CASES

Below, I elaborate on the three specific cases I choose to analyze in this study: Black Church arson attacks, mass shootings, and natural disasters.

Black Church arson attacks are a particularly heinous event in American history and society. There have been at least three major waves of arson attacks on Black Churches: the 1950s-1960s, the 1990s, and 2008 to present day. The attacks rarely cause fatalities or even injuries as most attacks are symbolic and economic attacks, meaning that they occur when the churches are empty. But, the attacks are terrorist attacks, intended to traumatize members of the church as well as Black Americans more generally. These events are also political in that they are not simply done out of rage or hatred, but are very clear in their target (Black Americans) and in their political message (stop demanding political, social, and economic equality that threatens white dominance).

A traumatic experience is an exposure to a certain type of social experience that often arises in the context of groups or in which an individual's membership in particular groups is salient, for example war, natural disasters, or terrorism (Muldoon, Lowe, Jetten, Cruwys, and Haslam 2020). The role of social groups, therefore, is important not only in identifying the distribution of trauma, but also in understanding responses to traumatic events. In this regard, Black Church arson attacks are an important case because they are clear traumatic events, whose impact extends beyond the parishioners of that church and to other Black Americans in the community who do not attend that church or who may not be Christian at all. These attacks are politically-relevant because of their political purpose explained above, but also because they are crimes, which the government has a legal and publicly-expected responsibility to investigate. Finally, they are politically-relevant because policy demanders (The National Association for the Advancement of Colored People and the Southern Christian Leadership Council) taught the American public of their political relevance as threats to public safety, religious liberty, and civil rights.

Gun violence is a growing problem in the U.S., a problem made especially evident in mass shootings. While the number is disputed, mass shootings are increasingly occurring in the United States and each event causes a chain reaction of traumatic exposure. Mass shootings are less tied to a particular social identity than are Black Church arson attacks, but are likewise public and (relatively) rare. While gun violence is a common and persistent problem in the United States, mass shootings, which cause at least three deaths and occur in public places, are few in number, but large in traumatic reach. Policy demanders (The March for Our Lives and Everytown for Gun Safety) draw connections for the public, and they represent public safety concerns (and are crimes), meaning they fall under the purview of governmental response.

Finally, natural disasters are a persistent and, due to climate change, increasingly serious concern in American life. Such events affect massive numbers of Americans and cause loss of life, physical harm, destruction of property and infrastructure, and displacement. Further, such events cause millions and sometimes billions of dollars in economic damage and lost economic activity. As such, these events are politically-relevant traumatic events because of their clear trauma-inducing effects and their incredibly wide reach of lives threatened or lost.

THEORETICAL ELABORATION

Much of the literature and common conversations in the media and everyday life regarding trauma are in connection with Post-Traumatic Stress Disorder. But, there are several issues with the terminology of "disorder" in the context of this study. First, the study focuses on identifying the aggregate trends of response to traumatic events, rather than with the designation of a psychological disorder. Second, and more importantly, the study seeks to avoid passing any normative judgment on individuals' reactions to traumatic stimuli, instead taking the approach common in psychology and psychiatry of seeing reactions on a scale of post-traumatic stress (PTS) (Summerfield 2001; Muldoon et al. 2020). In so doing, the study avoids classifying any reaction to a traumatic event as "disordered." Finally, there is a growing literature focused on identifying the positive reactions to traumatic events beyond resilience known as post-traumatic growth (Tedeschi and Calhoun 1996; Shakespeare-Finch and Barrington 2012). This provides the other half of the PTS scale and illustrates that there are a wide variety of non-mutually exclusive responses to a traumatic event, but outside a clinical diagnostic setting, it is inappropriate to categorize any as disordered. And so, in this study, I stick to language of post-traumatic stress (PTS) and post-traumatic growth (PTG)/resilience, avoiding language of disorder altogether.

EXPLANATION OF THE DATA

Mass Shootings Data

The Mother Jones U.S. Mass Shootings database only includes events with three or more independent sources that confirm the incident and it does not include what are considered "more conventional crimes," by which they mean shootings related to armed robbery or gang violence, and do not include domestic violence incidents. This definition is much stricter than many other commonly used databases, such as Stanford University's Mass Shootings in America Database, which includes shootings with no deaths.

Scholars and journalists debate the definition of mass shootings and thus which cases to include in databases tracking the patterns of such events, resulting in wildly different counts for the total number of mass shooting events (Hassell et al. 2020). And yet, I opt for the Mother Jones database, which sticks most closely with the Congressional Research Service and the Federal Bureau of Investigation's definition. These events are also likely to have the most potent traumatic effect, meaning it allows me to more precisely isolate the effect of a deadly mass shooting as a traumatic event on turnout. Further, for this study, the feasibility that those in the surrounding community are impacted matters. That is, a post-traumatic response is more likely among a larger group of individuals when the event could have reasonably involved or impacted more people. Gang-related or domestic mass shootings are, therefore, less likely to have as large a reach.

Natural Disasters Data

Because the FEMA database includes a wide range of disasters, I limit the analysis in this study to natural (non-anthropogenic, at least not directly anthropogenic) disasters: coastal storms, droughts, earthquakes, wild fires, toxic algae blooms in coastal waters, flooding, hurricanes, mudslides, snow storms, tornadoes, tsunamis, typhoons, and volcano eruptions. There are other means by which to identify counties affected by natural disasters, yet FEMA provides the most accurate and comprehensive data on this question.

Additional information on Control Variables

In the generalized two-way fixed effects models, I include controls for the percentage of the county population that is Black, the total population, and median household income. I do this because these variables ensure I account for important within-state differences between counties not captured by the fixed effects. In particular, these three variables account for important factors that could possibly influence turnout, especially as it relates to traumatic events. As Black Americans disproportionately experience trauma and experience more severe post-traumatic stress reactions from any given traumatic experience (Muldoon et al. 2020), including the percentage of the county population that is Black accounts for the changes to turnout as a result of Black population. Counties with larger populations and with higher median household income are likely to have more resources to prepare for traumatic events before they happen and receive greater attention and more resources in the wake of traumatic events, meaning that we might expect these variables to influence the effect on turnout. In the fixed effects model for mass shootings I also include controls for the number of fatalities and the number of individuals injured (neither include the shooter) as these are likely to influence the traumatic response and thus turnout.

Justification of Linear Regression for Dichotomous DV

Interpretation of linear regression specifications requires weaker assumptions of functional form and while logististic specifications are also appropriate for binary outcome models (Angrist and Pischke 2009), linear specifications produce unbiased and reliable estimates of a variable's average effect (Hellevik 2009; Hoffman et al. 2016; Allison 1999; Greene 2002; Mood 2010; Baetschmann et al. 2015). As such, I utilize the straight-forward, reliable and unbiased estimates of the variable's average effect, calculated by using a linear regression estimator or the ATT.

ROBUSTNESS CHECKS

Weighted Fixed Effects Modeling

In the main text, I use a two-way fixed effects estimation method, common in political science. The data I use in this study are not the canonical two-group/two-period difference-in-difference case, however, as treatment (traumatic event exposure) turns "on" and "off" over time with multiple units and multiple time periods. A number of studies have identified the short-comings of the two-way FE approach with such data, primarily that the multiple groups and time periods causes variation in the weight of each two group/two-period combination in the data (with some weights even being negative) (Goodman-Bacon 2018; Imai and Kim 2019; de Chaisemartin and D'Haultfoeuille 2019; Harden and Kirkland 2021). The variation of this weighting can bias the coefficient on the treatment variable, unless researchers can assume a constant treatment effect across multiple groups and time periods. In the tables below, I provide the results of Imai and Kim (2019)'s weighted fixed effects estimation approach, which relaxes this assumption and are robust to heterogeneous effects. While such a method reduces statistical power, the estimates from the models provide further evidence of the robustness of my findings. In fact, the weighted fixed effects models estimate stronger and consistently statistically significant. The weighted fixed effects models estimate a 6.5 percentage point decrease in turnout in the case of Black Church arsons, a 3.2 percentage point decrease in the case of mass shootings, and a 0.4 percentage point decrease in the case of natural disasters. All estimates are substantively and statistically significant.

TABLE D.1. Effect of Traumatic Event on Turnout, Weighted Fixed Effects (county-year) Estimator

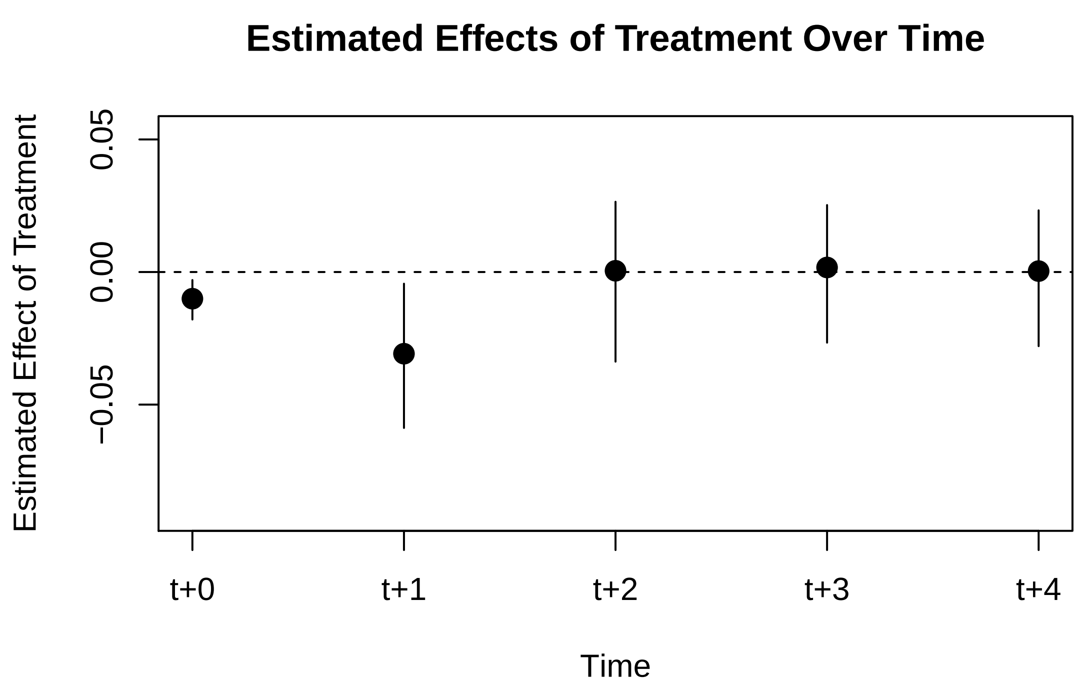
	Arson	Mass Shooting	Natural Disaster
Experience Traumatic Event	-0.065* (0.000)	-0.032* (0.000)	-0.004* (0.000)
% of County Pop. Black	-0.097* (0.000)	0.369* (0.000)	-0.130* (0.000)
Total Population	0.000* (0.000)	0.000 (0.000)	0.000* (0.000)
Med. Household Income	0.000* (0.000)	0.000* (0.000)	0.000* (0.000)
Fatalities		0.003* (0.000)	
Injured		0.000* (0.000)	
Year Fixed Effects	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes
Unique Units	2,889	2,889	2,889

Robust standard errors in parentheses.
$*p < 0.05$

Time-Series Cross-Sectional Matching

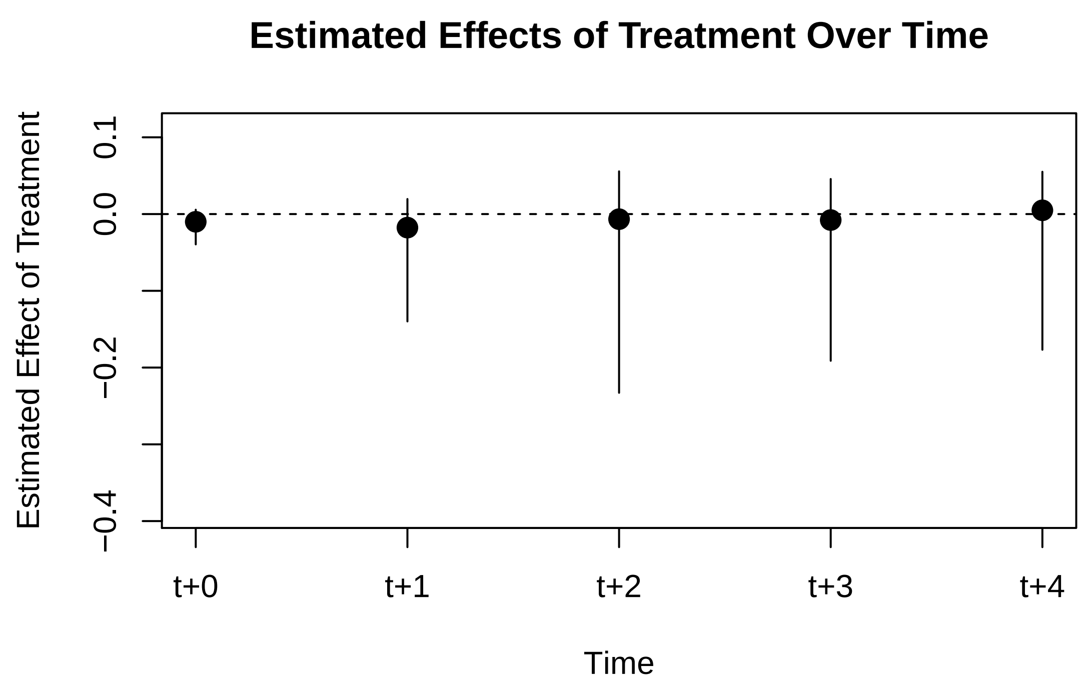
To further test the robustness of my results, my secondary analysis for the geographic proximity hypothesis utilizes a new time-series cross-sectional matching technique proposed by Imai et al. (2020), which provides a more reliable process of matching with time-series cross-sectional data (McQueen 2021). Building off of synthetic control (Abadie et al. 2011) and generalized synthetic control methods (Xu 2017), this method relaxes the parallel trends assumption and requires fewer pre-treatment periods than synthetic control methods by using within-county-over-year and within-year-across-county variation (Imai et al. 2020; McQueen 2021). In this approach, the process creates a matched set for each treated observation, refines it through a weighting method, and then computes the difference-in-differences estimator, which is the average treatment effect on the the treated (ATT), with model-based standard errors.

FIGURE D.1. Effect of Arson Attacks on Turnout, U.S. counties 1976-2016



To further test the robustness of these findings and identify long-term effects of traumatic events on voter turnout, I implement a time-series cross-sectional matching process. I plot the estimated effects of experiencing an arson attack, mass shooting, and natural disaster for the four election years after

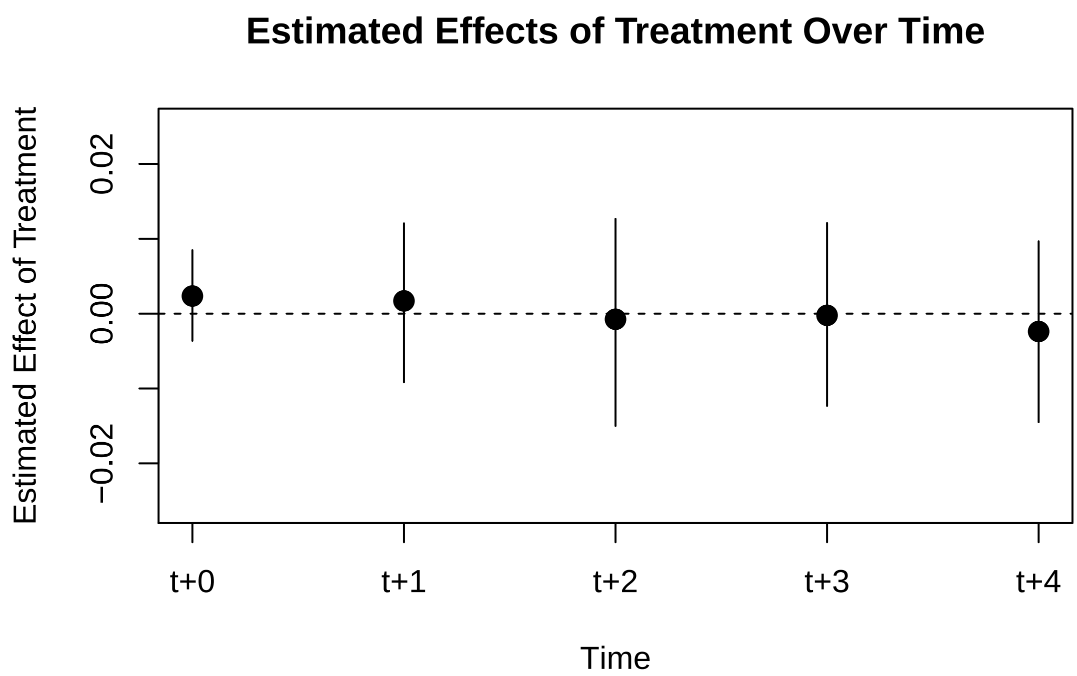
FIGURE D.2. Effect of Mass Shootings on Turnout, U.S. counties 1976-2016



the event occurs in figures D.1–D.3. In the case of arson attacks in figure D.1, the results confirm a statistically significant estimate, consistent with the magnitude and direction of the effect estimated in the the two-way FEs difference-in-differences and the lagged DV models. In the first election after the event, the model estimates a decrease in turnout of about 3 percentage points and the estimate is statistically different from zero. Interestingly, after an initial decrease, the model estimates increases in turnout in elections after the next election after the event. While none of these estimates are statistically different from zero, the direction implies that after an initial post-traumatic stress-demobilization response, targeted counties experience a post-traumatic growth-mobilization response or a return to the mean, lagged by one electoral cycle.

In figures D.2 and D.3, I do not find statistically significant results, but the estimate for the effect of mass shootings is in the right direction. There is no clear pattern in the results from the time-series cross sectional matching for the effects of these two events, but combined, the results tell a fairly consistent story. In four of the six models, I find statistically significant results that confirm my hypothesis about traumatic demobilization as a result of arson attacks, mass shootings, and natural disasters. In the

FIGURE D.3. Effect of Natural Disasters on Turnout, U.S. counties 1976-2016



matching analysis to test the robustness of these results, I find further confirmation for the effect of arson attacks, though the results are less clear for the effects of mass shootings and natural disasters. Full results of the TSCS matching models are in table D.2.

TABLE D.2. Effect of Traumatic Events on Turnout, TSCS Matching Analysis

	Black Church Arsons	Mass Shootings	Natural Disasters
$t+0$	-0.009* (0.004)	-0.005 (0.011)	0.002 (0.003)
$t+1$	-0.031* (0.014)	-0.025 (0.051)	0.002 (0.006)
$t+2$	-0.000 (0.009)	-0.010 (0.085)	-0.001 (0.007)
$t+3$	-0.000 (0.013)	-0.020 (0.081)	-0.000 (0.006)
$t+4$	-0.002 (0.013)	-0.007 (0.071)	-0.002 (0.006)

$*p < 0.05$

Note: Estimates are weighted difference-in-differences estimates using Mahalanobis Distance Matches and calculated using county-level turnout data. Bootstrapped standard errors in parentheses (1000 weighted bootstrapped samples).

Adding Unit-Specific Time Trends

Recent studies and proofs testing the two-way generalized fixed effects approach argue that the estimation method may not capture that causal effects of interest (Goodman-Bacon 2018; Wing et al. 2018; Imai and Kim 2019; de Chaisemartin and D'Haultfoeuille 2019; Kropko and Kubinec 2020; Hassell et al. 2020; Harden and Kirkland 2021). One way to address these concerns is as I have done in the above two SI sections using weighted fixed effects (Imai and Kim 2019) and the time series cross section matching approach for panel data (Imai et al. 2020). As a further test of the robustness of my findings, I run the same models from my primary analysis, adding an additional county-specific linear time trends (Hassell et al. 2020) with the following model form:

$$V_{ct} = \beta_0 + \beta_1 T_{ct} + +\beta_2 Controls + \theta_c + \lambda_t + \theta_c t + \epsilon_{ct}$$

The results in table D.3 confirm the findings in the main analysis using generalized two-way fixed effects difference-in-difference and lagged dependent variable estimation as well as those found in the time series cross sectional matching analysis above. I find consistent evidence that Black Church arson attacks have a demobilizing effect on counties that experience them, with coefficient estimates on the effect of mass shootings and natural disasters in the correct direction (negative), but of slightly smaller magnitude, and less consistently statistically significant.

Testing the Effect of Racial Social Identity

In the main text of the paper, I contend that the effects of social identity will be best detected in the case of Black Church arson attacks. This is because the traumatic event makes racial social identity salient in a way that mass shootings and natural disasters do not. I find and present statistically and substantively significant results in the main text, indicating that Black individuals who are in close geographic proximity to the traumatic event are more likely to turnout to vote in the wake of Black Church arson attacks and Hurricane Katrina relative to non-Black voters. One way to test if my theory is correct if to test the same model with mass shootings and natural disasters. If I detect a similar effect, it is not something about the way that a traumatic event primes social identity (as I contend), but rather something about Black voters in general.

TABLE D.3. Effect of Traumatic Event on Turnout, Generalized Two-Way FE Model with county, year, and unit-specific time trends Estimates

	Arson	Mass Shooting	Natural Disaster
Traumatic Event	-0.014* (0.003)	-0.008 (0.009)	0.000 (0.001)
% of County Pop.Black	-0.139* (0.045)	-0.144* (0.045)	-0.143* (0.045)
Total Population	-0.000* (0.000)	0.000* (0.000)	0.000* (0.000)
Med. Household Income	-0.000* (0.000)	0.000* (0.000)	0.000* (0.000)
Fatalities		-0.000 (0.001)	
Injured		0.001 (0.001)	
Intercept	0.625* (0.026)	0.262* (0.026)	
Year Fixed Effects	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes
Unit-Specific Time Trends	Yes	Yes	Yes
Observations	23,952	23,952	23,952
R^2	0.887	0.887	0.015
Adj. R^2	0.851	0.851	-0.121
F-statistic	24.7* (df = 5788; 18,163)	24.670* (df = 5790; 18,161)	79.53* (df = 4; 21051)

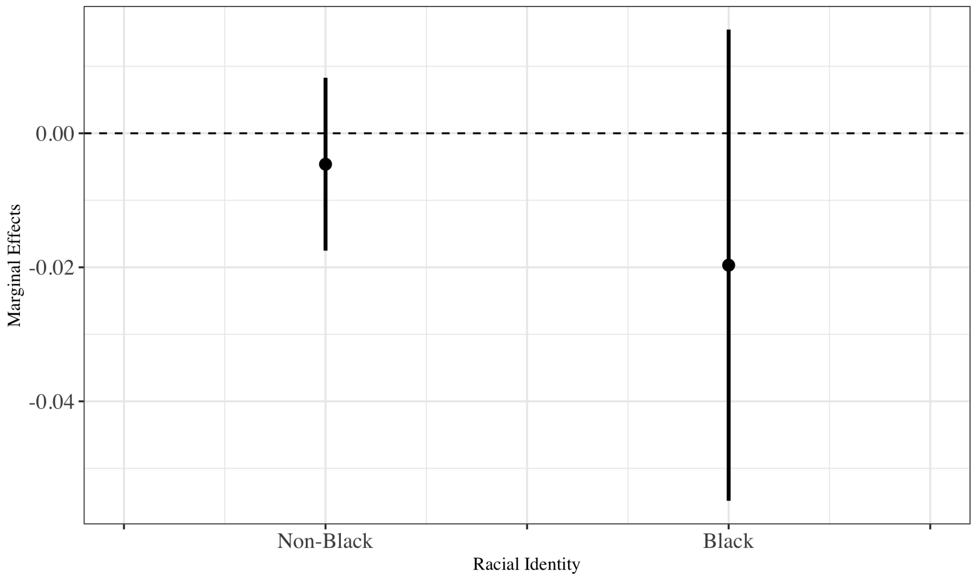
Standard errors in parentheses.
$*p < 0.05$

In figures D.4 and D.5, I present marginal effects plots of the same fixed-effects model presented in figures 3 and 4 in the main text, but with the treatment being mass shootings and all natural disasters, respectively. These results confirm that the effect of Black social identity conditions the effect of traumatic events on turnout only in the case of Black Church arson attacks with the interactive coefficient being nowhere near statistical significance.

Tables D.4 through D.8 contain the full results for the marginal effects presented in figures 3 and 4 in the main text and figures D.4 and D.5 above in the SI.

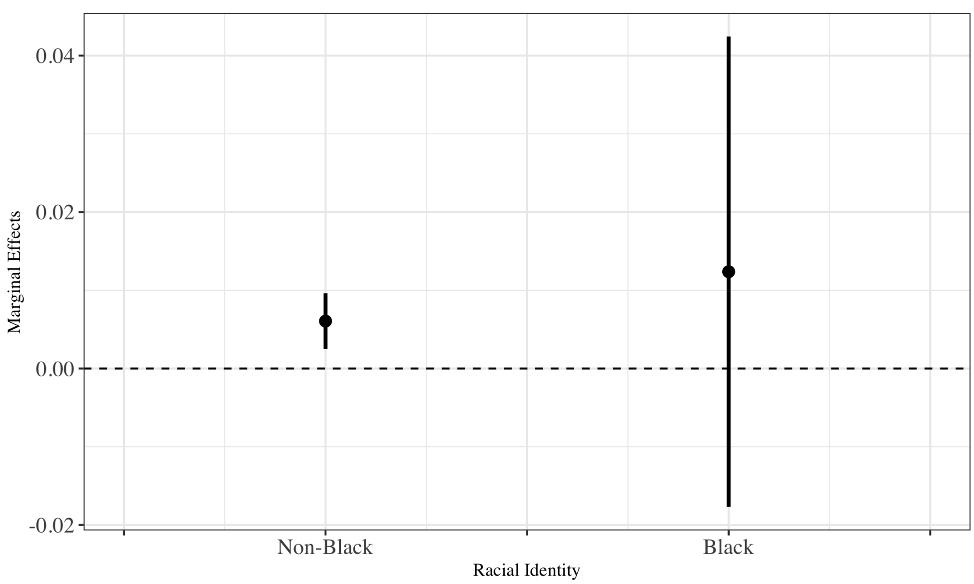
Given research that more than one lag should be included in lagged dependent variable models (Wilkins 2017), I have included an additional model with two lags included. The results are robust to the inclusion of multiple lags.

FIGURE D.4. Conditioning Effect of Black Social Identity on the Effect of Mass Shootings on Turnout



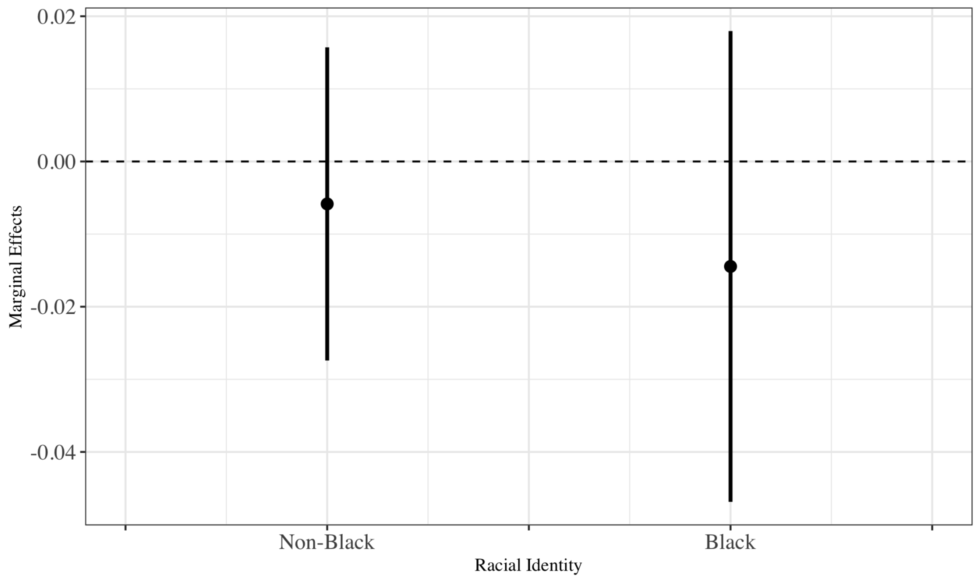
Note: The plot presents the marginal effect of Black racial identity on the effect of experiencing a mass shooting within the county of residence for respondents to the Current Population Survey (CPS) 1992-2016. Point estimates are the coefficient estimates from a two-way fixed effects model and error bars respresent 95% confidence intervals. Full results in table 10 in the SI.

FIGURE D.5. Conditioning Effect of Black Social Identity on the Effect of Natural Disasters on Turnout



Note: The plot presents the marginal effect of Black racial identity on the effect of experiencing a natural disaster within the county of residence for respondents to the Current Population Survey (CPS) 1992-2016. Point estimates are the coefficient estimates from a two-way fixed effects model and error bars respresent 95% confidence intervals. Full results in table 12 in the SI.

FIGURE D.6. Conditioning Effect of Black Social Identity on the Effect of Racialized Mass Shootings on Turnout



Note: The plot presents the marginal effect of Black racial identity on the effect of experiencing racialized mass shootings within the county of residence for respondents to the Current Population Survey (CPS) 1992-2016. Point estimates are the coefficient estimates from a two-way fixed effects model and error bars respresent 95% confidence intervals. Full results in table 11 in the SI.

TABLE D.4. Conditioning Effect of Black Social Identity on the Effect of Arson Attacks on Voting

	Vote (TWFE)	Vote (One-Lag DV)	Vote (Two-Lag DV)
Lagged Vote (1)		0.278* (0.001)	0.248* (0.002)
Lagged Vote (2)			0.005* (0.001)
Arson Attack	-0.010* (0.004)	-0.025* (0.003)	-0.022* (0.003)
Black	0.070* (0.013)	0.053* (0.002)	0.056* (0.002)
Gender	0.042* (0.002)	0.043* (0.001)	0.045* (0.001)
Education	0.630* (0.007)	0.575* (0.003)	0.611* (0.004)
Income	0.237* (0.007)	0.177* (0.003)	0.168* (0.003)
Arson Attack×Black	0.041* (0.015)	0.036* (0.007)	0.028* (0.008)
Intercept		-0.040* (0.003)	-0.041* (0.003)
Observations	841,165	621,143	443,184
R^2	0.109	0.640	0.1543
Adj. R^2	0.109	0.640	0.1543
F-statistic	129.1* (df = 799; 840,365)	18,030* (df = 7; 621,135)	10,110* (df = 8; 443,175)

$*p < 0.05$

Note: Estimates calculated using data from individual respondents to the Current Population Survey (CPS) 1992-2016. Robust Standard Errors in parentheses.

TABLE D.5. Conditioning Effect of Black Social Identity on the Effect of Mass Shootings on Voting

	Vote (TWFE)	Vote (LDV)
Lagged Vote		0.277* (0.001)
Mass Shooting	-0.005 (0.007)	-0.003 (0.006)
Black	0.072* (0.013)	0.054* (0.002)
Gender	0.042* (0.002)	0.043* (0.001)
Education	0.630* (0.007)	0.575* (0.003)
Income	0.237* (0.007)	0.176* (0.003)
Mass Shooting×Black	-0.015 (0.026)	0.011 (0.019)
Intercept		-0.041* (0.003)
Observations	841,165	621,143
R^2	0.109	0.169
Adj. R^2	0.108	0.169
F-statistic	129* (df = 799; 840,365)	18,020* (df = 7; 621,135)

$*p < 0.05$

Note: Estimates calculated using data from individual respondents to the Current Population Survey (CPS) 1992-2016. Robust Standard Errors in parentheses.

TABLE D.6. Conditioning Effect of Black Social Identity on the Effect of Racialized Mass Shootings on Voting

	Vote (TWFE)	Vote (LDV)
Lagged Vote		0.278* (0.001)
Racialized Mass Shooting	-0.006 (0.011)	-0.036* (0.013)
Black	0.072* (0.013)	0.054* (0.002)
Gender	0.042* (0.002)	0.043* (0.001)
Education	0.630* (0.007)	0.575* (0.003)
Income	0.237* (0.007)	0.176* (0.003)
Racialized Mass Shooting×Black	-0.009 (0.012)	0.030 (0.031)
Intercept		-0.047* (0.003)
Observations	841,165	621,143
R^2	0.109	0.169
Adj. R^2	0.108	0.169
F-statistic	129* (df = 707; 840,365)	18,020* (df = 7; 621,135)

$*p < 0.05$

Note: Estimates calculated using data from individual respondents to the Current Population Survey (CPS) 1992-2016. Robust Standard Errors in parentheses.

TABLE D.7. Conditioning Effect of Black Social Identity on the Effect of Natural Disasters on Voting

	Vote (TWFE)	Vote (LDV)
Lagged Vote		0.277* (0.001)
Disasters	0.006* (0.002)	-0.016* (0.001)
Black	0.070* (0.015)	0.053* (0.002)
Gender	0.042* (0.002)	0.043* (0.001)
Education	0.630* (0.007)	0.575* (0.003)
Income	0.237* (0.007)	0.177* (0.003)
Disasters×Black	0.006 (0.010)	0.005 (0.003)
Intercept		-0.036* (0.003)
Observations	841,165	621,143
R^2	0.109	0.169
Adj. R^2	0.109	0.169
F-statistic	129.1* (df = 799; 840,365)	18,050* (df = 7; 621,135)

$*p < 0.05$

Note: Estimates calculated using data from individual respondents to the Current Population Survey (CPS) 1992-2016. Robust Standard Errors in parentheses.

TABLE D.8. Conditioning Effect of Black Social Identity on the Effect of Hurricane Katrina on Turnout

	Vote (TWFE)	Vote (One-Lag DV)	Vote (Two-Lag DV)
Lagged Vote (1)		0.278* (0.001)	0.249* (0.002)
Lagged Vote (2)			0.003 (0.002)
Hurricane Katrina	0.019* (0.004)	0.046* (0.007)	0.044* 0.008)
Black	0.070* (0.014)	0.050* (0.002)	0.052* (0.002)
Gender	0.041* (0.002)	0.042* (0.001)	0.044* (0.001)
Education	0.636* (0.009)	0.581* (0.004)	0.616* (0.004)
Income	0.241* (0.006)	0.178* (0.003)	0.170* (0.003)
Katrina×Black	0.042* (0.016)	0.040* (0.018)	0.042* (0.022)
Intercept		-0.046* (0.003)	-0.046* (0.003)
Observations	697,182	517,228	370,427
R^2	0.111	0.170	0.155
Adj. R^2	0.110	0.170	0.155
F-statistic	123* (df = 707; 696,474)	15150* (df = 7; 517,220)	8500* (df = 8; 370,418)

$*p < 0.05$

Note: Estimates calculated using data from individual respondents to the Current Population Survey (CPS) 1992-2016. Robust Standard Errors in parentheses.

Full Results of Lagged Dependent Variable Models

In tables D.9 through D.11 below, I include the full results of alternate model specifications of the county-level Lagged Dependent Variable models including adding additional time varying controls (model 1 in each table), adding a second lag (model 2), and estimating the effect of the cumulative treatment effect with out the treatment identifier also in the model (model 3). This final model specification is more in line with the method recommended in Blackwell and Glynn (2018), though my approach of including the treatment variable *and* and the cumulative treatment variable in the same model in the main text demonstrates the robustness of my findings.

TABLE D.9. Effect of Black Church Arsons on Turnout, Lagged DV Analysis

	(1)	(2)	(3)
Lagged Vote (1)	0.783* (0.007)	0.629* (0.007)	0.630* (0.014)
Lagged Vote (2)		0.195* (0.007)	0.195* (0.012)
Arson Attack	-0.039* (0.003)	-0.038* (0.004)	
Cumulative Arsons			-0.023* (0.002)
% of County Pop. Black	-0.018* (0.003)	-0.004 (0.003)	-0.005 (0.003)
Total Population	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Med. Household Income	0.000* (0.000)	0.000* (0.000)	0.000* (0.000)
Intercept	0.105* (0.004)	0.068* (0.003)	0.067* (0.003)
Observations	21,116	18,281	18,281
R^2	0.679	0.690	0.689
Adj. R^2	0.679	0.690	0.689
F-statistic	8918* (df = 5; 21,110)	6766* (df = 6; 18,274)	6760* (df = 6; 18,274)

$*p < 0.05$

Note: Estimates calculated using county-level turnout data. Robust standard errors in parentheses.

TABLE D.10. Effect of Mass Shootings on Turnout, Lagged DV Analysis

	(1)	(2)	(3)
Lagged Vote (1)	0.784* (0.007)	0.632* (0.014)	0.632* (0.014)
Lagged Vote (2)		0.193* (0.012)	0.193* (0.012)
Mass Shooting	-0.011 (0.009)	-0.011 (0.010)	
Cumulative Shootings			-0.011 (0.010)
% of County Pop. Black	-0.021* (0.003)	-0.007* (0.003)	-0.007* (0.003)
Total Population	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Med. Household Income	0.000* (0.000)	0.000* (0.000)	0.000* (0.000)
Fatalities	0.002 (0.001)	0.002 (0.001)	0.002 (0.001)
Injured	-0.000 (0.000)	0.000 (0.001)	-0.000 (0.001)
Intercept	0.105* (0.004)	0.067* (0.003)	0.067* (0.003)
Observations	21,116	18,281	18,281
R^2	0.678	0.688	0.688
Adj. R^2	0.678	0.688	0.688
F-statistic	6335* (df = 7; 21,108)	5044* (df = 8; 18,272)	5044* (df = 8; 18,272)

$*p < 0.05$

Note: Estimates calculated using county-level turnout data. Robust standard errors in parentheses.

TABLE D.11. Effect of Natural Disasters on Turnout, Lagged DV Analysis

	(1)	(2)	(3)
Lagged Vote (1)	0.783* (0.004)	0.633* (0.007)	0.632* (0.003)
Lagged Vote (2)		0.191* (0.007)	0.191* (0.014)
Disaster	-0.007* (0.001)	-0.002 (0.001)	
Cumulative Disasters			-0.001* (0.000)
% of County Pop. Black	-0.019* (0.003)	-0.007* (0.003)	-0.007* (0.003)
Total Population	-0.000 (0.000)	-0.000* (0.000)	0.000 (0.000)
Med. Household Income	0.000* (0.000)	0.000* (0.000)	0.000* (0.000)
Intercept	0.106* (0.003)	0.068* (0.003)	0.068* (0.003)
Observations	21,116	18,281	18,281
R^2	0.678	0.688	0.688
Adj. R^2	0.678	0.688	0.688
F-statistic	8904* (df = 5; 21,110)	6727* (df = 6; 18,274)	6727* (df = 6; 18,274)

$*p < 0.05$

Note: Estimates calculated using county-level turnout data. Robust standard errors in parentheses.

Replicating Results with Alternative Data

In table D.12, I test the same two-way fixed effects difference-in-difference and lagged dependent variable models that I run on the Mother Jones data on the Stanford MSA data. The MSA data has a much larger N of 441 cases (that I was able to match with county-level turnout data). I find that the models predict strikingly similar effect sizes and both indicate a demobilizing effect with negative coefficient estimates. Neither estimate is statistically significant, but the size and direction are consistent with my findings using the Mother Jones data.

TABLE D.12. Effect of Mass Shooting on Turnout using the Stanford MSA Database

	Turnout (TWFE)	Turnout (Lagged DV)
Lagged Turnout		0.380* (0.185)
Experience Mass Shooting	-0.037 (0.046)	-0.038 (0.036)
% of County Pop. Black	-0.215 (0.175)	
Total Population	0.000 (0.000)	
Med. Household Income	0.000* (0.000)	
Fatalities	0.001 (0.000)	
Victims	0.001 (0.004)	
Intercept		0.370* (0.005)
Observations	23,992	24,203
R^2	0.013	0.130
Adj. R^2	-0.123	0.130
F-statistic	44.682* (df = 6; 21,089)	1806* (df = 2; 24,200)

$*p < 0.05$

Note: Estimates calculated using data from individual respondents to the Current Population Survey (CPS) 1992-2016. Robust Standard Errors in parentheses.

FULL RESULTS OF TEMPORAL PROXIMITY

In tables E.1 through E.6, I provide the full results for the data represented graphically in the main text of the analysis in figures 1 and 2.

TABLE E.1. Effect of Temporal Proximity of Black Church Arson Attacks to Election on Voting (Two Way FE Estimator)

	Three Months	Six Months	Election Year	Two Years
Temporal Proximity	-0.015 (0.008)	-0.008 (0.006)	-0.010 (0.005)	-0.012* (0.004)
% County Pop. Black	-0.110 (0.062)	-0.110 (0.062)	-0.110 (0.062)	-0.110 (0.063)
Population	0.000* (0.000)	0.000* (0.000)	0.000* (0.000)	0.000* (0.000)
Med. HH Income	0.000* (0.000)	0.000* (0.000)	0.000* (0.000)	0.000* (0.000)
Observations	23,952	23,952	23,952	23,952
R^2	0.015	0.015		0.015
0.015				
Adj. R^2	-0.121	-0.121	-0.121	-0.121
F-statistic	79.85* (df = 4; 21,051)	79.62* (df = 4; 21,051)	79.91* (df = 4; 21,051)	80.69* (df = 4; 21,051)

$*p < 0.05$

Note: Estimates calculated using county-level data. County-clustered standard errors in parentheses.

TABLE E.2. Effect of Temporal Proximity of Mass Shootings to Election on Voting (Two Way FE Estimator)

	Three Months	Six Months	Election Year	Two Years
Temporal Proximity	0.034 (0.024)	0.055* (0.013)	0.025 (0.014)	0.006 (0.011)
% County Pop. Black	-0.112 (0.063)	-0.112 (0.063)	-0.112 (0.063)	-0.112 (0.063)
Population	0.000* (0.000)	0.000* (0.000)	0.000* (0.000)	0.000* (0.000)
Med. HH Income	0.000* (0.000)	0.000* (0.000)	0.000* (0.000)	0.000* (0.000)
Fatalities	0.000 (0.001)	-0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
Injured	0.001 (0.000)	0.000 (0.00)	0.000 (0.000)	0.000 (0.000)
Observations	23,952	23,952	23,952	23,952
R^2	0.015	0.015		0.015
0.015				
Adj. R^2	-0.121	-0.121	-0.121	-0.121
F-statistic	53.59* (df = 6; 21,049)	54.88* (df = 6; 21,049)	53.92* (df = 6; 21,049)	53.43* (df = 6; 21,049)

$*p < 0.05$

Note: Estimates calculated using county-level data. County-clustered standard errors in parentheses.

TABLE E.3. Effect of Temporal Proximity of Natural Disasters to Election on Voting (Two Way FE Estimator)

	Three Months	Six Months	Election Year	Two Years
Temporal Proximity	0.017* (0.003)	0.004 (0.002)	0.003 (0.002)	0.002 (0.001)
% County Pop. Black	-0.108 (0.062)	-0.109 (0.062)	-0.110 (0.062)	-0.110 (0.062)
Population	0.000* (0.000)	0.000* (0.000)	0.000* (0.000)	0.000* (0.000)
Med. HH Income	0.000* (0.000)	0.000* (0.000)	0.000* (0.000)	0.000* (0.000)
Observations	23,952	23,952	23,952	23,952
R^2	0.016	0.015		0.015
0.015				
Adj. R^2	-0.119	-0.121	-0.121	-0.121
F-statistic	86.45* (df = 4; 21,051)	80.23* (df = 4; 21,051)	80.23* (df = 4; 21,051)	79.91* (df = 4; 21,051)

$*p < 0.05$

Note: Estimates calculated using county-level data. County-clustered standard errors in parentheses.

TABLE E.4. Effect of Temporal Proximity of Black Church Arson Attacks to Election on Voting (Lagged DV Estimator)

	Three Months	Six Months	Election Year	Two Years
Temporal Proximity	-0.065* (0.007)	-0.066* (0.005)	-0.067* (0.004)	-0.061* (0.004)
Lagged Turnout	0.796* (0.006)	0.796* (0.006)	0.796* (0.006)	0.795* (0.006)
Intercept	0.120* (0.002)	0.120* (0.003)	0.120* (0.003)	0.120* (0.003)
Observations	24,178	24,178	24,178	24,178
R^2	0.638	0.638		0.639
0.639				
Adj. R^2	0.638	0.638	0.639	0.639
F-statistic	21,300* (df = 2; 24,175)	21,340* (df = 2; 24,175)	21,370* (df = 2; 24,175)	21,410* (df = 2; 24,175)

$*p < 0.05$

Note: Estimates calculated using county-level data. Robust standard errors in parentheses.

TABLE E.5. Effect of Temporal Proximity of Mass Shootings to Election on Voting (Lagged DV Estimator)

	Three Months	Six Months	Election Year	Two Years
Temporal Proximity	0.050* (0.018)	0.041* (0.012)	0.012 (0.013)	0.010 (0.011)
Lagged Turnout	0.796* (0.006)	0.796* (0.006)	0.796* (0.006)	0.795* (0.006)
Fatalities	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
Injured	-0.000 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.000 (0.001)
Intercept	0.119* (0.003)	0.119* (0.003)	0.119* (0.003)	0.119* (0.003)
Observations	24,178	24,178	24,178	24,178
R^2	0.638	0.638		0.639
0.639				
Adj. R^2	0.638	0.638	0.639	0.639
F-statistic	10,630* (df = 4; 24,173)	10,640* (df = 4; 24,173)	10,630* (df = 4; 24,173)	10,630* (df = 4; 24,173)

$*p < 0.05$

Note: Estimates calculated using county-level data. Robust standard errors in parentheses.

TABLE E.6. Effect of Temporal Proximity of Natural Disasters to Election on Voting (Lagged DV Estimator)

	Three Months	Six Months	Election Year	Two Years
Temporal Proximity	0.016* (0.002)	0.007* (0.002)	-0.016* (0.002)	-0.010* (0.001)
Lagged Turnout	0.797* (0.006)	0.796* (0.006)	0.795* (0.006)	0.794* (0.006)
Intercept	0.118* (0.002)	0.119* (0.003)	0.121* (0.003)	0.122* (0.003)
Observations	24,178	24,178	24,178	24,178
R^2	0.638	0.638		0.639
0.639				
Adj. R^2	0.638	0.638	0.639	0.639
F-statistic	21,300* (df = 2; 24,175)	21,280* (df = 2; 24,175)	21,370* (df = 2; 24,175)	21,350* (df = 2; 24,175)

$*p < 0.05$

Note: Estimates calculated using county-level data. Robust standard errors in parentheses.

SI REFERENCES

Abadie, Alberto , Alexis Diamond, and Jens Hainmueller (2011). Synth: An r Pakage for Synthetic Control Methods in Comparative Case Studies. *Journal of Statistical Software 42*(13).

Allison, Paul D. (1999). Comparing Logit and Probit Coefficients Across Groups. *Sociological Methods & Research 28*(2), 186–208.

Angrist, Joshua D. and Jörn-Steffen Pischke (2009). *Mostly Harmless Econometrics*. Princeton, NJ: Princeton University Press.

Baetschmann, Gregori , Kevin R. Staub, and Rainer Winkelmann (2015). Consistent estimation of the fixed effects ordered logit model. *Journal of the Royal Statistical Society 178*(3), 685–703.

Blackwell, Matthew and Adam N. Glynn (2018). How to Make Causal inferences with Time-Series Cross-Sectional Data under Selection on Observables. *American Political Science Review 112*(4), 1067–1082.

de Chaisemartin, Clément and Xavier D'Haultfoeuille (2019). Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects. *NBER Working Paper 25904*.

Goodman-Bacon, Andrew (2018). Difference-in-Differences with Variation in Treatment Timing. *National Bureau of Economic Research Working Pa*.

Greene, William (2002). The Bias of the Fixed Effects Estimator in Nonlinear Models.

Harden, Jeffrey J. and Justin H. Kirkland (2021). Does Transparency Inhibit Political Compromise? *American Journal of Political Science 65*(2), 493–509.

Hassell, Hans J.G. , John B. Holbein, and Matthew Baldwin (2020). Mobilize for Our Lives? School Shootings and Democratic Accountability in U.S. Elections. *American Political Science Review 114*(4), 1375–1385.

Hellevik, Ottar (2009). Linear versus logistic regression when the dependent variable is a dichotomy. *Quality & Quantity 43*, 59–74.

Hoffman, Kelly M. , Sophie Trawalter, Jordan R. Axt, and M. Norman Oliver (2016). Racial bias in pain assessment and treatment recommendations, and false beliefs about biological differences between blacks and whites. *Proceedings of the National Academy of Sciences of the United States of America 113*(16), 4296–4301.

Imai, Kosuke and In Song Kim (2019). On the Use of Two-Way Fixed Effects Regression Models for Causal inference with Panel Data. *Harvard University IQSS Working Pa*.

Imai, Kosuke , In Song Kim, and Erik Wang (2020). Matching Methods for Causal Inference with Time-Series Cross-Sectional Data.

Kropko, Jonathan and Robert Kubinec (2020). Interpretation and Identification of Within-Unit and Cross-Sectional Variation in Panel Data Models. *PloS One 15*(4), e0231349.

McQueen, Shannon (2021). Pipeline or Pipedream: Gender Balance Legislation's Effect on Women's Presence in State Government. *State Politics & Policy Quarterly*, 1–23.

Mood, Carina (2010). Logistic Regression: Why We Cannot Do What We Think We Can Do, and What We Can Do About It. *European Sociological Review 26*(1), 67–82.

Muldoon, Orla T. , Robert D. Lowe, Jolanda Jetten, Tegan Cruwys, and S. Alexander Haslam (2020). Personal and Political: Post-Traumatic Stress Through the Lens of Social Identity, Power, and Politics. *Political Psychology*.

Shakespeare-Finch, Jane and Allysa J. Barrington (2012). Behavioural Changes Add Validity to the Construct of Posttraumatic Growth. *Journal of Traumatic Stress 25*(4), 433–439.

Summerfield, Derek (2001). The invention of post-traumatic stress disorder and the social usefulness of a psychiatric category. *British Medical Journal 322*, 95–98.

Tedeschi, Richard G. and Lawrence G. Calhoun (1996). The Posttraumtic Growth Inventory: Measuring the Positive Legacy of Trauma. *Journal of Traumatic Stress 9*, 455–471.

Wilkins, Arjun S. (2017). To Lag or Not to Lag?: Re-Evaluating the Use of Lagged Dependent Variables in Regression Analysis. *Political Science Research and Methods 6*(2), 393–411.

Wing, Coady , Kosali Simon, and Ricardo A. Bello-Gomez (2018). Designing Difference in Difference Studies: Best Practices for Public Health Policy Research. *Annual Review of Public Health 39*, 453–69.

Xu, Yiqing (2017). Generalized Synthetic Control Method: Causal Inference with Interactive Fixed Effects Models. *Political Analysis 25*, 57–76.