Information provision and acceptance of climate policies

EEA ESEM 2023, Barcelona

Antonia Schwarz [1], K. Kaestner [2], M. Pahle [1], S. Sommer [2,3] & A. Stünzi [4]

[1]Potsdam Institute for Climate Impact Research

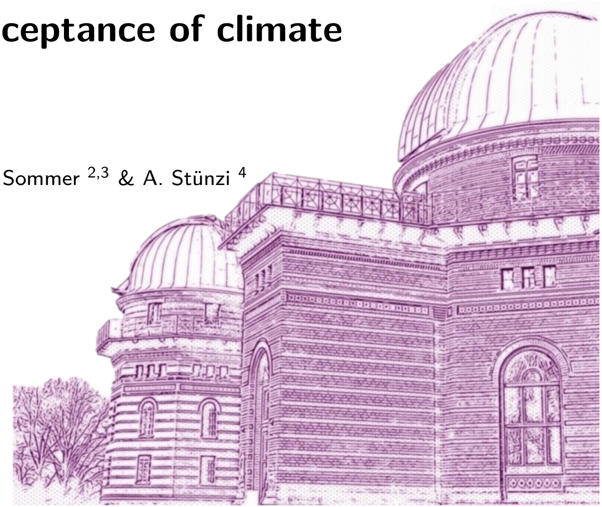
[2]RWI – Leibniz Institute for Economic Research

[3]Bochum University

[4]University of St.Gallen

August 28, 2023

We acknowledge financial support by the German BMWK
under grant 03EI5213D.

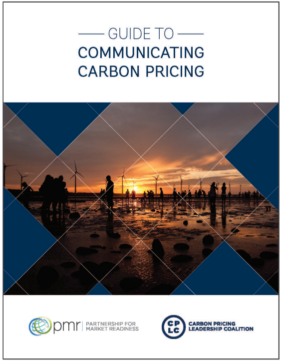


How to gain support for climate policy?

- Climate policies face a critical challenge: gaining public support but resistance remains despite all efforts.
- Vast growing literature on the determinants of public acceptance: cost concerns (Jagers and Hammar, 2009), fairness (Rivers and Schaufele, 2015) & inefficiency (Saelen and Kallbekken, 2011).
- If these concerns are **unjustified** and due to **lack of knowledge**, addressing them through communication may increase acceptance.

Research Question: Can tailored communication strategies enhance acceptance of the German cabron price?

Background



- Growing body of research explores the influence of communication on public support for carbon pricing (Douenne & Fabre, 2022).
- Effective messaging gaining focus (Haaland et al., 2023, JEL).
- Psychological research insights awaiting practical application:
  - Tailored, targeted & credible information crucial (Hine et al., 2014; Marshall et al., 2018).
  - Alignment of messages, messengers, and audiences key for effective climate policy communication (Moser, 2010).
  - Diverse population responses to climate change communication (Leiserowitz et al., 2021).
- We apply communication science recommendations to examine the potential of tailored communication in fostering public support for carbon pricing in Germany.

The survey

- Novel Survey Experiment in Germany (Summer 2021).
- 4,000 respondents aged 18 and above from forsa.omninent panel.
- Randomized control trial with tailored information videos.
- Tailored Video Treatments: addressing key concerns identified by the literature: personal cost, effectiveness & fairness.
- Control group: General video resembling governmental content.
- Extensive Controls: Socio-demographics, political orientation, environmental attitude, trust, fairness preferences, etc.

Experimental Design

Survey items:

- Level of concern: Assessed for cost burden, fairness, and effectiveness of carbon price (1 “not concerned at all” to 5 “very concerned”)
- Acceptance: Attitudes towards German carbon price (1 “totally disagree” to 5 “totally agree”, with 3 “neither agree nor disagree”)

Experimental Design

Survey items:

- Level of concern: Assessed for cost burden, fairness, and effectiveness of carbon price (1 “not concerned at all” to 5 “very concerned”)
- Acceptance: Attitudes towards German carbon price (1 “totally disagree” to 5 “totally agree”, with 3 “neither agree nor disagree”)

Assignment process based on two-stage random sorting:

- 1st Stage: 25% of the sample assigned to **general control**.
- Respondents assigned according to prime concern to **concern audiences** (costs, effectiveness & fairness)
- Stratified sorting used for equitable assignment when concerns ranked equally.
- Respondents with no concerns across all areas are excluded.
- 2nd Stage: Randomly assign $1/3$ within each concern audience to **concern control**

Experimental Process

Conjoint Effect of Tailoring and Targeting:

- Comparing tailored, targeted information vs. non-tailored, non-targeted communication.

Explicit Design Choices:

- Inclusion of relatable characters, trustworthy speaker, understandable language.
- Simple targeting strategy based on concern responses.
- Risk of positive treatment effect due to demand effect (Rosenthal, 1966; Zizzo, 2010) eliminated through comparison with control video.

Estimation of the ATE: Two methods employed

Simple difference-in-means (SDM) estimator:

- Under random assignment ATE can be retrieved using a SDM estimator (Imbens & Rubin, 2015).

$$Y_i = \alpha + \tau W_i + \epsilon_i, \tag{1}$$

- Y_i is the observed post treatment acceptance (binary) for individual i.
- W_i is the treatment indicator for individual i.
- the parameter α is a constant, τ yields the ATE and ϵ is a random error term.

Estimation of the ATE: Two methods employed

Simple difference-in-means (SDM) estimator:

- Under random assignment ATE can be retrieved using a SDM estimator (Imbens & Rubin, 2015).

$$Y_i = \alpha + \tau W_i + \epsilon_i, \tag{1}$$

- Y_i is the observed post treatment acceptance (binary) for individual i.
- W_i is the treatment indicator for individual i.
- the parameter α is a constant, τ yields the ATE and ϵ is a random error term.

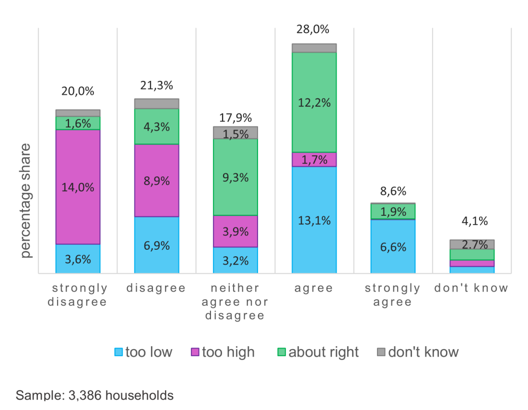
Regression adjustment (RA) estimator:

- Addresses imperfect random assignment, treatment heterogeneity.
- Control for pre-treatment covariates in regression.

$$Y_i = \alpha + \tau W_i + \mathbf{X_i}'\beta + W_i \dot{\mathbf{X}}_i' \delta + \epsilon_i, \tag{2}$$

- the vector $\dot{\mathbf{X}}_i$ contains the demeaned covariates given the sample averages $\bar{\mathbf{X}}$. .

Baseline acceptance and concern levels.



- N=3,386
- Baseline acceptance of €25 carbon price: 37%.
- 60% of those rejecting believe it is too high.
- However, 21% of those that reject do so because price is too low!
- Majority expresses concerns across cost burden, fairness, effectiveness dimensions.
- Strong correlation among concerns.

Tailored videos are jointly more effective.

Table 3: Treatment Effect on Acceptance Tailored/Targeted versus General Information

	POM	ATE		N
Model	control	effect	p-value	
logistic regression	0.441	0.036	0.033	3,386
regression adj.[a] logit outcome model	0.444	0.030	0.032	3,386

Note: For all models we apply robust standard errors.
[a] Regression adjustment methods applied exploiting differences in the averages of treatment-specific predicted outcomes. Covariates included in the two outcome models are: COV-19 cases per 100k, individual characteristics, cost burden indicators, political variables, other concerns, environmental knowledge and attitude measures as well as fairness preferences.

Effect is driven by cost video.

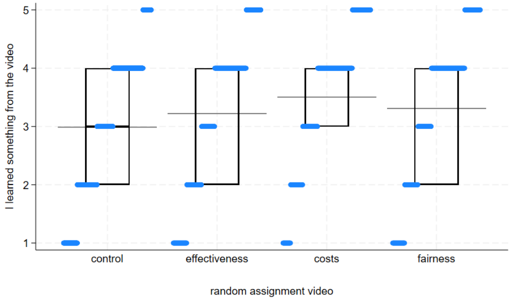
Table 4: Summary Treatment Effects on Acceptance (0/1)

	SDM methods			RA methods			N	
	POM	ATE		POM	ATE			
concern	control	effect	p-value	control	effect	p-value	T	C
personal costs	0.380	0.090	0.002	0.380	0.085	0.001	522	715
fairness	0.452	0.040	0.149	0.472	-0.003	0.887	557	749
effectiveness	0.429	0.056	0.039	0.438	0.034	0.157	583	794

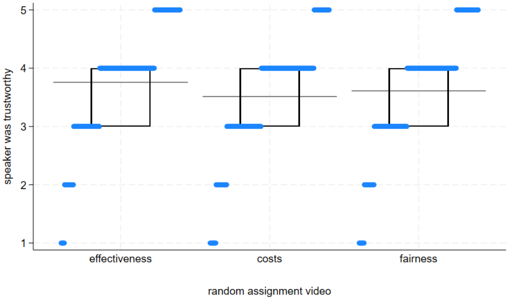
Note: For all models we apply robust standard errors. We employ regression adjustment methods, which exploit the differences in the averages of treatment-specific predicted outcomes. Covariates included in the two outcome models include COV-19 cases per 100k, individual characteristics, cost burden indicators, political variables, other concerns, environmental knowledge and attitude measures as well as fairness preferences.

Learning effect stronger for cost video. No issues with trust

I learned something.

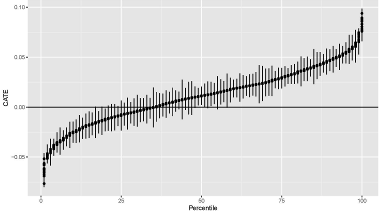


The speaker is trustworthy.

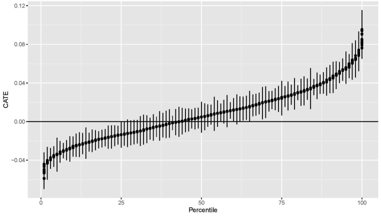


Fairness and Effectiveness group are more heterogeneous.

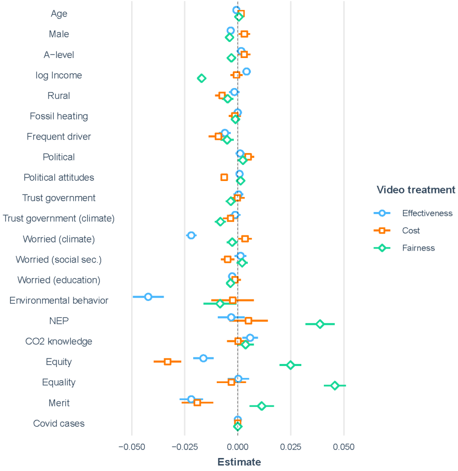
Ranked CAT Effectiveness Video



Ranked CAT Fairness Video

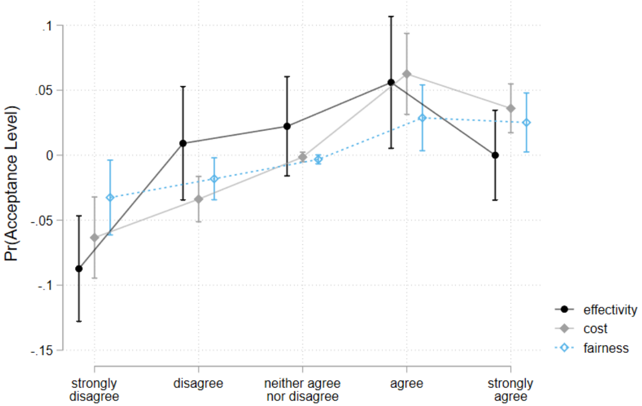


Conditional Average Treatment Effect



BUT clear booster of tolerance across videos.

Marginal effects from Generalized Order Logit.
Dependent variable: acceptance level (1-5).



Sample: 3,386 persons

Conclusion and Implications

- Tailored information boosts acceptance significantly.
- Effectiveness varies by concern audience.
- Results suggest learning impact of cost video on belief (concern) updating might drive change in acceptance.
- Machine learning reveals significant CATE heterogeneity.
- If done wrong, tailoring can perform worse than general information.
- **BUT**, increased tolerance across all audiences.
- Communicating effectively requires **precision**.

Any Questions?

schwarz@pik-potsdam.de