underlying economic preferences, thereby introducing bias across countries.

For most measures, we computed the z-scores of the component items from the survey (at the individual level) across the whole sample. For the first measure of altruism (donation decision), we computed the z-score within each country separately because the variable could range from 0 to 1000 for Brazil, China, and Germany, 0 to 1500 for the USA, and 0 to 3000 for Kenya. We then took the weighted average of these scores using the weights of the experimental validation procedure from Falk et al. (2023). Following Falk et al. (2018), these weighted measures were then standardized again to obtain the final economic preference measures with a mean of zero and a standard deviation of one. An overview of the survey items and their relevant weights used to construct the preference measures is available in Table SI.1 in the Supplementary Information. We randomized the ordering of the blocks for the economic preference measures, so that they appeared either before or after the questions on CDR support. Additional analyses showed that this order did not have an effect on the preference measures, in line with the interpretation of economic preferences as stable individual characteristics.

3.3. Control variables

Age is a continuous variable in years; gender is coded as a dummy variable for female (versus male and other or "prefer not to say"); categorical variables for income and education are coded from lowest to highest, respectively, without interpreting each category as these two variables are coded differently for the different countries; geographic area is also coded categorically (living in rural areas, in a large city, small- to medium-sized city, or suburban areas); number of people living in household is coded continuously with the highest category for six or more; whether the participant self-identifies as a member of an indigenous group or ethnic minority (both coded as "yes", "no" or "prefer not to say"); and numeracy as a continuous variable. Numeracy was measured using the validated 3-item Subjective Numeracy Scale (SNS-3) by McNaughton et al. (2015) which is based on self-assessments of respondents. Descriptive statistics for the final sample which is used for all regression analysis are shown in Table 1.

Table 1: Descriptive statistics for country samples of respondents

	BRA	CHN	GER	KEN	USA	Total
Observations	800 (20.0%)	799 (20.0%)	802 (20.1%)	804 (20.1%)	795 (19.9%)	4,000 (100.0%)
Age	39.52 (14.50)	40.44 (14.45)	46.65 (16.09)	35.54 (13.37)	44.86 (16.36)	41.40 (15.50)
Female	0.52 (0.50)	0.49 (0.50)	0.51 (0.50)	0.50 (0.50)	0.51 (0.50)	0.50 (0.50)
Income						
1 (= Lowest)	48 (6.0%)	14 (1.8%)	77 (9.6%)	94 (11.7%)	153 (19.2%)	386 (9.7%)
2	87 (10.9%)	19 (2.4%)	96 (12.0%)	91 (11.3%)	163 (20.5%)	456 (11.4%)
3	68 (8.5%)	19 (2.4%)	152 (19.0%)	74 (9.2%)	132 (16.6%)	445 (11.1%)
4	70 (8.8%)	38 (4.8%)	125 (15.6%)	68 (8.5%)	76 (9.6%)	377 (9.4%)
5	97 (12.1%)	65 (8.1%)	134 (16.7%)	94 (11.7%)	93 (11.7%)	483 (12.1%)
6	100 (12.5%)	195 (24.4%)	105 (13.1%)	194 (24.1%)	153 (19.2%)	747 (18.7%)
7	110 (13.8%)	249 (31.2%)	0 (0.0%)	114 (14.2%)	0 (0.0%)	473 (11.8%)
8	119 (14.9%)	199 (24.9%)	0 (0.0%)	65 (8.1%)	0 (0.0%)	383 (9.6%)
9 (= Missing)	101 (12.6%)	1 (0.1%)	113 (14.1%)	10 (1.2%)	25 (3.1%)	250 (6.2%)
Education						
1 (= Lowest)	21 (2.6%)	165 (20.7%)	103 (12.8%)	53 (6.6%)	40 (5.0%)	382 (9.6%)
2	215 (26.9%)	131 (16.4%)	131 (16.3%)	232 (28.9%)	204 (25.7%)	913 (22.8%)
3	45 (5.6%)	418 (52.3%)	240 (29.9%)	488 (60.7%)	41 (5.2%)	1,232 (30.8%)
4	93 (11.6%)	63 (7.9%)	144 (18.0%)	31 (3.9%)	130 (16.4%)	461 (11.5%)
5	63 (7.9%)	22 (2.8%)	143 (17.8%)	0 (0.0%)	60 (7.5%)	288 (7.2%)
6	264 (33.0%)	0 (0.0%)	41 (5.1%)	0 (0.0%)	175 (22.0%)	480 (12.0%)
7	76 (9.5%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	121 (15.2%)	197 (4.9%)
8 (= Missing)	23 (2.9%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	24 (3.0%)	47 (1.2%)
Geographic Area						
Large City	583 (72.9%)	605 (75.7%)	226 (28.2%)	309 (38.4%)	294 (37.0%)	2,017 (50.4%)
Small or Mid-sized City	180 (22.5%)	149 (18.6%)	279 (34.8%)	263 (32.7%)	130 (16.4%)	1,001 (25.0%)
Suburban	25 (3.1%)	34 (4.3%)	100 (12.5%)	149 (18.5%)	228 (28.7%)	536 (13.4%)
Rural	12 (1.5%)	11 (1.4%)	197 (24.6%)	83 (10.3%)	143 (18.0%)	446 (11.2%)
People in Household	3.21 (1.18)	3.11 (1.06)	2.32 (1.19)	3.93 (1.47)	2.91 (1.41)	3.10 (1.37)
Ethnic Group						
Yes	17 (2.1%)	118 (14.8%)	26 (3.2%)	350 (43.5%)	111 (14.0%)	622 (15.6%)
No	781 (97.6%)	676 (84.6%)	752 (93.8%)	422 (52.5%)	663 (83.4%)	3,294 (82.3%)
Prefer Not To Say	2 (0.2%)	5 (0.6%)	24 (3.0%)	32 (4.0%)	21 (2.6%)	84 (2.1%)
Minority						
Yes	134 (16.8%)	48 (6.0%)	43 (5.4%)	226 (28.1%)	194 (24.4%)	645 (16.1%)
No	654 (81.8%)	750 (93.9%)	743 (92.6%)	543 (67.5%)	581 (73.1%)	3,271 (81.8%)
Prefer Not to Say	12 (1.5%)	1 (0.1%)	16 (2.0%)	35 (4.4%)	20 (2.5%)	84 (2.1%)
Numeracy	-0.03 (1.02)	0.11 (0.70)	-0.05 (0.97)	0.34 (0.93)	-0.38 (1.18)	0.00 (1.00)

Note: Income and education were coded differently across the 5 countries. For this table, we present education and income variables from lowest to highest without specifying the exact values. The lowest level is always the lowest one for which there are recorded values for a given country. Standard deviations in parentheses for age, gender, people in household, and numeracy. Percentages in parentheses for income, education, geographic area, ethnic group, and minority represent the percentage of each category within the country sample. Percentages in parentheses for number of observations (N) relate the country sample to the total sample.

3.4. Data analysis

We present the results in four steps. First, we show the descriptive statistics for CDR support across the three technologies and the five countries as well as the six economic preference measures across the five countries. Second, we test the pre-registered hypothesis that economic preferences predict support for carbon removal technologies. In particular, we test whether risk, time, and social preferences predict general CDR support, not differentiating between the three technologies for each of the five countries. Third, we do differentiate between the technologies

testing the pre-registered hypothesis that the associations between the six economic preference measures and the support variable differ across the three CDR technologies. Finally, we test the pre-registered hypothesis that differences in CDR support across countries can be (partly) explained by the six economic preference measures. To facilitate readability, we present the regression equations throughout the following section.

4. Results

4.1. CDR support across countries and technologies

First, we present the cross-country support for the three CDR technologies in Table 2 (see also Figure S.1 in SI.2). As shown, support for CDR technologies differed significantly between the three technologies and across countries. Across all countries, support (on a -50 to +50 scale) was highest for afforestation and reforestation (mean, M=37.93; standard deviation, SD=15.95) followed by enhanced rock weathering (M=17.59; SD=27.04) and direct air capture (M=14.68; SD=30.07). For CDR in general, support was highest in Kenya (M=31.14; SD=25.39) followed by Brazil (M=29.17; SD=25.94), China (M=24.15; SD=21.44) and United States (M=21.62; SD=26.67). Support was much lower in Germany (M=10.82; SD=30.74). The most-supported combination of technology and country is afforestation and reforestation in Kenya (M=45.32; SD=10.14), and the least-supported was direct air capture in Germany (M=-5.78; SD=28.72).

Given such differences, any increases in mean levels of support should be interpreted in relation to the baseline which exists, both for a given country or a particular technology. For instance, the same increase in support will have greater practical significance for less-supported technologies such as novel CDR (rather than afforestation) and in a country like Germany (cf. Brazil, Kenya) where overall support for novel CDR is lower. Similarly, looking at the standard deviations, we note that divergence of opinion is much lower for afforestation and reforestation, while generally higher for direct air capture. Some country-specific differences are apparent as well, notably, there is greater divergence for support of afforestation in the United States, while support for the novel CDR methods is less heterogeneous among Chinese participants. Such differences are crucial to consider for interpreting the practical significance of the associations between the economic preference measures and CDR support in the following sub-sections.

Table 2: Opposition and Support for the three CDR technologies across the five countries (on a -50 to +50 scale)

	BRA	CHN	GER	KEN	USA	Total
Afforestation and Reforestation	42.18 (13.98) 800	33.90 (14.07) 799	36.31 (16.35) 792	45.32 (10.14) 804	31.70 (19.59) 780	37.93 (15.95) 3,975
Direct Air Capture	21.52 (29.80) 787	18.79 (23.39) 787	-5.78 (28.72) 761	23.06 (29.12) 802	14.96 (29.56) 777	14.68 (30.07) 3,914
Enhanced Rock Weathering	23.54 (26.12) 778	19.62 (22.20) 789	0.74 (26.75) 749	25.00 (26.08) 803	18.15 (26.86) 772	17.59 (27.04) 3,891

Note: Opposition/support for the respective CDR technology is measured on a scale from -50 (Strongly oppose) to +50 (Strongly support), and a "Don't know" option is included. The rows represent the means, standard deviations, and number of observations for each country/CDR technology combination, respectively. The number of observations differ across the columns because participants could indicate that they did not have an opinion.

4.2. Economic preferences across countries

Table 3 provides the country-level breakdown of the final (weighted) economic preference measures that we use in the analysis. The table shows how the respective populations vary, in relation to standardized means for the sample population. Each economic preference measure has an overall mean of zero and standard deviation of 1 so that negative values indicate a weaker economic preference compared to the survey average. For instance, the sample of German participants is less risk-taking (-0.465), altruistic (-0.325), and trusting (-0.288) than others; it is overall the most patient (0.506) however. Conversely, sample participants in China are more risk-taking (0.379), trusting (0.336), and negatively reciprocal (0.539); next only to Germany, they are much less altruistic (-0.313). Figure SI.2 in the Supplementary Information gives distributions of the standardized measures of the economic preferences for the five countries.

Table 3. Country-level breakdown of the standardized means for economic preferences.

	BRA	CHN	GER	KEN	USA	Total
N	800	799	802	804	795	4000
Risk	-0.197 (0.961)	0.379 (1.077)	-0.465 (0.841)	0.245 (0.824)	0.038 (1.038)	0 (1)
Patience	0.013 (1.019)	0.091 (1.017)	0.506 (0.994)	-0.369 (0.809)	-0.241 (0.912)	0 (1)
Positive reciprocity	0.054 (0.886)	-0.074 (1.026)	-0.063 (0.920)	0.264 (1.020)	-0.184 (1.080)	0 (1)
Negative reciprocity	-0.041 (0.964)	0.539 (0.791)	-0.251 (0.940)	-0.259 (1.027)	0.016 (1.044)	0 (1)
Altruism	0.118 (0.944)	-0.313 (1.028)	-0.325 (1.118)	0.394 (0.752)	0.126 (0.924)	0 (1)
Trust	-0.045 (1.035)	0.336 (0.856)	-0.288 (0.912)	-0.109 (1.073)	0.108 (0.998)	0 (1)

4.3. Risk, time, and social preferences predict general CDR support

We next assessed the associations between the six economic preference measures and overall CDR support in the five countries without differentiating between CDR technologies. This tests

Hypothesis 1 (economic preferences predict support for carbon removal technologies). To do so, we estimated five (one for each country) linear OLS regression models in which we predicted the average CDR support across the three technologies (or a subset of these if participants did not provide data for all three technologies) by standardized measures of the six economic preferences (risk taking, patience, positive reciprocity, negative reciprocity, altruism, trust). We specified the following models:

$$CDRSupport_i = \beta_0 + \beta_1 R_i + \beta_2 P_i + \beta_3 PR_i + \beta_4 NR_i + \beta_5 A_i + \beta_6 T_i + \delta' X_i + \epsilon_i, \quad (1)$$

where $CDRSupport_i$ represents the average CDR support of individual i, and the six standardized economic preferences are indicated by *R* for risk attitudes, *P* for patience, *NR* for negative reciprocity, *PR* for positive reciprocity, *A* for altruism, and *T* for trust. The intercept across all individuals is represented by β_0, and the coefficients β_1 to β_6 represent the regression-controlled associations between CDR support and the six economic preference measures. We also included numeracy and socio-demographic variables as controls (age, gender, income categories, education categories, geographic area categories, number of people living in household, member of indigenous group, and member of ethnic minority, as described in Table 1). δ' depicts the vector of coefficients indicating the associations between the controls and CDR support. Standard errors (ϵ_i) were robust. As we simultaneously investigated whether six economic preferences predicted CDR support, we corrected for multiple comparisons using the Holm-Bonferroni method (Holm 1979), a sequential step-down approach that controls for the familywise error rate, in our case for the economic preference predictors. In the following, we therefore discuss only the coefficients that stay significant after these corrections. Table 4 presents the key results, Table SI.2 presents the full regression results including covariates, and the associations between the six economic preference measures and CDR technology support are illustrated in Figure 1.

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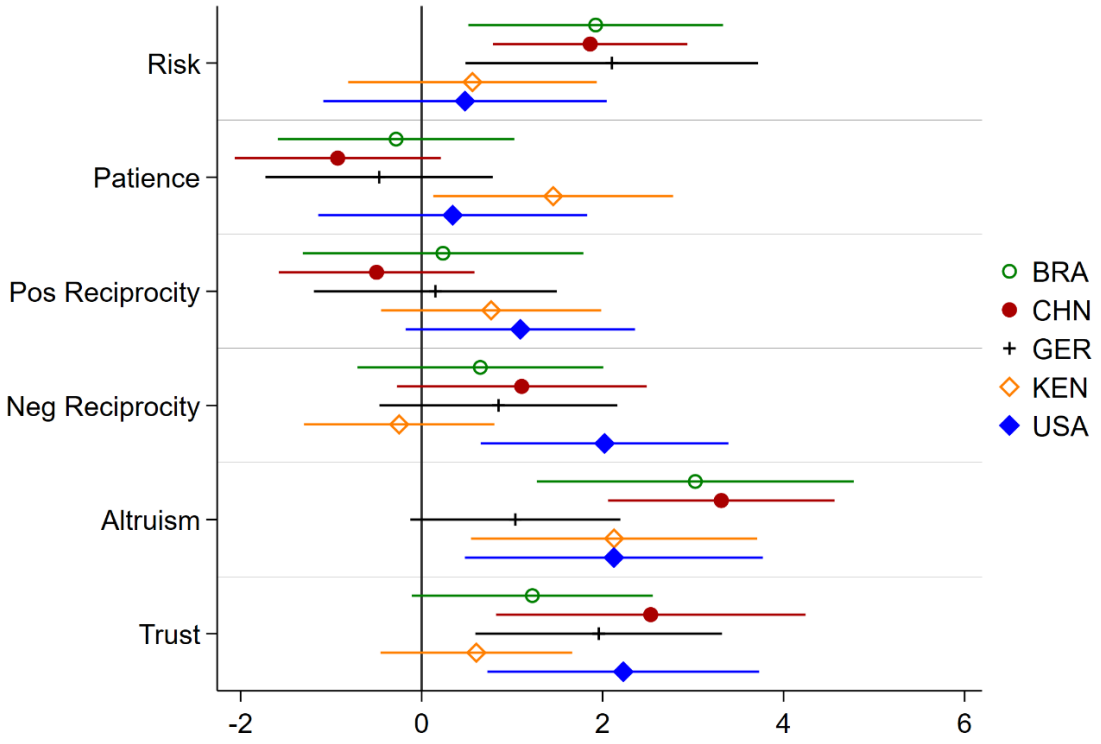


Figure 1. Associations between standardized measures of economic preferences and CDR support across countries.

Table 4. Associations between CDR support (averaged across the three technologies) and economic preferences from the linear OLS regression models.

	Average CDR Support				
VARIABLES	Brazil	China	Germany	Kenya	USA
Risk	1.923**†	1.863**†	2.102*	0.562	0.479
	(0.717)	(0.547)	(0.824)	(0.700)	(0.798)
Time	-0.282	-0.927	-0.470	1.454*	0.343
	(0.666)	(0.580)	(0.640)	(0.675)	(0.757)
Positive reciprocity	0.236	-0.498	0.151	0.768	1.091
	(0.790)	(0.551)	(0.684)	(0.620)	(0.646)
Negative reciprocity	0.648	1.106	0.849	-0.248	2.021**†
	(0.692)	(0.703)	(0.670)	(0.536)	(0.697)
Altruism	3.024**†	3.312**†	1.035	2.126**	2.124*†
	(0.892)	(0.638)	(0.591)	(0.806)	(0.839)
Trust	1.224	2.532**†	1.957**†	0.605	2.229**†
	(0.678)	(0.871)	(0.694)	(0.539)	(0.765)
Constant	75.890**	65.345**	68.102**	89.751**	87.526**
	(8.140)	(5.081)	(4.932)	(3.102)	(5.426)
Observations	800	799	802	804	795
R-squared	0.124	0.171	0.090	0.095	0.220

The analysis identifies positive associations between risk-taking and CDR support in Brazil (b=1.92, p=0.007) and China (b=1.86, p=0.001). Negative reciprocity and CDR support are

positively associated in the USA (b=2.02, p=0.004). Altruism positively predicts support in Brazil (b=3.02, p<0.001), China (b=3.31, p<0.001), and USA (b=2.12, p=0.012). Trust in people and their intentions is positively associated with CDR support in China (b=2.53, p=0.004), Germany (b=1.96, p=0.005), and USA (b=2.23, p=0.004).

Overall, altruism and trust emerge as the more consistent predictors of CDR support, indicating that pro-social motivations play a role in shaping public acceptance. Risk preferences also matter in two countries, consistent with the uncertainty surrounding CDR technologies, while reciprocity and patience seem to matter less.

4.4. Risk, time, and social preferences more significantly impact novel CDR

We then analysed the associations between the six economic preference measures and CDR support while distinguishing between the three technologies. This tests Hypothesis 2 (that the associations between the six economic preference measures and the support variable differ across the three CDR technologies). For this analysis, we estimated 30 (for five countries and six economic preference measures) linear random-effects regression models for repeated observation predicting CDR support by the six economic preference measures, a variable indicating the CDR technology, an interaction term between one of the economic preference measures and the CDR technology variable, and numeracy and socio-demographics as covariates. The models also included a random intercept for each respondent to capture individual-level heterogeneity in CDR support, assuming that this is uncorrelated with the explanatory variables. An example for risk is provided below:

$$CDRSupport_{it} = \alpha + \omega(R_i * CDRTechnology_t) + \beta_1 R_i + \beta_2 P_i + \beta_3 PR_i + \beta_4 NR_i + \beta_5 A_i + \beta_6 T_i + \gamma' CDRTechnology_t + \delta' X_i + u_i + \epsilon_{it}, \quad (2)$$

where $CDRSupport_{it}$ represents the support stated by respondent i for CDR technology t, the six standardized economic preferences are indicated as above, and X_i represents numeracy and demographics. Since each participant evaluated three CDR technologies (or expressed "don't know" for some), the data has an unbalanced panel structure with repeated observations nested within participants. To account for this, the intercept across all individuals is represented by α, the random intercept at the respondent level is u_i (allowing for unobserved individual-specific variation around α), and the standard errors were clustered at individual level, as indicated by the error term ϵ_{ip}. The coefficients β_1 to β_6 represent the associations between CDR support and the six economic preference measures for afforestation and reforestation, i.e. the reference

technology. Importantly, equation (2) includes the interaction between risk-taking and the CDR technology indicator, and ω represents the vector of two coefficients which show whether the association of risk-taking and support varies for novel CDR technologies versus afforestation.

Figure 2 and Table 5 present the key results from the 30 linear random-effects regression models as described in equation (2) where we additionally calculated the marginal effects using Stata's *margins* command to sum up the main effect of the relevant economic preference and the interaction effect of this preference measure with the respective CDR technology. Tables SI.5 to SI.10 in the Supplementary Information present the results for the regressions while Table 5 summarises the marginal effects. In Table 5, we also indicate whether the associations are significant after correcting for multiple hypotheses testing. For this, we assume that the family we correct for is composed of the three CDR technologies, since a focus of the paper is whether we find differences across the three technologies (for a given preference in a given country) rather than, e.g., differences across economic preference measures. We use the Holm-Bonferroni method and assume a familywise error rate across the three CDR technologies.

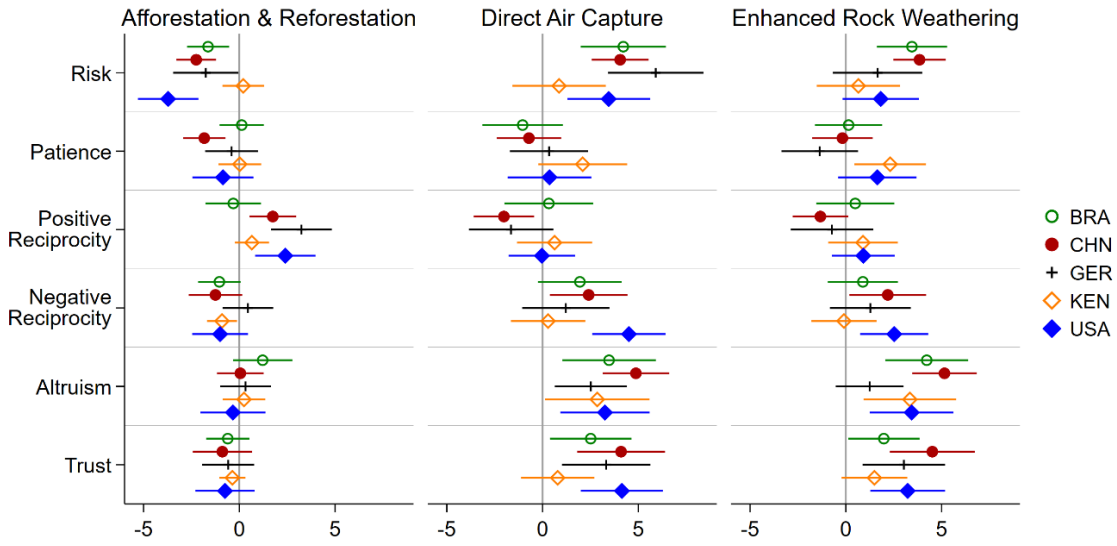


Figure 2. Associations between standardized measures of economic preferences and support for the three carbon dioxide removal (CDR) technologies across countries.

Table 5. Predicted associations between economic preferences and CDR support for the three technologies calculated from 30 linear random-effects regression models (6 economic preferences and 5 countries) that include the interactions between CDR technology and the respective economic preference measure.

	BRA	CHN	GER	KEN	USA
Associations between CDR Support and Risk					
Afforestation	-1.632**†	-2.251**†	-1.750*	0.205	-3.717**†
	(0.004)	(0.000)	(0.044)	(0.713)	(0.000)
DAC	4.216**†	4.052**†	5.910**†	0.862	3.454**†
	(0.000)	(0.000)	(0.000)	(0.488)	(0.002)
ERW	3.455**†	3.849**†	1.660	0.659	1.824
	(0.000)	(0.000)	(0.163)	(0.553)	(0.073)
Associations between CDR Support and Patience					
Afforestation	0.125	-1.830**†	-0.404	0.0249	-0.855
	(0.831)	(0.001)	(0.567)	(0.965)	(0.292)
DAC	-1.041	-0.711	0.339	2.097	0.363
	(0.332)	(0.408)	(0.745)	(0.076)	(0.745)
ERW	0.146	-0.177	-1.361	2.317*†	1.647
	(0.870)	(0.826)	(0.182)	(0.015)	(0.115)
Associations between CDR Support and Positive Reciprocity					
Afforestation	-0.315	1.749**†	3.246**†	0.656	2.402**†
	(0.669)	(0.005)	(0.000)	(0.150)	(0.003)
DAC	0.330	-2.019*†	-1.646	0.626	-0.0344
	(0.780)	(0.012)	(0.143)	(0.531)	(0.969)
ERW	0.493	-1.326	-0.720	0.898	0.916
	(0.636)	(0.072)	(0.513)	(0.333)	(0.273)
Associations between CDR Support and Negative Reciprocity					
Afforestation	-1.041	-1.247	0.446	-0.905*	-1.004
	(0.066)	(0.080)	(0.509)	(0.023)	(0.177)
DAC	1.949	2.408*	1.215	0.288	4.508**†
	(0.081)	(0.020)	(0.296)	(0.771)	(0.000)
ERW	0.890	2.191*	1.280	-0.0973	2.527**†
	(0.340)	(0.032)	(0.235)	(0.911)	(0.005)
Associations between CDR Support and Altruism					
Forest	1.218	0.0542	0.325	0.246	-0.333
	(0.123)	(0.930)	(0.631)	(0.664)	(0.701)
DAC	3.472**†	4.873**†	2.521**†	2.855*	3.260**†
	(0.005)	(0.000)	(0.009)	(0.040)	(0.006)
ERW	4.227**†	5.153**†	1.245	3.346**†	3.439**†
	(0.000)	(0.000)	(0.169)	(0.007)	(0.002)
Associations between CDR Support and Trust					
Forest	-0.605	-0.886	-0.582	-0.361	-0.747
	(0.294)	(0.262)	(0.401)	(0.297)	(0.345)
DAC	2.513*	4.101**†	3.322**†	0.790	4.141**†
	(0.021)	(0.000)	(0.005)	(0.419)	(0.000)
ERW	1.983*	4.519**†	3.031**†	1.492	3.230**†
	(0.037)	(0.000)	(0.006)	(0.088)	(0.001)
Observations	2365	2375	2302	2409	2329

P-values in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, † $p<0.05$ after correcting for multiple hypotheses testing (using Holm-Bonferroni approach). Regressions controlled for numeracy, age, gender, income, education, and geographical area. Economic preference measures are standardized.

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As illustrated in Figure 2 and Table 5, we observe that individuals who like to take risks tend to support afforestation and reforestation less in Brazil (b=-1.63, p=0.004), China (b=-2.25, p<0.001), and USA (b=-3.72, p<0.001). However, risk-taking is positively correlated with support for direct air capture in Brazil (b=4.22, p<0.001), China (b=4.05, p<0.001), Germany (b=5.91, p<0.001), and USA (b=3.45, p=0.002). Risk attitudes are positively associated with support for enhanced rock weathering in Brazil (b=3.46, p<0.001) and China as well (b=3.85, p<0.001). Risk attitudes do not play a significant role in Kenya for any technology, however.

Associations between patience and CDR support are comparatively weak. We identified only two significant coefficient estimates. Patience predicts lower support for afforestation and reforestation in China (b=-1.83, p=0.001) and higher support for enhanced rock weathering in Kenya (b=2.32, p=0.015).

Positive reciprocity predicts higher support for afforestation and reforestation in China (b=1.75, p=0.005), Germany (b=3.25, p<0.001), and the USA (b=2.40, p=0.003), and lower support for direct air capture in China (b=-2.02, p=0.012). Those willing to reciprocate good behavior from others were more likely in three of the countries to support planting trees, which was not true for novel CDR. There is even evidence of positive reciprocity having a countervailing role, among Chinese respondents, in the case of direct air capture.

Negative reciprocity predicts higher support for direct air capture only in the USA (b=4.51, p<0.001), and the same is true for enhanced rock weathering (b=2.53, p=0.005). Those more willing to punish the negative behavior of others were thus more supportive of the novel CDR technologies in the USA.

Altruism predicts higher support for novel CDR methods in multiple countries. We identified positive associations between altruism and direct air capture in all countries but Kenya (Brazil: b=3.47, p=0.005; China: b=4.87, p<0.001; USA: b=3.26, p=0.006; Germany: b=2.52, p=0.009). Altruism predicts higher support for enhanced rock weathering in all countries but Germany (Brazil: b=4.23, p<0.001; China: b=5.15, p<0.001; Kenya: b=3.35, p=0.007; USA: b=3.44, p=0.002). There are no significant relationships between altruism and afforestation and reforestation, however.

Trust positively predicts support for direct air capture in China (b=4.10, p<0.001), Germany (b=3.32, p=0.005), and USA (b=4.14, p<0.001). Respondents who were more trusting of others and their good intentions were also more likely to support enhanced rock weathering in China

(b=4.52, p<0.001), Germany (b=3.03, p=0.006), and USA (b=3.23, p=0.001). Trust in others and their good intentions thus emerges as more important for the support of novel CDR, though not for afforestation and reforestation.

4.5. Risk, time and social preferences explain cross-country differences in CDR support

To test whether risk, time, and social preferences can help explain cross-country differences in support (as predicted in hypothesis 3), Table 6 presents the results of the six linear regression models where CDR support is predicted for each technology using dummy variables for the respective countries, numeracy and demographics. Support for each CDR technology is predicted using two regressions, one without (the odd-numbered columns) and one with economic preferences (the even-numbered columns). Decreasing magnitudes of the country-specific coefficient estimates if economic preferences are added to the models suggest that cross-country differences can be partly explained by them. The full regression is available as Table SI.12 in the Supplementary Information (SI.5).

Comparing baseline (columns 1, 3, 5) and extended (columns 2, 4, 6) specifications of the regressions reveals how much the difference in support for each country (relative to Germany, which serves as the baseline) is attenuated (or magnified) by including economic preferences. Hence, the coefficient estimates for the economic preferences (in the extended models) indicate the overall importance of these preferences across all countries.

This analysis suggests sizable heterogeneity in how much cross-country differences in CDR support are explained by economic preferences. Regarding afforestation and reforestation, the addition of economic preferences generates only modest changes to the country coefficient estimates: for example, the Brazil/Germany gap declines by just 0.60 points, or12.15%. To calculate this percentage, we subtracted the full-model coefficient from the restricted-model coefficient (i.e. 4.940 - 4.336 = 0.604; from the models with and without economic preferences) and divided the difference by the restricted-model coefficient estimate (4.940). Similarly, the China/Germany gap attenuated by 0.68 points (16.51%), the Kenya/Germany gap by 0.63 points (9.32%) while the USA/Germany gap widened by 0.12 points (2.45%). On average, 9% of cross-country differences in support for afforestation, relative to Germany, are statistically accounted for by the variation in economic preferences. Overall, this average percentage is the average of the signed percentage reductions in the coefficient estimates, where the magnified coefficient estimate for USA is treated as a negative reduction in the cross-country difference.

In contrast, differences between the country-specific coefficient estimates attenuate much more when economic preferences are added to models predicting support for the novel, technological CDR options. For direct air capture, the difference in support (relative to Germany) shrinks by between 1.69 points (8.21%) in Brazil and 4.42 points (26.33%) in the USA, with an average reduction of 18%. There is a similar pattern for enhanced rock weathering, where reductions range from 1.42 points (7.63%) in Brazil to 3.49 points (22.78%) in USA, averaging 17%.

Table 6. Linear regressions predicting CDR support for the three technologies across countries, with numeracy and demographics included in all models and the six economic preferences in models (2), (4), and (6).

	Support for					
	Afforestation and Reforestation		Direct Air Capture		Enhanced Rock Weathering	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Country (Base = GER)						
BRA	4.940**	4.336**	20.538**	18.853**	18.622**	17.202**
	(0.918)	(0.930)	(1.725)	(1.734)	(1.584)	(1.578)
CHN	-4.120**	-3.439**	19.432**	15.124**	13.063**	9.999**
	(1.002)	(1.035)	(1.712)	(1.750)	(1.629)	(1.659)
KEN	6.756**	6.124**	22.355**	18.615**	17.027**	14.124**
	(0.961)	(1.041)	(1.828)	(1.884)	(1.693)	(1.725)
USA	-4.896**	-5.016**	16.812**	12.387**	15.317**	11.829**
	(1.052)	(1.100)	(1.702)	(1.758)	(1.555)	(1.595)
Risk		-0.742**		3.314**		2.294**
		(0.276)		(0.513)		(0.463)
Time		0.011		-0.342		0.250
		(0.278)		(0.481)		(0.435)
Positive reciprocity		1.871**		-0.761		-0.287
		(0.283)		(0.455)		(0.424)
Negative reciprocity		0.312		1.375**		1.052*
		(0.247)		(0.493)		(0.443)
Altruism		1.178**		2.995**		3.118**
		(0.309)		(0.525)		(0.487)
Trust		-0.165		2.725**		2.626**
		(0.258)		(0.505)		(0.462)
Constant	85.712**	86.551**	66.329**	66.566**	68.803**	69.229**
	(1.884)	(1.877)	(3.206)	(3.170)	(2.955)	(2.912)
Observations	3,975	3,975	3,914	3,914	3,891	3,891
R-squared	0.125	0.146	0.163	0.203	0.132	0.173

Robust standard errors in parentheses; ** p<0.01, * p<0.05; Significance results based on two-tailed *t*-testing. Constant reflects the dependent variable is coded from 0 to 100 for these models. Full regression results are available in Tables SI.12 in Supplementary Information.

To identify which economic preference measures are most responsible for the reduced cross-country differences in CDR support (relative to the baseline category Germany), we used Gelbach decompositions (Gelbach 2016). These decomposition analyses (full details in Tables SI.13 to SI.15) show that risk, altruism and positive reciprocity contribute to the explanation of cross-country differences in support for afforestation; but patience, negative reciprocity, and trust do not. Meanwhile, for direct air capture and enhanced rock weathering, we show that

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risk, altruism, trust, and to a lesser extent negative reciprocity explain cross-country differences in support.

For example, adding the economic preferences to models which predict support for direct air capture attenuates the difference in support between USA and Germany by 26.33%, from 16.81 to 12.39 (total change = 4.43, $p<0.01$). This is mainly from adding risk-taking ($b=1.62$, $p<0.01$), altruism ($b=1.28$, $p<0.01$), and trust ($b=1.04$, $p<0.01$), where each b reflects that preference's contribution to the total change. When describing these results, the reported p-values for total changes test whether the restricted and full-model coefficient estimates differ, and the p-values for individual preferences test whether each contribution differs from zero.

In some cases, however, economic preference measures have countervailing effects, such as for afforestation in Kenya (relative to Germany). Adding these measures attenuates support by 9.32%, from 6.76 to 6.12, but this total change is not statistically significant ($p=0.07$). On the other hand, this change masks the countervailing effects of the economic preferences, notably altruism ($b=0.72$, $p<0.01$) and positive reciprocity ($b=0.38$, $p<0.01$) attenuate differences in support, whereas risk-taking ($b=-0.39$, $p<0.01$) magnifies them.

5. Discussion and conclusion

Our findings reveal several core insights for understanding public perceptions and support of CDR technologies. First, we demonstrate that public support is broadly higher for conventional approaches such as afforestation rather than novel types like direct air capture or enhanced rock weathering (Wolske et al. 2019; Jobin and Siegrist 2020; Wenger et al. 2021; Bellamy 2022; Merk et al. 2023; Nawaz et al. 2023; Baum et al. 2024; Lee et al. 2025). Second, reinforcing the few studies which have examined publics in the global South (Atris et al. 2025; Aziz et al. 2025; Baum et al. 2024; Cox et al. 2025), we find evidence for higher support of novel CDR in the global South. We also establish that levels of support vary across the global South, being higher among Kenyan and Brazilian versus Chinese publics.

Indeed, such differences indirectly evoke debates about classifying China as "global South"; while such debates are beyond the scope of this paper, our findings underline the importance of more deeply engaging with global South publics rather than attempting to extrapolate their viewpoints from predominantly western-focused studies. While the current study represents an important step in this direction, our results of course do not represent a sufficient foundation to draw general conclusions for the global South, notably given that they draw on online samples

from three heterogeneous countries. Contributing to the very few studies investigating opinions of CDR in the global South, we nonetheless provide additional evidence that these perceptions differ between countries in the global North versus global South (Baum et al. 2024; Fritz et al. 2026) and, to an extent, also across global South countries (Atris et al. 2024; Fritz et al. 2026).

Significantly, the current article reveals the importance of economic preferences for explaining both individual and cross-country differences in public support for CDR technologies, thereby extending the literature that such preferences matter for climate-mitigation activities (Schleich et al. 2019; Engler et al. 2025), indeed with little discernible difference between global North and South countries (Nichols et al. 2026). Economic preferences, notably risk-taking, altruism, and trust, were broadly predictive of CDR support though the importance of specific preferences differs by CDR technology. Support of novel CDR is more strongly predicted by economic and social preferences, compared to tree-planting. Such findings reinforce the crucial importance of altruism and trust for pro-environmental and climate beliefs and activities (Lades et al. 2021; Engler et al. 2025; Goerg et al. 2025; Nichols et al. 2026), but also how effects vary depending on the behavior category (Nichols et al. 2026; Schleich et al. 2019; Qian et al. 2024) – for instance, patience has limited predictive effect on CDR support, contrary to the adoption of energy-efficient technologies (Schleich et al. 2019) or charitable donations to environmental groups (Engler et al. 2025; Andre et al. 2024). Moreover, we establish risk-taking as a positive predictor of novel CDR support but a negative one for forestation. The potential countervailing effect of risk preferences on CDR support is in line with findings of other studies whereby risk exerted a heterogeneous effect depending on the type of technology (Nichols et al. 2026; Qian et al. 2024). As such, the willingness to take risks emerges as a pivotal factor when it comes to support (or lack thereof) of diverse CDR technologies.

In terms of the practical significance of economic preferences for CDR support, we find that the largest effects are equal to four or five points more support (on a 101-point scale). As such, the associations are generally small, which mirrors findings for economic preferences for other climate-mitigation activities (Schleich et al. 2019; Lades et al. 2021; Engler et al. 2025; Nichols et al. 2026). Nonetheless, we contend that these effects are non-trivial, especially in relation to established associations between key factors such as climate beliefs or trust and CDR support. Taking Brutschin et al. (2024), which tested the importance of a battery of variables for CDR support across thirty countries, the greatest explanatory power of any variable is 7-8%: for trust in industry or national governments, and science and technology beliefs. Indeed, taking all their predictors together, total explanatory power ranged from 11% (for afforestation) to 14% (for

novel CDR methods). In comparison, the fact that the six economic preferences are additively associated with between 11- and 16-points more support for novel CDR approaches in each of the countries (except Kenya, where it is still 7 to 8 points) underscores their practical relevance. Moreover, as there is limited to moderate support for novel CDR in the countries we surveyed, and indeed some opposition in Germany, the joint contributions of these preferences potentially have greater relevance for explaining why such support does or does not exist, and why it might increase among certain types of individuals in the future.

Economic preferences also helped to reveal the extent to which support for CDR technologies varies between countries (in addition to individuals). The analysis demonstrated that economic preferences explain a sizable share (almost 20 percent) of cross-country differences in support for novel CDR options; but they play a much more limited role (less than 10 percent) for nature-based solutions. That economic preferences materially contribute to cross-country differences in CDR support suggests that such differences result from not only institutional but also cultural and psychological differences: differences in terms of stable, fundamental preferences matter as well. Indeed, the explanatory power of economic preferences is not driven uniformly by all preferences, for all countries. Support for novel CDR technologies was strongly linked to risk perceptions and trust (in others and their good intentions), as well as pro-social preferences like altruism. In contrast, support for the nature-based CDR option was more narrowly predicted by altruism and reciprocity (positive and negative). Cross-country differences in support for forestation were also, overall, more weakly predicted by economic preferences.

These findings invite further investigation into the relationships between economic preferences and CDR support, notably how and why these differ across countries. One salient example here is the association between negative reciprocity and higher support for novel CDR in the United States. Development and deployment of novel CDR thus assume the form, among individuals willing to punish negative behavior by others, of a punishment handed out for bad behavior. A similar effect, interestingly, was identified for taxes on fossil fuels and meat and dairy products in the United States (Baum et al. 2026). Depending on the broader socio-political context, some CDR technologies could come to be confronted by controversy and political polarization in a way mirroring public reactions to renewable energy (Stokes 2016; Olson-Hazboun et al. 2018).

More fundamentally, such findings point to the role of the broader cultures where deployment could occur (Malakar et al. 2025; Scott-Buechler and Wang 2025). To explain cross-country differences in pluralistic ignorance, for instance, Geiger et al. (2025) examined the role of the strength of social norms (i.e. cultural looseness or tightness). In analogous fashion, the current

article identifies the broad relevance of economic preferences such as risk-taking, altruism, and interpersonal trust as prospectively rich terrain for explaining cross-country differences. Thus, the positioning of information and engagement campaigns in relation to such factors could have deep impact for starting discussions around currently unfamiliar technologies such as CDR and how to better promote more just and fair approaches to deployment (Nawaz et al. 2023, 2024; Caggiano 2025).

While cross-country research is important for better understanding how public perceptions can differ, there are some potential limitations to keep in mind, particularly when it comes to trying to generalize about such differences. Notably, it is possible that the results could instead reflect the influence of unobserved factors or cultural differences in survey response styles. Instead of actual differences in CDR support, there is evidence, for instance, that Asian respondents are less likely to select extreme response categories and more susceptible to acquiescence bias, that is, agreeing if asked about statements or responding affirmatively (Smith et al. 2016; Beuthner et al. 2018).

While it is necessary to be circumspect about generalizing findings as a result, we remark that response styles are unable to fully explain the higher levels of support in the global South countries which we sampled. Similarly, inconsistencies can also emerge across countries due to translation issues or lack of measurement equivalence. Regarding economic preferences, however, any issues are substantially mitigated by the fact that these measures have been tested and experimentally validated globally (Falk et al. 2018, 2023), although we do recognize there can be limitations from relying on survey vis-à-vis incentivized or experimental measures here (Nichols et al. 2019). Finally, while samples are broadly nationally representative of respective country populations, we acknowledge that they were recruited from online panels. Especially in more developing countries, it cannot be presumed that such samples are fully representative of the entire population in these countries. **Declarations of interest:** We declare that we have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process: The visualization and images related to the technologies, which were presented to participants in the survey, were designed with the help of generative AI (ChatGPT 4.0). No AI tool or service was otherwise used during the preparation of this work, including to write the manuscript.

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Data and Code Availability: The dataset and code will be made available on the websites of the OSF.

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Highlights

- First systematic study linking validated economic preferences to CDR support.
- Global South publics show higher support for novel CDR than the Global North.
- Risk-taking, altruism, and trust positively predict support for novel CDR.
- Positive reciprocity drives support for tree-planting but not engineered methods.
- Economic preferences explain nearly 20% of global variation in novel CDR support.

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