

# Online Supplementary Information for: Thinking Fast and Furious: Emotional Intensity and Opinion Polarization in Online Media

David Asker\*    Elias Dinas<sup>†\*</sup>

## Appendix

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\*Department of Politics and International Relations, University of Oxford, Manor Road Building, OX1 3UQ, Oxford, [david.asker@gmail.com](mailto:david.asker@gmail.com).

<sup>†</sup>European University Institute, Department of Political and Social Sciences, Villa Sanfelice, San Domenico di Fiesole, I-50014, Italy, [elias.dinas@eui.eu](mailto:elias.dinas@eui.eu).

## A.1 Summary statistics on participants

Covariates are balanced across treatment groups: all differences between the treatment and control groups fail to attain statistical significance at conventional levels, as evidenced below. ‘Prior support for policy’ indicates the share of participants who expressed, during the pre-treatment questionnaire, that they were in favor of the policy discussed in the article to which they were assigned (gun control or the Trans-Pacific Partnership).

The final sample included only 548 participants, since we excluded those participants who failed an attention check, as is standard practice when recruiting crowdsourced samples.

**Table A1:** Summary statistics on participants

	All	Treatment	Control	Diff	CI low	CI high	p
Age	36.00	35.91	36.10	0.20	-1.68	2.07	0.84
Female	0.56	0.53	0.59	0.06	-0.15	0.03	0.20
Political knowledge	0.49	0.51	0.46	-0.05	-0.04	0.14	0.30
Democrats	0.50	0.53	0.46	-0.07	-0.02	0.16	0.12
Republicans	0.17	0.15	0.18	0.03	-0.17	0.07	0.47
Independents	0.30	0.28	0.33	0.04	-0.15	0.04	0.30
Prior support for policy	0.54	0.55	0.53	-0.02	-0.06	0.11	0.64
N	548.00	281.00	267.00				

## A.2 Political knowledge questions

The following four questions were used to gauge participants knowledge of poiltics in the pre-treatment questionnaire. The order in which the answers appeared was randomized for each participant.

1. *“Whose responsibility is it to determine if a law is constitutional or not?”*

	Q1_ answers
Don't know	16
The House of Representatives	6
The President	8
The Senate	10
The Supreme Court	508

2. *“What majority of votes is needed in each house of Congress to overturn a presidential veto?”*

	Q2_ answers
51 of the votes	9
Don't know	40
Three fifths of the votes	41
Three quarters of the votes	59
Two thirds of the votes	399

3. *“What political position is held by the man in this photo?”* (Portrait photo of then-Vice President Joe Biden)

	Q3_ answers
Vice President	548
Speaker of the House	0
Majority Leader of the Senate	0
Secretary of State	0
Don't know	0

4. *“Which party currently has the most members in the House of Representatives?”*

	Q4_ answers
Don't know	49
Democrats	44
Republicans	455

### A.3 Text of gun control article

#### Obama announces gun actions in emotional plea for congressional action

WASHINGTON — President Obama announced a series of executive actions on guns Tuesday, focusing on the victims of gun violence in a White House event intended to prod Congress to take further action.

The executive actions — first previewed by the White House on Monday — would attempt to clamp down on unlicensed gun sellers who exploit an exception for hobbyists and collectors in order to avoid having to run criminal background checks on gun purchasers. Many of those sellers, Obama said, are running a business by selling guns at gun shows and online.

“The problem is that some gun sellers have been operating by a different set of rules,” he said. “That doesn’t make sense.”

Obama said the administration is also beefing up enforcement, streamlining the background check system, investing \$500 million in mental health care and researching “smart gun” technology.

Obama said the actions he’s taking are consistent with gun rights.

“I believe in the Second Amendment. It’s there written on paper. It guarantees the right to bear arms. No matter how much people try to twist my words around, I taught constitutional law. I know a little bit about this. I get it,” he said. “This is not a plot to take away everybody’s guns.”

Congressional Republicans had a mixed reaction to Obama’s announcement. “The president’s actions are out of bounds and vastly exceed his executive authority,” said House Oversight Committee Chairman Jason Chaffetz, R-Utah, who promised vigorous oversight hearings. But House Majority Leader Kevin McCarthy, R-Calif., called the additional guidance on firearms licenses a “weak gesture” that falls short of what Obama really wanted to accomplish.

## A.4 Text of Trans-Pacific Partnership article

### U.S., allies strike Pacific Rim trade deal

*The United States and 11 other Pacific Rim nations struck a tentative trade agreement Monday, a landmark deal that has the potential to transform the global economy, divide political parties in Congress and roil the U.S. presidential race.*

*As President Obama and aides began selling the agreement to Congress and the public, critics denounced it as yet another free-trade deal that will help ship American jobs overseas.*

*The Trans-Pacific Partnership will “promote economic growth” and “support higher paying jobs,” said U.S. Trade Rep. Michael Froman, making the announcement along with other trade ministers in Atlanta after days of negotiations.*

*The massive proposed agreement — which faces months of debate in Congress — would tie together nearly 40% of the world’s economy, from Canada to Chile to Japan to Australia; it would be the largest regional trade agreement in history.*

*In hailing the agreement, Obama said, “Congress and the American people will have months to read every word” before he signs the deal that he described as a win for all sides.*

*“If we can get this agreement to my desk, then we can help our businesses sell more Made in America goods and services around the world, and we can help more American workers compete and win,” Obama said.*

*Critics said employers will use the agreement to move jobs to poorer countries that have lower wages and fewer regulations.*

*Arthur Stamoulis, executive director of the Citizens Trade Campaign, predicted Congress would reject the deal, especially on the eve of an election year.*

*“Heading into 2016 and beyond, Congress members know that American voters are not going to accept a massive trade agreement with undemocratic countries that offshores jobs and drives down wages,” he said.*

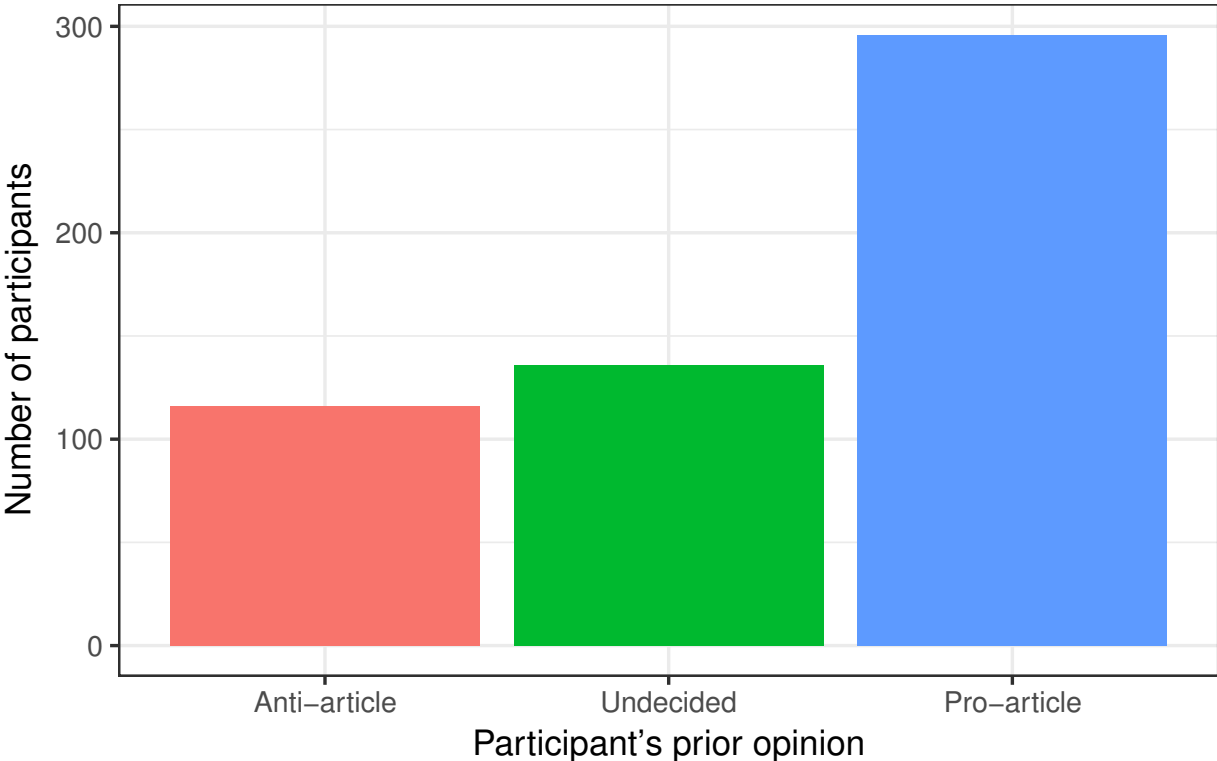
*In pledging to work with Congress, Obama said the pact includes “the strongest commitments on labor and the environment of any trade agreement in history” and removes trade barriers that have blocked U.S. products.*

### A.5 Distributions of participant priors and comment-article agreement

The pre-treatment questionnaire asked participants to report their prior view on the topic discussed in the article to which they had been assigned. Answers were coded to indicate whether they agreed with the policy described in each article, yielding three categories, which we label “Anti-article”, “Pro-article”, and “Undecided.”

The distribution of these categories is reported in Figure A1. Since both articles described policies supported by the Obama administration, and MTurk users are known to be somewhat more liberal than the electorate at large, the “Pro-article” category is somewhat overrepresented. However, participant priors are balanced across treatment conditions, as shown in table A1.

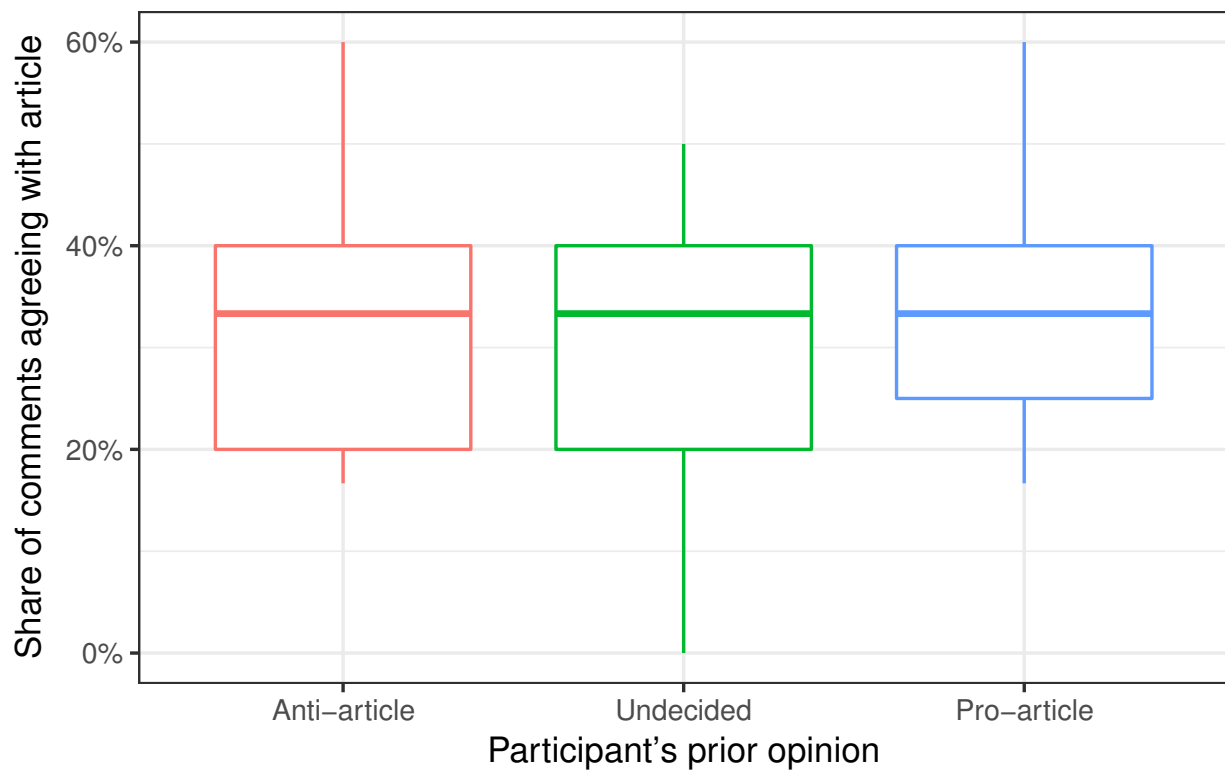
**Figure A1:** Distribution of participant priors



Each comment was also coded to reflect whether it agreed with the policy described in the article. In theory the coding scheme included three categories: pro-article comments, anti-article comments, and neutral comments; in practice, however, all comments were found to discernibly support or oppose the position in the article, such that no comments were coded as neutral. Figure A2 shows the distribution of the share of comments supporting the article shown to each participant, disaggregating by participant prior opinion. This demonstrates that the balance of comments was similar across categories of priors.

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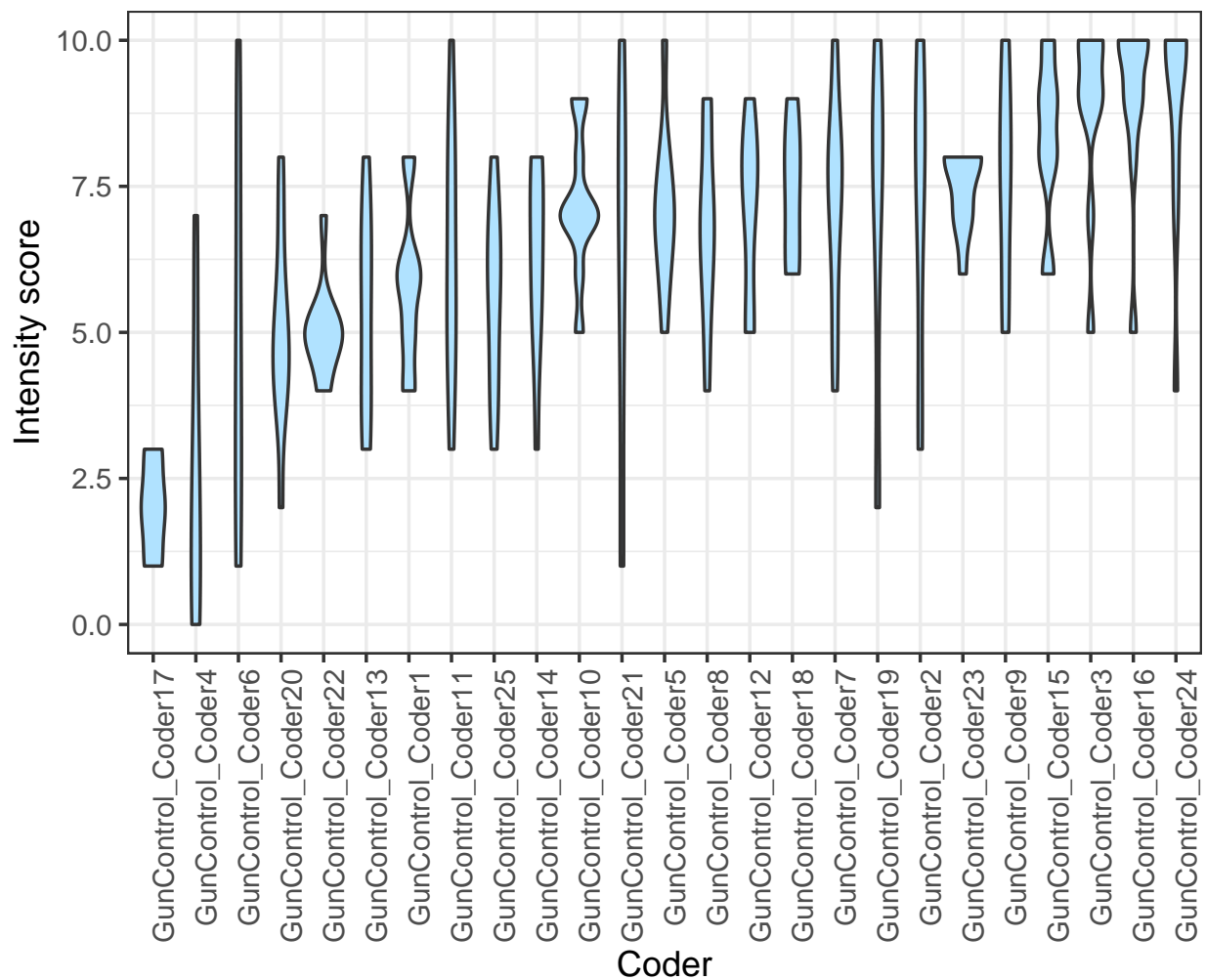
**Figure A2:** Distributions of comment direction by participant prior



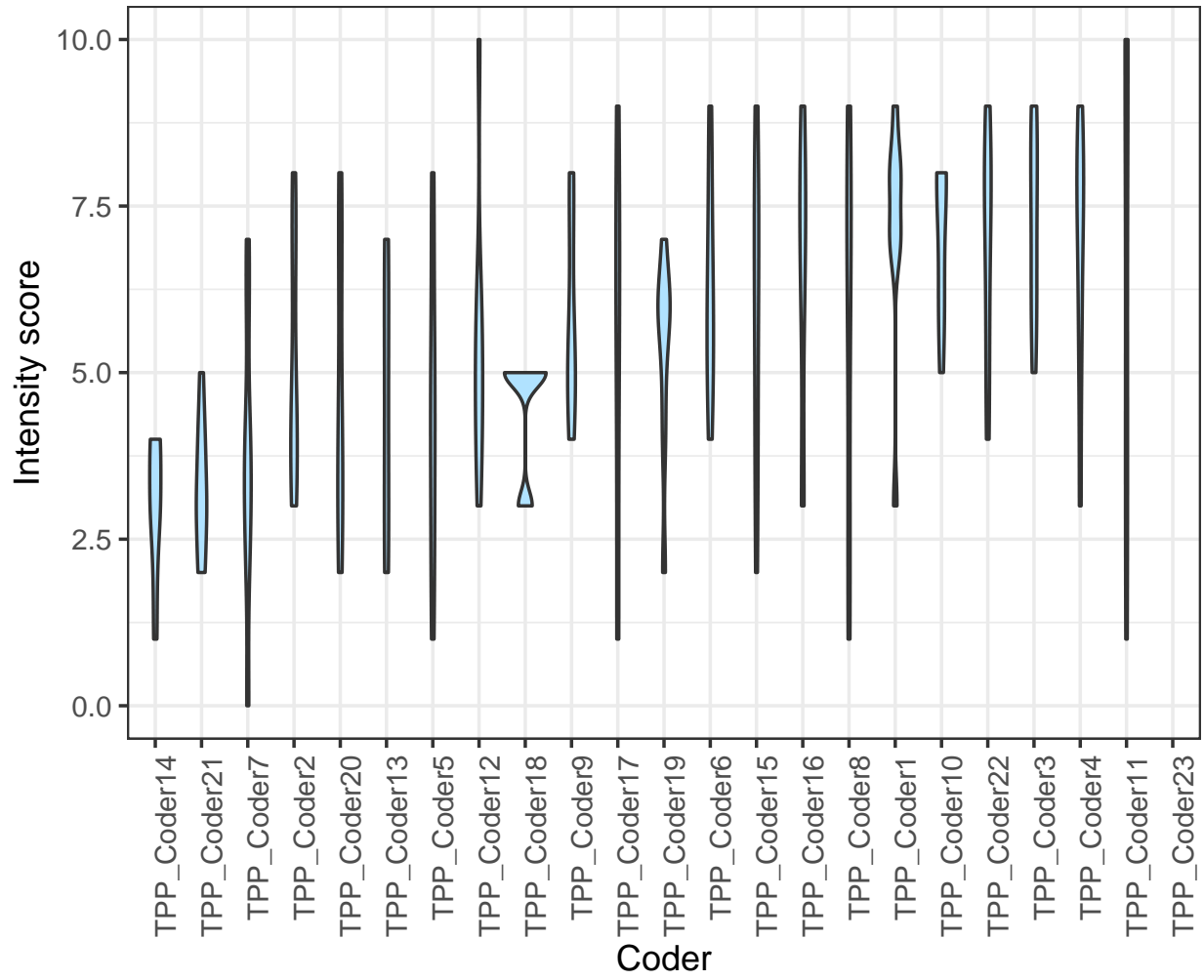
## A.6 Descriptive statistics on coders

This section displays the distribution of comment scores submitted by each crowdsourced coder, to provide a sense of the variation within and between coders. Because of the nature of crowdsourced non-expert coding, this variance is quite large, as we might expect.

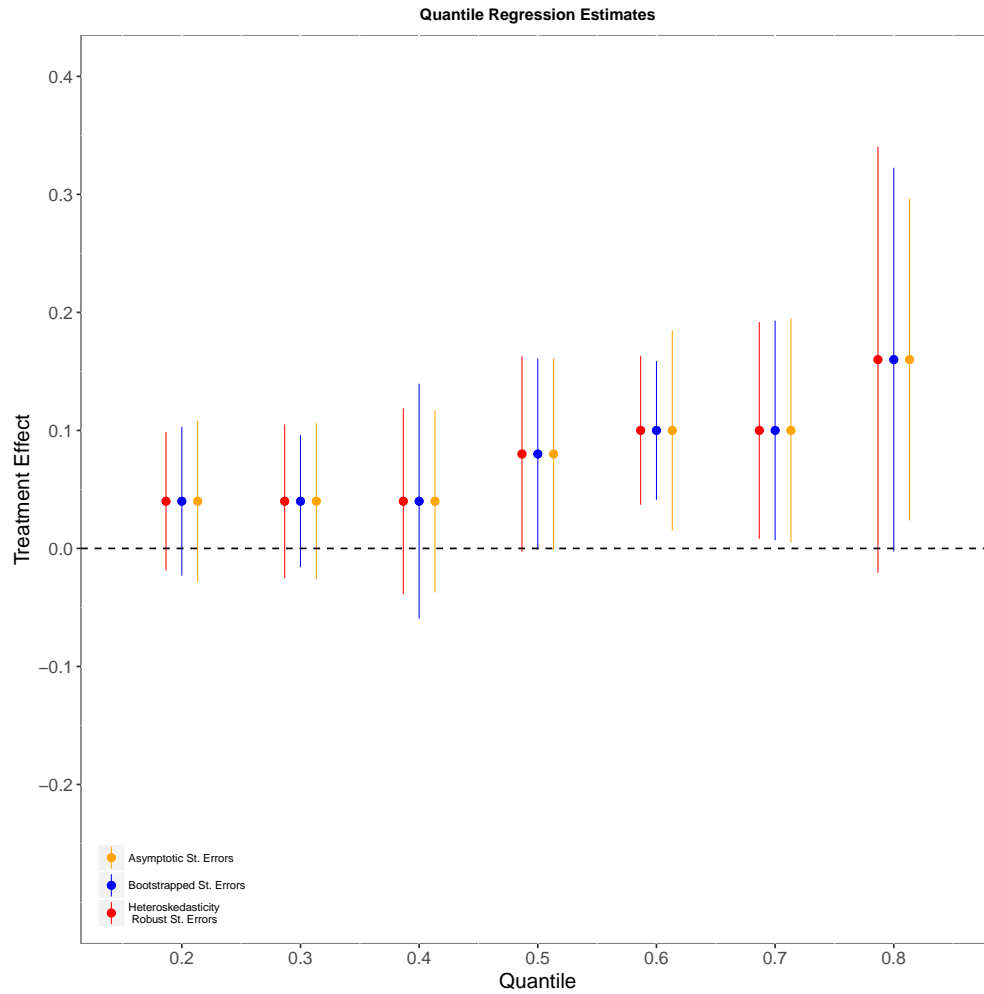
**Figure A3:** Distributions of crowdsourced coders' scores for Gun Control article



**Figure A4:** Distributions of crowdsourced coders' scores for TPP article



## A.7 Quantile regression results



**Figure A5:** Quantile regression estimates of the comments' section effect on the opinion intensity.

Note: Orange entries denote estimates with asymptotic 95% confidence intervals; blue entries denote bootstrapped-based 95% confidence intervals; red entries denote heteroskedasticity-robust 95% CIs.

## A.8 Alternative coding of the dependent variable

The results are robust to recoding the polarization score in a number of different ways.

First, we code the polarization score as the square of the distance from the midpoint of the scale  $[0,10]$  which, and try two different categorical codings: one giving a polarization score of 1 to all participants who picked an extreme endpoint on the scale (0 or 10) while giving everyone else 0, and another giving a polarization score of 1 to anyone who answered 8 or above or 2 or below, while giving everyone else 0.

In addition, we also code the variable as the deviation of from the mean of the participants' answers rather than the scale midpoint. We also try the square of this deviation, and we try making it categorical by scoring everyone who answered above the median deviation as 1, and all those who answered below as 0. Finally, we repeat the above exercise using the median instead of the mean as the neutral point.

The results are given in the tables below. As these tables make clear, the relationship between the polarization score and treatment remains intact regardless of which operationalization is used.

**Table A2:** Results with alternative codings of the polarization score

	<i>Dependent variable:</i>					
	Min / max score		Squared score		Categorical score	
	(1)	(2)	(3)	(4)	(5)	(6)
Intensity	0.096** (0.049)	0.094* (0.049)	0.102** (0.047)	0.095** (0.047)	0.132** (0.064)	0.122* (0.064)
Guns Article	0.159*** (0.030)	0.156*** (0.031)	0.189*** (0.029)	0.189*** (0.029)	0.215*** (0.040)	0.216*** (0.040)
Age		0.006 (0.009)		0.006 (0.009)		0.008 (0.012)
Age <sup>2</sup>		-0.0001 (0.0001)		-0.00005 (0.0001)		-0.0001 (0.0001)
Male		-0.054* (0.031)		-0.046 (0.029)		-0.047 (0.040)
Party: Ind		0.033 (0.034)		-0.009 (0.033)		-0.015 (0.045)
Party: Other		0.023 (0.083)		-0.088 (0.079)		-0.144 (0.108)
Party: Rep		0.030 (0.043)		-0.039 (0.041)		-0.079 (0.056)
Follows politics		0.041 (0.031)		0.068** (0.030)		0.108*** (0.041)
Constant	-0.271*** (0.075)	-0.422** (0.182)	-0.159** (0.072)	-0.319* (0.174)	-0.232** (0.099)	-0.472** (0.238)
Observations	548	548	548	548	548	548
R <sup>2</sup>	0.060	0.076	0.087	0.111	0.063	0.095
Adjusted R <sup>2</sup>	0.057	0.061	0.083	0.096	0.060	0.079

*Note:*

\*p&lt;0.1; \*\*p&lt;0.05; \*\*\*p&lt;0.01

**Table A3:** Results based on deviations from the mean opinion

	<i>Dependent variable:</i>					
	Diff from mean		Squared diff from mean		Diff from mean (binary)	
	(1)	(2)	(3)	(4)	(5)	(6)
Intensity	0.051** (0.022)	0.050** (0.022)	0.030** (0.012)	0.030** (0.012)	0.156** (0.068)	0.149** (0.068)
Guns Article	0.064*** (0.014)	0.062*** (0.014)	0.033*** (0.008)	0.031*** (0.008)	0.205*** (0.042)	0.198*** (0.042)
Age		0.003 (0.004)		0.002 (0.002)		0.020 (0.013)
Age <sup>2</sup>		-0.00003 (0.00005)		-0.00001 (0.00003)		-0.0002 (0.0002)
Male		-0.014 (0.014)		-0.010 (0.008)		-0.044 (0.043)
Party: Ind		0.004 (0.016)		0.008 (0.009)		-0.050 (0.048)
Party: Other		-0.034 (0.037)		-0.004 (0.021)		-0.160 (0.115)
Party: Rep		0.013 (0.019)		0.015 (0.011)		-0.022 (0.059)
Follows politics		0.035** (0.014)		0.022*** (0.008)		0.083* (0.043)
Constant	0.064* (0.034)	-0.019 (0.082)	-0.008 (0.019)	-0.057 (0.046)	-0.101 (0.105)	-0.505** (0.253)
Observations	548	548	548	548	548	548
R <sup>2</sup>	0.053	0.075	0.048	0.078	0.056	0.079
Adjusted R <sup>2</sup>	0.050	0.060	0.044	0.063	0.053	0.063

*Note:*

\*p&lt;0.1; \*\*p&lt;0.05; \*\*\*p&lt;0.01

**Table A4:** Results based on deviations from the median opinion

	<i>Dependent variable:</i>					
	Diff from median		Squared diff from median		Diff from median (binary)	
	(1)	(2)	(3)	(4)	(5)	(6)
Intensity	0.054** (0.023)	0.055** (0.023)	0.033** (0.013)	0.034*** (0.013)	0.171** (0.069)	0.166** (0.068)
Guns Article	0.047*** (0.014)	0.043*** (0.014)	0.022*** (0.008)	0.019** (0.008)	0.159*** (0.042)	0.149*** (0.043)
Age		0.003 (0.004)		0.002 (0.002)		0.026** (0.013)
Age <sup>2</sup>		-0.00003 (0.0001)		-0.00002 (0.00003)		-0.0003* (0.0002)
Male		-0.013 (0.014)		-0.009 (0.008)		-0.067 (0.043)
Party: Ind		0.013 (0.016)		0.016* (0.009)		-0.036 (0.048)
Party: Other		-0.014 (0.038)		0.009 (0.022)		-0.194* (0.116)
Party: Rep		0.038* (0.020)		0.034*** (0.012)		0.016 (0.060)
Follows politics		0.041*** (0.015)		0.026*** (0.008)		0.085* (0.044)
Constant	0.104*** (0.035)	0.012 (0.085)	0.019 (0.021)	-0.039 (0.049)	0.051 (0.106)	-0.456* (0.255)
Observations	548	548	548	548	548	548
R <sup>2</sup>	0.034	0.064	0.027	0.072	0.040	0.070
Adjusted R <sup>2</sup>	0.030	0.048	0.024	0.057	0.037	0.054

*Note:*

\*p&lt;0.1; \*\*p&lt;0.05; \*\*\*p&lt;0.01

## A.8 Robustness to covariates

**Table A5:** Average Treatment Effects, Conditional on pre-treatment covariates.

	Opinion Polarization w/out Individual-level controls	Opinion Polarization With Individual-level controls
Treatment	0.0538** (0.0265)	0.0502** (0.0265)
Guns Article	0.174*** (0.0268)	0.174*** (0.0270)
Male		-0.0324 (0.0267)
Age		0.00661 (0.00783)
Age <sup>2</sup>		-0.0000594 (0.0000941)
Independent		-0.0189 (0.0301)
Other-N/A		-0.128 (0.0971)
Republican		-0.0433 (0.0392)
Following Politics		0.0564* (0.0268)
Constant	0.375*** (0.0214)	0.224 (0.154)
Observations	548	548

Heteroskedasticity-robust standard errors in parentheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

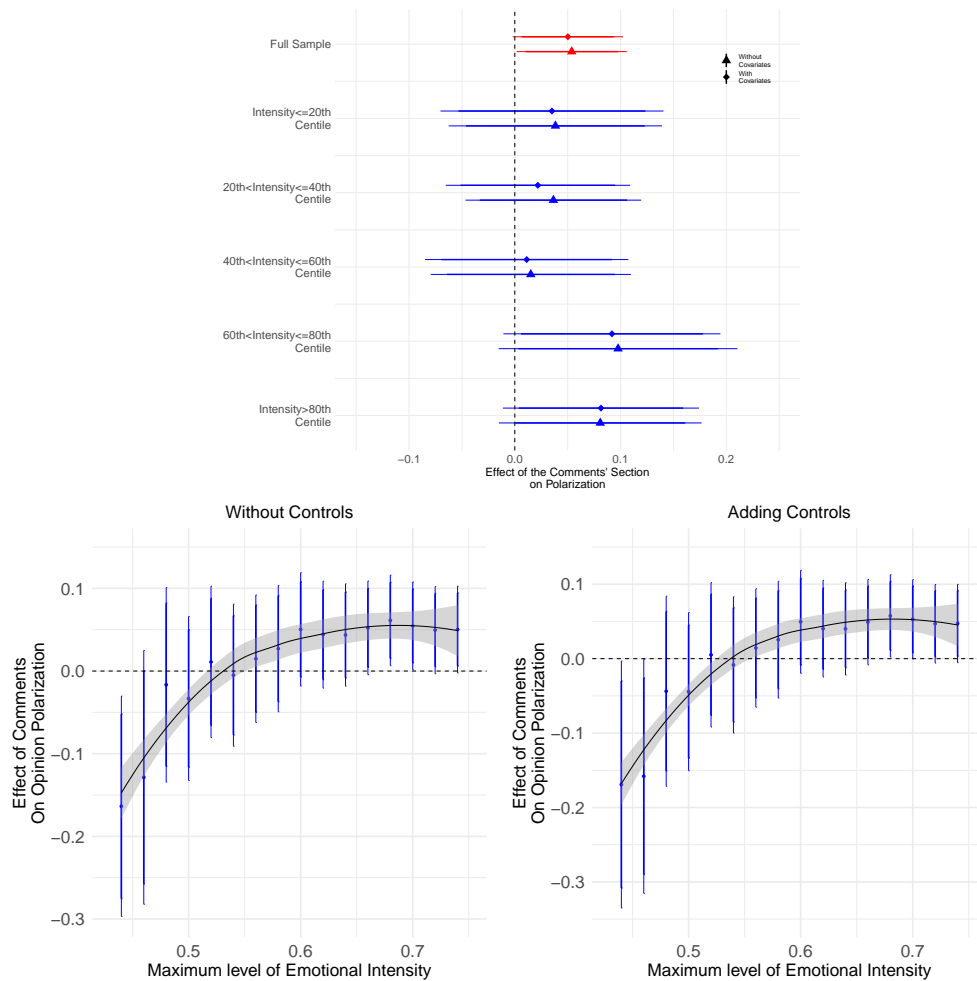
Certain subsets of participants received the same sample of comments on the article; the biggest such group contained 14 participants. As a robustness check we compare the treatment effect on this group alone against the control group. We find that the treatment effect is robust to limiting the treatment group to this subsample, as shown in Table A6.

**Table A6:** Subsample analysis with identical-comment treatment group

	N	intensity score	polarization score	CI low	CI high	p
Treatment subset	14	0.66	0.69	0.52	0.86	-
Control	267	-	0.45	0.42	0.49	-
Diff	-	-	0.24	0.05	0.43	0.02

## A.9 Robustness to alternative measures of emotional intensity.

**Figure A6:** Comments Section Effects According to the level of Emotional Intensity: Alternative Categorizations of Intensity



## A.10 Descriptive Statistics of Comment Characteristics

Table A7 gives descriptive statistics on the various comment characteristics included in Table 2 of the article. For consistency with that table, the unit of observation is the individual participant. The statistics presented in Table A7 give, for each indicator, the minimum and maximum value presented to any participant, the mean and median value presented to participants, and the standard deviation of values across participants.

**Table A7:** Descriptive statistics on comment characteristics

Variable	Min	Max	Mean	Median	Std. dev.
Intensity	0.42	0.75	0.61	0.62	0.08
Agreement	0.00	0.6	0.183	0.2	0.181
Informativeness	1.18	3.57	2.38	2.47	0.61
Time	100	1291	274	231	171.2
Size	173	452	309	306	64.9

## A.11 Treatment Effects Conditional on the Duration of the Experimental Session.

**Table A8:** Treatment Effect Conditional on the Duration of the Session.

	Opinion Polarization No Controls	Opinion Polarization Adding Controls
Treatment	0.0452 (0.0506)	0.0454 (0.0511)
Duration	-0.0000170 (0.000130)	-0.0000194 (0.000131)
T×Duration	0.0000345 (0.000173)	0.0000209 (0.000178)
Guns-Article	0.174*** (0.0273)	0.174*** (0.0275)
Male		-0.0324 (0.0267)
Age		0.00665 (0.00785)
Age <sup>2</sup>		-0.0000598 (0.0000943)
Independent		-0.0186 (0.0304)
Other-N/A		-0.127 (0.0973)
Republican		-0.0428 (0.0399)
Follow Politics		0.0565* (0.0269)
Constant	0.379*** (0.0394)	0.227 (0.155)
Observations	548	548

Heteroskedasticity-robust standard errors in parentheses

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

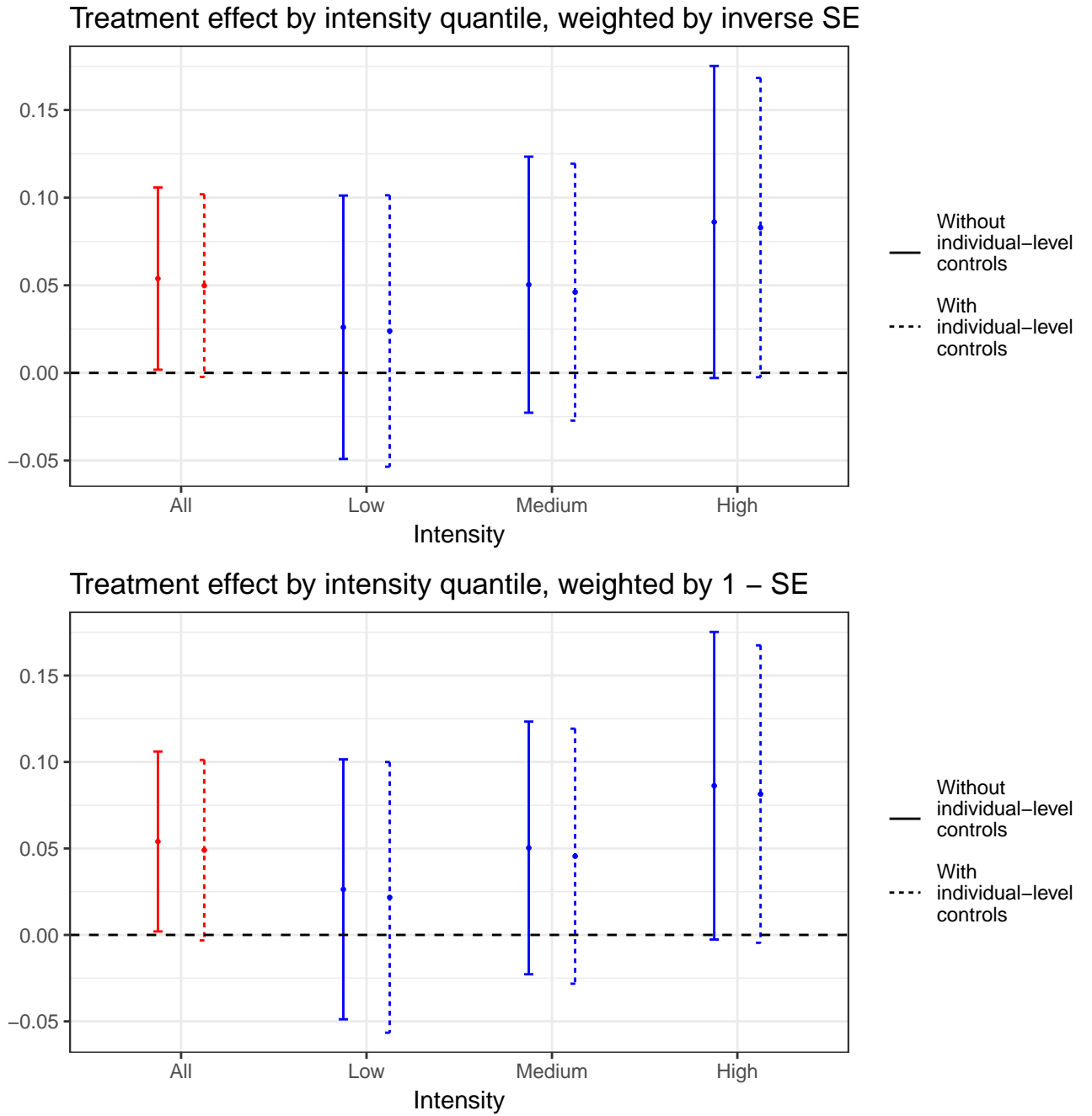
## A.12 Results weighted by comment standard errors

Since we rely on non-expert crowdsourced coders to rate the intensity of comments, we expect a large degree of noise and variation that cancels out when we average the ratings across all coders. We can make use of the degree of variation in the crowdsourced coding for each comment to gauge our confidence in the coding of any particular comment. For instance, the crowdsourced coding procedure gives us a standard error for the estimated intensity score of each individual data point (i.e. each comment).

One way to use this information is to re-run our analysis using an OLS regression weighted by the inverse of the standard error of the intensity score for each comment. Since the intensity coding are represented as values in the range  $[0, 1]$ , and their standard errors also fall within this range, we also try weighting the regression by one minus the pooled standard error of the intensity codings. If our results are largely driven by uncertain codings for a handful of controversial comments, the effect of comment intensity on polarization should be more meaningfully muted when the regression is weighted in these ways.

That is not what we observe. As Figure [A7](#) shows, the results are almost completely unchanged when weighting the intensity scores by the inverse of their standard errors.

Figure A7: Results weighted by scoring certainty



### A.13 Jackknife analysis

The rationale for relying on crowdsourcing to code the comments rests on the assumption any idiosyncratic noise in codings by non-experts cancels out if the number of non-expert coders is sufficiently large, such that the mean of their scores is a good indicator of the phenomenon being captured.

As a way to test this assumption, we iteratively remove one coder at a time and re-run the analysis with all remaining coders in a jackknife setup. This shows that no one coder, no matter how large the potential errors in their coding, has a meaningful impact on the results. The figures below demonstrate this is indeed the case, as the results are robust to the exclusion of any given coder.

Figure A8: Results for TPP article when iteratively excluding each coder

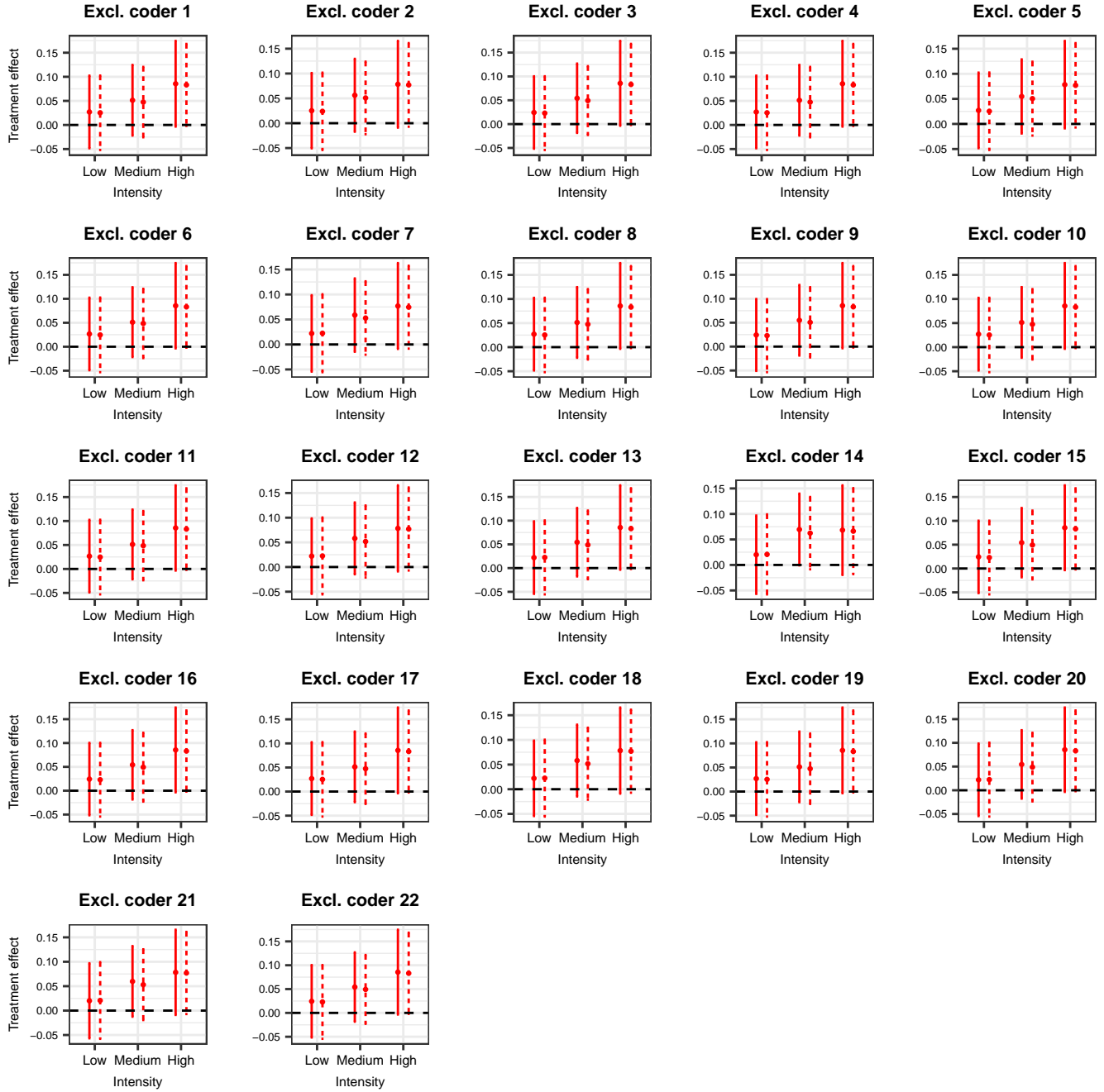


Figure A9: Results for gun control article when iteratively excluding each coder

