

Does Mass Shooting Influence Attitudinal Change?

New Evidence from Orlando 2016

Muzhou Zhang^{1, *} and Joseph Kelly¹

¹Department of Government, University of Essex, UK

*Corresponding author. Email: muzhou.zhang@essex.ac.uk

This version: 12 October 2020

[Latest version](#)

Abstract

Does mass shooting event influence gun control attitude? Previous research conducted by Rogowski and Tucker (2019) suggests that attitude towards gun control remained unchanged following the 2012 Sandy Hook Elementary School shooting. Given this finding's counterintuitive nature and both scholarly and practical significance, we employ a similar research design while using a new exogenous gun violence incident to explore the extent to which this null effect holds. By leveraging the pre- and post-shooting responses for wave 55 of The American Panel Survey, we show that American's gun control attitude did not change after the 2016 Orlando shooting. Our null finding has meaningful implications for the deadlocked gun control issue in the US.

1. We are grateful to Carolina Garriga and Seonghui Lee for providing helpful suggestions on this work. All errors are our own. The replication files for this article are available at the corresponding author's GitHub repository: https://github.com/zmuzhou/zhang_kelly_2020.

1 Introduction

Bloody mass shootings repeatedly happen in the US while shocking the world. Compared to Australia, Canada, Great Britain, and New Zealand, which all experienced horrific gun-related massacres and then introduced legislations to tighten gun control,¹ no significant gun control progress has been made in the US in recent years. In representative democracies, public support is, though not necessarily, an important factor to drive policy changes. However, Hassell, Holbein, and Baldwin (2020) found that the occurrence of school shootings even cannot mobilize American voters to make an electoral change, let alone legislative progress. The deadlocked gun control issue in the US leads us to ask is mass shooting even able to galvanize public support for gun control? Existing research on this very topic has produced contradictory results. Newman and Hartman (2019) argued that geographical proximity has an influential effect on support for increasing gun control following mass shooting events. They found those who live within a 100-mile radius of a shooting event are more likely to prefer stricter laws covering the sale of firearms. In contrast, Barney and Schaffner (2019) later found this effect is null, even when varying the proximity threshold. In their response, Hartman and Newman (2019) contested the null finding, arguing that pre-treatment exposure to mass shootings matter and the geographical proximity to mass shooting events do increase support for firearm restrictions. Using the 2012 Sandy Hook Elementary School shooting as a case, Rogowski and Tucker (2019, RT hereafter) found such a painful event, which took 26 people's lives (including 20 children's), failed to increase American's support for gun control. According to RT, this striking null finding holds even for subgroups whose predispositions are more in favor of progressive gun legislation, such as parents and Democrats.

The null effect reported by RT is counterintuitive while possessing both scholarly and practical significance. In this research note, we extend their work by using the 2016 Orlando nightclub shooting as a new yet comparable case. Employing the same data source (The American Panel Study, TAPS) and a similar research design—the unexpected-event-during-survey design (Muñoz, Falcó-Gimeno, and Hernández 2020), we corroborate RT's null finding. By using

1. See Port Arthur 1996 (Australia), Nova Scotia 2020 (Canada), Dunblane 1996 (Great Britain), and Christchurch 2019 (New Zealand).

TAPS wave 55 data and comparing the respondents who completed the survey before (*Pre-shooting*) and after (*Post-shooting*) June 12, 2016, when the Orlando shooting happened, we find American people's support for gun control legislation did not increase following this tragic gun violence incident, which left 49 dead and 53 wounded. This insignificant result remains no matter we use a bivariate specification or include control variables aiming for the covariate imbalance between the two groups. Further, our null finding holds too when we use 5 subsamples defined by various criteria.

2 Research Design

We employ the unexpected-event-during-survey design, which leverages mass shooting's exogenous timing and survey's staggered participation, to evaluate the effect of mass shooting on people's gun control support. By comparing the respondents who answered the survey questionnaire before and after the shooting by randomness, we are able to minimize the confounding factors that select certain respondents to expose themselves more to shooting event. We select the 2016 Orlando shooting for three reasons. First, by its occurrence, it was the deadliest gun violence event in US history. Its severity and impact makes this case comparable to the 2012 Sandy Hook shooting, the one used in RT. Second, the Orlando shooting happened in a presidential election year like the Sandy Hook shooting did so that our case selection largely guarantees that any result discrepancy between ours and RT's should not be driven by the difference of macro political context, such as the intensity gun debate. Third, the Orlando shooting occurred in mid-month. This feature enables the *Pre-shooting* and the *Post-shooting* group to have a relatively equal sample size.²

Our data come from TAPS wave 55, which was conducted online mainly in June 2016—the month when the Orlando shooting happened. To measure American's support for gun control, our outcome variable, we uses a question asking: “Do you generally support or oppose gun control legislation?” The substantive answers to this question are binary: “Support” or “Oppose”. We code “Support” as 1 in our analysis. Our treatment indicator is determined by whether a respondent finished the questionnaire before or after the day when the Orlando shooting hap-

2. This is why we do not select the 2017 Las Vegas shooting which happened on October 1.

pened. Those who answered the questionnaire on and after June 13 are in the *Post-shooting* (treatment) group, in which the treatment is the exposure to the real-happening tragic mass shooting event. Those who participated the survey on and before June 11 are in the *Pre-shooting* (control) group. After importing the original survey data, we have 1704 observations in total. Filtering out the cases whose completion date or survey weight are missing and the respondents who participated the survey exactly on June 12 gives us 1519 observations remaining.³ Among them, 57.08% are in the *Pre-shooting* group (Appendix Table 1).

The respondents in our sample are “as-if” randomly assigned into the *Pre-shooting* or the *Post-shooting* group so ideally, there would be a covariate balance between these two. We choose 6 variables, namely *Female*, *Parent*, *Political interest*, *News everyday*, *Ideology*, and *Political knowledge*, to check if our treatment and control groups are comparable in terms of these personal characteristics that are likely to affect one’s self-exposure to gun violence incident and attitude towards gun control simultaneously.⁴ *Political interest* is ordered at four categories: “Not at all”, “Slightly”, “Somewhat”, and “Very”. (We drop “Refused”.) *News everyday* refers to whether a respondent consumes news on a daily basis. *Ideology* is on a 6-point scale in which 1 means liberal while 6 means conservative. Among a battery of political knowledge questions in the questionnaire, we select the one asking the term limit of the US senators. We code those who correctly gave an answer of six-year as 1 while others, including “Don’t know” and “Refused”, as 0.⁵ By conducting difference-in-means tests, we find in the *Post-shooting* group, there are more females, parents, people with greater interest in politics, everyday news consumers, conservatives, and people with more political knowledge (Appendix Table 3). In this situation, ignoring these control variables would confound our results if any. Hence, besides our bivariate specification, which simply regresses our outcome variable on the treatment indicator, we also include a full specification that incorporate these controls.

In RT’s article, they did a panel (first-difference) analysis that compared the same respondent’s answer regarding gun control question between the two survey waves—one before and

3. We exclude the June 12 respondents since we hardly determine who are the treated.

4. Some should-be-included variables, such as age, are missing since there is no relevant questions in the questionnaire.

5. For this insensitive and straightforward political knowledge question, we argue there is no reason for a person who firmly knew the correct answer to give a “Don’t know” or “Refused” response.

one after the shooting. Two considerations prevent us from using this approach along with our cross-sectional design (comparing the respondents within a same wave). First, after wave 55 (June 2016), our gun control question was then asked in wave 57 (August 2016). This one-month gap likely to diminish the treatment effect that some respondents received. Second, if we used the first-difference approach, we would compare the wave 55 respondents who answered the questionnaire before June 12 and themselves in wave 57. As we've shown earlier, however, those who completed the survey before the shooting date are not comparable to those who finished after the day in terms of their personal characteristics that are correlated to gun control support. This means we would suffer from a non-random sample selection problem if we used the first-difference approach.

In our sample, 7% of the respondents chose “No Opinion” when asked for their gun control legislation support. If the exposure to the Orlando shooting led some respondents more or less likely to have an opinion regarding gun control attitude, discarding these observations would bias our results. To alleviate this concern, we regress an binary outcome indicating whether a respondent has an opinion (“Support” or “Oppose” = 1, “No opinion” = 0) to our treatment indicator to see if the rate of having an opinion is different between the two groups. The logit model results show the treatment indicator is statistically insignificant, suggesting there is no statistically distinguishable difference in terms of the rate of “No opinion” answer among the *Pre-shooting* and the *Post-shooting* group (Appendix Table 4). Therefore, we safely drop the “No opinion” observations from our sample. Only 1% of the respondents refused to answer our gun control question and we simply filter them out from the sample. After doing these two steps, we have a sample size of 1400.

In an unexpected-event-during-survey design, whether respondents really absorb treatment is a concern. In our research context, the previously reported null finding might be driven by that the *Post-shooting* group respondents forgot the shock of tragic shooting when they answered the relevant question or they even did not pay enough attention to the event when it occurred. To address these two possibilities, we narrow our sample down temporally and spatially. For our *Narrow time window* sample, we only keep the respondents who answered the questionnaire one day before and after June 12 to make the Orlando shooting's treatment ef-

fect (if any) remains as much as possible for the treated. For our *Proximity* sample, we only keep the respondents who lived in Florida (where Orlando locates) and its two contiguous states: Georgia and Alabama. The rationale behind this restriction is that local people might be more responsive to local incidents, as argued in Newman and Hartman (2019). For an online survey like TAPS, respondents' attentiveness is another common problem. In our sample, the minimum survey duration is only 7 minutes, which is too short to a considerate answer. Even worse, the distribution of survey duration is extremely right-skewed with a maximum of 34586 and a mean of 1049. We suspect some respondents went to do other things while remaining signing-in the survey page. The unreasonably long survey duration does not convince us that the answers were carefully produced. To address this attentiveness concern, we define a *Reasonable duration* sample, in which we only keep the respondents whose documented survey duration is between 15–60 minutes. Finally, we use the intersection between the *Narrow time window* sample and the *Reasonable duration* sample and the intersection between the *Proximity* sample and the *Reasonable duration* sample to make two more subsamples.⁶ Plus the *Full* sample, we have 6 samples in total prepared for analysis.

Table 1 shows the percentage of gun control legislation supporters before and after the Orlando shooting. In all samples, the percentage of gun control legislation supporters increased following the shooting. In the next section, for each of our 6 samples, we run two logit models (with bivariate and full specification) for estimation. We apply the Internet-sample adjusted weight, which is provided by the survey team in the original dataset, to make our results as representative to the population (English-speaking adults in the US) as possible. Besides logit models, we also run linear probability models to ensure that any results we have are not model-dependant.

3 Results

We find the 2016 Orlando shooting did not elicit statistically significant attitudinal change in favor of gun control legislation among Americans. Given the binary nature of our treatment

6. We do not use the intersection between the *Narrow time window* sample and the *Proximity* sample because doing so leaves us a too small sample size.

Table 1: Percentage of gun control legislation supporters before and after the 2016 Orlando shooting

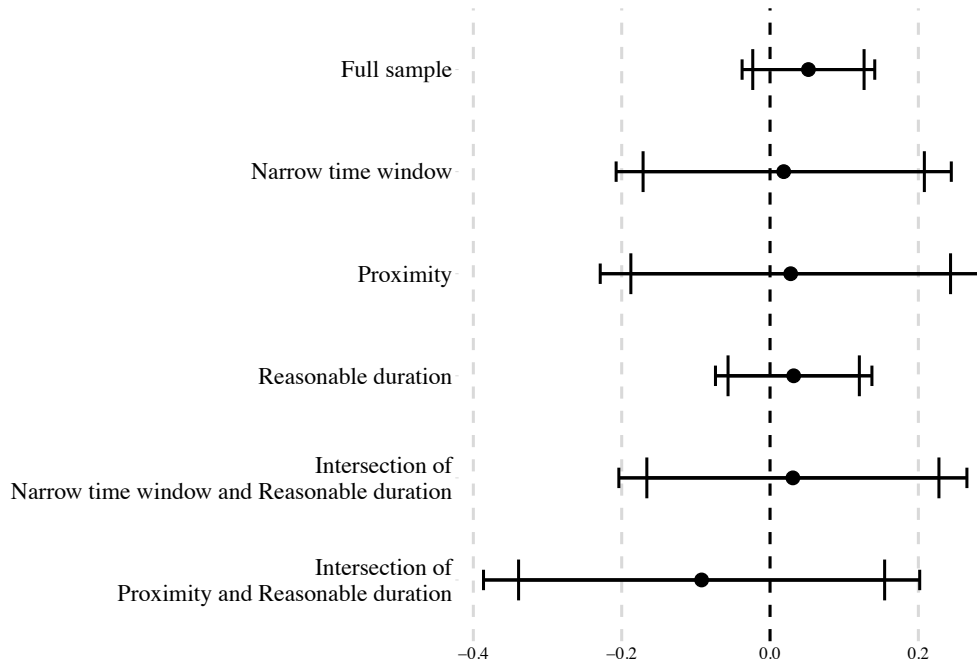
	Pre-shooting	Post-shooting
Full sample	53.789	62.017
Narrow time window	55.914	64.000
Proximity	54.651	61.538
Reasonable duration	52.568	59.580
Narrow time window \cap Reasonable duration	52.239	58.696
Proximity \cap Reasonable duration	54.412	56.410

Note: See Appendix Table 5 for their sample sizes.

variable, we use the differenced predicted probabilities to present our substantive effects. When doing so based on our full specification, we hold the control variables fixed at their median values. [Figure 1](#) shows our bivariate specification results while [Figure 2](#) shows our full specification results. When the *Full* sample is used, the differenced predicted probabilities are positive, meaning that the probability of supporting gun control legislation is higher among Americans after the Orlando shooting. However, even the 90% confidence interval goes across the value of 0, suggesting this gun control legislation support difference is not statistically significant. When we use our subsamples, the confidence intervals still go across 0. It means even we only focus on the respondents who were most likely to remain in the treated status (*Narrow time window* sample), who lived close to and thus likely to pay attention to the shooting (*Proximity* sample), and who had more attentiveness during the survey (*Reasonable duration* sample), and their intersections, we still find no sufficient statistical evidence to claim that American's gun control attitude is responsive to mass shooting.

In binary response models, unbiased coefficients not necessarily translate into unbiased quantities of interest (Rainey 2017). So, only relying on the confidence intervals of our differenced probabilities for statistical inference might be problematic. We therefore also report conventional regression tables underpinning [Figure 1](#) and [Figure 2](#) in Appendix Table 6–11. The statistical insignificance of our treatment indicator (*Post-shooting*) confirms our null finding is not a product of transformation-induced bias as discussed in Rainey (2017). When we use linear probability models instead of logit models, our results are substantively the same (see Appendix Table 12–17). It suggests our null finding is not dependent on any single statistical

Figure 1: Differenced predicted probabilities of gun control legislation support (*Pre-shooting versus Post-shooting*), bivariate specification



Note: Wider error bars indicate the 95% confidence intervals while narrower error bars indicate the 90% confidence intervals. The standard errors necessary for calculating the confidence intervals are derived from the Delta method.

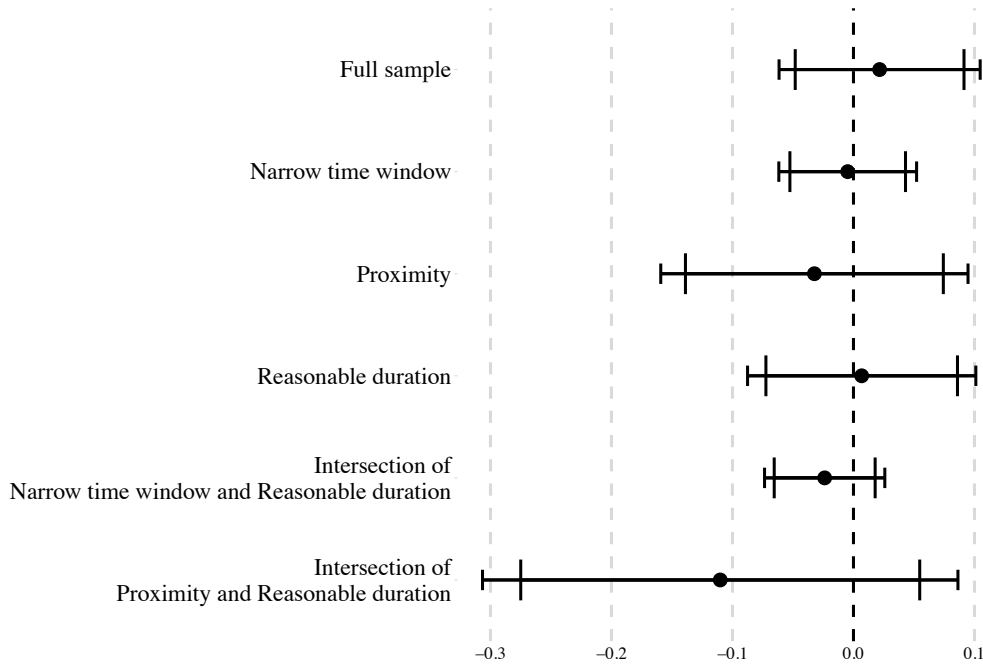
model or its assumptions.

We finally use the exact same statistical routine as RT did—running the bivariate specification on subsamples defined by respondents’ personal characteristics. We use our control variables to define these subsamples.⁷ We do not follow this approach for our main results since under the covariate imbalance problem we have, simply doing so would lead us to suffer from the non-random sample selection issue. However, we present this approach’s results here to show that our null finding is not an outcome of any single way of statistical analysis. Also, since we aim to extend RT’s study, presenting the results based on their approach is also helpful for cross-study comparison. Appendix Table 17 shows these results. Our treatment indicator is not statistically significant even at the $\alpha = 0.10$ level among all of the 12 subsamples defined by our 6 control variables.⁸ This means the 2016 Orlando shooting were unable to influence American’s enough attitudinal change in favor of gun control, even among the people whose predisposition are more aligned to progressive gun policy, such as parents and liberals.

7. These subsamples are produced on the basis of our *Full* sample.

8. For *Political interest*, we code “Very” as 1 while all others as 0. For *Ideology*, we code 1–3 as “Liberal” and 4–6 as “Conservative”. So that now our 6 control variables are all binary and we have 12 subsamples defined by them.

Figure 2: Differenced predicted probabilities of gun control legislation support (*Pre-shooting* versus *Post-shooting*), full specification



Note: Covariates are held at their median values. Wider error bars indicate the 95% confidence intervals while narrower error bars indicate the 90% confidence intervals. The standard errors necessary for calculating the confidence intervals are derived from the Delta method.

4 Conclusion

The repeatedly happening mass shootings and the deadlocked gun control issue in the US puzzle scholars while taking too many lives away. In this research note, we ask is mass shooting able to galvanize public support for gun control? We use TAPS wave 55 data and employ the unexpected-event-during-survey design to answer this question. By comparing the respondents who completed the survey before and after the occurrence of the 2016 Orlando shooting, we find such a tragic gun violence event did not elicit American's statistically distinguishable attitudinal change in favor of gun control legislation. This null finding holds regardless of which model specification or estimation framework we apply or what subsamples we use. Our results contribute to the literature by adding new evidence demonstrating mass shootings fail to influence American's attitudinal change towards gun control support (Rogowski and Tucker 2019; Barney and Schaffner 2019). This counterintuitive finding partly explains why there is no significant progress in gun control policy change in the US, even the repeatedly happening mass shootings have been causing too many tragedies. Future research may consider to explore the mechanism underlying American's attitudinal nonresponse to mass shootings.

References

- Barney, David J, and Brian F Schaffner. 2019. "Reexamining the Effect of Mass Shootings on Public Support for Gun Control." *British Journal of Political Science* 49 (4): 1555–65.
- Hartman, Todd K, and Benjamin J Newman. 2019. "Accounting for Pre-Treatment Exposure in Panel Data: Re-Estimating the Effect of Mass Public Shootings." *British Journal of Political Science* 49 (4): 1567–76.
- Hassell, Hans JG, John B Holbein, and Matthew Baldwin. 2020. "Mobilize for Our Lives? School Shootings and Democratic Accountability in US Elections." *American Political Science Review*: 1–11.
- Muñoz, Jordi, Albert Falcó-Gimeno, and Enrique Hernández. 2020. "Unexpected Event during Survey Design: Promise and Pitfalls for Causal Inference." *Political Analysis* 28 (2): 186–206.
- Newman, Benjamin J., and Todd K. Hartman. 2019. "Mass Shootings and Public Support for Gun Control." *British Journal of Political Science* 49 (4): 1527–53.
- Rainey, Carlisle. 2017. "Transformation-induced Bias: Unbiased Coefficients Do Not Imply Unbiased Quantities of Interest." *Political Analysis* 25 (3): 402–9.
- Rogowski, Jon C., and Patrick D. Tucker. 2019. "Critical Events and Attitude Change: Support for Gun Control After Mass Shootings." *Political Science Research and Methods* 7 (4): 903–11.

Appendix

Table 1: Number of TAPS wave 55 (June 2016) participants by date

Date	Number of Participants	Cumulative Percentage
2016-06-08	434	28.571
2016-06-09	165	39.434
2016-06-10	169	50.560
2016-06-11	99	57.077
2016-06-13	134	65.899
2016-06-14	63	70.046
2016-06-15	36	72.416
2016-06-16	40	75.049
2016-06-17	30	77.024
2016-06-18	27	78.802
2016-06-19	16	79.855
2016-06-20	60	83.805
2016-06-21	34	86.043
2016-06-22	26	87.755
2016-06-23	13	88.611
2016-06-24	7	89.072
2016-06-25	8	89.598
2016-06-26	10	90.257
2016-06-27	27	92.034
2016-06-28	15	93.022
2016-06-29	12	93.812
2016-06-30	13	94.668
2016-07-01	18	95.853
2016-07-02	10	96.511
2016-07-03	16	97.564
2016-07-04	9	98.157
2016-07-05	16	99.210
2016-07-06	8	99.737
2016-07-07	2	99.868
2016-07-08	2	100.000

Note: 2016-06-12, when the Orlando shooting happened, is excluded from our analysis and this table. Observations without date information or survey weight are dropped as well. Some participants completed the June survey in July and they are counted.

Table 2: Summary statistics of variables

	Min	Median	Max	Mean	SD	<i>N</i>
Gun control legislation support	0	1	1	0.573	0.495	1400
Post-shooting	0	0	1	0.429	0.495	1519
Narrow time window	0	1	1	0.739	0.439	1519
Proximity	0	0	1	0.153	0.360	1519
Reasonable duration	0	0	1	0.107	0.309	1519
Female	0	1	1	0.501	0.500	1513
Parent	0	1	1	0.760	0.427	1507
Political interest	1	3	4	3.097	0.897	1508
Newseveryday	0	1	1	0.590	0.492	1511
Ideology	1	3	6	3.235	1.240	1471
Political knowledge	0	1	1	0.511	0.500	1519

Table 3: Covariate balance between *Pre-shooting* and *Post-shooting*, difference-in-means results

	$\hat{\beta}$	SE	<i>p</i> -value	<i>N</i>
Female	0.496	0.018	0.000	1512
Parent	0.437	0.015	0.000	1506
Political interest	0.124	0.004	0.000	1507
Newseveryday	0.382	0.016	0.000	1510
Ideology	0.114	0.004	0.000	1470
Political knowledge	0.370	0.017	0.000	1518

Table 4: Having opinion, gun control legislation support or not, linear probability model results

	Bivariate	Full
Post-shooting	−0.151 (0.202)	0.037 (0.219)
Female		0.450* (0.227)
Parent		0.293 (0.244)
Political interest		0.512*** (0.131)
Newseveryday		0.377 (0.260)
Ideology		−0.252** (0.086)
Political knowledge		0.836*** (0.250)
Constant	2.648*** (0.137)	1.057* (0.531)
Deviance	766.402	651.006
<i>N</i>	1506	1436

Note: Standard errors in parentheses. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table 5: Sizes of samples

	N
Full sample	1400
Narrow time window	218
Proximity	151
Reasonable duration	1043
Narrow time window \cap Reasonable duration	159
Proximity \cap Reasonable duration	107

Note: N reflects the sample size in the bivariate specification case.

Table 6: The 2016 Orlando shooting and gun control legislation support, logit model results, *Full* sample

	Bivariate	Full
Post-shooting	0.210 (0.186)	0.113 (0.220)
Female		0.547* (0.217)
Parent		0.086 (0.257)
Political interest		-0.251 (0.145)
Newseveryday		0.484* (0.242)
Ideology		-0.873*** (0.125)
Political knowledge		-0.027 (0.223)
Constant	0.121 (0.120)	3.280*** (0.678)
Deviance	1861.040	1463.043
<i>N</i>	1400	1336

Note: Standard errors in parentheses. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table 7: The 2016 Orlando shooting and gun control legislation support, logit model results, *Narrow time window*

	Bivariate	Full
Post-shooting	0.074 (0.464)	−0.095 (0.595)
Female		1.547** (0.546)
Parent		1.258 (0.864)
Political interest		−0.520 (0.406)
Newseveryday		1.974** (0.697)
Ideology		−1.720*** (0.407)
Political knowledge		−0.233 (0.561)
Constant	0.119 (0.350)	5.104** (1.622)
Deviance	282.151	153.831
<i>N</i>	218	202

Note: Standard errors in parentheses. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table 8: The 2016 Orlando shooting and gun control legislation support, logit model results, *Proximity*

	Bivariate	Full
Post-shooting	0.115 (0.540)	−0.287 (0.558)
Female		0.588 (0.612)
Parent		−0.200 (0.706)
Political interest		−0.830 (0.449)
Newseveryday		1.262 (0.819)
Ideology		−1.017* (0.399)
Political knowledge		1.286* (0.616)
Constant	0.279 (0.372)	4.657* (2.266)
Deviance	198.194	150.811
<i>N</i>	151	144

Note: Standard errors in parentheses. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table 9: The 2016 Orlando shooting and gun control legislation support, logit model results,
Reasonable duration

	Bivariate	Full
Post-shooting	0.128 (0.216)	0.037 (0.260)
Female		0.750** (0.247)
Parent		0.159 (0.286)
Political interest		−0.325 (0.171)
Newseveryday		0.598* (0.267)
Ideology		−0.916*** (0.159)
Political knowledge		−0.101 (0.266)
Constant	0.058 (0.131)	3.425*** (0.846)
Deviance	1411.822	1066.630
<i>N</i>	1043	995

Note: Standard errors in parentheses. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table 10: The 2016 Orlando shooting and gun control legislation support, logit model results, *Narrow time window* \cap *Reasonable duration*

	Bivariate	Full
Post-shooting	0.125 (0.484)	−0.750 (0.695)
Female		1.495 (0.795)
Parent		2.216* (0.889)
Political interest		−0.858 (0.507)
Newseveryday		2.438* (1.072)
Ideology		−2.305*** (0.444)
Political knowledge		−0.019 (0.722)
Constant	−0.266 (0.343)	7.138** (2.198)
Deviance	201.077	91.016
<i>N</i>	159	145

Note: Standard errors in parentheses. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table 11: The 2016 Orlando shooting and gun control legislation support, logit model results, *Proximity* \cap *Reasonable duration*

	Bivariate	Full
Post-shooting	−0.370 (0.606)	−0.879 (0.717)
Female		0.667 (0.720)
Parent		−1.291 (0.748)
Political interest		−1.532* (0.597)
Newseveryday		2.115* (0.853)
Ideology		−1.431*** (0.415)
Political knowledge		1.617* (0.673)
Constant	0.135 (0.432)	7.992** (2.815)
Deviance	144.147	91.891
<i>N</i>	107	102

Note: Standard errors in parentheses. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table 12: The 2016 Orlando shooting and gun control legislation support, linear probability model results, *Full* sample

	Bivariate	Full
Post-shooting	0.052 (0.046)	0.028 (0.042)
Female		0.102* (0.041)
Parent		0.015 (0.048)
Political interest		−0.054* (0.026)
Newseveryday		0.097* (0.047)
Ideology		−0.178*** (0.019)
Political knowledge		−0.007 (0.044)
Constant	0.530*** (0.030)	1.182*** (0.116)
Deviance	334.197	247.859
<i>N</i>	1400	1336

Note: Maximum likelihood estimation. Standard errors in parentheses. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table 13: The 2016 Orlando shooting and gun control legislation support, linear probability model results, *Narrow time window*

	Bivariate	Full
Post-shooting	0.018 (0.115)	0.053 (0.082)
Female		0.175* (0.072)
Parent		0.154 (0.117)
Political interest		−0.095 (0.051)
Newseveryday		0.258** (0.094)
Ideology		−0.238*** (0.029)
Political knowledge		−0.025 (0.089)
Constant	0.530*** (0.087)	1.265*** (0.226)
Deviance	50.782	26.292
<i>N</i>	218	202

Note: Maximum likelihood estimation. Standard errors in parentheses.
 *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table 14: The 2016 Orlando shooting and gun control legislation support, linear probability model results, *Proximity*

	Bivariate	Full
Post-shooting	0.028 (0.131)	−0.056 (0.102)
Female		0.125 (0.115)
Parent		−0.026 (0.129)
Political interest		−0.147* (0.067)
Newseveryday		0.210 (0.132)
Ideology		−0.191*** (0.052)
Political knowledge		0.250* (0.118)
Constant	0.569*** (0.091)	1.341*** (0.325)
Deviance	35.457	25.417
<i>N</i>	151	144

Note: Maximum likelihood estimation. Standard errors in parentheses.
 *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table 15: The 2016 Orlando shooting and gun control legislation support, linear probability model results, *Reasonable duration*

	Bivariate	Full
Post-shooting	0.032 (0.054)	0.012 (0.048)
Female		0.139** (0.045)
Parent		0.024 (0.053)
Political interest		−0.065* (0.030)
Newseveryday		0.116* (0.052)
Ideology		−0.182*** (0.022)
Political knowledge		−0.020 (0.051)
Constant	0.515*** (0.033)	1.192*** (0.137)
Deviance	254.304	179.782
<i>N</i>	1043	995

Note: Maximum likelihood estimation. Standard errors in parentheses.
 *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table 16: The 2016 Orlando shooting and gun control legislation support, linear probability model results, *Proximity* \cap *Reasonable duration*

	Bivariate	Full
Post-shooting	0.031 (0.120)	−0.014 (0.082)
Female		0.153 (0.082)
Parent		0.255* (0.115)
Political interest		−0.120** (0.046)
Newseveryday		0.235* (0.099)
Ideology		−0.264*** (0.025)
Political knowledge		0.050 (0.098)
Constant	0.434*** (0.084)	1.321*** (0.209)
Deviance	36.166	16.119
<i>N</i>	159	145

Note: Maximum likelihood estimation. Standard errors in parentheses.
 *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table 17: The 2016 Orlando shooting and gun control legislation support, linear probability model results, *Narrow time window* \cap *Reasonable duration*

	Bivariate	Full
Post-shooting	−0.092 (0.150)	−0.147 (0.110)
Female		0.162 (0.122)
Parent		−0.192 (0.122)
Political interest		−0.221*** (0.063)
Newseveryday		0.317* (0.127)
Ideology		−0.230*** (0.046)
Political knowledge		0.237* (0.113)
Constant	0.534*** (0.107)	1.688*** (0.304)
Deviance	25.936	15.270
<i>N</i>	107	102

Note: Maximum likelihood estimation. Standard errors in parentheses.
 *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table 18: The 2016 Orlando shooting and gun control legislation support, bivariate linear probability models running on different subgroups defined by personal characteristics

	$\hat{\beta}$	SE	<i>p</i> -value	<i>N</i>
Females	0.048	0.062	0.441	696
Males	0.052	0.067	0.436	700
Parents	0.039	0.051	0.440	1058
Non-parents	0.071	0.101	0.481	330
Political interest: Yes	0.070	0.053	0.188	1097
Political interest: No	−0.004	0.092	0.961	295
News everyday: Yes	0.004	0.063	0.947	542
News everyday: No	0.023	0.053	0.667	814
Liberals	0.040	0.060	0.507	848
Conservatives	0.060	0.070	0.390	545
Political knowledge: Yes	0.051	0.064	0.426	743
Political knowledge: No	0.051	0.064	0.433	657