

A Appendix

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A.1 Survey description

We draw on novel data from a original survey project. The overall goal of the survey was to understand how citizens in various countries think about the impact of technological change and its drivers — including global technology companies — on their country’s society and economy. The survey was commissioned by the authors of this study and conducted by the research firm Kantar Public, which fielded the survey in June and July of 2022 in the following six countries: Germany, Japan, Poland, Spain, Sweden, and the United States. The sample consists of 3,300 individuals per country (19,800 in

total). Respondents were sampled based on quota targets for gender, age (we surveyed only individuals aged 18 to 64), and education in order to match the structure of the underlying population universe.

A.2 Study of Big Tech views

A.2.1 Descriptive statistics

Distribution of Big Tech views. Figure A1 shows the distribution of responses for each item (see items below the dotted line). We design the graph such that the horizontal axis, which represents the percentage of responses for each category, is divided into two sections: the percentages to the right of zero reflect agreement (*agree* and *strongly agree*), while the percentages to the left display neutrality (*neither agree nor disagree*) and disagreement (*disagree* and *strongly disagree*). Agreement is particularly strong with the statements that global technology companies provide useful services (51%) and promote innovation and economic development (48%), as well as with the statement that Big Tech companies undermine the national welfare state (43%). The level of disagreement with these three items is low (between 10% and 15%), with around 40% expressing neutrality. Among the remaining three items, agreement is highest with the statement that global tech companies are a threat to democracy (38%), followed by the belief that Big Tech weakens labor standards (35%) and aids democracy (31%). Disagreement with these three items is around 20%, while neutrality — the most frequently chosen response category — consistently exceeds 40%, reaching almost 50% in the case of the potentially democracy-aiding role of global technology companies.

Factor analysis. We assess the dimensionality of the six-item attitude battery using Horn’s parallel analysis (polychoric correlations; minres extraction; 200 replications). Parallel analysis presented in Table A1 indicates two latent factors: the first two observed factor eigenvalues (1.59 and 1.02) exceed the corresponding simulated eigenvalues (0.36 and 0.02), while subsequent observed eigenvalues are non-positive.

Figure A1: Distribution of responses (in percent) across each of the six items on public perceptions of Big Tech companies and across the two items on Big Tech-related political preferences.

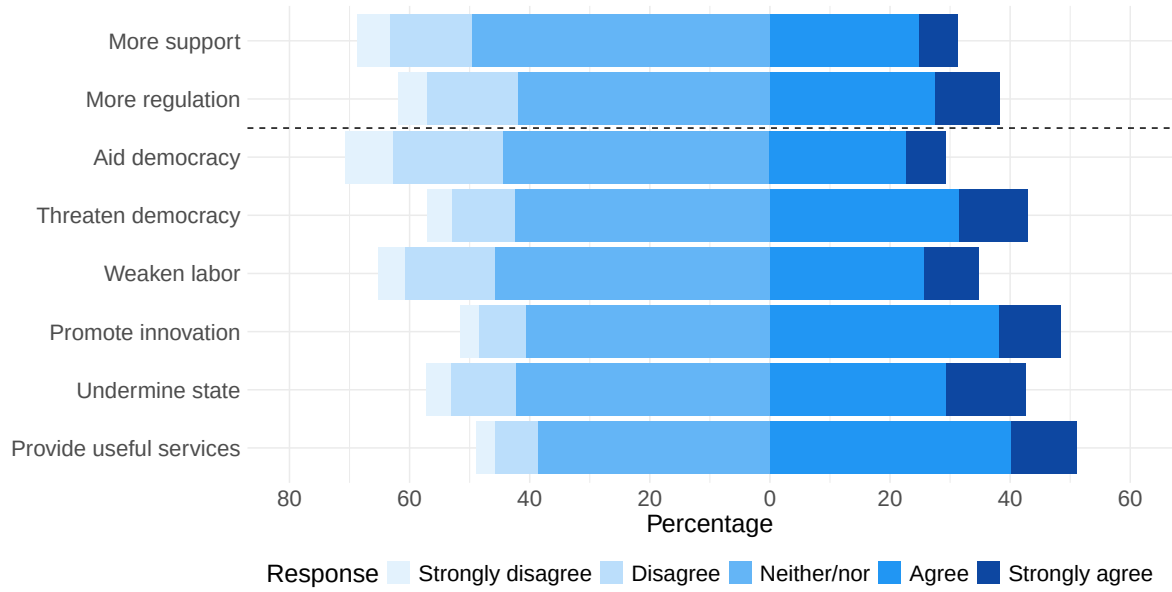


Table A1: Parallel analysis for six-item attitude battery (pooled sample)

	Factor number					
	1	2	3	4	5	6
Observed factor eigenvalues	1.59	1.02	-0.01	-0.09	-0.38	-0.55
Simulated factor eigenvalues	0.36	0.02	0.01	0.00	-0.01	-0.02

Notes: Horn's parallel analysis based on polychoric correlations; minres extraction; 200 simulation replications. Two factors are retained because the first two observed eigenvalues exceed simulated eigenvalues.

As shown in Table A2, parallel analyses conducted separately for each country uniformly indicate a two-factor solution. In every case, the first two observed eigenvalues exceed the simulated eigenvalues, while the third eigenvalue does not.

Table A3 demonstrates that Tucker's congruence coefficients between the pooled and country-specific solutions are uniformly above .99, indicating virtually identical factor structures across countries.

Table A4 shows that the negative Big Tech items load strongly on the first factor and weakly on the second, while positive Big Tech items show the opposite pattern. Table

Table A2: Country-specific parallel analyses.

Country	Obs. EV1	Obs. EV2	Sim. EV1	Sim. EV2
Germany	1.57	1.01	0.46	0.04
Japan	2.28	0.88	0.50	0.04
Poland	1.63	1.05	0.52	0.04
Spain	1.54	0.95	0.41	0.04
Sweden	1.51	0.79	0.48	0.04
US	1.91	0.95	0.49	0.04

Notes: Two factors are retained in all countries because the first two observed factor eigenvalues exceed the corresponding simulated eigenvalues in Horn's parallel analysis.

Table A3: Tucker's congruence coefficients between pooled and country-specific EFAs

Country	Factor 1	Factor 2
Germany	1.00	1.00
Japan	0.99	1.00
Poland	1.00	0.99
Spain	1.00	1.00
Sweden	0.99	1.00
US	1.00	1.00

Notes: Coefficients compare each country-specific factor solution to the pooled solution after factor alignment. Values above .95 indicate structural equivalence.

A5 replicates this pattern in each country.

Optimal numbers of clusters Using *k*-means clustering, Figure **A2** suggests five clusters substantially minimize the within-cluster sum of squares, with diminishing returns beyond this point.

A.2.2 Controls

We control for four additional factors. We cover basic demographics with variables for age, gender, and the country in which a person resides. Moreover, to capture respondents' personal economic situation, we use a subjective measure of how individuals state to live on their current income. Individuals were asked whether living on their current income is *very difficult*, *difficult*, they are *coping*, or *comfortable*.

Table A4: Exploratory factor analysis (pooled sample)

	Factor 1	Factor 2
Provide useful services	–	0.71
Undermine state	0.65	–
Promote innovation	–	0.77
Weaken labor	0.72	–
Threaten democracy	0.72	–
Aid democracy	–	0.56
SS Loadings	1.46	1.41
Proportion of Variance	0.24	0.24

Notes: Entries are standardized pattern loadings. Loadings below 0.20 are suppressed (shown as “–”). The correlation between the two factors is low ($\rho_{Factor1,Factor2} = 0.1$). Model fit is excellent (RMSEA = .028, TLI = .99, RMSR = .01).

Table A5: Exploratory factor loadings by country.

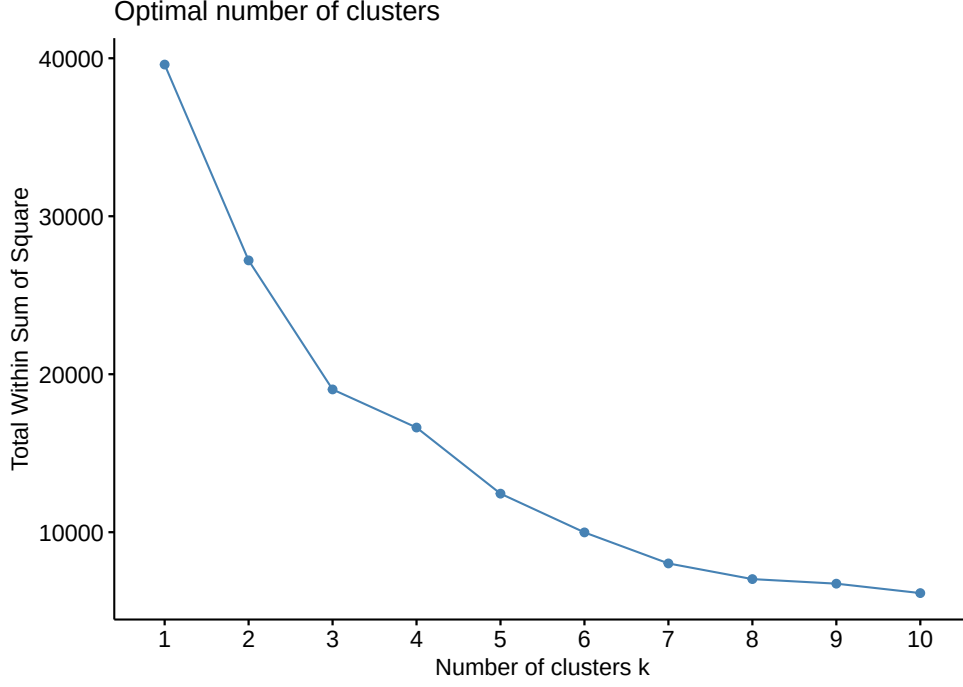
Item	Germany		Japan		Poland		Spain		Sweden		US	
	F1	F2	F1	F2	F1	F2	F1	F2	F1	F2	F1	F2
Provide useful services	.78	–	.83	–	.81	–	.70	–	.66	–	.75	–
Undermine state	–	.69	–	.74	–	.67	–	.67	–	.73	–	.62
Promote innovation	.81	–	.87	–	.77	–	.82	–	.71	–	.85	–
Weaken labor	–	.73	–	.80	–	.76	–	.74	–	.68	–	.78
Threaten democracy	–	.74	–	.78	–	.75	–	.74	–	.71	–	.80
Aid democracy	.53	–	.60	–	.61	–	.56	–	.51	–	.63	–
Prop. var. (F1)	.26		.30		.27		.26		.25		.29	
Prop. var. (F2)		.26		.30		.27		.25		.20		.27

Notes: Loadings below 0.20 are suppressed (shown as “–”). Factors are labeled for comparability across countries. Because oblique rotations may permute factor order, F1/F2 correspond to the common item groupings observed across countries (items 1/3/6 vs. items 2/4/5).

A.2.3 Statistical specification

We argue that attitudes toward Big Tech companies are shaped by the interplay of education and ideology. To test this argument, we estimate how education, ideology, and their interaction affect the probability of belonging to one of the five clusters of Big Tech

Figure A2: Five as optimal number of clusters.



attitudes identified above. The equation without interaction is given by:

$$\begin{aligned}
 \text{Membership}_{ic} &\sim \text{NominalCategorical}(\mathbf{p}_{ic}) \\
 \text{logit}(\mathbf{p}_{ic}) &= \beta_{1c} \text{Education}_i + \beta_{2c} \text{Ideology}_i + \beta_{2c} \text{Ideology}_i^2 \\
 &\quad + \beta_{3c} \mathbf{z}_i + \alpha_c + \epsilon_{ic} \\
 \beta_{1c,2c,3c} &\sim \mathcal{N}(0, 1) \\
 \alpha_c &\sim t(3, 0, 2.5),
 \end{aligned} \tag{1}$$

where Membership_{ic} denotes the membership of individual i in cluster c , and the vector $\mathbf{p}_{ic} = \{p_{i,\text{supporters}}, p_{i,\text{skeptics}}, p_{i,\text{ambivalent}}, p_{i,\text{dismissive}}, p_{i,\text{neutral}}\}$ contains the relative probabilities of belonging to each cluster. The logit link constrains the multinomial model predictions to the probability space between 0 and 1.

Cluster membership is modeled as a function of an individual's education level (Education_i), ideological predisposition (Ideology_i), and a squared transformation of the political left-right scale to allow for potential nonlinearities (Ideology_i^2). Finally, $\mathbf{z}_i$ represents a vector

of control variables, α_c are cluster-specific intercepts, and ϵ_{ic} is the error term.

The interaction model is given by:

$$\begin{aligned}
\text{Membership}_{ic} &\sim \text{NominalCategorical}(\mathbf{p}_{ic}) \\
\text{logit}(\mathbf{p}_{ic}) &= \beta_{1c} \text{Education}_i + \beta_{2c} \text{Ideology}_i + \beta_{2c} \text{Ideology}_i^2 \\
&\quad + \beta_{4c} \text{Education}_i \cdot \text{Ideology}_i + \beta_{5c} \text{Education}_i \cdot \text{Ideology}_i^2 \\
&\quad + \beta_{6c} \mathbf{z}_i + \alpha_c + \epsilon_{ic} \\
\beta_{1c, 2c, 3c, 4c, 5c, 6c} &\sim \mathcal{N}(0, 1) \\
\alpha_c &\sim t(3, 0, 2.5),
\end{aligned} \tag{2}$$

We estimate both models in a Bayesian framework using 8,000 Markov chain Monte Carlo iterations, with 4,000 iterations used as burn-in. Normal priors with a mean of 0 and a standard deviation of 1 are placed on the β -coefficients, while half-Student- t priors (with 3 degrees of freedom, location 0, and scale 2.5) are used for the intercepts. In addition, we weight the likelihood contribution of each observation using survey weights.

A.2.4 Full results

The full results based on Equations 1 and 2 are presented in Figure A3.

A.2.5 Convergence diagnostics

We assessed MCMC convergence using $\hat{R}$, effective sample sizes (Bulk ESS and Tail ESS), and visual inspection of trace plots. Across all model parameters, $\hat{R} = 1.00$, indicating no evidence of non-convergence. Effective sample sizes are high (Bulk ESS and Tail ESS generally in the thousands; minimum values exceed common thresholds), and trace plots show stable mixing across chains without trends or sticking. Given the large number of coefficients in the categorical model, we do not present parameter-by-parameter diagnostics or trace plots; however, we inspected them and found no indications of convergence problems. We therefore conclude that the posterior draws provide a reliable basis for

Figure A3: Full results.

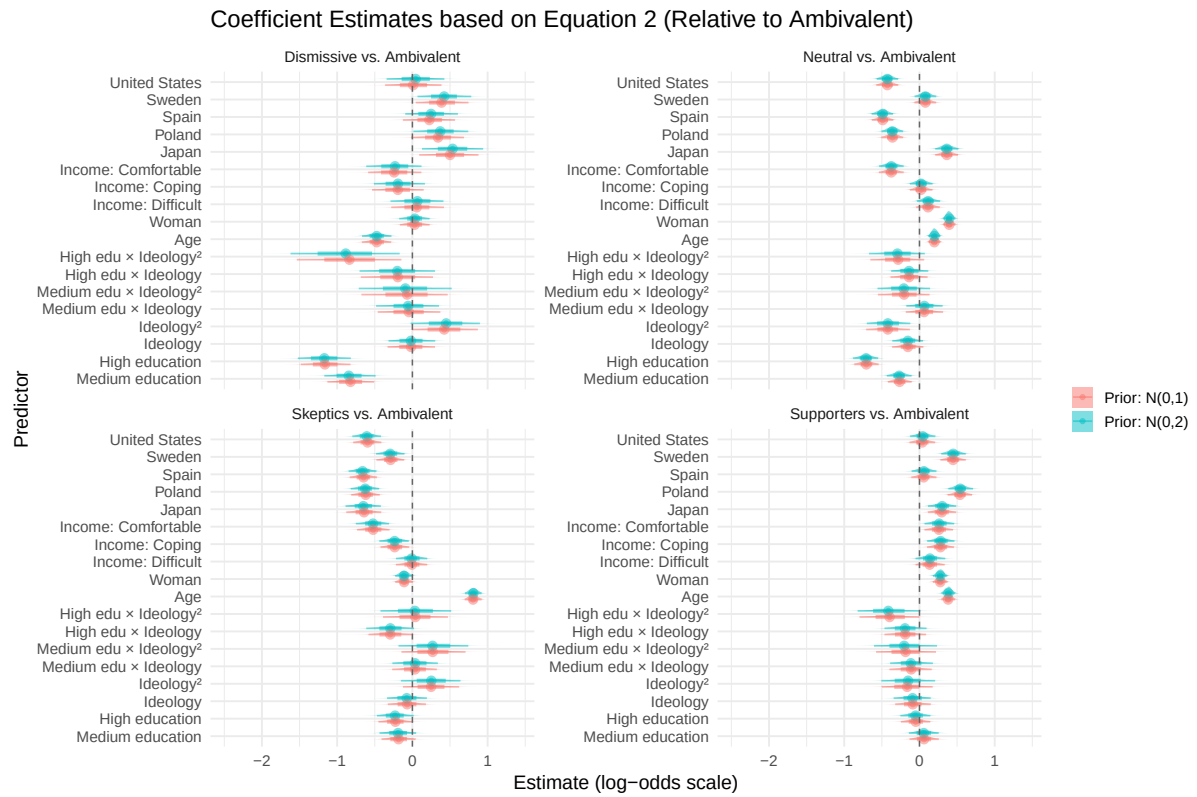
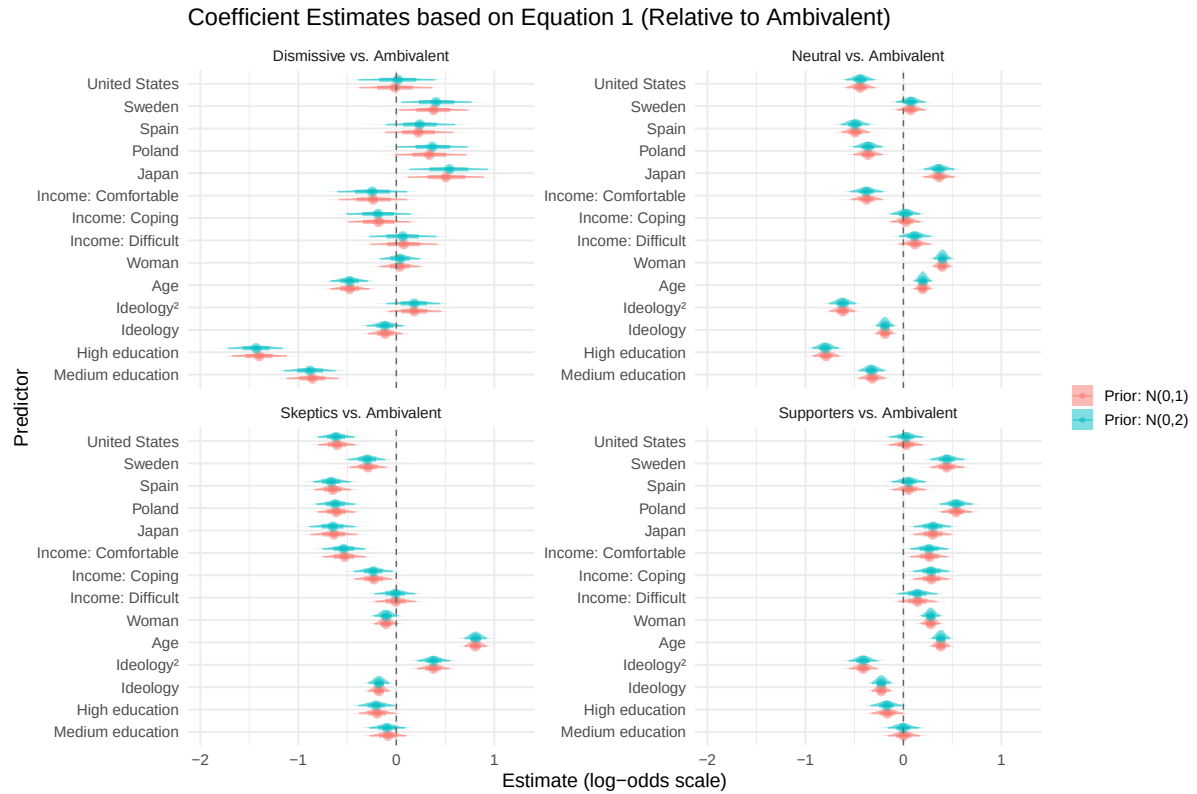


Figure A4: Effect of education based on country-specific regressions.



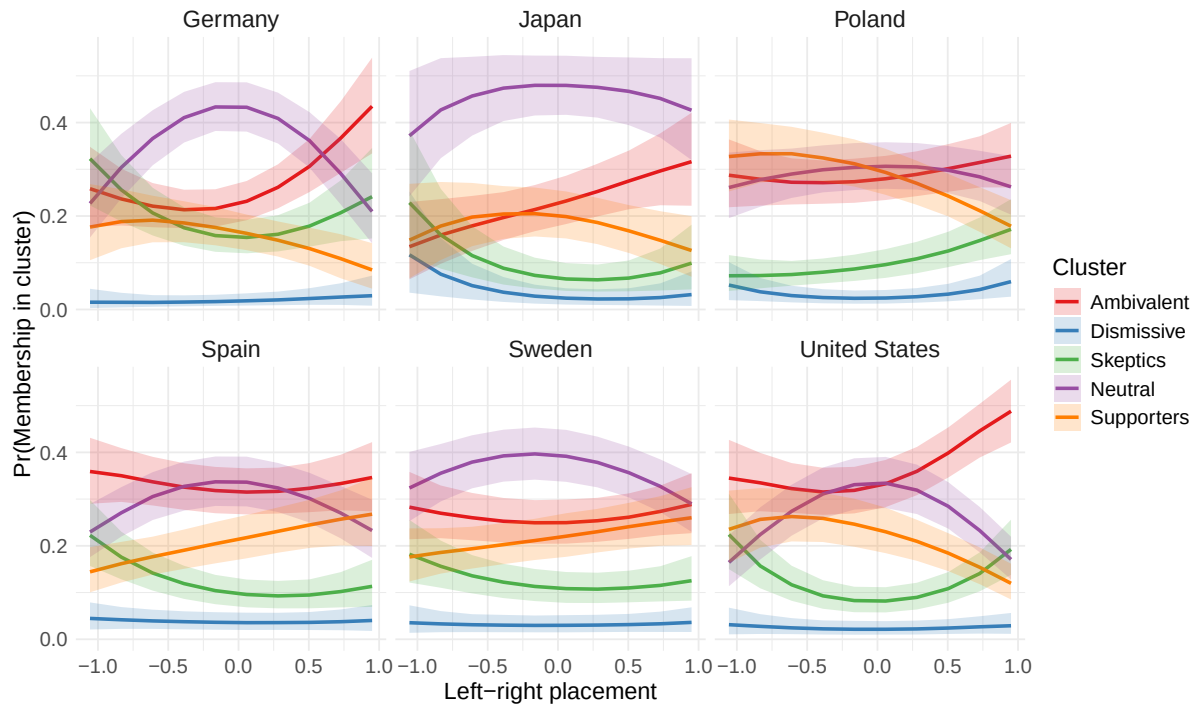
inference.

A.2.6 Sensitivity of main results

Country-specific regressions. Figure A4 presents the average marginal predicted probabilities of cluster membership by level of education for each country individually. These estimates are derived from country-specific regressions based on Equation 1, excluding country fixed effects. The results suggest that the pattern of decreasing neutrality and increasing ambivalence with higher levels of education holds consistently across countries. The one notable exception is Germany, where the probability of belonging to the ambivalent cluster does not appear to vary meaningfully with educational attainment.

Figure A5 replicates this analysis using political ideology, measured by respondents' self-placement on the left-right scale. Across all countries, we observe an inverse-U-shaped relationship for neutrality, with the highest probability of neutrality among centrists and lower probabilities at both ideological extremes. This pattern is more pronounced in some countries (e.g., Germany and the United States) than in others (e.g., Japan and Poland).

Figure A5: Effect of political ideology based on country-specific regressions.

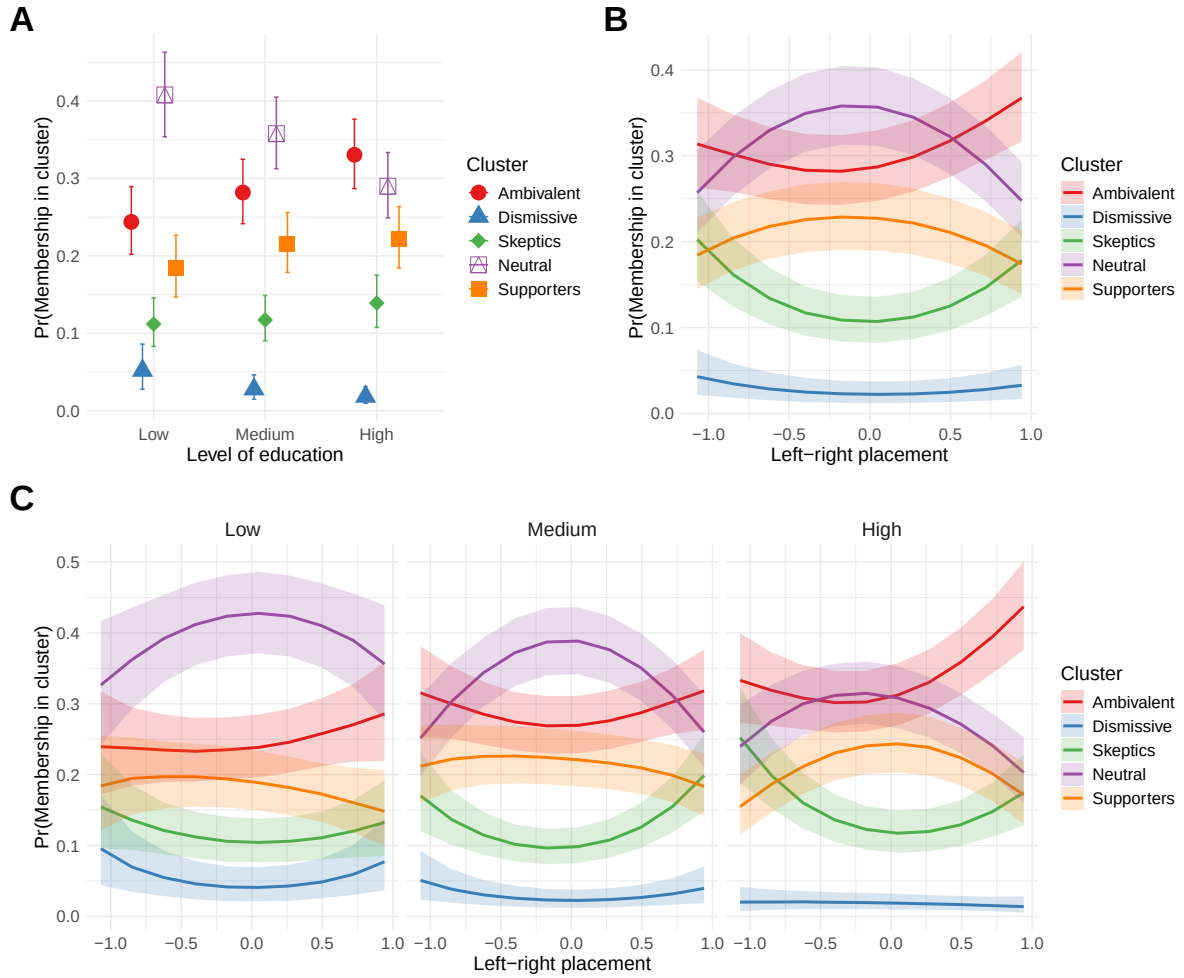


We also find that skepticism is most prevalent among individuals on the left end of the ideological spectrum—consistent with our earlier findings—though Poland appears to be an exception. Conversely, individuals on the right are generally more likely to belong to the ambivalent cluster, with this tendency especially pronounced in Germany, Japan, and the United States.

Additional controls for technology use at home and at work. As a robustness check, we include three measures of technology use in both personal and professional contexts. These variables are based on responses to the following survey questions:

1. *How often do you use the internet in your personal life, be it with a computer, laptop, tablet, or smartphone?*
2. *How often do you use digital information and communication technologies (ICT) such as computers, laptops, or tablets in your work?*
3. *How often do you use or have you used complex technology in your job, such as*

Figure A6: Replication of Figure 2 with additional controls for technology use at home and at work.



robots or specialist software?

Each question is measured on a five-point Likert scale ranging from (1) *constantly, most of the day* to (5) *less than several times a month*.

We include these three variables as additional controls in the models specified in Equations 1 and 2. The results, presented in Figure A6, support our main findings. The estimated posterior means remain virtually unchanged, although the 95% credibility intervals widen slightly, as expected when additional covariates are introduced.

A.2.7 Latent Class Analysis (LCA)

As a complementary model-based analysis, we estimated latent class models directly from the six attitudinal items. This analysis examines whether the observed response patterns can be represented as a finite number of qualitatively distinct latent groups. It differs conceptually from the factor-based analysis in the main text, which represents attitudes as positions on two continuous dimensions and uses k -means to construct a descriptive partition of that two-dimensional space. The two approaches therefore make different assumptions about the form of the underlying heterogeneity and need not yield equivalent classifications.

Class enumeration and model fit. Table A6 shows that model fit improves monotonically as the number of classes increases. Both AIC and BIC continue to decline through the eight-class solution, which has the lowest values among the models considered. The information criteria therefore do not identify a clear stopping point or provide statistical support for selecting exactly five classes.

Inspection of the conditional response profiles indicates, however, that solutions with more than five classes largely subdivide broader response patterns according to response intensity and generate several increasingly small classes. For example, the eight-class solution contains a class comprising approximately one percent of respondents. A small class does not by itself establish overfitting, but, together with the continuing subdivision of substantively similar profiles, it makes the higher-class solutions difficult to interpret as distinct attitudinal types.

We therefore examine the five-class solution below as a relatively parsimonious representation that facilitates comparison with the five-cluster typology in the main text. This choice should not be interpreted as a claim that the five-class solution is statistically preferred by BIC or that the population necessarily consists of exactly five discrete latent groups. To assess sensitivity to local maxima, we re-estimated the five-through eight-class models using 200 random starting values. These estimations reproduced the

reported maximum log-likelihoods to numerical precision.

Table A6: Latent class model fit statistics

Classes (K)	Log-likelihood	AIC	BIC
2	-145288.3	290674.7	291061.4
3	-138504.6	277157.1	277741.3
4	-136130.8	272459.6	273241.0
5	-134509.6	269267.3	270246.1
6	-133276.4	266850.8	268026.9
7	-132259.8	264867.6	266241.1
8	-131444.2	263286.5	264857.3

Notes: Models were initially estimated using 20 random starting values. The five- through eight-class models were subsequently re-estimated using 200 random starting values and reproduced the reported maximum log-likelihoods to numerical precision. AIC and BIC are reported as comparative fit measures. Both continue to decline through the largest model considered and therefore do not identify a unique class solution.

Five-class profiles and their relationship to the main typology. Table A7 reports expected item responses for the illustrative five-class solution. Several of the resulting profiles have clear analogues in the factor-space typology. Class 2 is characterized by relatively positive and comparatively weak negative evaluations and can therefore be interpreted as a *supporters* profile. Class 4 combines weak positive evaluations with relatively strong negative evaluations and resembles the *skeptics* profile. Class 3 is concentrated near the response midpoint on all six items and resembles the *neutral* profile, although this group is substantially smaller than in the main typology (4,517 vs. 8,140).

The correspondence is not, however, one-to-one. In particular, the five-class LCA does not recover a separate profile corresponding closely to the low-positive, low-negative *indifferent* cluster in the main analysis. Instead, it divides respondents expressing simultaneously positive and negative evaluations into two classes differentiated mainly by response intensity: a relatively large moderate-ambivalence class and a smaller high-intensity ambivalence class. The LCA therefore reproduces some of the broad contrasts visible in the two-dimensional factor space, but it does not independently confirm the original five-cluster classification.

This divergence is substantively informative. It suggests that some of the heterogeneity captured by the LCA reflects gradations in response intensity rather than sharply separated qualitative types. Together with the absence of a clearly preferred class-enumeration solution, this limits the extent to which the LCA can be interpreted as evidence that respondents belong to a fixed set of discrete latent populations.

Table A7: Illustrative profiles from the five-class LCA model (expected item responses)

	Supporters	Ambivalent (mod.)	Ambivalent (high)	Skeptics	Neutrals
Provide useful services	3.72	3.58	4.65	2.33	3.04
Undermine state	2.86	3.81	3.73	3.50	3.04
Promote innovation	3.66	3.53	4.66	2.17	3.03
Weaken labor	2.56	3.65	3.46	3.44	3.01
Threaten democracy	2.58	3.71	3.51	3.63	3.01
Aid democracy	3.24	3.16	4.22	1.79	2.99
Mean (positive items) ^a	3.54	3.43	4.51	2.10	3.02
Mean (negative items) ^b	2.67	3.72	3.57	3.52	3.02
Class size (N)	4,998	7,237	1,617	1,431	4,517
Class size (%)	25.2	36.5	8.2	7.2	22.8

Notes: Entries report expected responses on the 1–5 scale, computed from the estimated conditional response probabilities $\Pr(Y_{ij} = r \mid C_i = k)$. ^aPositive items are: provide useful services, promote innovation, and aid democracy. ^bNegative items are: undermine the state, weaken labor, and threaten democracy. The substantive labels are interpretive summaries of the estimated response profiles and should not be understood as independently validated population categories.

Latent class model. Let $i = 1, \dots, N$ index respondents and $j = 1, \dots, J$ index items ($J = 6$). Each item Y_{ij} takes categorical values in $\{1, \dots, R_j\}$, with $R_j = 5$ in the present application. Let $C_i \in \{1, \dots, K\}$ denote an unobserved latent class. Conditional on class membership, item responses are assumed to be locally independent:

$$\Pr(\mathbf{Y}_i = \mathbf{y}_i \mid C_i = k) = \prod_{j=1}^J \Pr(Y_{ij} = y_{ij} \mid C_i = k), \quad (\text{A1})$$

where $\Pr(Y_{ij} = r \mid C_i = k) = \theta_{jkr}$ denotes the class-specific response probability and $\sum_{r=1}^{R_j} \theta_{jkr} = 1$ for all j and k .

Class-membership model. For the illustrative five-class solution, we additionally estimated a one-step latent class regression. Let $\mathbf{x}_i$ contain standardized education, standardized ideology, squared ideology, the interaction between education and ideology, and country indicators. With Class 1 as the reference category, class-membership probabilities are modeled as follows:

$$\begin{aligned} \Pr(C_i = k \mid \mathbf{x}_i) &= \frac{\exp(\eta_{ik})}{\sum_{\ell=1}^K \exp(\eta_{i\ell})}, \quad k = 1, \dots, K, \\ \eta_{i1} &= 0, \\ \eta_{ik} &= \alpha_k + \beta_{1k} \text{edu}_i + \beta_{2k} \text{lr}_i + \beta_{3k} \text{lr}_i^2 + \beta_{4k} (\text{edu}_i \text{lr}_i) \\ &\quad + \sum_{g=2}^G \gamma_{kg} \mathbb{I}\{\text{country}_i = g\}, \quad k = 2, \dots, K. \end{aligned} \tag{A2}$$

Here, $\mathbb{I}\{\cdot\}$ denotes a country indicator, with Germany serving as the reference country.

Marginal likelihood. The model implies the following mixture representation:

$$\Pr(\mathbf{Y}_i = \mathbf{y}_i \mid \mathbf{x}_i) = \sum_{k=1}^K \Pr(C_i = k \mid \mathbf{x}_i) \prod_{j=1}^J \Pr(Y_{ij} = y_{ij} \mid C_i = k). \tag{A3}$$

The class-specific response probabilities and the class-membership coefficients are estimated jointly by maximum likelihood. This one-step estimation incorporates uncertainty in respondents' class membership conditional on the selected five-class specification. It does not, however, account for uncertainty concerning the appropriate number of classes.

Predicted class membership. Figure A7 presents predicted class-membership probabilities from the illustrative five-class model across standardized ideology and education. Predictions are shown for education values one standard deviation below the mean, at the mean, and one standard deviation above the mean, separately by country. The specification includes standardized education, standardized ideology, squared ideology, their interaction, and country fixed effects. Because the model does not include interactions

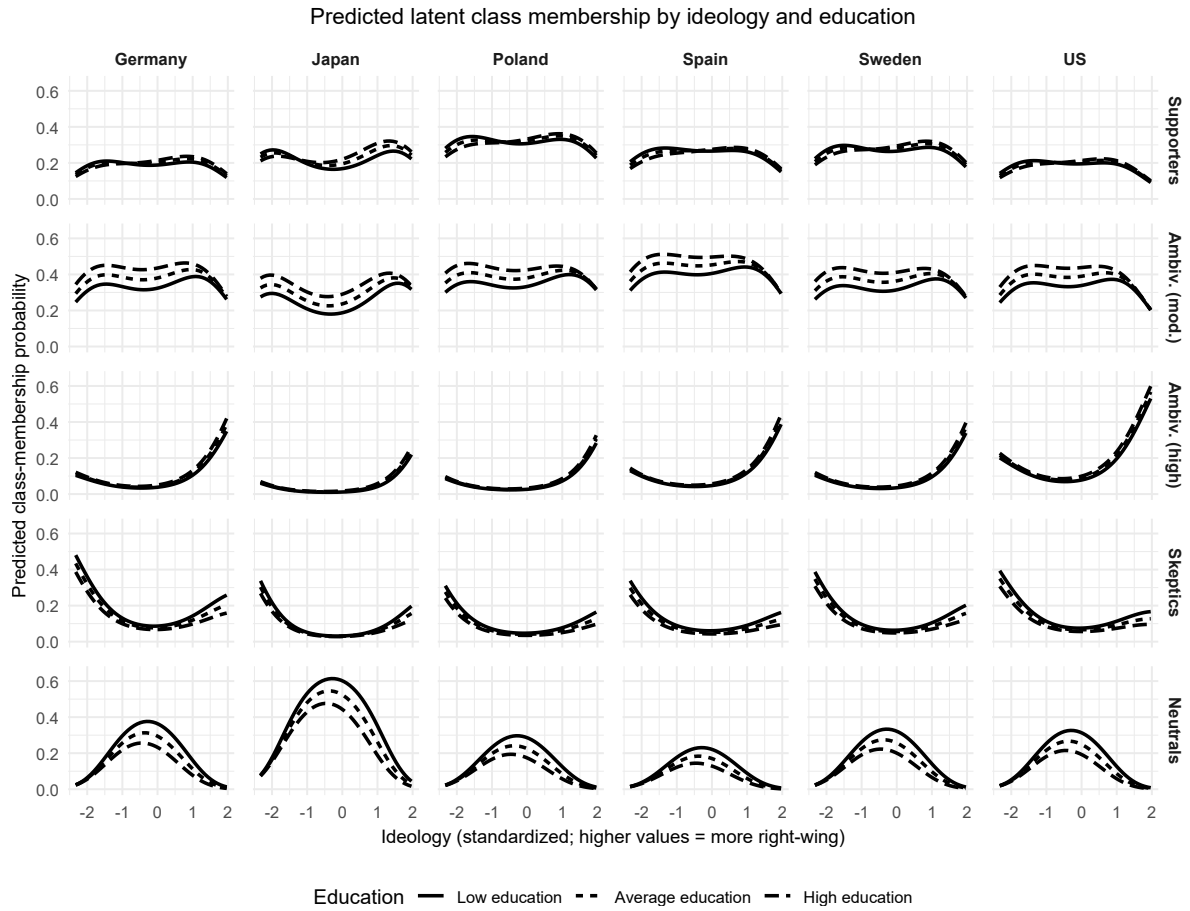
between country and the other covariates, country differences primarily represent shifts in the overall prevalence of the classes, while the estimated education and ideology relationships have the same functional form across countries.

The results reproduce several broad patterns found in the factor-space analysis. Most notably, the probability of belonging to the neutral profile is highest near the ideological center and declines toward both ends of the left–right scale. Neutral-class membership is also generally less likely among respondents with higher education. At the ideological extremes, the decline in neutrality is associated with different response profiles: skepticism increases particularly strongly toward the left, whereas the probability of high-intensity ambivalence rises sharply toward the right. The moderate-ambivalence profile is also generally more prevalent among respondents with average or high education than among those with low education. These patterns broadly parallel the education and ideology relationships reported for the descriptive typology in the main text.

The correspondence is nevertheless incomplete. The education gradient is weaker for some LCA profiles, particularly the high-intensity ambivalent class, and the LCA divides the ambivalent response pattern into moderate-and high-intensity variants while failing to recover a separate indifferent profile. The resulting classes therefore cannot be matched one-to-one to the clusters used in the main analysis. Country differences are also pronounced in the overall prevalence of some profiles, with Japan, for example, displaying a substantially higher predicted probability of neutral class membership.

We consequently interpret Figure [A7](#) as evidence that several of the principal education and ideology patterns are also visible under a finite-mixture specification, rather than as an exact replication or independent validation of the original typology. The absence of a uniquely preferred number of latent classes and the incomplete correspondence between the classifications continue to support the use of the two-dimensional factor-space representation as the principal analysis.

Figure A7: Predicted latent class-membership probabilities across ideology and education



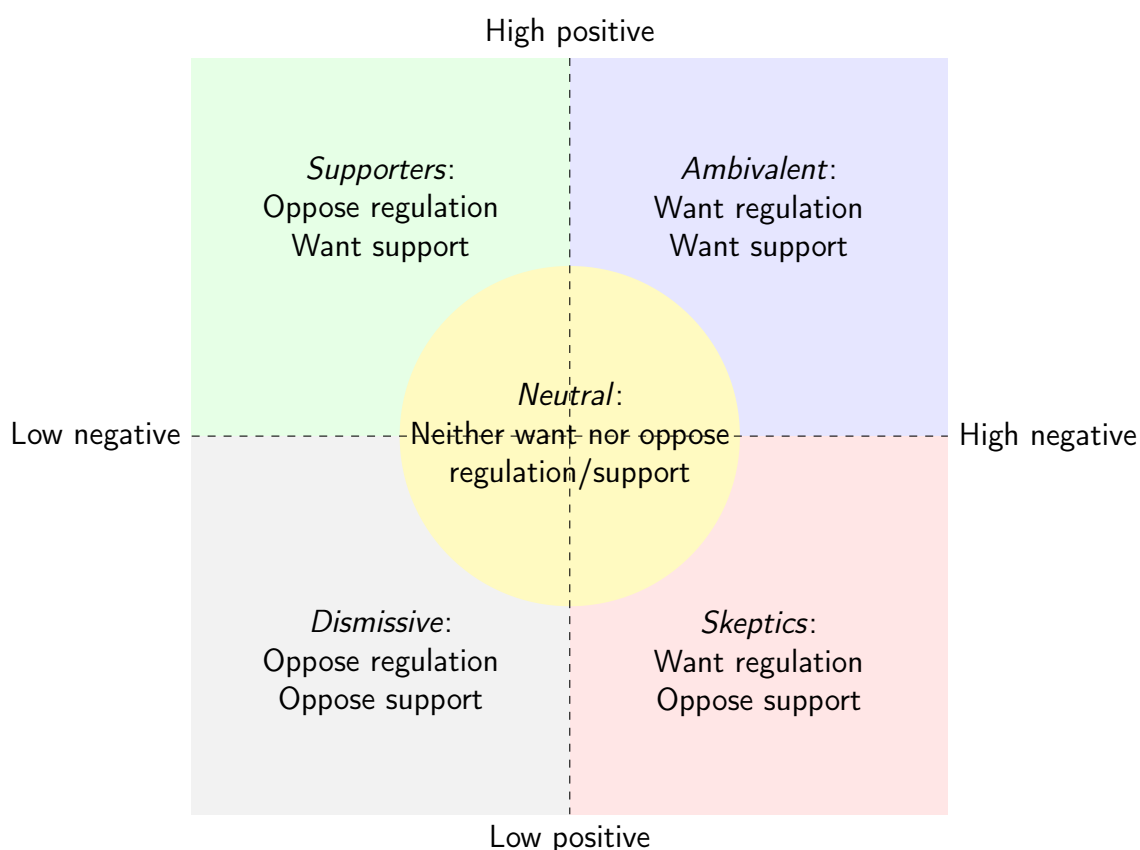
Notes: Predictions are based on the illustrative five-class solution and are conditional on that class enumeration. The model includes standardized education, standardized ideology, squared ideology, an education $\times$ ideology interaction, and country fixed effects. Education is shown at one standard deviation below the mean, at the mean, and one standard deviation above the mean. The figure should not be interpreted as evidence that five classes constitute a uniquely identified population typology.

A.3 Study of policy preferences on Big Tech regulation

A.3.1 Empirical expectations of effect of Big Tech views on policy preferences

Figure A8 summarizes the types of Big Tech views and their corresponding policy preferences. In the top-left corner, we have *Big Tech supporters*, individuals with high positive and low negative views of Big Tech. They generally oppose regulation and restrictions

Figure A8: Fivefold table of Big Tech views and corresponding policy preferences.



on these companies and may support government actions that favor Big Tech.

In the top-right corner, we identify the *ambivalent* group, characterized by both positive and negative views of Big Tech. These individuals are expected to simultaneously support regulation and government action in favor of Big Tech.

The bottom-right corner represents *Big Tech skeptics*, who hold high negative and low positive views. This group typically supports regulation while opposing government support for Big Tech.

Finally, in the bottom-left corner, we describe the *dismissive* group, with both low positive and low negative views of Big Tech. These individuals tend to oppose both regulation and government support. Given their unusual stance, this group is expected to be the smallest of the four.

A.3.2 Measuring political preferences towards global technology companies

We measure political preferences toward Big Tech using the following two survey items:
In the past decade, global technology companies such as Amazon, Apple, Google, Facebook, and Microsoft have become important players in today's economies. To what extent do you agree or disagree with the following statements?

1. *Governments should impose more restrictions and regulations on global technology companies.*
2. *Governments should provide more political and economic support to global technology companies.*

Answers were recorded using the same five-point Likert scale as described earlier. Figure A1 displays the response distribution for the two items (refer to the items above the dotted line). There is significantly more agreement than disagreement with both statements. For the Big Tech regulation item, 38% of respondents agree (with 11% strongly agreeing), while 20% disagree (with 5% strongly disagreeing). Similarly, the statement regarding increased government support is agreed upon by 31% of respondents (6% strongly agree), and 19% disagree (5% strongly disagree). However, the most commonly selected response is neutrality, with 42% expressing neutrality on regulation and 50% on government support.

A.3.3 Modeling strategy

To examine how different Big Tech attitudes (measured by cluster membership) influence policy preferences, we estimate the following ordered categorical model:

$$\begin{aligned} \text{Preferences}_{ip} &\sim \text{OrdinalCategorical}(\mathbf{p}_{ipr}) \\ \text{logit}(\mathbf{p}_{ipr}) &= \gamma_{1p} \text{Membership}_i + \gamma_{2p} \mathbf{z}_i + \alpha_{pr} + \epsilon_{ip} \\ \gamma_{1p, 2p} &\sim \mathcal{N}(0, 1) \\ \alpha_{pr} &\sim t(3, 0, 2.5). \end{aligned} \tag{A4}$$

Here, Preferences_{ipr} represents the policy preferences of individual i regarding policy p (e.g., regulation or government support). The vector $\mathbf{p}_{ipr}$ contains the relative probabilities of each response value r , ordered from 1 (“strongly disagree”) to 4 (“agree”), below the maximum response value of “strongly agree,” which has a cumulative probability of 1 by definition.

The main explanatory variable, Membership_i , is a dummy indicating membership in one of the five clusters of Big Tech attitudes. Our theoretical expectations for supporters, skeptics, the ambivalent, the dismissive, and the neutral are summarized in Figure A8. The model also includes a vector of control variables $\mathbf{z}_i$, intercepts α_{rp} for each response value below the maximum, and an error term ϵ_{ip} .

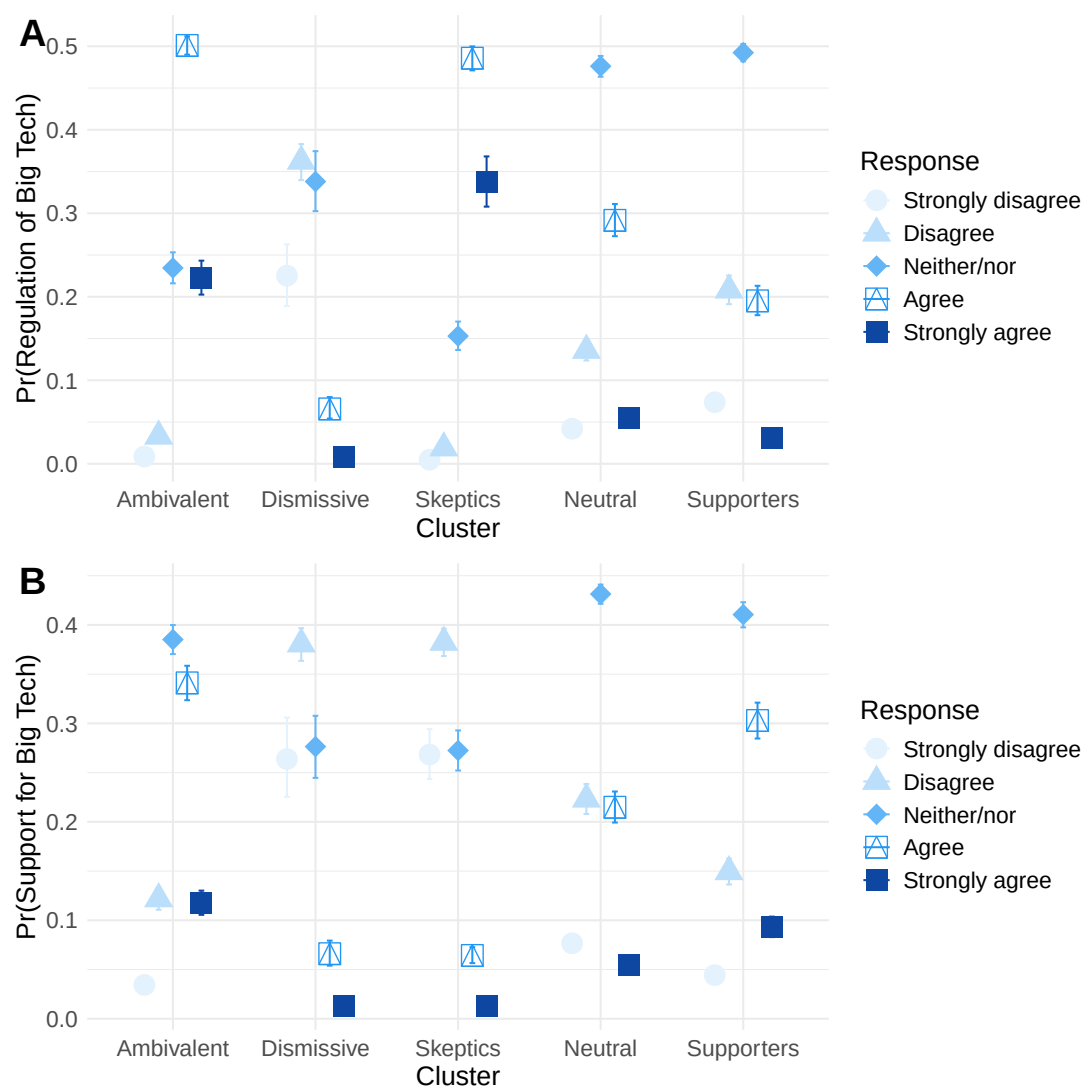
A.3.4 Empirical results

As summarized in Figure A8, we expect that (1) Big Tech supporters oppose regulation and possibly want government support, (2) Big Tech skeptics want regulation and oppose government support, (3) ambivalent individuals want both regulation and support, (4) dismissive respondents oppose both policy proposals, and (5) neutral individuals neither oppose nor favor either policy.

The results presented in Figure A9 largely corroborate our expectations. Ambivalent individuals have an approximately 72 percent predicted probability of generally agreeing with regulation, consisting of a 50 percent probability of agreeing and a 22 percent probability of strongly agreeing. They also exhibit a relatively high probability (approximately 46 percent) of generally agreeing with government support, with 34 percent probability of agreeing and 12 percent probability of strongly agreeing.

Comparing these estimates with the preferences of Big Tech skeptics and supporters, skeptics have a higher probability of generally agreeing with regulation (approximately 82 percent, including a 34 percent probability of strongly agreeing) but a much lower probability of generally agreeing with government support (approximately 8 percent). In contrast, Big Tech supporters exhibit a relatively low probability of generally agreeing

Figure A9: Predicted probability of supporting regulation of and government support for Big Tech conditional on cluster membership.



with regulation (approximately 23 percent, with only 3 percent probability of strongly agreeing) while having a probability of generally agreeing with government support similar to that of ambivalent individuals (approximately 39 percent).

Moreover, as expected, dismissive individuals display a high predicted probability of generally disagreeing with both policies, whereas neutral individuals are most likely to neither agree nor disagree.