Online Appendix for: "Promoting COVID-19 Vaccine Confidence through Public Responses to Misinformation: The Joint Influence of Message Source and Message Content"

Professor Reed M. Wood (University of Essex)
Dr. Marie Juanchich (University of Essex)
Dr. Mark Ramirez (Arizona State University)
Dr. Shenghao Zhang (Tsinghua University)

Ethics Approval: The Social Sciences Ethics Sub-Committee at the University of Essex reviewed and approved the application for ethical approval of this study (ETH-2122-0259).

Data for this project was collected via an online survey managed by the polling firm YouGov. Surveys were deployed in the United States and United Kingdom and comprised two waves. Wave 1 of the survey was deployed between 17 January 2022 and 21 January 2202, while Wave 2 was deployed between 7 February 2022 and 16 February 2022.

Queries and concerns about the project should be directed to the project lead at: Professor Reed Wood (reed.wood@essex.ac.uk). You can also contact the researchers in writing at: The Department of Government, University of Essex, Colchester CO4 3SQ, United Kingdom

Replication Materials: Data, codebooks, and commands to replicate all analyses reported in the manuscript and in this appendix can be found here: https://osf.io/nwkp3/

For any additional information, please contact Professor Wood at reed.wood@essex.ac.uk

Pre-registration: The study that led to this article was pre-registered with the Open Science Framework (OSF) (https://osf.io/wc854). We note, however, that one key aspect of the study deviated from the pre-registration plan. The hypotheses and analyses presented in this manuscript represent a subset of those proposed in our original pre-registration plan. In that plan, we originally presented nine hypotheses. The first subset of these hypotheses focused on the effects of misinformation correction strategies on respondent beliefs about the harms and side effects potentially associated with COVID-19 vaccines. We retain these in our current manuscript. The second subset of hypotheses focused on the effects of misinformation correction on respondent attitudes toward anti-vax protesters. We have reserved this second set of hypotheses for a separate manuscript. After filing the registration plan, we ultimately decided that questions regarding attitudes toward anti-vax protesters exceeded the scope of the argument we developed in the paper, and that journal space constraints would normally not allow for their inclusion.

At the time of this manuscript's acceptance, we have not fully analyzed the data necessary to evaluate the hypotheses on attitudes toward anti-vax protesters. Regardless, results from these analyses would be unlikely to change the findings presented in the manuscript at hand. In the interest of transparency, we make available all of the data associated with the original pre-registration plan. These data are located with our replication materials for this paper (https://osf.io/nwkp3/). Readers interested in these data may wish to specifically examine the variables entitled: "protest_benefitsociety", "protest_credible", "protest_raisequestions", protest_influencepeople", and "protest_threat". Information on these variables is available in the code book, which available with the rests of our replication materials. While we intend to use these data in a subsequent study, we welcome other scholars to use them in their own work.

Descriptive Statistics and Additional Analyses

Table A1.1: Summary Statistics by Country (US Sample)

Variable	N	Mean	Std. Dev.	Min	Max
White	1229	0.509	0.5	0	1
Black	1229	0.138	0.345	0	1
Latino	1229	0.112	0.316	0	1
Asian	1229	0.067	0.25	0	1
Other Race/Ethnicity	1229	0.175	0.38	0	1
Female	1229	0.541	0.499	0	1
Parent (Child < 12)	1229	1.731	0.443	1	2
Income	1058	7.956	4.012	1	14
Age	1229	47.564	17.627	18	94
University Education	1229	0.318	0.466	0	1
Ideology US	1120	2.971	1.229	1	5
Democrat	1229	0.379	0.485	0	1
Republican	1229	0.258	0.438	0	1
Trust National Govt.	1229	2.599	1.254	1	5
Trust Health Professionals	1229	3.587	1.074	1	5

Table A1.2: Summary Statistics by Country (UK Sample)

Variable	N	Mean	Std. Dev.	Min	Max
White	1276	0.833	0.373	0	1
Black	1276	0.049	0.217	0	1
South Asian	1276	0.048	0.213	0	1
Arab	1276	0.008	0.088	0	1
Chinese	1276	0.009	0.097	0	1
White Mixed	1276	0.012	0.108	0	1
Other Non-white	1276	0.026	0.159	0	1
Female	1276	0.542	0.498	0	1
Parent (Child < 12)	1276	1.767	0.423	1	2
Income	934	7.637	3.768	1	14
Age	1276	50.997	16.588	18	88
University Education	1276	0.339	0.473	0	1
Ideology UK	1203	3.81	1.19	1	7
Liberal Democrat	1276	0.068	0.252	0	1
Conservative	1276	0.265	0.441	0	1
SNP	1276	0.029	0.17	0	1
Labour	1276	0.244	0.43	0	1
UKIP/Brexit	1276	0.049	0.217	0	1
Trust National Govt.	1276	2.686	1.115	1	5
Trust Health Professionals	1276	3.697	0.962	1	5

Table A1.3: Summary Statistics by Experimental Condition (Control) (US)

Variable	N	Mean	Std. Dev.	Min	Max
White	247	0.466	0.5	0	1
Black	247	0.146	0.354	0	1
Latino	247	0.113	0.318	0	1
Asian	247	0.069	0.254	0	1
Other Race/Ethnicity	247	0.206	0.406	0	1
Female	247	0.51	0.501	0	1
Parent (Child < 12)	247	1.721	0.45	1	2
Income	217	8.014	3.914	1	14
Age	247	47.777	17.57	19	84
University Education	247	0.332	0.472	0	1
Ideology US	221	2.905	1.234	1	5
Democrat	247	0.364	0.482	0	1
Republican	247	0.231	0.422	0	1
Trust National Govt.	247	2.652	1.243	1	5
Trust Health Professionals	247	3.692	0.977	1	5

Table A1.4: Summary Statistics by Experimental Condition (Debunking Health) (US)

Variable	N	Mean	Std. Dev.	Min	Max
White	247	0.514	0.501	0	1
Black	247	0.146	0.354	0	1
Latino	247	0.121	0.327	0	1
Asian	247	0.049	0.215	0	1
Other Race/Ethnicity	247	0.17	0.376	0	1
Female	247	0.563	0.497	0	1
Parent (Child < 12)	247	1.729	0.446	1	2
Income	208	7.385	3.973	1	14
Age	247	46.206	17.825	18	91
University Education	247	0.283	0.452	0	1
Ideology US	225	2.893	1.175	1	5
Democrat	247	0.385	0.487	0	1
Republican	247	0.239	0.427	0	1
Trust National Govt.	247	2.636	1.238	1	5
Trust Health Professionals	247	3.575	1.105	1	5

Table A1.5: Summary Statistics by Experimental Condition (Debunking Political) (US)

Variable	N	Mean	Std. Dev.	Min	Max
White	245	0.535	0.5	0	1
Black	245	0.155	0.363	0	1
Latino	245	0.11	0.314	0	1
Asian	245	0.065	0.248	0	1
Other Race/Ethnicity	245	0.135	0.342	0	1
Female	245	0.571	0.496	0	1
Parent (Child < 12)	245	1.755	0.431	1	2
Income	209	7.9	4.003	1	14
Age	245	49.282	16.805	18	80
University Education	245	0.318	0.467	0	1
Ideology US	227	2.907	1.285	1	5
Democrat	245	0.404	0.492	0	1
Republican	245	0.245	0.431	0	1
Trust National Govt.	245	2.665	1.31	1	5
Trust Health Professionals	245	3.571	1.134	1	5

Table A1.6: Summary Statistics by Experimental Condition (Discrediting Health) (US)

Variable	N	Mean	Std. Dev.	Min	Max
White	244	0.529	0.5	0	1
Black	244	0.127	0.334	0	1
Latino	244	0.094	0.293	0	1
Asian	244	0.057	0.233	0	1
Other Race/Ethnicity	244	0.193	0.395	0	1
Female	244	0.533	0.5	0	1
Parent (Child < 12)	244	1.738	0.441	1	2
Income	212	8.547	4.106	1	14
Age	244	46.934	17.147	18	88
University Education	244	0.324	0.469	0	1
Ideology US	224	2.951	1.214	1	5
Democrat	244	0.393	0.49	0	1
Republican	244	0.279	0.449	0	1
Trust National Govt.	244	2.533	1.297	1	5
Trust Health Professionals	244	3.525	1.12	1	5

Table A1.7: Summary Statistics by Experimental condition (Discrediting Political) (US)

Variable	N	Mean	Std. Dev.	Min	Max
White	246	0.5	0.501	0	1
Black	246	0.114	0.318	0	1
Latino	246	0.122	0.328	0	1
Asian	246	0.093	0.292	0	1
Other Race/Ethnicity	246	0.171	0.377	0	1
Female	246	0.528	0.5	0	1
Parent (Child < 12)	246	1.715	0.452	1	2
Income	212	7.92	4.016	1	14
Age	246	47.626	18.715	18	94
University Education	246	0.333	0.472	0	1
Ideology US	223	3.202	1.219	1	5
Democrat	246	0.35	0.478	0	1
Republican	246	0.297	0.458	0	1
Trust National Govt.	246	2.508	1.181	1	5
Trust Health Professionals	246	3.573	1.027	1	5

Table A1.8: Summary Statistics by Experimental Condition (Control) (UK)

Variable	N	Mean	Std. Dev.	Min	Max
White	256	0.793	0.406	0	1
Black	256	0.062	0.243	0	1
South Asian	256	0.062	0.243	0	1
Arab	256	0.012	0.108	0	1
Chinese	256	0.008	0.088	0	1
White Mixed	256	0.004	0.062	0	1
Other Non-white	256	0.035	0.185	0	1
Female	256	0.555	0.498	0	1
Parent (Child < 12)	256	1.762	0.427	1	2
Income	180	7.717	3.916	1	14
Age	256	50.543	17.232	18	84
University Education	256	0.355	0.48	0	1
Ideology UK	238	3.693	1.237	1	7
Liberal Democrat	256	0.062	0.243	0	1
Conservative	256	0.254	0.436	0	1
SNP	256	0.027	0.163	0	1
Labour	256	0.238	0.427	0	1
UKIP/Brexit	256	0.035	0.185	0	1
Trust National Govt.	256	2.758	1.146	1	5
Trust Health Professionals	256	3.742	0.988	1	5

Table A1.9: Summary Statistics by Experimental Condition (Debunking Health) (UK)

Variable	N	Mean	Std. Dev.	Min	Max
White	255	0.855	0.353	0	1
Black	255	0.031	0.175	0	1
South Asian	255	0.043	0.204	0	1
Arab	255	0.004	0.063	0	1
Chinese	255	0.008	0.088	0	1
White Mixed	255	0.02	0.139	0	1
Other Non-white	255	0.031	0.175	0	1
Female	255	0.545	0.499	0	1
Parent (Child < 12)	255	1.78	0.415	1	2
Income	200	7.48	3.844	1	14
Age	255	52.337	16.479	18	87
University Education	255	0.325	0.469	0	1
Ideology UK	242	3.975	1.085	1	7
Liberal Democrat	255	0.075	0.263	0	1
Conservative	255	0.29	0.455	0	1
SNP	255	0.027	0.164	0	1
Labour	255	0.243	0.43	0	1
UKIP/Brexit	255	0.059	0.236	0	1
Trust National Govt.	255	2.773	1.117	1	5
Trust Health Professionals	255	3.698	0.947	1	5

Table A1.10: Summary Statistics by Experimental Condition (Debunking Political) (UK)

Variable	N	Mean	Std. Dev.	Min	Max
White	251	0.861	0.347	0	1
Black	251	0.032	0.176	0	1
South Asian	251	0.052	0.222	0	1
Arab	251	0	0	0	0
Chinese	251	0.012	0.109	0	1
White Mixed	251	0.008	0.089	0	1
Other Non-white	251	0.024	0.153	0	1
Female	251	0.506	0.501	0	1
Parent (Child < 12)	251	1.749	0.434	1	2
Income	186	7.645	3.575	1	14
Age	251	51.084	16.646	18	85
University Education	251	0.315	0.465	0	1
Ideology UK	240	3.829	1.251	1	7
Liberal Democrat	251	0.064	0.245	0	1
Conservative	251	0.259	0.439	0	1
SNP	251	0.032	0.176	0	1
Labour	251	0.227	0.42	0	1
UKIP/Brexit	251	0.056	0.23	0	1
Trust National Govt.	251	2.681	1.114	1	5
Trust Health Professionals	251	3.693	0.979	1	5

Table A1.11: Summary Statistics by Experimental condition (Discrediting Health) (UK)

Variable	N	Mean	Std. Dev.	Min	Max
White	255	0.851	0.357	0	1
Black	255	0.055	0.228	0	1
South Asian	255	0.035	0.185	0	1
Arab	255	0.004	0.063	0	1
Chinese	255	0.012	0.108	0	1
White Mixed	255	0.012	0.108	0	1
Other Non-white	255	0.024	0.152	0	1
Female	255	0.569	0.496	0	1
Parent (Child < 12)	255	1.741	0.439	1	2
Income	186	7.457	3.92	1	14
Age	255	51.012	16.24	19	88
University Education	255	0.365	0.482	0	1
Ideology UK	241	3.9	1.147	1	7
Liberal Democrat	255	0.075	0.263	0	1
Conservative	255	0.286	0.453	0	1
SNP	255	0.031	0.175	0	1
Labour	255	0.22	0.415	0	1
UKIP/Brexit	255	0.059	0.236	0	1
Trust National Govt.	255	2.631	1.152	1	5
Trust Health Professionals	255	3.643	0.973	1	5

Table A1.12: Summary Statistics by Experimental condition (Discrediting Political) (UK)

Variable	N	Mean	Std. Dev.	Min	Max
White	259	0.807	0.395	0	1
Black	259	0.066	0.248	0	1
South Asian	259	0.046	0.211	0	1
Arab	259	0.019	0.138	0	1
Chinese	259	0.008	0.088	0	1
White Mixed	259	0.015	0.124	0	1
Other Non-white	259	0.015	0.124	0	1
Female	259	0.537	0.5	0	1
Parent (Child < 12)	259	1.803	0.398	1	2
Income	182	7.907	3.587	1	14
Age	259	50.027	16.368	18	82
University Education	259	0.332	0.472	0	1
Ideology UK	242	3.649	1.2	1	7
Liberal Democrat	259	0.066	0.248	0	1
Conservative	259	0.236	0.425	0	1
SNP	259	0.031	0.173	0	1
Labour	259	0.29	0.454	0	1
UKIP/Brexit	259	0.039	0.193	0	1
Trust National Govt.	259	2.587	1.04	1	5
Trust Health Professionals	259	3.71	0.926	1	5

Table A1.13: Effects of Treatment Conditions on Respondent Vaccine Beliefs

	Model 1 Severe Side Effects US	Model 2 Severe Side Effects UK	Model 3 Harm Vulnerable US	Model 4 Harm Vulnerable UK
Severe Side Effects (w1)	0.815***	0.752***		
	(0.020)	(0.022)		
Harm Vulnerable (w1)			0.723***	0.646***
			(0.022)	(0.024)
Debunking (Health)	-0.163+	-0.186*	-0.084	-0.237**
	(0.089)	(0.073)	(0.100)	(0.082)
Debunking (Political)	0.057	-0.080	0.008	-0.031
	(0.088)	(0.074)	(0.099)	(0.083)
Discrediting (Health)	-0.022	-0.025	0.119	-0.009
	(0.088)	(0.073)	(0.098)	(0.082)
Discrediting (Political)	0.061	0.023	0.115	-0.053
	(0.088)	(0.073)	(0.098)	(0.082)
Intercept	0.557***	0.602***	0.740***	0.856***
	(0.084)	(0.074)	(0.097)	(0.085)
Num. Obs.	1054	1203	1054	1203
R2	0.619	0.506	0.503	0.385
R2 Adj.	0.617	0.504	0.501	0.382
AIC	2793.1	2889.8	3037.2	3166.9
BIC	2827.8	2925.5	3071.9	3202.5
Log.Lik.	-1389.535	-1437.905	-1511.604	-1576.428
RMSE	0.90	0.80	1.02	0.90

Coefficients and standard errors (in parentheses) from OLS models. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A1.14: Conditional Effect of Vaccination Status - Debunking (Health)

	Model 1 Severe Side Effects US	Model 2 Severe Side Effects UK	Model 3 Harm Vulnerable US	Model 4 Harm Vulnerable UK
Debunking (Health) × Unvaccinated	0.123	-0.262	-0.084	0.123
	(0.182)	(0.233)	(0.200)	(0.259)
Unvaccinated	0.585***	0.762***	0.751***	0.855***
	(0.088)	(0.120)	(0.094)	(0.134)
Severe Side Effects (w1)	0.728***	0.685***		
	(0.023)	(0.023)		
Harm Vulnerable (w1)			0.634***	0.565***
			(0.024)	(0.025)
Debunking (Health)	-0.217*	-0.182*	-0.107	-0.256**
	(0.095)	(0.073)	(0.105)	(0.081)
Debunking (Political)	0.024	-0.093	-0.062	-0.041
	(0.087)	(0.073)	(0.096)	(0.081)
Discrediting (Health)	-0.018	-0.056	0.058	-0.045
	(0.087)	(0.072)	(0.096)	(0.081)
Discrediting (Political)	0.062	0.016	0.054	-0.059
	(0.087)	(0.072)	(0.096)	(0.080)
Intercept	0.683***	0.731***	0.882***	1.018***
	(0.085)	(0.075)	(0.095)	(0.085)
Num.Obs.	1003	1194	1003	1194
R2	0.635	0.514	0.544	0.402
R2 Adj.	0.633	0.511	0.541	0.399
AIC	2611.4	2826.5	2799.8	3085.3
BIC	2655.6	2872.3	2844.0	3131.1
Log.Lik.	-1296.684	-1404.270	-1390.887	-1533.671
RMSE	0.88	0.78	0.97	0.87

Coefficients and standard errors (in parentheses) from OLS models. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A1.15: Conditional Effect of Vaccination Status- Debunking (Political)

	Model 1 Severe Side Effects US	Model 2 Severe Side Effects UK	Model 3 Harm Vulnerable US	Model 4 Harm Vulnerable UK
Debunking (Political) × Unvaccinated	-0.239	-0.045	0.055	-0.233
	(0.170)	(0.238)	(0.187)	(0.265)
Unvaccinated	0.658***	0.709***	0.724***	0.938***
	(0.088)	(0.120)	(0.095)	(0.133)
Severe Side Effects (w1)	0.730***	0.685***		
	(0.023)	(0.023)		
Harm Vulnerable (w1)			0.633***	0.564***
			(0.024)	(0.025)
Debunking (Health)	-0.194*	-0.198**	-0.123	-0.250**
	(0.089)	(0.072)	(0.098)	(0.080)
Debunking (Political)	0.074	-0.089	-0.073	-0.028
	(0.094)	(0.074)	(0.103)	(0.082)
Discrediting (Health)	-0.020	-0.054	0.058	-0.048
	(0.087)	(0.072)	(0.096)	(0.081)
Discrediting (Political)	0.062	0.016	0.054	-0.059
	(0.087)	(0.072)	(0.096)	(0.080)
Intercept	0.664***	0.732***	0.888***	1.018***
	(0.085)	(0.075)	(0.095)	(0.085)
Num.Obs.	1003	1194	1003	1194
R2	0.636	0.513	0.544	0.403
R2 Adj.	0.633	0.510	0.541	0.399
AIC	2609.8	2827.8	2799.9	3084.8
BIC	2654.0	2873.5	2844.1	3130.6
Log.Lik.	-1295.917	-1404.889	-1390.933	-1533.395
RMSE	0.88	0.78	0.97	0.87

Coefficients and standard errors (in parentheses) from OLS models. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A1.16: Conditional Effect of Vaccination Status - Discrediting (Health)

	Model 1 Severe Side Effects US	Model 2 Severe Side Effects UK	Model 3 Harm Vulnerable US	Model 4 Harm Vulnerable UK
Discrediting (Health) × Unvaccinated	0.083	0.224	-0.070	0.297
	(0.175)	(0.221)	(0.192)	(0.246)
Unvaccinated	0.591***	0.638***	0.750***	0.804***
	(0.089)	(0.123)	(0.095)	(0.136)
Severe Side Effects (w1)	0.728***	0.685***		
	(0.023)	(0.023)		
Harm Vulnerable (w1)			0.633***	0.564***
			(0.024)	(0.025)
Debunking (Health)	-0.193*	-0.196**	-0.123	-0.246**
	(0.089)	(0.072)	(0.098)	(0.080)
Debunking (Political)	0.024	-0.090	-0.062	-0.039
	(0.087)	(0.073)	(0.096)	(0.081)
Discrediting (Health)	-0.035	-0.069	0.072	-0.067
	(0.094)	(0.074)	(0.103)	(0.082)
Discrediting (Political)	0.062	0.016	0.054	-0.059
	(0.087)	(0.072)	(0.096)	(0.080)
Intercept	0.682***	0.734***	0.882***	1.023***
	(0.085)	(0.075)	(0.095)	(0.085)
Num.Obs.	1003	1194	1003	1194
R2	0.635	0.513	0.544	0.403
R2 Adj.	0.633	0.511	0.541	0.400
AIC	2611.6	2826.8	2799.8	3084.1
BIC	2655.8	2872.5	2844.0	3129.9
Log.Lik.	-1296.801	-1404.391	-1390.910	-1533.051
RMSE	0.88	0.78	0.97	0.87

Coefficients and standard errors (in parentheses) from OLS models. + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table A1.17: Conditional Effect of Vaccination Status - Discrediting (Political)

	Model 1 Severe Side Effects US	Model 2 Severe Side Effects UK	Model 3 Harm Vulnerable US	Model 4 Harm Vulnerable UK
Discrediting (Political) × Unvaccinated	0.024	-0.224	0.185	-0.362
	(0.181)	(0.288)	(0.199)	(0.321)
Unvaccinated	0.603***	0.728***	0.699***	0.931***
	(0.089)	(0.113)	(0.095)	(0.125)
Severe Side Effects (w1)	0.728***	0.686***		
	(0.023)	(0.023)		
Harm Vulnerable (w1)			0.635***	0.567***
			(0.024)	(0.025)
Debunking (Health)	-0.193*	-0.199**	-0.123	-0.250**
	(0.089)	(0.072)	(0.098)	(0.080)
Debunking (Political)	0.024	-0.092	-0.060	-0.043
	(0.087)	(0.073)	(0.095)	(0.081)
Discrediting (Health)	-0.018	-0.055	0.058	-0.048
	(0.087)	(0.072)	(0.096)	(0.081)
Discrediting (Political)	0.058	0.024	0.021	-0.045
	(0.093)	(0.073)	(0.103)	(0.081)
Intercept	0.680***	0.728***	0.888***	1.012***
	(0.085)	(0.076)	(0.095)	(0.085)
Num.Obs.	1003	1194	1003	1194
R2	0.635	0.513	0.544	0.403
R2 Adj.	0.633	0.510	0.541	0.399
AIC	2611.8	2827.2	2799.1	3084.3
BIC	2656.0	2873.0	2843.3	3130.1
Log.Lik.	-1296.906	-1404.604	-1390.543	-1533.144
RMSE	0.88	0.78	0.97	0.87

Coefficients and standard errors (in parentheses) from OLS models. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A1.18: Conditional Effect of Political Ideology- Debunking (Health)

	Model 1 Severe Side Effects US	Model 2 Severe Side Effects UK	Model 3 Harm Vulnerable US	Model 4 Harm Vulnerable UK
Debunking (Health) × Ideology US	0.158**		0.169*	
	(0.060)		(0.067)	
Debunking (Health) × Ideology UK		0.002		0.064
		(0.053)		(0.059)
Severe Side Effects (w1)	0.770***	0.737***		
	(0.022)	(0.022)		
Harm Vulnerable (w1)			0.674***	0.633***
			(0.024)	(0.024)
Debunking (Health)	-0.580**	-0.228	-0.519*	-0.530*
	(0.196)	(0.221)	(0.218)	(0.246)
Debunking (Political)	0.052	-0.071	0.028	-0.037
	(0.087)	(0.075)	(0.097)	(0.083)
Discrediting (Health)	-0.010	-0.025	0.114	-0.045
	(0.088)	(0.075)	(0.098)	(0.083)
Discrediting (Political)	0.012	-0.011	0.041	-0.105
	(0.088)	(0.074)	(0.098)	(0.082)
Ideology UK		0.048*		0.025
		(0.022)		(0.025)
Ideology US	0.136***		0.167***	
	(0.027)		(0.030)	
Intercept	0.275**	0.458***	0.382***	0.793***
	(0.102)	(0.108)	(0.115)	(0.122)
Num.Obs.	972	1145	972	1145
R2	0.650	0.504	0.550	0.389
R2 Adj.	0.648	0.501	0.547	0.385
AIC	2498.9	2726.4	2706.9	2971.9
BIC	2542.8	2771.8	2750.8	3017.3
Log.Lik.	-1240.453	-1354.208	-1344.450	-1476.934
RMSE	0.87	0.79	0.96	0.88

Coefficients and standard errors (in parentheses) from OLS models. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A1.19: Conditional Effect of Ideology - Debunking (Political)

	Model 1 Severe Side Effects US	Model 2 Severe Side Effects UK	Model 3 Harm Vulnerable US	Model 4 Harm Vulnerable UK
Debunking (Political) × Ideology US	-0.042		0.024	
	(0.055)		(0.061)	
Debunking (Political) × Ideology UK		0.018		0.006
		(0.049)		(0.054)
Ideology UK		0.044+		0.035
		(0.023)		(0.025)
Ideology US	0.171***		0.190***	
	(0.028)		(0.031)	
Severe Side Effects (w1)	0.773***	0.736***		
	(0.022)	(0.022)		
Harm Vulnerable (w1)			0.676***	0.634***
			(0.024)	(0.024)
Debunking (Health)	-0.118	-0.218**	-0.028	-0.279***
	(0.090)	(0.074)	(0.100)	(0.082)
Debunking (Political)	0.175	-0.140	-0.040	-0.060
	(0.181)	(0.200)	(0.202)	(0.222)
Discrediting (Health)	-0.011	-0.024	0.114	-0.047
	(0.088)	(0.075)	(0.098)	(0.083)
Discrediting (Political)	0.002	-0.011	0.035	-0.104
	(0.089)	(0.074)	(0.099)	(0.082)
Intercept	0.163	0.471***	0.308**	0.756***
	(0.104)	(0.110)	(0.116)	(0.124)
Num.Obs.	972	1145	972	1145
R2	0.648	0.505	0.547	0.388
R2 Adj.	0.646	0.501	0.544	0.384
AIC	2505.4	2726.3	2713.2	2973.0
BIC	2549.3	2771.7	2757.1	3018.4
Log.Lik.	-1243.684	-1354.139	-1347.597	-1477.516
RMSE	0.87	0.79	0.97	0.88

Coefficients and standard errors (in parentheses) from OLS models. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A1.20: Conditional Effect of Ideology - Discrediting (Health)

	Model 1 Severe Side Effects US	Model 2 Severe Side Effects UK	Model 3 Harm Vulnerable US	Model 4 Harm Vulnerable UK
Discrediting (Health) × Ideology US	0.019		-0.004	
	(0.057)		(0.063)	
Discrediting (Health) × Ideology UK		-0.013		0.030
		(0.051)		(0.057)
Ideology UK		0.050*		0.031
		(0.022)		(0.025)
Ideology US	0.159***		0.196***	
	(0.027)		(0.030)	
Severe Side Effects (w1)	0.772***	0.737***		
	(0.022)	(0.022)		
Harm Vulnerable (w1)			0.676***	0.634***
			(0.024)	(0.024)
Debunking (Health)	-0.119	-0.220**	-0.028	-0.278***
	(0.090)	(0.074)	(0.100)	(0.082)
Debunking (Political)	0.054	-0.071	0.030	-0.038
	(0.088)	(0.075)	(0.098)	(0.083)
Discrediting (Health)	-0.065	0.027	0.126	-0.162
	(0.189)	(0.211)	(0.210)	(0.235)
Discrediting (Political)	0.006	-0.011	0.033	-0.104
	(0.089)	(0.074)	(0.099)	(0.082)
Intercept	0.202*	0.447***	0.290*	0.772***
	(0.103)	(0.109)	(0.116)	(0.123)
Num.Obs.	972	1145	972	1145
R2	0.648	0.505	0.547	0.388
R2 Adj.	0.645	0.501	0.544	0.385
AIC	2505.8	2726.3	2713.3	2972.8
BIC	2549.8	2771.7	2757.3	3018.2
Log.Lik.	-1243.924	-1354.175	-1347.673	-1477.385
RMSE	0.87	0.79	0.97	0.88

Coefficients and standard errors (in parentheses) from OLS models. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A1.21: Conditional Effect of Ideology - Discrediting (Political)

	Model 1 Severe Side Effects US	Model 2 Severe Side Effects UK	Model 3 Harm Vulnerable US	Model 4 Harm Vulnerable UK
Discrediting (Political) × Ideology US	-0.062		-0.105	
	(0.058)		(0.064)	
Discrediting (Political) × Ideology UK		0.018		0.001
		(0.049)		(0.055)
Ideology UK		0.044+		0.036
		(0.023)		(0.025)
Ideology US	0.175***		0.216***	
	(0.027)		(0.030)	
Severe Side Effects (w1)	0.772***	0.737***		
	(0.022)	(0.022)		
Harm Vulnerable (w1)			0.675***	0.634***
			(0.024)	(0.024)
Debunking (Health)	-0.118	-0.218**	-0.028	-0.279***
	(0.090)	(0.074)	(0.100)	(0.082)
Debunking (Political)	0.054	-0.070	0.031	-0.038
	(0.088)	(0.075)	(0.097)	(0.083)
Discrediting (Health)	-0.010	-0.024	0.114	-0.048
	(0.088)	(0.075)	(0.098)	(0.083)
Discrediting (Political)	0.202	-0.078	0.365	-0.109
	(0.202)	(0.194)	(0.225)	(0.216)
Intercept	0.156	0.470***	0.233*	0.752***
	(0.102)	(0.109)	(0.115)	(0.123)
Num.Obs.	972	1145	972	1145
R2	0.648	0.505	0.548	0.388
R2 Adj.	0.646	0.501	0.545	0.384
AIC	2504.8	2726.3	2710.6	2973.0
BIC	2548.7	2771.7	2754.6	3018.4
Log.Lik.	-1243.387	-1354.138	-1346.320	-1477.521
RMSE	0.87	0.79	0.97	0.88

Coefficients and standard errors (in parentheses) from OLS models. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A1.22: Results with complete sample of respondents

	Model 1 Severe Side Effects US	Model 2 Severe Side Effects UK	Model 3 Harm Vulnerable US	Model 4 Harm Vulnerable UK
Severe Side Effects (w1)	0.790***	0.744***		
	(0.019)	(0.021)		
Harm Vulnerable (w1)			0.694***	0.646***
			(0.022)	(0.023)
Debunking (Health)	-0.157+	-0.177*	-0.062	-0.239**
	(0.086)	(0.074)	(0.096)	(0.082)
Debunking (Political)	0.039	-0.074	-0.002	-0.017
	(0.086)	(0.074)	(0.097)	(0.082)
Discrediting (Health)	-0.081	-0.027	0.085	-0.006
	(0.086)	(0.074)	(0.097)	(0.082)
Discrediting (Political)	0.034	0.001	0.091	-0.044
	(0.086)	(0.074)	(0.097)	(0.081)
Intercept	0.653***	0.651***	0.840***	0.876***
	(0.082)	(0.075)	(0.095)	(0.084)
Num. Obs.	1229	1276	1229	1276
R2	0.584	0.495	0.461	0.386
R2 Adj.	0.583	0.493	0.459	0.383
AIC	3382.8	3167.8	3665.6	3422.7
BIC	3418.6	3203.9	3701.4	3458.7
Log.Lik.	-1684.411	-1576.915	-1825.783	-1704.334
RMSE	0.95	0.83	1.07	0.92

Coefficients and standard errors (in parentheses) from OLS models. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Results include speeders and respondents who failed attention check.

Table A1.23: Results including Control Variables

	Model 1 Severe Side Effects US	Model 2 Severe Side Effects UK	Model 3 Harm Vulnerable US	Model 4 Harm Vulnerable UK
Severe Side Effects (w1)	0.663***	0.627***		
	(0.027)	(0.029)		
Harm Vulnerable (w1)			0.572***	0.544***
			(0.028)	(0.031)
Debunking (Health)	-0.180+	-0.183*	-0.108	-0.263**
	(0.097)	(0.086)	(0.105)	(0.094)
Debunking (Political)	0.050	-0.061	0.009	-0.081
	(0.093)	(0.088)	(0.100)	(0.096)
Discrediting (Health)	0.005	0.028	0.077	-0.073
	(0.093)	(0.088)	(0.101)	(0.096)
Discrediting (Political)	0.013	-0.075	0.021	-0.161+
	(0.094)	(0.089)	(0.101)	(0.097)
Trust Health Professionals	-0.142***	-0.085*	-0.125**	-0.149***
	(0.036)	(0.034)	(0.038)	(0.037)
Trust National Govt.	-0.136***	-0.050+	-0.151***	-0.042
	(0.032)	(0.028)	(0.035)	(0.031)
Black (US/UK)	0.196+	0.113	0.364***	0.290**
	(0.100)	(0.133)	(0.108)	(0.146)
South Asian (UK)		0.406**		0.266
		(0.158)		(0.171)
Arab (UK)		0.181		0.779*
		(0.331)		(0.360)
Chinese (UK)		-0.178		-0.086
		(0.331)		(0.359)
Latino (US)	-0.087		0.079	
	(0.110)		(0.118)	
Asian (US)	0.011		0.059	
	(0.133)		(0.143)	
White Mixed (UK)		-0.092		
		(0.235)		
Other Non-white (UK)		0.051		0.167
		(0.184)		(0.229)
Other Race (US)	-0.003		0.253**	
	(0.090)		(0.097)	
Female	-0.065	0.049	-0.050	0.011
	(0.061)	(0.056)	(0.066)	(0.061)
Parent (Child < 12)	0.088	0.096	0.194*	0.205**
	(0.073)	(0.071)	(0.079)	(0.078)
Age	-0.002	-0.003	-0.003	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)
University Education	-0.003	-0.083	-0.084	-0.088
	(0.070)	(0.064)	(0.075)	(0.070)
Income	-0.014	-0.009	-0.010	-0.011
	(0.009)	(0.008)	(0.009)	(0.009)
Ideology UK		0.061*		0.049

		(0.029)		(0.032)
Liberal Democrat		0.090		0.104
		(0.111)		(0.121)
UKIP		0.276*		0.063
		(0.128)		(0.139)
SNP		-0.106		-0.058
		(0.159)		(0.173)
Labour		0.099		0.050
		(0.075)		(0.082)
Ideology US	0.104**		0.131***	
	(0.032)		(0.034)	
Democrat	0.022		0.047	
	(0.081)		(0.087)	
Republican	0.199*		0.209*	
	(0.083)		(0.090)	
Intercept	1.695***	1.239***	1.771***	1.779***
	(0.250)	(0.250)	(0.269)	(0.271)
Num.Obs.	836	851	836	851
R2	0.662	0.496	0.593	0.422
R2 Adj.	0.654	0.483	0.583	0.406
AIC	2143.7	2047.7	2270.3	2190.3
BIC	2243.0	2161.6	2369.6	2304.2
Log.Lik.	-1050.849	-999.859	-1114.127	-1071.128
RMSE	0.85	0.80	0.92	0.85

Coefficients and standard errors (in parentheses) from OLS models. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A1.24: Comparison of Wave 2 Samples to Corresponding Populations

	US Population	US Sample	UK Population	UK Sample
Female	51%	54%	51%	54%
65 or over	17%	20%	23%	27%
High school degree or some college (US)	55%	56%	NA	NA
Level 3 Qualification or higher (UK)*	NA	NA	66%	62%
University degree	33%	32%	30%	34%
White	59%	51%	81%	83%
Black	13%	14%	3%	5%
Hispanic	18%	11%	NA	NA
Asian (US) South Asian (UK)	6%	7%	9%	5%
Conservative (US)/Tory (UK)**	31%	31%	28%	26%
Liberal/Labour**	33%	34%	35%	25%

U.S. population data is taken from the 2020 U.S. Census (https://www.census.gov/quickfacts/fact/table/US/POP010210). U.K. Census data is taken from the 2021 Census (https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/bulletins/populationandhouseholdestimatesenglandandwales/census2021). Note, the study oversampled non-White respondents by design. *Level 3 UK education includes A-levels, University degrees, and various post-secondary professional certificates/diplomas. Data on UK education from "Education and Training Statistics for the UK" (https://explore-education-statistics.service.gov.uk/find-statistics/education-and-training-statistics-for-the-uk).**Political ideology are population estimates taken from the 2021 General Social Survey (https://gssdataexplorer.norc.org/variables/178/vshow) and the 2019 British National Election Survey (https://www.britishelectionstudy.com/data/#.Y476EC-B1Z0).

Table A1.25: Additional Summary Statistics by Country (Wave 2 sample)

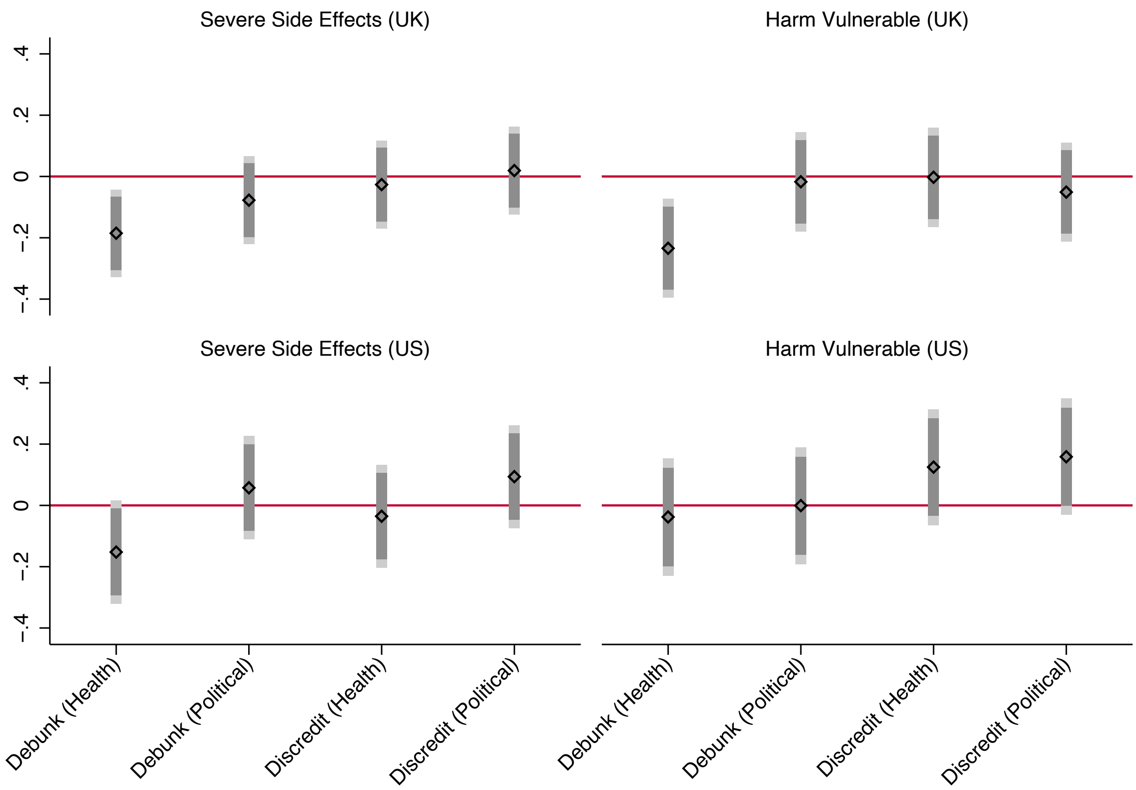
US Sample	N	% of Sample
White	625	51
Black	169	14
Latino	138	11
Asian	82	7
Other Race/Ethnicity	215	17
Female	665	54
Male	564	46
University Degree	391	32
Republican	317	26
Democrat	466	38
UK Sample	N	% of Sample
White	1063	83
Black	63	5
South Asian	61	5
Arab	10	1
Chinese	12	1
White Mixed	15	1
Other Non-white	33	3
Female	692	54
Male	484	46
University Degree	432	34
Tory Voter	338	27
Labour Voter	311	24

Table A1.26: Bayesian ANCOVA Results

	Severe side effects			*Harm Vulnerable*		
US Sample	**Model comparisons**		**Effects**	**Model comparisons**		**Effects**
	BF_M	BF_{01}	BF(Excl)	BF_M	BF_{01}	B(Excl)
	US					
Baseline perceptions (T1)	20.84	1	$5.77e^{-15}$	16.77	1	$2.67e^{-15}$
Discrediting by health professionals (vs. control)	$1.43e^{-96}$	$1.84e^{+96}$	6.95	$7.18e^{-72}$	$3.55e^{+71}$	5.59
Baseline + discrediting mis-informants by health professionals	0.43	6.95	--	0.54	5.59	--
	Severe side effects			*Harm Vulnerable*		
UK Sample	**Model comparisons**		**Effects**	**Model comparisons**		**Effects**
	BF_M	BF_{01}	BF(Excl)	BF_M	BF_{01}	B(Excl)
Baseline perceptions (T1)	28.65	1	$8.44e^{-15}$	30.46	1	0.00
Discrediting by health professionals (vs. control)	$4.11e^{-82}$	$6.29e^{-82}$	9.55	$3.56e^{-72}$	$7.59e^{+71}$	10.16
Baseline + discrediting mis-informants by health professionals	0.31	9.55	--	0.30	10.16	--

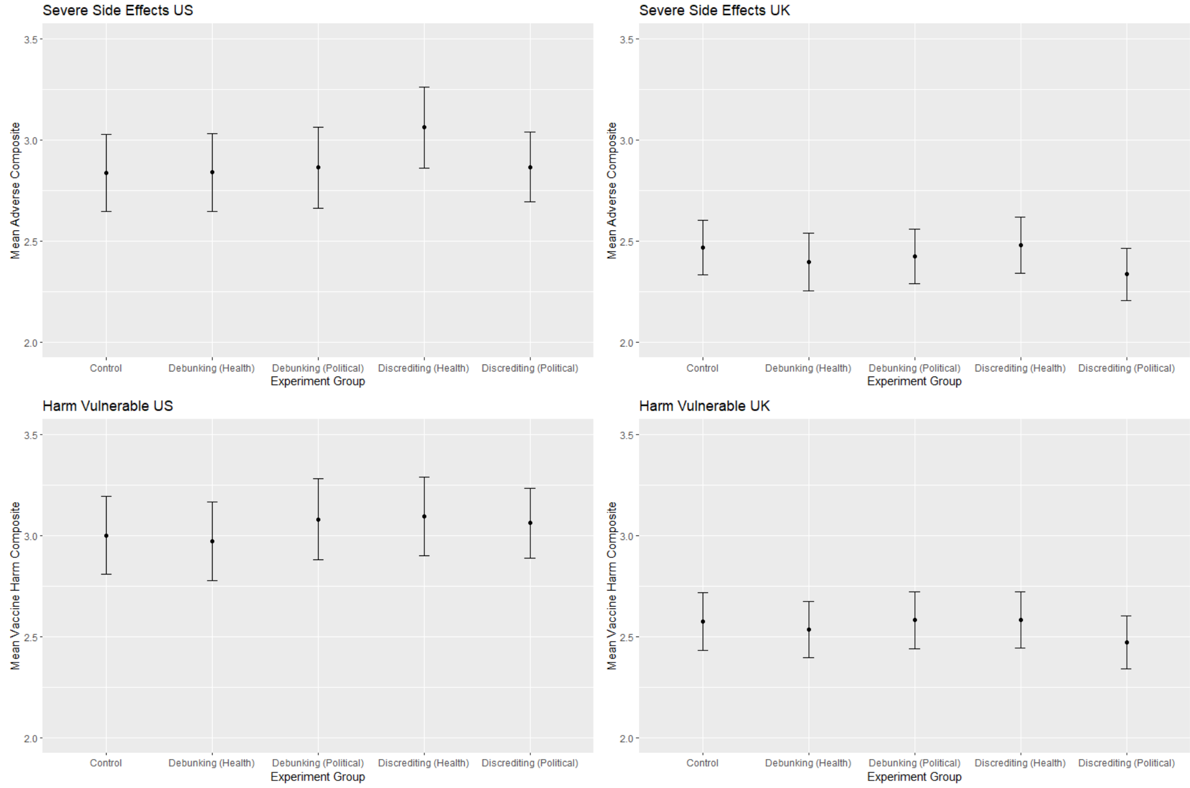
Results from Bayesian ANCOVA models. Note: e stands for * 10

Figure A1.1: Effects of Treatment Conditions on Respondent Beliefs



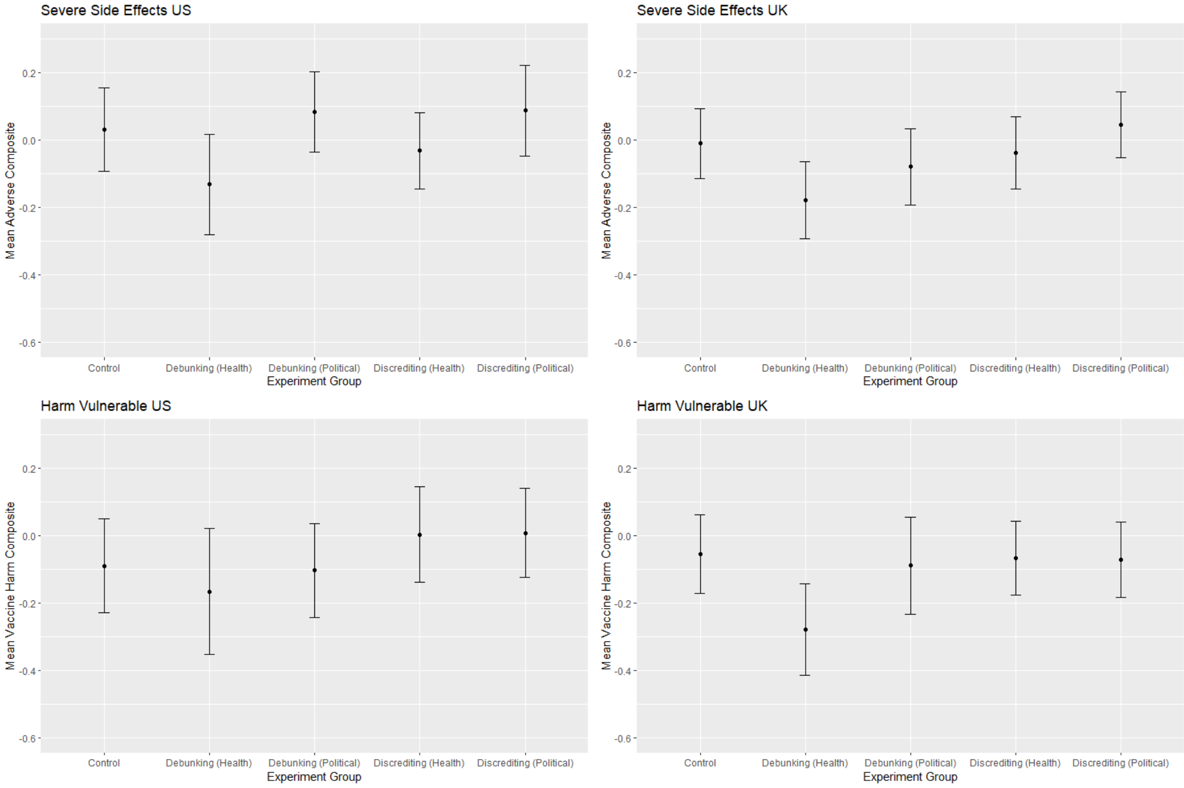
Regression coefficients (black diamonds) with 90% (dark grey bars) 95% (light grey bars) confidence interval from Ordinary Least Squares (OLS) models predicting the influence of treatment conditions (x-axis) on respondent beliefs about vaccine risks (y-axis), controlling for respondent beliefs observed in pre-treatment study wave.

Figure A1.2: Pre-treatment Respondent Beliefs



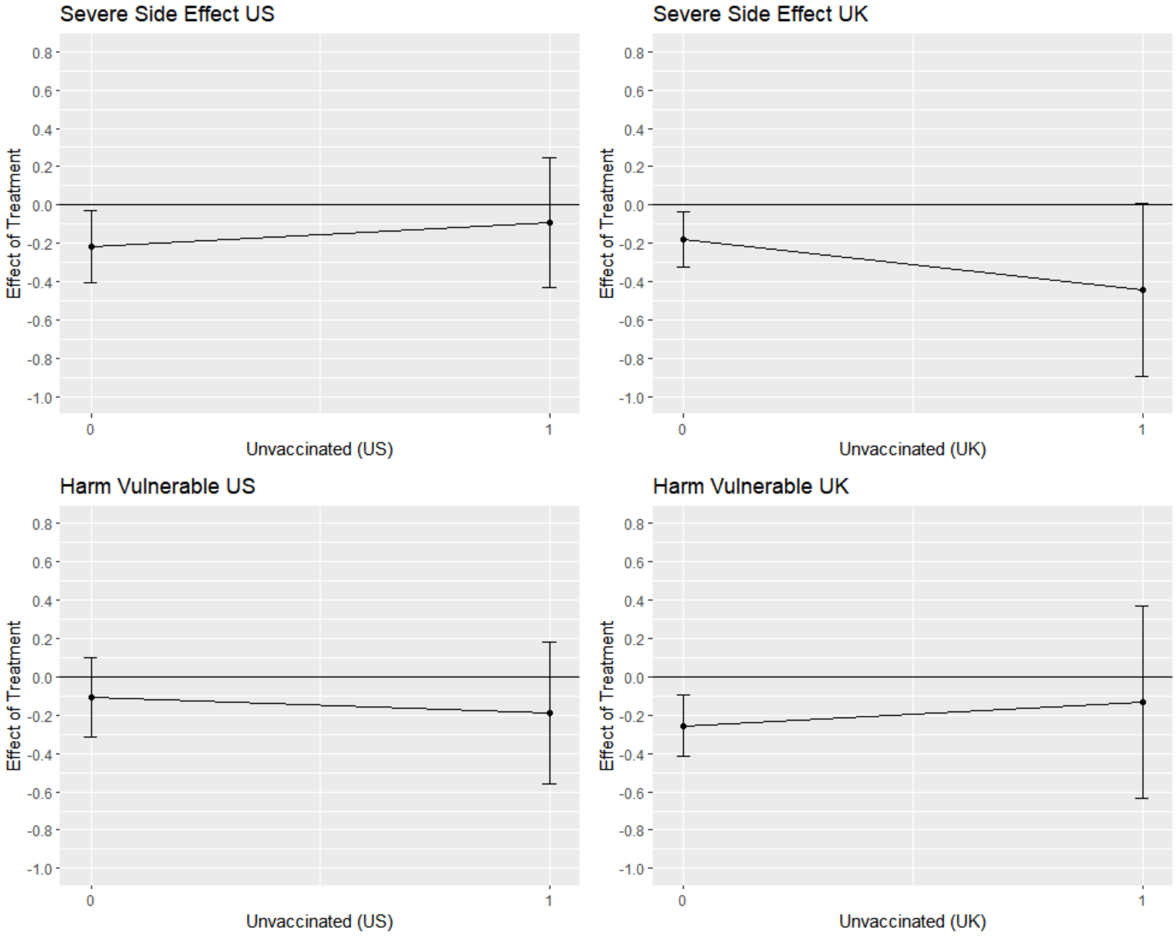
Means by condition (dots) with 95% CIs (vertical lines).

Figure A1.3: Change between Pre-treatment and Post-treatment Respondent Beliefs



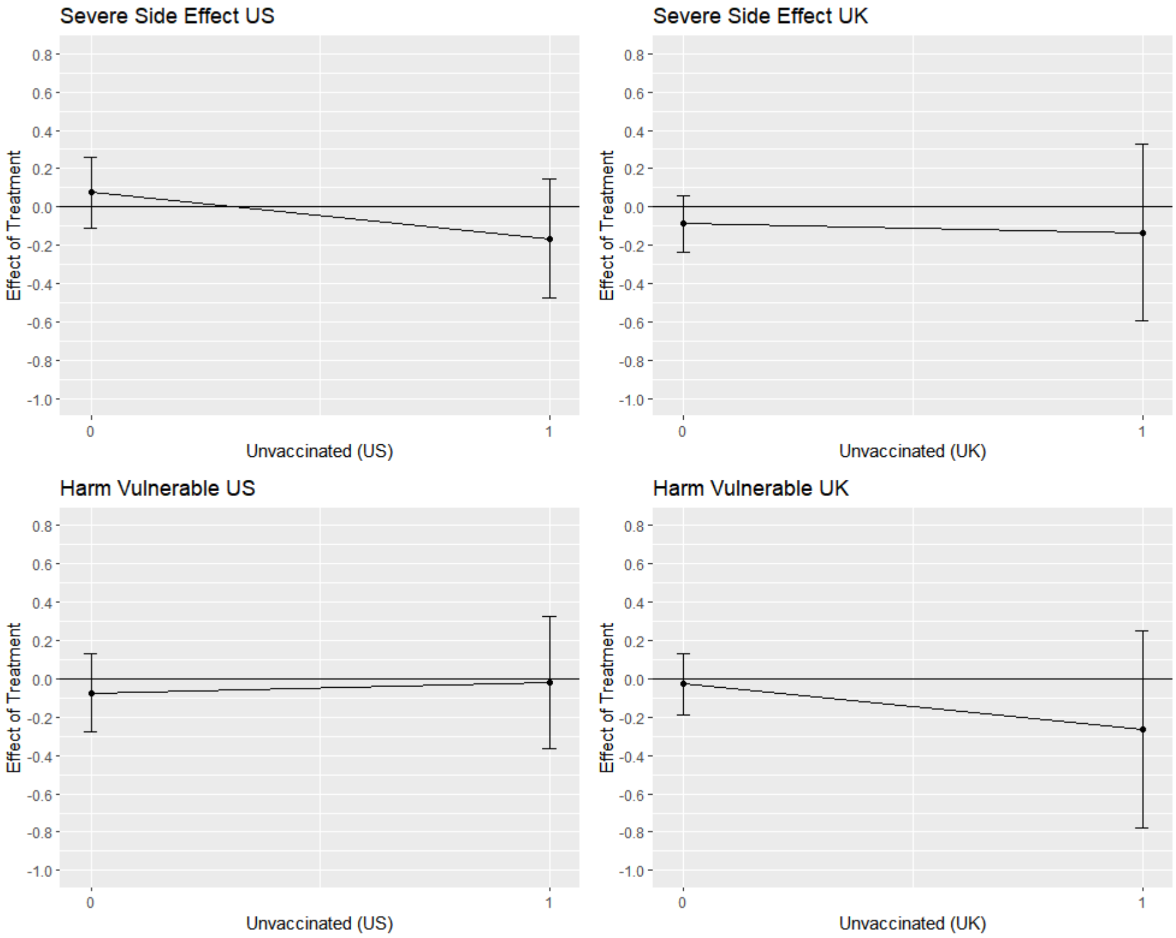
Change in means (Wave 2 – Wave 1) by condition (dots) with 95% CIs (vertical lines).

Figure A1.4: Conditional Effect of Vaccination Status - Debunking (Health)



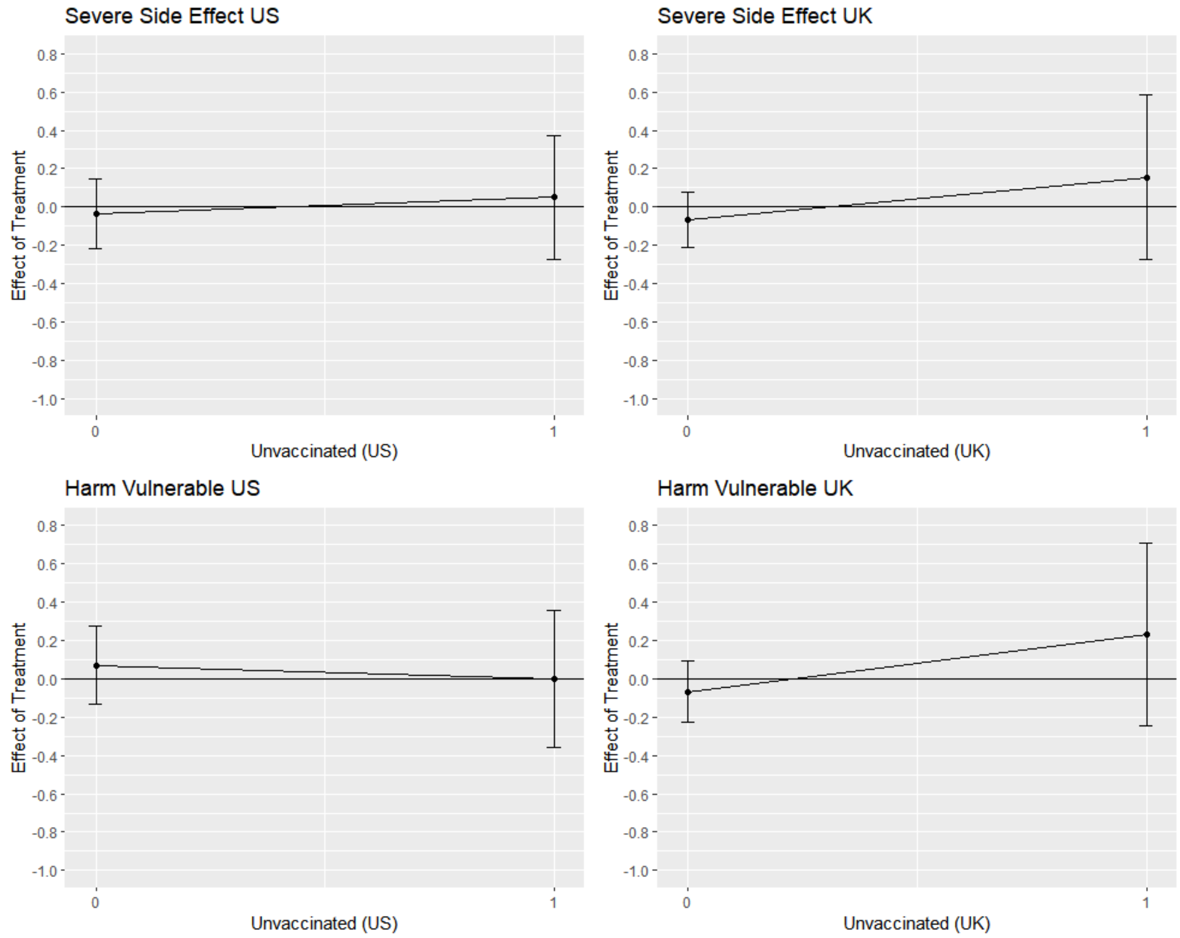
Plots of the marginal effect of treatment condition by vaccination status (unvaccinated=1). Black line depicts effect of treatment group relative to control group. Grey shading represents 95% confidence intervals.

Figure A1.5: Conditional Effect of Vaccination Status- Debunking (Political)



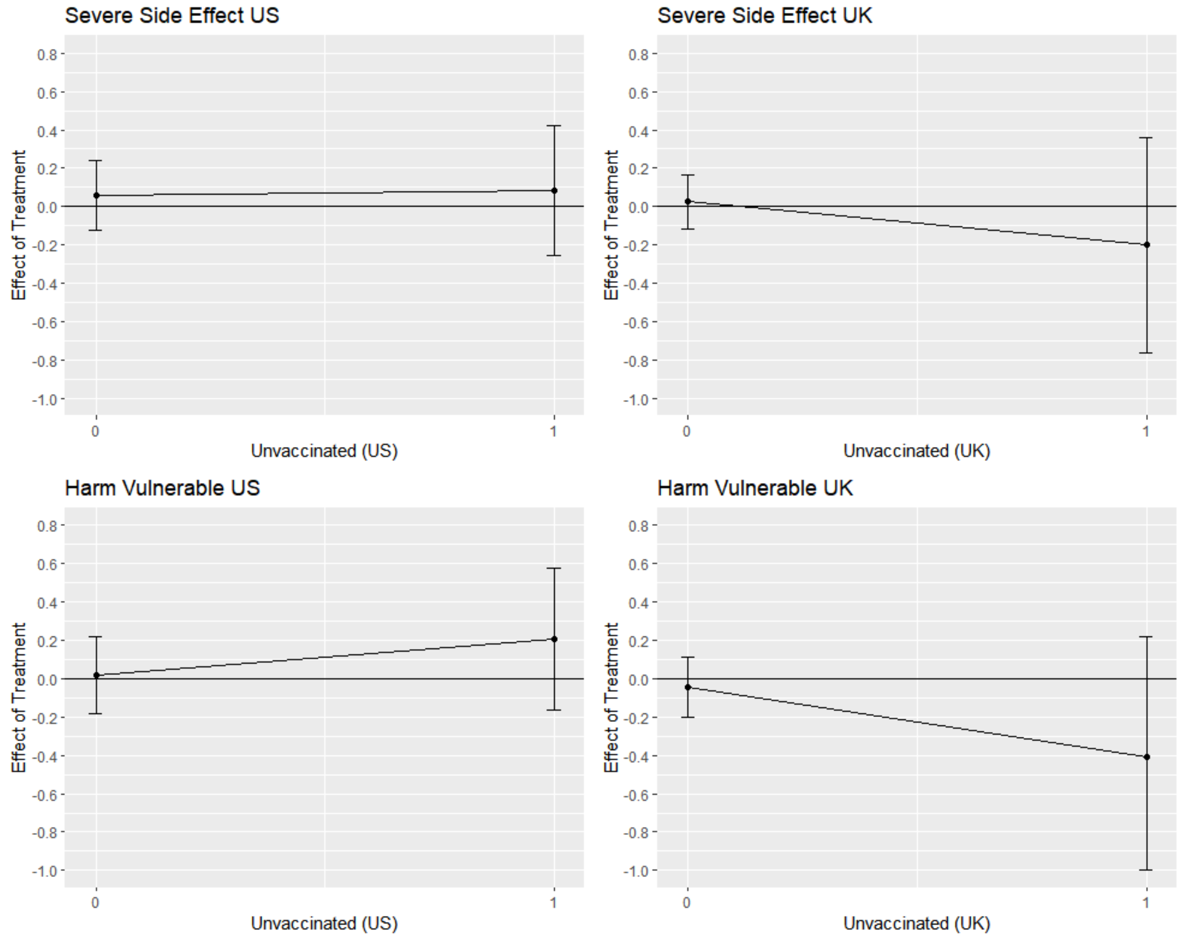
Plots of the marginal effect of treatment condition by vaccination status (unvaccinated=1). Black line depicts effect of treatment group relative to control group. Grey shading represents 95% confidence intervals.

Figure A1.6: Conditional Effect of Vaccination Status - Discrediting (Health)



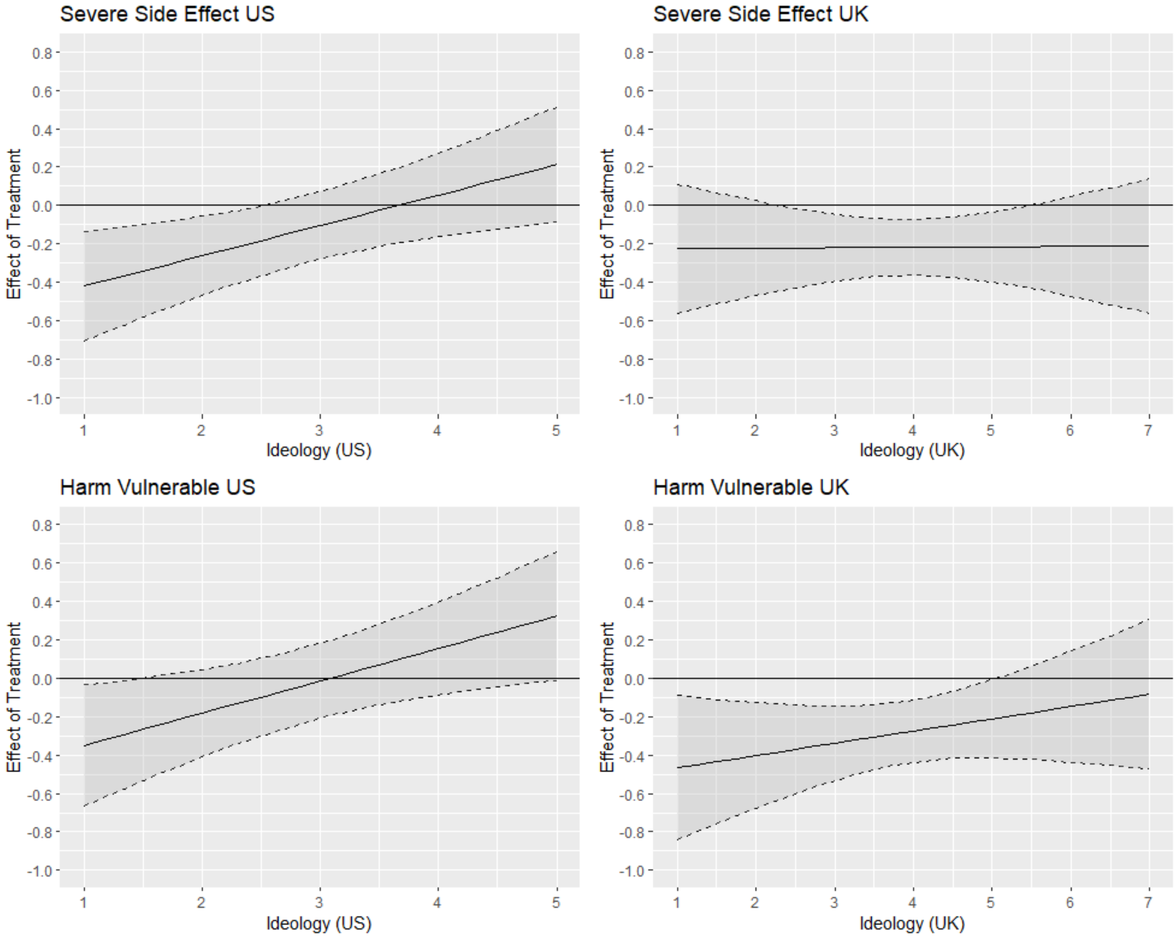
Plots of the marginal effect of treatment condition by vaccination status (unvaccinated=1). Black line depicts effect of treatment group relative to control group. Grey shading represents 95% confidence intervals.

Figure A1.7: Conditional Effect of Vaccination Status - Discrediting (Political)



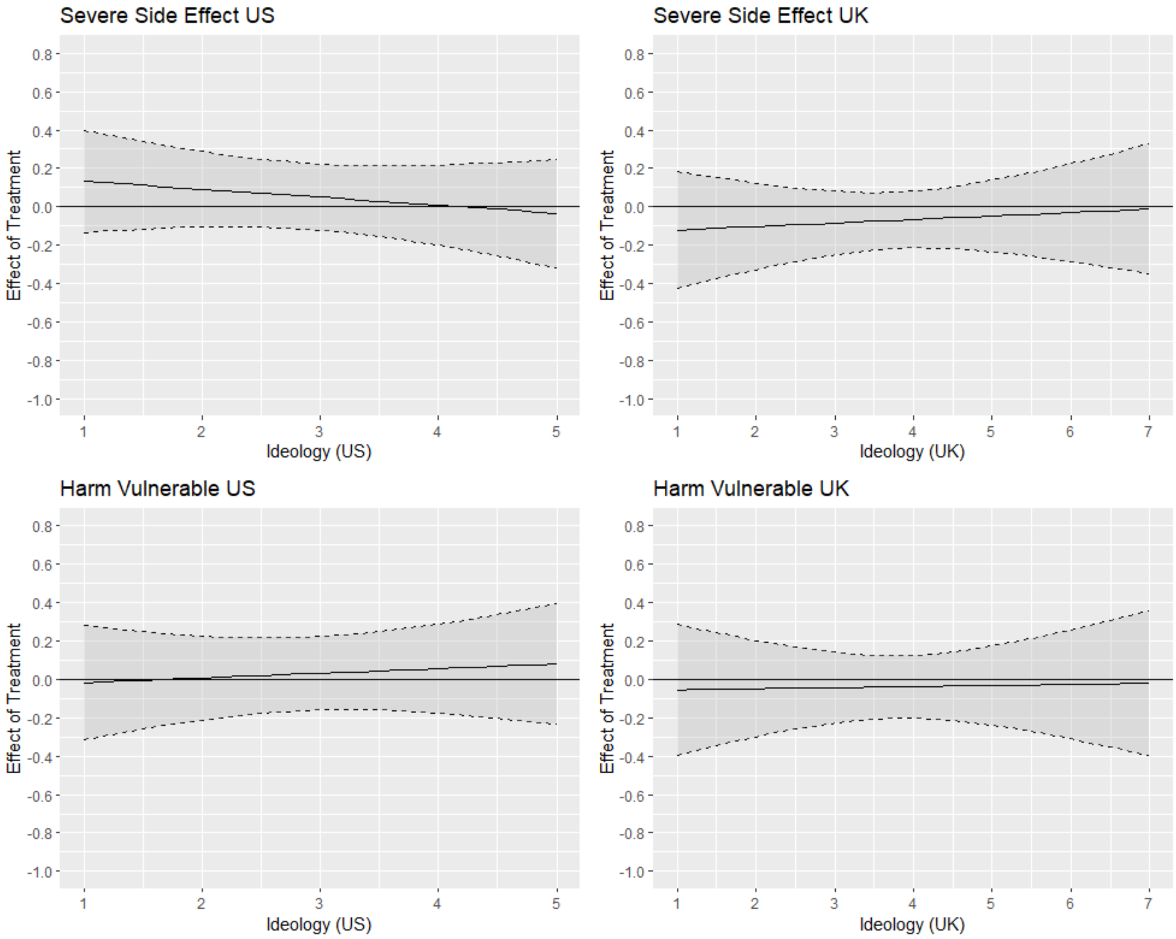
Plots of the marginal effect of treatment condition by vaccination status (unvaccinated=1). Black line depicts effect of treatment group relative to control group. Grey shading represents 95% confidence intervals.

Figure A1.8: Conditional Effect of Political Ideology - Debunking (Health)



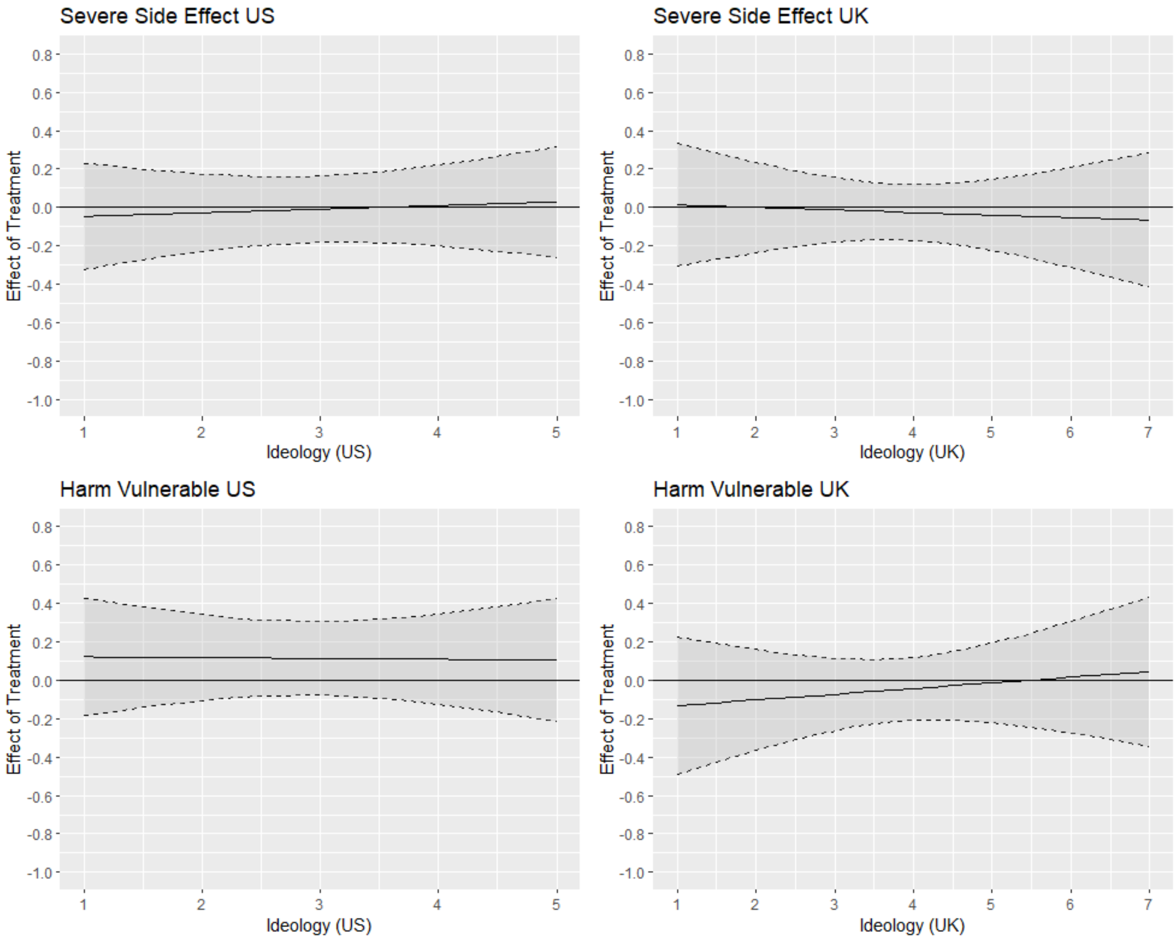
Plots of the marginal effect of treatment condition over the scale of respondent political ideology (Liberal-Conservative). Black line depicts effect of treatment group relative to control group. Grey shading represents 95% confidence intervals. Based on the results from OLS models interacting Political Ideology and specified treatment condition.

Figure A1.9: Conditional Effect of Ideology - Debunking (Political)



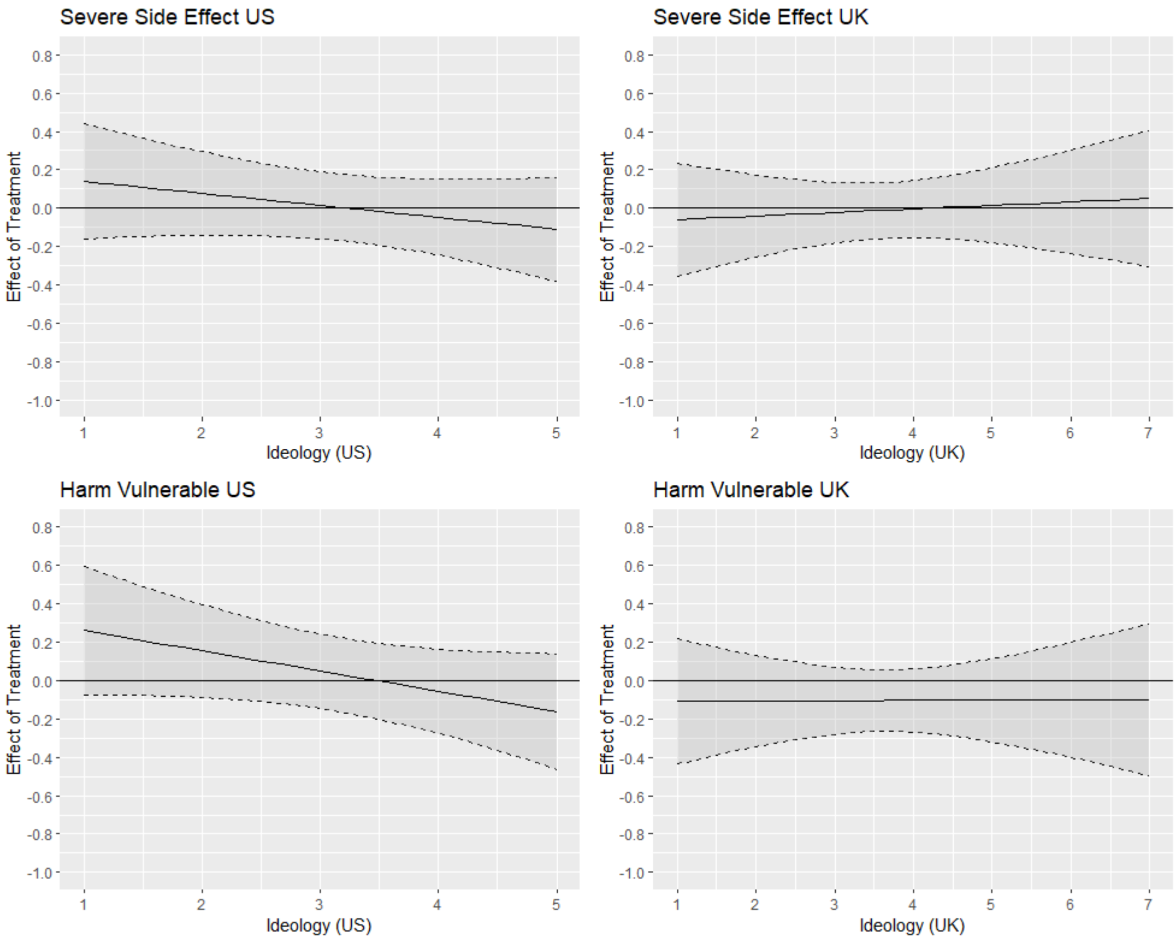
Plots of the marginal effect of treatment condition over the scale of respondent political ideology (Liberal-Conservative). Black line depicts effect of treatment group relative to control group. Grey shading represents 95% confidence intervals. Based on the results from OLS models interacting Political Ideology and specified treatment condition.

Figure A1.10: Conditional Effect of Ideology - Discrediting (Health)



Plots of the marginal effect of treatment condition over the scale of respondent political ideology (Liberal-Conservative). Black line depicts effect of treatment group relative to control group. Grey shading represents 95% confidence intervals. Based on the results from OLS models interacting Political Ideology and specified treatment condition.

Figure A1.11: Conditional Effect of Ideology - Discrediting (Political)



Plots of the marginal effect of treatment condition over the scale of respondent political ideology (Liberal-Conservative). Black line depicts effect of treatment group relative to control group. Grey shading represents 95% confidence intervals. Based on the results from OLS models interacting Political Ideology and specified treatment condition.

Figure A1.12: Moderating Effect of Wave 1 Vaccine Attitudes on the Relationship between Treatments and Wave 2 Value of *Severe Side Effects* (US Respondents)

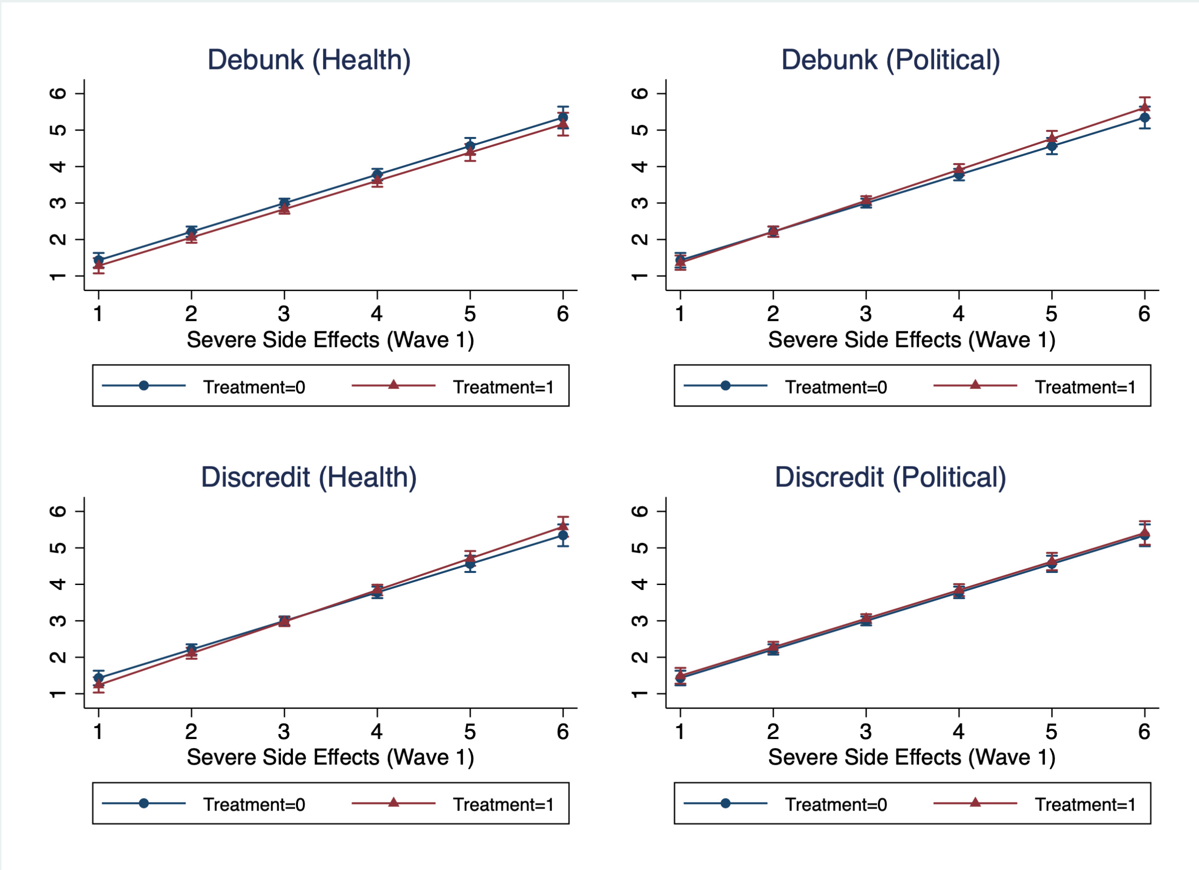


Figure plots predicted probabilities from OLS models interacting the stated treatment condition with respondents' Wave 1 vaccine attitudes. The predictions illustrate the effects of the specified treatment on respondents' vaccine attitude recorded in Wave 2 over the attitude recorded in Wave 1. Circles and triangles represent point estimates for the observed value of *Severe Side Effects* in Wave 2 while vertical capped bars represent 95% CIs.

Figure A1.13: Moderating Effect of Wave 1 Vaccine Attitudes on the Relationship between Treatments and Wave 2 Value of *Harm Vulnerable* (US Respondents)

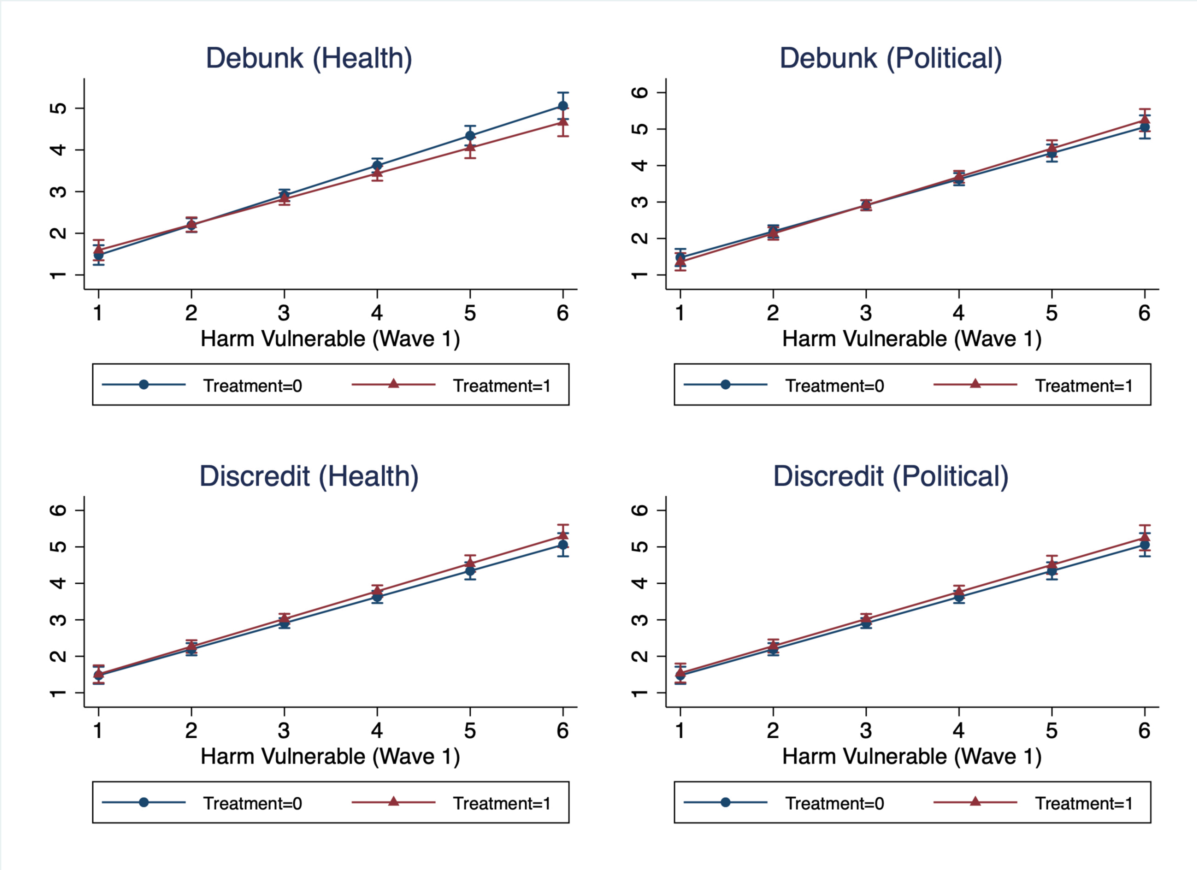


Figure plots predicted probabilities from OLS models interacting the stated treatment condition with respondents' Wave 1 vaccine attitudes. The predictions illustrate the effects of the specified treatment on respondents' vaccine attitude recorded in Wave 2 over the attitude recorded in Wave 1. Circles and triangles represent point estimates for the observed value of *Harm Vulnerable* in Wave 2 while vertical capped bars represent 95% CIs.

Figure A1.14: Moderating Effect of Wave 1 Vaccine Attitudes on the Relationship between Treatments and Wave 2 Value of *Severe Side Effects* (UK Respondents)

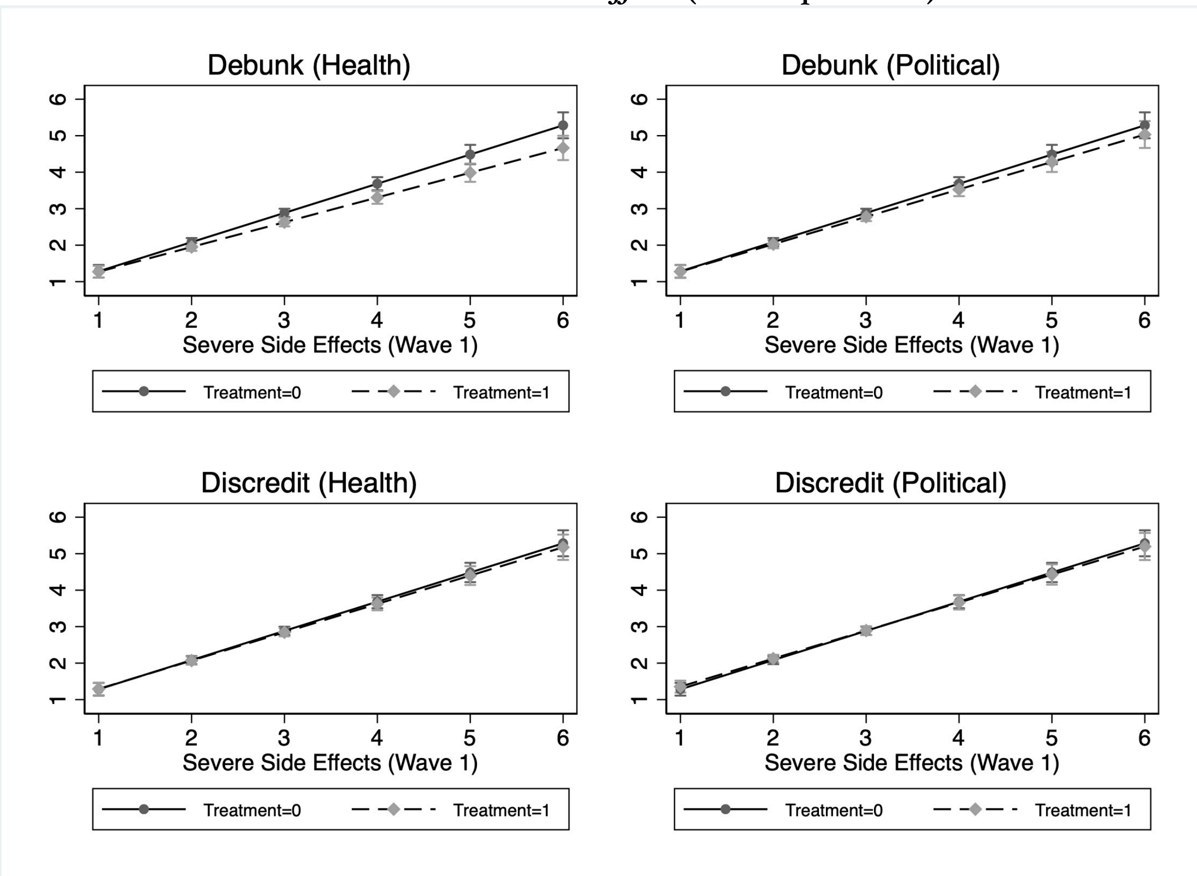


Figure plots predicted probabilities from OLS models interacting the stated treatment condition with respondents' Wave 1 vaccine attitudes. The predictions illustrate the effects of the specified treatment on respondents' vaccine attitude recorded in Wave 2 over the attitude recorded in Wave 1. Circles and diamonds represent point estimates for the observed value of *Severe Side Effects* in Wave 2 while vertical capped bars represent 95% CIs.

Figure A1.15: Moderating Effect of Wave 1 Vaccine Attitudes on the Relationship between Treatments and Wave 2 value of *Harm Vulnerable* (UK Sample)

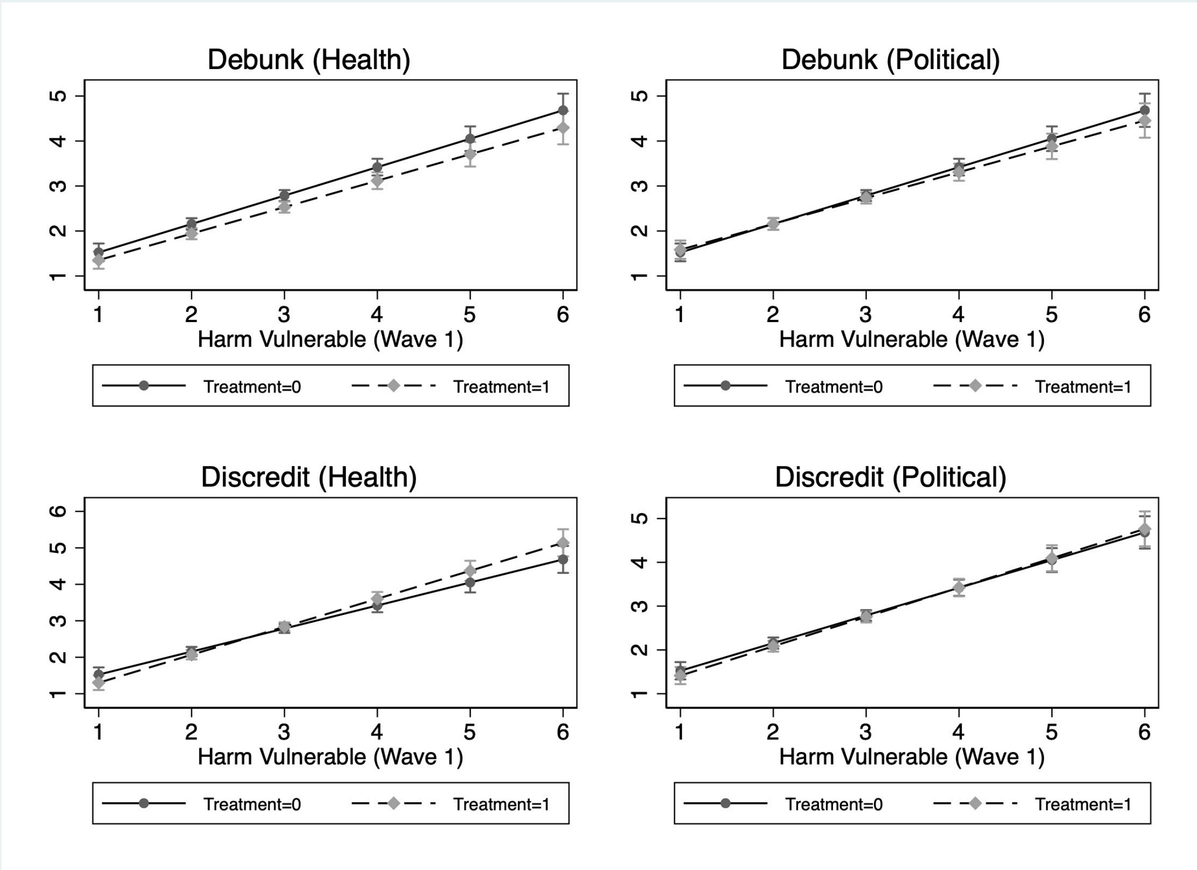
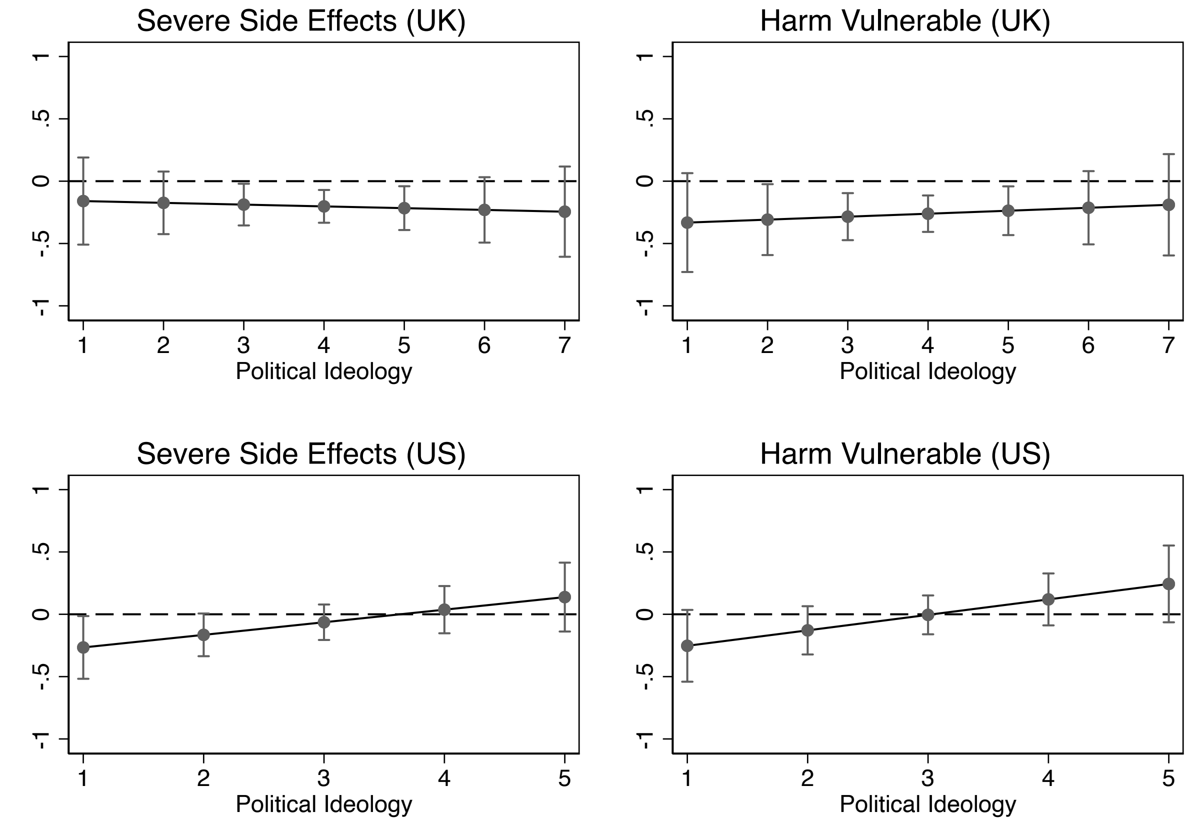


Figure plots predicted probabilities from OLS models interacting the stated treatment condition with respondents' Wave 1 vaccine attitudes. The predictions illustrate the effects of the specified treatment on respondents' vaccine attitude recorded in Wave 2 over the attitude recorded in Wave 1. Circles and diamonds represent point estimates for the observed value of *Harm Vulnerable* in Wave 2 while vertical capped bars represent 95% CIs.

Figure A1.16: Effects of Treatments on Respondent Beliefs about COVID-19 Vaccines (Imputed Data)

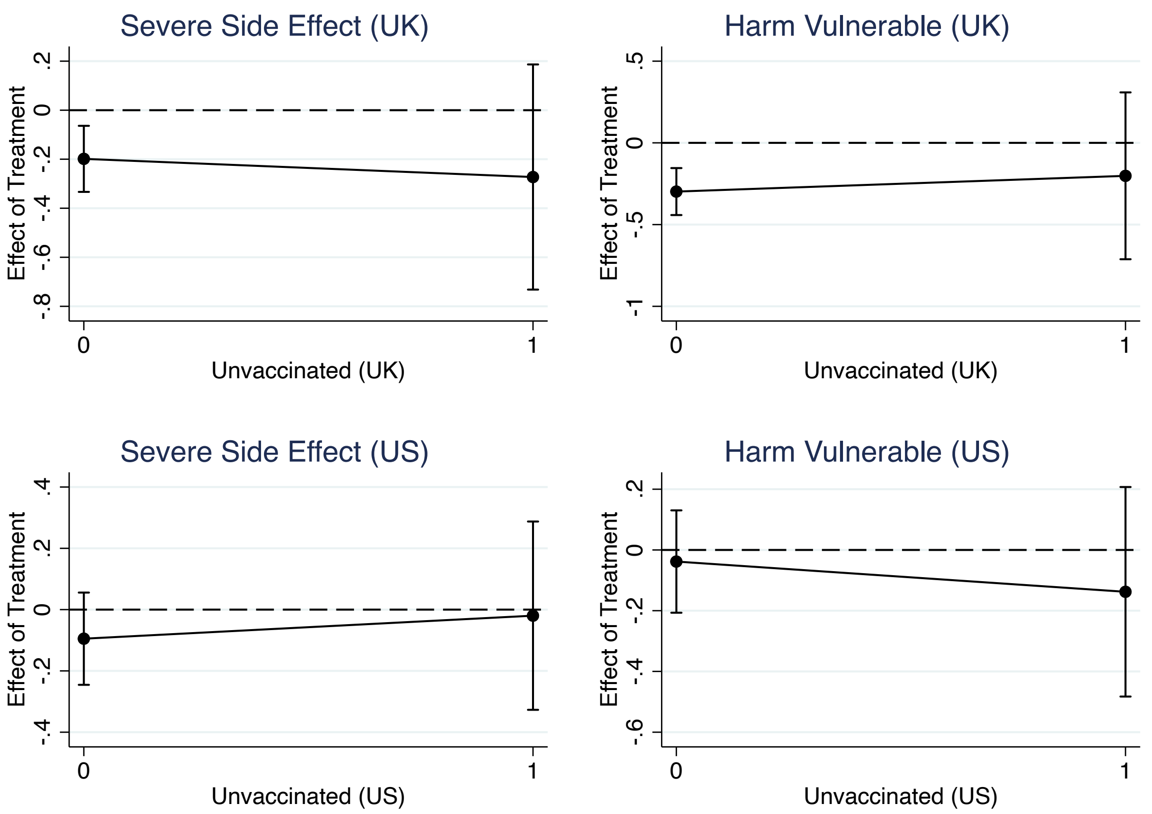
Regression coefficients (black dots) with 90% (thick bars) 95% (thin bars) confidence interval from Ordinary Least Squares (OLS) models predicting the influence of treatment conditions (x-axis) on respondent beliefs about vaccine risks (y-axis), controlling for respondent beliefs observed in pre-treatment study wave. Missing observations imputed from 100 simulations using MCMC draws from a joint MVN distribution.

Figure A1.17: Moderating Effect of Political Ideology on the Relationship between Debunking by Health Professionals and Respondent Vaccine Beliefs (Imputed Data)



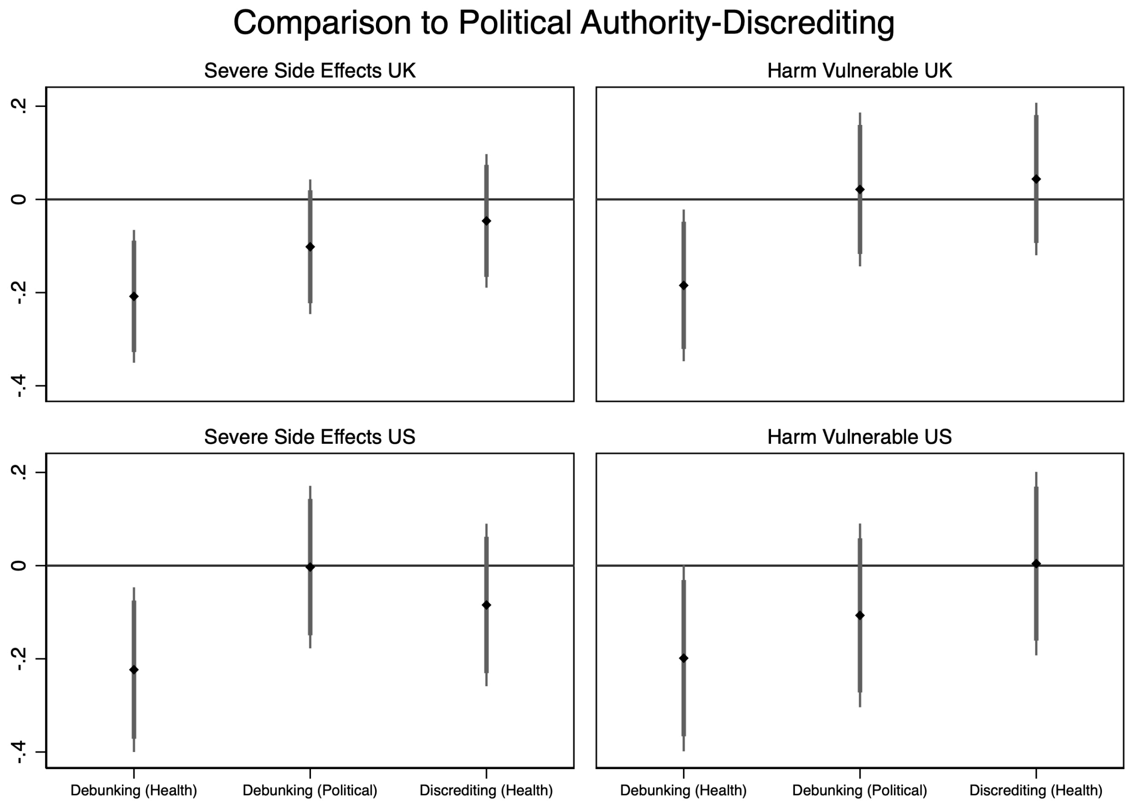
Plots of the marginal effect (y-axis) of debunking treatment attributed to healthcare professionals over the scale of respondent political ideology (Liberal-Conservative) (x-axis). Black line depicts effect of treatment group relative to control group. Capped vertical lines represent 95% confidence intervals. Based on the results from OLS models interacting Political Ideology and specified treatment condition.

Figure A1.18: Conditional Effect of Vaccination Status-Debunking (Health) (Imputed Data)



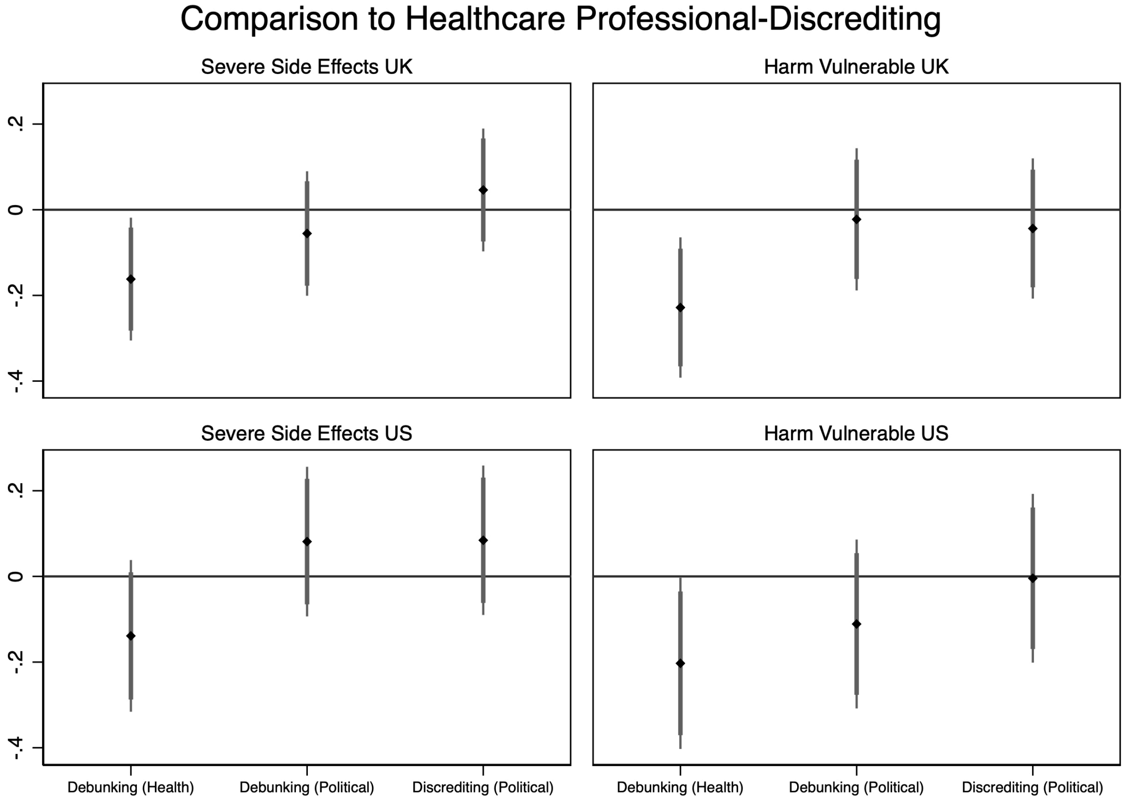
Plots of the marginal effect of treatment condition over the scale of respondent political ideology (Liberal-Conservative). Black line depicts effect of treatment group relative to control group. Grey shading represents 95% confidence intervals. Based on the results from OLS models interacting Vaccine Status and specified treatment condition.

Figure A1.19: Direct Comparison to Political Authority-Discrediting



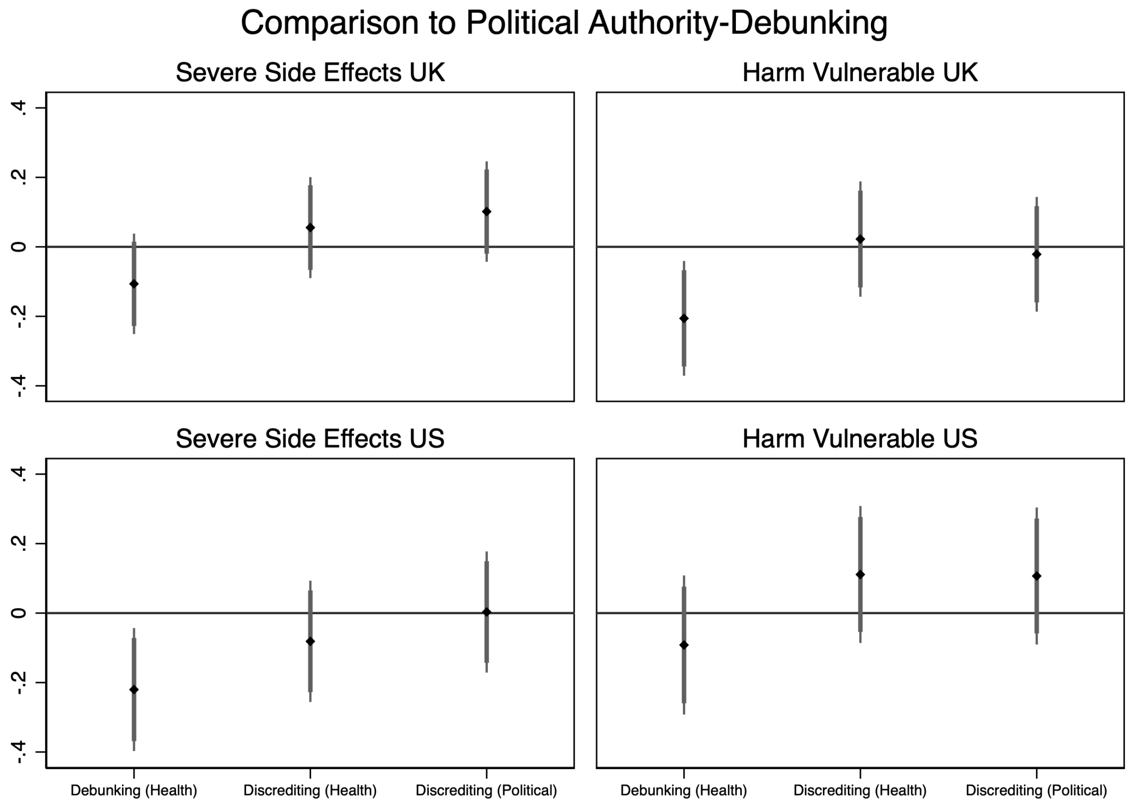
Coefficients estimates (black diamonds) with 90% (thick bars) 95% (thin bars) CIs from OLS models predicting the effect of treatment conditions (x-axis) on respondent beliefs about vaccine risks (y-axis), controlling for respondent beliefs in pre-treatment study wave. *Discrediting (Political)* represents the excluded category to which other treatment conditions are compared. We exclude the control condition reported in the paper from these analyses.

Figure A1.20: Direct Comparison to Political Authority-Discrediting



Coefficients estimates (black diamonds) with 90% (thick bars) 95% (thin bars) CIs from OLS models predicting the effect of treatment conditions (x-axis) on respondent beliefs about vaccine risks (y-axis), controlling for respondent beliefs in pre-treatment study wave. *Discrediting (Health)* represents the excluded category to which other treatment conditions are compared. We exclude the control condition reported in the paper from these analyses.

Figure A1.20: Direct Comparison to Political Authority-Discrediting



Coefficients estimates (black diamonds) with 90% (thick bars) 95% (thin bars) CIs from OLS models predicting the effect of treatment conditions (x-axis) on respondent beliefs about vaccine risks (y-axis), controlling for respondent beliefs in pre-treatment study wave. *Debunking (Political)* represents the excluded category to which other treatment conditions are compared. We exclude the control condition reported in the paper from these analyses.

Additional Notes and Comments

Data imputation and Analysis

Missing data derives from two sources in our analysis. The first results from respondent attrition between Wave 1 and Wave 2 of the survey: some respondents who completed the first wave of the survey did not complete the second wave of the survey. This amounts to 1,381 missing cases for all the variables measured in Wave 2 (UK=650; US=731) from the original sample of 5,900 who completed fully the wave 1 survey (UK=2,953; US=2,947). This gives us an impressive recontact rate of 77%. In this second wave, 55% of these successful recontacts were randomly assigned to one of five experimental conditions used in this study (described below); the remaining recontacts were reserved for a different study.

The missing cases—those that were not successfully re-contacted—were originally subjected to listwise deletion in the analyses, meaning they were simply excluded from the analyses. To address this issue, we impute values on the 1,381 missing cases of respondents from Wave 1 who did not complete Wave 2 for this study. These are the only cases of missing observations on our outcome variables (*Severe Side Effects* and *Harm Vulnerable*). To account for missing observations on the DVs, we first estimated whether the respondent is missing in Wave 2 based on observed variables from Wave 1, including the Wave 1 measures of the missing outcome variables.[1] Older and less educated respondents were less likely to return for Wave 2 of the study, but there is no indication that missingness is related to our outcome variables, which were measured and tested for all respondents in Wave 1. Thus, we conclude that the data is missing at random (MAR)—in other words, attitudes toward vaccines did not influence the probability of successful recontact.

Given that missing at random data might result in biased estimates using listwise deletion (Sidi and Harel 2018), we used multiple imputation to estimate those missing values for the second wave of the survey using values on those exact variables from Wave 1 of the survey, as well as theoretically relevant variables as recommended by Enders (2010) (also see White 2011).[2] Because we have data for each missing respondent on each outcome in wave 1 of the survey, our imputation model is likely to yield valid estimates of the missing data in wave 2 (e.g., wave 1 and wave 2 values are highly correlated 0.75 [*Severe Side Effects*] and 0.68 [*Harm Vulnerable*]).

We performed 100 simulations using Markov Chain Monte Carlo draws from a joint multivariate normal distribution (Lee and Carlin 2010). This resulted in imputed values on each outcome in wave two of the survey for our two key outcome variables: *Severe Side Effects* and *Harm Vulnerable*. Since these cases were untreated (i.e., those participants were not allocated to any of the experimental conditions), we relegate them to the control group of the study and re-estimate the regression model in the manuscript. The results are shown in figure **SA1.16**. The conclusions remain unchanged from when we excluded these observations from the data. We therefore conclude that the absence of the cases that failed to return for Wave 2 did not bias our results.[3]

[1] This model includes beliefs about severe side effects of vaccines, Harm Vulnerable (w1)vulnerability, trust in healthcare professionals, trust in the national government, social reactance, authoritarianism, political ideology, age, gender, social media use, income, race, and education.

[2] The auxiliary variables in the imputation equation consists of the observed values of each missing case measured in wave 1 of the survey (severe side effects and harm vulnerability), trust in the national government, trust in healthcare professionals, vaccination status, social media use, gender, age, authoritarianism, and social reactance. We did not find that changes to the auxiliary equation altered the results of the impute values nor did it alter the efficiency of estimates. Trace plots and diagnostic tests suggest stable convergence in each model.

[3] These results also replicate when we use Multiple Imputation Chained Equations (MICE) as an alternative to the multivariable normal Markov Chain Monte Carlo imputation method (White et al. 2011).

The second source of missing data concerns sociodemographic characteristics, specifically political ideology. Some respondents in the conditional models reported in Figure 3 of the paper did not select a political ideology. Among successful recontacts for Wave 2, we record 73 missing observations for political ideology among UK respondents and 109 missing observations for US respondents. These missing observations were imputed using the same methodology as described above. Figure **SA1.17** shows the moderating effect of political ideology on the relationship between debunking by health professionals and respondent vaccine beliefs using the imputed data. These estimates are similar to those reported when listwise deletion is used with one exception: political ideology no longer moderates the relationship between debunking by health care professionals and harm vulnerability beliefs in the UK at the extreme left category. However, it is does moderate beliefs at less extreme left categories similar to when listwise deletion is used. We therefore conclude that the results are highly similar and largely unaffected by missingness in the data.

Next, like the ideology variables, we observe some missing on the variable accounting for vaccine status (*Unvaccinated*). There are 24 missing observations for this variable in Wave 2 in the US sample and 79 missing observations in the US sample. Because we use this variable as a predictor (particularly to interact with the treatments) in our analyses, we likewise impute the missing values and rerun the analyses. As before, the using these imputed values does not affect the results of the models, and in this case, we continue to find that vaccination status does not moderate the relationship between the treatments and respondents' Wave 2 beliefs (**see SA1.18** in the appendix).

Enders, Craig K. 2010. *Applied Missing Data Analysis*. The Guilford Press. New York.

Lee, Katherine J. and John B. Carlin. 2010. "Multiple Imputation for Missing Data: Fully Conditional Specification versus Multivariate Normal Imputation." *American Journal of Epidemiology*, 171(5): 624-632.

Sidi, Yulia and Ofer Harel. 2018. "The Treatment of Incomplete Data: Reporting, Analysis, Reproducibility, and Replicability." *Social Science & Medicine*, 209: 169-173.

White, Ian R., Patrick Royston, and Angela M. Wood. 2011. "Multiple Imputation using Chained Equations: Issues and Guidance for Practice." *Statistics in Medicine*, 30(4): 377-399.

Effect size and statistical power

Using the software G*Power (Faul et al. 2007), we conducted three sensitivity analyses on our analytical samples (i.e., the participants for whom we have data for time 1 and time 2). We conducted one sensitivity analysis for the UK sample, one for the US sample, and one for the overall sample. We conducted the sensitivity analyses for linear multiple regressions focusing on R^2 increase, including four main predictors (resulting from the comparisons of our four experimental conditions to the control one) and a total number of five predictors (the four main predictors and a covariate representing participants' baseline vaccination status or vaccine risk attitudes).

Assuming power=0.8 and alpha=0.05, the sensitivity analyses showed that we could identify an effect size of $f^2 = 0.010$ to test our hypotheses in the UK sample ($n = 1{,}203$), and a similar effect size of $f^2 = 0.011$ to test the same hypotheses in the US sample ($n = 1{,}054$). In the overall sample ($n = 2{,}257$), we had more statistical power and could detect an f^2 effect of 0.005. (Note: For all sensitivity analyses we use the sample sizes used to conduct the regression analyses reported in the manuscript, which exclude speeders and individuals that failed the attention checks.) The sensitivity analyses thus indicate that we are able to detect small effects at 80% power.

We compute the effect size (f^2) of the 4 predictors used in the regression analyses using the formula described in the G*Power 3.1 Manual. For the UK sample, the effect size of model predicting *Severe Side Effects* is 0.010 while the effect size for the model predicting *Harm Vulnerable* is also 0.010. For the US sample, the effect size of model predicting *Severe Side Effects* is 0.009 while the effect size for the model predicting *Harm Vulnerable* is 0.006. For the combined sample (US+UK), the effect size of model predicting *Severe Side Effects* is 0.007 while the effect size for the model predicting *Harm Vulnerable* is 0.006.

Our overall effect sizes are small; nonetheless, we had sufficient sample sizes to detect such effects at 80% power in both the UK and combined samples. In the case of the US sample, our sample sizes were too small to confidently detect the reported effect. Put slightly differently, the UK analyses were sufficiently powered (power=80% [both models]), as were the analyses using the combined samples (power=91% [*Severe Side Effects* & 85% [*Harm Vulnerable*]). But in the US sample, our analyses were under powered (power=69% [*Severe Side Effects* & 49% [*Harm Vulnerable*]).

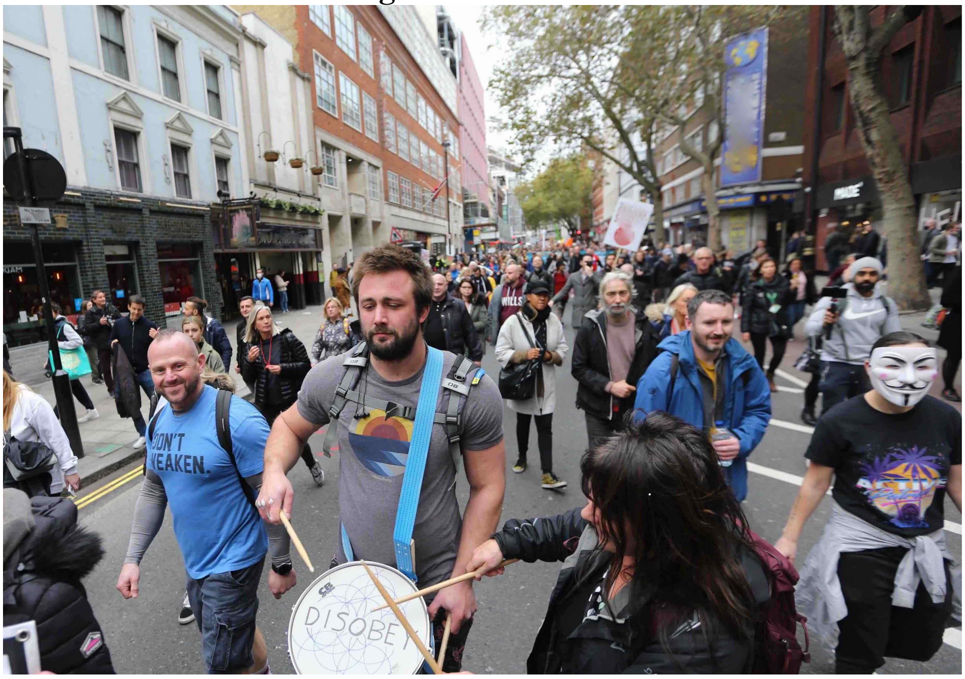
Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods, 39*(2), 175–191. https://doi.org/10.3758/BF03193146

Treatment Vignettes

US Respondents

Condition 1: Control (misinformation only)

Protesters March in Washington DC



By Gemma Wallace

WASHINGTON—Crowds of demonstrators marched through the streets of Washington DC to voice their concerns about the risks of COVID-19 vaccines. During the march, a group of protesters gathered at a local vaccine clinic, chanting "COVID Doesn't Kill Children, Vaccines Kill Children" and "Trust Your Body, Not Big Pharma" as patients waited in line to receive their vaccinations.

A spokesperson for Vaccine Truth Now claimed the protest was necessary because the medical community and the government are lying to people about the risks of COVID-19 vaccines. "These so-called vaccines cause heart damage in 1 in 10 children. They cause miscarriages and infertility in women. People need to know the truth."

Carol Richards expressed concerns shared by many. "I'm not anti-vax, but I worry about the dangers of an experimental vaccine. My children aren't guinea pigs." Protester Karen Johnson added, "Women need to know more about the risks of these vaccines, especially if they're pregnant."

Similar protests have occurred in cities around the world, indicating the uncertainty many people feel about COVID-19 vaccines.

Condition 2: Debunking (Health)

Protesters March in Washington DC

(Photo identical to condition 1)

By Gemma Wallace

WASHINGTON—Crowds of demonstrators marched through the streets of Washington DC to voice their concerns about the risks of COVID-19 vaccines. During the march, a group of protesters gathered at a local vaccine clinic, chanting "COVID Doesn't Kill Children, Vaccines Kill Children" and "Trust Your Body, Not Big Pharma" as patients waited in line to receive their vaccinations.

A spokesperson for Vaccine Truth Now claimed the protest was necessary because the medical community and the government are lying to people about the risks of COVID-19 vaccines. "These so-called vaccines cause heart damage in 1 in 10 children. They cause miscarriages and infertility in women. They aren't safe"

Carol Richards expressed concerns shared by many. "I'm not anti-vax, but I worry about the dangers of an experimental vaccine. My children aren't guinea pigs." Protester Karen Johnson added, "Women need to know more about the risks of these vaccines, especially if they're pregnant."

Asked for her response, pediatrician Theresa Robinson stated: "Millions of children—including both of my own kids —have been vaccinated against COVID-19. The vaccines are very safe and provide children and their families high levels of protection against a very serious disease."

Damien Gordon, head of Intensive Care at St. Mary's Hospital, added "There is zero evidence that vaccination poses a risk to pregnant women. Getting vaccinated is the best way for expectant mothers to protect themselves and their babies against COVID-19."

Similar protests have occurred in cities around the world, indicating the uncertainty many people feel about COVID-19 vaccines.

Condition 3: Debunking (Political)

Protesters March in Washington DC

(Photo identical to condition 1)

By Gemma Wallace
WASHINGTON—Crowds of demonstrators marched through the streets of Washington DC to voice their concerns about the risks of COVID-19 vaccines. During the march, a group of protesters gathered at a local vaccine clinic, chanting "COVID Doesn't Kill Children, Vaccines Kill Children" and "Trust Your Body, Not Big Pharma" as patients waited in line to receive their vaccinations.

A spokesperson for Vaccine Truth Now claimed the protest was necessary because the medical community and the government are lying to people about the risks of COVID-19 vaccines. "These so-called vaccines cause heart damage in 1 in 10 children. They cause miscarriages and infertility in women. People need to know the truth."

Carol Richards expressed concerns shared by many. "I'm not anti-vax, but I worry about the dangers of an experimental vaccine. My children aren't guinea pigs." Protester Karen Johnson added, "Women need to know more about the risks of these vaccines, especially if they're pregnant."

Asked for her response, Congresswoman Theresa Robinson stated "Millions of children—including both of my own kids —have been vaccinated against COVID-19. The vaccines are very safe and provide children and their families high levels of protection against a very serious disease."

Damien Gordon, a spokesperson for the Office of the President, added, "There is zero evidence that vaccination poses a risk to pregnant women. Getting vaccinated is the best way for expectant mothers to protect themselves and their babies against COVID-19."

Similar protests have occurred in cities around the world, indicating the uncertainty many people feel about COVID-19 vaccines.

Condition 4: Discrediting (Health)

Protesters March in Washington DC

(Photo identical to condition 1)

By Gemma Wallace

WASHINGTON—Crowds of demonstrators marched through the streets of Washington DC to voice their concerns about the risks of COVID-19 vaccines. During the march, a group of protesters gathered at a local vaccine clinic, chanting "COVID Doesn't Kill Children, Vaccines Kill Children" and "Trust Your Body, Not Big Pharma" as patients waited in line to receive their vaccinations.

A spokesperson for Vaccine Truth Now claimed the protest was necessary because the medical community and the government are lying to people about the risks of COVID-19 vaccines. "These so-called vaccines cause heart damage in 1 in 10 children. They cause miscarriages and infertility in women. People need to know the truth."

Carol Richards expressed concerns shared by many. "I'm not anti-vax, but I worry about the dangers of an experimental vaccine. My children aren't guinea pigs." Protester Karen Johnson added, "Women need to know more about the risks of these vaccines, especially if they're pregnant."

Pediatrician Theresa Robinson denounced the protesters: "I have lost all patience with anti-vaxxers and their nonsense. They are discouraging people from protecting themselves and putting lives at risk. They should be ashamed."

Damien Gordon, head of Intensive Care at St. Mary's Hospital, also condemned the demonstrators: "They are selfish idiots and their actions are dangerous. So many of us have worked tirelessly throughout the pandemic to save people. Groups like that are an insult to our sacrifices."

Similar protests have occurred in cities around the world, indicating the uncertainty many people feel about COVID-19 vaccines.

Condition 5: Discrediting (Political)

Protesters March in Washington DC

(Photo identical to condition 1)

By Gemma Wallace

WASHINGTON—Crowds of demonstrators marched through the streets of Washington DC to voice their concerns about the risks of COVID-19 vaccines. During the march, a group of protesters gathered at a local vaccine clinic, chanting "COVID Doesn't Kill Children, Vaccines Kill Children" and "Trust Your Body, Not Big Pharma" as patients waited in line to receive their vaccinations.

A spokesperson for Vaccine Truth Now claimed the protest was necessary because the medical community and the government are lying to people about the risks of COVID-19 vaccines. "These so-called vaccines cause heart damage in 1 in 10 children. They cause miscarriages and infertility in women. People need to know the truth."

Carol Richards expressed concerns shared by many. "I'm not anti-vax, but I worry about the dangers of an experimental vaccine. My children aren't guinea pigs." Protester Karen Johnson added, "Women need to know more about the risks of these vaccines, especially if they're pregnant."

Congresswoman Theresa Robinson denounced the protesters: "I have lost all patience with anti-vaxxers and their nonsense. They are discouraging people from protecting themselves and putting lives at risk. They should be ashamed."

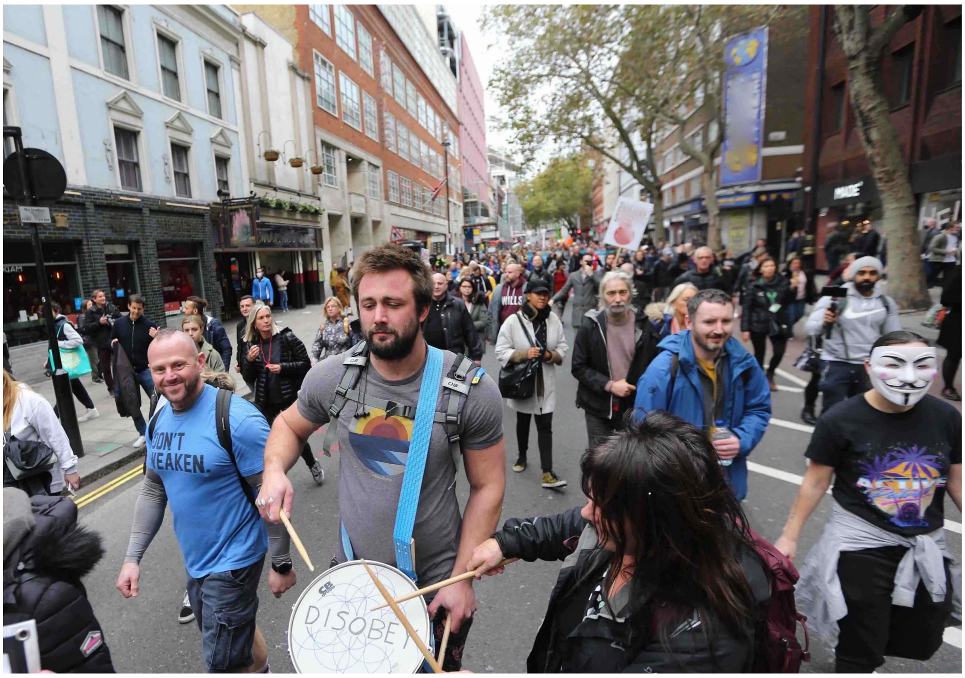
Damien Gordon, a spokesperson for the Office of the President, also condemned the demonstrators: "They are selfish idiots, and their actions are dangerous. So many doctors and nurses across the country have worked tirelessly throughout the pandemic to save people. Groups like that are an insult to their sacrifices."

Similar protests have occurred in cities around the world, indicating the uncertainty many people feel about COVID-19 vaccines.

<u>UK Respondents</u>

Condition 1: Control (misinformation only)

Protesters March in London



By Gemma Wallace

London— Crowds of demonstrators marched through the streets of London to voice their concerns about the risks of COVID-19 vaccines. During the march, a group of protesters gathered at a walk-in vaccine clinic, chanting "COVID Doesn't Kill Children, Vaccines Kill Children" and "Trust Your Body, Not Big Pharma" as patients queued to receive their jabs.

A spokesperson for Vaccine Truth Now claimed the protest was necessary because the medical community and the government are lying to people about the risks of COVID-19 vaccines. "These so-called vaccines cause heart damage in 1 in 10 children. They cause miscarriages and infertility in women. People need to know the truth."

Carol Richards expressed concerns shared by many. "I'm not anti-vax, but I worry about the dangers of an experimental vaccine. My children aren't guinea pigs." Protester Karen Johnson added, "Women need to know more about the risks these jabs carry, especially if they're pregnant."

Similar protests have occurred in cities around the world, indicating the uncertainty many people feel about COVID-19 vaccines.

Condition 2: Debunking (Health)

Protesters March in London

(Photo identical to condition 1)

By Gemma Wallace

London— Crowds of demonstrators marched through the streets of London to voice their concerns about the risks of COVID-19 vaccines. During the march, a group of protesters gathered at a walk-in vaccine clinic, chanting “COVID Doesn’t Kill Children, Vaccines Kill Children” and “Trust Your Body, Not Big Pharma” as patients queued to receive their jabs.

A spokesperson for Vaccine Truth Now claimed the protest was necessary because the medical community and the government are lying to people about the risks of COVID-19 vaccines. “These so-called vaccines cause heart damage in 1 in 10 children. They cause miscarriages and infertility in women. They aren’t safe”

Carol Richards expressed concerns shared by many. “I’m not anti-vax, but I worry about the dangers of an experimental vaccine. My children aren’t guinea pigs.” Protester Karen Johnson added, “Women need to know more about the risks these jabs carry, especially if they’re pregnant.”

Asked for her response, GP Theresa Robinson stated: “Millions of children—including both of my own kids—have been vaccinated against COVID-19. The vaccines are very safe and provide children and their families high levels of protection against a very serious disease.”

Damien Gordon, head of Intensive Care at St. Mary’s Hospital, added “There is zero evidence that vaccination poses a risk to pregnant women. Getting vaccinated is the best way for expectant mothers to protect themselves and their babies against COVID-19.”

Similar protests have occurred in cities around the world, indicating the uncertainty many people feel about COVID-19 vaccines.

Condition 3: Debunking (Political)

Protesters March in London

(Photo identical to condition 1)

By Gemma Wallace

London— Crowds of demonstrators marched through the streets of London to voice their concerns about the risks of COVID-19 vaccines. During the march, a group of protesters gathered at a walk-in vaccine clinic, chanting "COVID Doesn't Kill Children, Vaccines Kill Children" and "Trust Your Body, Not Big Pharma" as patients queued to receive their jabs.

A spokesperson for Vaccine Truth Now claimed the protest was necessary because the medical community and the government are lying to people about the risks of COVID-19 vaccines. "These so-called vaccines cause heart damage in 1 in 10 children. They cause miscarriages and infertility in women. People need to know the truth."

Carol Richards expressed concerns shared by many. "I'm not anti-vax, but I worry about the dangers of an experimental vaccine. My children aren't guinea pigs." Protester Karen Johnson added, "Women need to know more about the risks these jabs carry, especially if they're pregnant."

Asked for her response, MP Theresa Robinson stated "Millions of children—including both of my own kids —have been vaccinated against COVID-19. The vaccines are very safe and provide children and their families high levels of protection against a very serious disease."

Damien Gordon, a spokesperson for the Cabinet Office, added, "There is zero evidence that vaccination poses a risk to pregnant women. Getting vaccinated is the best way for expectant mothers to protect themselves and their babies against COVID-19."

Similar protests have occurred in cities around the world, indicating the uncertainty many people feel about COVID-19 vaccines.

Condition 4: Discrediting (Health)

Protesters March in London

(Photo identical to condition 1)

By Gemma Wallace

London— Crowds of demonstrators marched through the streets of London to voice their concerns about the risks of COVID-19 vaccines. During the march, a group of protesters gathered at a walk-in vaccine clinic, chanting "COVID Doesn't Kill Children, Vaccines Kill Children" and "Trust Your Body, Not Big Pharma" as patients queued to receive their jabs.

A spokesperson for Vaccine Truth Now claimed the protest was necessary because the medical community and the government are lying to people about the risks of COVID-19 vaccines. "These so-called vaccines cause heart damage in 1 in 10 children. They cause miscarriages and infertility in women. People need to know the truth."

Carol Richards expressed concerns shared by many. "I'm not anti-vax, but I worry about the dangers of an experimental vaccine. My children aren't guinea pigs." Protester Karen Johnson added, "Women need to know more about the risks these jabs carry, especially if they're pregnant."

GP Theresa Robinson denounced the protesters: "I have lost all patience with anti-vaxxers and their nonsense. They are discouraging people from protecting themselves and putting lives at risk. They should be ashamed."

Damien Gordon, head of Intensive Care at St. Mary's Hospital, also condemned the demonstrators: "They are selfish idiots, and their actions are dangerous. So many of us have worked tirelessly throughout the pandemic to save people. Groups like that are an insult to our sacrifices."

Similar protests have occurred in cities around the world, indicating the uncertainty many people feel about COVID-19 vaccines.

Condition 5: Discrediting (Political)

Protesters March in London

(Photo identical to condition 1)

By Gemma Wallace

London— Crowds of demonstrators marched through the streets of London to voice their concerns about the risks of COVID-19 vaccines. During the march, a group of protesters gathered at a walk-in vaccine clinic, chanting "COVID Doesn't Kill Children, Vaccines Kill Children" and "Trust Your Body, Not Big Pharma" as patients queued to receive their jabs.

A spokesperson for Vaccine Truth Now claimed the protest was necessary because the medical community and the government are lying to people about the risks of COVID-19 vaccines. "These so-called vaccines cause heart damage in 1 in 10 children. They cause miscarriages and infertility in women. People need to know the truth."

Carol Richards expressed concerns shared by many. "I'm not anti-vax, but I worry about the dangers of an experimental vaccine. My children aren't guinea pigs." Protester Karen Johnson added, "Women need to know more about the risks these jabs carry, especially if they're pregnant."

MP Theresa Robinson denounced the protesters: "I have lost all patience with anti-vaxxers and their nonsense. They are discouraging people from protecting themselves and putting lives at risk. They should be ashamed."

Damien Gordon, a spokesperson for the Cabinet Office, also condemned the demonstrators: "They are selfish idiots, and their actions are dangerous. So many doctors and nurses across the country have worked tirelessly throughout the pandemic to save people. These groups are an insult to their sacrifices."