

Supporting Carbon Pricing Markets with Probabilistic Cash Rebates

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Outline

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Introduction and Motivation

- This is the first environmental & natural resources experiment for me and Andreas. [Crowd-sourcing Designs.]
- Setting market prices for carbon emissions provides economic incentives for companies to reduce their footprint in a free-market environment.
- Implementing these markets at the level required to produce meaningful results requires coordinated global action.
- However, carbon pricing markets often meet popular resistance (e.g., Boyce, 2018).
- Carbon price operates through two main channels:
 - Direct pricing of emissions: either via carbon taxes or emissions trading systems (cap-and-trade).
 - Pass-through effects: the cost of carbon is reflected in higher prices for carbon-intensive goods and services.

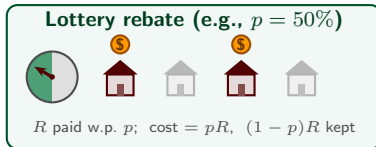
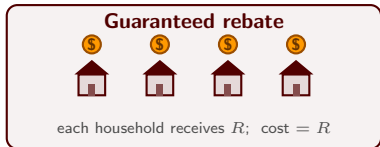
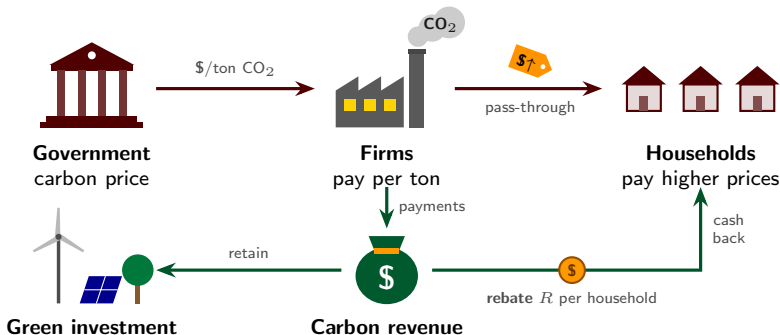
Introduction and Motivation

- Many skeptics view carbon pricing as a *concealed tax*, producing strong political polarization.
- Cash *rebates* make carbon pricing more transparent and improve their public perception and acceptance (Woerner et al., 2024).
- **Drawback:** revenue recycling through rebates considerably reduces the net revenue that could otherwise fund green investment.

The (Big Problem) Policy Tradeoff:

Rebates buy higher public **acceptance** and consumer behavioral responses (i.e., lower **consumption**), but every rebate dollar is taken away from the program **revenue** and not invested in mitigation efforts.

How Carbon Pricing Rebates Work



We Explore Rebate Design as Policy Instrument

- A **guaranteed** rebate pays R to every eligible household with certainty.
- A **probabilistic** (lottery) rebate pays the *same* amount R , but only with probability p .
 - Expected rebate expenditure scales roughly with p .
 - If people overweight small probabilities or enjoy lotteries, behavior might be preserved at a fraction of the rebate cost.

Our Main Research Question:

How much of the behavioral effect of a guaranteed rebate survives when the payment becomes probabilistic?

Research Question

We explore a novel strategy of implementing carbon cash rebate **lotteries** to promote consumer action while reducing expected rebate expenditure.

- 1 Does a guaranteed 100% cash rebate reduce consumption and increase carbon-emission offsets?
- 2 Can probabilistic rebates paid with 10%, 25%, or 50% probability reproduce the effect of a guaranteed rebate?
- 3 If not, what is the **effectiveness–expenditure** tradeoff between rebate probability, behavior, and expected cost?

Why Lottery Rebates?

- People like playing lotteries even though they are not good financial investments.
 - Entertainment consumption value.
 - Prospect Theory suggests people systematically overweight small probabilities.
 - Risk-seeking behavior among those with prolonged low or negative wealth.
- People also like to get rebates.
- Previous work documents 10% probabilistic incentives produce statistically indistinguishable valuations from full incentives (Ahles et al., 2024). [► Details](#)

From Incentive Device to Policy Instrument

- In an earlier version of this experiment, a 10% lottery on all payments produced effects statistically indistinguishable to a full payment. [► Details](#)
- This motivated the focal preregistered comparison in Wave 1: **10% vs. 100%** and subsequent comparison in Wave 2: **50% vs. 100%**.
- But there is an important difference:
 - In BRIS, the lottery scales *all* payoffs; relative incentives across choices are unchanged.
 - Here, the lottery scales *only the rebate*, so the privately optimal choice **changes with** p .
- Probabilistic mechanisms preserve behavior for incentive compatibility, but that does not hold when the expected value of the policy lever is an element of the payoff.

Our Contribution

- **Rebate Policy design:** first evidence on *probabilistic* carbon-pricing rebates as an instrument, rather than as a payment device.
- **Quantifies a trade-off** instead of a yes/no answer: the incremental cost per additional ton of CO₂ offset from guaranteeing the rebate.
- **Methodological caution:** the “10% rule” for lottery incentives in experiments does not carry over when the lottery *is* an element (i.e., consumption) and not as incentive compatibility mechanism.

Overview of the Experiment Design

Wave 1 (AEARCTR-0015002)

- $N = 1,067$
- Five carbon-pricing treatments: 100%, 50%, 25%, 10%, 0%
- Focal test: 10% vs. 100%

Wave 2 (AEARCTR-0017601)

- $N = 1,044$
- 50% vs. 100% only
- Pooled non-inferiority test

- Four repeated incentivized decision rounds; one round randomly selected for payment.
- Trade-off between private consumption and real carbon-emission offsets.
- Feedback after each round on the choice, the associated payment, and the carbon offset.

The Market

- In each of four rounds, subjects choose how many units (0–4) of a *fictitious* good with real economic value to buy at a fixed price of **\$13.0** per unit.
- Diminishing marginal benefit of consumption:

$$v_1 = \$15.0, \quad v_2 = \$14.5, \quad v_3 = \$14.0, \quad v_4 = \$13.5$$

- Payoff:

$$\Pi = \sum_{i=1}^n v_i - 13.0 n + R, \quad R = \sum_{i=1}^{4-n} r_i, \quad r_i = \$2$$

where n is the number of units purchased and R is any rebate realized under the assigned treatment ($R = 0$ if $n = 0$, $n = 4$ or no rebate).

Linking Consumption to Real Carbon Emission Offsets

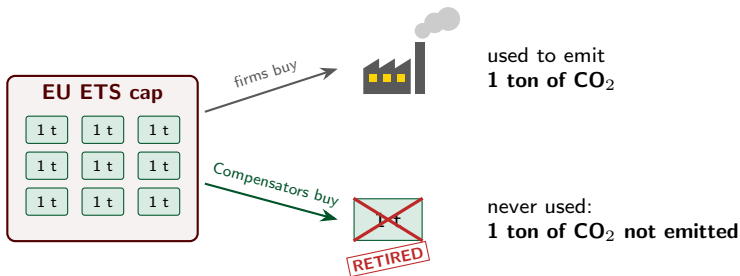
- Researchers commit to purchasing up to **200 lbs** of real carbon pollution rights per participant via [Compensators](#), a non-profit that retires surplus emission allowances.
- Each unit purchased reduces the offset by 50 lbs:

Units purchased	0	1	2	3	4
CO ₂ offset (lbs)	200	150	100	50	0

- One randomly selected round determines both monetary and environmental outcomes.
- Retirement certificates are publicly available ([Certificate 1](#), [Certificate 2](#)).

The Non-profit: Compensators

- Volunteer-run non-profit association based in Germany; 28,029 tons of CO₂ retired to date.
- Buys **EU Emissions Trading System (EU ETS)** allowances and **retires** them: each allowance = the right to emit 1 ton of CO₂.
- The EU caps the total number of allowances, so a retired allowance can no longer be used by polluters.



In our study: for each unit not purchased, we buy and retire allowances for 50 lbs of CO₂ through Compensators (up to 200 lbs per participant).

Real Environmental Impact

399,742 lbs of CO₂ retired

(181.32 metric tons; Exp 1 + Waves 1 + 2, through Compensators)

... equivalent to:



15,427

Cars off U.S. roads
for a day



8,883

Homes' energy use
for a day



3,022

Tree seedlings
grown for 10 years



14.6M

Smartphones
charged

Equivalences from the U.S. EPA Greenhouse Gas Equivalencies Calculator (cars: 4.29 t CO₂/vehicle/year; homes: 7.45 t CO₂/home/year; daily figures = annual × 365).

Treatment Conditions

Five between-subjects carbon-pricing treatments:

- ➊ **No-Rebate:** carbon consequence of purchases, no rebate ($R = 0$).
 - ➋ **Guaranteed Rebate (100%):** \$2 for each unit *not* purchased $n \in \{1, 2, 3\}$, paid with certainty.
 - ➌ **50% Lottery Rebate**
 - ➍ **25% Lottery Rebate**
 - ➎ **10% Lottery Rebate**
- In the lottery arms, the rebate is still \$2 per unit not purchased, but is paid with the assigned probability.
 - The design holds the consumption task and carbon mapping constant while varying only the *probability* of the rebate.

Payoffs, Carbon Offsets, and Expected Payoffs

Units n	Consumption payoff (\$)	CO ₂ offset (lbs)	Rebate if paid (\$)	Expected payoff by rebate probability p				
				No rebate	10%	25%	50%	100%
0	0.00	200	0	0.00	0.00	0.00	0.00	0.00
1	2.00	150	6	2.00	2.60	3.50	5.00	8.00
2	3.50	100	4	3.50	3.90	4.50	5.50	7.50
3	4.50	50	2	4.50	4.70	5.00	5.50	6.50
4	5.00	0	0	5.00	5.00	5.00	5.00	5.00

- Expected payoff = $\sum_{i \leq n} v_i - 13n + p \cdot 2(4 - n) \cdot 1\{n \geq 1\}$.
- Shaded cells maximize expected monetary payoff.

The Choice Interface

Please select how many units of the Product you want to purchase.

You selected to purchase 4 units.

Total value is: \$57 (= 15.0 + 14.5 + 14.0 + 13.5)

Total Payoff = Revenue - Cost + Rebate

Total Payoff = \$57 - \$52 + \$0 = \$5

Emissions are equal to **200** lbs of CO₂. We, the researchers, will remove from the market **0** lbs of CO₂.

Please make a selection using the slider below.



Units selected: **4** → 3 → 2 → 1 → 0

The slider updates the payoff (revenue - cost + rebate) and the CO₂ removed in real time.

The Choice Interface

Please select how many units of the Product you want to purchase.

You selected to purchase 3 units.

Total value is: \$43.5 (= 15.0 + 14.5 + 14.0)

Total Payoff = Revenue - Cost + Rebate

Total Payoff = \$43.5 - \$39 + \$2 = \$6.5

Emissions are equal to **150** lbs of CO₂. We, the researchers, will remove from the market **50** lbs of CO₂.

Please make a selection using the slider below.



Units selected: 4 → **3** → 2 → 1 → 0

The slider updates the payoff (revenue - cost + rebate) and the CO₂ removed in real time.

The Choice Interface

Please select how many units of the Product you want to purchase.

You selected to purchase 2 units.

Total value is: \$29.5 (= 15.0 + 14.5)

Total Payoff = Revenue - Cost + Rebate

Total Payoff = \$29.5 - \$26 + \$4 = \$7.5

Emissions are equal to **100** lbs of CO₂. We, the researchers, will remove from the market **100** lbs of CO₂.

Please make a selection using the slider below.



Units selected: 4 → 3 → **2** → 1 → 0

The slider updates the payoff (revenue - cost + rebate) and the CO₂ removed in real time.

The Choice Interface

Please select how many units of the Product you want to purchase.

You selected to purchase 1 units.

Total value is: \$15

Total Payoff = Revenue - Cost + Rebate

Total Payoff = \$15 - \$13 + \$6 = \$8

Emissions are equal to 50 lbs of CO₂. We, the researchers, will remove from the market 150 lbs of CO₂.

Please make a selection using the slider below.



Units selected: 4 → 3 → 2 → 1 → 0

The slider updates the payoff (revenue - cost + rebate) and the CO₂ removed in real time.

The Choice Interface

Please select how many units of the Product you want to purchase.

You selected to purchase 0 units.

Total value is: \$0

Total Payoff = Revenue - Cost + Rebate

Total Payoff = \$0 - \$0 + \$0 = \$0

Emissions are equal to 0 lbs of CO₂. We, the researchers, will remove from the market 200 lbs of CO₂.

Please make a selection using the slider below.

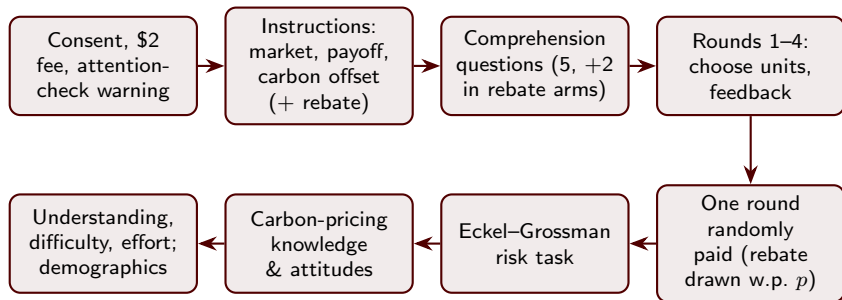


The slider is a horizontal line with a blue circle at the left end, labeled '0'. Above the line, there are tick marks and labels for 0, 1, 2, 3, and 4. The slider is currently set to 0.

Units selected: 4 → 3 → 2 → 1 → 0

The slider updates the payoff (revenue - cost + rebate) and the CO₂ removed in real time.

Timeline of the Study



Mean completion time 15.35 minutes (median 12.55). See instructions on Zenodo.

Data Quality Safeguards

- **Warning:** Initial warning about attention to instructions.
- **Time recording:** Speeders (< 3 seconds on key instruction screens) were terminated.
- **Attention checks:** failing two AC or TD ended the study.
- **Comprehension questions:** 5 common for everyone, plus 2 rebate-specific (7 total):
 - payoff-relevant round, value of units, carbon-removal mapping, rebate probability and amount, role of the spinner, whether probabilities change across rounds.

Correct answers were required to proceed; # attempts were recorded for robustness analysis.

- **Self-reports:** reading of instructions, clarity, difficulty, mental effort, understanding of the rebate. [▶ Results](#)

Subject Pool

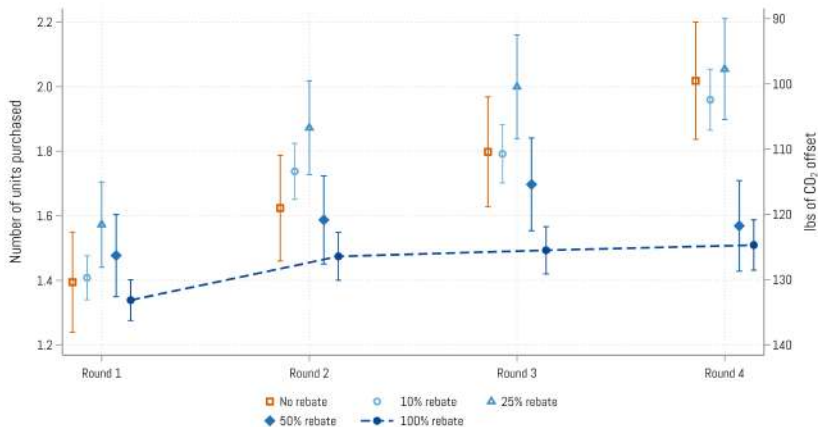
- Forthright Access, a U.S. online panel; adults residing in the U.S.
- Sample balanced on age, gender, race/ethnicity, and region (not nationally representative on all characteristics).
- \$2 participation fee for a $\approx$ 15-minute study, plus incentivized bonus payments.
- Final analysis samples: **1,067** (Wave 1) and **1,044** (Wave 2).
- IRB approval: Texas A&M University (STUDY2024-1534).

Wave 1: Preregistration, Power, and Allocation

- Preregistered analyses:
 - ① Omnibus test across treatments
 - ② Focal pairwise comparison **100% vs. 10%**
 - ③ Trend test across rebate probabilities.
- Power: 361 per group to detect $\delta = 0.25$ units (80% power, $\alpha = 0.05$), using variance from the prior experiment.
- Intentionally **unbalanced** allocation, oversampling the focal arms:

	No rebate	10%	25%	50%	100%	Total
N (Wave 1)	109	370	110	109	369	1067

Wave 1: Units Purchased and CO₂ Offsets by Round

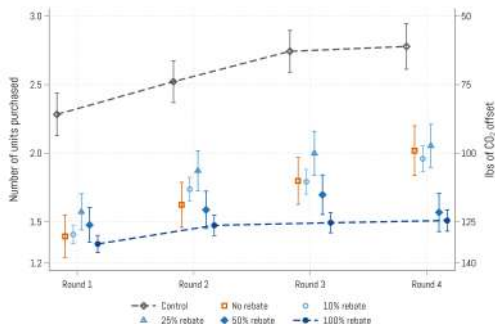


Treatment-by-round means; bars are 83% CIs (non-overlap $\approx$ two-sided 5% test; Goldstein and Healy, 1995; Cumming and Finch, 2005).

Wave 1: Key Patterns

- Suggestive **inverted-U**: purchases slightly *higher* under 10% and 25% than no rebate, *lower* under 50% and 100%.
 - Not designed to test functional form $\Rightarrow$ interpreted as suggestive only.
- **Learning**: Purchases *increase over rounds*: in No-Rebate, from 1.39 to 2.02 units (+44.7%, paired t -test $p < 0.001$).
- **Dynamic Adjustment**: Differences across treatments are small in Rounds 1–2 and become more pronounced in Rounds 3–4.
- **Environmental Response**: Purchases are far below the max monetary benchmark (4 units) even without a rebate: participants value the offsets.

Neutral-Pricing Benchmark



- Separate amendment ($N = 113$): same task, no carbon, offset, or rebate references.
- Purchases 2.28–2.78 units: still below the optimum of 4.
- Below-optimal buying linked to comprehension ($\beta = -0.547$ per extra attempt, $p < 0.001$).
- Descriptive only, not a randomized comparison.

► Comprehension

Wave 1: Pairwise Comparisons in Later Rounds

	No rebate	10%	25%	50%	100%
Round 3 mean	1.798	1.792	2.000	1.697	1.493
vs. 100%: p	0.011	<0.001	<0.001	0.073	–
Round 4 mean	2.018	1.959	2.055	1.569	1.509
vs. 100%: p	<0.001	<0.001	<0.001	0.616	–
vs. 50%: p	0.008	0.005	0.002	–	0.616

- Round 3: 100% significantly lower than no rebate, 10%, and 25%.
- Round 4: *both* 50% and 100% significantly lower than no rebate, 10%, and 25% (Cohen's d 0.31–0.49).

Wave 1: How Close Is the 50% Rebate?

	Round 1	Round 2	Round 3	Round 4
M_{50}	1.477	1.587	1.697	1.569
M_{100}	1.339	1.474	1.493	1.509
Difference	0.138	0.113	0.204	0.059
p -value	0.161	0.319	0.073	0.616

- Among lotteries, 50% rebate has point estimates **closest** to the guaranteed rebate; no round is significantly different.
- But **Null differences do not establish equivalence**.
- The 50% rebate reduces purchases by an average of only 0.126 units vs. no rebate ($p = 0.308$); no evidence the reduction exceeds 0.18 units (one-sided $p = 0.669$).

Wave 1: Regression-Based Tests

Dependent variable: units purchased (0–4), by round				
	Round 1	Round 2	Round 3	Round 4
<i>Omnibus test: rebate indicators jointly zero (vs. no rebate)</i>				
<i>F</i>	1.42	3.89	5.47	9.86
<i>p</i>	0.224	0.004	<0.001	<0.001
<i>R</i> ²	0.005	0.014	0.020	0.036
<i>Linear trend in rebate probability (rebate arms only, $N = 958$)</i>				
β	−0.109	−0.325	−0.379	−0.529
s.e.	(0.074)	(0.089)	(0.092)	(0.095)
<i>p</i>	0.142	<0.001	<0.001	<0.001

 shaded: $p < 0.05$

- Treatment separation **emerges after Round 1** and **strengthens with experience**.
- Robust to sociodemographic controls, and to pooling both waves with wave FE (omnibus significant in *all* rounds).

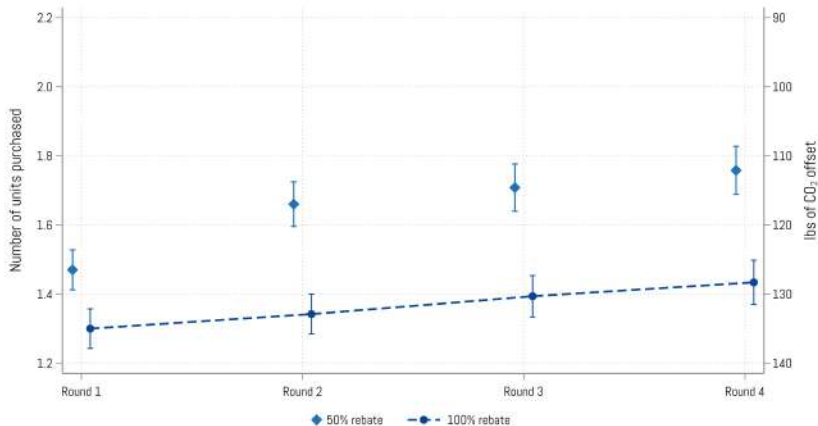
Wave 2: A Preregistered Non-Inferiority Test

- New participants randomized only between the **50%** and **100%** rebates.
- Estimand: $D = \mu_{50} - \mu_{100}$ (units purchased). $D > 0$: more consumption, fewer offsets under 50%.
- Non-inferiority margin: $\Delta = 0.18$ units ≈ 0.15 SD ($0.18/1.197 = 0.15$).

$$H_0 : D \geq \Delta \quad \text{vs.} \quad H_1 : D < \Delta$$

- Pooled with Wave 1 (wave FE, round FE, SEs clustered by participant); 80% power assuming $D = 0$, one-sided $\alpha = 0.025$.
- Final sample: **521** (50%) and **523** (100%).

Wave 2: 50% vs. 100% Rebate



Treatment-by-round means with 83% CIs. $N = 521$ (50%) and $N = 523$ (100%).

Wave 2: Round-by-Round Differences

	Round 1	Round 2	Round 3	Round 4
M_{50}	1.470	1.660	1.708	1.758
M_{100}	1.300	1.342	1.394	1.434
$D = \mu_{50} - \mu_{100}$	0.170	0.318	0.314	0.324
95% CI	[0.054, 0.286]	[0.194, 0.442]	[0.184, 0.445]	[0.189, 0.459]
p -value	0.004	<0.001	<0.001	<0.001

- With a larger sample powered to detect Cohen's D of 0.15 SD (0.18 units), purchases are **significantly lower under the guaranteed rebate in every round**.
- Standardized differences 0.18–0.31 SD; the gap widens after Round 1.

Pooled Estimate (Wave 1 + Wave 2)

- Pool 50% and 100% observations from both waves; wave FE, round FE, SEs clustered at the participant level.

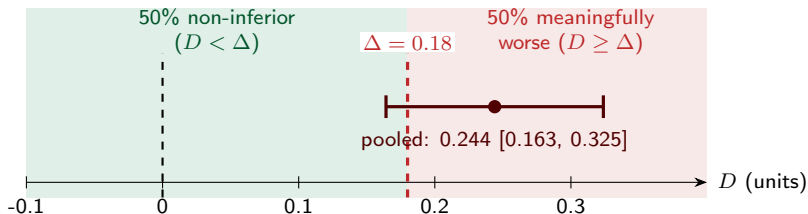
Pooled difference

$$\hat{D} = 0.244 \text{ units} \quad (95\% \text{ CI: } 0.163, 0.325; p < 0.001)$$

Standardized: 0.234 SD (95% CI: 0.157, 0.312)

- Treatment $\times$ wave interaction: 0.153 units (95% CI: -0.033 , 0.339 ; $p = 0.107$).
 - Larger gap in Wave 2, but not detectably different across waves.
- The 100% rebate produces lower purchases (larger offsets) than the 50% rebate.

Preregistered Non-Inferiority Test



- Upper 97.5% bound ($0.325 > 0.18 \Rightarrow$ **cannot conclude non-inferiority** ($p = 0.940$).
- Excess over margin: 0.064 units (95% CI: $-0.017, 0.145$), ≈ 0.054 SD; one-sided test of $D > 0.18$: $p = 0.060$.

Interpreting the Non-Inferiority Result

- Wave 2 provides evidence that the guaranteed rebate reduces purchases *more* than the 50% rebate.
- The 50% rebate does **not** satisfy the preregistered non-inferiority criterion.
- But its disadvantage exceeds the policy-relevant margin only modestly and not conclusively.
- Wave 2 overturned an interpretation that the less precise Wave 1 could not rule out.

Key: Power Analysis and Small Effect Sizes

- Not driven by risk attitudes: results hold controlling for risk preferences. ▶ Risk

Bottom line

A 50% lottery is *not* an equivalent substitute for a guaranteed rebate; it creates an **effectiveness–expenditure trade-off**.

Expected Outlays and Incremental Cost-Effectiveness

Treatment	<i>N</i>	Units purchased	Mean units not purchased	Expected rebate expenditure (\$)	Reduction in purchases	Additional CO ₂ offsets (lbs)	CO ₂ offsets per dollar
<i>Panel A: Wave 1 (benchmark: no rebate)</i>							
No rebate	109	1.709	2.291	0.00	—	—	—
10% rebate	370	1.724	2.276	0.34	-0.016	-0.78	-2.32
25% rebate	110	1.875	2.125	0.89	-0.166	-8.31	-9.39
50% rebate	109	1.583	2.417	1.96	0.126	6.31	3.22
100% rebate	369	1.454	2.546	4.04	0.255	12.74	3.15
<i>Panel B: Wave 2 (benchmark: 50% rebate)</i>							
50% rebate	521	1.649	2.351	1.86	—	—	—
100% rebate	523	1.368	2.632	4.00	—	—	—
100% vs. 50%	—	—	—	2.13	0.282	14.08	6.60

- The 50% rebate reduces expected rebate expenditure by $\approx 53\%$ relative to the guaranteed rebate (■ shaded). [► Formula](#)
- Low-probability lotteries (10%, 25%) are cheap but deliver **no reduction** (negative values).
- Guaranteeing the rebate costs **\$2.13 more** per participant for **14.08 lbs** more CO₂ offset or **\$334 per ton**.

What Does Guaranteeing the Rebate Cost?

Wave 2: moving from the 50% to the guaranteed rebate adds

- +\$2.13 expected rebate expenditure per participant (+114.6%)
- -0.282 units purchased $\Rightarrow$ +14.08 lbs CO₂ offset

$$\frac{\$2.13}{14.08 \text{ lb}} = \$0.152/\text{lb} \Rightarrow \times 2,204.6 \approx \textbf{\$334/metric ton}$$

Cost per metric ton of CO₂

Guaranteed rebate

\$334

per additional ton offset

Compensators (direct)

$\approx$ \$50–100

14.08 lbs $\approx$ \$0.32–0.64

EPA social cost (2026)

\$133–365

2.5%–1.5% discount rate

Compensators: EU ETS allowance price plus VAT and fees. \$334 exceeds EPA's \$133 (2.5%) and \$215 (2.0%) but is below \$365 (1.5%) (U.S. EPA, 2023). A benchmark, not a cost-benefit test: excludes administrative costs and long-run responses.

Summary of Findings

- A guaranteed \$2 rebate reduces consumption and increases real carbon offsets relative to no rebate.
- Low-probability lotteries (10%, 25%) do **not** reproduce this effect, unlike the “10% rule” for experimental incentives.
- The 50% lottery comes closest, but fails a preregistered non-inferiority test (pooled $D = 0.244$, $\Delta = 0.18$).
- Treatment effects emerge with experience: differences grow across rounds.
- Results are robust to comprehension, risk preferences, demographics, and attrition corrections.
- Contrast of the “**10% Rule**” for *incentive compatibility* versus One Policy Lever “**Element**” in the Payoff.

Policy Implications

- Probabilistic rebates are *not* a free lunch: lowering the probability lowers the behavioral response.
- A 50% rebate keeps a substantial part of the behavioral response effect while cutting expected rebate expenditure by $\approx 53\%$.
- The relevant question is how much extra response the *additional* spending on a guaranteed rebate buys:
 - $\approx \$334$ per additional metric ton of CO_2 in our setting.
 - Above EPA's 2026 social cost of carbon at 2.5% and 2.0% (\$133, \$215), but below the 1.5% value (\$365).
 - Above the $\approx \$50$ – 100 direct offset cost through Compensators.
- Savings could be redirected to green investment; the right design depends on the value of CO_2 and alternative mitigation costs.

Limitations and Future Research

- **Short-run proof of concept:** stylized market, online sample; field trials or policy pilots needed.
- **Long-run dynamics:** trust, perceived fairness, and winner–loser dynamics if people repeatedly fail to receive rebates.
- **Full cost-effectiveness:** administrative and distributional costs are not included.

Thank You!!!

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Data and code: Zenodo. Preregistrations: AEARCTR-0015002, AEARCTR-0017601.



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Supplementary Slides

Comprehension and Engagement

- Comprehension checks were nontrivial: 1.31 attempts per item on average; first-attempt success 32.3%–89.3% across items.
- 74.0% read all instructions carefully; 23.7% mostly did.
- 7-point scales: clarity 4.84, difficulty 3.63, mental effort 4.77; rebate understanding 4.35–4.96.

Robustness of main results

- Controlling for mean comprehension attempts: omnibus test insignificant in Round 1, significant in Rounds 2–4 (both waves).
- Excluding the lowest-comprehension group: same pattern; pooled 50%–100% difference significant in every round (0.147–0.233 units).

◀ Back Quality

◀ Back Neutral

Participant Flow and Post-Randomization Screening

Outcome	Wave 1 treatment (%)					<i>p</i>
	No rebate	10%	25%	50%	100%	
Administrative termination	16.67	17.81	9.20	14.91	13.05	0.042
Voluntary pre-outcome attrition	14.81	18.15	22.70	16.15	18.57	0.411
Reached at least one outcome	68.52	64.04	68.10	68.94	68.38	0.510
Eventually included	67.28	63.36	67.48	67.70	67.83	0.539

	Wave 2 (%)		<i>p</i>
	50%	100%	
Eventually included	74.96	71.84	0.183

differs across arms ($p < 0.05$)

no significant difference

- Screening occurred **after treatment disclosure but before outcomes** (Montgomery et al., 2018).
- Termination rates differ in Wave 1, but **reaching an outcome and final inclusion do not**.

◀ Back

Attrition Robustness: IPW and Lee Bounds

Contrast	Unweighted	IPW		Lee bounds	
	Estimate	Estimate	95% CI	Bounds	95% effect CI
Wave 2: 50% – 100%	0.282***	0.281***	[0.185, 0.376]	[0.200, 0.353]	[0.092, 0.474]
Pooled: 50% – 100%	0.244***	0.251***	[0.168, 0.333]	[0.147, 0.315]	[0.063, 0.419]
Wave 1: 50% – 100%	0.129	0.155	[−0.014, 0.323]	[0.126, 0.133]	[−0.111, 0.479]
Wave 1: 50% – no rebate	−0.126	−0.150	[−0.381, 0.080]	[−0.141, −0.116]	[−0.570, 0.216]
Wave 1: 100% – no rebate	−0.255**	−0.271***	[−0.475, −0.067]	[−0.273, −0.243]	[−0.564, 0.020]

95% CI excludes zero

- IPW: stabilized weights from pre-treatment covariates (Robins et al., 2000; Cole and Hernán, 2008); weights well behaved (max 3.17).
- Lee bounds under monotone selection (Lee, 2009; Tauchmann, 2014): **Wave 2 effect CI stays above zero.**
- **Differential attrition does not explain the main contrasts.**

► Participant Flow

Risk Preferences and Heterogeneity

Risk preferences (Eckel–Grossman task; Eckel and Grossman, 2008)

- Mean 3.46 (SD 1.76, range 1–6); no treatment shift ($p = 0.133$).
- Controlling for risk: pooled 100% vs. 50% reduction of 0.152, 0.259, 0.276, 0.245 units in Rounds 1–4 (all $p \leq 0.003$).

Carbon-pricing knowledge and attitudes

- 76.2% answered both knowledge questions correctly; familiarity 2.92/7; support 4.66/7.
- Preferred use of revenue: renewables 56.1%, cash rebates 20.0%.
- Treatment $\times$ knowledge significant only in Round 1; treatment $\times$ support never significant.

Power Analysis Sensitivity

Wave 1: 100% vs. 10% (per group, 80% power, $\alpha = 0.05$)

δ (units)	0.15	0.20	0.25
Required N per group	1,002	564	361

Wave 2: pooled non-inferiority ($D = 0$, **SD = 1.197, one-sided $\alpha = 0.025$)**

Margin Δ	0.15	0.18	0.20	0.25
Total N per treatment	1,001	695	563	361
Required Wave 2 additions	778	480	353	164

■ preregistered

design

Omnibus test powered for incremental $R^2 \approx 0.03$; trend test for $R^2 = 0.01$.

Pooled Omnibus Tests (Wave FE)

	Round 1	Round 2	Round 3	Round 4
<i>No controls ($N = 2,111$)</i>				
<i>F</i>	3.46	9.41	10.91	14.93
<i>p</i>	0.008	<0.001	<0.001	<0.001
<i>Sociodemographic controls ($N = 2,035$)</i>				
<i>F</i>	3.60	10.26	10.94	15.19
<i>p</i>	0.006	<0.001	<0.001	<0.001
<i>Wave 1 with controls ($N = 1,028$)</i>				
<i>F</i>	1.54	4.35	5.87	10.38
<i>p</i>	0.190	0.002	<0.001	<0.001

Maroon: $p < 0.05$

Treatment differences are significant in every round of the pooled sample and **grow stronger as rounds progress**.

Sample Characteristics

Variable	Statistic	Wave 1	Wave 2
Age	Mean (SD)	48.51 (16.54)	50.67 (14.71)
Female	%	49.20	44.64
Bachelor's degree or higher	%	42.92	44.54
White/Caucasian	%	78.26	78.83
Household income $\geq$ \$100,000	%	23.81	24.81
Liberal / Moderate / Conservative	%	40.5 / 32.2 / 27.4	40.4 / 29.5 / 30.1
Democrat / Republican	%	47.42 / 30.46	47.03 / 30.17
Support for carbon pricing (1–7)	Mean (SD)	4.63 (1.65)	4.70 (1.67)
Familiarity with carbon pricing (1–7)	Mean (SD)	2.84 (1.72)	3.00 (1.72)
Risk preference (1–6)	Mean (SD)	3.50 (1.78)	3.42 (1.75)
Preferred revenue use: renewables	%	53.98	58.24
Preferred revenue use: cash rebate	%	19.96	20.02

The two waves look **very similar**. Participants mildly support carbon pricing but are **unfamiliar with it**, and few prefer cash rebates.

Baseline Balance

	Wave 1: max std. diff.	Wave 2: std. diff.	Between waves
Political ideology	0.469 (No rebate–50%)	0.140	0.220
Party preference	0.462 (No rebate–50%)	0.035	0.332
Marital status	0.445 (25%–50%)	0.112	0.177
Education	0.419 (No rebate–25%)	0.117	0.240
Age	0.226 (50%–100%)	0.063	0.183
Gender	0.271 (25%–50%)	0.065	0.170
Support for carbon pricing	0.221 (No rebate–50%)	0.019	0.198
Household income	0.185 (No rebate–10%)	0.117	0.248
Risk preference	0.127 (10%–50%)	0.138	0.105

■ |std. diff.| > 0.25

Largest Wave 1 imbalances involve the **small arms** (No rebate, 25%, 50%); Wave 2 is **well balanced** (all < 0.15). Results are **robust** to controlling for these covariates.

Ahles, Palma, and Drichoutis (2024)

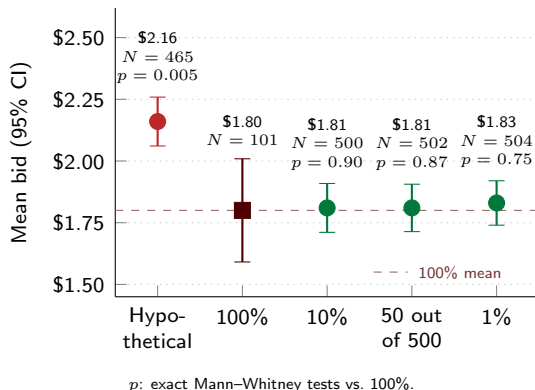
Ahles et al. (2024), *AJAE*

- $N = 2,072$ U.S. beef consumers.
- BDM bid to swap a conventional for a sustainable Criollo steak.
- Real steaks shipped on dry ice to winners (200 shipped, $\approx \$42$ each).
- Treatments vary the probability that the decision is realized.

Findings

- 10%, “50 out of 500”, and even 1% are statistically indistinguishable from 100%.
- Hypothetical bids $\approx 20\%$ higher ($+\$0.35$, $p < 0.01$).

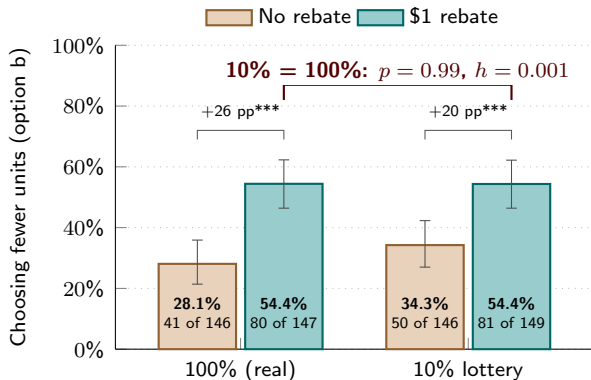
Key difference: there the lottery scales *all* payoffs (incentives); here it scales *only the rebate*, so the money-maximizing choice changes with p .



Earlier Experiment: 10% = 100%

Design ($N = 588$)

- Part I: buy 0–3 units at 10 prices; each unit not bought retires 100 lbs CO₂.
- \$1 rebate for choosing fewer units $\times 100\%$ vs. 10% payment.



95% CIs; tests of proportions; *** $p < 0.001$.

Takeaway: Lottery on *all* payoffs shows that the 10% payment reproduces the 100% payment (54.4% vs. 54.4%), as in Ahles et al. (2024).

◀ Back

Expected Rebate Expenditure

- With rebate probability p_j and mean purchases $\bar{Y}_j$ (one round paid):

$$\bar{C}_j = \frac{1}{N_j R} \sum_{i=1}^{N_j} \sum_{r=1}^R 2p_j(4 - Y_{ir})\mathbf{1}\{Y_{ir} \geq 1\}$$

- Incremental CO₂ offset per expected rebate dollar** (vs. no rebate):

$$\frac{50(\bar{Y}_0 - \bar{Y}_j)}{\bar{C}_j}$$

- Captures expected experimental rebate payments *only*; **excludes** administrative costs and the cost of purchasing offsets.