Appendix [1]

A. Survey items measuring conspiracy theory beliefs

Thinking about the coronavirus, to what extent do you believe the following statements to be true or false?

(very certain it's false/somewhat certain it's false, uncertain whether it's true or false, somewhat certain it's true, very certain it's true)

- The vaccine against the coronavirus has already been developed, but big pharmaceutical companies are hiding it from us to increase profit
- The coronavirus is a bioweapon that has been deliberately created by China to harm people
- The coronavirus is the accidental leak of a US military secret experiment

[1] In case of publication this content will be uploaded to an online repository.

B. Test of potential systematic differences across countries in belief in the origins of coronavirus

Figure A1: Means of answers endorsing the conspiracy beliefs pointing, respectively, at China and US as the origin of COVID-19

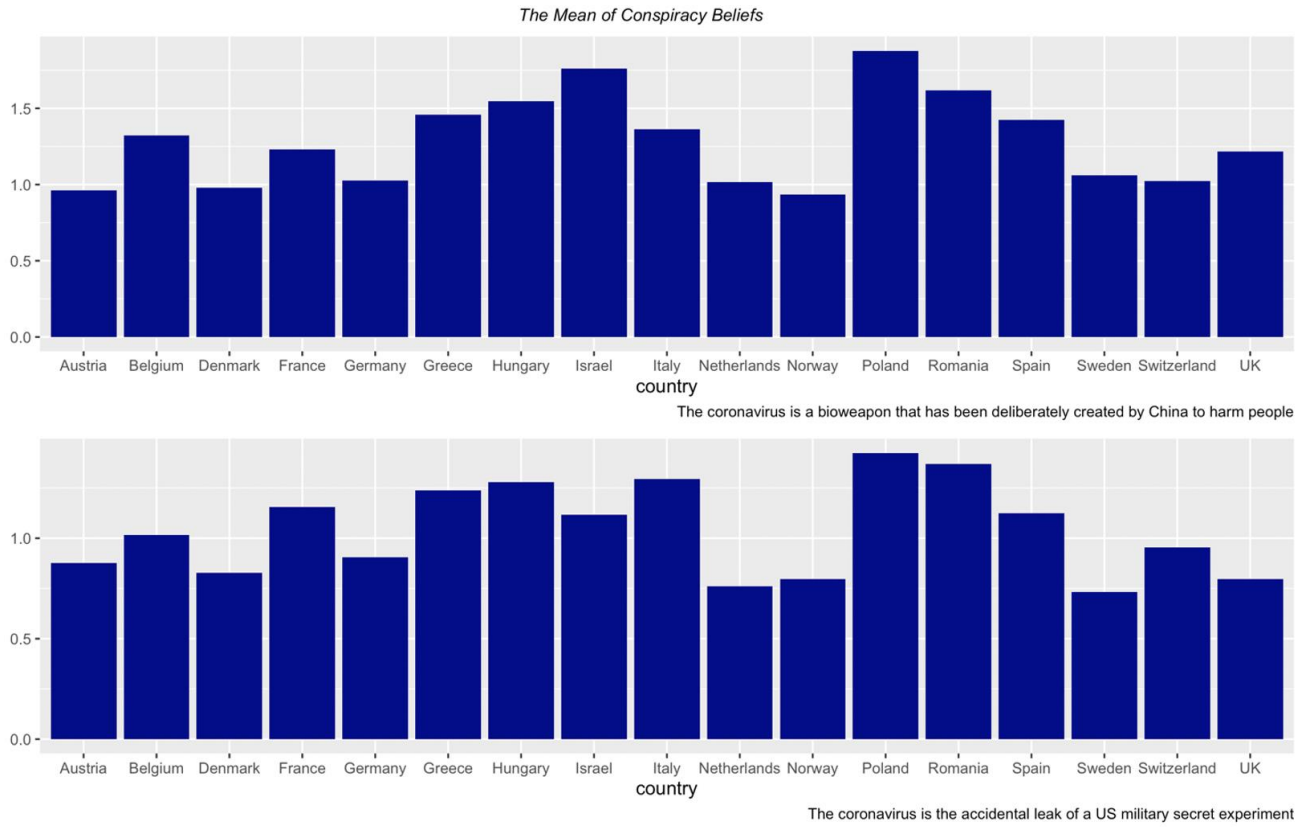
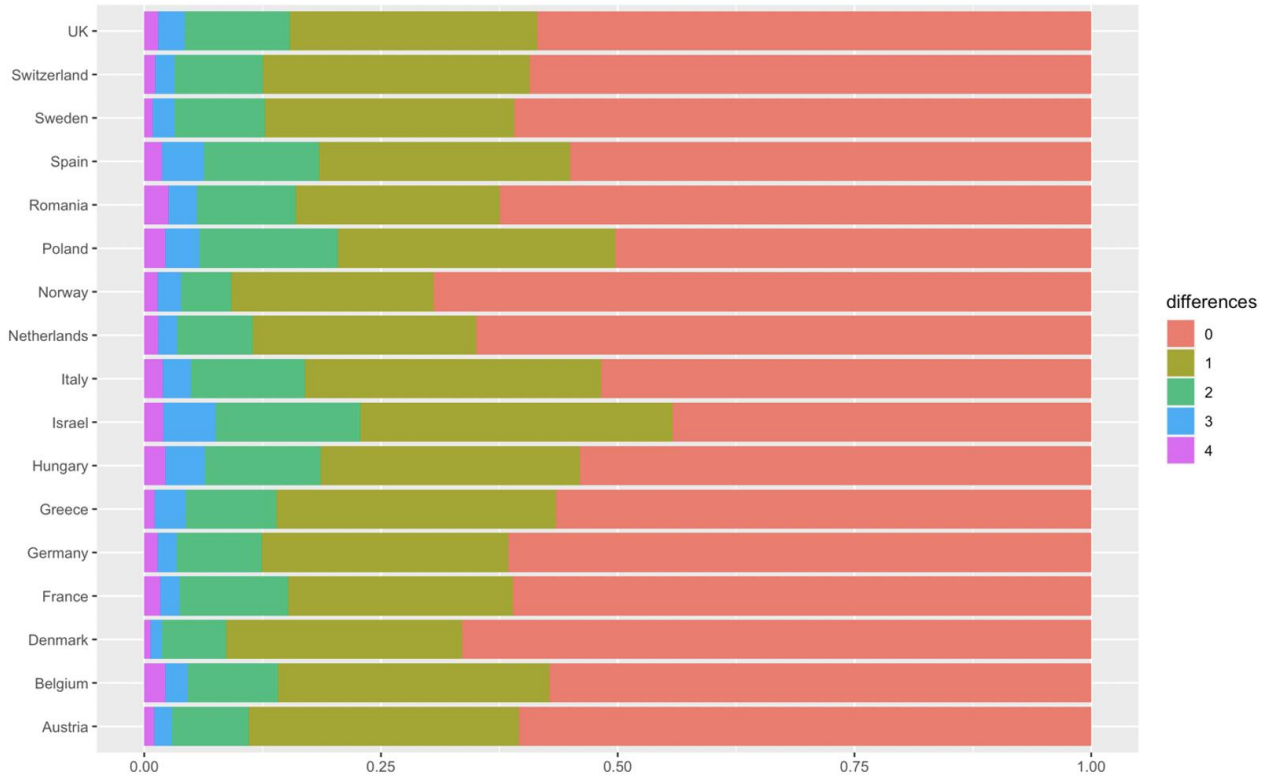


Figure A2: Stacked plot of individual-level differences in endorsing China and US as the origin of COVID-19



C. Robustness tests with dichotomous measurement and logit modelling

We also modelled the relationships in question using a dichotomous measure whereby we assigned 1 to respondents that are certain or very certain about *any* of the three statements concerning conspiracy theories, and a 0 otherwise. Figure A1 below plots the coefficients for the dichotomous measure using logit and multilevel mixed-effects logistic regressions.

Figure A3

Conspiracy Beliefs by Country (Dichotomous Measure)

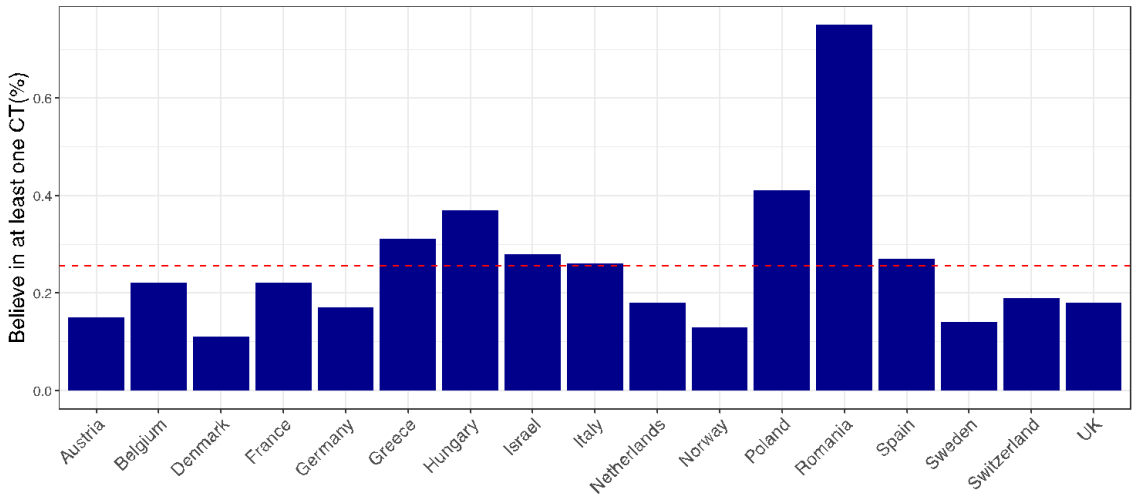


Figure A4

Platforms Coefficients for Logit and Multilevel Logit Models

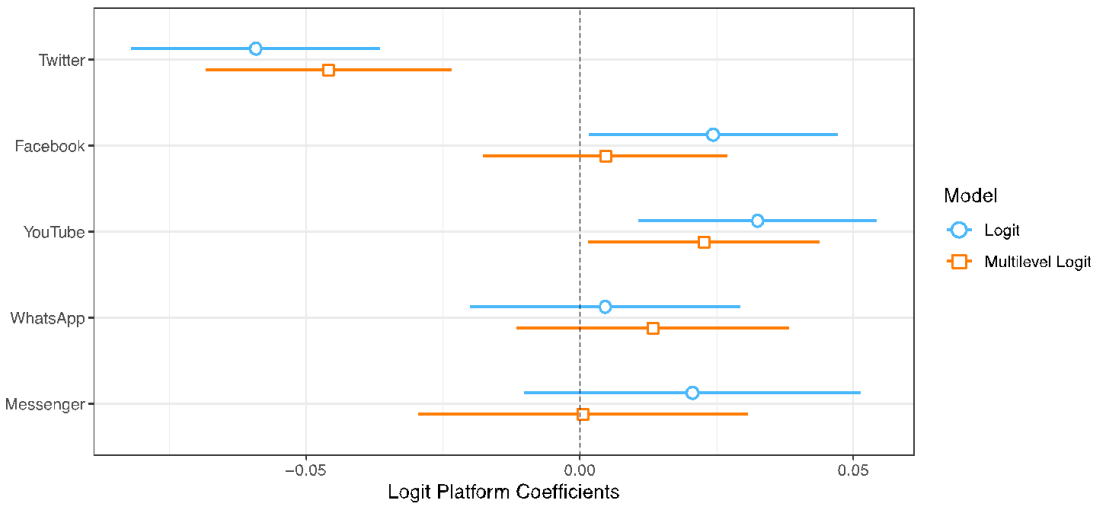


Table A1

Results from Non-linear Models

	Dependent variable:	
	Conspiracy Beliefs (Dic)	
	logit	*mixed-effects*
	(1)	(2)
Twitter	-0.059***	-0.046***
	(0.012)	(0.011)
Facebook	0.024**	0.005
	(0.012)	(0.011)
YouTube	0.032***	0.023**
	(0.011)	(0.011)
WhatsApp	0.005	0.013
	(0.013)	(0.013)
Messenger	0.021	0.001
	(0.016)	(0.015)
Age	-0.0005	-0.001***
	(0.0004)	(0.0004)
Male	0.001	-0.005
	(0.010)	(0.009)
Education	0.011	-0.025***
	(0.008)	(0.008)
Left-Right Self-Placement (0-10)	0.024***	0.021***
	(0.002)	(0.002)
Political Interest	-0.005	-0.003
	(0.004)	(0.004)
Trust in Pol. Parties	-0.035***	-0.014*
	(0.008)	(0.007)
Trust in Government	-0.004	-0.003
	(0.007)	(0.007)
Media Trust	-0.017***	-0.012***
	(0.003)	(0.003)

Extremism	0.002***	0.002***
	(0.001)	(0.001)
Political Knowledge W1	-0.170***	-0.124***
	(0.025)	(0.025)
Political Knowledge W2	-0.142***	-0.137***
	(0.025)	(0.025)
News Frequency	0.065***	0.058***
	(0.008)	(0.008)
SMedia Frequency	0.010***	0.007***
	(0.003)	(0.003)
Internet Frequency	-0.024***	-0.022***
	(0.004)	(0.004)
Income	-0.043***	-0.034***
	(0.005)	(0.005)
Subjective Knowledge Politics W2	0.008	0.001
	(0.005)	(0.005)
Subjective Knowledge Corona W2	0.009**	0.007
	(0.004)	(0.004)
Know Someone Infected Corona (No/Yes)	-0.016*	-0.001
	(0.010)	(0.010)
Constant	0.437***	0.500***
	(0.039)	(0.050)
Observations	9,620	9,620
Log Likelihood	-5,503.928	-5,267.239
Akaike Inf. Crit.	11,055.860	10,586.480
Bayesian Inf. Crit.		10,772.940
Note:	*p<0.1; **p<0.05; ***p<0.01	

D. Results from linear models used in the text

Table A2

Results from Linear Models Used in the Text

	Dependent variable:	
	Conspiracy Index	
	OLS	*mixed-effects*
	(1)	(2)
Twitter	-0.029***	-0.027***
	(0.006)	(0.006)
Facebook	0.018***	0.005
	(0.006)	(0.006)
YouTube	0.031***	0.025***
	(0.005)	(0.005)
WhatsApp	0.013**	0.017***
	(0.006)	(0.006)
Messenger	0.025***	0.015*
	(0.008)	(0.007)
Age	-0.0003*	-0.0004**
	(0.0002)	(0.0002)
Male	0.0001	-0.002
	(0.005)	(0.004)
Education	-0.012***	-0.028***
	(0.004)	(0.004)
Left-Right Self-Placement (0-10)	0.014***	0.013***
	(0.001)	(0.001)
Political Interest	-0.008***	-0.007***
	(0.002)	(0.002)
Trust in Pol. Parties	-0.021***	-0.009**
	(0.004)	(0.004)
Trust in Government	-0.018***	-0.017***
	(0.004)	(0.003)

Media Trust	-0.008***	-0.005***
	(0.002)	(0.002)
Extremism	0.001***	0.001***
	(0.0003)	(0.0003)
Political Knowledge W1	-0.108***	-0.086***
	(0.012)	(0.012)
Political Knowledge W2	-0.171***	-0.166***
	(0.012)	(0.012)
News Frequency	0.050***	0.050***
	(0.004)	(0.004)
SMedia Frequency	0.005***	0.004***
	(0.001)	(0.001)
Internet Frequency	-0.019***	-0.019***
	(0.002)	(0.002)
Income	-0.024***	-0.019***
	(0.003)	(0.003)
Subjective Knowledge Politics W2	0.007***	0.004
	(0.002)	(0.002)
Subjective Knowledge Corona W2	-0.007***	-0.010***
	(0.002)	(0.002)
Know Someone Infected Corona (No/Yes)	-0.011**	-0.003
	(0.005)	(0.005)
Constant	0.587***	0.605***
	(0.019)	(0.024)
Observations	9,620	9,620
R^2	0.180	
Adjusted R^2	0.178	
Log Likelihood		1,619.723
Akaike Inf. Crit.		-3,187.446
Bayesian Inf. Crit.		-3,000.984
Residual Std. Error	0.208 (df = 9596)	
F Statistic	91.404*** (df = 23; 9596)	
Note:	*p<0.1; **p<0.05; ***p<0.01	

E. Propensity Score Matching application details and covariate balance for different platforms

Rosenbaum and Rubin (1983) have shown that the propensity score is a balancing score, meaning that at each value of the propensity score the distribution of the covariates defining the propensity score is the same in the treated and control groups. Once we had the propensity scores for the matching, we applied caliper matching, a variation of nearest neighbor (NN) matching. We applied the matching within a maximum distance (caliper) of .02, as it is the width recommended by Austin (2011) and a standard in the literature. Procedure-wise this means that for each treated unit in the sample, the algorithm searches for the closest control unit in terms of propensity score. If no control unit is available in the range defined by the caliper, the treated unit is discarded from the matched sample. The process was repeated to find the ideal balance–until the absolute standardized differences in means was smaller than 0.2. In some instances, when a sufficient number of treated subjects were discarded and no balance was achieved, propensity score weighting was applied (see Guo & Fraser, 2015 for a detailed explanation). Lastly, when the number of treated subjects exceeded the controlled subjects significantly so that the sufficient number of the match was not achieved, we did matching with replacement, where the same control unit can be used several times for the match. Regarding our set of covariates, Rubin and Thomas (2000) show that more covariates are better than less or that "the general multivariate matching is superior to methods that focus only on a subset of the prognostically most important covariates" (p. 574). They even argue that the set of covariates on which the matching is applied does not necessarily have to be limited to "true" confounders. As such, following Rubin and Thomas (2000), propensity scores were estimated using the largest possible set of covariates, although smaller sets of covariates were also tried (for a longer elaboration of our application of propensity score matching see supplementary material)

References (not already mentioned in main text)

Austin PC (2011) Optimal caliper widths for propensity-score matching when estimating differences in means and differences in proportions in observational studies. *Pharmaceutical statistics* 10(2): 150-161.

Cannas M and Arpino B (2015) Propensity Score Matching with Clustered Data. *19th European Young Statisticians Meeting.* 24.

Guo S and Fraser MW (2014) *Propensity score analysis: Statistical methods and applications.* SAGE publications.

Rosenbaum PR and Rubin DB (1983) The central role of the propensity score in observational studies for causal effects. *Biometrika* 70(1): 41-55.

Figure A5

Covariate Balance for Twitter

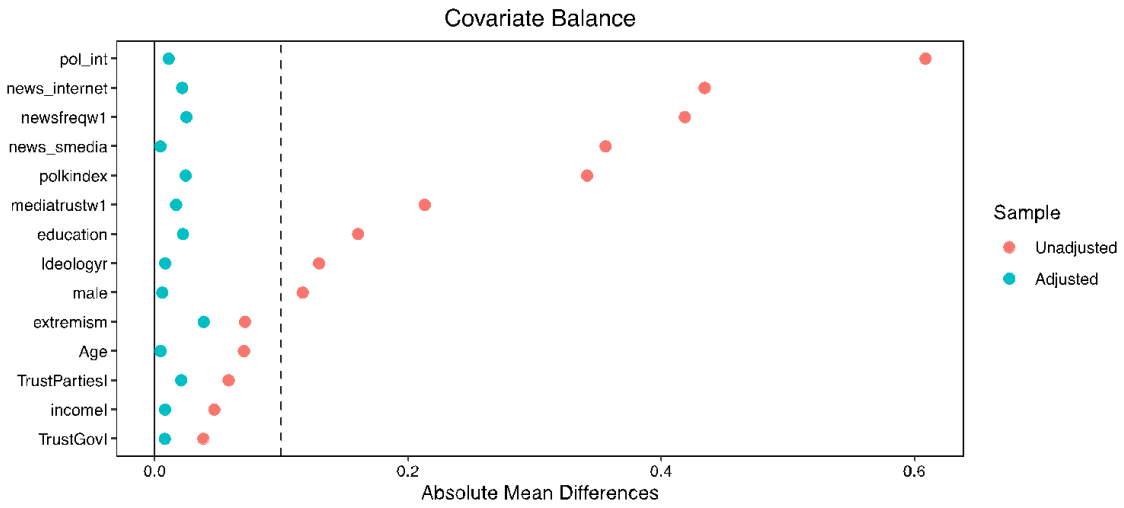


Figure A6

Covariate Balance for Facebook

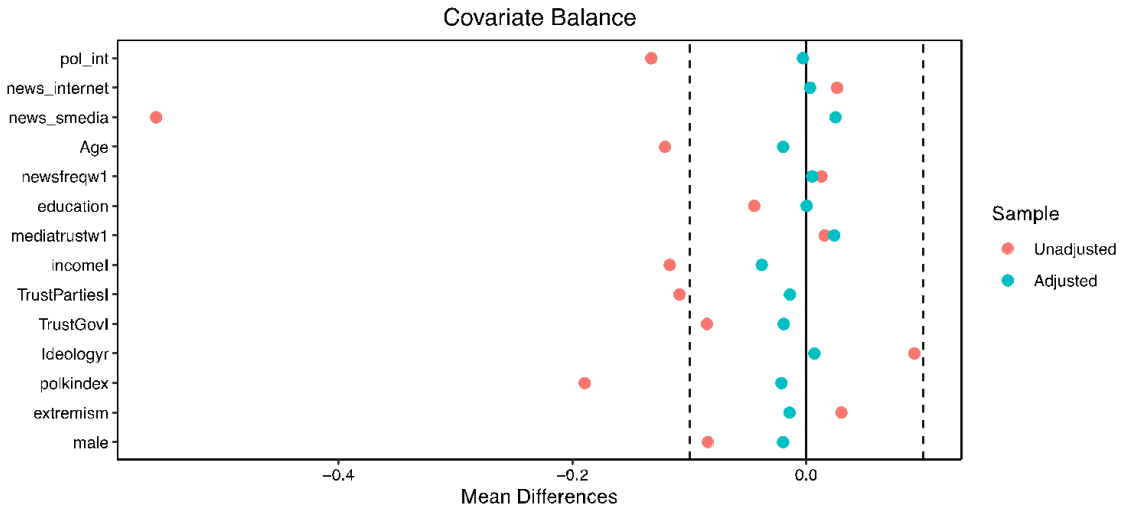


Figure A7

Covariate Balance for YouTube

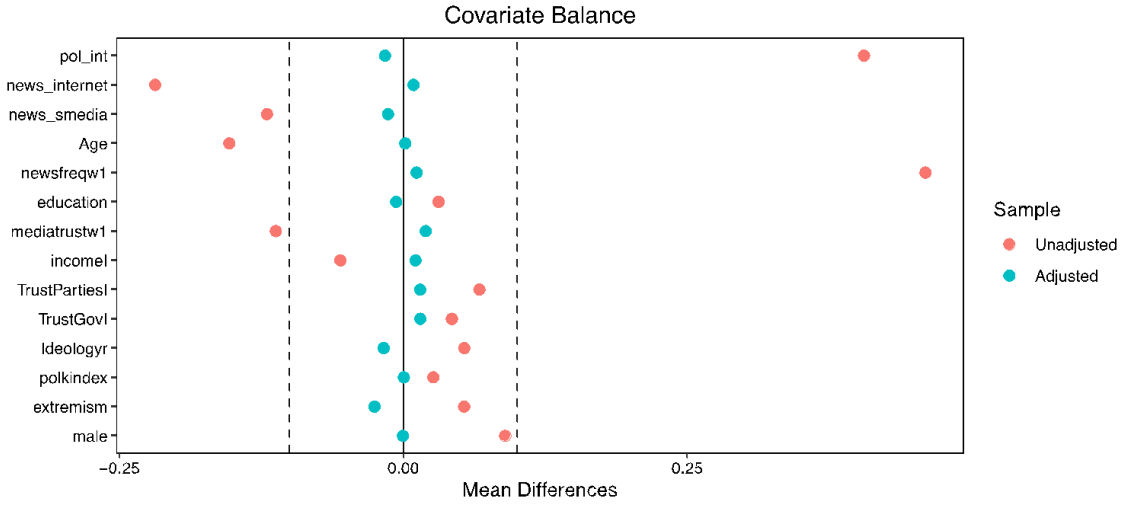


Figure A8

Covariate Balance for WhatsApp

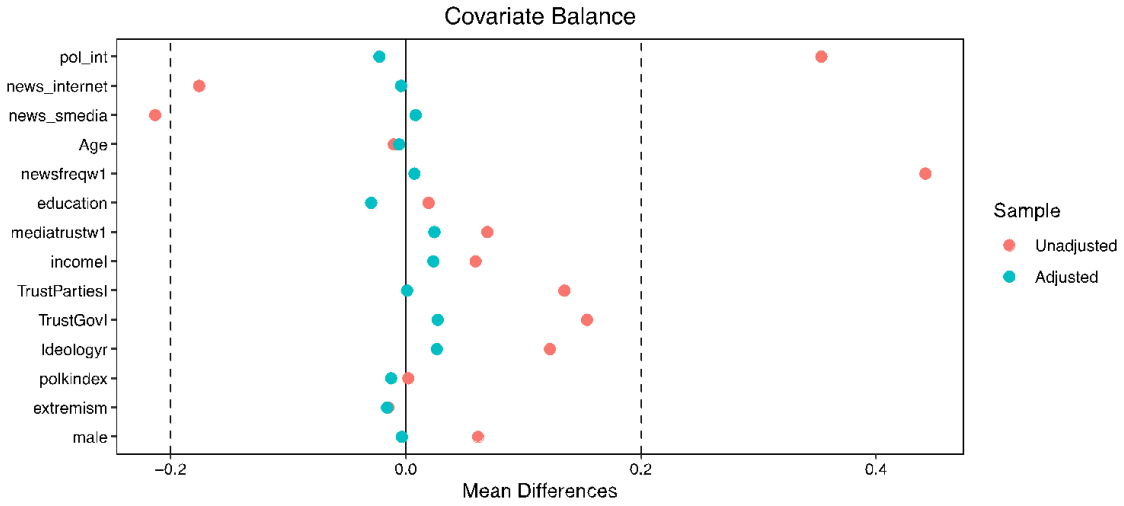


Figure A9

Covariate Balance for Messenger