

# Collective Evidence on Behavioral Interventions Targeting Carbon Pricing Support

A Many-Designs Approach with 55 Studies

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Joint work with Armando Holzknicht, Esther Blanco, Jürgen Huber, and Michael Kirchler

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**Direct route:** Change individual behaviors (e.g. green electricity tariffs, public transport, meat consumption etc.) → Recent studies cast doubt on consistency and external validity (e.g., Byerly et al. 2018; DellaVigna & Linos, 2022; Bruns et al. 2025; Kaiser et al. 2025).

**Indirect route:** Application to *increase public support* for climate policies—especially carbon pricing, which is economically efficient but under-adopted.

**Reality check:** Only ~25 % of global emissions are priced—and typically below social-cost levels (IPCC, 2022; World Bank Group, 2024).

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Meta-analytic heterogeneity reflects many factors—not just **study design** → less precise meta-effects. At the same time, meta-analyses are prone to **publication bias**, driven by academic incentives → post hoc correction is only approximate.

→ **Important policy question** → demands methodology that also prevents *p*-hacking, and HARKing.

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→ 55 independent randomized controlled trials by international research teams **only differing in experimental conditions and support measures** → **in one study**—all addressing the same research question to accelerate knowledge generation by years!

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# #MANYDESIGNSCARBON

## PROCEDURE



- Registration of a **comprehensive pre-analysis plan** including detailed protocols, planned analyses, and extensive **power simulations** **hosted on OSF**: all raw datasets, all analyses scripts, software packages, team proposals, and IRB-approvals.
- **Project website launched**: [www.manydesignscarbon.online](http://www.manydesignscarbon.online).
- **Open call**: Distributed via LinkedIn and society mailing lists (Economics, Finance, Behavioral Science) to recruit research teams (up to 2 members each).

# #MANYDESIGNSCARBON

## PROCEDURE



- In total, **135 research teams (RTs)** applied to take part in the project.
  - In a first step, we **randomly selected 42 RTs** (pre-registered STATA script).
  - Additionally, we **added 25 randomly selected RTs** (Addendum to the PAP), which could signal to fund themselves (funding was **no** pre-requisite).
  - Of the 67 selected teams, **55 completed the full study protocol** and were included in the data analysis.

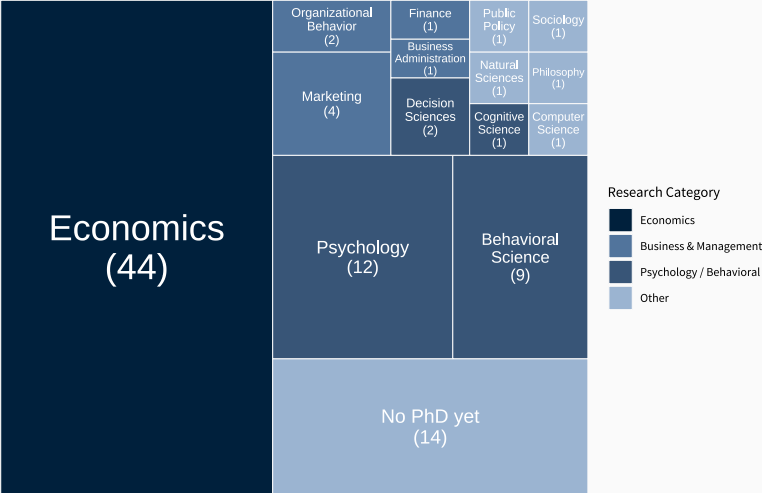
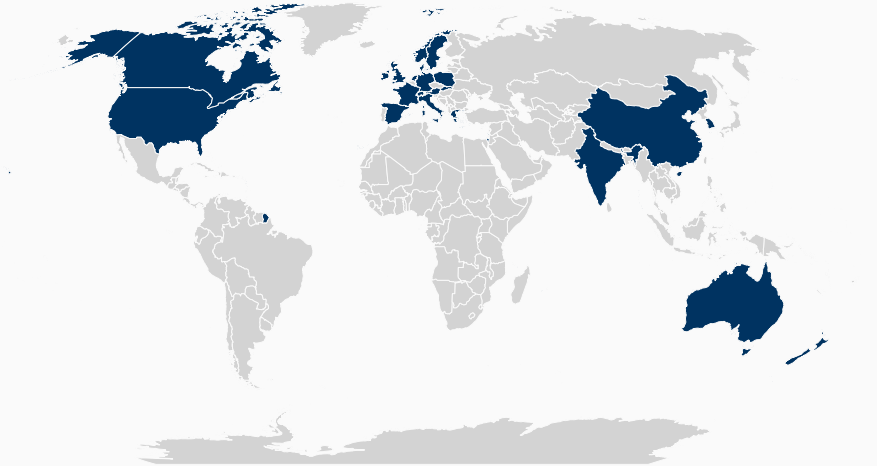


Figure 1: Distribution of research fields the final 55 RTs hold their PhDs in.

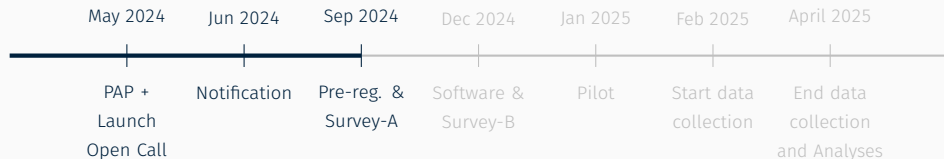


**Figure 2:** Geographical locations among the final 55 RTs.



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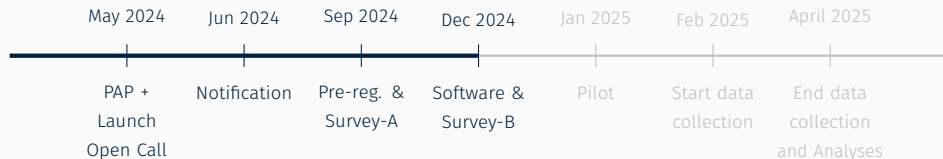
## PROCEDURE



- **Pre-Registration:** All teams submitted a **standardized pre-registration** detailing their experimental conditions and outcome measures. **The PIs validated the designs including the outcome measures → real-world impact.**
- **Survey A (Self-Assessment):** Immediately after pre-registration, teams predicted the standardized effect size (Cohen's  $d$ ) of their own design.

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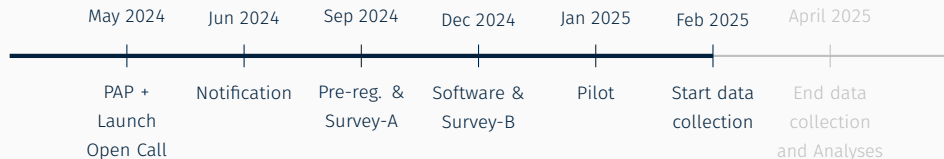
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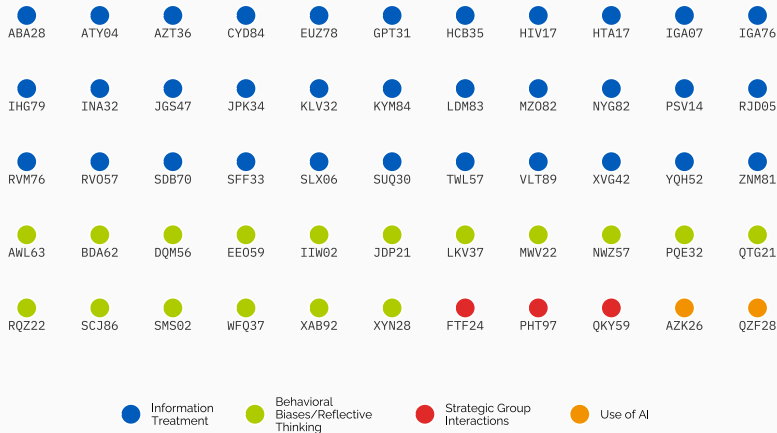
- **Software:** RTs programmed the software with one control and one intervention condition (*oTree* or *Qualtrics*). Common survey battery implemented across all studies to ensure consistency (Vlasceanu et al. 2024; Dechezleprêtre et al. 2025).
- **Survey B (Peer-Assessment):** Each team anonymously evaluated 10 randomly assigned peer designs, including the intervention's (i) *predicted effect*, (ii) *informativeness*, and (iii) its *categories*.

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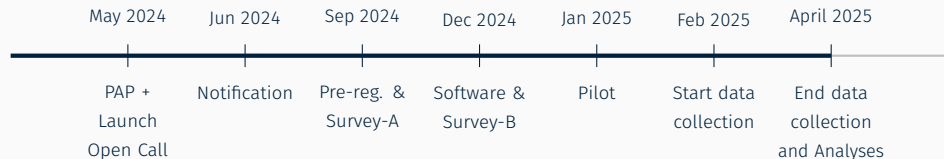
- **Main Launch:** Over 20,000 U.S. adults via Prolific—randomly assigned to each of the 110 conditions ( $55 \text{ designs} \times 2 \text{ arms}$ ,  $n = 175$  participants per arm) over 6 weeks.



**Figure 3:** Peer (Survey B) + AI classification of types of interventions across teams (registered prompt with GPT-4o).

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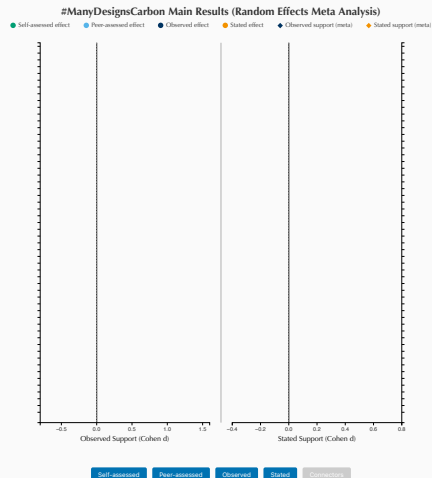
- **Uniform estimation**—For each study  $i = 1, \dots, 55$  (with  $N_i$  participants), estimate the univariate OLS

$$Y_{ij} = \alpha_i + \beta_i T_{ij} + \varepsilon_{ij}, \quad j = 1, \dots, N_i.$$

- **Standardized synthesis**—convert each  $\beta_i$  to Cohen's  $d_i$  (with CIs) and pool via a random-effects meta-analysis.

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## MAIN RESULTS (PRE-REGISTERED)

[▶ Open Dynamic Version](#)

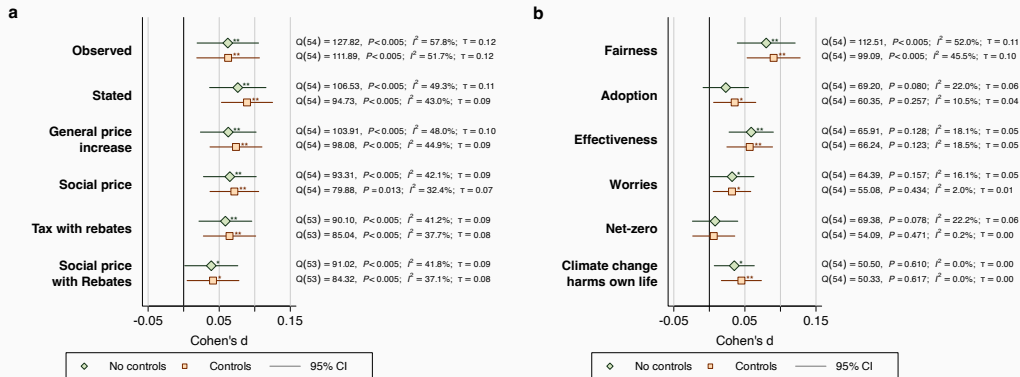


Figure 4: Panel (a): Meta-analytical results across primary support outcomes. Panel (b): Meta-analytical results across secondary outcomes.

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META REGRESSIONS WITH MODERATOR VARIABLES (PRE-REGISTERED)

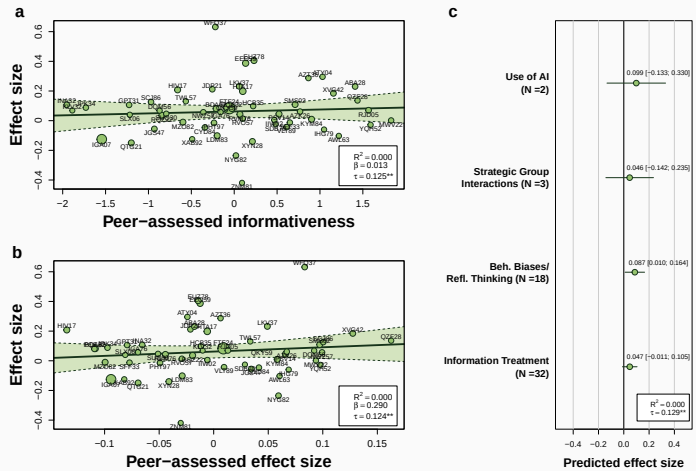


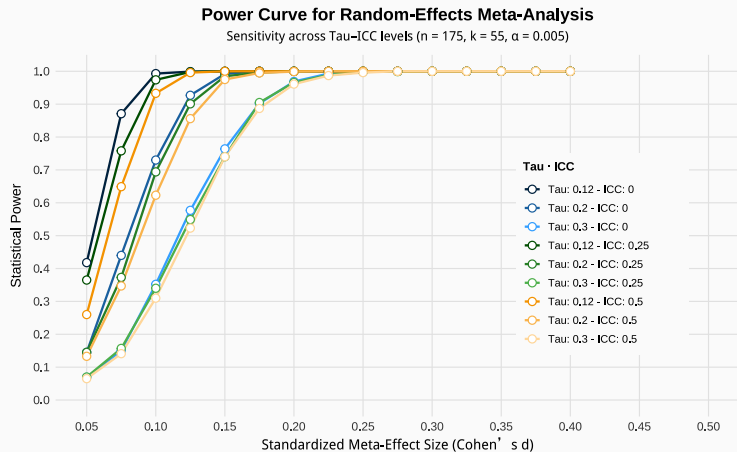
Figure 5: Results of meta-regressions exploring potential pre-registered peer assessed moderators.



- First Many-Designs study on the effect of behavioral interventions on support for carbon pricing (**observed & stated**).
- Meta-analysis finds a **very small but robust positive effect**.
- small-to-medium **heterogeneity** across designs underscores certain context-dependence (see prediction intervals).
- Interventions can **backfire**—they're not always “innocent”.
- Peer assessed **moderators cannot explain** results.
- Teams **overestimated** both their own and others' effects before data collection.

# Questions & Discussion

Your feedback helps us improve!



**Figure 6:** Power simulation for a random-effects meta-analysis, including sensitivity to between-study heterogeneity and intra-cluster correlation (ICC).

**AZK26 (AI):** 4-min AI chatbot on carbon tax vs open-topic chatbot; outcome: proof of contacting a representative or posting pro-carbon-tax message within 24 h.

**EEO59 (Bias/Reflective Thinking):** 3-min  $\geq 100$ -word letter to future generations on climate policy vs reading neutral text; outcome: \$0–4 donation to Citizens' Climate Lobby.

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