Supplementary Information/Online Appendices

Do Citizens Care About Government Debt?

Evidence from Survey Experiments on Budgetary Priorities

December 2021

Table of Contents

A Operationalization, survey flow, and summary statistics

Table A.1: Operationalization of variables

Variable	Question wording	Measurement
Age	What year were you born?	Numerical variable: 18-88
Female	What is your sex?	Binary variable: 1 female; 0 men or no answer
Married	What is your marital status?	Binary variable: 1 married; 0 not married
Children	How many children are living in your household?	Binary variable: 1 children; 0 no children
Education	What is the highest level of education that you have achieved so far?	Categorical variable: 1 primary / lower secondary; 2 secondary; 3 tertiary
Class*	What is/was your occupation?	Categorical variable: 1 = employer; 2 = middle class; 3 = working class; 4 = routine worker
Income	Please indicate the answer that includes your total household income in the previous month, after taxes and compulsory deductions.	Numerical variable by percentile: 1-10 OR categorical variable by percentile: 1 1st-3rd; 2 4th-7th; 3 8th-10th
Unemployed	Which of these descriptions applies to what you have been doing for the last months?	Binary variable: 1 unemployed; 0 otherwise
Retired	Which of these descriptions applies to what you have been doing for the last months?	Binary variable: 1 retried; 0 otherwise
Union	Are you or have you ever been a member of a trade union or similar organization?	Binary variable: 1 current union member; 0 otherwise
Partisanship*	Which party did you vote for in the last (COUNTRY) election in (MONTH/YEAR)?	Categorical variable: 1 far left; 2 center left; 3 center right; 4 far right; 5 other party; 0 abstention
Left-right scale	Where would you place yourself, where 0 means the left and 10 means the right?	Categorical variable: 0-4 left; 5-6 center; 7-10 right
Political interest	How interested are you in politics on a scale from 0 to 10?	Numerical variable: 0-10
Political trust	How much do you personally trust the (COUNTRY) government?	Numerical variable: 0-10
Home ownership	About how much money would be left if the home or apartment you and/or your immediate family live in was sold, and any debts on it, such as mortgage or personal loan, would have been paid off?	Binary variable: 1 creditor (positive wealth from home ownership); 0 debtor (negative or no wealth from home ownership)
Asset ownership	About how much money would be left if you and/or your immediate family converted to cash all savings, stocks, or bonds you own, and then paid off any personal debts you have (excl. home loan)?	Binary variable: 1 creditor (positive wealth from assets); 0 debtor (negative or no wealth from assets)

Note: * Please see next page for further information on the exact operationalization.

Class was coded according to the following occupational groups: (1) small and large employers: self-employed farmers, fishermen, professionals, owner shop/business proprietor; (2) middle classes: employed professionals, general management, middle management, employed position desk with upper secondary education, employed position travelling with upper secondary education and employed position service with upper secondary; (3) working classes: skilled manual workers, supervisors and unskilled workers with an upper secondary education; (4) routine workers: unskilled worker without upper secondary, employed position desk without upper secondary education, employed position travel- ling without upper secondary education and employed position service without upper secondary

Partisanship was coded according to the ParlGov database, which classifies parties into families by their position in an economic (state/market) and a cultural (liberty/authority) left/right dimension. The party families were then simplified into five political groups, as shown below. For some subgroup analyses analyses, we further simplify partisanship into the following three categories by dropping respondents who support other parties: left (far left, center left), right (far right, center right), abstention.

Table A.2: Classification of political parties into five groups

	Germany	**Italy**	**Spain**	**UK**
Far right	AfD	Lega Nord, Fratelli d'Italia		UK Independence Party
Center right	CDU, CSU, FDP	SC, Nuovo Centrodestra, Forza Italia	PP, Ciudadanos, Convergencia, EAJ-PNV, CC-PNC	Conservative, Liberal Democrats
Center left	SPD, Grüne/Bündnis90	PD, Radicali Italiani, Articolo 1/MDP	PSOE	Labour, SNP, Greens
Far left	Die Linke	Sinistra Italiana, Movimento Cinque Stelle, Rifondazione Comunista	Unidos Podemos, En Comu Podem, Compromis-Podemos-EUPV, En Marea, EH Bildu	
Others	Piratenpartei	Südtiroler Volkspartei	ERC	Plaid Cymru

Survey Flow:

- Basic survey information and consent form

- Demographic questions (age, household size, children, marital status, urban-rural)

- Political and socio-economic questions (left-right, vote choice, education level, income, occupation, employment, asset/house ownership, ...)

- Conjoint experiment

- Split experiment

Summary Statistics:

Table A.3: Summary statistics

Statistic	N	Mean	St. Dev.	Min	Max
Fiscal consolidation (control)	1,200	7.201	2.326	0	10
Fiscal consolidation (lower spending)	1,204	5.625	2.583	0	10
Fiscal consolidation (higher taxes)	1,203	4.571	2.615	0	10
Age	4,800	46.670	15.851	18	88
Female	4,797	0.512	0.500	0	1
Married	4,800	0.480	0.500	0	1
Children	4,800	0.434	0.496	0	1
Education	4,785	2.249	0.674	1	3
Occupation	4,051	2.175	0.819	1	4
Income	4,595	5.177	2.805	1	10
Unemployed	4,768	0.072	0.259	0	1
Retired	4,800	0.197	0.398	0	1
Union	4,738	0.253	0.435	0	1
Partisanship	4,488	2.156	1.336	0	5
Left-right placement	4,800	1.817	0.743	1	3
Interest	4,800	5.928	2.686	0	10
Trust	4,800	3.453	2.686	0	10
House ownership	4,107	1.282	0.928	0	2
Asset ownership	4,066	1.311	0.913	0	2

B Case selection, sampling, and quality tests

B.1 Case selection

Table A.4: Case selection

	DE	IT	ES	UK
Welfare regime	Continental	Southern	Southern	Liberal
Varieties of capitalism	CME	MME	MME	LME
Unemployment rate	3.7	11.2	17.2	4.3
Youth unemployment rate	6.8	34.8	38.7	12.1
Government debt (% of GDP)	72	153	115	117
Education spending (% of GDP)	3.6	3.3	3.5	4.2
Pension spending (% of GDP)	10.1	16.2	11.0	6.2

Notes: (Youth) unemployment rate and government debt from 2017; education and pension spending from 2015 (all OECD data).

B.2 Sampling

Our survey was fielded in four large European countries in January 2018: Germany, Italy, Spain, and the United Kingdom. In each country, 1,200 respondents were recruited to participate in the survey. A large online panel provided by *Qualtrics* was used with tens of thousands of panelists across all age brackets. Qualtrics only uses double-opt in online panels that allow their panelists to take a survey no more than once every two weeks. Respondents were then drawn from a pool of eligible voters in each country and the sample was representative of all eligible voters based on gender and age, meaning we introduced quota sampling based on age and gender.

Given our subgroups comparisons, we are particularly interested in having roughly representative income and partisan groups. Even without quotas sampling by income and ideology, our sample is already fairly representative in terms of both variables. Figure A.1 plots the share of respondents by income decile for all countries (left) and by country (right). Overall, our income variable is almost equally distributed across income decile, only with a slightly higher representation of low-income respondents compared to high-income respondents. While the German and the Spanish samples are quite well balanced across income decile, the Italian and British samples are slightly more skewed towards low-income respondents. However, the differences are overall not particularly large.

In addition, we compared the party vote share in the closest election to the share of voters in our survey. We distinguish between the far right, center right, center left, and the far left, as explained in more detail in Table A.2. Especially in Italy and Spain, our sample matches the actual vote share that these four blocks received very well. In Germany, far left and center left voters are slightly over-represented, while center right voters are underrepresented. In the United Kingdom, center right voters are also underrepresented while center left and far right voters are slightly over-represented. Overall, the survey vote share matches fairly well the actual vote share.
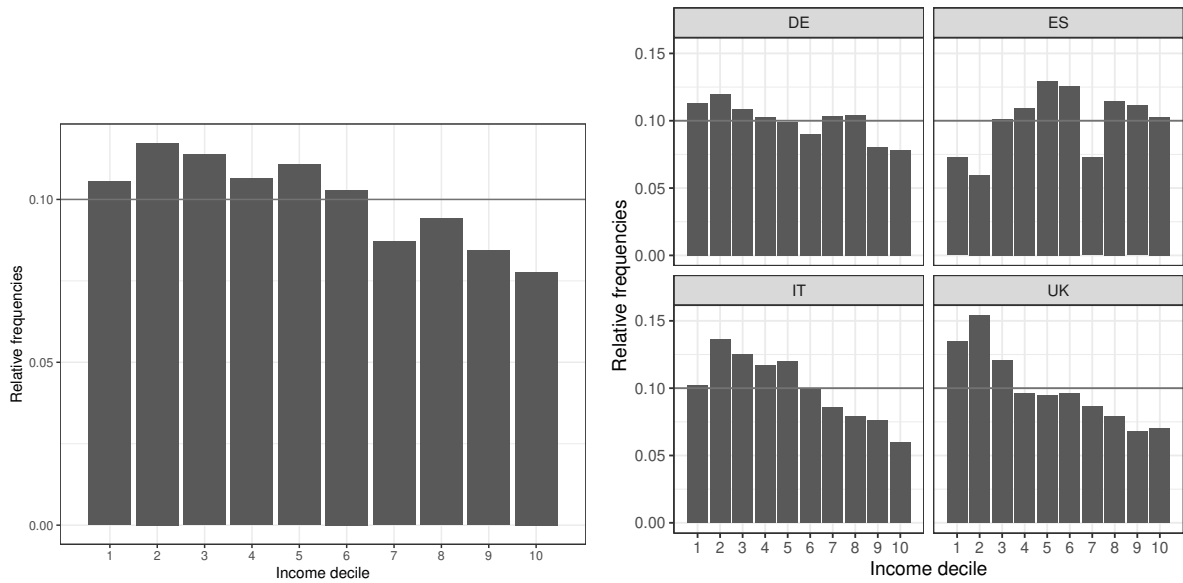

Figure A.1: Share of respondents by income decile (left: all countries; right: by country)

Table A.5: Survey vote share versus actual vote share

		Far Left	Center Left	Center Right	Far Right
DE	Election	9.2	29.4	43.7	12.6
	Survey	15.9	32.1	33.2	11.2
	Diff.	6.7	2.7	-10.5	-1.4
ES	Election	21.1	22.7	46.1	0.0
	Survey	25.1	18.4	45.4	0.0
	Diff.	4.0	-4.3	-0.7	0.0
IT	Election	34.4	22.2	18.8	21.8
	Survey	38.5	22.1	15.6	19.9
	Diff.	4.1	-0.1	-3.2	-1.9
UK	Election	0.0	47.0	49.9	1.8
	Survey	0.0	51.6	40.9	5.7
	Diff.	0.0	4.6	-9.0	3.9

We also used weights to match the demographic characteristics of the population in each country as closely as possible using entropy balancing (Hainmueller 2012). Please see Appendix G for a detailed explanation and the presentation of the results using entropy balancing.

B.3 Quality checks and screening out of respondents

To ensure the quality of our sample, the survey included an attention check and a speeding check. We implemented a common attention check in the middle of the survey. Respondents were shown the following question:

We are interested in learning about your preferences on a variety of topics, including colours. To demonstrate that you have read this question, please go ahead and select both red and green from the alternatives below, no matter what your favourite color is. Yes, ignore the question below and select both of those options. What is your favourite color?

The answer options were: blue, red, purple, orange, yellow, green, brown, gray. Those who did not select the two correct color, were excluded from the survey. Additionally, we implemented a speeding check for the whole survey and one specifically for the conjoint experiment. Respondents who had a response time below 1/3 of the median response time were excluded. Overall, 712 respondents failed the attention check and 394 respondents failed the speeding checks (104 for overall speeding, 290 for conjoint speeding).

B.4 Balance tests for the split-sample experiment

Variable	Control		Lower spending		Higher taxes	
	Mean	SD	Mean	SD	Mean	SD
Age	46.28	15.83	46.30	15.85	47.08	16.03
Female	0.54	0.50	0.52	0.50	0.48	0.50
Married	0.48	0.50	0.49	0.50	0.49	0.50
Children	0.44	0.50	0.45	0.50	0.44	0.50
Education	2.28	0.68	2.24	0.67	2.25	0.67
Occupation	2.16	0.80	2.16	0.82	2.20	0.84
Income	5.30	2.81	5.15	2.86	5.16	2.76
Unemployment	0.07	0.25	0.07	0.26	0.08	0.27
Retired	0.19	0.39	0.20	0.40	0.20	0.40
Union	0.25	0.43	0.25	0.43	0.26	0.44

Table A.6: Balance tests comparing treatment groups with the control group (linear probability models)

| | Treatment = 1, Control = 0 | | | |
| | Lower spending | Lower spending | Higher taxes | Higher taxes |
	(1)	(2)	(3)	(4)
Age	0.0001	0.0000	0.0001	0.0000
	(0.001)	(0.001)	(0.001)	(0.001)
Female	−0.02	−0.02	−0.02	−0.02
	(0.02)	(0.02)	(0.02)	(0.02)
Married	0.05	0.05	0.05	0.05
	(0.03)	(0.03)	(0.03)	(0.03)
Children	0.01	0.003	0.01	0.003
	(0.03)	(0.03)	(0.03)	(0.03)
Education (ref: primary/lower secondary)				
. Secondary	−0.02	−0.03	−0.02	−0.03
	(0.04)	(0.04)	(0.04)	(0.04)
. Tertiary	−0.06	−0.07	−0.06	−0.07
	(0.04)	(0.04)	(0.04)	(0.04)
Class (ref: Working Class)				
. Employer	0.07	0.06	0.07	0.06
	(0.04)	(0.04)	(0.04)	(0.04)
. Middle Class	0.05	0.05	0.05	0.05
	(0.04)	(0.04)	(0.04)	(0.04)
. Routine Worker	0.06	0.06	0.06	0.06
	(0.05)	(0.05)	(0.05)	(0.05)
Income	−0.004	−0.004	−0.004	−0.004
	(0.005)	(0.005)	(0.005)	(0.005)
Unemployed	−0.03	−0.03	−0.03	−0.03
	(0.05)	(0.05)	(0.05)	(0.05)
Retired	−0.01	−0.01	−0.01	−0.01
	(0.04)	(0.04)	(0.04)	(0.04)
Union membership	−0.02	−0.01	−0.02	−0.01
	(0.03)	(0.03)	(0.03)	(0.03)
Partisanship (ref: Center Left)				
. Far left	−0.08*	−0.09*	−0.08*	−0.09*
	(0.04)	(0.04)	(0.04)	(0.04)
. Center Right	−0.03	−0.02	−0.03	−0.02
	(0.03)	(0.03)	(0.03)	(0.03)
. Far right	−0.09	−0.10*	−0.09	−0.10*
	(0.05)	(0.05)	(0.05)	(0.05)
. Other party	0.06	0.05	0.06	0.05
	(0.06)	(0.06)	(0.06)	(0.06)
. Abstention	−0.01	−0.01	−0.01	−0.01
	(0.04)	(0.04)	(0.04)	(0.04)
Country (ref: Germany)				
. Spain		0.01		0.01
		(0.03)		(0.03)
. Italy		0.03		0.03
		(0.04)		(0.04)
. UK		0.001		0.001
		(0.04)		(0.04)
Constant	0.53***	0.53***	0.53***	0.53***
	(0.07)	(0.08)	(0.07)	(0.08)
Country fixed effects	*No*	*Yes*	*No*	*Yes*
Observations	1,840	1,840	1,840	1,840
R^2	0.01	0.01	0.01	0.01
Adjusted R^2	0.001	-0.0004	0.001	-0.0004
Residual Std. Error	0.50	0.50	0.50	0.50
F Statistic	1.09	0.97	1.09	0.97

Note: *p<0.05; **p<0.01; ***p<0.001

C Additional results from the split-sample experiments

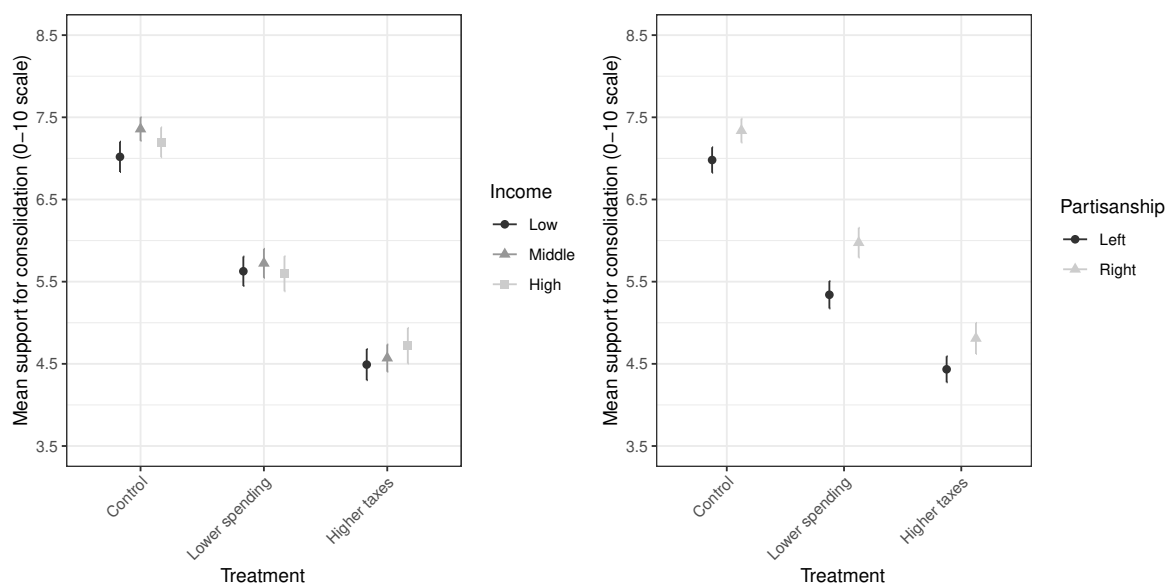## C.1 Mean plots for support for fiscal consolidation by income, partisanship, and country

Figure A.2: Average support for fiscal consolidation by trade-off and income/partisanship
Note: Mean support levels and 95 confidence intervals by trade-off and income/partisanship. The left-hand side distinguishes between three income groups based on the relative income distribution in each country; the right-hand side distinguishes between left- and right-wing voters.
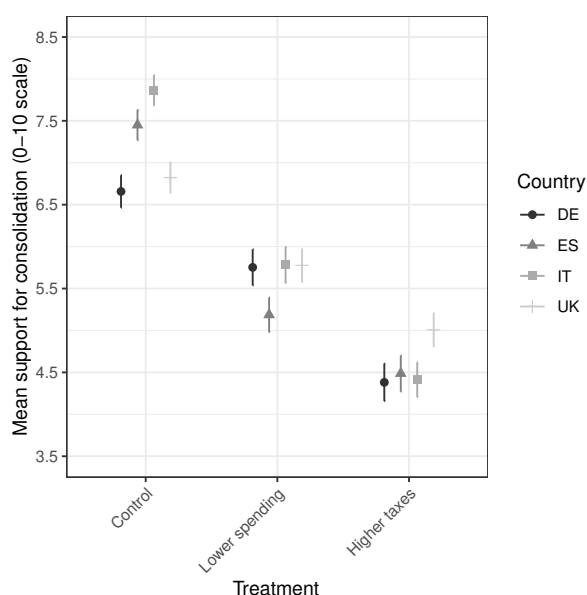

Figure A.3: Average support for fiscal consolidation by trade-off and country
Note: Mean support levels and 95 confidence intervals for fiscal consolidation by trade-off and country.

C.2 Tests for other heterogeneous treatment effects from the split-sample experiment
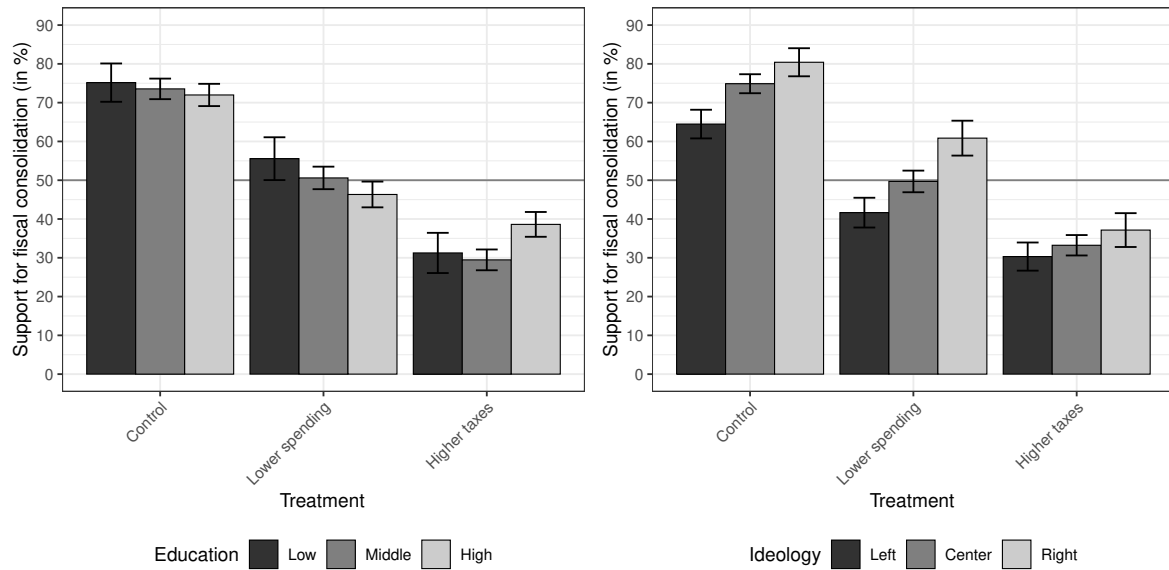

Figure A.4: Support for fiscal consolidation by trade-off and education/ideology
Note: Share of respondents who support fiscal consolidation and 95 confidence intervals by trade-off and education/ideology. The left-hand side distinguishes between three education groups; the right-hand side distinguishes between three ideological groups based on respondents' left-right self-placement.
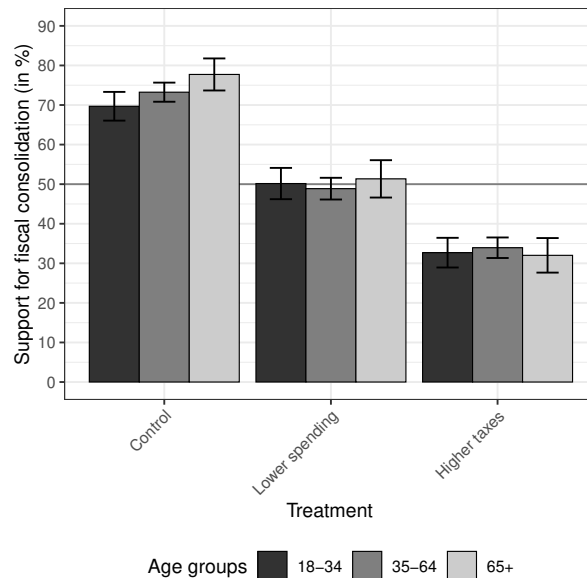

Figure A.5: Support for fiscal consolidation by trade-off and age group
Note: Share of respondents who support fiscal consolidation and 95 confidence intervals by trade-off and three age groups.

C.3 OLS regression analysis for split-sample experiment

Table A.7: Average treatment effects on support for lower government debt (OLS regressions corresponding to Figure 1 in the main text)

	Support for lower debt		
	No covariates	Covariates	Covariates + country-FE
	(1)	(2)	(3)
Treatment (ref: control group)			
. Lower Spending	−1.58***	−1.55***	−1.56***
	(0.10)	(0.12)	(0.12)
. Higher taxes	−2.63***	−2.59***	−2.60***
	(0.10)	(0.12)	(0.12)
Age		−0.001	−0.002
		(0.004)	(0.004)
Female		−0.30**	−0.30**
		(0.10)	(0.10)
Married		0.003	0.01
		(0.11)	(0.11)
Children		0.19	0.16
		(0.11)	(0.11)
Education (ref: primary/lower secondary)			
. Secondary		−0.12	−0.20
		(0.16)	(0.16)
. Tertiary		−0.20	−0.29
		(0.17)	(0.18)
Class (ref: Working Class)			
. Employer		−0.12	−0.16
		(0.17)	(0.17)
. Middle Class		0.12	0.09
		(0.14)	(0.14)
. Routine Worker		0.13	0.11
		(0.21)	(0.21)
Income		0.01	0.02
		(0.02)	(0.02)
Unemployed		0.19	0.21
		(0.21)	(0.21)
Retired		0.04	0.07
		(0.16)	(0.16)
Union membership		−0.23*	−0.24*
		(0.11)	(0.11)
Partisanship (ref: Center Left)			
. Far left		0.10	0.12
		(0.15)	(0.16)
. Center Right		0.58***	0.64***
		(0.13)	(0.13)
. Far right		0.28	0.22
		(0.20)	(0.20)
. Other party		0.06	0.20
		(0.24)	(0.24)
. Abstention		0.23	0.26
		(0.16)	(0.17)
Country (ref: Germany) . Spain			−0.04
			(0.14)
. Italy			0.40**
			(0.15)
. UK			0.30*
			(0.14)
Constant	7.20***	7.11***	7.03***
	(0.07)	(0.31)	(0.32)
Country fixed effects	*No*	*No*	*Yes*
Observations	3,607	2,768	2,768
R²	0.16	0.16	0.17
Adjusted R²	0.16	0.16	0.16
Residual Std. Error	2.51	2.52	2.51
F Statistic	333.69***	26.76***	23.95***

Note: *p<0.05; **p<0.01; ***p<0.001

Table A.8: The correlates of support for lower government debt (OLS regressions)

	Support for lower debt		
	Control	Lower spending	Higher taxes
	(1)	(2)	(3)
Age	−0.003	−0.002	0.0002
	(0.01)	(0.01)	(0.01)
Female	−0.07	−0.33	−0.48**
	(0.16)	(0.18)	(0.17)
Married	−0.02	0.21	−0.17
	(0.18)	(0.20)	(0.20)
Children	0.30	0.47*	−0.26
	(0.18)	(0.20)	(0.20)
Education (ref: primary/lower secondary)			
. Secondary	−0.56*	−0.16	−0.01
	(0.27)	(0.30)	(0.28)
. Tertiary	−0.61*	−0.45	0.04
	(0.29)	(0.33)	(0.31)
Class (ref: Working Class)			
. Employer	−0.37	0.003	−0.003
	(0.28)	(0.32)	(0.31)
. Middle Class	−0.31	0.23	0.42
	(0.23)	(0.27)	(0.25)
. Routine Worker	0.25	0.17	0.06
	(0.34)	(0.38)	(0.35)
Income	0.06	−0.003	0.01
	(0.03)	(0.04)	(0.04)
Unemployed	0.76*	0.03	−0.04
	(0.34)	(0.40)	(0.37)
Retired	0.35	−0.16	0.01
	(0.25)	(0.28)	(0.28)
Union membership	−0.37*	−0.24	−0.05
	(0.18)	(0.20)	(0.19)
Partisanship (ref: Center Left)			
. Far left	0.06	0.05	0.21
	(0.25)	(0.30)	(0.28)
. Center Right	0.47*	0.72**	0.68**
	(0.21)	(0.23)	(0.23)
. Far right	0.23	0.47	−0.08
	(0.30)	(0.37)	(0.37)
. Other party	0.45	0.01	0.06
	(0.40)	(0.40)	(0.47)
. Abstention	0.25	0.54	−0.12
	(0.26)	(0.29)	(0.30)
Country (ref: Germany) . Spain	0.55*	−0.79**	0.13
	(0.22)	(0.25)	(0.25)
. Italy	1.01***	−0.05	0.21
	(0.23)	(0.27)	(0.27)
. UK	0.16	0.04	0.65**
	(0.23)	(0.26)	(0.25)
Constant	6.97***	5.65***	4.25***
	(0.49)	(0.56)	(0.55)
Country fixed effects	*Yes*	*Yes*	*Yes*
Observations	915	925	928
R^2	0.06	0.05	0.04
Adjusted R^2	0.04	0.03	0.02
Residual Std. Error	2.27	2.62	2.57
F Statistic	2.75***	2.27***	2.00**

Note: *p<0.05; **p<0.01; ***p<0.001

Table A.9: The correlates of support for lower government debt (OLS regressions with additional control variables)

	Support for lower debt		
	Control	Lower spending	Higher taxes
	(1)	(2)	(3)
Age	−0.0004	−0.001	−0.003
	(0.01)	(0.01)	(0.01)
Female	−0.12	−0.32	−0.41*
	(0.17)	(0.19)	(0.19)
Married	−0.05	0.29	−0.08
	(0.19)	(0.22)	(0.22)
Children	0.29	0.32	−0.28
	(0.20)	(0.21)	(0.21)
Education (ref: primary/lower secondary)			
. Secondary	−0.70*	−0.04	0.10
	(0.30)	(0.32)	(0.30)
. Tertiary	−0.74*	−0.42	0.06
	(0.32)	(0.35)	(0.33)
Class (ref: Working Class)			
. Employer	−0.50	0.06	−0.04
	(0.30)	(0.34)	(0.32)
. Middle Class	−0.29	0.14	0.33
	(0.25)	(0.29)	(0.26)
. Routine Worker	0.29	0.26	0.18
	(0.39)	(0.42)	(0.39)
Income	0.06	0.004	−0.03
	(0.04)	(0.04)	(0.04)
Unemployed	0.87*	0.44	−0.03
	(0.37)	(0.44)	(0.41)
Retired	0.43	−0.17	0.05
	(0.28)	(0.30)	(0.29)
Union membership	−0.42*	−0.32	−0.22
	(0.19)	(0.21)	(0.20)
Partisanship (ref: Center Left)			
. Far left	0.15	0.26	0.33
	(0.27)	(0.32)	(0.30)
. Center Right	0.49*	0.66**	0.61*
	(0.23)	(0.25)	(0.25)
. Far right	0.28	0.77	0.12
	(0.33)	(0.41)	(0.42)
. Other party	0.55	0.28	0.31
	(0.44)	(0.44)	(0.51)
. Abstention	0.26	0.71*	−0.05
	(0.30)	(0.33)	(0.33)
Political interest	−0.05	−0.01	0.01
	(0.04)	(0.04)	(0.04)
Trust in government	−0.002	0.12**	0.17***
	(0.04)	(0.04)	(0.04)
House ownership (ref: no house), . Debtor	0.29	−0.61	−0.17
	(0.39)	(0.45)	(0.51)
. Creditor	0.05	−0.12	−0.20
	(0.22)	(0.26)	(0.24)
Asset ownership (ref: no assets) . Debtor	−1.00**	0.47	0.98*
	(0.38)	(0.42)	(0.47)
. Creditor	0.30	0.25	0.44
	(0.22)	(0.26)	(0.25)
Country (ref: Germany) . Spain	0.53*	−0.62*	0.34
	(0.25)	(0.28)	(0.29)
. Italy	0.85**	0.30	0.46
	(0.26)	(0.30)	(0.30)
. UK	−0.05	0.32	0.84**
	(0.25)	(0.28)	(0.27)
Constant	7.22***	4.92***	3.48***
	(0.57)	(0.66)	(0.61)
Country fixed effects	*Yes*	*Yes*	*Yes*
Observations	788	818	804
R²	0.09	0.07	0.09
Adjusted R²	0.06	0.04	0.06
Residual Std. Error	2.28	2.61	2.54
F Statistic	2.76***	2.22***	2.76***

Note:	*p<0.05; **p<0.01; ***p<0.001

D   Instructions for the conjoint survey experiment

The full instructions for the conjoint tasks are shown below. First, respondents were presented the following introduction to the experiment.

Please take your time and read the information below very carefully. It contains the instructions for the next part of the survey.

Every year the [COUNTRY] government collects taxes and spends money in a variety of different areas. A large share of taxes are paid by citizens like you and they are used to pay for government spending on education or pensions. We are interested in what you think about how your government should change its budget.

We will now show you several proposals for possible changes to the government's budget. We will always show you two possible proposals in comparison. For each comparison we would like to know which of the two proposals you prefer. You may like both proposals or neither. In any case, please choose the proposal that you like the most. In total, we will show you five comparisons.

The possible proposals only include changes with regard to a few selected types of government spending and taxation. Please assume that spending in all other areas as well as all other taxes do not change.

People have different opinions about this issue and there are no right or wrong answers. Please always take your time when reading the proposals.

This introduction was followed by a screen with two proposals for a budgetary change, as shown below in Figure A.6. In this way, respondents are asked five times to choose (i) between two packages ("choice" variable) and (ii) to indicate how likely they are to support each of the proposals ("ranking" variable).

Please carefully review the options detailed below, then please answer the questions.

Which of these proposals do you prefer?

	Proposal 1	Proposal 2
Income tax (for all citizens)	Decrease	No change
Tax on high incomes	Increase	No change
Value added tax (VAT)	Decrease	Increase
Government debt	Increase	Decrease
Old-age pensions	Decrease spending	Decrease spending
Education	Increase spending	Increase spending

Proposal 1

Proposal 2

How would you rate proposal 1 on a scale from 0 to 10, where 0 indicates that the government should definitely not adopt the proposal and 10 indicates that the government should definitely adopt it?

0 - Definitely not adopt	1	2	3	4	5	6	7	8	9	10 - Definitely adopt

How would you rate proposal 2?

0 - Definitely not adopt	1	2	3	4	5	6	7	8	9	10 - Definitely adopt

Figure A.6: Screenshot of a conjoint task presented to respondents

E Explanation of ridge regression to analyze the conjoint experiment

We propose ridge regression as a novel method to analyse conjoint survey experiments with dependencies. In our design, the values that each attribute can take are linearly dependent on the other attributes to ensure that the budget is balanced. Therefore, there is explicit confounding between the features of the fiscal packages, due to the restrictions to the randomization protocol that we introduced. We included these restrictions to increase external validity, as recommended by Hainmueller et al. (2014, p. 26). They argued that "researchers should employ restrictions and exclude attribute combinations whenever they are deemed so unrealistic that a counterfactual would essentially be meaningless." We took this recommendation to the extreme because the budget constraint of the public budget is binding: changing the government's expenditure or revenue on one dimension necessarily has consequences for another dimension. This poses difficulties for traditional regression analysis, but it ensures external validity.

To see this, imagine the alternative: We could have introduced combinations that are unrealistic to break the super-collinearity that exists in reality. This would have allowed us isolate the effect of each attribute independently of other attributes, but it poses a threat to external validity. Respondents would have probably most preferred atypical profiles, which increase government spending, decrease taxation, and cut government debt all at the same time. Given our interest in citizens' priorities in the face of hard budgetary tade-offs, this would not have been satisfactory. As Bansak et al. (2020, p. 24-25) argue, "the AMCE averages the effect of an attribute over two different distributions: the randomization distribution of the other attributes and the distribution of respondents." The AMCEs of a fully randomized design, therefore, are not of interest to us. We only wanted to make inferences about realistic budgetary combinations, i.e., those that are fully balanced.

The resulting experimental design necessitates a modelling approach which accounts for the design-based super collinearity. One common solution to enable OLS standard regression analysis in instances of super collinearity is to drop one of the correlated variable. This strategy usually works well, but it is not useful in our case because it defeats the point of the design. We are interested in the support for a fiscal package as a function of all of its individual attributes. Moreover, dropping one attribute from the analysis may lead to specification bias.

We, therefore, propose to use regularization to analyse the results from conjoint experiments, which are perfectly multicollinear. Specifically, we use ridge regression, which is a common regularization method that adds a penalty term to the common OLS regression. Hoerl (1962) and Hoerl and Kennard (1970) suggested to use a ridge regression as an ad-hoc fix to address instances of high multicollineary, including instances of design-based collinearity. It allows one to estimate coefficients for all independent variables in the model even in the presence of super collinearity, and consequently, the method is also used in fields such as genetics where a set of related genetic predictors may jointly cause certain diseases.

To see how ridge regression works, recall that OLS regression attempts to minimize the sum of errors squared, as shown in the equation below:

$$\sum_{i=1}^{M}(y_i - \hat{y}_i)^2 = \sum_{i=0}^{M}(y_i - \sum_{j=0}^{p} w_j w_{ij})^2 \qquad (1)$$

Ridge regression adds the following term to this model:

$$+ \lambda \sum_{j=0}^{p} w_j^0 \qquad (2)$$

This term is referred to as the ridge penalty and λ is the penalty parameter. If λ is zero, then ridge regression is essentially an OLS regression. However, if λ is above zero, then it adds a constraint to the coefficient. This constraint minimizes the coefficients (which is called shrinkage), which results in a lower variance and a lower error value. Consequently, ridge regression is a way to decrease the complexity of a model without reducing the number of variables. It is a solution to a constrained estimation problem.

Importantly, the ridge penalty shrinks large regression coefficients of correlated predictors and reduces overfitting. Contrary to Lasso regression, an alternative regularization method, ridge regression does not shrink coefficients to zero.[16] It includes all independent variables in the data and is thus a good way to analyze results from conjoint survey experiments with a large number of restrictions. The "shrinkage estimators" performs better than OLS when the data matrix is

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[16]Lasso regression is thus especially useful for model selection.

relatively sparse, but it introduces a bias in the estimates due to the ridge penalty. Given that the bias introduced by the ridge penalty is systematic, it still allows us to make inferences about respondents' priorities in our case. Our empirical strategy thus provides a modelling strategy for the underlying utility function behind respondents' choice of fiscal packages, while maintaining predictive performance and interpretability.

We use the R package `glmnet` to find the best value of λ through cross-validation. We then proceed by using this optimal λ to estimate the regression coefficients (also referred to as AMCEs) and marginal means. Ridge regression does not provide standard errors for coefficients, but we rely on non-parametric boot-strapping to calculate standard errors and confidence intervals. To this end, we wrote a R function which calculates the same ridge regression 1000 times with a random sample of our observations and calculates standard errors based on the uncertainty of the results. This is a popular method for parametric inference, and it allows us to assign a measure of accuracy to the coefficients obtained from the ridge regression.

F   Additional results from the conjoint experiment

F.1   Marginal mean plots from the conjoint experiment

To test the robustness of our findings, we further calculated the marginal means for different groups in our conjoint survey experiments (following the recommendations of (Leeper et al., 2020). First, we calculated the marginal means for the overall sample to map the levels of favorability towards the multidimensional fiscal package across the various attribute levels (Figure A.7).

Second, we calculated marginal means for subgroups to test for heterogeneous effects by occupation, party family, ideology (left-right self placement), electoral participation (voting vs. abstention), asset ownership, different income groups (top 10 vs. bottom 90), employment activity, gender, and age (not shown). The results indicate that there are only few heterogeneous effects which are all very small.
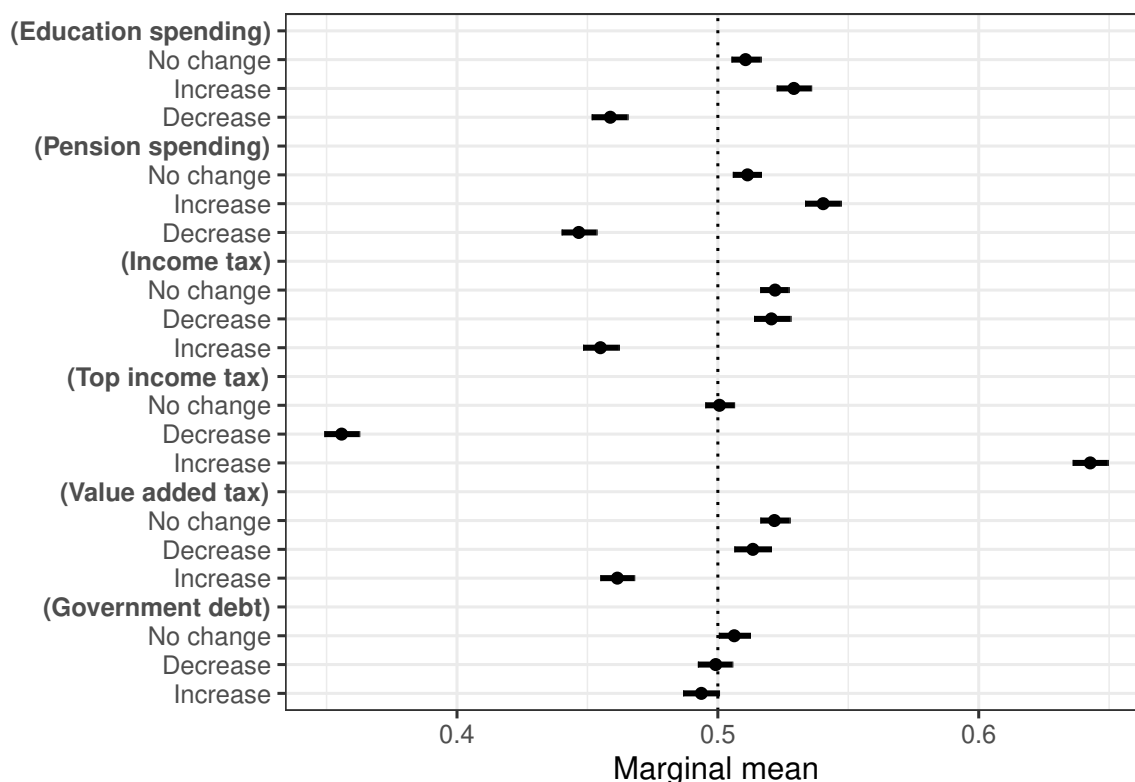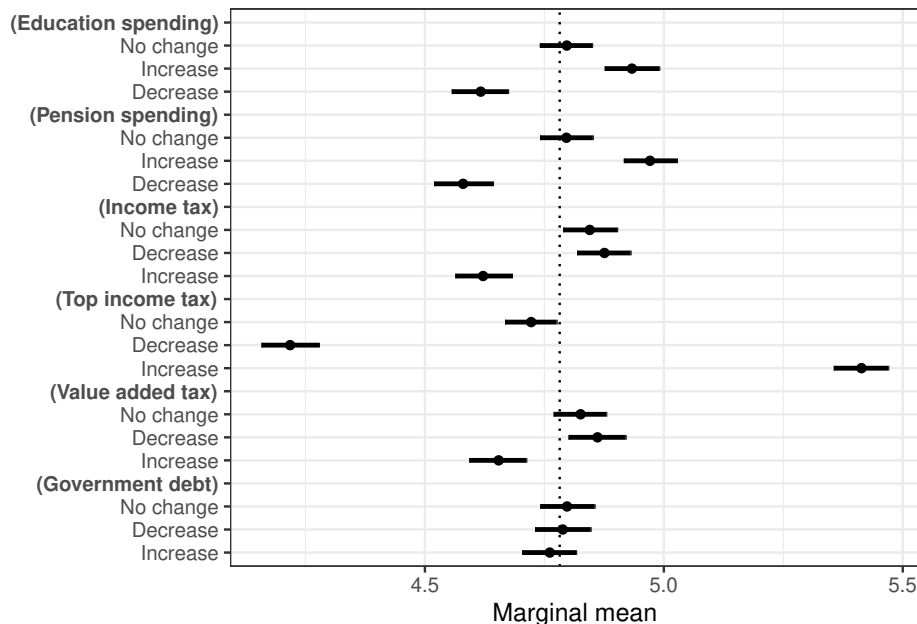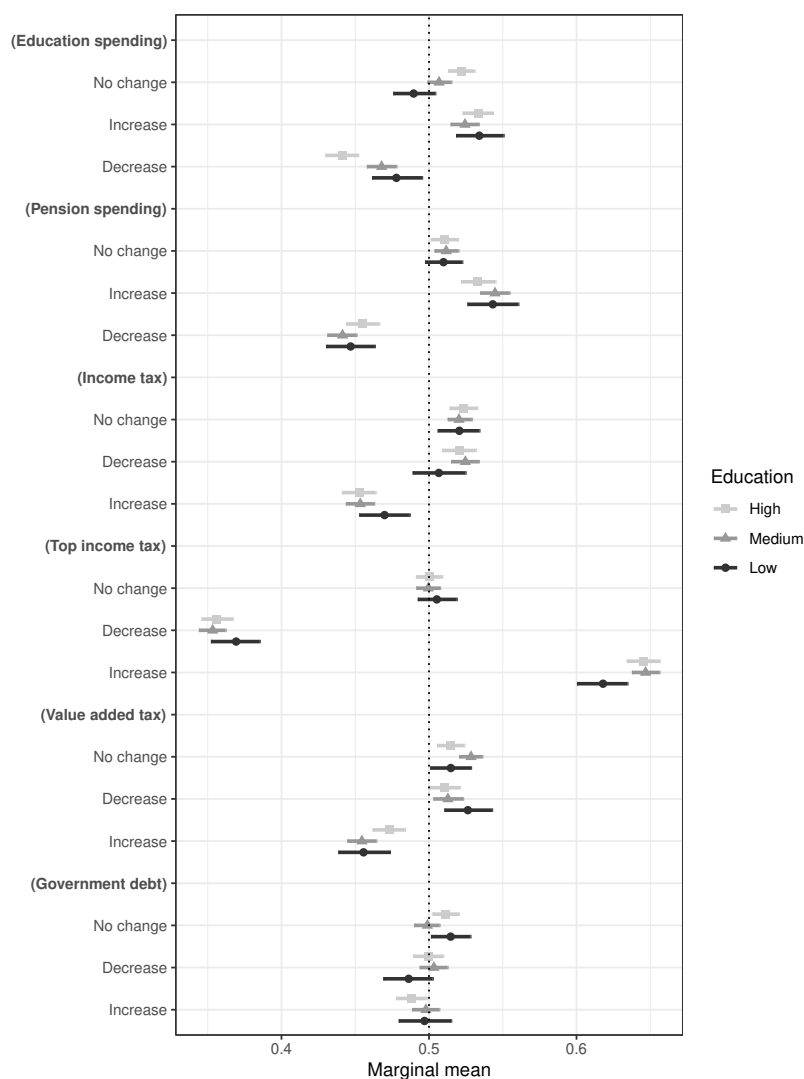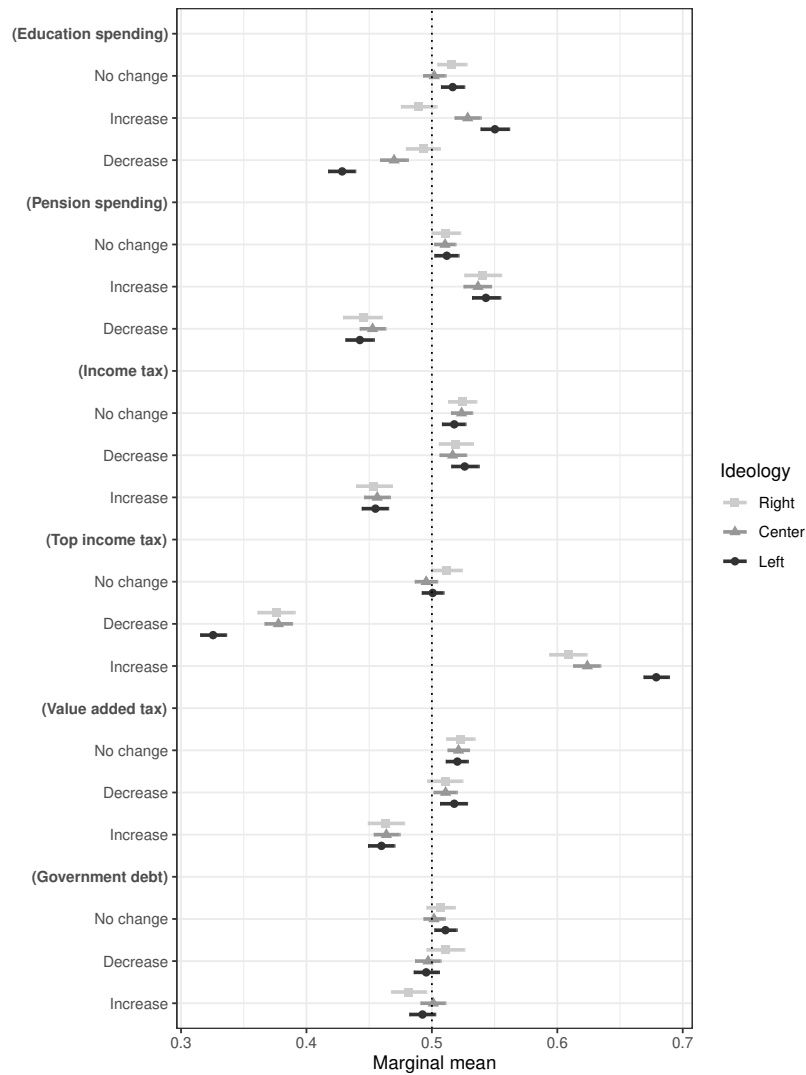

Figure A.7: Estimated marginal means from conjoint survey experiment, pooled.
Note: The figure shows the the conditional marginal means for all attribute levels. The marginal means measure how favorable respondents are to a given feature of the reform package.

F.2 Distribution plots based on rating variable
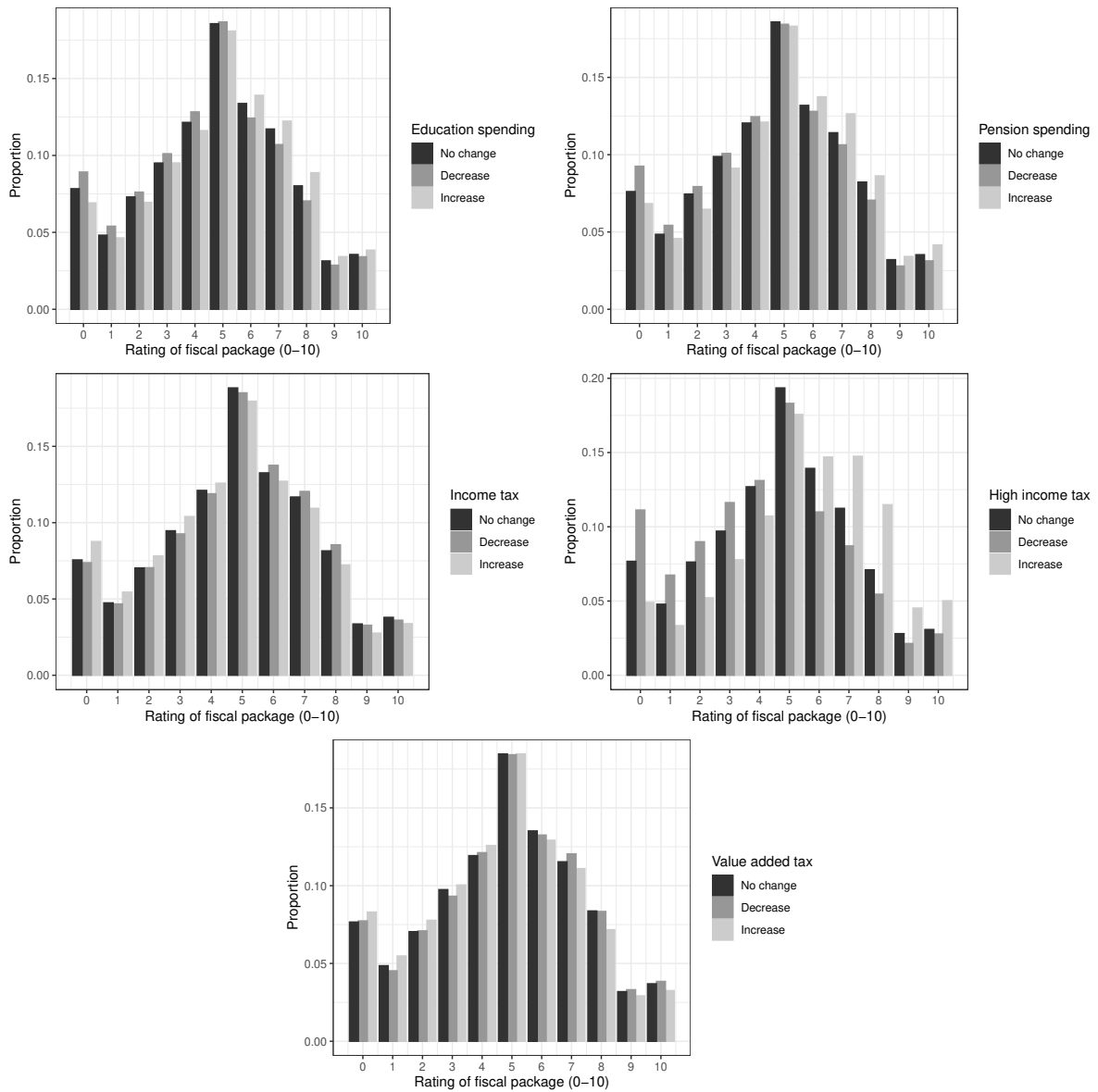
Figure A.8: Distribution of the ratings of all fiscal packages by changes of all attributes other than debt

Note: The figure shows the distribution of ratings of all conjoint packages by the attribute level for all attributes other than debt (e.g., no change, increase government debt, decrease government debt). The dependent variable asked respondents to rate each fiscal package on an 11-point Likert scale from 0 to 10.

F.3   Conjoint analysis with the rating variable
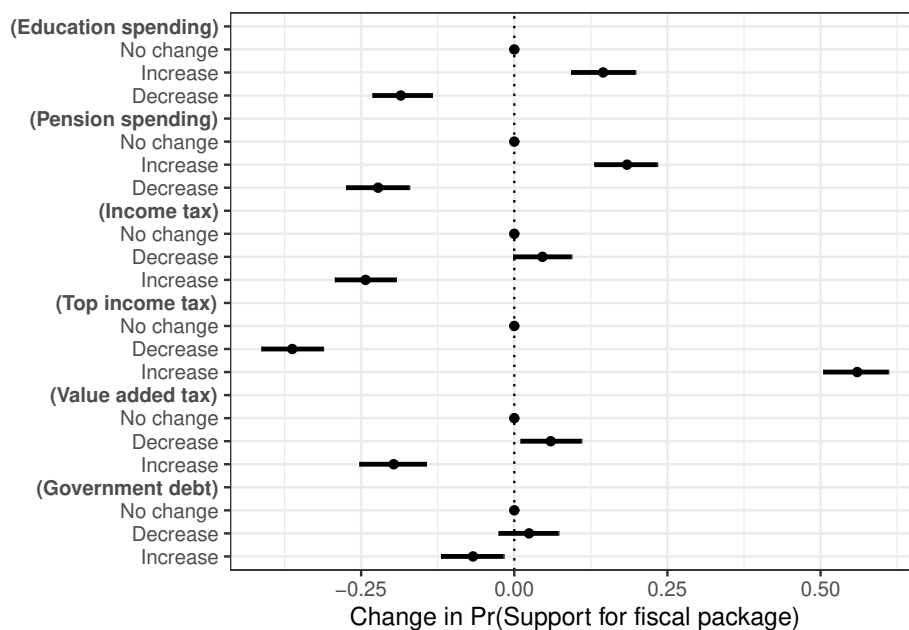
Figure A.9: AMCEs from conjoint survey experiment with rating variable, pooled.
Note: The figure shows the average marginal component effect (AMCE) of a change in the value of one of our six dimensions on the probability that the fiscal package is chosen by the respondent.

Figure A.10: Estimated marginal means from conjoint survey experiment with rating variable, pooled.
Note: The figure shows the the conditional marginal means for all attribute levels. The marginal means measure how favorable respondents are to a given feature of the reform package.

## F.4 Tests for other heterogeneous treatment effects from the conjoint experiment

Figure A.11: Estimated marginal means from the conjoint survey experiment by education
Note: The figure shows the conditional marginal means for all attribute levels by education. The marginal means measure how favorable respondents are to a given feature of the reform package. The figure distinguishes between three education groups (low, middle, high).

Figure A.12: Estimated marginal means from the conjoint survey experiment by ideology
Note: The figure shows the conditional marginal means for all attribute levels by ideology. The marginal means measure how favorable respondents are to a given feature of the reform package. The figure distinguishes between three ideological groups based on respondents' left-right self-placement.
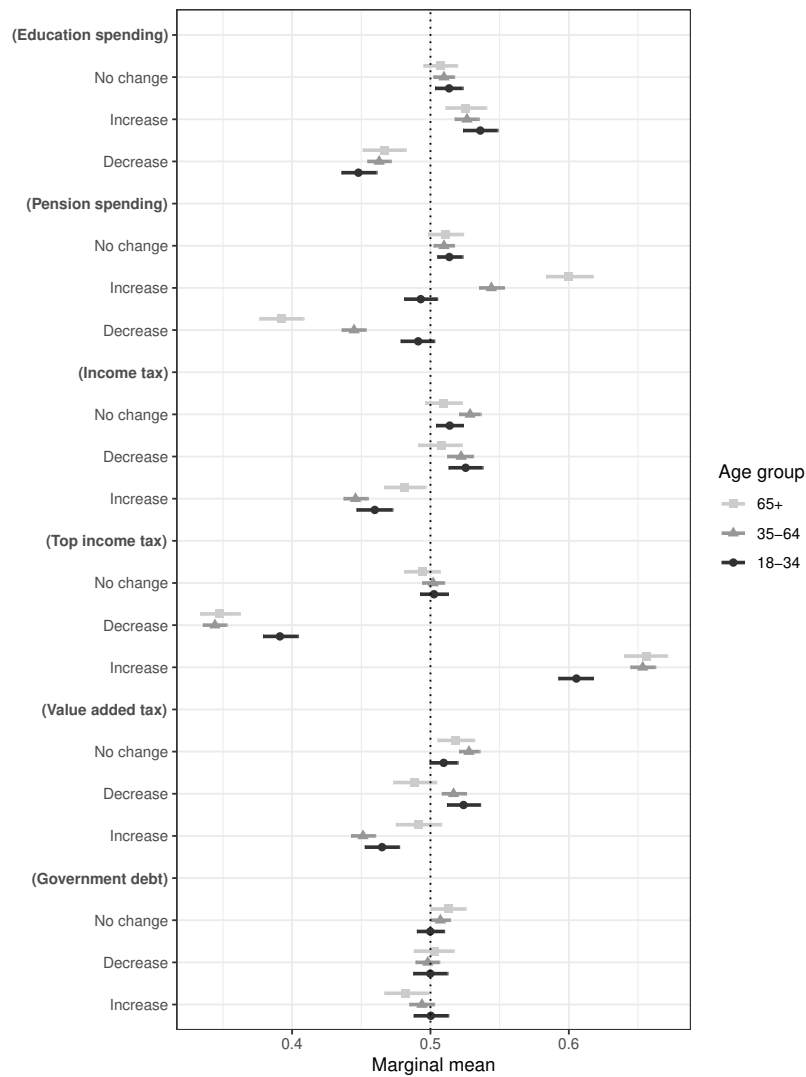
Figure A.13: Estimated marginal means from the conjoint survey experiment by age
Note: The figure shows the conditional marginal means for all attribute levels by age. The
marginal means measure how favorable respondents are to a given feature of the reform package.
The figure distinguishes between three age groups.

G Analysis with entropy balancing

We worked with the survey company *Qualtrics* to obtain an online sample that was representative of the population based on key indicators such as age and gender in each country. To test that there were no other biases in our sample that influence our results, however, we also used entropy balancing to create survey weights using the R package `ebal`. Based on margins from the population in each country, we created these weights based on age, gender, and education. We then replicated our analyses and the results are shown below. We also created weights based on income (not shown). Substantively, the results with the weighted analyses are not different from the results shown in the main text.
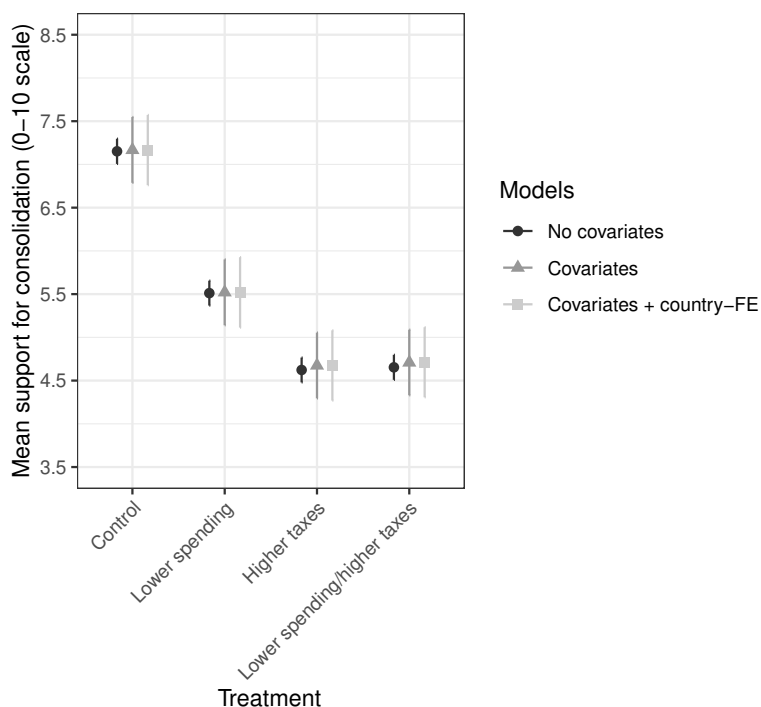
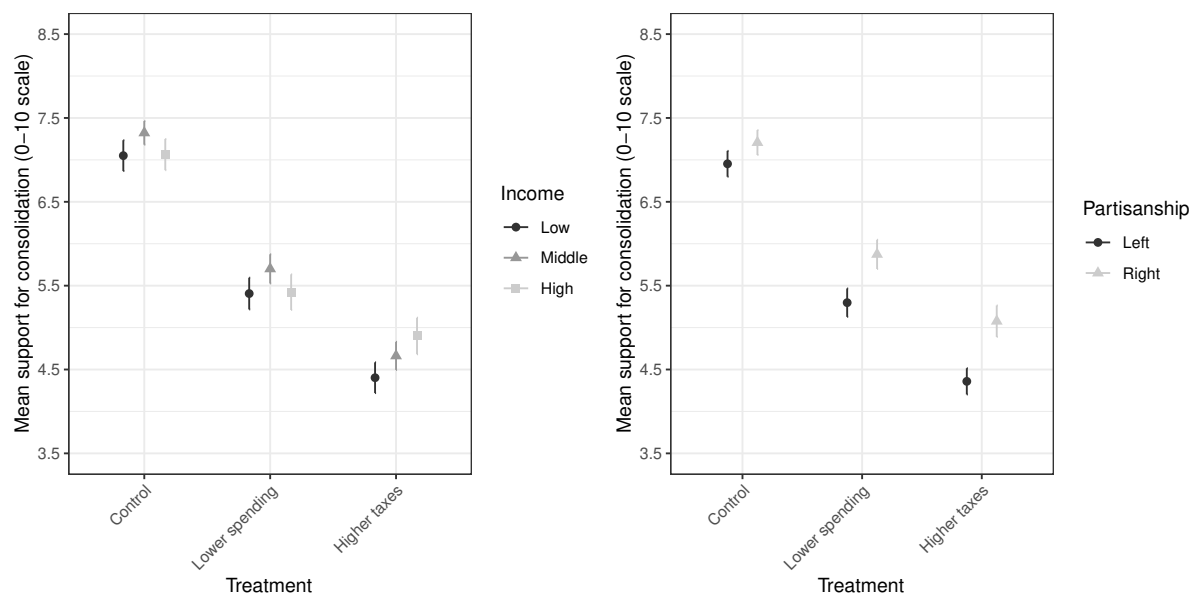Figure A.14: Weighted average support for fiscal consolidation by treatment

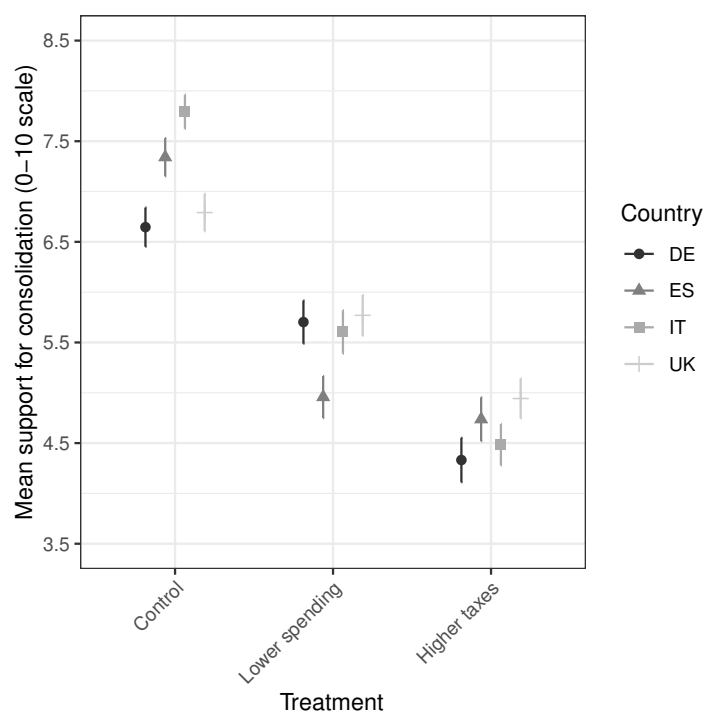Figure A.15: Weighted average support for fiscal consolidation by trade-off and income/partisanship

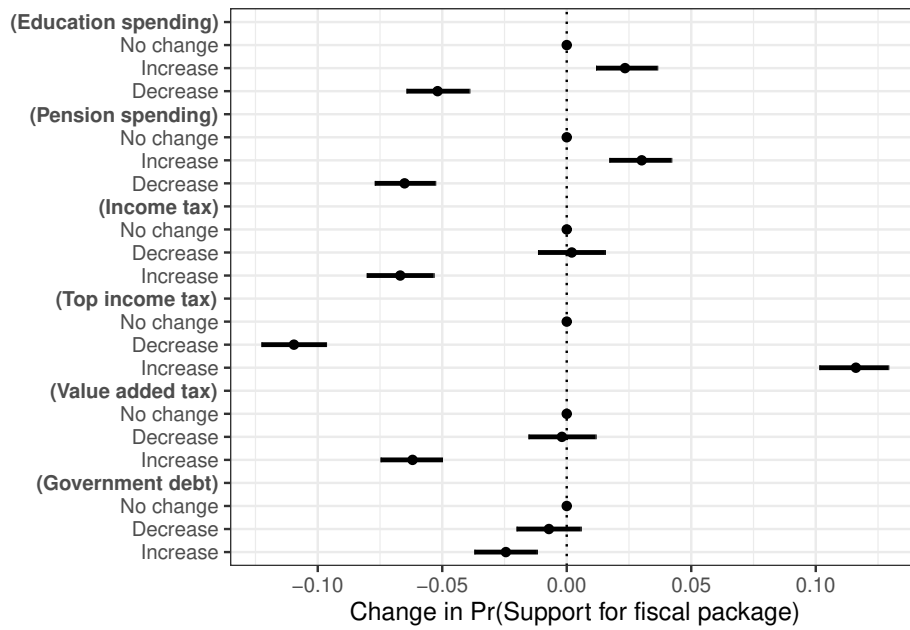Figure A.16: Weighted average support for fiscal consolidation by trade-off and country

Figure A.17: Weighted AMCEs from conjoint survey experiment
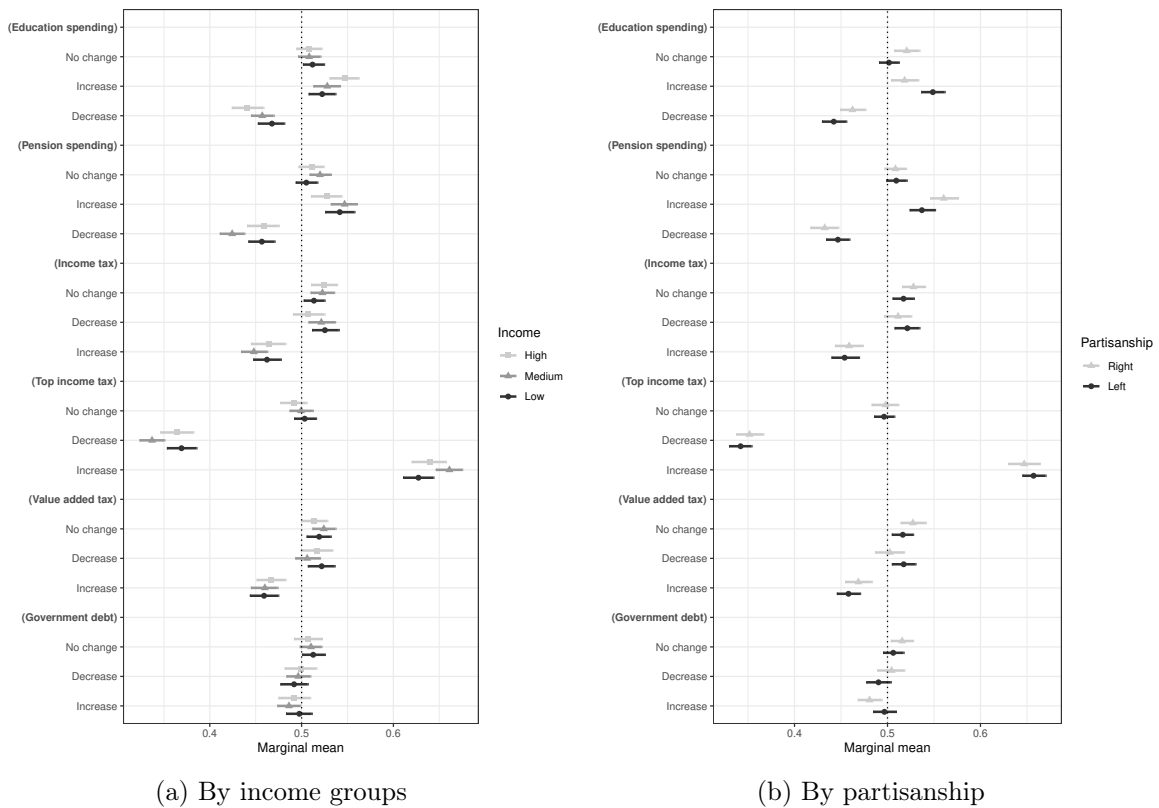

(a) By income groups

(b) By partisanship

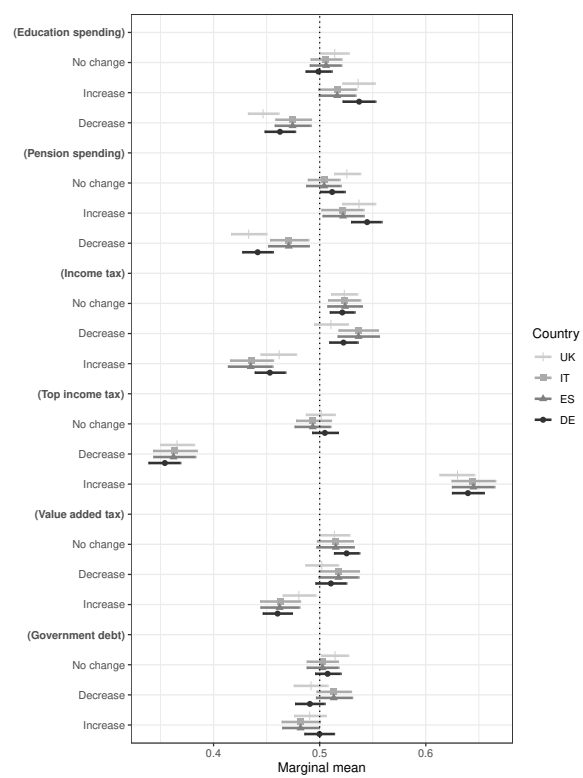Figure A.18: Weighted marginal means from conjoint survey experiment by income and party

Figure A.19: Weighted marginal means from conjoint survey experiment by country

H   Robustness tests for the conjoint survey experiment

We used a series of tests to confirm that the results are robust. These robustness tests were designed to check that the common assumptions involved in conjoint analysis are satisfied and to probe potential concerns about the validity of the results. On the one hand, we conducted several diagnostic tests suggested by Hainmueller et al. (2014). First, conjoint analyses relies on the assumption that there are no carryover effects between the different rounds of conjoint tasks. To test whether this assumption holds, we estimated AMCEs separately for each of the five rounds of conjoint tasks.

Second, we checked whether there are profile order effects, i.e., whether the AMCEs depend on whether the attribute occurs in the first or second profile in a given task. To this end, we estimated AMCEs separately for all the observations where attribute levels occurred in the first and the second profile respectively.

Finally, note that we already addressed the concern about atypical profiles raised by Hainmueller et al. (2014) in the research design. Specifically, we included a large number of restrictions to prevent profiles that are unrealistic and would not occur in the real world. This allows us to analyze the priorities of respondents under the presence of strong *and* realistic trade-offs.

One the other hand, we also used further robustness tests, which are important due to the design of the survey. First, we checked whether respondents lost concentration throughout the survey by estimating all results based on the first two (out of five) conjoint comparisons only. Moreover, we included round or task fixed effects to take account of the fact that respondents might make different choices in later stages of the conjoint experiment, for example due to fatigue or lack of concentration.

Second, we assessed the relative time that respondents took to complete the conjoint tasks and we excluded those respondents that speed through the conjoint tasks, comparing the results with the overall sample. We also distinguished respondents by the time that they took overall for the survey and used subgroup analysis to test whether our results are robust across groups.

Third, the conjoint survey experiment described above was embedded in a survey, which included two different set of conjoint tasks. The order in which these conjoint experiments

occurs in the survey was randomized. Still, we checked whether respondents are influenced in their evaluations of the conjoint profiles if they have already completed a different set of conjoint tasks beforehand. For this purpose, we split the sample and analyzed the results separately depending on whether the conjoint experiment occurred before or after the other conjoint experiment in the survey.

Fourth, there is also a possibility that the screen size might affect the way respondents evaluate the conjoint tasks. We therefore also separately analyzed responses from mobile versus non-mobile respondents and checked to what extent they differ. All of these robustness checks yielded similar results to the ones shown here.

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