Supplemental Material for: Self-directed information search reinforces climate policy evaluations and polarization across 15 countries

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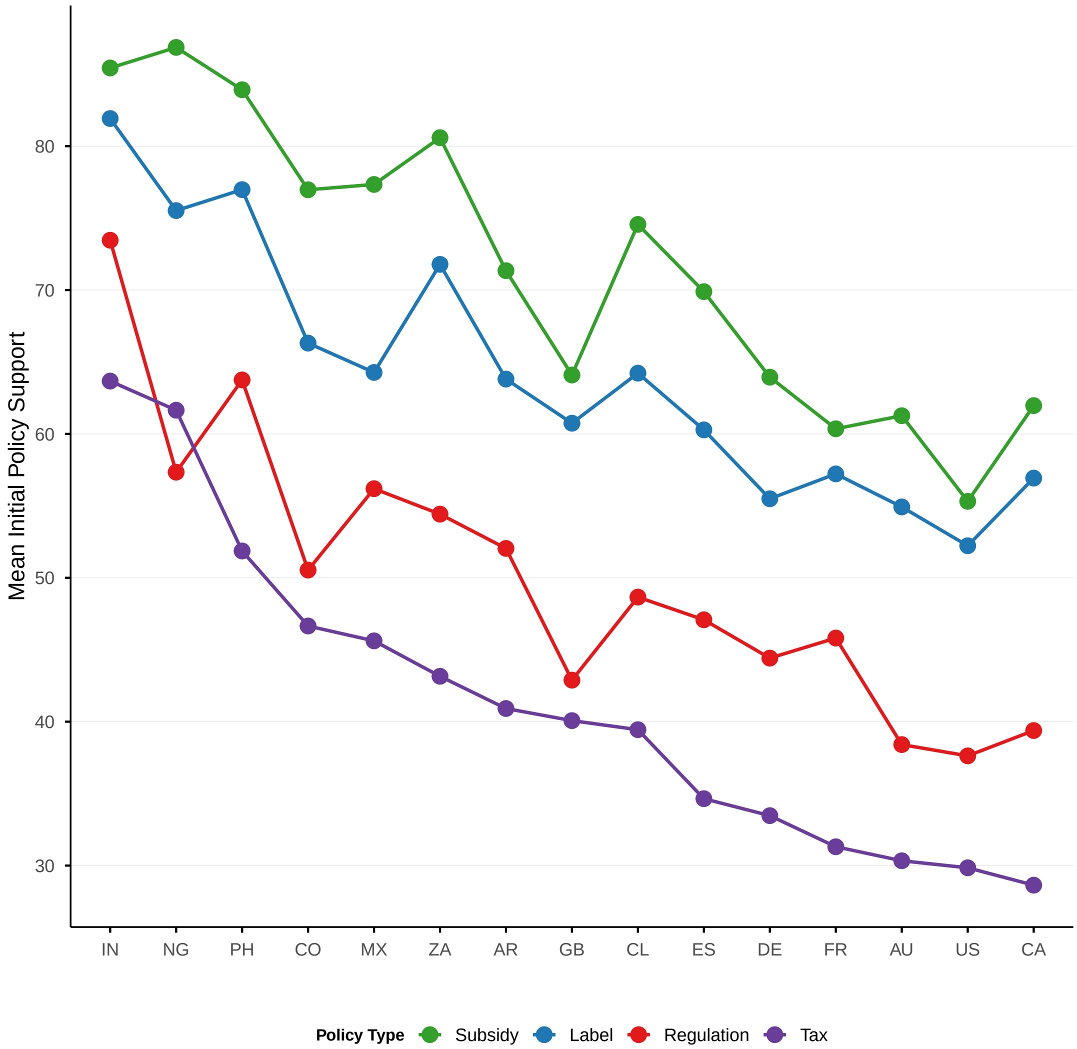
1 Additional Analyses

1.1 Rank Stability of Policy Support

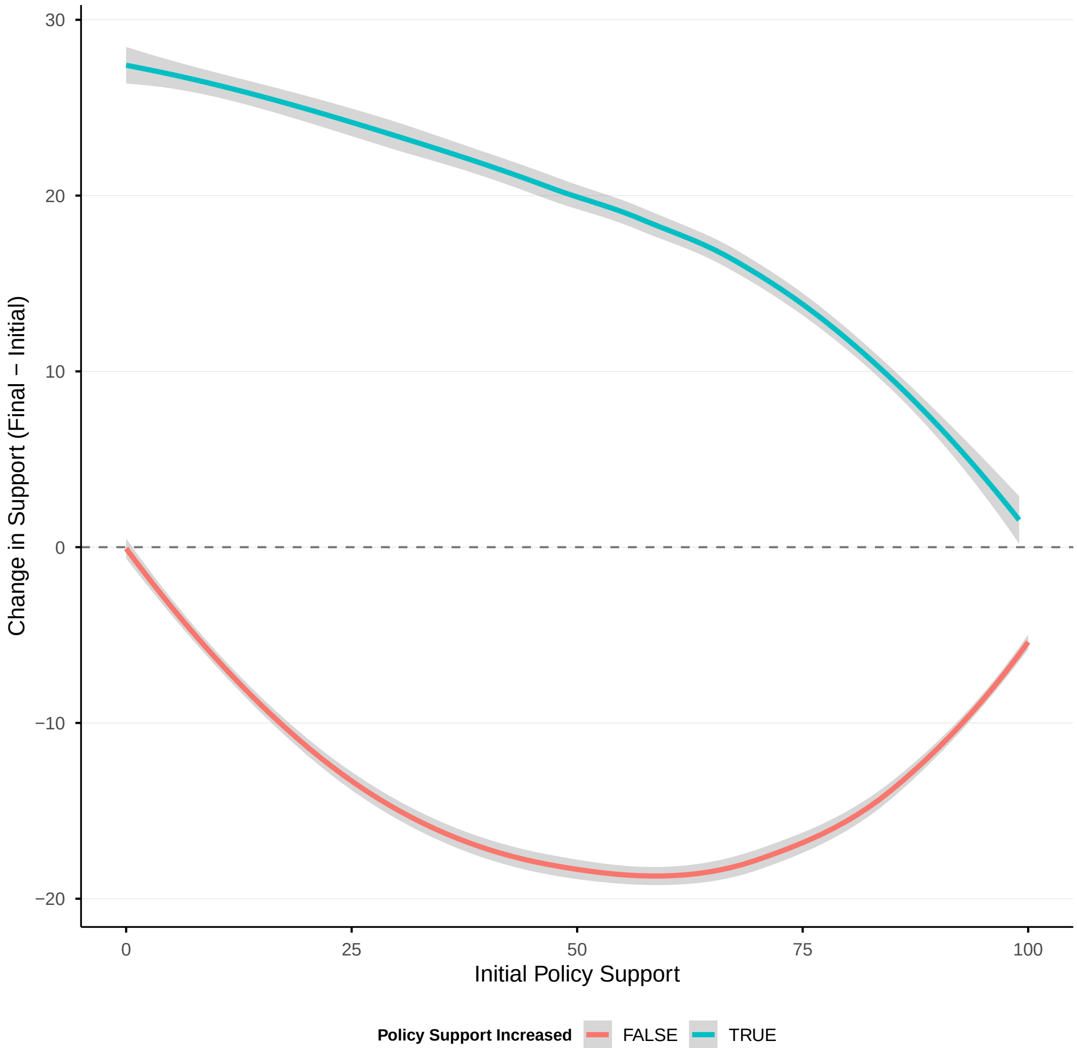
Fig. S1: Mean Initial Policy Support by Policy and Country



Rank stability of policy evaluations was very high with subsidies being most popular, followed by labels, regulation and taxes.

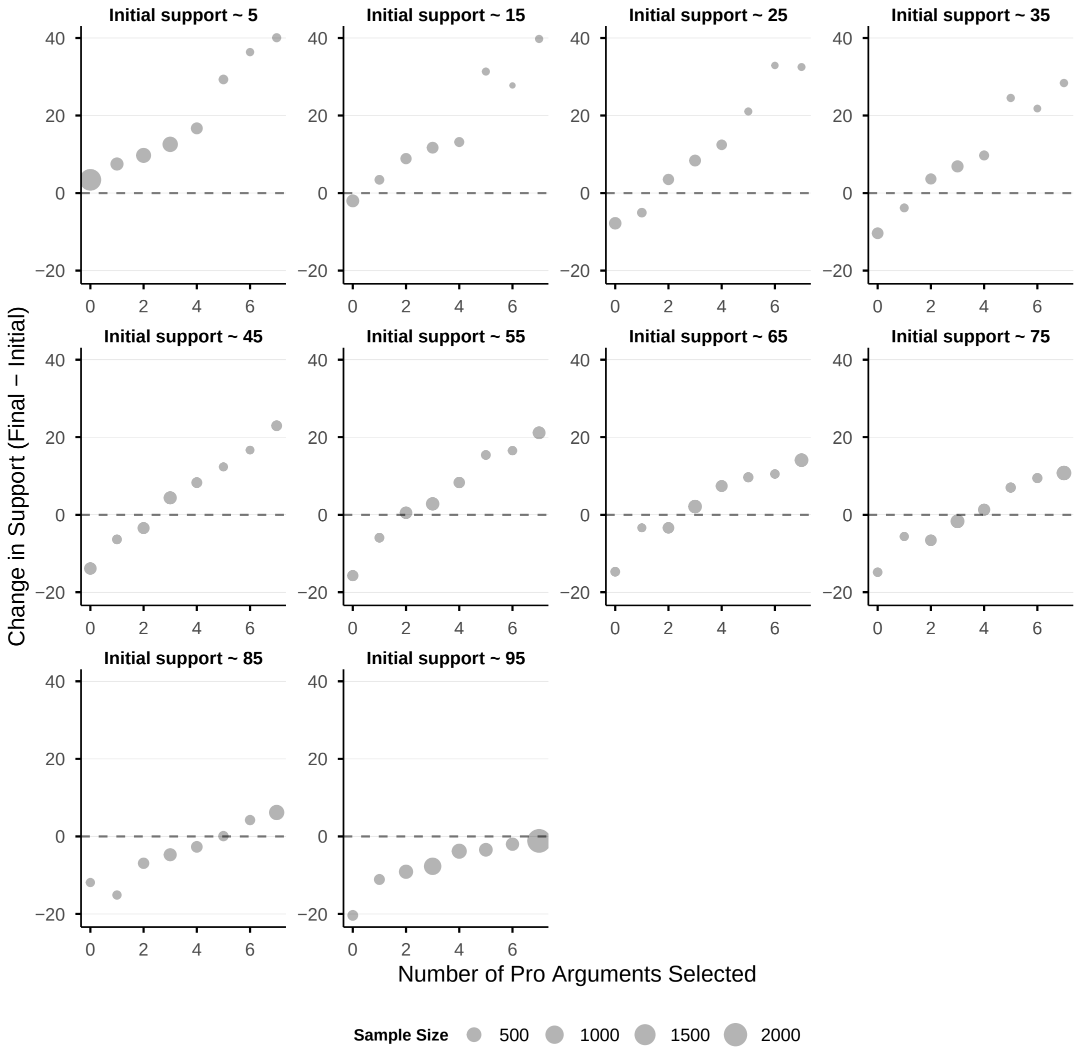
1.2 Changes in Policy Support as a function of initial policy support

Fig. S2: Changes in Pre/Post Policy Support as a function of Support Increase/Decrease and Pre-Support



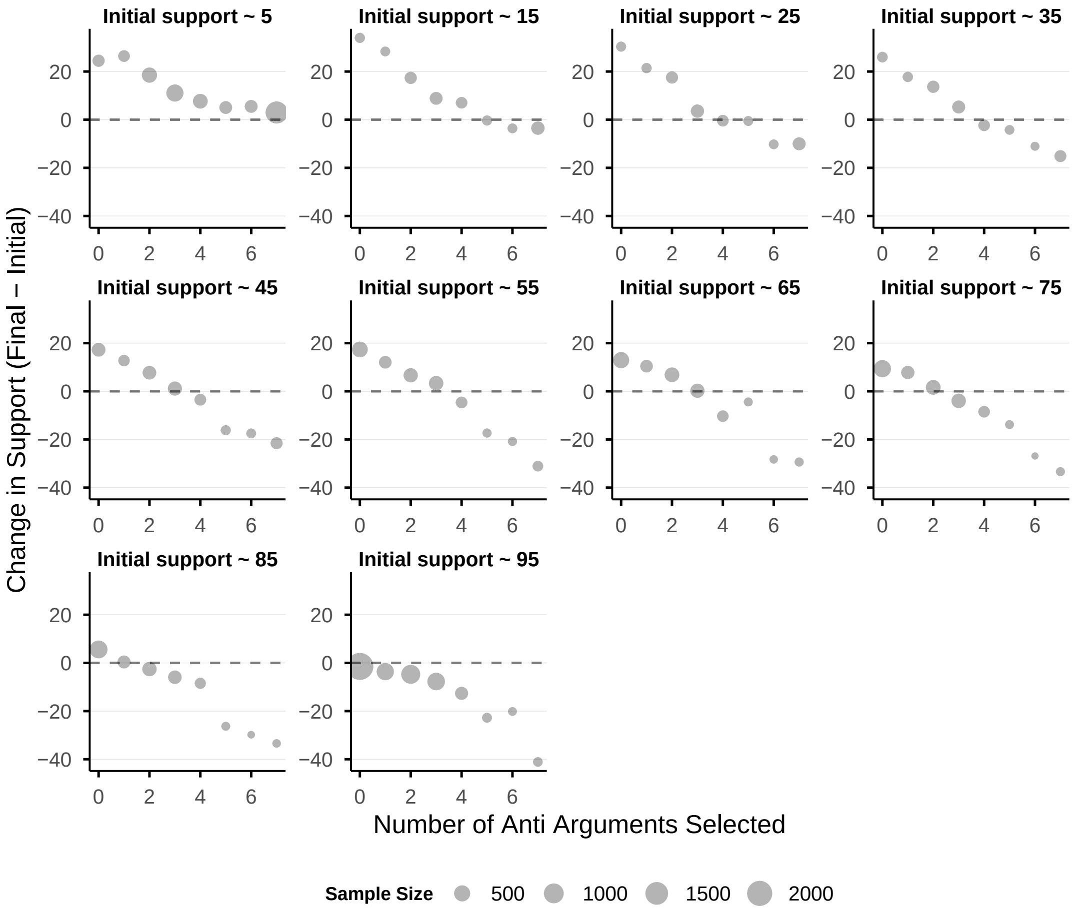
In those cases where policy support decreased over the course of the sampling (red line), malleability was highest for medium level of initial support. This aligns with consolidation of policy support while taking into account scale limit effects (for participants with low initial support, room for decrease in support is lower). Interestingly, for cases where policy support increased, absolute changes are larger than for the decreasing cases. Also, the most strong changes where observed at the low end of the scale, i.e., participants starting with very low levels of support showed strongest changes.

Fig. S3: Changes in Pre/Post Policy Support as a function of Pre-Support and Pro Argument Choices



In cases where participants sampled counter-factually (i.e. against their initial tendencies), changes in support were largest. Otherwise, changes in support were observed as a function of number of pro arguments selected with somewhat diminishing effects and taking into account scale limit effects for very high or very low levels of policy support.

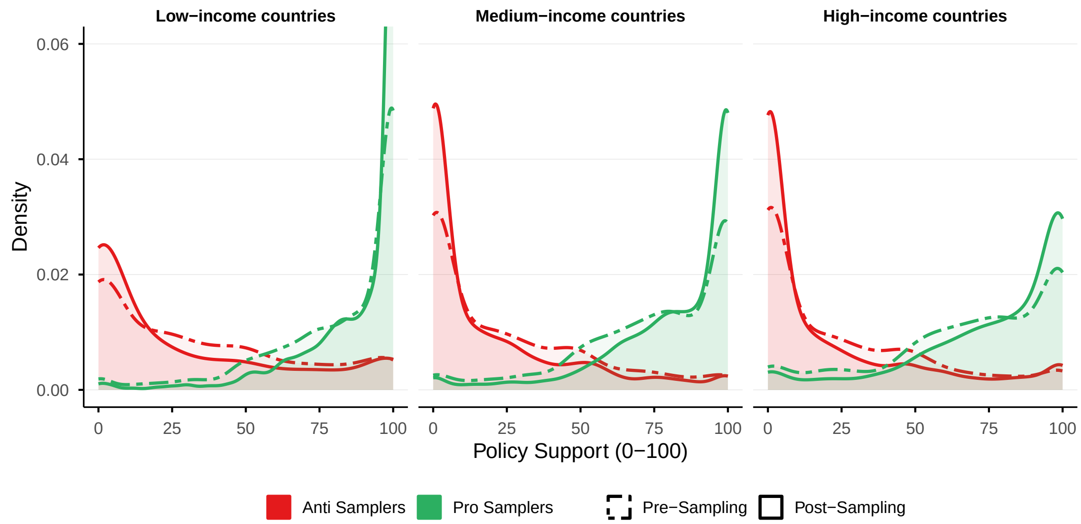
Fig. S4: Changes in Pre/Post Policy Support as a function of Pre-Support and Anti Argument Choices



Similar, but reverse patterns as before. Changes in support were observed as a function of number of pro arguments selected with somewhat diminishing effects and taking into account scale limit effects for very high or very low levels of policy support.

1.3 Increased Polarization after sampling

Fig. S5: Distribution of Policy Support before/after sampling task



Density of policy support for Pro-samplers (i.e., sampled at least 2 more Pro- than Anti-policy arguments; green) and Anti-samplers (red) before (dashed) and after (solid) sampling by GDP group. Density at the poles increases and decreases in the central areas after sampling compared to before sampling.

Table 1. Bimodality Coefficients Before and After Information Sampling by Country

Country	Pre-Sampling	Post-Sampling	Increased
Argentina	0.663	0.774	TRUE
Australia	0.648	0.735	TRUE
Canada	0.655	0.756	TRUE
Chile	0.660	0.774	TRUE
Colombia	0.657	0.784	TRUE
Germany	0.621	0.686	TRUE
Spain	0.668	0.760	TRUE
France	0.633	0.710	TRUE
United Kingdom	0.678	0.748	TRUE
India	0.739	0.819	TRUE
Mexico	0.713	0.802	TRUE
Nigeria	0.767	0.845	TRUE
Philippines	0.723	0.829	TRUE
United States	0.686	0.763	TRUE
South Africa	0.734	0.828	TRUE

Note. Bimodality coefficients [1, 2] as a proxy for polarization are shown for each country before and after information sampling, with every country showing an increase.

2 Additional Preregistered Analyses

2.1 Support for food climate policies across nations

a. Countries with higher per capita meat consumption show lower support for climate food policies overall. This hypothesis is supported, see Table 1.

Table 2. Linear Mixed Effects Model of Country's Meat Supply on Baseline Policy Support

	Initial Policy Evaluation		
Predictors	**Estimates**	**95% CI**	***p***
(Intercept)	64.15	61.40 – 66.89	**<.001**
Meat Supply per Capita (z)	-7.88	-10.54 – -5.22	**<.001**
Policy[Regulation]	-14.06	-15.05 – -13.07	**<.001**
Policy [Subsidy]	7.38	6.39 – 8.37	**<.001**
Policy [Tax]	-22.72	-23.71 – -21.73	**<.001**
Random Effects			
σ^2	624.44		
$\tau_{00\ \mathrm{pcode}}$	433.19		
$\tau_{00\ \mathrm{country\_code}}$	26.20		
ICC	0.42		
$\mathrm{N}_{\mathrm{pcode}}$	4898		
$\mathrm{N}_{\mathrm{country\_code}}$	15		
Observations	19592		
Marginal R^2 / Conditional R^2	0.156 / 0.514		

b. Countries with higher individualism scores show lower support for the tax and regulation policy than countries with lower individualism scores. This difference will not occur for the other policies (labels and subsidies). Higher individualism scores did indeed predict lower policy support. However, this effect occurred for all policies and was strongest for the tax and subsidy policies, partially supporting the hypothesis.

Table 3. Linear Mixed Effects Model of Country's Individualism on Policy Evaluation

	Initial Policy Evaluation		
Predictors	**Estimates**	**95% CI**	***p***
(Intercept)	64.11	60.34 – 67.88	**<.001**
idv score	-5.15	-8.91 – -1.40	**0.007**
Policy [regu]	-14.06	-15.05 – -13.07	**<.001**
Policy [subsidy]	7.38	6.39 – 8.37	**<.001**
Policy [tax]	-22.72	-23.71 – -21.73	**<.001**
idv score × regu	-0.85	-1.84 – 0.14	0.092
idv score × subsidy	-2.37	-3.36 – -1.39	**<.001**
idv score × tax	-1.49	-2.48 – -0.50	**0.003**
Random Effects			
σ^2	623.56		
$\tau_{00\ \mathrm{pcode}}$	433.42		
$\tau_{00\ \mathrm{country\_code}}$	52.30		
ICC	0.44		
N_{pcode}	4898		
$N_{\mathrm{country\_code}}$	15		
Observations	19592		
Marginal R^2 / Conditional R^2	0.139 / 0.516		

2.2 Malleability of attitudes towards climate policies across nations

a. Effect of initial opinion certainty: We expect that malleability is greater for participants with lower certainty in their initial policy support evaluation than for those with high certainty. This hypothesis was supported.

Table 4. Linear Mixed Effects Model of Initial Attitude Certainty on Policy Malleability

	Absolute Malleability		
Predictors	**Estimates**	**95% CI**	***p***
(Intercept)	25.43	24.15 – 26.71	**<.001**
Initial Certainty	-1.49	-1.61 – -1.36	**<.001**
Policy [regu]	-0.66	-1.31 – -0.02	**0.043**
Policy [subsidy]	-1.43	-2.07 – -0.79	**<.001**
Policy [tax]	0.80	0.16 – 1.45	**0.014**
Random Effects			
σ^2	263.31		
$\tau_{00\ \mathrm{pcode}}$	26.12		
$\tau_{00\ \mathrm{country\_code}}$	1.28		
ICC	0.09		
N_{pcode}	4898		
$N_{\mathrm{country\_code}}$	15		
Observations	19592		
Marginal R^2 / Conditional R^2	0.033 / 0.124		

b. Countries with higher per capita meat supply (and higher share of livestock in their total agricultural value) show less malleability in policy support. Countries with more political polarization will show less malleability in policy support. Both hypotheses were not supported.

Table 5. Linear Mixed Effects Model of Meat consumption and Political Polarization on Policy Malleability

	Absolute Malleability			**Absolute Malleability**		
Predictors	**Estimates**	**95% CI**	***p***	**Estimates**	**95% CI**	***p***
(Intercept)	13.03	12.39 – 13.66	**<.001**	13.03	12.37 – 13.68	**<.001**
meat supply per capita kg	-0.28	-0.77 – 0.21	0.265			
policyType [regu]	-0.58	-1.24 – 0.07	0.079	-0.58	-1.24 – 0.07	0.079
policyType [subsidy]	-1.68	-2.33 – -1.03	**<.001**	-1.68	-2.33 – -1.03	**<.001**
policyType [tax]	1.02	0.37 – 1.68	**0.002**	1.02	0.37 – 1.68	**0.002**
political polarization				-0.01	-0.53 – 0.50	0.962
Random Effects						
σ^2	271.21			271.21		
τ_{00}	26.26_{pcode} $0.66_{\text{country\_code}}$			26.26_{pcode} $0.75_{\text{country\_code}}$		
ICC	0.09			0.09		
N	4898_{pcode} $15_{\text{country\_code}}$			4898_{pcode} $15_{\text{country\_code}}$		
Observations	19592			19592		
Marginal R^2 / Conditional R^2	0.003 / 0.093			0.003 / 0.093		

2.3 Information search about climate policies across nations

a. We expect that higher climate beliefs and more liberal political orientation predict that participants select pro-policy [anti-policy] arguments more [less] often. Both hypotheses were confirmed. Because the models did not converge when using countries as random effects, we instead included GDP as a fixed effect to account for between country variance, deviating from the preregistered model specification (however, the effect remains significant when using the non-converging models as preregistered).

Table 6. Item Response Tree Model of individual differences on direction of argument choice

	response			**response**		
Predictors	**Odds Ratios**	**95% CI**	***p***	**Odds Ratios**	**95% CI**	***p***
node [node1_engage]	16.03	14.98 – 17.16	**<.001**	13.06	10.05 – 16.98	**<.001**
node [node2_dir]	1.61	1.53 – 1.69	**<.001**	0.17	0.14 – 0.20	**<.001**
engage × liberal z	1.07	1.01 – 1.15	**0.027**			
dir × liberal z	1.12	1.06 – 1.17	**<.001**			
engage × gdp z	1.05	0.98 – 1.11	0.170	1.07	1.00 – 1.14	**0.040**
dir × gdp z	0.66	0.63 – 0.70	**<.001**	0.78	0.74 – 0.81	**<.001**
engage × CC Beliefs				1.03	0.99 – 1.06	0.110
dir × CC Beliefs				1.32	1.29 – 1.35	**<.001**
Random Effects						
σ^2	3.29			3.29		
$\tau_{11 \text{pcode.engage}}$	3.89			3.90		
$\tau_{11 \text{pcode.dir}}$	2.70			2.38		
ICC	0.50			0.49		
N pcode	4898			4898		
Observations	254466			254466		
Marginal R^2 / Conditional R^2	0.174 / 0.590			0.192 / 0.591		

b. We expect that participants who indicate higher certainty in their initial policy support select the disengaged statements more often. This hypothesis was not confirmed, in fact, the observed results point in the opposite direction, with higher certainty leading to less disengagement. Because the model did not converge when using countries as random effects, we instead included GDP as a fixed effect to account for between country variance.

Table 7. Item Response Tree Model of Initial Attitude Certainty on Engagement in Information Choice

	response		
Predictors	**Odds Ratios**	**95% CI**	***p***
node [node1_engage]	16.05	15.00 – 17.18	**<.001**
node [node2_dir]	1.61	1.54 – 1.70	**<.001**
node1_engage × certainty z	1.06	1.04 – 1.09	**<.001**
node2_dir × certainty z	1.07	1.05 – 1.09	**<.001**
node1_engage × gdp z	1.06	1.00 – 1.13	0.068
node2_dir × gdp z	0.68	0.65 – 0.71	**<.001**
Random Effects			
σ^2	3.29		
τ_{11} pcode.node1_engage	3.89		
τ_{11} pcode.node2_dir	2.71		
ICC	0.50		
N_{pcode}	4898		
Observations	254466		
Marginal R^2/ Conditional R^2	0.173 / 0.590		

c. We expect that participants in countries with low political polarization, low Income, and lower per capita meat supply, will select a disengaged statement less often. None of the hypotheses were supported.

Table 8. Item Response Tree Model of nation level indicators on Engagement in Information Choice

	response		
Predictors	**Odds Ratios**	**95% CI**	***p***
node [node1_engage]	16.04	14.99 – 17.17	**<.001**
node [node2_dir]	1.61	1.54 – 1.70	**<.001**
engage × meat z	0.99	0.90 – 1.08	0.770
dir × meat z	0.81	0.76 – 0.87	**<.001**
engage × pol polar z	0.96	0.90 – 1.03	0.267
dir × pol polar z	1.09	1.03 – 1.15	**0.002**
engage × gdp z	1.06	0.97 – 1.16	0.206
dir × gdp z	0.79	0.73 – 0.85	**<.001**
Random Effects			
σ^2	3.29		
τ_{11} pcode.node1_engage	3.90		
τ_{11} pcode.node2_dir	2.68		
ICC	0.50		
N_{pcode}	4898		
Observations	254466		
Marginal R^2 / Conditional R^2	0.174 / 0.590		

2.4 Evaluation of arguments about climate food policies

a. We expect that higher initial policy support, higher climate beliefs and more liberal political orientation predict that participant like [dislike] pro-policy [anti-policy] arguments more. All hypotheses are supported, however, effect size is strongest for initial policy support and very small for liberal political orientation (in fact, more liberal participants like pro arguments better than anti arguments, but not more than trivia statements).

Table 9. Linear Mixed Effect Model of person level variables on argument ratings

	Statement Liking			**Statement Liking**			**Statement Liking**		
Predictors	**Est.**	**95% CI**	***p***	**Est.**	**95% CI**	***p***	**Est.**	**95% CI**	***p***
(Intercept)	56.57	54.79–58.35	**<.001**	59.51	57.51–61.52	**<.001**	60.26	57.71–62.82	**<.001**
init Eval	-5.55	-5.82– -5.28	**<.001**						
disengaged	12.39	11.91–12.87	**<.001**	10.72	10.22–11.21	**<.001**	10.48	9.98–10.98	**<.001**
pro	14.66	14.31–15.01	**<.001**	14.81	14.46–15.15	**<.001**	15.27	14.92–15.62	**<.001**
init Eval × disengaged	7.38	6.91–7.85	**<.001**						
init Eval × pro	20.32	19.96–20.67	**<.001**						
ccConcern				-0.42	-0.87–0.04	0.073			
ccConcern × disengaged				4.20	3.70–4.70	**<.001**			
ccConcern × pro				10.49	10.13–10.85	**<.001**			
liberal							-0.54	-1.02– -0.05	**0.030**
lib × disengaged							2.46	1.95–2.97	**<.001**
lib × pro							1.91	1.57–2.26	**<.001**
Random Effects									
σ^2	613.86			661.59			676.81		
τ_{00}	160.77_{pcode}			191.15_{pcode}			204.07_{pcode}		
	11.60_{country}			14.84_{country}			24.63_{country}		
ICC	0.22			0.24			0.25		
N	4898_{pcode}			4898_{pcode}			4898_{pcode}		
	15_{country}			15_{country}			15_{country}		
Observations	137144			137144			137144		
Marginal/ Cond. R^2	0.163/0.347			0.097/0.312			0.053/0.292		

b. Momentary policy support is higher [lower] immediately after selecting a pro [anti] argument. This hypothesis was supported.

Table 10. Linear Mixed Effect Models of argument type on momentary policy evaluations

	Momentary Policy Support		
Predictors	**Estimates**	**CI**	***p***
(Intercept)	53.86	51.54 – 56.18	**<0.001**
initialEvaluation	10.11	9.00 – 11.21	**<0.001**
boxChoice [disengaged]	9.61	7.91 – 11.32	**<0.001**
boxChoice [pro]	12.93	10.89 – 14.98	**<0.001**
Random Effects			
σ^2	581.53		
$\tau_{00\ \text{pcode}}$	195.33		
$\tau_{00\ \text{statementID}}$	5.23		
$\tau_{00\ \text{country\_code}}$	11.34		
$\tau_{11\ \text{statementID.initialEvaluation}}$	19.12		
$\varrho_{01\ \text{statementID}}$	0.04		
ICC	0.28		
N_{pcode}	4898		
$N_{\text{country\_code}}$	15		
$N_{\text{statementID}}$	65		
Observations	137144		
Marginal R^2 / Conditional R^2	0.186 / 0.417		

c. This effect is moderated by agreement with the argument, such that higher agreement predicts greater changes in momentary policy support. This hypothesis was also supported.

Table 11. Linear Mixed Effect Models of argument type and argument rating on momentary policy evaluations

	Momentary Policy Support		
Predictors	**Estimates**	**95% CI**	***p***
(Intercept)	60.14	59.38 – 60.89	**<0.001**
initialEvaluation	9.43	9.28 – 9.58	**<0.001**
boxChoice [disengaged]	3.29	2.92 – 3.66	**<0.001**
boxChoice [pro]	5.42	5.15 – 5.69	**<0.001**
range like statement	16.61	16.44 – 16.78	**<0.001**
boxChoice [disengaged] × range like statement	5.40	5.03 – 5.77	**<0.001**
boxChoice [pro] × range like statement	4.87	4.60 – 5.13	**<0.001**
Random Effects			
σ^2	356.94		
$\tau_{00\ \mathrm{pcode}}$	133.89		
$\tau_{00\ \mathrm{country\_code}}$	1.65		
ICC	0.28		
N_{pcode}	4898		
$N_{\mathrm{country\_code}}$	15		
Observations	137144		
Marginal R^2 / Conditional R^2	0.563 / 0.683		

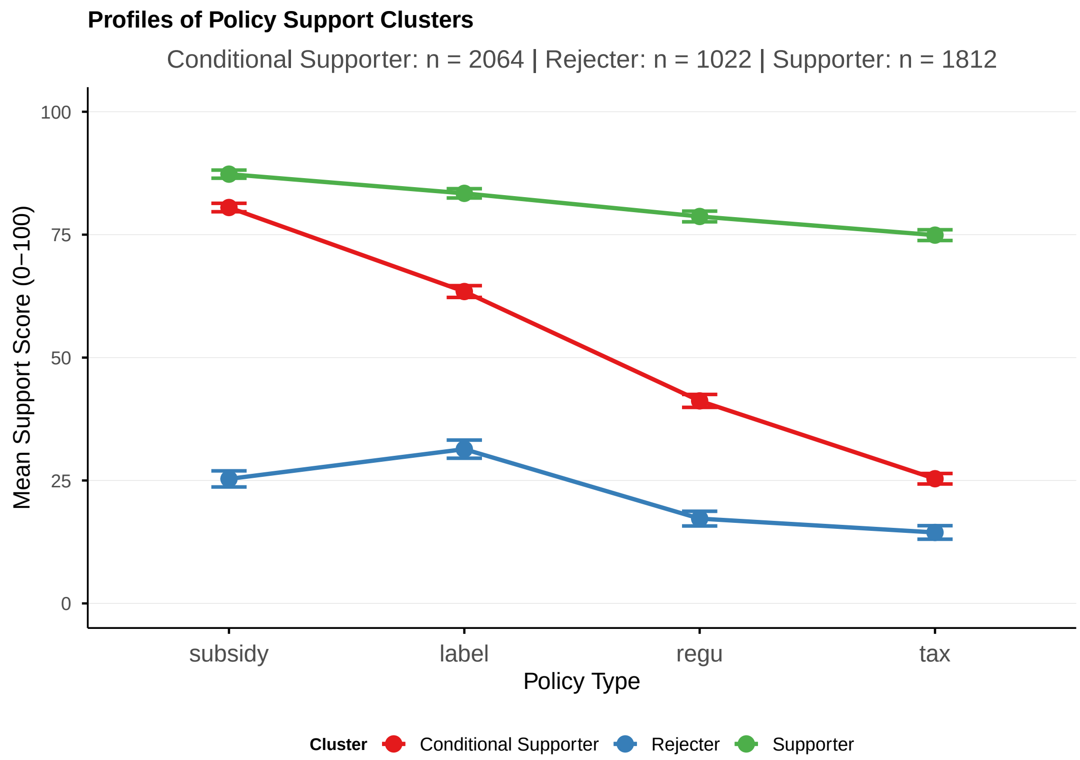
d. In countries with high political polarization, arguments will have a lesser effect on momentary policy support compared with countries with low political polarization. This hypothesis was not supported. However, the predicted effect was significant when using within sample variance of climate beliefs, GDP/capita or emissions/capita.

Table 12. Linear Mixed Effect Models of argument type and GDP/capita on momentary policy evaluations

	Momentary policy support		
Predictors	**Estimates**	**95% CI**	***p***
(Intercept)	60.14	59.38 – 60.89	**<0.001**
initialEvaluation	9.43	9.28 – 9.58	**<0.001**
boxChoice [disengaged]	3.29	2.92 – 3.66	**<0.001**
boxChoice [pro]	5.42	5.15 – 5.69	**<0.001**
range like statement	16.61	16.44 – 16.78	**<0.001**
boxChoice [disengaged] × range like statement	5.40	5.03 – 5.77	**<0.001**
boxChoice [pro] × range like statement	4.87	4.60 – 5.13	**<0.001**
Random Effects			
σ^2	356.94		
$\tau_{00\ pcode}$	133.89		
$\tau_{00\ country\_code}$	1.65		
ICC	0.28		
N_{pcode}	4898		
$N_{country\_code}$	15		
Observations	137144		
Marginal R^2 / Conditional R^2	0.563 / 0.683		

2.5 k-Means Clustering of Participants

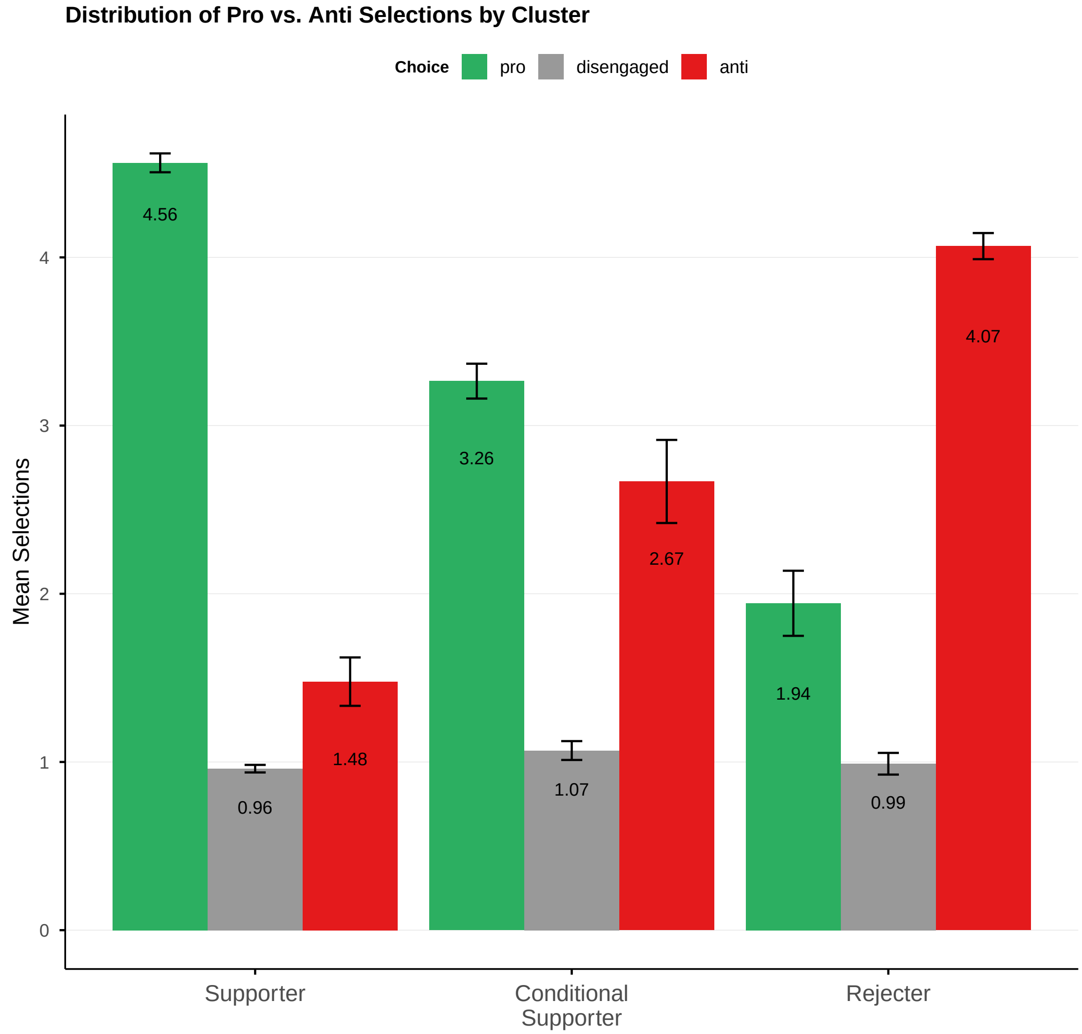
Fig. S6: Mean Initial Policy Support by Cluster and Policy



Three clusters emerged: supporters with high support levels for all policies, conditional supporters who only like soft, but not hard policies and rejecters with low policy ratings across all policies.

As preregistered as part of the additional analyses, we clustered participants into three clusters based on their initial policy support. Figure 1 shows the mean levels of support for the four distinct policies within each cluster. Figure 2 shows the Average Choice Proportion of participants within each cluster, showing that even within participant cluster, preferences for Pro/Anti arguments switched as a function of policy type.

Fig. S7: Mean Initial Policy Support by Cluster and Policy



Supporters selected much more pro than anti arguments on average, conditional supports were relatively balanced and rejecters selected more anti than pro arguments.

3 Stimuli used in Sampling Experiment

Semi-partial correlations between the average interestingness ratings and the political orientation (higher values = more liberal) when controlling for curiosity are shown for every statement. Only statements with partial correlations $|r| < .2$ were included.

Table 13. Disengaged Trivia Statements

N°	Text	Partial r
1	The International Space Station travels at about 17,500 mph (28,000 km/h), orbiting Earth approximately every 90 minutes.	0.18
2	An octopus has three hearts and nine brains – one central brain and a smaller brain in each of its eight arms.	0.10
3	Apples float in water because about 25% of their volume is air.	0.06
4	Honey never spoils; archaeologists have found pots of honey in ancient Egyptian tombs that are thousands of years old and still edible.	-0.08
5	A bolt of lightning is technically hotter than the surface of the sun.	0.11
6	The Baader-Meinhof phenomenon (or frequency illusion) describes what happens when you learn about something new and then suddenly seem to notice it everywhere.	0.06
7	Humans share about 50% of their DNA with bananas.	0.11
8	Bubble wrap was originally invented in 1957 as an attempt to create textured wallpaper.	0.07
9	The sandwich is widely believed to be named after John Montagu, the 4th Earl of Sandwich, who requested meat between bread to eat while gambling.	0.05
10	The first computer mouse, invented by Douglas Engelbart in the 1960s, was carved out of wood.	0.09
11	In ancient Rome, purple dye (Tyrian purple) was so expensive to produce (requiring thousands of sea snails) that only emperors or the very wealthy could afford purple clothing.	0.05
12	The longest professional tennis match lasted 11 hours and 5 minutes, played over three days at Wimbledon in 2010 (Isner vs Mahut).	0.07
13	The height difference between the shortest (Muggsy Bogues, 5 ft 3) and tallest (Manute Bol/Gheorghe Mureșan, 7 ft 7) players in NBA history is over 2 feet.	0.09
14	Golf is one of the only two sports confirmed to have been played on the Moon (the other being javelin throwing).	0.07
15	Your fingernails grow about four times faster than your toenails.	-0.09
16	The small intestine is actually the longest part of the human digestive system, averaging about 20-23 feet (6 to 7 meter) in adults.	-0.02

N°	Text	Partial r
17	In Switzerland, it is illegal to own just one guinea pig; they are considered social animals and must be kept in pairs or groups.	-0.01
18	The Incas developed a complex system of knotted strings called quipu to record numbers and data, functioning like record-keeping without a written alphabet.	0.03
19	Machu Picchu, the famous Inca citadel, was built without mortar; the massive stones were cut so precisely that they fit together perfectly.	0.03
20	The ancient Egyptians used unique hieroglyphs for powers of 10 (1, 10, 100, 1000, etc.) in their base-10 number system.	0.02
21	If you could fold a standard piece of paper in half 42 times, its thickness would theoretically reach the Moon (though physically impossible).	-0.09
22	Due to time dilation, astronauts on the International Space Station age slightly slower than people on Earth (by fractions of a second over months).	0.12
23	Neutron stars are so dense that a teaspoonful of their material would weigh about as much as Mount Everest.	0.11
24	In a group of just 23 people, there's a greater than 50% chance that at least two people share the same birthday.	0.00
25	The movement of Earth's tectonic plates typically happens at about the same speed your fingernails grow (a few centimeters/inch per year).	0.02
26	Most natural diamonds form deep within the Earth's mantle under extreme heat and pressure, not from coal.	0.03
27	The Dead Sea is so salty (nearly 10 times saltier than the ocean) that floating is very easy.	0.11
28	The first modern Olympic Games in 1896 awarded silver medals to winners, not gold; second place received bronze.	0.05
29	Research suggests the human nose can distinguish at least 1 trillion different scents, far more than previously thought.	0.04
30	An anechoic chamber at Orfield Laboratories in the US holds the record for the world's quietest place (-9.4 decibels), where you can hear your own internal organs.	0.08
31	The recipe for ancient Roman concrete was so effective, partly due to volcanic ash, that structures like the Pantheon have survived for nearly 2,000 years.	-0.02
32	The world's oldest known written recipe is for a Sumerian beer, dating back about 4,000 years to ancient Mesopotamia.	0.09
33	The Margherita pizza's colors (red tomato, white mozzarella, green basil) are commonly said to represent the Italian flag, named for Queen Margherita of Savoy in 1889.	-0.07
34	One theory suggests yawning helps cool the brain; stretching the jaw increases blood flow, and inhaling cooler air may lower brain temperature.	-0.05

N°	Text	Partial r
35	Storing rubber bands in the refrigerator can help them last longer by slowing down the degradation of the rubber.	-0.05
36	The fingerprints of koalas are remarkably similar to human fingerprints, potentially making them difficult to distinguish even under a microscope.	0.12
37	Psychology trick: If you want someone to like you more, subtly mimic their body language during conversation.	-0.05
38	The urge to gossip might be deeply ingrained: Some scientists believe it evolved as a way to share vital social information and build group bonds.	0.15
39	Surprising attraction factor: People often rate others as more attractive when seen in a group ('cheerleader effect') than when seen alone.	0.09
40	That weird feeling of wanting to squeeze something overwhelmingly cute (like a puppy or baby) has a name: 'cute aggression'.	-0.06
41	Many incredibly successful people, including famous performers, secretly struggle with 'imposter syndrome' – feeling like a fraud despite their achievements.	0.04
42	The driest place on Earth isn't a sandy desert, but the continent of Antarctica, due to extremely low precipitation.	0.00
43	Simple tip for appearing more confident: Maintain steady eye contact slightly longer than feels initially comfortable during conversations.	-0.06
44	The 'placebo effect' is so powerful that even surgeries using fake procedures have shown measurable health benefits in some studies.	0.11
45	Some species of penguins 'propose' to their lifelong mates by searching for and presenting the perfect pebble.	0.18

Table 14. Arguments in favor of a carbon tax

N°	Text
1	Eating more vegetables, fruits or lentils is healthier for our bodies, takes a much lesser toll on the environment and avoids animal suffering. A climate tax would lead to higher consumption of these groceries. It is time we take a small step towards more sustainable and healthy eating habits.
2	Most families will actually end up with more money in their pocket from the tax cashback. Since wealthy households consume the most high-emission luxury foods, they pay the most into the pot.
3	Cheap meat or dairy comes at the cost of animal welfare. In factory farming, animals are treated like an industrial product and suffer throughout their lives.
4	By making greener foods cheaper by comparison, the tax boosts the development of exciting and delicious new plant-based and low-carbon alternatives.
5	A climate food tax fixes a broken market that subsidizes climate damage. Cheap meat is not actually cheap: the environmental costs are just pushed to society and young generations in particular. It would be better if those who inflict harm on the climate also pay for it.
6	Unlike other government programs, a climate food tax does not cost taxpayer money. With the cashback equally returned to citizens, people who adopt a more sustainable diet will end up with more money in their pocket.
7	Many people want to live more sustainably, but, right now, this requires hours of research. The climate tax does the math for you, making the eco-friendly choice the affordable choice. This makes it easy and cheap to live a more sustainable life.
8	Livestock farming alone has a greater climate impact than all the world's cars combined. If you look at deforestation or freshwater use, livestock farming fares even worse. We cannot solve climate change if we neglect the food system and a climate tax is one of the best ways to tackle it.
9	While it feels like a persoanl choice, our diets have a huge global impact. Shifting to a more sustainable diet is one of the most powerful actions a person can take to protect the climate and nature (think deforestation, freshwater use or biodiversity).
10	Livestock has a triple impact on the environment: it drives deforestation, requires large amounts of water and land, and releases methane, a potent greenhouse gas. A climate tax on food would include some of these environmental damages in the price which seems only fair.
11	This measure means that food that is healthier for you and better for the planet also becomes cheaper. That's a clear win-win.

Table 15. Arguments against a carbon tax

N°	Text
1	This policy creates financial anxiety for families living paycheck to paycheck. Even if the money is returned later, facing higher prices today creates stress and hardship that a future government payment cannot erase.
2	The government might break its promise and use the tax money on other projects in the future. This would leave citizens with the high prices but without the financial relief.
3	This is a grocery tax that will raise the cost of your weekly shopping. It means paying more for everyday staples like minced meat, cheese, and milk, adding another financial pressure on families.
4	People just don't want to pay more for their food. After a long day, families want to put a familiar meal on the table without being penalized by a complicated new tax.
5	This policy unfairly targets the food traditions we have enjoyed for generations. It puts a price on cultural staples, from the Sunday roast to the summer barbecue, making them a luxury.
6	What you choose to eat is a personal decision, not a political one. We should not allow the government to interfere in our kitchens and on our dinner plates.
7	We should trust people to make responsible choices instead of dictating choices from above. Education is the right way to encourage sustainable eating, not a punitive tax.
8	A government rebate tomorrow doesn't help with a higher grocery bill today. This system would create immediate financial stress for families, who can't wait for a government check to balance their budget.

Table 16. Arguments in favor of meal regulation

N°	Text
1	With this policy, cafeterias can introduce healthy and delicious new meal options. It's a chance for guests to discover flavorful plant-based foods that are good for our bodies.
2	Vegetarian meals are high in fiber and vitamins, and lower in saturated fat. By making them the standard in public places, we can help improve the long-term health of our communities.
3	This helps establish healthy eating habits for children and young adults from early on. Vegetarian school meals can help to prepare for a lifetime of better nutrition.
4	Serving more vegetarian meals in our public canteens is a powerful way to lower our community's carbon footprint. Plant-based foods require far less land, water, and energy to produce.
5	This is a practical action with a guaranteed impact. Thousands of meals served every day will immediately be more climate-friendly.
6	Public money should support public goals. It makes no sense for the government to fight climate change while simultaneously using tax dollars to serve high-emission meals in schools and hospitals. This puts our money where our mouth is.
7	Meat has a much higher climate impact than plant-based foods. Switching just one beef-based meal to a bean-based one cuts the emissions from that meal by over 95%.
9	Canteens are the lever for massive change. Asking individuals to change is hard, but changing the menu is easy. By reducing meat consumption in large cafeterias, we can save thousands of tons of emissions immediately without anyone having to change their lifestyle at home.
10	Shifting away from red and processed meats towards more plant-based diets can lead to lower rates of heart disease, diabetes, and certain cancers. This can reduce the costs of public healthcare systems.

Table 17. Arguments against meal regulation

N°	Text
1	This is a classic case of government overreach telling people what to eat. First, it's our public canteens; next, they'll be telling us what to cook in our own kitchens.
2	Menus should be based on what people actually want to eat, not on arbitrary government percentages. This policy artificially restricts our freedom of choice by limiting the availability of the dishes people prefer.
3	This policy disrespects our culture and traditions. For generations, our meals have been built around meat.
4	Forcing people to eat food they do not enjoy is bad for morale. A lunch break that caters to everyone's tastes is important for students and workers.
5	Canteens should follow demand, not force supply. If people want vegetarian food, canteens will serve it naturally to make a profit. We don't need a heavy-handed government law to force it to happen.
6	The emissions from a few canteens are a drop in the ocean compared to the global energy and industrial sectors.
7	This is a slippery slope. If we allow this restriction today, it makes it easier for the government to push for a 100% ban in the future. We need to draw the line at government interference in the kitchen.
8	There are better, voluntary ways to promote sustainable eating. We should focus on Education, not on enforcing menus.

Table 18. Arguments in favor of a vegetable subsidy

N°	Text
1	This policy puts money directly back in your pocket, giving you a discount on a wide range of healthy and sustainable foods.
2	It makes healthy eating more affordable for everyone. This discount applies to everyday essentials like fruits, vegetables, beans, and whole grains, helping families on a budget.
3	This policy is about 'carrots, not sticks': it encourages climate-friendly choices by making them cheaper, not by punishing people.
4	This policy respects your freedom of choice. It doesn't ban any foods; it simply makes the climate-friendly options more attractive.
5	The discount is applied automatically at the checkout, making it a simple and hassle-free way for everyone to save money.
6	The government should ensure that very basic food staples are affordable for everyone.
7	By making plant-based options more affordable, this policy encourages diets that are proven to be better for heart health and overall well-being.
8	This is a direct and effective way to lower our country's carbon footprint. It rewards the food choices that require less land, use less water, and create far less pollution.
9	By reducing the demand for land-intensive livestock farming, this policy helps to reach our climate targets and to protect our nation's forests, rivers, and wildlife for future generations.

Table 19. Arguments against a vegetable subsidy

N°	Text
1	This is a massive, open-ended spending program funded entirely by taxpayers that would create an enormous and unpredictable hole in the national budget.
2	This is a misuse of public funds. Your tax money should be funding essential services like schools and healthcare, not giving a discount on groceries.
3	This isn't a 'discount'; it just shuffles the costs around. Either we are paying for the subsidy with higher taxes now or we are passing the debt on to our children.
4	A discount for an avocado that was transported by airplane from overseas? Sounds like a very bad idea.
5	The government should not meddle in our diets. Food choices should be personal, not directed by the government.
6	The effect on people's behavior will be minimal. People who enjoy meat and dairy will likely continue to buy them; this subsidy will give a financial bonus to people who are already buying plant-based foods.
7	The savings from the subsidy can be used for purchases that harm the climate. The money saved on vegetables can be used to buy a high-emission product one otherwise would have skipped. This eliminates the climate benefit from the subsidy.
8	It could lead to increased food waste as people might buy more fruits and vegetables but not consume more of them.
9	A blanket-approach where wealthy households receive the same discount – if not more – as poor families is unfair and unnecessarily expensive.

Table 20. Arguments in favor of a carbon food label

N°	Text
1	Climate labels on food help consumers make more informed choices aligned with their values.
2	Companies are free to decide if they want to print a label or not: the government should not enforce such things.
3	Climate labels raise public awareness of product-related emissions and climate issues in general.
4	Many consumers are willing to pay more for products with lower carbon footprints when this information is made visible.
5	Studies show that climate labels can increase demand for lower-emission products.
6	Climate food labels are cheap to implement and do not require large government investments.
7	Climate food labels can address misperceptions. For instance, many people believe that eating regional foods is best for the climate, but transport is only a tiny fraction of food emissions. A person getting 20g of protein from beef causes 60 times more emissions than getting 20g of protein from beans.
8	Many people are not aware that farming, especially cattle farming, is a major contributor to climate change and other environmental challenges like the use of water and land. Labels can help raise awareness about this.
9	Many people are unaware that our global food system is responsible for roughly one-third (about 34%) of all human-caused greenhouse gas emissions. Labels can show that their day-to-day choices matter.

Table 21. Arguments against a carbon food label

N°	Text
1	Climate food labels won't actually help the climate, since most consumers do not base their decisions on labels. Instead, people are most sensitive to the price.
2	Focusing on product labels distracts from measures that would actually work. It is time we tackle the food sector, one of the largest contributors to climate change and deforestation, with more ambitious measures.
3	Products often already have other labels regarding nutrition or health. Overloaded product packaging with multiple labels can lead to confusion and further reduce their effectiveness.
4	With a climate label, it becomes clear what options are more sustainable. But it does not make the sustainable option cheaper or more accessible.
5	This is a sham, not serious climate protection. Why would producers of high-emission foods use a voluntary label that makes their products look bad?
6	Government effort is a limited resource. It should be focused on measures with the biggest climate impact, not on monitoring the fine print on product labels.
7	We have tried to address climate change with awareness campaigns and information for a long time. It has hardly increased sustainable behavior. It is time we changed the financial incentives for green choices.
8	A kilogram of beef causes over 60 kilograms of greenhouse gases, while a kilogram of peas causes just 1 kilogram of emissions. A red or green label does not properly show these huge differences.

4 Sample size per country

Table 22. National Sample Sizes

Country Name	Country Code	N
Argentina	AR	358
Australia	AU	308
Canada	CA	338
Chile	CL	322
Colombia	CO	286
Germany	DE	304
Spain	ES	316
France	FR	347
United Kingdom	GB	392
India	IN	299
Mexico	MX	351
Nigeria	NG	343
Philippines	PH	331
United States of America	US	299
South Africa	ZA	304

5 Demographic Composition of National Samples compared to nationally representative target quotas

Table 23. Demographic Composition of Sample in AR

	N	Actual %	Target %
Gender			
female	174	48.6%	52.0%
male	184	51.4%	48.0%
Age Group			
18-24	28	7.8%	15.0%
25-34	122	34.1%	22.0%
35-44	68	19.0%	20.0%
45-54	69	19.3%	16.0%
55-64	40	11.2%	13.0%
65+	31	8.7%	13.0%
Education			
academic	147	41.1%	
non-academic	211	58.9%	
Income			
high	88	24.6%	
low	179	50.0%	
middle	91	25.4%	

Table 24. Demographic Composition of Sample in AU

	N	Actual %	Target %
Gender			
diverse	1	0.3%	
female	185	60.1%	50.0%
male	122	39.6%	50.0%
Age Group			
18-24	2	0.6%	12.0%
25-34	54	17.5%	20.0%
35-44	70	22.7%	19.0%
45-54	57	18.5%	17.0%
55-64	57	18.5%	15.0%
65+	68	22.1%	17.0%
Education			
academic	129	41.9%	
non-academic	179	58.1%	
Income			
high	57	18.5%	
low	145	47.1%	
middle	106	34.4%	

Table 25. Demographic Composition of Sample in CA

	N	Actual %	Target %
Gender			
diverse	1	0.3%	
female	188	55.6%	50.0%
male	149	44.1%	50.0%
Age Group			
18-24	24	7.1%	11.0%
25-34	63	18.6%	19.0%
35-44	57	16.9%	18.0%
45-54	54	16.0%	16.0%
55-64	63	18.6%	17.0%
65+	77	22.8%	19.0%
Education			
academic	149	44.1%	
non-academic	189	55.9%	
Income			
high	92	27.2%	
low	139	41.1%	
middle	107	31.7%	

Table 26. Demographic Composition of Sample in CL

	N	Actual %	Target %
Gender			
diverse	2	0.6%	
female	196	60.9%	51.0%
male	124	38.5%	49.0%
Age Group			
18-24	45	14.0%	12.0%
25-34	74	23.0%	22.0%
35-44	68	21.1%	20.0%
45-54	67	20.8%	17.0%
55-64	49	15.2%	15.0%
65+	19	5.9%	14.0%
Education			
academic	123	38.2%	
non-academic	199	61.8%	
Income			
high	65	20.2%	
low	160	49.7%	
middle	97	30.1%	

Table 27. Demographic Composition of Sample in CO

	N	Actual %	Target %
Gender			
diverse	1	0.3%	
female	149	52.1%	52.0%
male	136	47.6%	48.0%
Age Group			
18-24	45	15.7%	16.0%
25-34	77	26.9%	23.0%
35-44	58	20.3%	20.0%
45-54	53	18.5%	16.0%
55-64	40	14.0%	14.0%
65+	13	4.5%	11.0%
Education			
academic	75	26.2%	
non-academic	211	73.8%	
Income			
high	83	29.0%	
low	144	50.3%	
middle	59	20.6%	

Table 28. Demographic Composition of Sample in DE

	N	Actual %	Target %
Gender			
diverse	1	0.3%	
female	126	41.4%	50.0%
male	176	57.9%	50.0%
other	1	0.3%	
Age Group			
18-24	4	1.3%	10.0%
25-34	26	8.6%	17.0%
35-44	65	21.4%	17.0%
45-54	65	21.4%	17.0%
55-64	72	23.7%	20.0%
65+	72	23.7%	20.0%
Education			
academic	95	31.2%	
non-academic	209	68.8%	
Income			
high	148	48.7%	
low	90	29.6%	
middle	66	21.7%	

Table 29. Demographic Composition of Sample in ES

	N	Actual %	Target %
Gender			
female	158	50.0%	51.0%
male	158	50.0%	49.0%
Age Group			
18-24	25	7.9%	9.0%
25-34	42	13.3%	14.0%
35-44	59	18.7%	18.0%
45-54	74	23.4%	14.0%
55-64	67	21.2%	18.0%
65+	49	15.5%	18.0%
Education			
academic	105	33.2%	
non-academic	211	66.8%	
Income			
high	122	38.6%	
low	77	24.4%	
middle	117	37.0%	

Table 30. Demographic Composition of Sample in FR

	N	Actual %	Target %
Gender			
female	193	55.6%	51.0%
male	154	44.4%	49.0%
Age Group			
18-24	26	7.5%	11.0%
25-34	61	17.6%	16.0%
35-44	66	19.0%	17.0%
45-54	57	16.4%	18.0%
55-64	70	20.2%	17.0%
65+	67	19.3%	21.0%
Education			
academic	153	44.1%	
non-academic	194	55.9%	
Income			
high	111	32.0%	
low	109	31.4%	
middle	127	36.6%	

Table 31. Demographic Composition of Sample in GB

	N	Actual %	Target %
Gender			
female	195	49.7%	51.0%
male	197	50.3%	49.0%
Age Group			
18-24	31	7.9%	11.0%
25-34	91	23.2%	18.0%
35-44	61	15.6%	17.0%
45-54	67	17.1%	18.0%
55-64	68	17.3%	17.0%
65+	74	18.9%	19.0%
Education			
academic	176	44.9%	
non-academic	216	55.1%	
Income			
high	132	33.7%	
low	143	36.5%	
middle	117	29.8%	

Table 32. Demographic Composition of Sample in IN

	N	Actual %	Target %
Gender			
female	113	37.8%	49.0%
male	186	62.2%	51.0%
Age Group			
18-24	85	28.4%	17.0%
25-34	93	31.1%	25.0%
35-44	70	23.4%	21.0%
45-54	34	11.4%	17.0%
55-64	12	4.0%	11.0%
65+	5	1.7%	9.0%
Education			
academic	148	49.5%	
non-academic	151	50.5%	
Income			
high	184	61.5%	
low	81	27.1%	
middle	34	11.4%	

Table 33. Demographic Composition of Sample in MX

	N	Actual %	Target %
Gender			
female	194	55.3%	51.0%
male	157	44.7%	49.0%
Age Group			
18-24	64	18.2%	17.0%
25-34	72	20.5%	22.0%
35-44	70	19.9%	20.0%
45-54	64	18.2%	18.0%
55-64	57	16.2%	13.0%
65+	24	6.8%	10.0%
Education			
academic	183	52.1%	
non-academic	168	47.9%	
Income			
high	137	39.0%	
low	125	35.6%	
middle	89	25.4%	

Table 34. Demographic Composition of Sample in NG

	N	Actual %	Target %
Gender			
female	182	53.1%	50.0%
male	161	46.9%	50.0%
Age Group			
18-24	87	25.4%	24.0%
25-34	107	31.2%	27.0%
35-44	81	23.6%	22.0%
45-54	48	14.0%	18.0%
55-64	14	4.1%	8.0%
65+	6	1.7%	5.0%
Education			
academic	270	78.7%	
non-academic	73	21.3%	
Income			
high	123	35.9%	
low	143	41.7%	
middle	77	22.4%	

Table 35. Demographic Composition of Sample in PH

	N	Actual %	Target %
Gender			
female	195	58.9%	50.0%
male	136	41.1%	50.0%
Age Group			
18-24	102	30.8%	21.0%
25-34	88	26.6%	25.0%
35-44	67	20.2%	20.0%
45-54	44	13.3%	14.0%
55-64	21	6.3%	11.0%
65+	9	2.7%	7.0%
Education			
academic	233	70.4%	
non-academic	98	29.6%	
Income			
high	139	42.0%	
low	109	32.9%	
middle	83	25.1%	

Table 36. Demographic Composition of Sample in US

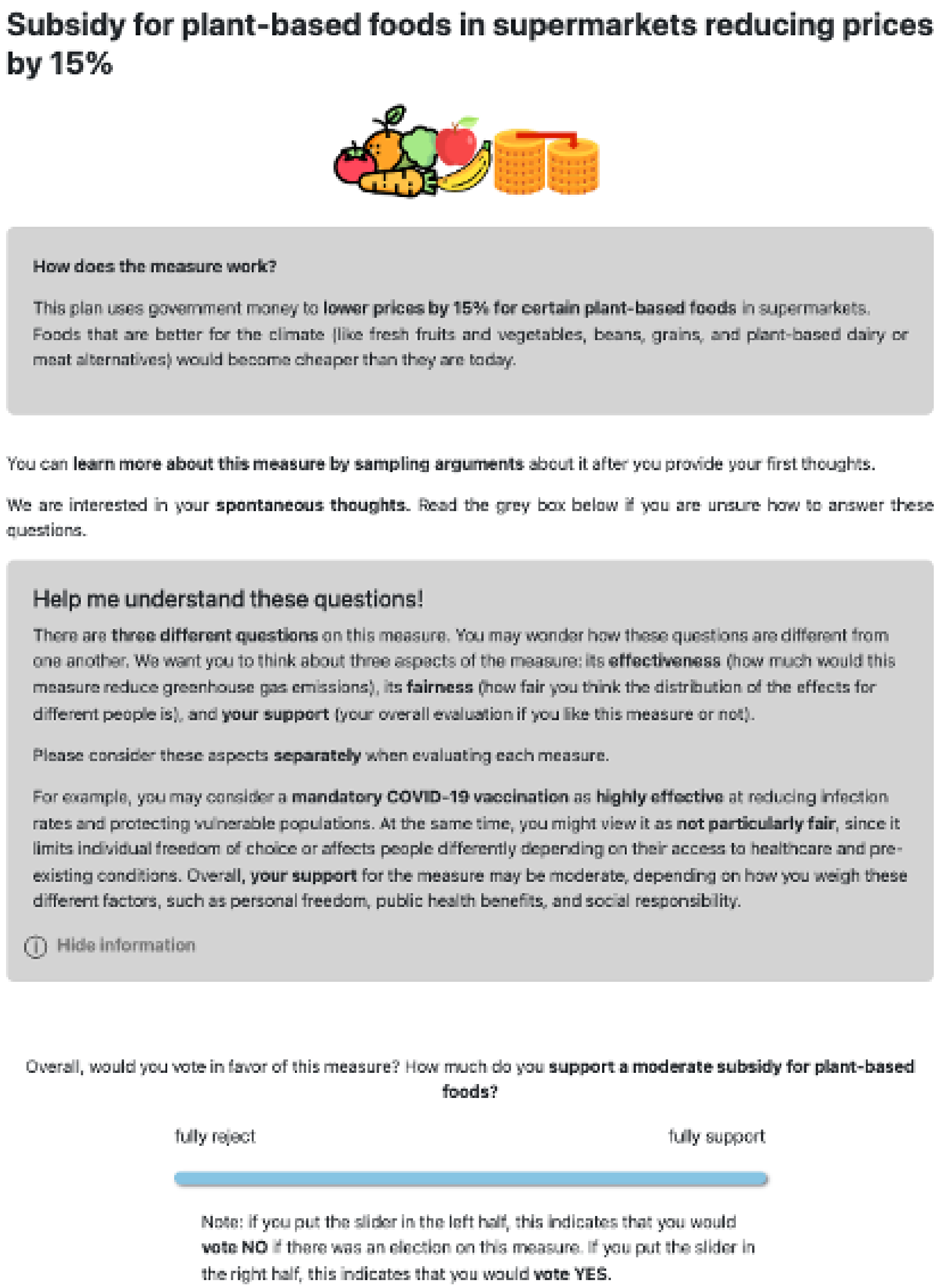
	N	Actual %	Target %
Gender			
diverse	4	1.3%	
female	176	58.9%	51.0%
male	119	39.8%	49.0%
Age Group			
18-24	8	2.7%	13.0%
25-34	26	8.7%	18.0%
35-44	68	22.7%	17.0%
45-54	77	25.8%	17.0%
55-64	63	21.1%	18.0%
65+	57	19.1%	17.0%
Education			
academic	118	39.5%	
non-academic	181	60.5%	
Income			
high	99	33.1%	
low	127	42.5%	
middle	73	24.4%	

Table 37. Demographic Composition of Sample in ZA

	N	Actual %	Target %
Gender			
female	178	58.6%	52.0%
male	126	41.4%	48.0%
Age Group			
18-24	31	10.2%	17.0%
25-34	84	27.6%	27.0%
35-44	78	25.7%	22.0%
45-54	47	15.5%	15.0%
55-64	44	14.5%	11.0%
65+	20	6.6%	8.0%
Education			
academic	100	32.9%	
non-academic	204	67.1%	
Income			
high	216	71.1%	
low	40	13.2%	
middle	48	15.8%	

6 Experimental Materials Shown to Participants

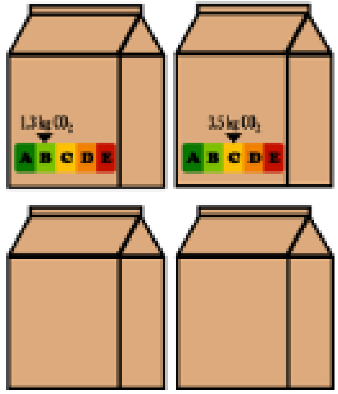
Fig. S8: Screenshot for Initial Policy Support Rating for Subsidies



Participant screen with a description of the policy subsidy, initial support and certainty ratings. Certainty measure is cropped to fit on this page.

Fig. S9: Screenshot for Initial Policy Support Rating for Labels

Voluntary climate labels on food products



How does the measure work?

This policy would let food producers **voluntarily show** a **standardized label**. This label would show how many climate emissions were caused by the product (including production, transport, and packaging), but companies do not have to use it.
Some foods would then have this emissions label, showing their climate impact with a traffic light system, but not all, depending on what the company decides.

You can **learn more about this measure by sampling arguments** about it after you provide your first thoughts.

We are interested in your **spontaneous thoughts**. Read the grey box below if you are unsure how to answer these questions.

ⓘ What do I need to do here?

Overall, would you vote in favor of this measure? How much do you **support a voluntary climate label on food products?**

fully reject fully support

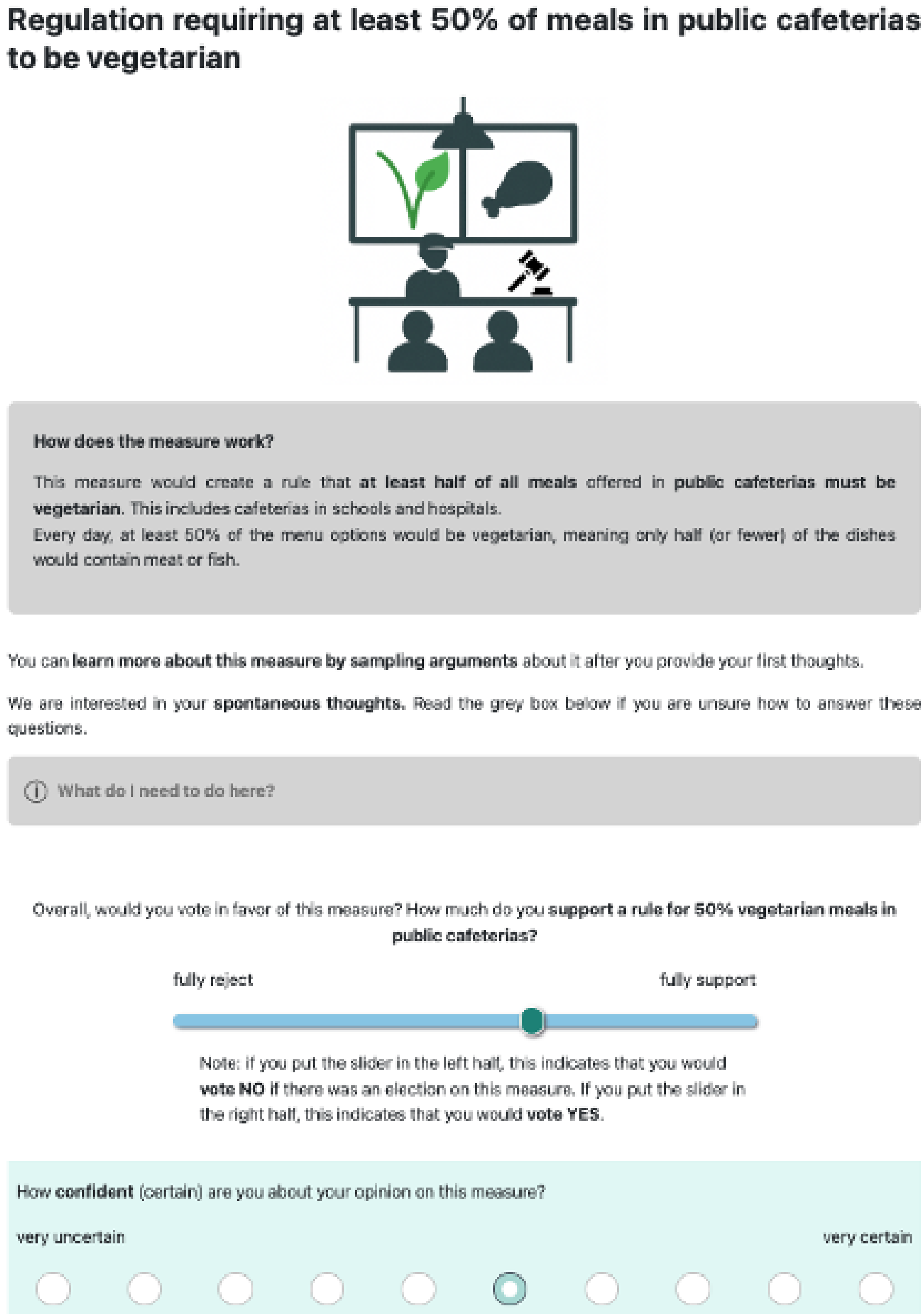
Note: if you put the slider in the left half, this indicates that you would **vote NO** if there was an election on this measure. If you put the slider in the right half, this indicates that you would **vote YES**.

How **confident** (certain) are you about your opinion on this measure?

very uncertain very certain

Participant screen with a description of the policy label, initial support and certainty ratings.

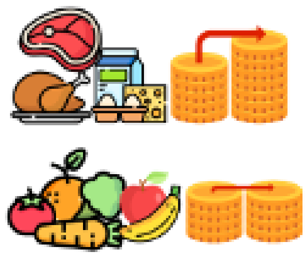
Fig. S10: Screenshot for Initial Policy Support Rating for Regulation



Participant screen with a description of the policy regulation, initial support and certainty ratings.

Fig. S11: Screenshot for Initial Policy Support Rating for Taxes

Climate tax on food increasing the price of high-emission foods by 20%



How does the measure work?

This climate tax would make groceries with high climate impacts, such as beef, about **20% more expensive.** This tax would make dairy milk around 10% more expensive, while plant-based milk would stay the same price. Overall, this tax would make climate-friendly groceries cheaper by comparison. The amount of the tax depends on how many emissions each product causes.
The money collected by the tax would **be fully paid back to all citizens in equal shares.**

You can **learn more about this measure by sampling arguments** about it after you provide your first thoughts.

We are interested in your **spontaneous thoughts.** Read the grey box below if you are unsure how to answer these questions.

ⓘ What do I need to do here?

Overall, would you vote in favor of this measure? How much do you **support a moderate food climate tax?**

fully reject | fully support

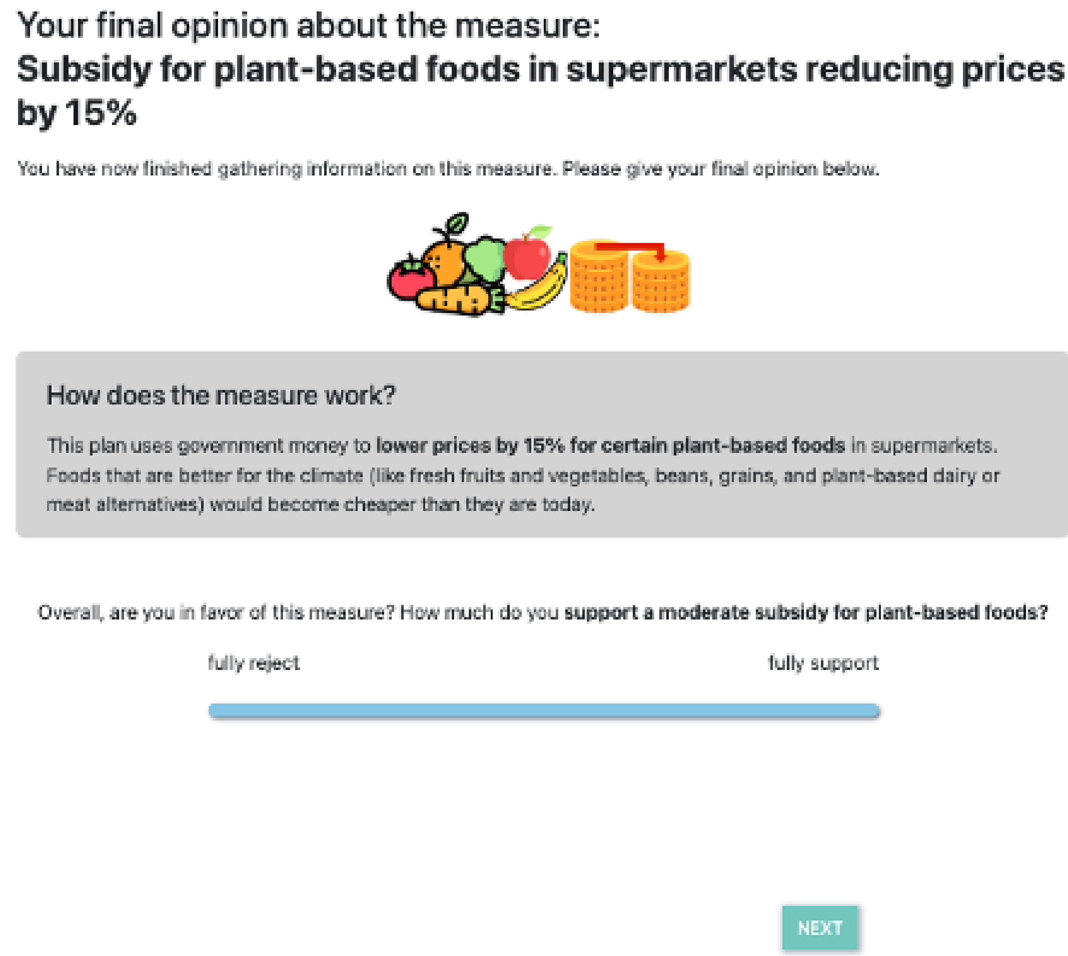
Note: if you put the slider in the left half, this indicates that you would **vote NO** if there was an election on this measure. If you put the slider in the right half, this indicates that you would **vote YES.**

How **confident** (certain) are you about your opinion on this measure?

very uncertain | very certain

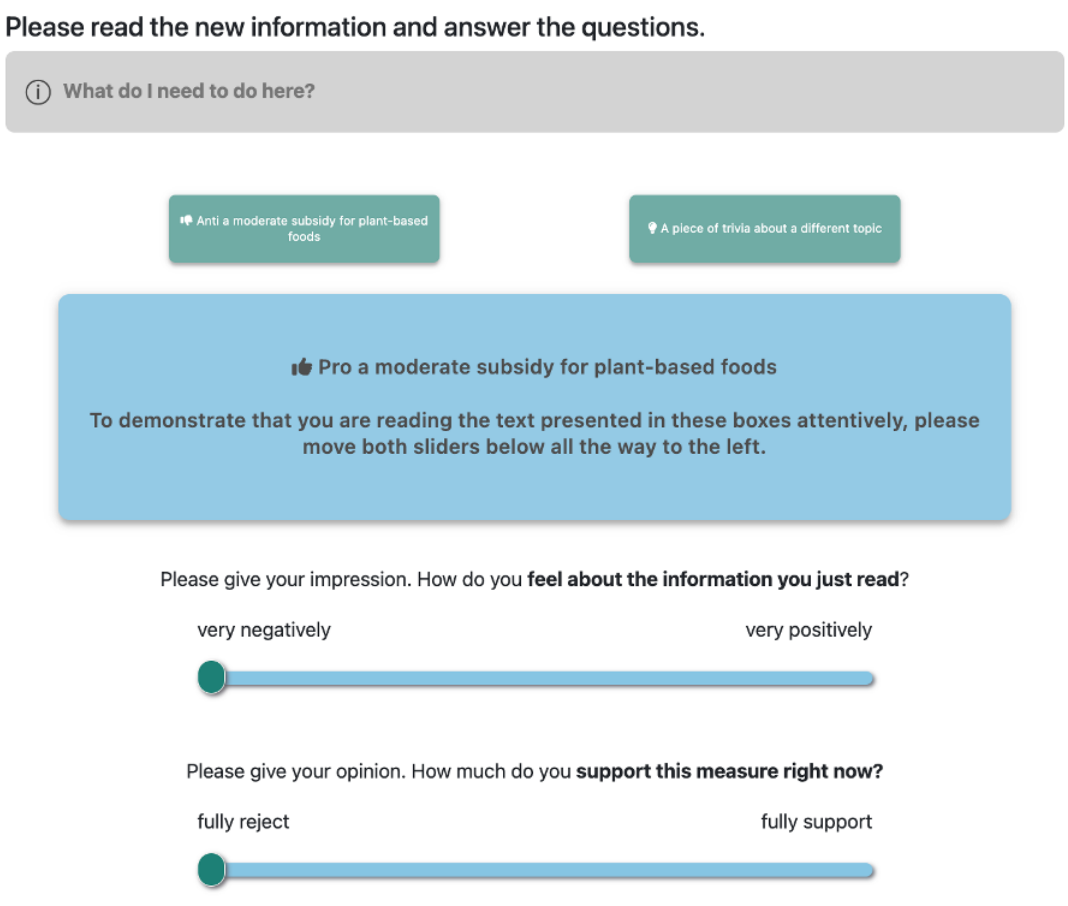
Participant screen with a description of the policy taxes, initial support and certainty ratings.

Fig. S12: Screenshot for Final Policy Support Rating for Subsidies



Participant screen to rate final (post-sampling) policy support for subsidies. Screens were analogous for all policies.

Fig. S13: Screenshot for Attention Check



Participant screen to indicate that they read the sampled information carefully. Text in box says that participants are required to move both sliders all the way to the left. This attention check was employed twice during the sampling task. Participants who failed to correctly respond to this task were excluded from the statistical analyses.

7 R Packages Used for this Research

We used the following R packages: `brms` v. 2.22.0 [3], `broom.mixed` v. 0.2.9.6 [4], `cluster` v. 2.1.8.1 [5], `effectsize` v. 1.0.1 [6], `emmeans` v. 1.11.1 [7], `fabricatr` v. 1.0.2 [8], `flextable` v. 0.9.9 [9], `ggdist` v. 3.3.3 [10], `glmmTMB` v. 1.1.11 [11], `here` v. 1.0.1 [12], `lmerTest` v. 3.1.3 [13], `parallel` v. 4.4.0 [14], `partR2` v. 0.9.2 [15], `performance` v. 0.15.0 [16], `psych` v. 2.5.6 [17], `ranger` v. 0.17.0 [18], `rmarkdown` v. 2.29 [19], `rnaturalearth` v. 1.2.0 [20], `rnaturalearthdata` v. 1.0.0 [21], `scales` v. 1.4.0 [22], `sjPlot` v. 2.8.17 [23], `tidyverse` v. 2.0.0 [24], `vip` v. 0.4.1 [25], and `vroom` v. 1.6.5 [26].

8 References for per capita meat consumption in the different countries

We used per capita annual meat consumption indices from the following references: Argentina [27], Australia [28], Canada [29], Chile [30], Colombia [31], France [32], Germany [33], India [34], Mexico [35], New Zealand [36], Nigeria [37], Philippines [38], South Africa [39], Spain [40], UK [41], USA [42].

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