

395	Supplementary Information	
396	Unproductive rebound: Experimental evidence from four countries	
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S1 Experimental design details

Participants were recruited via an online panel company and redirected to the experiment hosted on Qualtrics. Before accessing the study, participants only saw the estimated duration and the corresponding incentive offered by the panel company. The experiment was available in the official language of each country and could be completed on desktop, tablet, or mobile devices. In the Spanish-speaking countries, the local researchers adapted the project to the local vocabulary and currency. Colorblind participants were screened out prior to the task given its visual nature, and all participants were required to be at least 18 years old. Instructions are available at: <https://www.protocols.io/file/bf5u4c37p7.docx>.

Upon entering the study, participants read a set of instructions explaining the task mechanics, including how brightness and time affect the visual puzzle, how the budget is allocated, and how earnings are determined. The task consisted of 10 rounds. In each round, participants received an endowment of 100 points and allocated units of brightness (0–10) and time (0–10) to solve a visual search puzzle. Each unit of brightness reduced image opacity by 10% (See Figure S5), and each unit of time added 2 seconds to the display duration. Any unspent budget was saved and added to round earnings. Successfully identifying the target character awarded a prize of 250 points.

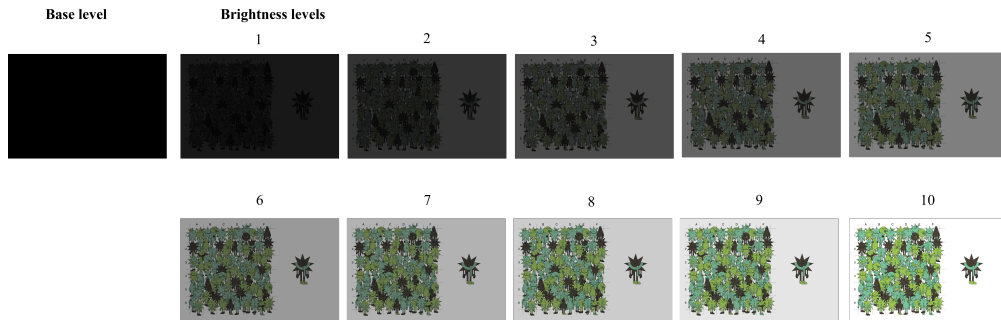


Figure S1: Task brightness levels

Before starting the main rounds, participants completed a practice round to ensure familiarity with the interface. The practice round was identical in structure to the main rounds but did not count toward earnings. Figures S2 and S3 show examples of the decision-making and feedback screens.

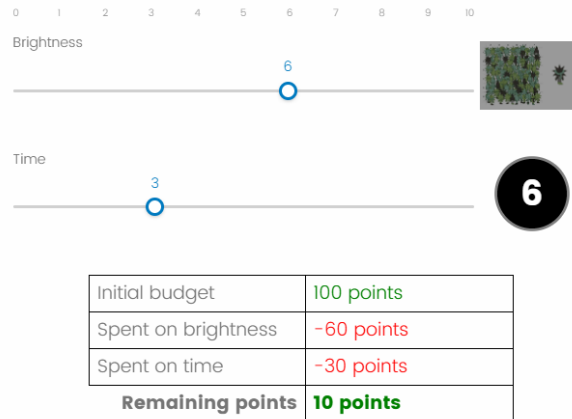


Figure S2: Round-level decision-making screen

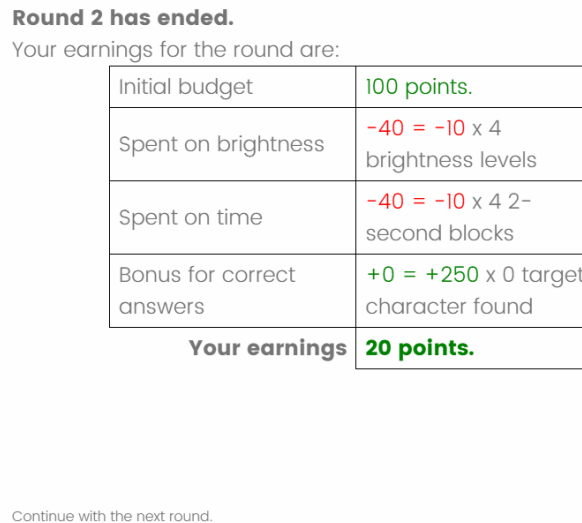


Figure S3: Round-level feedback screen

The task included two attention checks. The first one was embedded within the instructions. Participants were shown the brightness slider without a time constraint in order for them to get familiar with the brightness levels. On that screen, they were instructed to set the slider to a specific level (a random integer between 0 and 10) before proceeding. Subjects who failed to set the slider to the correct level were flagged as inattentive. The second attention check was presented after the 10 rounds and before they completed the fluid intelligence and energy literacy tasks. They were shown the following item: “Please select ‘Strongly agree’ to show you are paying attention to this question,” with response options ranging from Fully agree to Fully disagree.

We pre-registered two exclusion criteria. The first one is based on inattention: those who

449 failed *both* attention checks were excluded from the analysis. The second one is based on low
 450 budget engagement in rounds 1–5, defined as meeting any of the following criteria: mean
 451 brightness spending below 20% of the budget across rounds 1–5; brightness spending below
 452 20% of the budget in three or more individual rounds; or zero brightness spending in two or
 453 more individual rounds. Exclusion was triggered by failing *either* the inattention criterion
 454 *or* the low engagement criterion.

455 We implemented random between-subject assignment with equal probability to either one
 456 of the following treatments: Control, Price-Drop, or Externality. In the Control condition,
 457 each brightness unit cost 10 points throughout all 10 rounds. In the Price-Drop condition,
 458 the brightness price was 10 points in rounds 1–5 and dropped to 5 points in rounds 6–10.
 459 The Externality condition was identical to Price-Drop in terms of pricing, but addition-
 460 ally informed participants from the outset that their brightness consumption would reduce
 461 a donation to Renewable Energy Certificates (REC) through Terrapass: for each unit of
 462 brightness purchased, €0.10 was subtracted from a stated €1.00 donation per round (see
 463 Figure S4). Participants in the Externality condition received feedback on the REC amount
 464 after each round and were informed that two randomly selected rounds would determine the
 465 actual donation.

One more thing: we will donate to **mitigate climate change**. English ▼

We will purchase a **Renewable Energy Certificate (REC)** in [Terrapass](#) to support clean energy and displace emissions associated with fossil fuel-powered electric generation.

This **donation won't affect your round earnings**, but **your brightness consumption matters**. The amount of the REC will depend on your brightness level in each round, as follows:

REC = €1.0 – your brightness level in the round * €0.1

For example, if you consumed in brightness:

0 levels	→	REC donation = €1.0 – 0 * €0.1 = €1.0
5 levels	→	REC donation = €1.0 – 5 * €0.1 = €0.5
10 levels	→	REC donation = €1.0 – 10 * €0.1 = €0.0

Figure S4: Task environmental externality instructions

466 After completing the 10 rounds, subjects responded a final questionnaire including the *energy*
 467 *literacy* and *fluid intelligence* tasks. *Energy literacy* was measured using a task in which
 468 participants are asked to estimate how many units of energy each of the following six devices
 469 uses in one hour: a central air conditioner, an electric clothes dryer, a dishwasher, a portable
 470 heater, a room air conditioner, and a laptop computer. As a reference, they are told that
 471 a 100-Watt incandescent light bulb uses 100 units of energy per hour.²⁴ For each device,
 472 the absolute log-scale deviation between the participant's estimate and the true value was
 473 computed as $|\log_{10}(\hat{e}_{ik}) - \log_{10}(e_k)|$, where $\hat{e}_{ik}$ is participant i 's estimate for device k and
 474 e_k is the true energy value. Zero and negative responses were set to missing before taking
 475 logarithms. The person-level misperception score is the mean absolute log deviation across
 476 the six devices. The *energy literacy* variable used in regressions is the negative of this

score ($literacy = -|\log_{10}(\hat{e}_{ik}) - \log_{10}(e_k)|$), so that higher values indicate greater accuracy. Outliers on the misperception score were identified using the interquartile range method ($1.5 \times \text{IQR}$) and excluded from H4 analyses only. *Fluid intelligence* was measured using a 5-item test based on Raven-like matrices.²⁵

S2 Task calibration and pilot

The task, its calibration, and the pre-tests summarized in this section are described in full in the paper introducing the real-effort task used in this paper: Allocation-based Real Effort Production App (AREPA).⁷ We reproduce the key design properties here so that this study is self-contained; the original source contains the complete pre-test protocols, parametrizations, and results.

The final design of the task resulted from a series of four pre-tests (PT1–PT4) conducted between April and December 2024, followed by a pilot study in February 2025. Across all studies, a total of 581 unique participants were recruited from two subject pools — Prolific ($n = 475$) and university students ($n = 106$) — with no individual participating in more than one study. Each pre-test addressed a specific set of design questions, collectively establishing four key properties of the final task: (1) a 6×6 puzzle grid with balanced difficulty across blocks; (2) brightness as a productivity-enhancing input with decreasing returns; (3) input expenditure levels sufficiently above zero to avoid floor effects; and (4) a price parametrization that generates meaningful variation in brightness consumption.

S2.1 Pre-test 1: Puzzle difficulty calibration

The first pre-test ($n = 100$, Prolific) established the basic properties of the visual puzzle. Participants were exposed to illustrations of small (4×4 grid, 36 characters), medium (6×6 , 90 characters), and large (8×8 , 144 characters) size at exogenously fixed brightness levels of 1 or 10, without budget allocation. Medium-size illustrations were selected for the main experiment on two grounds. First, brightness had a strong effect on the probability of a correct response (78.5% vs. 53% under high vs. low brightness; +25.5 percentage points; $p < 0.001$) but no effect on time spent per illustration (mean: 10.5 seconds; $p = 0.943$). Second, small illustrations were discarded for being too easy (78% correct responses), making brightness differences less salient; large illustrations produced similar results to medium ones but risked introducing uncontrolled heterogeneity across participants due to differences in screen resolution. PT1 also revealed low willingness to pay for brightness (median WTP = 0), informing the price parametrization in subsequent pre-tests.

PT1 also revealed substantial heterogeneity in difficulty across puzzle configurations: the proportion of correct responses ranges from 0.06 to 0.92 depending on illustration size, character shade, and accessory design. Compared to small 4×4 illustrations, larger grid sizes significantly reduced the probability of a correct response (size 6: -0.469^{***} ; size 8: -0.455^{***}),

while brightness had a strong positive effect on accuracy (0.177***) but not on time spent. Character shade and accessory design also affected difficulty significantly. This heterogeneity motivated the stratification of puzzle difficulty across blocks in the final design, ensuring that pre- and post brightness price-shock performance comparisons are not confounded by systematic differences in image difficulty.

Finally, PT1 allowed testing the effect of individual characteristics on task performance. Findings revealed that age has a significant and negative impact on game earnings, the number of correct answers, and the time taken by players. Participants who have corrected vision, either by wearing glasses or contact lenses, are more likely to play fast. The following individual characteristics have no impact on the task: screen resolution, being female, being white, being employed, and level of activity in Prolific.

S2.2 Pre-tests 2 and 3: Task structure calibration

PT2 ($n = 390$ on Prolific) tested an early version of the task with treatments across 3 rounds of 5 images each. Subjects were endowed with 10 seconds to complete each round. Two findings drove structural changes. First, brightness consumption was close to zero for approximately 30% of participants, indicating a floor effect. Second, learning was pronounced across rounds, with time consumption increasing sharply from round 1 to round 2. These patterns motivated a restructuring to 10 rounds of 1 image each, the removal of a free time endowment, and the introduction of an enhanced brightness slider with greater contrast at low levels.

PT3 replicated the 10-round structure with students at Loyola Andalucía University ($n = 106$) and confirmed that both brightness and time have significant positive effects on the probability of a correct response (approximately 5 percentage points per unit purchased), that puzzle difficulty is heterogeneous across images, and that randomizing round order while balancing difficulty across blocks is necessary to ensure comparability between pre- and post-shock performance.

PT3 also validated the subset of matrices included in the *fluid intelligence* task across subject pools: both the student and Prolific samples understood the task correctly and produced similar average cognitive scores, although students showed lower attention check pass rates (50% vs. approximately 70%), confirming that the task and measures are suitable for online panel recruitment.

S2.3 Pre-test 4: Brightness slider calibration

A final pre-test ($n = 20$, Prolific) with an enhanced brightness slider was implemented. In this design, each unit of brightness reduced image opacity by 10% as shown in Figure S5. PT4 confirmed that the redesign successfully increased brightness consumption and reduced floor effects, supporting its adoption in the final design.

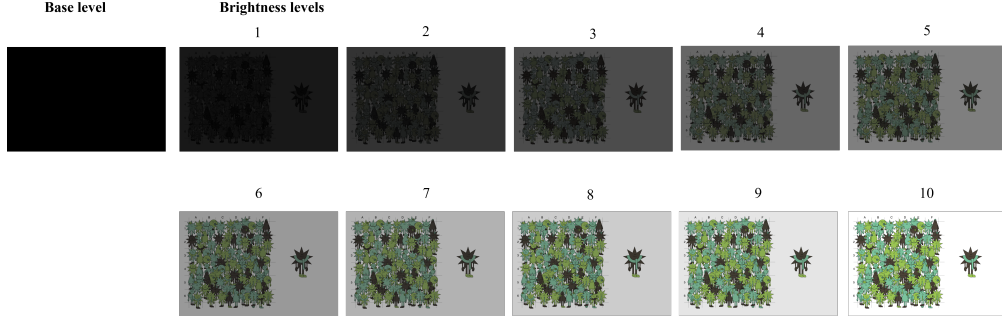


Figure S5: Task brightness levels

S2.4 Pilot study

The final pilot ($n = 95$, Prolific) implemented the complete design — including all three treatment conditions (Control: $n = 31$; Price-Drop: $n = 30$; Externality: $n = 34$) — with the parametrization used in the main study. Median completion time was 12 minutes. Participants earned a Prolific base payment of £1.75 plus incentives (mean bonus: £1.74; range: £0–£5.9). The pilot was restricted to desktop users. A post-hoc power analysis based on the pilot data indicated that the observed Price-Drop effect ($R^2 = 0.12$, Cohen’s $f^2 = 0.14$) was detectable with 80% power at $\alpha = 0.05$ with $n = 59$ participants, confirming that the target sample of $n > 1,200$ per country in the main study was well-powered to detect effects of this magnitude.

S2.5 Task properties

Difficulty and learning

Figure S6 shows the learning curve and task difficulty across rounds in the Control condition of the main study ($n = 1,551$). The mean proportion of correct answers is approximately 0.10 in round 1 and increases to around 0.20 by round 3, where it stabilizes. The inset panel confirms that round-to-round changes in performance are negligible from round 3 onward, with differences consistently close to zero and within the confidence interval of the dashed reference line. Two features of this pattern are important for our design. First, the task is genuinely difficult — with a mean correct response rate of approximately 20% — ensuring that participants face a real productivity constraint and have a meaningful incentive to spend their budget on brightness and time rather than saving it. Second, learning stabilizes by round 3, justifying the exclusion of rounds 1–2 from the pre-shock block in the baseline specification and supporting the comparability of performance between the pre- and post-shock blocks.

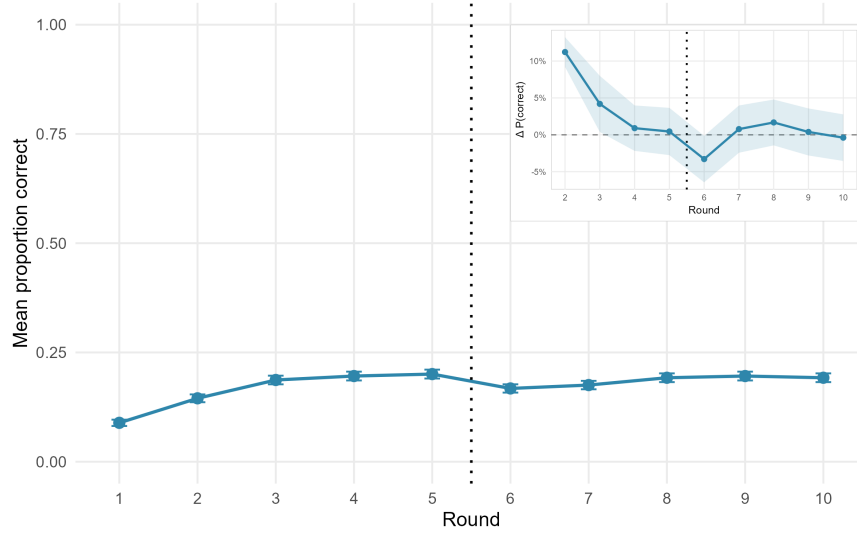


Figure S6: Performance and learning across rounds (Control)

Input productivity

Figure S7 reports input productivity across the 10 rounds for control participants ($n = 1,551$), confirming input diminishing returns, all of which are task properties established during calibration. Specifically, the data reveals a concave, non-monotonic relationship for both brightness and time, where productivity peaks at intermediate levels—around a brightness of 5 and a time allocation of 6 to 7—before declining. In contrast, the savings graph demonstrates a clear diminishing return, where the mean proportion of correct responses drops steadily as the unspent budget increases, eventually plateauing near zero.

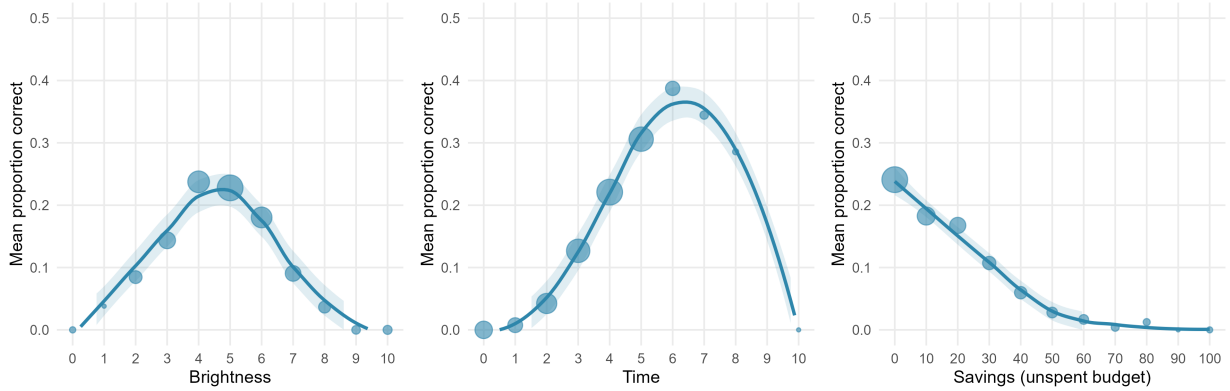


Figure S7: Input productivity (Control)

S3 Sample

S3.1 Descriptive statistics

Table S1 reports descriptive statistics by country for all the variables included in the regression analyses.

Control variables are grouped into three categories. Sociodemographic controls include *female*, a binary variable equal to 1 if the subject is identified as female; *age group*, recorded in six categories; and *education*, the highest educational attainment recorded in eight categories. All three were collected by the panel company from their subject pool. Task controls include *mean savings*, the mean unspent budget across the 10 rounds (0–100); *attention check 1*, a binary variable equal to 1 if the participant set the brightness slider to the instructed level during the instructions screen; *attention check 2*, a binary variable equal to 1 if the participant passed the post-task attention check; *mobile*, a binary variable equal to 1 if the participant completed the experiment on a mobile device; *energy literacy*, the negative of the mean absolute log-scale deviation between estimated and true energy use across six household appliances using a 100-W incandescent light bulb as reference (higher values indicate greater accuracy; range -2.29 to -0.05 ; outliers identified via the interquartile range method ($1.5 \times \text{IQR}$) are excluded from H4 analyses); and *fluid intelligence*, the score on a 5-item test based on Raven-like matrices (0–5). Additional controls (not included in our pre-registration) include *utility bill payer*, a binary variable equal to 1 if the participant reported being responsible for paying the utility bill in their household; *home owner*, a binary variable equal to 1 if the participant reported owning their home; *data sharing reluctance*, the minimum percentage saving in monthly electricity bill required to accept sharing energy use information with AI appliances, elicited on a slider from 0 (accept even without savings) to 20 (need 20% or more to accept); and *climate action*, self-reported frequency of personal actions taken for climate change mitigation on a scale from 1 (never) to 10 (always).

Table S1: Sample descriptive statistics by country

	Spain	Uruguay	Dom. Republic	Poland
N	1063	1049	1107	1279
<i>A. Sociodemographic</i>				
Female	49.7	58.2	47.3	54.4
Age group				
18–24	13.8	16.2	26.6	4.6
25–34	18.9	28.2	35.2	16.5
35–44	23.3	28.7	25.4	22.1
45–54	23.6	17.6	9.4	18.8
55–64	19.1	9.2	3.1	21.7
65+	1.2	—	0.4	16.2
Education				
No formal education	—	1.4	0.3	0.3
Primary education	0.8	2.7	1.2	1.3
Secondary education	8.9	16.6	3.3	5.5
High school	15.8	34.4	23.3	22.8
Vocational training	24.2	22.4	15.9	19.0
University degree	34.1	5.0	47.2	18.1
Post-graduate degree	11.8	16.2	7.4	32.2
Doctorate	4.4	1.3	1.5	0.9
<i>B. Tasks</i>				
Mean savings	23.07 (19.23)	21.49 (17.87)	20.27 (17.74)	22.80 (18.34)
Attention check 1	60.7	56.3	41.9	66.0
Attention check 2	98.1	93.6	96.7	97.0
Mobile	71.6	77.3	68.9	41.6
Energy literacy ^a	−1.11 (0.45)	−0.91 (0.42)	−1.13 (0.46)	−0.99 (0.42)
Fluid intelligence	1.58 (1.27)	1.41 (1.25)	1.02 (1.10)	1.62 (1.28)
<i>C. Other controls</i>				
Utility bill payer	94.6	89.9	88.3	89.4
Home owner	62.7	53.1	33.5	67.8
Data sharing reluctance	12.29 (5.46)	13.05 (6.21)	12.18 (5.97)	13.10 (6.07)
Climate action	6.46 (2.50)	6.56 (2.69)	6.80 (2.89)	5.70 (3.03)

Note: Binary variables reported as percentages (%). Continuous variables reported as mean (SD). Sample restricted to non-excluded participants with complete control variables ($n = 4,498$). Climate action: personal actions for climate change mitigation (1–10 scale). ^aEnergy literacy reported for the subsample additionally passing the pre-registered outlier exclusion criterion ($n = 4,158$).

S3.2 Balance across treatments

Table S2 reports balance across treatment condition for all control variables in the analytic sample (non-excluded participants with complete control variables $n = 4,498$; see Methods section in the main text), confirming that randomization produced balanced groups on observables.

Table S2: Balance across treatments

	Control	Price-Drop	Externality	p (C vs PD)	p (C vs E)
N	1519	1485	1494		
Female (%)	52.0	52.9	52.3	0.613	0.854
Age group [†]	—	—	—	0.060	0.307
Education [†]	—	—	—	0.496	0.288
Fluid intelligence (mean)	1.44	1.39	1.41	0.288	0.520
Attention check 1 (%)	56.6	56.3	56.8	0.888	0.878
Attention check 2 (%)	96.2	96.6	96.3	0.569	0.918
Mobile (%)	62.3	65.4	63.5	0.083	0.504
Utility bill payer (%)	91.2	90.6	89.6	0.608	0.148
Home owner (%)	53.7	56.2	54.3	0.167	0.756
Data-sharing reluctance (mean)	12.61	12.87	12.53	0.241	0.711
Climate action (mean)	6.36	6.31	6.39	0.595	0.826

Note: Sample restricted to non-excluded participants with complete control variables ($n = 4,498$). Binary variables are reported as percentages and continuous variables as means. p -values are from two-sided t -tests for continuous and binary variables and from χ^2 tests for the categorical variables, testing Control vs. Price-Drop and Control vs. Externality.

[†] No single summary statistic is reported for categorical variables *age group* (six categories) and *education* (eight categories). In these cases, balance is assessed over the full distribution via the χ^2 test.

S3.3 Country renewable energy profiles

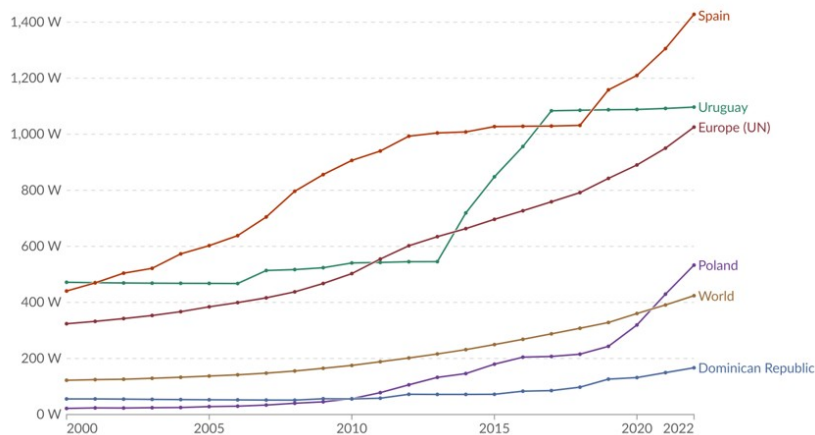
For the H3 analysis, countries are grouped by their structural renewable energy profiles into a higher-profile group (Spain and Uruguay) and a lower-profile group (Dominican Republic and Poland). The grouping follows the preregistration, which classified Spain and Uruguay as more committed to renewable energy than the Dominican Republic and Poland based on renewable electricity generating capacity (Figure S8) and renewable energy use as a share of total energy consumption (Figure S9).

Figure S8 shows installed renewable electricity-generating capacity per person (watts per capita) from 2000 to 2022. Spain and Uruguay both exceed the world average, with Spain reaching approximately 1,400 W per capita by 2022—more than three times the world average—and Uruguay reaching approximately 1,050 W per capita, also well above it. By contrast, Poland remains close to the world average at approximately 400 W per capita, while the Dominican Republic falls far below it at under 100 W per capita. Likewise, Figure S9 shows that Uruguay and Spain are above the world average share of energy use that comes from renewable resources, while Poland and the Dominican Republic are below.

Renewable electricity-generating capacity per person, 2000 to 2022

The installed capacity of power plants that generate electricity from renewable energy sources. This includes hydropower, marine (ocean, tidal and wave), wind, solar (photovoltaic and thermal energy), bioenergy, and geothermal energy.

Our World
in Data



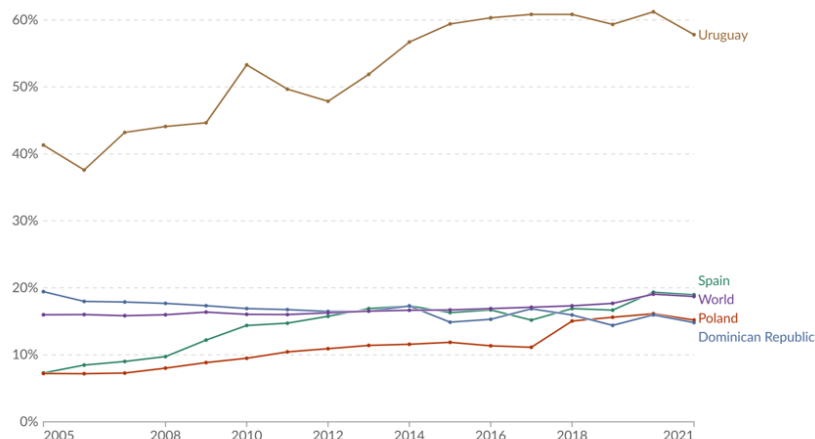
Data source: International Renewable Energy Agency and United Nations World Population Prospects
OurWorldinData.org/renewable-energy | CC BY

Figure S8: Renewable electricity-generating capacity per person, 2000–2022 (watts per capita). Data source: International Renewable Energy Agency and United Nations World Population Prospects, via Our World in Data.

Share of final energy use that comes from renewable sources, 2005 to 2021

Renewable energy includes solar, wind, geothermal, hydropower, bioenergy, and marine sources.

Our World
in Data



Data source: International Energy Agency, International Renewable Energy Agency and United Nations Statistics Division
OurWorldinData.org/renewable-energy | CC BY

Figure S9: Renewable energy share in the total final energy consumption (%), 2005–2021. International Energy Agency, International Renewable Energy Agency, and United Nations Statistics Division – processed by Our World in Data.

626 Figure S10 shows complementary data from a non-registered indicator that confirms our
627 country grouping: the carbon intensity of energy production (kg CO₂ per kilowatt-hour)

628 from 2005 to 2023. Spain and Uruguay consistently produce energy with a lower-than-
629 average carbon intensity, reflecting a greater reliance on low-carbon sources. Poland and the
630 Dominican Republic remain substantially above the world average throughout the period,
631 consistent with continued dependence on fossil fuels.

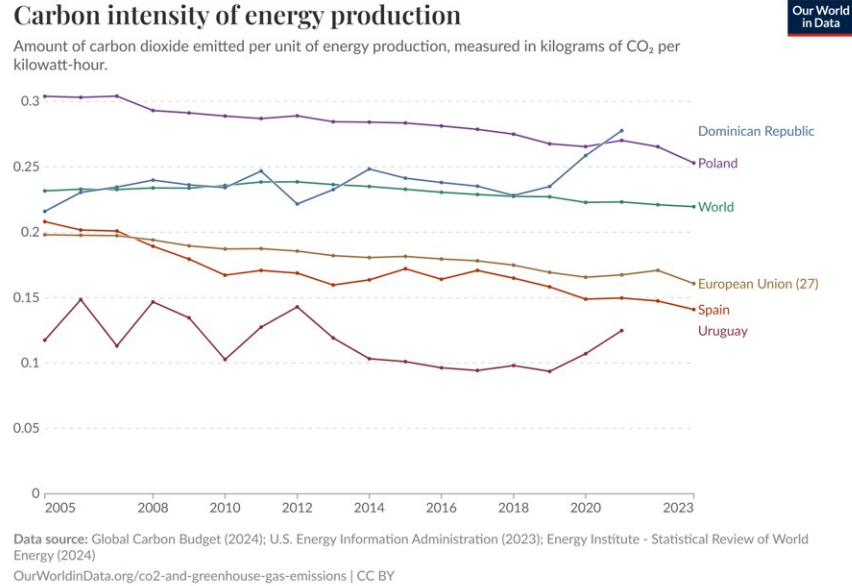


Figure S10: Carbon intensity of energy production, 2005–2023 (kg CO₂ per kilowatt-hour). Data source: Global Carbon Budget (2024); U.S. Energy Information Administration (2023); Energy Institute — Statistical Review of World Energy (2024), via Our World in Data.

632 Together, these indicators support grouping Spain and Uruguay as structurally more com-
633 mitted to renewable energy than the Dominican Republic and Poland. This grouping is
634 not intended as a comprehensive ranking of environmental performance. Broader composite
635 indices, such as the Environmental Performance Index (EPI), capture additional dimensions
636 of environmental quality and policy and may order these countries differently. Our grouping
637 should therefore be read as a narrow, energy-sector-based proxy for the country-level policy
638 and system context of energy use, tailored to the specific focus of our experimental design,
639 rather than as a measure of individual environmental attitudes.

640 S4 Robustness checks

641 S4.1 Brightness overuse intensive margin

642 In the main text we focus on the *extensive* margin brightness overuse definition as our pre-
643 registered primary outcome, which captures the share of subjects who increase brightness
644 without improving output. In this section we replicate the analyses with the *intensive* margin

definition, which quantifies the aggregate resources wasted.

We define $b_{1,i}^-$ and $b_{2,i}^-$ as participant i 's average brightness expenditure in Blocks 1 and 2, and $c_{1,i}^-$ and $c_{2,i}^-$ as the average target characters found in Blocks 1 and 2. The *intensive* margin brightness overuse metric is defined as the difference in mean brightness between rounds 6–8 and rounds 3–5 ($\bar{b}_{2,i} - \bar{b}_{1,i}$), divided by $10 - \bar{b}_{1,i}$, conditional on not having improved in output ($\bar{c}_{2,i} \leq \bar{c}_{1,i}$).

Table S3 presents alternative estimates to those in Table 1 to assess the intensity of brightness overuse, keeping the controls, OLS estimator, and sample unchanged. Intensive margin results (Table S3) replicate the main findings for H1 ($\beta = 0.102$, $p < 0.001$), H2 ($\beta = -0.004$, $p > 0.05$), and H4 ($\beta = 0.021$, $p < 0.01$). For H3, however, the negative externality effect observed among countries with lower renewable energy profiles on the extensive margin does not replicate to the brightness overuse intensity metric ($\beta = -0.013$, $p > 0.05$), meaning that in these countries the externality is effective in reducing the share of subjects who overuse brightness after a price drop, but not in mitigating the magnitude of the wasteful input consumption.

Table S3: Brightness overuse intensive margin

	(1)	(2)
<i>Panel A: Price-Drop effect (H1)</i>		
Price-Drop	0.088*** (0.006)	0.102*** (0.006)
Constant	0.026*** (0.004)	0.019 (0.047)
Observations	3,068	3,004
R-squared	0.065	0.102
Controls	No	Yes
<i>Panel B: Environmental externality effect (H2)</i>		
Environmental externality	-0.005 (0.008)	-0.004 (0.008)
Constant	0.115*** (0.006)	0.132 (0.070)
Observations	3,035	2,979
R-squared	0.000	0.069
Controls	No	Yes
<i>Panel C: Renewable energy profile heterogeneity (H3)</i>		
Lower renewable energy profile countries	-0.017 (0.011)	-0.013 (0.011)
Higher renewable energy profile countries	0.006 (0.011)	0.004 (0.011)
Observations	3,035	2,979
Controls	No	Yes
<i>Panel D: Energy literacy and fluid intelligence (H4)</i>		
Energy literacy	0.022** (0.007)	0.021** (0.007)
Fluid intelligence	0.004 (0.002)	0.000 (0.002)
Constant	0.042*** (0.010)	0.063 (0.049)
Observations	4,227	4,158
R-squared	0.053	0.094
Controls	No	Yes

OLS estimates. Panels A, B, and D report estimated coefficients; Panel C reports marginal effects by country group. Robust standard errors in parentheses. Dependent variable: rebound (intensive margin; rounds 3–8). * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

S4.2 Replications with logit and tobit model specifications

Table S4 reports robustness checks of the extensive margin estimates in Table 1. The dependent and independent variables are identical, but the model is estimated using a logit specification. All main results replicate: the Price-Drop treatment increases brightness overuse probability (H1: marginal effect = 0.199, $p < 0.001$), the environmental externality has no significant overall effect (H2: -0.012 , $p > 0.05$), lower renewable energy profile countries exhibit a significant reduction in brightness overuse under the externality (H3: -0.052 , $p < 0.05$), and energy literacy is positively associated with brightness overuse (H4: 0.065 , $p < 0.001$).

Table S4: Logit estimates

	(1)	(2)
<i>Panel A: Price-Drop effect (H1)</i>		
Price-Drop	0.181*** (0.014)	0.199*** (0.015)
Observations	3,068	3,004
Controls	No	Yes
<i>Panel B: Environmental externality effect (H2)</i>		
Environmental externality	-0.011 (0.017)	-0.012 (0.017)
Observations	3,035	2,979
Controls	No	Yes
<i>Panel C: Renewable energy profile heterogeneity (H3)</i>		
Lower renewable energy profile countries	-0.056^* (0.024)	-0.052^* (0.023)
Higher renewable energy profile countries	0.035 (0.024)	0.030 (0.024)
Observations	3,035	2,979
Controls	No	Yes
<i>Panel D: Energy literacy and fluid intelligence (H4)</i>		
Energy literacy	0.066^{***} (0.015)	0.065^{***} (0.016)
Fluid intelligence	0.010 (0.005)	0.004 (0.006)
Observations	4,227	4,158
Controls	Treatment only	Yes

Logit estimates. Panels A, B, and D report estimated marginal effects; Panel C reports marginal effects by country group. Robust standard errors in parentheses. Dependent variable: rebound (extensive margin; rounds 3–8). * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table S5 reports robustness checks of the intensive margin estimates in Table S3 using a Tobit specification, which accounts for the censored nature of the dependent variable (bounded below at zero). Results for H1, H2, and H4 replicate in full ($p < 0.001$, $p > 0.05$, and $p < 0.001$, respectively). For H3, the negative marginal effect among lower renewable energy profile countries is significant in the specification without controls (-0.019 , $p < 0.05$) but falls short of conventional significance once controls are included (-0.016 , $p > 0.05$), consistent with the OLS intensive margin estimates in Table S3.

Table S5: Tobit estimates

	(1)	(2)
<i>Panel A: Price-drop effect (H1)</i>		
Price-drop	0.081*** (0.006)	0.089*** (0.006)
Observations	3,068	3,004
Controls	No	Yes
<i>Panel B: Environmental externality effect (H2)</i>		
Environmental externality	-0.005 (0.007)	-0.004 (0.006)
Observations	3,035	2,979
Controls	No	Yes
<i>Panel C: Renewable energy profile heterogeneity (H3)</i>		
Lower renewable energy profile countries	-0.019* (0.009)	-0.016 (0.009)
Higher renewable energy profile countries	0.010 (0.009)	0.009 (0.009)
Observations	3,035	2,979
Controls	No	Yes
<i>Panel D: Energy literacy and fluid intelligence (H4)</i>		
Energy literacy	0.025*** (0.006)	0.025*** (0.006)
Fluid intelligence	0.003 (0.002)	0.001 (0.002)
Observations	4,227	4,158
Controls	No	Yes

Tobit estimates with lower censoring at zero. Marginal effects on the observed outcome evaluated at the mean, computed as $\partial E[y | x] / \partial x$ using `predict(e(0, .))`. Panels A, B, and D report treatment marginal effects; Panel C reports marginal effects by country group. Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

S4.3 Alternative block definitions

The main specification defines pre- and post-shock blocks as rounds 3–5 and 6–8, respectively, excluding the first two rounds to account for task familiarization and using a symmetric three-round window on each side of the price shock. This section presents alternative estimates varying the rounds considered in the brightness overuse variable definition, for both the extensive and intensive margins.

Tables S6 and S7 present alternative estimates to tables 1 and S3, respectively, across different block specifications, keeping the controls, OLS estimator, and sample unchanged. The dependent variables are the extensive and intensive margin definitions of *overuse*, respectively, but the rounds considered in the variable definition vary across columns. Each column label denotes the number of rounds included before and after the price shock that occurs after round 5 and before round 6. For example, in the +5/ – 5 column, the dependent variable is comparing rounds 1-5 with 6-10. In the columns 6-9, the pre-treatment block –3 corresponds to rounds 3-5 and the comparison blocks vary from 6-10 to round 6 only.

The Price-Drop effect (H1) is robust across all block definitions on both margins, with coefficients increasing monotonically as shorter post-shock windows are used (Figures S11 and S12). Likewise, the null result for H2 is similarly robust throughout. Instead, findings for H3 and H4 are unstable.

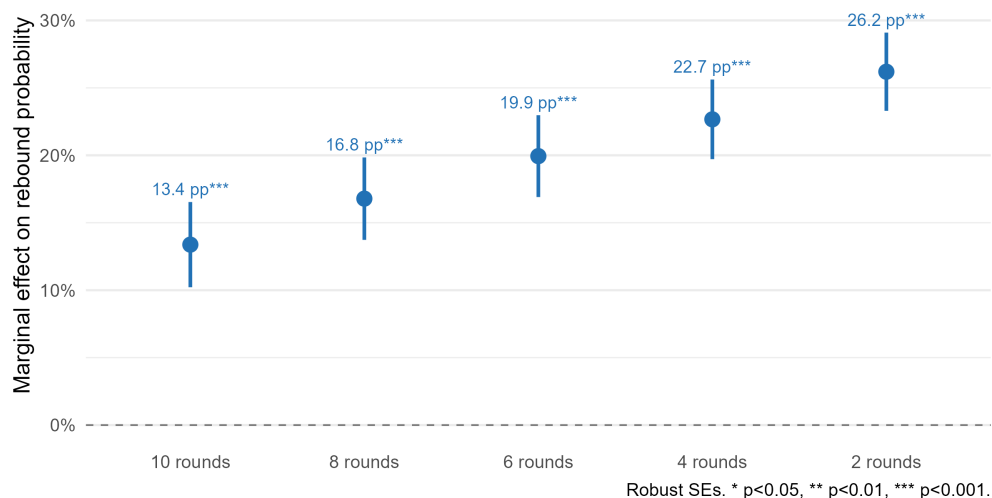


Figure S11: H1 under alternative block definitions (extensive margin)

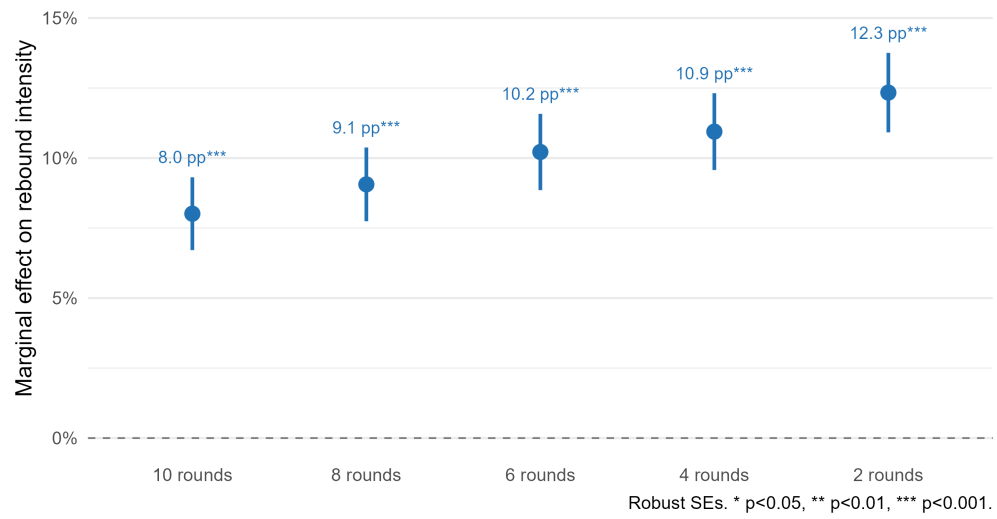


Figure S12: H1 under alternative block definitions (intensive margin)

Table S6: Alternative block definitions (extensive margin)

	(1) +5/−5	(2) +4/−4	(3) +3/−3	(4) +2/−2	(5) +1/−1	(6) +5/−3	(7) +4/−3	(8) +2/−3	(9) +1/−3
<i>Panel A: Price-drop effect (H1)</i>									
Price-drop	0.134*** (0.016)	0.168*** (0.015)	0.199*** (0.015)	0.227*** (0.015)	0.262*** (0.014)	0.144*** (0.014)	0.157*** (0.015)	0.179*** (0.015)	0.203*** (0.015)
Observations	3,004	3,004	3,004	3,004	3,004	3,004	3,004	3,004	3,004
R-squared	0.041	0.056	0.071	0.088	0.121	0.050	0.055	0.062	0.071
<i>Panel B: Environmental externality effect (H2)</i>									
Externality	−0.021 (0.017)	−0.008 (0.017)	−0.013 (0.017)	−0.013 (0.017)	−0.019 (0.016)	−0.006 (0.016)	−0.008 (0.016)	−0.002 (0.017)	0.004 (0.017)
Observations	2,979	2,979	2,979	2,979	2,979	2,979	2,979	2,979	2,979
R-squared	0.023	0.027	0.035	0.040	0.069	0.017	0.024	0.023	0.033
<i>Panel C: Renewable energy profile heterogeneity (H3)</i>									
Lower renewable profile countries	−0.034 (0.023)	−0.040 (0.023)	−0.052* (0.023)	−0.042 (0.023)	−0.044 (0.023)	−0.041 (0.022)	−0.042 (0.022)	−0.029 (0.023)	−0.020 (0.023)
Higher renewable profile countries	−0.006 (0.024)	0.026 (0.024)	0.030 (0.024)	0.017 (0.024)	0.008 (0.024)	0.031 (0.023)	0.028 (0.023)	0.027 (0.024)	0.031 (0.025)
Observations	2,979	2,979	2,979	2,979	2,979	2,979	2,979	2,979	2,979
<i>Panel D: Energy literacy and fluid intelligence (H4)</i>									
Literacy	0.038* (0.016)	0.057*** (0.016)	0.064*** (0.016)	0.064*** (0.015)	0.058*** (0.015)	0.026 (0.015)	0.044** (0.015)	0.068*** (0.015)	0.071*** (0.016)
Fluid intelligence	0.004 (0.006)	0.005 (0.006)	0.004 (0.006)	0.002 (0.006)	0.015** (0.005)	0.000 (0.005)	0.000 (0.006)	−0.006 (0.006)	0.004 (0.006)
Observations	4,158	4,158	4,158	4,158	4,158	4,158	4,158	4,158	4,158
R-squared	0.033	0.050	0.064	0.078	0.109	0.040	0.048	0.056	0.070

Notes: This table presents alternative estimates to Table 1 across different block specifications, keeping the controls, OLS estimator, and sample unchanged. Each column label denotes the number of rounds included before and after the price shock (after round 5 and before round 6). For example, in the +5/−5 column, the dependent variable is comparing rounds 1-5 with 6-10. In the columns 6-9, the pre-treatment block −3 corresponds to rounds 3-5 and the comparison block vary from 6-10 to round 6 only. Panels A, B, and D report estimated coefficients; Panel C reports marginal effects by country group. In all cases, robust standard errors are in parentheses. Statistical significance is based on two-sided tests: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Table S7: Alternative block definitions (intensive margin)

	(1) +5/-5	(2) +4/-4	(3) +3/-3	(4) +2/-2	(5) +1/-1	(6) +5/-3	(7) +4/-3	(8) +2/-3	(9) +1/-3
<i>Panel A: Price-drop effect (H1)</i>									
Price-drop	0.080*** (0.006)	0.091*** (0.006)	0.102*** (0.006)	0.109*** (0.006)	0.123*** (0.006)	0.076*** (0.006)	0.082*** (0.006)	0.089*** (0.006)	0.103*** (0.006)
Observations	3,004	3,004	3,004	3,004	3,004	3,004	3,004	3,004	3,004
R-squared	0.074	0.088	0.102	0.113	0.131	0.074	0.081	0.087	0.098
<i>Panel B: Environmental externality effect (H2)</i>									
Externality	-0.010 (0.007)	-0.006 (0.008)	-0.004 (0.008)	-0.003 (0.008)	-0.004 (0.008)	-0.005 (0.007)	-0.003 (0.007)	0.004 (0.008)	0.005 (0.008)
Observations	2,979	2,979	2,979	2,979	2,979	2,979	2,979	2,979	2,979
R-squared	0.053	0.062	0.069	0.076	0.096	0.049	0.054	0.056	0.068
<i>Panel C: Renewable energy profile heterogeneity (H3)</i>									
Lower renewable profile countries	-0.014 (0.010)	-0.012 (0.011)	-0.013 (0.011)	-0.007 (0.011)	-0.005 (0.011)	-0.009 (0.010)	-0.007 (0.010)	0.003 (0.011)	0.005 (0.011)
Higher renewable profile countries	-0.007 (0.011)	-0.001 (0.011)	0.004 (0.011)	0.000 (0.012)	-0.004 (0.012)	-0.002 (0.010)	-0.000 (0.011)	0.003 (0.011)	0.005 (0.012)
Observations	2,979	2,979	2,979	2,979	2,979	2,979	2,979	2,979	2,979
<i>Panel D: Energy literacy and fluid intelligence effects on rebound (H4)</i>									
Literacy	0.012 (0.006)	0.018** (0.007)	0.021** (0.007)	0.023*** (0.007)	0.024*** (0.007)	0.007 (0.006)	0.015* (0.006)	0.023*** (0.007)	0.025*** (0.007)
Fluid intelligence	-0.001 (0.002)	0.000 (0.002)	0.000 (0.002)	0.000 (0.003)	0.005 (0.003)	-0.001 (0.002)	-0.002 (0.002)	-0.003 (0.002)	0.002 (0.003)
Observations	4,158	4,158	4,158	4,158	4,158	4,158	4,158	4,158	4,158
R-squared	0.068	0.082	0.094	0.105	0.121	0.066	0.074	0.083	0.096

Notes: Robust standard errors in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

S5 Additional results

S5.1 The unproductive dimension within the standard rebound measure

The standard rebound measure classifies as rebound any participant who increases brightness after the price shock ($\bar{b}_{2,i} > \bar{b}_{1,i}$), regardless of output. In Figure S13 below, each bar splits participants into those who do not increase brightness, those who increase brightness with a corresponding output gain, and those who increase brightness without an output gain (unproductive rebound, or *overuse*). Under both Price-Drop and Externality, overuse accounts for roughly 71% of total rebound.

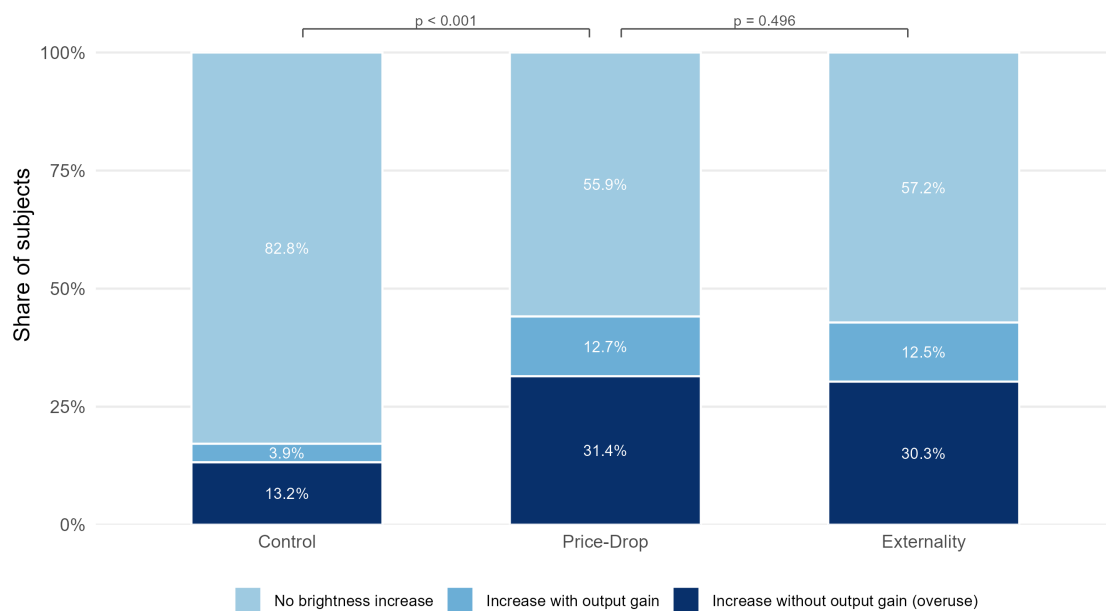


Figure S13: Brightness use and output after a price shock across treatments

S5.2 Full regression results

Table S8 reports the full model estimates for Table 1, including all control variables.

Table S8: Full model estimates

	H1	H2	H3	H4
<i>Treatment</i>				
Price-Drop	0.199*** (0.015)			0.207*** (0.016)
Externality		−0.013 (0.017)	−0.052* (0.023)	0.198*** (0.016)
EC countries			−0.071** (0.025)	
EC × Externality			0.082* (0.034)	
Energy literacy				0.064*** (0.016)
Fluid intelligence	0.003 (0.006)	0.013 (0.007)	0.015* (0.007)	0.004 (0.006)
Female	0.008 (0.015)	−0.007 (0.017)	−0.009 (0.017)	0.008 (0.013)
Mean savings	−0.002*** (0.000)	−0.003*** (0.000)	−0.003*** (0.000)	−0.002*** (0.000)
Attention check 1	0.028 (0.015)	0.060*** (0.018)	0.063*** (0.017)	0.042** (0.014)
Attention check 2	0.032 (0.041)	0.040 (0.047)	0.043 (0.047)	0.047 (0.038)
Mobile	0.050** (0.017)	0.014 (0.019)	0.012 (0.019)	0.028 (0.015)
<i>Education</i>				
Primary education	0.053 (0.119)	0.090 (0.149)	0.085 (0.148)	−0.030 (0.114)
Secondary education	−0.011 (0.101)	−0.001 (0.135)	−0.003 (0.135)	−0.023 (0.100)
High school	−0.004 (0.100)	0.075 (0.133)	0.073 (0.133)	0.006 (0.099)
Vocational training	0.011 (0.100)	0.042 (0.134)	0.040 (0.133)	−0.000 (0.099)
University degree	0.023 (0.100)	0.052 (0.134)	0.051 (0.133)	0.006 (0.099)
Post-graduate degree	0.027 (0.100)	0.058 (0.134)	0.058 (0.133)	−0.002 (0.099)
Doctorate	0.092	0.042	0.042	0.093

	H1	H2	H3	H4
	(0.113)	(0.144)	(0.143)	(0.109)
<i>Age group</i>				
25–34	0.039 (0.025)	0.028 (0.029)	0.030 (0.029)	0.031 (0.023)
35–44	0.015 (0.026)	0.020 (0.030)	0.024 (0.030)	0.010 (0.023)
45–54	0.014 (0.028)	0.000 (0.033)	0.008 (0.032)	0.008 (0.026)
55–64	−0.005 (0.031)	0.013 (0.036)	0.024 (0.034)	0.004 (0.028)
65+	0.016 (0.043)	0.034 (0.050)	0.047 (0.048)	0.034 (0.038)
Utility bill payer	−0.026 (0.028)	−0.043 (0.030)	−0.044 (0.030)	−0.027 (0.024)
Home owner	0.008 (0.017)	0.007 (0.019)	0.008 (0.019)	0.004 (0.015)
Data sharing reluctance	0.004** (0.001)	0.004** (0.001)	0.004** (0.001)	0.004** (0.001)
Climate action	−0.005 (0.003)	−0.003 (0.003)	−0.003 (0.003)	−0.005* (0.002)
<i>Countries</i>				
Uruguay	−0.001 (0.023)	−0.022 (0.026)		−0.015 (0.021)
Dominican Republic	0.031 (0.023)	0.007 (0.026)		0.020 (0.021)
Poland	0.064** (0.023)	0.030 (0.026)		0.026 (0.020)
Constant	0.031 (0.115)	0.226 (0.149)	0.259 (0.146)	0.123 (0.113)
Observations	3,004	2,979	2,979	4,158
R-squared	0.071	0.035	0.037	0.064

OLS estimates. The omitted reference categories are the Control treatment, Primary Education not completed, ages 18–24, and Spain. Robust standard errors in parentheses. Dependent variable: rebound (extensive margin; rounds 3–8). * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

S5.3 Country heterogeneity analyses

Figures S14, S15, and S16 report meta-analytic summaries of the H2 and H4 estimates across countries, obtained using a two-stage individual participant data meta-analysis approach pre-registered for H3.²⁶ Figure S14 shows that the externality effect on overuse is close to zero in all four countries, with an overall pooled estimate of -0.00 (95% CI: $-0.02, 0.01$) and no statistically significant heterogeneity ($I^2 = 0.0\%$; $p = 0.744$), confirming the null result for H2. Figure S15 shows that the positive association between energy literacy and overuse is consistent across countries, with an overall estimate of 0.06 (95% CI: $0.03, 0.09$) and no heterogeneity ($I^2 = 0.0\%$; $p = 0.995$). Figure S16 shows that the fluid intelligence coefficient is zero in all countries, with an overall estimate of 0.00 (95% CI: $-0.01, 0.02$); the moderate $I^2 = 56.2\%$ ($p = 0.077$) reflects small variation in the sign of country-level estimates but no statistically significant heterogeneity.

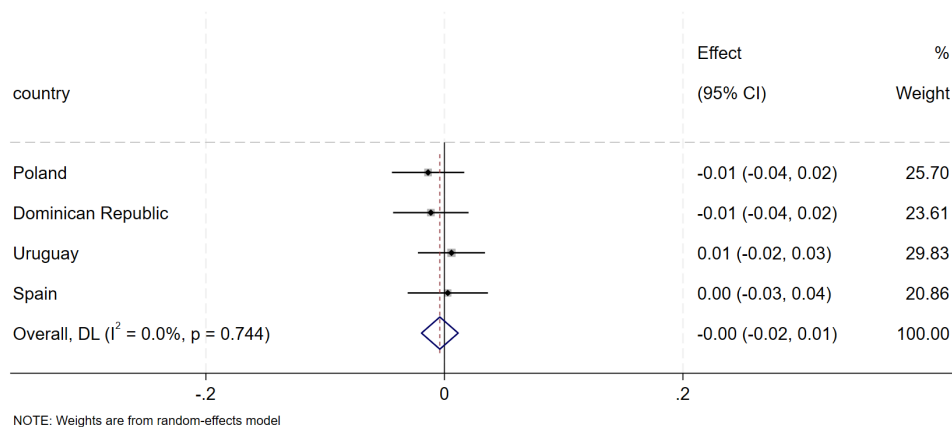


Figure S14: H2 meta-analytic summary

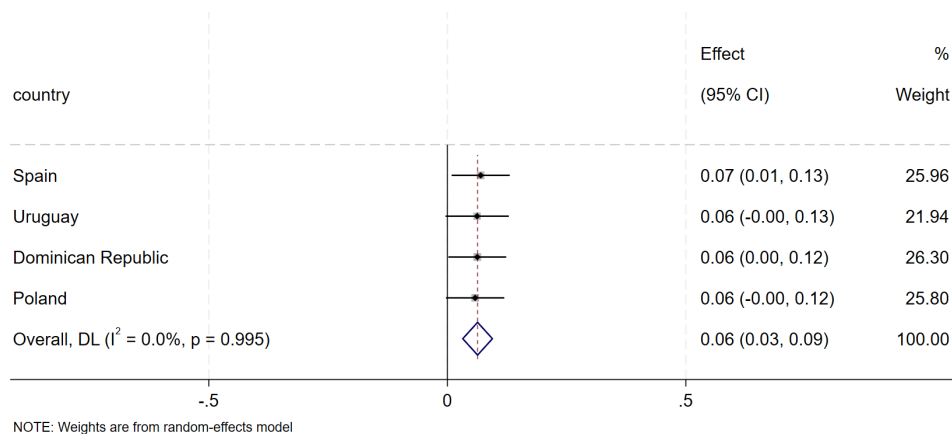


Figure S15: H4 meta-analytic summary (energy literacy)

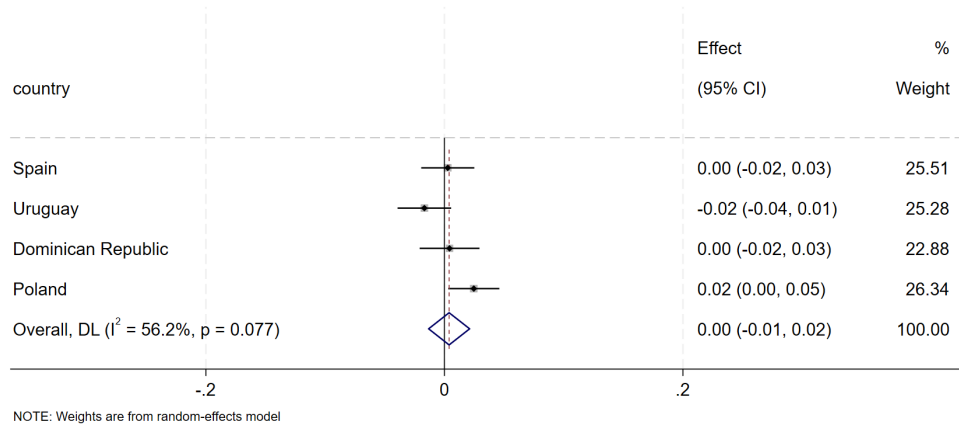


Figure S16: H4 meta-analytic summary (fluid intelligence)

Figure S17 replicates the H3 analyses disaggregating by country instead of grouping them into lower and higher renewable energy profiles, revealing no statistically significant differences in any of the four cases. Table S9 presents the H3 heterogeneity effect by country using the same model as in Table 1. The reduction in overuse under the environmental externality is statistically significant only in Poland ($\beta = -0.064$, $p < 0.05$), while the Dominican Republic displays a negative but individually insignificant coefficient ($\beta = -0.039$, $p > 0.05$), suggesting that the aggregate effect among lower renewable energy profile countries reported in Table 1 is primarily driven by the Polish sample.

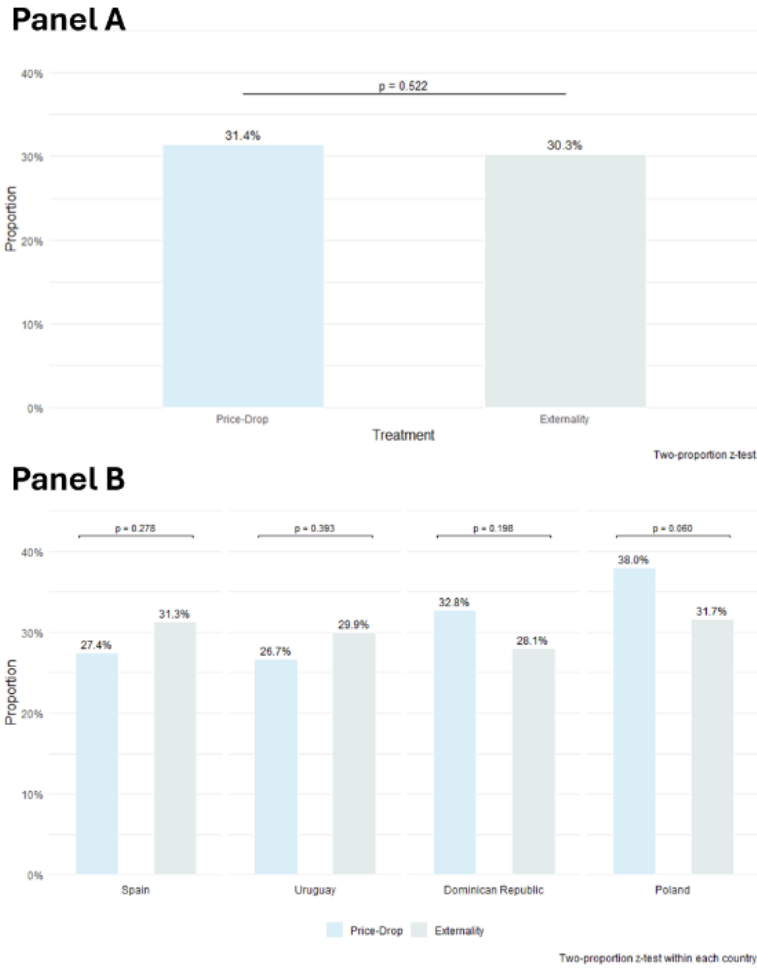


Figure S17: H2 and H3 (Externality vs. Price-Drop). Panel A shows the brightness overuse comparison by treatment condition. The proportion of participants exhibiting unproductive rebound is 31.4% under Price-Drop and 30.3% under Externality (difference = 1.1 percentage points; two-proportion z -test, $p = 0.522$; $n = 3,035$). Panel B reports country-level comparisons between the same treatments, indicating no statistically significant differences in any country.

Table S9: Main regression results for H3 by countries

	(1)	(2)
<i>Country-level heterogeneity (H3)</i>		
Spain	0.039 (0.034)	0.031 (0.034)
Uruguay	0.032 (0.035)	0.031 (0.035)
Dominican Republic	−0.047 (0.034)	−0.039 (0.034)
Poland	−0.063* (0.031)	−0.064* (0.031)
Observations	3,035	2,979
Controls	No	Yes

OLS estimates. Reports marginal effects by country. Robust standard errors in parentheses. Dependent variable: rebound (extensive margin; rounds 3–8). * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

S6 Pre-analysis plan

This section details the deviations from the pre-analysis plan registered on OSF prior to data collection (<https://osf.io/azcqu/registrations>). The deviations described below are limited to variable labeling, operationalization and specification choices made to improve statistical precision and interpretability; all main results are robust to the preregistered alternatives.

Country classification: terminology. The preregistration classifies Spain and Uruguay as “more environmentally concerned” than the Dominican Republic and Poland, based on two indicators of renewable energy commitment — renewable electricity generating capacity and renewable energy use as a share of total energy consumption — reported from Ember (2024). We retain the same four countries and the same two groups, but adjust the terminology precision; neither alters the classification or any result. We replace the label “environmentally concerned” with “higher versus lower renewable energy profiles,” describing the groups by their structural energy characteristics rather than by an implied attitude. Because the classification is built from country-level energy-sector indicators rather than from any measure of individual attitudes, the original label risks being read as a claim about participants’ environmental preferences, which we do not measure; we therefore reserve the notion of environmental concern for the country-level policy and system context that motivates H3.

Pre- and post-shock block definition. The preregistration defines brightness overuse by comparing rounds 1–5 (pre-shock) with rounds 6–10 (post-shock). In the main analysis we adopt a narrower +3/−3 block (rounds 3–5 vs. 6–8), which excludes the first two rounds

to account for learning while retaining a symmetric round window before and after the price shock. Section S4.3 shows that the main results are robust across all alternative block definitions, with H1 estimates increasing monotonically as shorter windows are used.

Intensive margin definition. The preregistration does not specify an intensive margin outcome. In the main analysis we define the intensive margin as $(\bar{b}_{2,i} - \bar{b}_{1,i})/(10 - \bar{b}_{1,i})$, the change in mean brightness expenditure between the post- and pre-shock blocks scaled by the maximum brightness level, bounded on $[-1, 1]$ and left-censored at zero for the Tobit specification. This operationalization quantifies the magnitude of unproductive input use among participants who exhibit brightness overuse on the extensive margin and is reported in Section S4.1.

Energy literacy operationalization. The preregistration defines *misperception* as the sum of absolute deviations between participants' energy estimates and true values. In the main analysis we reverse the sign of this variable so that higher values indicate greater accuracy and apply a log transformation to reduce skewness, labelling the resulting variable *energy literacy*. The underlying variable construction is unchanged.

Control variables. The preregistered control set include *female*, *attention check 1*, *attention check 2*, *mobile*, *fluid intelligence* and country fixed effects. The main specifications additionally include *mean savings*, *age group*, *education*, *utility bill payer*, *home owner*, *data sharing reluctance*, and *climate action*. These variables were selected on the grounds of conceptual relevance to energy behavior and data availability for the case of *age group* and *education*, which were collected by the survey company and provided to us. Tables S10 and S11 report robustness checks of the estimates presented in Table 1 and Table S3, for the main results in both the extensive and intensive margins definitions of brightness overuse, respectively. All main results are replicated using only the preregistered controls.

Table S10: Pre-registered control variables (extensive margin)

	(1)	(2)
<i>Panel A: Price-Drop effect (H1)</i>		
Price-Drop	0.182*** (0.015)	0.183*** (0.015)
Constant	0.132*** (0.010)	0.012 (0.047)
Observations	3,068	3,068
R-squared	0.048	0.055
Controls	No	Yes
<i>Panel B: Environmental externality effect (H2)</i>		
Environmental externality	-0.011 (0.017)	-0.013 (0.017)
Constant	0.314*** (0.012)	0.197*** (0.055)
Observations	3,035	3,035
R-squared	0.000	0.011
Controls	No	Yes
<i>Panel C: Renewable energy profile heterogeneity (H3)</i>		
Lower renewable energy profile countries	-0.056* (0.023)	-0.059* (0.023)
Higher renewable energy profile countries	0.035 (0.024)	0.036 (0.024)
Observations	3,035	3,035
Controls	No	Yes
<i>Panel D: Energy literacy and fluid intelligence (H4)</i>		
Energy literacy	0.065*** (0.015)	0.065*** (0.015)
Fluid intelligence	0.010 (0.005)	0.010 (0.005)
Constant	0.187*** (0.022)	0.082 (0.049)
Observations	4,227	4,227
R-squared	0.045	0.049
Controls	Treatment only	Yes

OLS estimates. Panels A, B, and D report estimated coefficients; Panel C reports marginal effects by country group. Robust standard errors in parentheses. Dependent variable: rebound (extensive margin; rounds 3–8). * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table S11: Pre-registered control variables (intensive margin)

	(1)	(2)
<i>Panel A: Price-drop effect (H1)</i>		
Price-drop	0.088*** (0.006)	0.089*** (0.006)
Constant	0.026*** (0.004)	0.005 (0.020)
Observations	3,068	3,068
R-squared	0.065	0.068
Controls	No	Yes
<i>Panel B: Environmental externality effect (H2)</i>		
Environmental externality	-0.005 (0.008)	-0.006 (0.008)
Constant	0.115*** (0.006)	0.111*** (0.026)
Observations	3,035	3,035
R-squared	0.000	0.008
Controls	No	Yes
<i>Panel C: Renewable energy profile heterogeneity (H3)</i>		
Lower renewable energy profile countries	-0.017 (0.011)	-0.019 (0.011)
Higher renewable energy profile countries	0.006 (0.011)	0.007 (0.011)
Observations	3,035	3,035
Controls	No	Yes
<i>Panel D: Energy literacy and fluid intelligence effects on rebound (H4)</i>		
Energy literacy	0.022** (0.007)	0.023*** (0.007)
Fluid intelligence	0.004 (0.002)	0.003 (0.002)
Constant	0.042*** (0.010)	0.044* (0.021)
Observations	4,227	4,227
R-squared	0.053	0.055
Controls	No	Yes

OLS estimates. Panels A, B, and D report estimated coefficients; Panel C reports marginal effects by country group. Robust standard errors in parentheses. Dependent variable: rebound intensity (+/- 3 specification). * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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