ENVIRONMENTAL RESEARCH LETTERS

LETTER • OPEN ACCESS

Drivers and attitudes of public support for technological solutions to climate change in 30 countries

To cite this article: Elina Brutschin *et al* 2024 *Environ. Res. Lett.* **19** 114098

IOP Publishing Environ. Res. Lett. 19 (2024) 114098 https://doi.org/10.1088/1748-9326/ad7c67

ENVIRONMENTAL RESEARCH
LETTERS

OPEN ACCESS

RECEIVED
7 March 2024

REVISED
27 August 2024

ACCEPTED FOR PUBLICATION
18 September 2024

PUBLISHED
22 October 2024

LETTER

Drivers and attitudes of public support for technological solutions to climate change in 30 countries

Elina Brutschin[1,*], Chad M Baum[2], Livia Fritz[2], Sean Low[2], Benjamin K Sovacool[2,3,4] and Keywan Riahi[1]

1 International Institute for Applied Systems Analysis, Laxenburg, Austria
2 Department of Business Development and Technology, Aarhus University, Birk Centerpark 15, 7400 Herning, Denmark
3 Science Policy Research Unit (SPRU), University of Sussex Business School, Jubilee Building, Arts Rd, Falmer, Brighton BN1 9SL, United Kingdom
4 Department of Earth and Environment, Boston University, 685 Commonwealth Ave, Boston, MA 02215, United States of America
* Author to whom any correspondence should be addressed.

E-mail: brutschin@iiasa.ac.at

Keywords: public support, carbon dioxide removal, climate solutions

Supplementary material for this article is available online

Abstract

Some experts contend that addressing global climate challenges requires consideration of technologies such as Carbon Dioxide Removal (CDR) and, possibly, Solar Radiation Modification (SRM). Previous studies, primarily centered on the OECD region, have indicated that most of these technologies are contentious, eliciting low levels of public support. By conducting a set of nationally representative surveys examining seven CDR and three SRM technologies in 30 countries, we show that public skepticism is most prominent in wealthier countries. Respondents from these countries express lower confidence in the potential of science and technology to address climate change, diminished trust in industry, and expect to experience less personal harm from climate change. At the same time, there are many countries, not previously studied, where the levels of support for CDR and SRM are relatively high. As middle-income countries, their capability to effectively implement these technologies may be deficient; additionally, there is a risk of the unilateral implementation of certain technologies with uncertain implications in terms of their impacts on climate. This underscores the necessity for long term climate strategies that are context-specific and tailored to individual countries, while moreover emphasizing the imperative for extensive international collaboration, including through technological and financial transfers. Finally, strong international governance structures, especially in the context of SRM, are crucial to ensure a responsible approach towards these technologies.

1. Introduction

In light of the recent record-breaking heat levels and other extreme climate related events, the need to provide insights and evidence to policymakers on a diverse array of prospective solutions is more pressing than ever. With the global community well off track with its near-term climate mitigation efforts (Rogelj *et al* 2023), especially the phase-out of fossil fuels (Brutschin *et al* 2022, Trencher *et al* 2022, Minx *et al* 2024), the debate surrounding carbon dioxide removal (CDR) (Smith *et al* 2024) and solar radiation modification (SRM) technologies (Baur *et al* 2023) is intensifying in both the public and research spheres. Previous research has demonstrated that public support plays a pivotal role in the development and deployment of specific technologies (Boudet 2019), such as renewable energy (Susskind *et al* 2022), genetically modified food (Costa-Font *et al* 2008, Cui and Shoemaker 2018), artificial photosynthesis (Sovacool and Gross 2015), nuclear fusion (Jones *et al* 2019) and nuclear fission (Lehtonen *et al* 2020). In some EU countries, geological storage of CO_2 is currently prohibited, despite ongoing discussions to lift these bans (European Commission 2023). In the context of genetically modified food it was shown that public opposition can be persistent (Bonny 2003) and result in deployment bans as demonstrated in a number of the European countries (Rabesandratana 2014).

A better understanding of public opinion regarding novel technologies can support discussions on the national contexts under which certain technologies might be deployed or not. This could be an essential contribution to the advancement of long-term climate strategies, such as for example, through Integrated Assessment Models (IAMs), where assumptions about techno-economic potential dominate, and socio-cultural barriers are not considered (Jewell and Cherp 2020, Peng *et al* 2021, Pianta and Brutschin 2022, Ju *et al* 2023). Moreover, social attitudes and preferences can entail more active modes of participation, energy democracy, and involvement in climate policymaking and planning, when particular conditions such as high degrees of trust or a social license to operate are evident (Komendantova and Battaglini 2016, Verrier *et al* 2022). In the context of SRM technologies wide discrepancies between regions can highlight the importance of establishing international governance structures that would aim to prevent individual regions from unilaterally deploying SRM technologies without considering potential global or regional consequences (Floyd 2023).

Nevertheless, reliable data and analysis on the social and public perceptions of CDR and SRM is limited and in some cases nonexistent. So far, surveys on public perception of CDR or SRM technologies have primarily concentrated on a narrow number of countries, particularly OECD member states (Cummings *et al* 2017, Tcvetkov *et al* 2019, Sovacool *et al* 2023), especially Germany, the United Kingdom, and United States. Conversely, knowledge about other regions is limited (Visschers *et al* 2017, Sugiyama *et al* 2020). Existing surveys consistently reveal that people generally self-identify as having limited knowledge about these technologies. Additionally, the overall level of support for their wider implementation remains relatively low (Jobin and Siegrist 2020, Raimi 2021, Wenger *et al* 2021). This limited support may also be driven by more negative media coverage and public framing of these technologies (Bolsen *et al* 2022, 2023). It is however not clear whether the findings from past research are robust in other national contexts, especially in countries that are not Western, Educated, Industrialized, Rich Democracies, or WEIRD (Henrich *et al* 2010).

In this study, by building on the efforts of large-scale, nationally representative surveys discussed and presented in Baum *et al* (2024) and Fritz *et al* (2024), we focus on the interplay of different individual attributes and core beliefs to gain a better understanding of why there is a pronounced difference in the support of certain technologies between Global North and Global South regions as also highlighted in Baum *et al* (2024), which we represent through income group categorization developed by the World Bank. With 30 284 respondents and at least 300 observations per technology and country pairing, this study provides one of the first comprehensive examinations of public perceptions of CDR and SRM technologies across a diverse range of national contexts. Unlike Baum *et al* (2024), which analyzed country level means (and almost entirely focusing on contrasts between Global North and Global South cohorts, e.g. for perceived risks and benefits and support variables), this study also explores individual-level data by performing pooled regression analyses and analyses for each individual country, as well as for a much broader set of independent variables. Additionally, our focus is broader than that of the study by Fritz *et al* (2024), which specifically examined the role of climate beliefs in technology support, focusing on a subset of countries and using a mixed-methods approach with qualitative data collected through focus groups.

We find that respondents from wealthier countries are generally more skeptical of all technologies alongside broader support for many technologies in countries which have not been previously surveyed. By linking our analysis to other strands of related literature, we argue that technological skepticism in the wealthier countries can be explained by looking at some of the characteristic core beliefs in those countries. Wealthier countries tend to have lower beliefs in the ability of science and technology to deliver solutions to climate change and lower trust in industry, in addition to expecting to experience less personal harm from climate change. This is in line with findings in the context of climate beliefs research, where it was suggested that weaker sense of personal dangers from climate change (Lo and Chow 2015), and a greater concern for bearing the mitigation costs (Sandvik 2008) in wealthier countries might lead to lower support of certain climate mitigation and adaptation measures. Among other key results, we demonstrate that higher levels of biospheric values like caring about and responsibility towards nature, familiarity with the technology, and other socio-economic predictors remain robust across different types of national contexts, confirming many insights from previous research (Visschers *et al* 2017, Wolske *et al* 2019, Bellamy 2022, Nawaz *et al* 2023, Satterfield *et al* 2023).

By offering a detailed analysis of individual attitudes and core beliefs across various national contexts, we present a more nuanced understanding of regional differences in support for certain technologies. This serves as a useful starting point for refining our assumptions about medium—and long-term climate mitigation strategies, where there is currently little attention to variations in regional capacity and public preferences.

2. Methods

2.1. Survey data

The original survey investigated a set of ten technologies, categorized into three distinct types (for a more detailed overview see supplementary information (SI), section SI1). Participants from 30 countries were randomly allocated to one of the following groups, each focusing on a different cluster of technologies: (1) SRM (Stratospheric Aerosol Injection (SAI), Marine Cloud Brightening, Space-based Geoengineering), (2) ecosystem-based CDR (CDRn) (Afforestation and Reforestation, Soil Carbon Sequestration, Marine Biomass and Blue Carbon), and engineered CDR (CDRe) (Direct Air Capture with Carbon Storage, Bioenergy with Carbon Capture and Storage, Enhanced Weathering, Biochar). The countries were selected to ensure regional diversity, representation of countries where research and testing of CDR and SRM is ongoing, and to include major GHG emitters. Following the World Bank's classification as of 2023, the following countries are categorized as high income: Australia (AUS), Austria (AUT), Canada (CAN), Switzerland (CHE), Chile (CHL), Germany (DEU), Denmark (DNK), Spain (ESP), Estonia (EST), France (FRA), UK (GBR), Greece (GRC), Italy (ITA), Japan (JPN), The Netherlands (NLD), Norway (NOR), Poland (POL), Saudi Arabia (SAU), Singapore (SGP), Sweden (SWE) and United States (USA). The following countries from the World Bank's classification of the upper middle-income and lower middle-income countries are included in our sample: Brazil (BRA), China (CHN), Dominican Republic (DOM), Indonesia (IDN), India (IND), Kenya (KEN), Nigeria (NGA), Turkey (TUR) and South Africa (ZAF).

Data collection was administered by Norstat using quota sampling vis-à-vis age, gender, income, education, and geographic region, with at least 1000 adult participants per country and conducted between August and November 2022. With thirty countries and participants randomly allocated to one of the three technology groups mentioned above, this resulted in approximately 9000 observations per technology. Given the relatively low levels of familiarity with included technologies, all respondents were provided with brief descriptions for each technology (SI, section SI1.3) and could proceed to the main part of the survey after answering a set of comprehension questions and additional attention checks (SI, section SI1.4). The survey included questions pertaining to support for different activities (research or deployment) of considered technologies along with questions on sociodemographic characteristics, beliefs about climate change and environment, and trust in institutions and actors (for a full overview of all included survey items and scales see SI, section SI1.2).

2.2. Model specification

Our work contributes to the broader literature which seeks to understand public support for certain technologies (Huijts *et al* 2012, Perlaviciute and Steg 2014, Upham *et al* 2015, Bergquist *et al* 2022). In figure 1, which guides our quantitative analysis, we depict a set of drivers of attitudes towards a given technology by highlighting two broader groups: (1) technology characteristics and (2) individual core beliefs. Especially in the context of different CDR technologies it has been shown that familiarity with a given technology as well as perceived naturalness are relatively good predictors of support for a given technology (Corner and Pidgeon 2015, Cummings *et al* 2017). At the same time individuals might have varying sets of core beliefs which mediate whether a given technology or climate policy is deemed to be acceptable (Visschers *et al* 2017). Among such core beliefs are religiosity (Saroglou *et al* 2004), political views (Wolsko *et al* 2016), climate vulnerability perceptions (Lo and Chow 2015), biospheric values such as concerns about nature and environment (Bouman *et al* 2020), general attitudes towards science and trust in different types of agents such as industry and government (Perlaviciute and Steg 2014). Many of those core values are in turn affected by individual attributes such as gender (Zelezny *et al* 2000), age, education and income (Bergquist *et al* 2022), and are shaped by the local context, including the political regime and governance structures (Perlaviciute and Steg 2014). The theoretical insights from past studies guide the selection of predictors for our key dependent variable of interest (where the dependent variable is *support for a broader deployment of a technology*). Additionally, we use a variety of econometric techniques to explore which set of predictors remains robust across different units of analysis and model specifications. To gain a better understanding of the descriptive evidence, we first aggregate individual data into country level data by computing the share of respondents from a given country for a particular survey item of interest. This way we are able to trace differences across certain groups of countries, and the general trends based on our data. To better understand the additional characteristics of the identified groups of countries, we further conduct an explorative principal component analysis (Lê *et al* 2008), which sheds light on the more systematic differences across the countries included in the survey, and highlights which variables explain most of the variation. Finally, to test whether some of the initial insights remain robust at the individual level of analysis, we combine individual level data for all countries, and present results from different specifications of linear regressions with country dummies as fixed effects predictors and standard errors clustered by country.

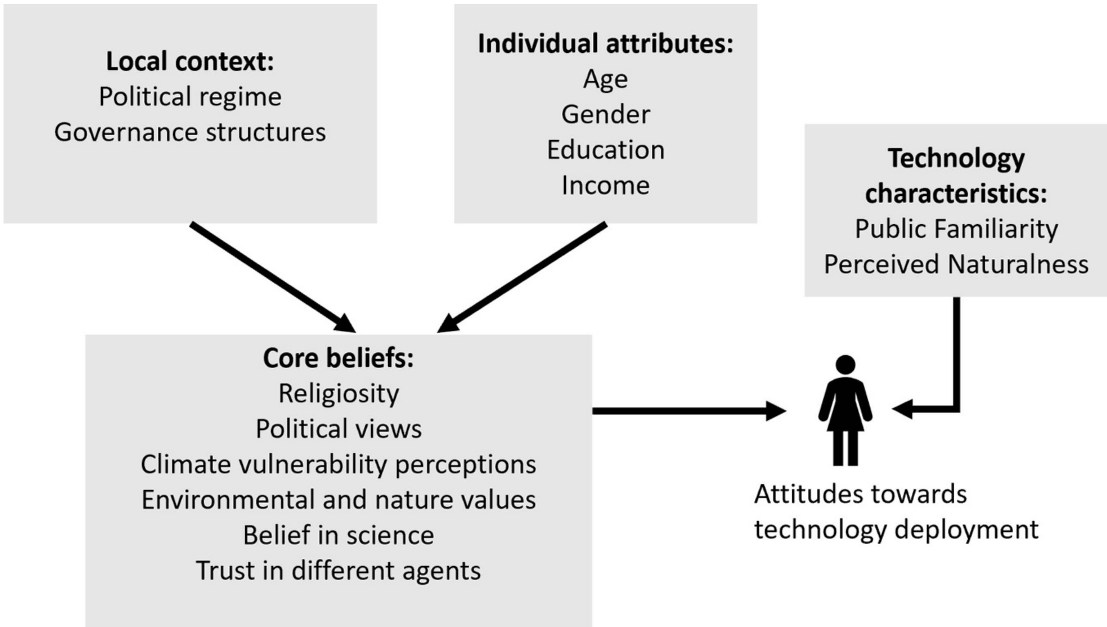


Figure 1. A conceptual framework for the drivers of technology perceptions. Own elaboration based on insights from (Huijts *et al* 2012, Perlaviciute and Steg 2014, Upham *et al* 2015, Bergquist *et al* 2022).

We compare different models specifications by looking at the levels of explained variation and highlight predictors which remain robust. In our supplementary analysis, we additionally show the results of regressions performed for each country separately and of variable importance analysis using machine learning techniques (appendix, sections A1.3 and A1.4).

3. Results

In figure 2 we provide a general overview of levels of support across all technologies, with countries grouped into two income levels (high/H and middle/M, which include upper and lower middle-income classification) based on the World Bank's classification. Responses here, measured on a 5-point scale, are to the question: '*How much do you support the broader deployment of each of the technologies to limit the effects of climate change*?'.

Similarly to the findings presented in Baum *et al* (2024) and Fritz *et al* (2024), we can trace two major patterns. First, that technologies that are generally perceived as more natural or more founded in ecosystems, such as afforestation and reforestation (AF), have higher support (Mean equal to 4.35 in high income group versus 4.5 in middle-income group), compared to technologies such as SAI (Mean equal to 3.05 in high income and 3.68 in middle-income). This finding confirms insights from surveys in Switzerland (Jobin and Siegrist 2020), USA (Sweet *et al* 2021) and Germany (Klaus *et al* 2020), and the broader insight from past research that it matters how technologies are perceived in relation to nature (Corner *et al* 2013). We also note that the difference in the levels of support between high-income versus middle-income countries is lowest for ecosystem-based CDR (Afforestation/AF, Soil carbon sequestration/SCS, Marine biomass and blue carbon/MBBC) and greatest for SRM (Marine cloud brightening/MCB, Space-based geoengineering/SBG, stratospheric aerosol injection/SAI). The second pattern is that high income countries are generally more skeptical of all technologies compared to middle-income countries. Interestingly, more than sixty percent of respondents from middle-income countries expressed general support for technologies such as stratospheric aerosol injection, space-based geoengineering, and marine cloud brightening. In contrast, this level of support is indicated by only around forty percent of respondents in high-income countries.

We explore this cross-country variation through a more in-depth descriptive analysis in figure 3 that makes use of key variables aggregated to a country level (share of respondents that indicated agreement on the Likert scale): beliefs in science to solve climate change ('science'), beliefs that one should not meddle with nature ('nature'), trust in industry ('trusti') and in national government ('trustn') to solve climate change, perceiving oneself as environmentally concerned ('environment') and expecting personal harm ('harm') from climate change. We also included additional external data from the World Bank indicators, adding GDP per capita and age (share of population above 65 years) as two additional characteristics that might drive cross country differences. As initial descriptive exploration, we conduct a principal component analysis (Lê *et al* 2008),

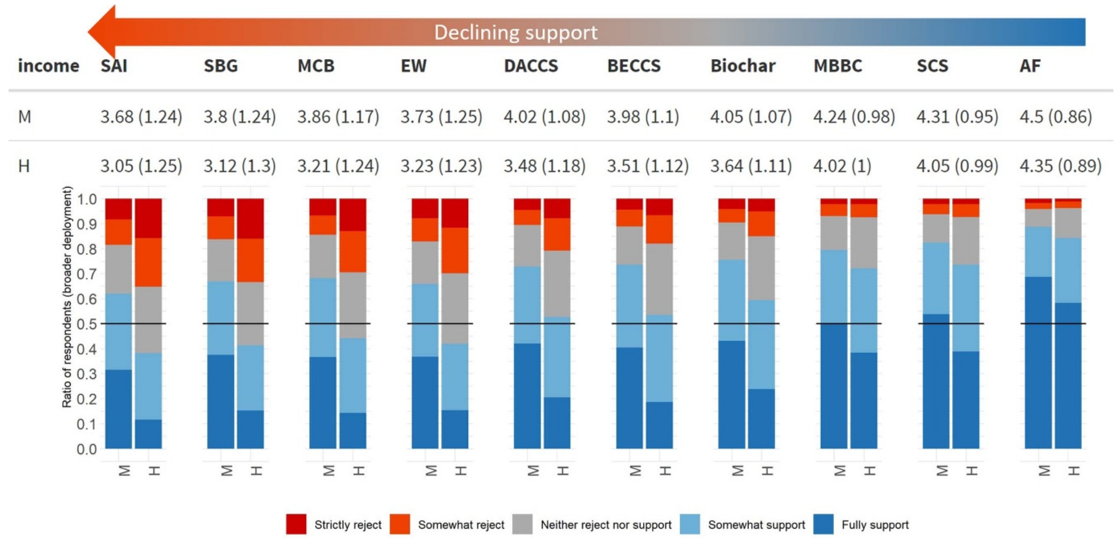
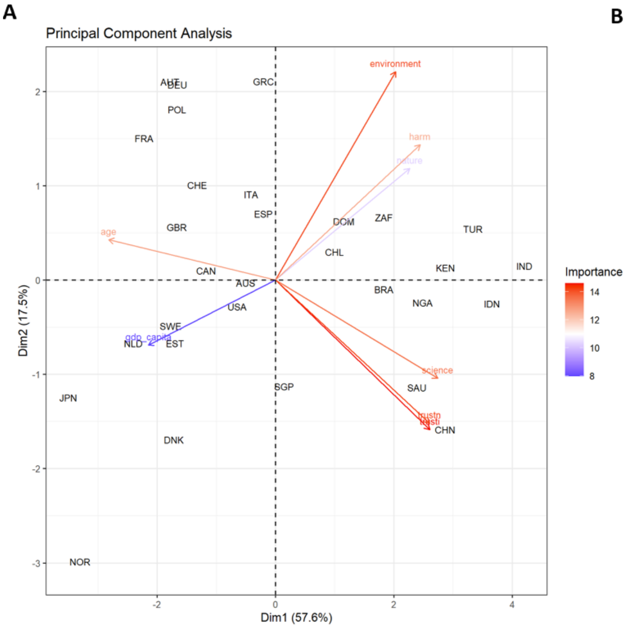


Figure 2. Overview of support for deployment different technologies across 30 countries (N = 30 284 respondents): SAI = Stratospheric aerosol injection, SBG = Space-based geoengineering, MCB = Marine cloud brightening, EW = Enhanced weathering, DACCS = Direct air capture with carbon storage, BECCS = Bioenergy with carbon capture and storage, MBBC = Marine biomass and blue carbon, SCS = Soil carbon sequestration, AF = Afforestation. The countries are categorized into different income groups based on World Bank's classification (latest available year): **M = lower middle-income + upper middle-income, H = high income**. The table reports the mean and standard deviation in brackets for each income group and technology. High income countries include Saudi Arabia, Denmark, Singapore, Greece, Sweden, Estonia, Chile, Spain, Italy, Norway, Netherlands, Australia, United States, Canada, United Kingdom, Poland, Switzerland, Austria, Germany, France, and Japan, while upper middle income countries are China, Turkey, Brazil, South Africa, and Dominican Republic, and lower middle income countries are India, Kenya, Nigeria, and Indonesia.

the results of which are presented in figure 3, panel (A). The position of each point indicates the score on the principal components, while direction and length of the vectors indicate the contribution of the variables to the principal components. Longer arrows suggest stronger contributions. We can trace a clustering of middle income countries (right side of the plot) where respondents have higher trust in industry to solve climate change, more agreement that science and technology will eventually solve our problems with climate change, and higher expected personal harm from climate change (for a more detailed figure on trust in industry across all countries, see appendix, figure A1.2). Furthermore, in panel (B), we observe that a group of countries, primarily from the high-income category, including Austria, Poland, Germany, Greece, and France, particularly stand out with low levels of trust in the industry's ability to address climate change, where only less than 40% of respondents have higher levels of trust. Such a lack of trust in industry also correlates with general attitudes towards science to solve climate problems in our sample (see also Baum *et al* (2024) for similar lines of argumentation). In addition, although the majority of respondents across all countries express high levels of environmental concern, stark differences emerge when respondents are asked about expected personal harm from climate change. In this context, Norway particularly stands out as a country where respondents (more than two thirds) do not anticipate being majorly harmed by climate change on a personal level (for a detailed analysis of this item, including insights from the focus groups, see also Fritz *et al* (2024)). Japan has a surprisingly low number of respondents who believe that science will eventually solve our climate change problems and who consider themselves concerned about the environment. A similar trend is reported for Japan regarding general trust in science in the study by Cologna *et al* (2024). Most countries from the middle-income group are characterized by higher levels of trust in industry and science (over sixty five percents of respondents), as well as higher levels of perceived harm from climate change.

In figure 4, panel (A), we explore whether and how some of the individual characteristics and core beliefs are related to support for technology deployment by performing linear regressions at the individual level (for regression tables instead of coefficient plots, see appendix, section A1.3, tables A1.3.1–A1.3.3). We include country fixed effects to control for potential variation of the local contexts and standard errors clustered by country. In panel (B) we display the R-squared (within) for bivariate regressions (where only one predictor is included at a time) and for models when all predictors are included. Overall, we can evidence that core beliefs such as trust in industry (in relation to climate change), beliefs about science, and perceptions about personal harm from climate change particularly stand out in terms of size of the effect (regression coefficient), contribution to model fit (R-squared), and robustness as predictors across all technologies. Additionally, we

A



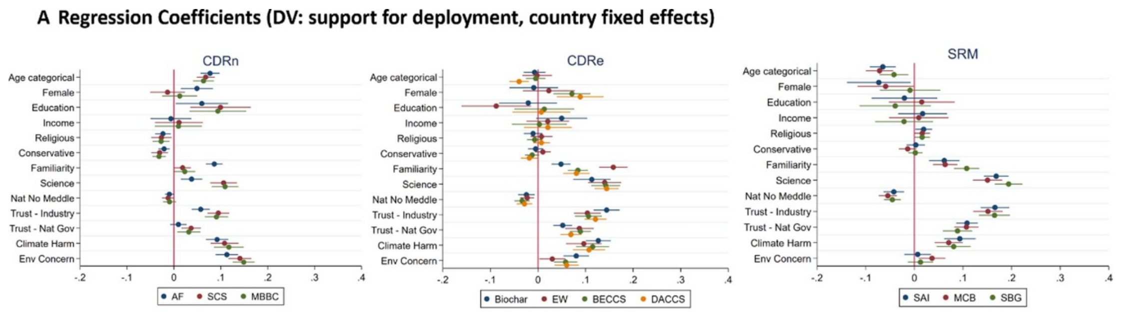
B

country	Science	Trust (industry)	Environment	Harm	Income
Austria	40	31	91	65	H/N
Poland	45	31	85	65	H/N
Germany	40	32	88	77	H/N
Greece	60	36	87	82	H/N
France	31	37	83	72	H/N
Netherlands	53	42	65	52	H/N
United Kingdom	47	43	77	54	H/N
Switzerland	41	45	87	69	H/N
Sweden	59	48	75	52	H/N
Norway	54	51	46	28	H/N
Canada	48	51	76	63	H/N
Japan	28	56	42	64	H/N
Australia	52	57	79	59	H/N
Estonia	56	57	74	47	H/N
United States	51	58	76	62	H/N
Italy	54	58	87	68	H/N
Spain	55	59	84	82	H/N
Denmark	62	61	71	42	H/N
Singapore	60	65	76	79	H/S
Kenya	74	67	92	88	M/S
Chile	56	67	82	89	H/S
South Africa	62	69	89	82	M/S
Brazil	71	69	81	84	M/S
Saudi Arabia	71	71	82	73	H/S
Dominican Republic	48	72	88	90	M/S
Nigeria	74	73	93	74	M/S
India	85	74	91	88	M/S
Turkey	75	78	91	94	M/N
Indonesia	73	80	87	79	M/S
China	76	85	78	83	M/S

Figure 3. Key social and environmental explanatory factors for all countries included in the survey of CDR and SRM. In panel (A), the results of an explanatory principal component analysis are displayed showing the loading of variables for individual countries, including World Bank Indicators such as GDP per capita and age (share of population above 65 years). The position of each point indicates the score on the principal components, while direction and length of the vectors indicate the contribution of the variables to the principal components. Longer arrows suggest stronger contributions. Panel (B) displays the share of respondents for a given country that indicated agreement on the Likert scale for a subset of items that stood out based on the analysis in panel (A). 'Science' relates to the question: 'To what extent do you agree with the following statement about science: Science and technology will eventually solve our problems with climate change' (Scale 1–5), 'Trust' in industry relates to the question 'How much trust do you have in the following groups and institutions, when it comes to their responsibility [and ability] to use these technologies to limit the effects of climate change?' (Scale 1–6), 'Environment' relates to 'I think of myself as someone who is concerned about the environment' (Scale 1–7), 'Harm' relates to the question "How much do you think climate change will harm you personally? (Scale 1–4). In the 'Income' column, we additionally indicate the classification of countries based on the World Bank's criteria and the Global North ('N') and Global South ('S') classification as used in the study by Baum *et al* (2024).

perform regression analyses for each country and technology separately (appendix, figure A1.3.1) and report variance importance after conducting a random forest analysis (appendix, figure A1.4.1). The additional analysis confirms the robustness of the variables identified as core drivers of support for considered technologies.

The effect of age of individuals, for example, depends on technology type: while higher age is correlated with higher support for ecosystem-based technologies (CDRn), the effect is reversed in the context of solar radiation management technologies, and not statistically significant in the context of engineered CDR (CDRe). We find statistically significant results for education and political beliefs only in the context of ecosystem-based technologies. As expected higher education is associated with higher support for those technologies, while more conservative individuals tend to indicate lower support. Similarly, the level of religiosity has a statistically significant influence on support of ecosystem based CDR and SRM, but not in the context of other technologies. We can observe that increased religiosity is associated with higher support for SRM, whereas the opposite relationship is evident in the context of ecosystem-based CDR. Gender and income, with a few exceptions for some technologies, fail to reach statistically significant levels in the context of our analysis. Familiarity and environmental concern emerge as robust predictors, particularly for ecosystem based technologies. Additionally, expectations of climate harm prove to be a relatively robust predictor for all technologies, albeit somewhat less so for SRM technologies. Trust in industry and beliefs in science and technology as solutions to climate change remain statistically significant across the board for all technologies, and their predictive power appears to strengthen as we shift toward more technologically engineered solutions. The primary finding from this analysis highlights that, when it comes to estimating an individual's expressed support for deployment of the considered technologies, having insights into their beliefs about industry (see also (Sugiyama *et al* 2020) in the context of SRM) and science could be more informative than solely relying on knowledge of their socio-economic background. A striking disparity in core



B Rsq - within

	AF	SCS	MBBC	Biochar	EW	BECCS	DACCS	SAI	MCB	SBG
Age	1.2%	0.7%	0.1%	0.2%	0.1%	0.1%	0.4%	0.9%	1.0%	0.4%
Gender	0.2%	0.0%	0.0%	0.0%	0.1%	0.2%	0.3%	0.0%	0.0%	0.0%
Education	0.5%	0.7%	0.6%	0.1%	0.0%	0.2%	0.1%	0.1%	0.1%	0.0%
Income	0.1%	0.2%	0.2%	0.2%	0.1%	0.2%	0.1%	0.1%	0.1%	0.1%
Religious	0.0%	0.0%	0.0%	0.2%	0.6%	0.3%	0.3%	0.5%	0.4%	0.5%
Conservative	0.6%	0.8%	0.9%	0.1%	0.1%	0.1%	0.1%	0.0%	0.1%	0.0%
Familiarity	4.4%	1.4%	1.2%	2.5%	5.6%	3.9%	3.7%	2.8%	3.1%	3.9%
Science	1.8%	4.1%	4.1%	5.5%	5.9%	7.0%	6.7%	7.9%	7.4%	8.6%
Nat No Meddle	0.0%	0.0%	0.0%	0.3%	0.1%	0.4%	0.3%	1.5%	1.8%	1.5%
Trust - Industry	2.5%	5.3%	5.1%	8.5%	6.8%	7.5%	7.8%	11.2%	10.5%	10.1%
Trust - Nat Gov	1.3%	3.4%	3.1%	5.6%	6.4%	6.9%	6.3%	8.4%	8.0%	7.4%
Env Concern	5.7%	6.1%	6.4%	2.5%	0.9%	2.1%	1.8%	0.7%	1.0%	0.8%
Climate Harm	2.7%	3.4%	3.5%	3.4%	2.0%	2.7%	2.4%	1.6%	1.8%	1.5%
All predictors	11.1%	13.8%	13.8%	13.2%	13.3%	14.6%	14.1%	17.0%	16.8%	17.0%

Figure 4. Results of public perceptions of CDR and SRM in 30 countries (with 8000–9000 observations per technology, for exact number of considered respondents for each model specification please refer to the SI, section A2.3, tables 1–3). Panel (A): Regression coefficients with country fixed effects across all technologies for a model specification that includes all variables. These are broken down according to technology category. Panel (B): R squared (within) for model specification including only one key variable while controlled for country fixed effects, compared to a model specification with all variables ('All predictors'). Explained variance from 'all predictors' is always different compared to the sum of the variance explained by the different variables as this represents a different model specification. Please note that China is excluded from this analysis because it is missing information on the political views (variable 'Conservative') but we report the results with China in the SI, section A2.3.

beliefs, particularly trust in industry, between high-income and middle-income countries, may be a key factor explaining the pronounced regional variations in support of the considered technologies.

4. Discussion and conclusion

While it is clear what needs to be done globally to limit raising temperatures (substantially reduce GHG emissions), it is less clear what kind of role emerging technologies such as CDR and SRM could or should play. In light of the insufficient pace of emissions reductions, there is now a range of climate strategies that are being explored through global IAMs, with many scenarios relying on various engineered CDR options (Strefler *et al* 2021). In the context of SRM, scholars are warning about key uncertainties that are linked to SRM technologies (Baur *et al* 2023).

Our study makes a key contribution to gaining a better understanding of where and why certain technologies might gain greater support. While it confirms many general insights identified in previous literature that focused on specific countries or regions, it extends the scope by encompassing a broader range of technologies and regions. Such understanding provides critical insights on the contours and development of context-specific climate mitigation and adaptation strategies. In line with the recent research on support and adoption of practices of behavioral changes (Dechezleprêtre *et al* 2022), we find that socio-economic predictors such as gender, income and education are less powerful compared to some of the core individual beliefs. This is notable given the variance of core beliefs across regions—as well as their persistence (Inglehart and Baker 2000).

In our analysis of CDR and SRM technologies, we find that, except for afforestation, deployment in the majority of high-income countries might be challenging because of the visible outlines of public opposition, already even for some options that remain mostly hypothetical. High-income countries, many of which can be broadly described as WEIRD, tend to express lower beliefs in the capacity of science and technology to deliver solutions to climate change and lower trust in industry, in addition to expecting to experience less personal harm from climate change. This work could be particularly valuable for research focused on integrating novel technologies into IAMs, such as DACCS. For example, Gidden *et al* (2023) assumed that DACCS deployment would begin diffusing in high-income countries, given their financial and technological capacity.

Our results imply that more region-specific approaches (e.g. to better account for factors explaining differences in support for emerging technologies) to developing the narratives and assumptions that inform IAM modeling efforts might be warranted. Rather than assuming technology diffusion is mostly driven by technical or economic potential, or that support is motivated by the same logic across the globe, insights from surveys and other public-centering exercises represent a key complementary tool to IAM and other climate-modeling efforts, by providing more regional specificity and adding more nuance to the techno-economic constraints.

The observation that some high-income countries exhibit notably low levels of trust in the ability of industry to address climate change aligns with broader findings from other surveys, such as the Edelman Trust Barometer (2023) or another recent global study of trust in science (Cologna *et al* 2024), both of which highlight a general decline in trust within developed regions. Many studies have emphasized the pivotal role of trust in the agents of change for the successful diffusion of technology (Siegrist and Cvetkovich 2000, Whitfield *et al* 2009, Perlaviciute and Steg 2014), and consequently, for the effective implementation of climate policies. By demonstrating how support for deployment of potentially useful technologies also depends on such factors, addressing the emerging societal polarization and the decline in trust again emerges as of paramount importance in the formulation of global climate strategies.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://github.com/brutschki/erl_survey. Data will be available from 31 December 2024.

Appendix

A1.1. Distribution of age

Here we present the distribution of age of respondents for all countries included in the survey. For the subsequent regression analyses we recoded the age variable into 'age categorical': (1) for younger than 20 years, (2) between 20 and 30 years, (3) between 30 and 40 years, (4) between 40 and 50 years, (5) older than 50 years.

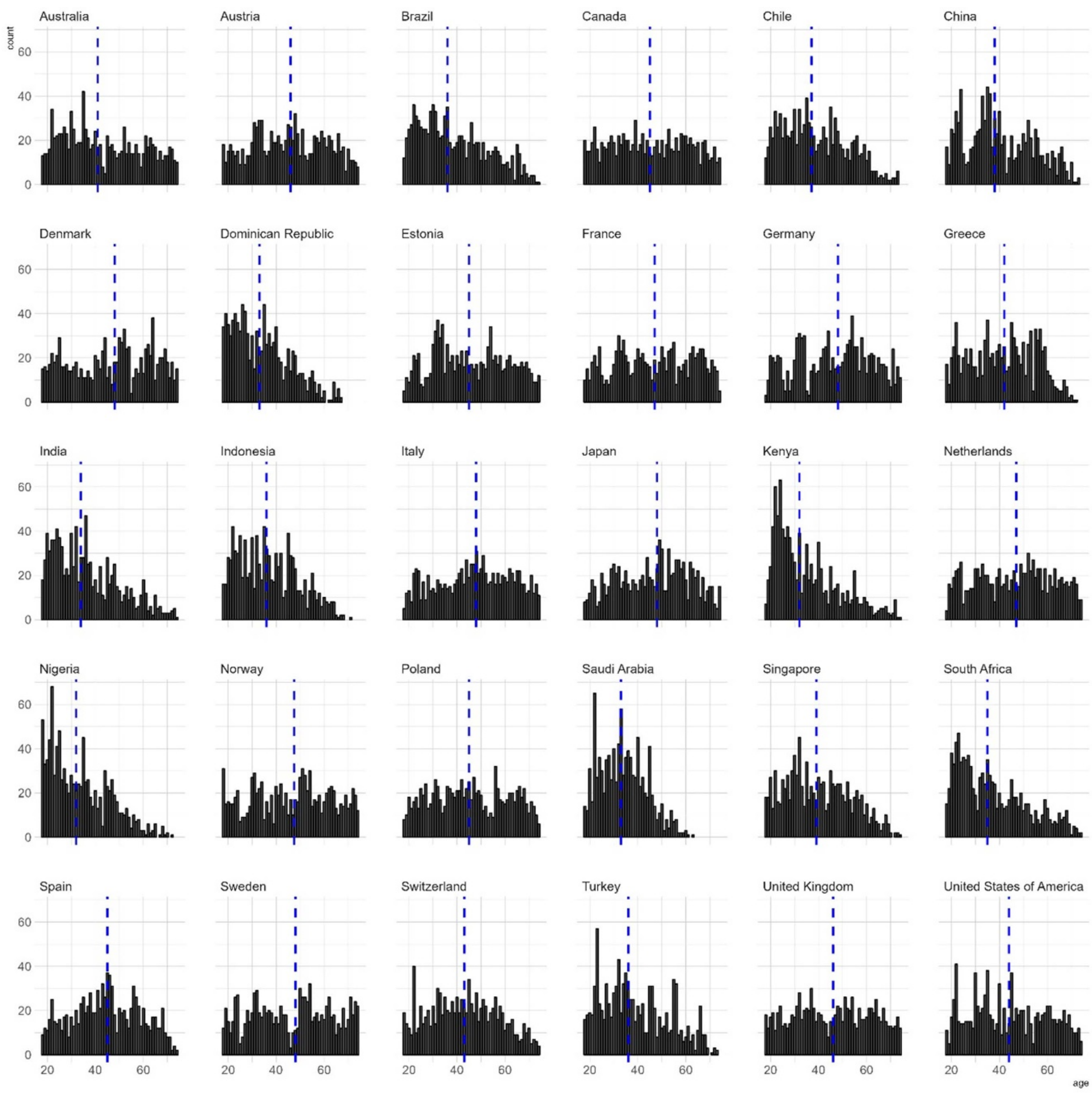


Figure A1.1. Distribution of age for all countries included in the survey.

A1.2 Additional descriptive figures

To support figure 3 in the main article and the main argument about importance of trust, we present a more detailed breakdown of response items for the variable pertaining to trust in industry to solve climate change.

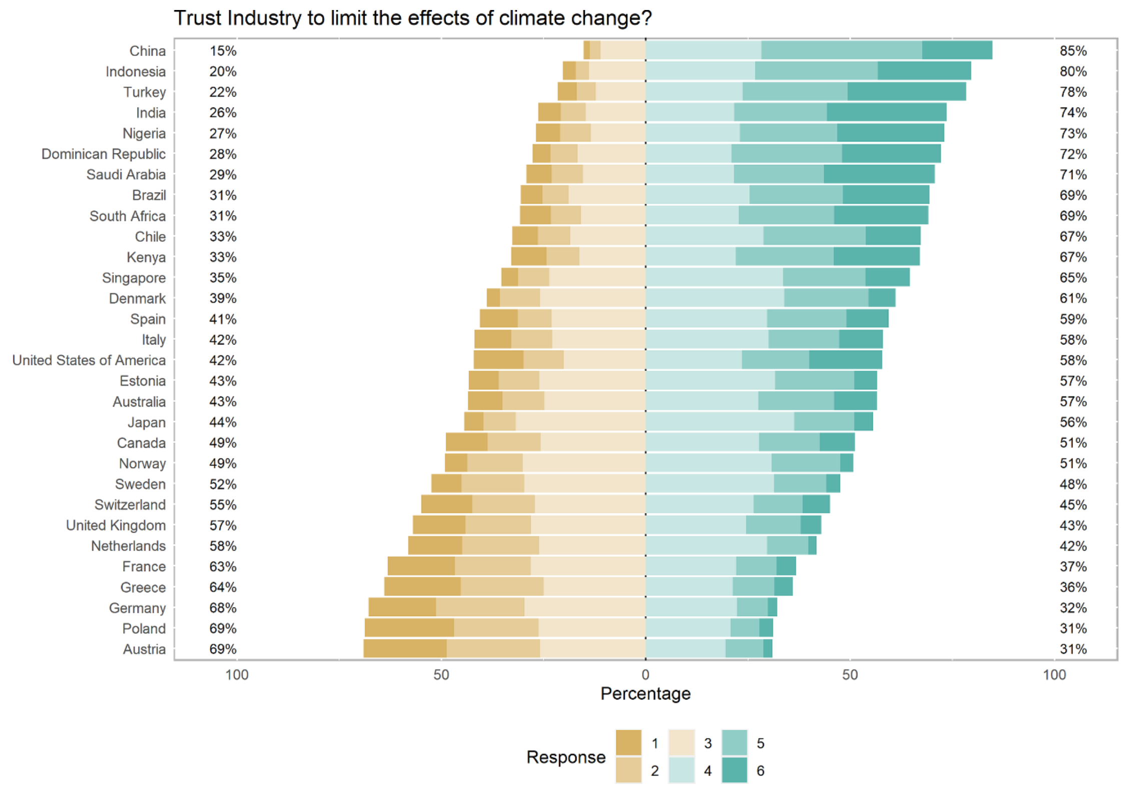


Figure A1.2. Trust in Industry across all countries. Trust was measured on a scale from 1–6. 1 = 'No trust' to 6 = 'Very high trust'.

A1.3 Regression methods and sensitivities

In our main analysis part (figure 4) we utilized cross country data, specifying a fixed effect model with standard errors clustered by country. Here we present regression tables (table 1–3) to help the additional interpretation of the coefficient plots. The utilization of a fixed effects model in cross-country survey analysis serves as a robust method for mitigating unobserved heterogeneity at the country level. Fixed effects account for time-invariant characteristics specific to each country that may influence the observed variables. Additionally, clustering standard errors by country accounts for potential correlation among observations within the same country, recognizing that responses from individuals within a particular country may exhibit similarities that are not present across different countries.

Table A1.3.1. Regression Results for CDRn group (ecosystems based CDR). Results with * exclude 'conservative' variable to make sure that China is included in the cross-country analysis. We can trace that results do not change substantively with inclusion of China. Note that the total number of observations is below 9000 because there are missing values within the income variable.

	(1)	(2)	(3)	(4)	(5)	(6)
	AF	AF*	SCS	SCS*	MBBC	MBCC*
Age	0.0770***	0.0778***	0.0677***	0.0687***	0.0631***	0.0646***
	(0.00993)	(0.00939)	(0.00938)	(0.00912)	(0.0109)	(0.0106)
Female	0.0491***	0.0592***	−0.0136	−0.00710	0.0124	0.0205
	(0.0167)	(0.0177)	(0.0181)	(0.0184)	(0.0181)	(0.0182)
Education	0.0595**	0.0642**	0.0994***	0.102***	0.0938***	0.0954***
	(0.0273)	(0.0264)	(0.0315)	(0.0319)	(0.0296)	(0.0295)
Income	−0.00634	−0.0176	0.0109	0.0102	0.00975	0.0117
	(0.0214)	(0.0235)	(0.0249)	(0.0238)	(0.0245)	(0.0231)
Religion	−0.0234***	−0.0303***	−0.0266**	−0.0325***	−0.0274***	−0.0342***
	(0.00815)	(0.00737)	(0.0106)	(0.00993)	(0.00894)	(0.00925)
Conservative	−0.0209***		−0.0304***		−0.0317***	
	(0.00591)		(0.00879)		(0.00699)	
Familiarity	0.0861***	0.0912***	0.0187**	0.0239**	0.0231**	0.0291**
	(0.00859)	(0.00974)	(0.00856)	(0.0105)	(0.0110)	(0.0129)
Science	0.0377***	0.0395***	0.106***	0.106***	0.109***	0.109***
	(0.0111)	(0.0108)	(0.0139)	(0.0138)	(0.0139)	(0.0140)
Nat No Meddle	−0.00979**	−0.0129**	−0.0123*	−0.0138**	−0.00936	−0.0102
	(0.00456)	(0.00490)	(0.00650)	(0.00646)	(0.00686)	(0.00674)
Trust-Industry	0.0572***	0.0584***	0.0947***	0.0961***	0.0908***	0.0945***
	(0.00947)	(0.00942)	(0.0113)	(0.0111)	(0.0121)	(0.0125)
Trust-Nat Gov	0.00958	0.0138	0.0366***	0.0381***	0.0317**	0.0299**
	(0.00856)	(0.00973)	(0.0102)	(0.0103)	(0.0121)	(0.0120)
Climate Harm	0.0921***	0.0926***	0.108***	0.110***	0.117***	0.119***
	(0.0116)	(0.0119)	(0.0145)	(0.0149)	(0.0153)	(0.0159)
Env Concern	0.113***	0.112***	0.141***	0.141***	0.149***	0.151***
	(0.0116)	(0.0115)	(0.0120)	(0.0119)	(0.0114)	(0.0113)
Constant	2.708***	2.601***	2.132***	1.970***	2.034***	1.856***
	(0.0867)	(0.0752)	(0.0744)	(0.0770)	(0.0807)	(0.0758)
N	8102	8452	8041	8390	8017	8362
R^2	0.111	0.111	0.138	0.135	0.138	0.135

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Apart from a model where we looked at all countries together, we also ran regressions for each country and technology individually to explore the direction and the size of the effect of key variables of interest. In this context, we focus on 'climate harm', 'science' and 'trust' variables. We can trace that the effect of all variables remains robust and in the expected direction also in this slightly different model specification, despite the size of the effect varying by country and technology.

Table A1.3.2. Regression Results for CDRe group (engineered CDR). Results with * exclude 'conservative' variable to make sure that China is included in the cross-country analysis. We can trace that results do not change substantively with inclusion of China. Note that the total number of observations is below 9000 because there are missing values within the income variable.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Biochar	Biochar*	EW	EW*	BECCS	BECCS*	DACCS	DACCS*
Age	−0.00717	−0.00345	−0.00181	0.00274	−0.00490	−0.00168	−0.0397***	−0.0335***
	(0.0112)	(0.0111)	(0.0152)	(0.0150)	(0.0100)	(0.0100)	(0.00999)	(0.0113)
Female	−0.00890	−0.00117	0.0227	0.0186	0.0714***	0.0688***	0.0888***	0.0855***
	(0.0249)	(0.0248)	(0.0266)	(0.0252)	(0.0190)	(0.0187)	(0.0241)	(0.0235)
Education	−0.0205	−0.0196	−0.0878**	−0.0866**	0.0132	0.0161	0.00698	0.0134
	(0.0298)	(0.0289)	(0.0357)	(0.0349)	(0.0308)	(0.0297)	(0.0296)	(0.0288)
Income	0.0497*	0.0466*	0.0205	0.0200	0.00288	0.00282	0.0208	0.0180
	(0.0263)	(0.0257)	(0.0219)	(0.0214)	(0.0282)	(0.0271)	(0.0246)	(0.0234)
Religion	−0.0103	−0.00930	0.00733	0.0112	−0.00697	−0.00870	0.00720	0.00404
	(0.00953)	(0.00892)	(0.0113)	(0.0107)	(0.00782)	(0.00743)	(0.00872)	(0.00851)
Conservative	−0.00500		0.0101		−0.0123		−0.0182**	
	(0.00771)		(0.00800)		(0.00726)		(0.00864)	
Familiarity	0.0484***	0.0549***	0.158***	0.166***	0.0839***	0.0888***	0.0808***	0.0875***
	(0.00981)	(0.0113)	(0.0146)	(0.0155)	(0.0104)	(0.0120)	(0.0135)	(0.0159)
Science	0.113***	0.113***	0.140***	0.139***	0.142***	0.142***	0.144***	0.145***
	(0.0192)	(0.0188)	(0.0169)	(0.0164)	(0.0148)	(0.0142)	(0.0123)	(0.0117)
Nat No Meddle	−0.0244***	−0.0235***	−0.0228***	−0.0203***	−0.0334***	−0.0320***	−0.0284***	−0.0278***
	(0.00852)	(0.00826)	(0.00718)	(0.00728)	(0.00777)	(0.00778)	(0.00797)	(0.00780)
Trust-Industry	0.144***	0.144***	0.104***	0.108***	0.106***	0.108***	0.121***	0.125***
	(0.0134)	(0.0133)	(0.0138)	(0.0141)	(0.0138)	(0.0136)	(0.0113)	(0.0122)
Trust-Nat Gov	0.0519***	0.0533***	0.0871***	0.0852***	0.0891***	0.0877***	0.0691***	0.0677***
	(0.00960)	(0.00935)	(0.0147)	(0.0145)	(0.0108)	(0.0104)	(0.0108)	(0.0106)
Climate Harm	0.127***	0.127***	0.0963***	0.0930***	0.115***	0.114***	0.107***	0.109***
	(0.0130)	(0.0132)	(0.0183)	(0.0177)	(0.0170)	(0.0171)	(0.0165)	(0.0163)
Env Concern	0.0804***	0.0794***	0.0300**	0.0250*	0.0580***	0.0588***	0.0602***	0.0589***
	(0.0131)	(0.0129)	(0.0135)	(0.0134)	(0.0120)	(0.0116)	(0.0124)	(0.0126)
Constant	1.993***	1.922***	1.623***	1.639***	1.797***	1.715***	1.854***	1.732***
	(0.128)	(0.119)	(0.129)	(0.111)	(0.0907)	(0.0854)	(0.122)	(0.112)
N	7968	8308	7962	8303	7965	8305	7965	8301
R^2	0.132	0.134	0.133	0.136	0.146	0.147	0.141	0.144

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

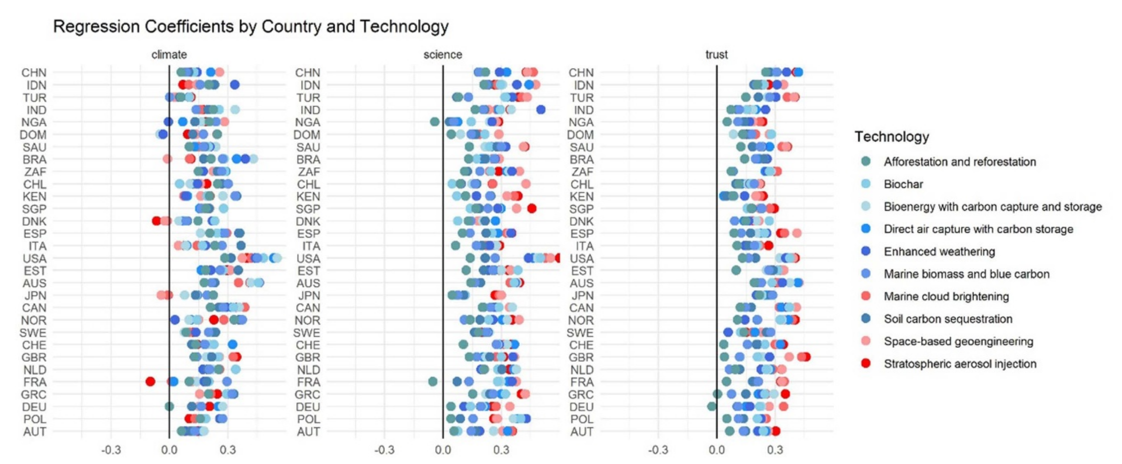


Figure A1.3.1. Regression coefficients for each country and each technology.

Table A1.3.3. Regression Results for SRM group. Results with * exclude 'conservative' variable to make sure that China is included in the cross-country analysis. We can trace that results do not change substantively with inclusion of China. Note that the total number of observations is below 9000 because there are missing values within the income variable.

	(1)	(2)	(3)	(4)	(5)	(6)
	SAI	SAI*	MCB	MCB*	SBG	SBG*
Age	−0.0649***	−0.0598***	−0.0716***	−0.0632***	−0.0420***	−0.0349**
	(0.0131)	(0.0133)	(0.0137)	(0.0146)	(0.0145)	(0.0153)
Female	−0.0732**	−0.0721**	−0.0592**	−0.0600**	−0.00890	−0.0125
	(0.0320)	(0.0299)	(0.0283)	(0.0267)	(0.0303)	(0.0295)
Education	−0.0206	−0.0214	0.0151	0.0212	−0.0394	−0.0397
	(0.0330)	(0.0327)	(0.0330)	(0.0317)	(0.0358)	(0.0352)
Income	0.0171	0.00878	0.00902	−0.00261	−0.0213	−0.0275
	(0.0246)	(0.0259)	(0.0299)	(0.0292)	(0.0290)	(0.0278)
Religion	0.0191**	0.0250**	0.0162*	0.0156	0.0160*	0.0195**
	(0.00843)	(0.00970)	(0.00797)	(0.00938)	(0.00802)	(0.00829)
Conservative	0.00285		−0.0138		0.00203	
	(0.00918)		(0.00875)		(0.00713)	
Familiarity	0.0616***	0.0822***	0.0633***	0.0843***	0.108***	0.120***
	(0.0152)	(0.0240)	(0.0124)	(0.0239)	(0.0127)	(0.0167)
Science	0.168***	0.171***	0.151***	0.158***	0.194***	0.195***
	(0.0124)	(0.0124)	(0.0147)	(0.0151)	(0.0139)	(0.0136)
Nat No Meddle	−0.0423***	−0.0414***	−0.0547***	−0.0541***	−0.0453***	−0.0443***
	(0.0104)	(0.00999)	(0.00905)	(0.00886)	(0.00842)	(0.00819)
Trust-Industry	0.166***	0.168***	0.151***	0.155***	0.165***	0.167***
	(0.0144)	(0.0146)	(0.0149)	(0.0148)	(0.0156)	(0.0156)
Trust-Nat Gov	0.108***	0.102***	0.107***	0.0969***	0.0888***	0.0862***
	(0.0108)	(0.0124)	(0.0121)	(0.0140)	(0.0147)	(0.0145)
Climate Harm	0.0936***	0.0886***	0.0707***	0.0691***	0.0809***	0.0800***
	(0.0158)	(0.0161)	(0.0141)	(0.0146)	(0.0171)	(0.0163)
Env Concern	0.00683	0.00717	0.0363**	0.0388***	0.0126	0.0127
	(0.0134)	(0.0130)	(0.0134)	(0.0133)	(0.0127)	(0.0125)
Constant	1.751***	1.704***	2.062***	1.927***	1.682***	1.632***
	(0.143)	(0.142)	(0.134)	(0.127)	(0.166)	(0.158)
N	8034	8379	8044	8390	8010	8351
R^2	0.170	0.172	0.168	0.169	0.170	0.173

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A2.3.4. VIF for SAI specification—Exploring the possible issues caused by multicollinearity.

Variable	VIF	1/VIF
Env Concern	18.52	0.05
Climate Harm	13.79	0.07
Science	13.57	0.07
Education	12.08	0.08
Trust-Industry	11.21	0.09
Income	10.48	0.10
Trust-Nat Gov	9.63	0.10
Female	9.32	0.11
Age categorical	8.63	0.12
Nat No Meddle	7.02	0.14
Conservative	6.8	0.15
Religion	5.74	0.17
Familiarity	3.78	0.26

Table A3.3.5. Comparing Models for SAI when dropping variables with high VIF(>10) and exploring the possible issues caused by multicollinearity.

	(1)	(2)
	Full SAI	Reduced SAI
Age categorical	-0.0649^{***}	-0.0862^{***}
	(0.0131)	(0.0159)
Female	-0.0732^{**}	-0.0675^{**}
	(0.0320)	(0.0289)
Education	−0.0206	0.0119
	(0.0330)	(0.0349)
Income	0.0171	
	(0.0246)	
Religion	0.0191^{**}	0.0238^{**}
	(0.00843)	(0.00930)
Conservative	0.00285	−0.0146
	(0.00918)	(0.00863)
Familiarity	0.0616^{***}	0.0872^{***}
	(0.0152)	(0.0170)
Science	0.168^{***}	
	(0.0124)	
Nat No Meddle	-0.0423^{***}	-0.0633^{***}
	(0.0104)	(0.0118)
Trust-Industry	0.166^{***}	
	(0.0144)	
Trust-Nat No Meddle	0.108^{***}	0.231^{***}
	(0.0108)	(0.0126)
Climate Harm	0.0936^{***}	
	(0.0158)	
Env Concern	0.00683	
	(0.0134)	
Constant	1.751^{***}	2.970^{***}
	(0.143)	(0.151)
N	8034	8947
R^2	0.170	0.109

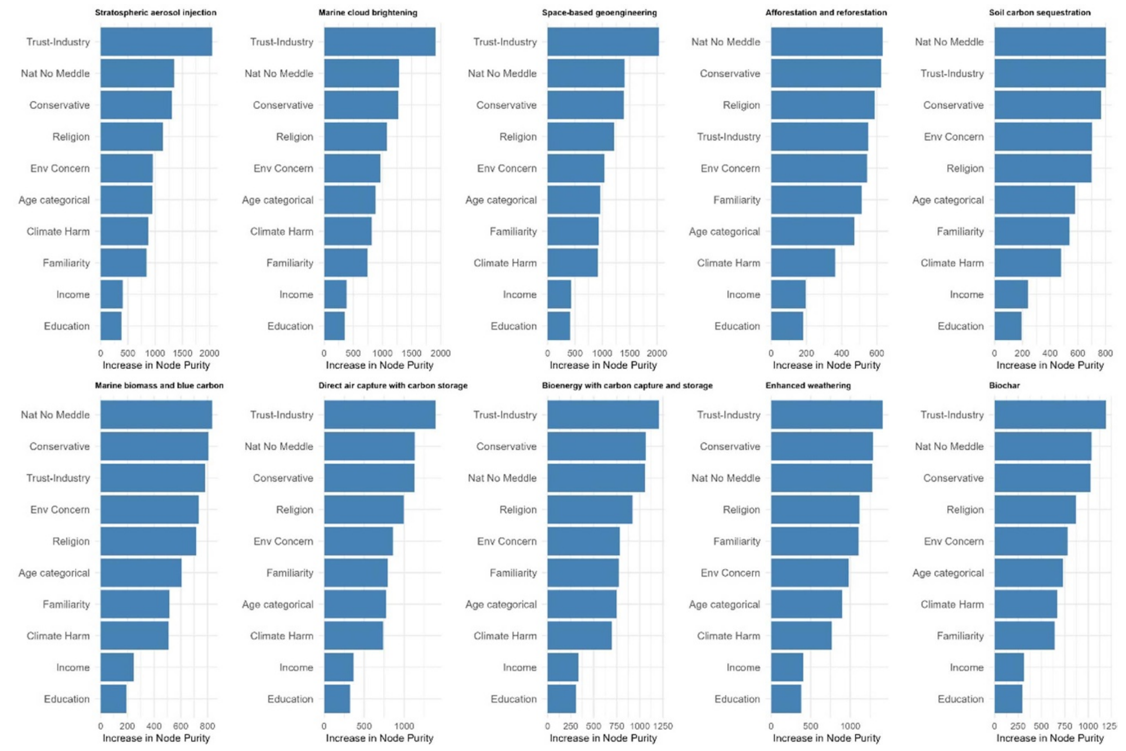


Figure A1.4.1. Variance importance across all technologies (all countries included).

A1.4 Exploratory random forest analysis

A variance importance plot in the context of random forest analysis provides insights into the significance of each predictor variable in explaining the variability of the response variable (in our case the support for deployment of a given technology). Random forests operate by constructing an ensemble of decision trees (in our case we ran 500), each trained on a different subset of the data and variables. The plot displays the contribution of each predictor to the overall model performance. Higher values on the plot indicate greater importance, suggesting that the corresponding variable plays a more substantial role in the model's predictive accuracy. In this context, we performed the analysis on all data not accounting for country differences. In figure A1.4.1 we find similarly as in our main analysis that the role of the variable 'trust in industry' is most pronounced in the context of SRM technologies but remains robust but less prominent in the context of ecosystem based technologies.

ORCID iDs

Elina Brutschin https://orcid.org/0000-0001-7040-3057
Chad M Baum https://orcid.org/0000-0002-6513-5518
Livia Fritz https://orcid.org/0000-0001-7710-2193
Sean Low https://orcid.org/0000-0002-3654-5964
Benjamin K Sovacool https://orcid.org/0000-0002-4794-9403
Keywan Riahi https://orcid.org/0000-0001-7193-3498

References

Baum C M, Fritz L, Low S and Sovacool B K 2024 Public perceptions and support of climate intervention technologies across the global north and global south *Nat. Commun.* **15** 2060

Baur S, Nauels A, Nicholls Z, Sanderson B M and Schleussner C-F 2023 The deployment length of solar radiation modification: an interplay of mitigation, net-negative emissions and climate uncertainty *Earth Syst. Dyn.* **14** 367–81

Bellamy R 2022 Mapping public appraisals of carbon dioxide removal *Glob. Environ. Change* **76** 102593

Bergquist M, Nilsson A, Harring N and Jagers S C 2022 Meta-analyses of fifteen determinants of public opinion about climate change taxes and laws *Nat. Clim. Change* **12** 3

Bolsen T, Palm R and Kingsland J T 2022 Effects of conspiracy rhetoric on views about the consequences of climate change and support for direct carbon capture *Environ. Commun.* **16** 209–24

Bolsen T, Palm R and Luke R E 2023 Public response to solar geoengineering: how media frames about stratospheric aerosol injection affect opinions *Clim. Change* **176** 112

Bonny S 2003 Why are most Europeans opposed to GMOs? Factors explaining rejection in France and Europe *Electron. J. Biotechnol.* **6** 7–8

Boudet H S 2019 Public perceptions of and responses to new energy technologies *Nat. Energy* **4** 6

Bouman T, Verschoor M, Albers C J, Böhm G, Fisher S D, Poortinga W, Whitmarsh L and Steg L 2020 When worry

about climate change leads to climate action: how values, worry and personal responsibility relate to various climate actions *Glob. Environ. Change* **62** 102061
Brutschin E, Schenuit F, van Ruijven B and Riahi K 2022 Exploring enablers for an ambitious coal phaseout *Politics Gov.* **10** 200–12
Cologna V *et al* 2024 *Trust in Scientists and their Role in Society Across 68 Countries* (OSF) (https://doi.org/10.31219/osf.io/6ay7s)
Corner A, Parkhill K, Pidgeon N and Vaughan N E 2013 Messing with nature? Exploring public perceptions of geoengineering in the UK *Glob. Environ. Change* **23** 938–47
Corner A and Pidgeon N 2015 Like artificial trees? The effect of framing by natural analogy on public perceptions of geoengineering *Clim. Change* **130** 425–38
Costa-Font M, Gil J M and Traill W B 2008 Consumer acceptance, valuation of and attitudes towards genetically modified food: review and implications for food policy *Food Policy* **33** 99–111
Cui K and Shoemaker S P 2018 Public perception of genetically-modified (GM) food: a nationwide Chinese consumer study *npj Sci. Food* **2** 1
Cummings C L, Lin S H and Trump B D 2017 Public perceptions of climate geoengineering: a systematic review of the literature *Clim. Res.* **73** 247–64
Dechezleprêtre A, Fabre A, Kruse T, Planterose B, Sanchez Chico A and Stantcheva S 2022 Fighting climate change: international attitudes toward climate policies *SSRN Scholarly Paper* 4165337 (available at: https://papers.ssrn.com/abstract=4165337)
Edelman Trust Barometer 2023 2023 edelman trust barometer (Edelman) (available at: www.edelman.com/trust)
European Commission 2023 Report from the commission to the european parliament and the council on implementation of directive 2009/31/EC on the geological storage of carbon dioxide COM(2023) 657 final (available at: https://climate.ec.europa.eu/document/download/0708ff12-02b6-4af2-bac7-1ea0ef16bac1_en)
Floyd R 2023 Solar geoengineering: the view from just war/securitization theories *J. Glob. Secur. Stud.* **8** ogad012
Fritz L, Baum C M, Brutschin E, Low S and Sovacool B K 2024 Climate beliefs, climate intervention technologies and transformation: contextualizing public perceptions in 22 countries *Glob. Environ. Change* **87** 102880
Gidden M J, Brutschin E, Ganti G, Unlu G, Zakeri B, Fricko O, Mitterrutzner B, Lovat F and Riahi K 2023 Fairness and feasibility in deep mitigation pathways with novel carbon dioxide removal considering institutional capacity to mitigate *Environ. Res. Lett.* **18** 074006
Henrich J, Heine S J and Norenzayan A 2010 Most people are not WEIRD *Nature* **466** 7302
Huijts N M A, Molin E J E and Steg L 2012 Psychological factors influencing sustainable energy technology acceptance: a review-based comprehensive framework *Renew. Sustain. Energy Rev.* **16** 525–31
Inglehart R and Baker W E 2000 Modernization, cultural change, and the persistence of traditional values *Am. Sociol. Rev.* **65** 19–51
Jewell J and Cherp A 2020 On the political feasibility of climate change mitigation pathways: is it too late to keep warming below 1.5 °C? *WIREs Clim. Change* **11** e621
Jobin M and Siegrist M 2020 Support for the deployment of climate engineering: a comparison of ten different technologies *Risk Anal.* **40** 1058–78
Jones C R, Yardley S and Medley S 2019 The social acceptance of fusion: critically examining public perceptions of uranium-based fuel storage for nuclear fusion in Europe *Energy Res. Soc. Sci.* **52** 192–203
Ju Y, Sugiyama M and Shiraki H 2023 Perceived feasibility and potential barriers of a net-zero system transition among Japanese experts *Commun. Earth Environ.* **4** 1–13
Klaus G, Ernst A and Oswald L 2020 Psychological factors influencing laypersons' acceptance of climate engineering, climate change mitigation and business as usual scenarios *Technol. Soc.* **60** 101222
Komendantova N and Battaglini A 2016 Beyond decide-announce-defend (DAD) and not-in-my-backyard (NIMBY) models? Addressing the social and public acceptance of electric transmission lines in Germany *Energy Res. Soc. Sci.* **22** 224–31
Lê S, Josse J and Husson F 2008 FactoMineR: an R package for multivariate analysis *J. Stat. Softw.* **25** 1–18
Lehtonen M, Kojo M, Jartti T, Litmanen T and Kari M 2020 The roles of the state and social licence to operate? Lessons from nuclear waste management in Finland, France, and Sweden *Energy Res. Soc. Sci.* **61** 101353
Lo A Y and Chow A T 2015 The relationship between climate change concern and national wealth *Clim. Change* **131** 335–48
Minx J C *et al* 2024 Coal transitions—part 2: phase-out dynamics in global long-term mitigation scenarios *Environ. Res. Lett.* **19** 033002
Nawaz S, Peterson St-Laurent G and Satterfield T 2023 Public evaluations of four approaches to ocean-based carbon dioxide removal *Clim. Policy* **23** 379–94
Peng W, Iyer G, Bosetti V, Chaturvedi V, Edmonds J, Fawcett A A, Hallegatte S, Victor D G, van Vuuren D and Weyant J 2021 Climate policy models need to get real about people—Here's how *Nature* **594** 174–6
Perlaviciute G and Steg L 2014 Contextual and psychological factors shaping evaluations and acceptability of energy alternatives: integrated review and research agenda *Renew. Sustain. Energy Rev.* **35** 361–81
Pianta S and Brutschin E 2022 Emissions lock-in, capacity, and public opinion: how insights from political science can inform climate modeling efforts *Politics Gov.* **10** 186–99
Rabesandratana T 2014 E.U. to let wary members ban genetically modified crops *Science* **346** 1280
Raimi K T 2021 Public perceptions of geoengineering *Curr. Opin. Psychol.* **42** 66–70
Rogelj J, Fransen T, den Elzen M G J, Lamboll R D, Schumer C, Kuramochi T, Hans F, Mooldijk S and Portugal-Pereira J 2023 Credibility gap in net-zero climate targets leaves world at high risk *Science* **380** 1014–6
Sandvik H 2008 Public concern over global warming correlates negatively with national wealth *Clim. Change* **90** 333–41
Saroglou V, Delpierre V and Dernelle R 2004 Values and religiosity: a meta-analysis of studies using Schwartz's model *Personality Individual Differences* **37** 721–34
Satterfield T, Nawaz S and St-Laurent G P 2023 Exploring public acceptability of direct air carbon capture with storage: climate urgency, moral hazards and perceptions of the 'whole versus the parts' *Clim. Change* **176** 14
Siegrist M and Cvetkovich G 2000 Perception of hazards: the role of social trust and knowledge *Risk Anal.* **20** 713–20
Smith S M *et al* 2024 The state of carbon dioxide removal *The State of Carbon Dioxide Removal* 2nd edn (available at: https://osf.io/f85qj/)
Sovacool B K, Baum C M and Low S 2023 Reviewing the sociotechnical dynamics of carbon removal *Joule* **7** 57–82
Sovacool B K and Gross A 2015 The social acceptance of artificial photosynthesis: towards a conceptual framework *Interface Focus* **5** 20140089
Strefler J, Bauer N, Humpenöder F, Klein D, Popp A and Kriegler E 2021 Carbon dioxide removal technologies are not born equal *Environ. Res. Lett.* **16** 074021
Sugiyama M, Asayama S and Kosugi T 2020 The north–south divide on public perceptions of stratospheric aerosol geoengineering?: a survey in six Asia-Pacific Countries *Environ. Commun.* **14** 641–56
Susskind L, Chun J, Gant A, Hodgkins C, Cohen J and Lohmar S 2022 Sources of opposition to renewable energy projects in the United States *Energy Policy* **165** 112922

Sweet S K, Schuldt J P, Lehmann J, Bossio D A and Woolf D 2021 Perceptions of naturalness predict US public support for soil carbon storage as a climate solution *Clim. Change* **166** 22

Tcvetkov P, Cherepovitsyn A and Fedoseev S 2019 Public perception of carbon capture and storage: a state-of-the-art overview *Heliyon* **5** e02845

Trencher G, Rinscheid A, Rosenbloom D and Truong N 2022 The rise of phase-out as a critical decarbonisation approach: a systematic review *Environ. Res. Lett.* **17** 123002

Upham P, Oltra C and Boso À 2015 Towards a cross-paradigmatic framework of the social acceptance of energy systems *Energy Res. Soc. Sci.* **8** 100–12

Verrier B, Smith C, Yahyaei M, Ziemski M, Forbes G, Witt K and Azadi M 2022 Beyond the social license to operate: whole system approaches for a socially responsible mining industry *Energy Res. Soc. Sci.* **83** 102343

Visschers V H M, Shi J, Siegrist M and Arvai J 2017 Beliefs and values explain international differences in perception of solar radiation management: insights from a cross-country survey *Clim. Change* **142** 531–44

Wenger A, Stauffacher M and Dallo I 2021 Public perception and acceptance of negative emission technologies—framing effects in Switzerland *Clim. Change* **167** 53

Whitfield S C, Rosa E A, Dan A and Dietz T 2009 The future of nuclear power: value orientations and risk perception *Risk Anal.* **29** 425–37

Wolske K S, Raimi K T, Campbell-Arvai V and Hart P S 2019 Public support for carbon dioxide removal strategies: the role of tampering with nature perceptions *Clim. Change* **152** 345–61

Wolsko C, Ariceaga H and Seiden J 2016 Red, white, and blue enough to be green: effects of moral framing on climate change attitudes and conservation behaviors *J. Exp. Soc. Psychol.* **65** 7–19

Zelezny L C, Chua P-P and Aldrich C 2000 New ways of thinking about environmentalism: elaborating on gender differences in environmentalism *J. Soc. Issues* **56** 443–57