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Leonardo Baccini
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University of Ottawa and IZA

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IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Terrorism and Voting Behavior: Evidence from the United States

This paper examines the impact of terrorism on voting behavior in the United States. We rely on an exhaustive list of terror attacks over the period 1970-2016 and exploit the inherent randomness of the success or failure of terror attacks to identify the political impacts of terrorism. We first confirm that the success of terror attacks is plausibly random by showing that it is orthogonal to potential confounders. We then show that on average successful attacks have no effect on presidential and non-presidential elections. As a benchmark, we also rely on a more naïve identification strategy using all the counties not targeted by terrorists as a comparison group. We show that using this naïve identification strategy leads to strikingly different results overestimating the effect of terror attacks on voting behavior. Overall, our results indicate that terrorism has less of an influence on voters than is usually thought.

JEL Classification: D72, D74
Keywords: terrorism, voting behavior

Corresponding author:
Abel Brodeur
Department of Economics
Faculty of Social Sciences
University of Ottawa
120 University
Ottawa, ON K1N 6N5
Canada
E-mail: abrodeur@uottawa.ca

The political economy literature on electoral accountability (Barro 1973; Ferejohn 1986) provides a theoretical framework for investigating the effect of terrorism on electoral outcomes. Voters often find it hard to determine the level of public goods provided by the government. For instance, voters have no complete information on the counter-terrorism activities of their government. However, they do observe terror attacks. Therefore, voters use the amount of terrorism that they face as a signal to assess the competence of the incumbent. If the electorate believes that the level of terror under the current government is too high (relative to the expected level of terror under a different government), the incumbent government is more likely to lose votes, and eventually office.

While the theoretical framework linking terrorism to voting behavior is relatively straightforward, empirical results are contradictory. There are two broad sources of disagreement in the current literature. First, there is evidence that incumbents lose electoral support following attacks and casualties (Gassebner et al. 2008; Gelpi et al. 2006; Karol and Miguel 2007). However, Berrebi and Klor (2008) and Koch and Tkach (2012) find that in Israel incumbents are not punished for suicide attacks. Second, while there is some evidence that right-wing parties increase their vote shares after terrorist events (Abramson et al. 2007; Berrebi and Klor 2008; Kibris 2011; Koch and Tkach 2012), other studies show that terrorism may also shift the entire political spectrum to the left, as was the case of the 2004 train bombings in Madrid (Bali 2007; Gould and Klor 2010; Montalvo 2011).

These conflicting findings are possibly a product of the difficulties in assessing the effect of terrorism on electoral outcomes due to selection bias. Indeed, terrorist attacks are not random, but rather terrorists are likely to choose the targets and the timing of their attacks strategically. In particular, they target populations that are more likely to respond in the desired manner, either by voting for right-wing parties (if the terrorists' goal is to spoil talks or facilitate recruitment) or for left-wing parties (if the goal is to extract concessions). In short, there is a concrete risk of *overestimating* the impact of terrorism on voting behavior.

We address these challenges by relying on an identification strategy that allows us to recreate a quasi-experiment. Following Brodeur (2018), we use an exhaustive list of terror attacks in the U.S. from 1970 to 2016 and directly compare the effects of successful terror attacks with those of failed attacks. The definition of a successful/failed attack depends on the type of attack. For instance, an assassination is considered successful if the target is killed, while an explosion is considered successful if the explosive device detonates. The identification assumption is that, conditional on being a location targeted by a terror attack, the success or failure of the attack is plausibly exogenous. We confirm this assumption by showing that potential confounders are orthogonal to our treatment, i.e. successful vs failed attacks. This setting is attractive since successful terror attacks are more salient than failed attacks. On average, successful attacks receive more national media coverage and lead to more casualties, results that our empirical analysis validate.

We benchmark the results of our novel identification strategy with the results of a more naïve approach which compares counties in which terrorist attacks take place with those in which they do not. Using two-way fixed effects, these traditional difference-in-differences show that terrorism *increases* the vote for the Republican party in US presidential elections. On the contrary, when we rely on our identification strategy, which recreates a natural experiment comparing successful attacks with failed ones, we find *no effect* of terrorism on presidential elections. The null effect persists even when we explore the effect of terrorist attacks by motives and when we account for incumbency. The key contribution of this paper is to show that there is very limited evidence of a causal effect of terrorism on voting behavior in the U.S.

Data

Our data on terrorist attacks come from the Global Terrorism Database (GTD), which is a continually updated database of terrorist incidents across the globe (START, 2019). Originally an effort by the Pinkerton Global Intelligence Service, additions to the GTD since its inception in 1970 have been overseen by several organizations, with the National Consortium for the Study of Terrorism and Responses to Terrorism (START) most recently taking control in 2011.[1] The GTD records several dozen descriptive variables for incidents, including measures of casualties and material damage caused, attack logistics, information on perpetrators when available and, crucially, an indicator of whether an attempted attack was successful or unsuccessful.[2] We restrict our use of the GTD to attacks in the U.S. for the periods covered by our data on voting, which varies depending on the election type. Our full sample covers attacks which took place in the U.S. between and including 1970 and 2016. Additionally, we manually code a broad categorization of attack motives from the descriptions provided in the GTD.[3] It should be noted that the vast majority of the attacks in our sample are domestic.[4]

We map the distribution of successful and failed attacks across the U.S. mainland in Figure A1 in Online Appendix A. Counties which experience a large number of attacks are concentrated along the east and west coasts and tend to contain large cities. In Figure A2, we plot the distribution of successful and failed attacks over time. The number of both types of attacks has experienced a precipitous decline since the political violence of the early 1970s, although recent years have seen the annual numbers of attacks again rise to the levels of later in that decade. These figures provide suggestive evidence that the location and timing of terror attacks is not random. Table A1 in Online Appendix A includes descriptive statistics for the dataset, which comprises a total of 2639 attacks, disaggregated by attack type, target, weapon and logistics. In Table A2, we summarize our added motives and sub-motives.[5]

[1]Data for the year 1993 are missing due to a loss of paper records, although an ongoing recent effort has attempted to reconstruct the data for this year.

[2]The GTD defines successful attacks according to their "tangible effects" and not whether they served a broader goal of the perpetrators. This is coded by assessing if the designated attack type actually took place.

[3]Attacks are classified as either anti-abortion motivated, politically motivated, hate motivated or of unknown motive. Although attacks are given a single classification, in reality the categories are neither exhaustive nor mutually exclusive. We also code a more disaggregated "sub-motive" when adequate information is available.

[4]Transnational attacks are defined as attacks targeting non-Americans and/or in which the nationality of the terrorist group is not U.S.

[5]In decreasing order of prominence, the ten most common attack sub-motives are: left-wing, anti-

Our data on elections are sourced from David Leip's Election Atlas (Leip 2019). The vote totals which we use to merge with GTD terrorist incidents are at the county level. The vote counts are disaggregated into three categories: votes for the Republican candidate, votes for the Democratic candidate and votes for any other candidates in an election. County-level vote data are available for presidential elections from 1972 to 2016, while data on elections to the House of Representatives and the Senate begin in 1994 and end in 2016. We also collect data on potential confounding variables, which we describe in the appendix.

Identification Strategy

As a benchmark, we begin by estimating a standard identification strategy at the county-election year level which includes the full sample of observed units for presidential elections i.e. over 30,000 observations and two-way fixed effects. More formally, our model specification takes the following form:

$$Y_{c,t} = \alpha_c + \gamma_t + \beta Attacks_{c,t} + \delta^\top \mathbf{Z}_{c,t} + \epsilon_{c,t} \tag{1}$$

where $Y_{c,t}$ is the Republican two-party vote share in county c during election year t. $Y_{c,t}$ is variously reported for presidential elections and elections to the two chambers of congress separately.[6] $Attacks_{c,t}$ is the count of successful attacks that took place in county c since the last election and before election t. County and election year fixed effects are represented by α_c and γ_t respectively. County fixed effects control for time-invariant characteristics at the county level, while election year fixed effects net out year-specific trends that are common to all cells. Finally, $\epsilon_{c,t}$ represents a cluster-robust error term. In some models, we also include a vector $\mathbf{Z}_{c,t}$ of potential time-varying confounding variables as controls.

Despite our attempt to control for confounding variables by isolating the causal effect of

abortion, racial animosity, Puerto-Rico, Cuba, environmental, Jewish right wing, black nationalism, animal rights and anti-war. Although unexplored here, the distribution of motives is almost certainly heterogeneous across time and geography.

[6] We report results for congressional elections in the appendix.

terrorist attacks at the election-year level, concerns about a potential omission of time varying confounders remain. We therefore rely on a sharper identification strategy, estimating the difference between voting in counties where successful attacks took place and counties where attacks were attempted but failed. More formally, we estimate the following model specification:

$$Y_{c,t} = \alpha_c + \gamma_t + \beta Success_{c,t} + \epsilon_{c,t} \tag{2}$$

where $Y_{c,t}$ is the Republican two-party vote share in election t following an attempted attack in county c.[7] $Success_{c,t}$ is a binary indicator of whether the attempted attack was successful and $\epsilon_{c,t}$ is a cluster-robust error term. This model specification too includes county and election year fixed effects.

Table A3 in Online Appendix A assesses whether local area characteristics (e.g., violent crime, unemployment) together predict the success of a terror attack. Overall, we find that none of the thirteen variables included in our analysis are statistically significant at the 5% level and that the variables do not jointly predict the success of terrorist attacks, reinforcing the validity of our quasi-experiment.

We further consider the possibility that comparing successful to failed attacks may overcorrect for the selection bias inherent in the naïve approach. The concern in this case is that even failed attacks are likely to receive media coverage and may have caused casualties.[8] Table A4 in Online Appendix A assesses the effect of successful attacks on news coverage using a new dataset covering all of the attacks in our sample.[9] In Panel A, looking at pooled

[7] We report the results for the House and Senate in the appendix.

[8] Consider for example a failed assassination attempt which does not result in the death of its target, but which instead results in the death or injury of a bystander. If the media coverage or destruction of life and property associated with failed attacks is comparable to that caused by successful attacks, we may expect both to result in political effects, leading to an underestimation of the treatment effect.

[9] News abstracts are generously provided by Sood and Laohaprapanon (2020). We collect all stories from the Vanderbilt News Archive from the major broadcast networks ABC, CBS, and NBC. We focus on these networks because they operate across the time-period of our sample. Using a dictionary of attack specific terms we then count the number and length of news stories which mentioned the targeted town or city and the attack, covering the day of the event and the following 10 days. We also collect the number of stories about that town or city which are not related to the attack for inclusion as a control.

coverage we show that successful attacks in our dataset are associated with .27 more news stories (about 21 percent above the average number of stories for failed attacks, 1.26), and in Panel B that they receive 470 seconds longer coverage, an increase of more than double the average for unsuccessful attacks of 219 seconds. Both of these estimates are statistically significant at $p < 0.05$ using cluster-robust standard errors, and they are robust to the inclusion of attack-level controls and multi-dimensional fixed effects.[10]

Results

Naive analysis. Table 1 reports the findings from equation 1. The first column includes all county-election years and all attacks from 1972 to 2016, while the subsequent columns restrict the sample to counties where successful attacks took place within smaller windows before the election.[11] When considering all attacks, we find that each successful terrorist attack in a county is associated with an increase in the Republican two-party vote share of about half a percent.

Interestingly, attacks that occur in smaller windows before the election appear to have a more pronounced effect. Individual attacks within 9 months of voting are associated with a considerable increase in the Republican vote share of 1.6 percent. Restricting the sample to 6 months yields an increase of over 1.9 percent, while within a 3-month window attacks have no significant effect.

To corroborate our findings, we perform a set of robustness checks. While we leave many of the details in Online Appendix B, here we summarize a few interesting results. First, we find some support for variation in the effect identified in Table 1 depending on incumbency. In particular, terrorism increases the vote for the Republican party almost exclusively when

[10]These findings are in line with previous work, which has shown successful attacks to be associated with longer and more numerous stories on broadcast news, in addition to decreased earnings and employment in targeted counties, relative to failed attacks (Brodeur 2018).

[11]These models include counties where no attacks took place but not counties where successful attacks took place outside of the specified window so as to maintain county-election years free of attacks as the counter-factual.

Table 1: Effect of Terrorist Attacks on the Republican Two-Party Vote Share in Presidential Elections, Naïve Analysis

	Republican Two-Party Vote Share			
	All Attacks	9 months	6 months	3 months
	(1)	(2)	(3)	(4)
Attack Count	0.478**	1.597**	1.929**	2.166
	(0.147)	(0.491)	(0.673)	(1.172)
Year Fixed Effects	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes
Number of Attacks	2033	311	218	97
Observations	36,096	35,404	35,358	35,283
R^2	0.746	0.748	0.748	0.749

Notes: The outcome is the Republican two-party vote share in U.S. presidential elections. *Attack Count* is a count of successful terrorist attacks that took place in a county in the period since the last election or 9, 6 or 3 months before the election at time t. The unit of analysis is county-election. Standard errors are clustered by county. *p<0.05; **p<0.01

the president is Republican (Tables B5 and B6).

Moreover, we find evidence that effect heterogeneity plays a role in this analysis. Specifically, when disaggregating by motive it turns out that only hate and political attacks are significantly related to increases in Republican votes for the presidency (Table B7). In addition, as the number of fatalities increases, terrorist attacks are less likely to electorally favor the Republicans than the Democrats (Table B8). Furthermore, our results indicate that the Republicans benefited from terrorism before 9/11 (Table B9) whereas they did not after 2001 (Table B10).

In Table B11 we find that in the pre-9/11 period, the positive association between attacks and voting for Republican presidential candidates is driven by hate motivated attacks and political attacks. To better understand the character of these attacks, in Table B12 we count attacks in the pre-9/11 period by sub-motive. We find that hate attacks in this sample are overwhelmingly racist in nature, with 146 racist attacks, and only 20 attacks in the next-largest category, anti-Semitic attacks. Similarly, political attacks during this period are dominated by left-wing sub-motives, which comprise 391 incidents, followed by 181 political attacks where the sub-motive is unknown, and 161 concerning Puerto Rico.

In Table B13 we show that in the post-9/11 sample our findings are driven by the now negative estimates for hate motivated attacks and attacks of unknown motive. Counting hate attacks by sub-motive in this sample in Table B14, we find that the character of such attacks differs substantially from those in the prior sample, with 34 racist attacks still forming the largest category, but followed closely by 33 Islamophobic attacks and 10 anti-Semitic attacks, the latter two categories numbering more than the count of racist attacks.

This evidence suggests that the targeting of terrorists changes following the 9/11 attacks. Before 9/11 hate attacks were overwhelming racist and political attacks were mostly left-leaning, and they targeted counties where Republican candidates did well in the following election. Following 9/11 hate attacks become dominated by those targeting Muslims and Jews, a sharp divergence from the racial attacks of the earlier period. The genre of left-wing terrorism which features prominently during the first decade of the GTD data becomes exceedingly rare during this period, and political attacks lose any significant association. These divergent results could explain the lack of convergence in findings in studies of the relationship between terrorism and partisan politics, and the pattern above is preliminary evidence that terrorist targeting is dynamic, with the 9/11 attacks marking a crucial moment of pivot in the character of terrorism in the United States.

In a nutshell, the findings of this naïve analysis indicate that the Republican party enjoys an advantage on security issues and they support the results of recent studies showing that U.S. voters tend to view Republicans more favorably in times of significant terrorist threats (Merolla and Zechmeister 2013), although this effect vanishes after 9/11. We find no support for an anti-incumbent effect of terrorism.

Success vs. failed attacks.. Table 2 reports the results for the model specification in equation 2. Remember that in this analysis the counterfactual is no longer the absence of a successful attack but instead the failure of an attempted attack. We find that the positive association between terrorist attacks and the Republican vote share no longer holds in this specification. In no model do we estimate a significant effect of a successful attack on the Republican two-party vote share. In each model, the size of the coefficient is a small fraction of that estimated for the same window in Table 1. Moreover, the sign of the coefficient switches between positive and negative depending on the window.

Table 2: Effect of Successful vs Failed Terrorist Attacks on the Republican Two-Party Vote Share in Presidential Elections

	Republican Two-Party Vote Share			
Pre-Election Window:	All Attacks	9 months	6 months	3 months
	(1)	(2)	(3)	(4)
Success	−0.164	0.574	0.828	−0.534
	(0.254)	(1.024)	(1.045)	(0.468)
Year Fixed Effects	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes
Observations	2,455	341	243	106
R^2	0.943	0.973	0.984	0.994

Notes: The outcome is the Republican two-party vote share in US presidential elections. *Success* is a binary indicator of whether the attempted attack is successful or unsuccessful. The unit of analysis is the attempted attack. Standard errors are clustered by county. *p<0.05; **p<0.01

Moreover, we explore effect heterogeneity across motives to check whether a subset of terrorist attacks affect electoral behaviour. In Table 3 we subset our sample for the 9 sub-motives for which we have more than 100 observations.[12] We estimate the effect of successful attacks on the Republican vote share in presidential elections both with and without an interaction between success and the party of the incumbent president. The findings from this test strongly confirm our initial null result. Of 18 models and 25 unique estimates we identify

[12] After accounting for missing data this drops to a minimum of 90 attacks. In decreasing order of frequency, these are left-wing, anti-abortion, racial animosity, Puerto Rico, Cuba, environmental, Jewish right-wing, black nationalism, and animal rights. The category Racial Animosity is coded to include all attacks which are primarily racially motivated regardless of the target, though the majority are by white supremacists. Results are unchanged if we consider separately the few racially motivated attacks against white targets.

Table 3

	Dependent variable:					
	Republican Two-Party Vote Share					
Attack Sub-motive:	Left-Wing		Anti-Abortion		Racial Animosity	
	(1)	(2)	(3)	(4)	(5)	(6)
Success	0.348	1.558	−0.375	−1.780*	0.000	0.000
	(0.263)	(1.760)	(0.499)	(0.696)	(0.000)	(0.000)
Success × Rep. Incumbent		−1.432		2.696**		−0.000
		(1.885)		(0.963)		(0.000)
Observations	393	393	250	250	158	158
R^2	0.978	0.978	0.989	0.989	0.999	0.999
	Puerto Rico		Cuba		Environmental	
	(7)	(8)	(9)	(10)	(11)	(12)
Success	−0.673**	−0.216	−0.270	−1.052	−0.398	−0.911
	(0.182)	(0.293)	(0.288)	(0.935)	(0.226)	(0.719)
Success × Rep. Incumbent		−1.577		0.979		0.883
		(0.738)		(1.036)		(0.984)
Observations	161	161	115	115	101	101
R^2	0.977	0.978	0.957	0.957	0.999	0.999
	Jewish Right-Wing		Black Nationalism		Animal Rights	
	(13)	(14)	(15)	(16)	(17)	(18)
Success	0.137	0.557	0.393	0.393	−0.177	−0.222
	(0.478)	(0.562)	(0.284)	(0.284)	(0.258)	(0.328)
Success × Rep. Incumbent		−0.519		-		0.222
		(0.770)		-		(0.328)
Observations	111	111	103	103	90	90
R^2	0.993	0.993	0.989	0.989	0.999	0.999

Notes: This table reports the results for the model specification in Equation 2, alternatively also including an interaction with the party of the incumbent president, estimated separately for the nine most common attack sub-motives. The outcome is the Republican two-party vote share in US presidential elections. *Success* is a binary indicator of whether the attempted attack is successful or unsuccessful. *Rep. Incumbent* is a dummy variable for if the incumbent president is a Republican, and is only included in interaction with *Success*. The unit of analysis is the attempted attack. All models include county and year fixed effects. Standard errors are clustered by county. Model 16 is identical to Model 15, as no attacks in that sample took place during a Republican presidency. *$p<0.05$; **$p<0.01$

two significant relationships. In Model 4 there is a significant negative relationship between successful anti-abortion attacks and the Republican vote share, only when a Democrat is incumbent. The estimate when a Republican is incumbent is insignificant when examining a marginal effects plot (omitted for space). In Model 7, without including incumbency, there is a negative relationship between successful attacks by Puerto Rican independence militants and the Republican vote share.

While these results could suggest that a small subset of terrorist attacks in the United States may result in political effects, in both cases the effects identified are in the opposite direction of our results from Table 1, and we cannot rule out the likelihood that they are the result of sampling error. In sum, there is no reliable evidence that effect heterogeneity affects our null results.

Similarly to the naïve analysis, we perform a series of tests, which confirm the main findings, in Online Appendix C. First, our results are similar if we include state-election fixed effect (Table C1) and if we include third party votes (Table C2). Furthermore, the results do not change if we estimate models with Democrat presidents and Republican presidents separately, indicating that incumbency plays no role here (Table C3). Moreover, the results do not change if we leverage the intensity of terrorist attacks by looking at the number of fatalities (Table C4). Finally, our estimates are the same if we split the sample pre- and post-9/11 (Tables C5 and C6).

All in all, once we rely on the correct counterfactual we find that the naïve analysis largely overestimates the effect of terrorism on elections and that on average U.S. voters do not respond to terrorist attacks.

Conclusion

This paper has implemented a novel identification strategy to explore the electoral consequences of terrorism. Specifically, we have recreated a quasi-experiment by comparing the effects of successful terror attacks with those of failed attacks due to idiosyncratic reasons in U.S. elections over more than four decades. By relying on this sharp research design, which allows us to build a credible counterfactual, we find no evidence that terrorism affects voting behavior in the U.S. Neither the Republicans nor the Democrats seem to gain electorally from terrorist attacks, regardless of the party of the incumbent president or the type of terrorist attacks.

Our findings have important implications. First, our results indicate that terrorists do not act spontaneously but strategically. Therefore, without taking proper care of this non-randomness, estimates are likely to be flawed. Second, our findings provide evidence that on average domestic terror attacks do not decide elections. Of course, it may be that the results would be different for other Western democracies with different electoral and party systems or large transnational attacks such as Sept. 11, 2001. Third, assuming that terrorists aim to affect political outcomes in target countries, we show that terrorism is ineffective, a result in line with Abrahms (2006). To conclude, our results indicate that terrorism has less of an influence on voters than is usually thought.

References

Abrahms, M. (2006). Why Terrorism Does Not Work. *International Security 31*(2), 42–78.

Abramson, P. R., J. H. Aldrich, J. Rickershauser, and D. W. Rohde (2007). Fear in the Voting Booth: The 2004 Presidential Election. *Political Behavior 29*(2), 197–220.

Bali, V. A. (2007). Terror and Elections: Lessons from Spain. *Electoral Studies 26*(3), 669–687.

Barro, R. J. (1973). The Control of Politicians: An Economic Model. *Public choice 14*(1), 19–42.

Berrebi, C. and E. F. Klor (2008). Are Voters Sensitive to Terrorism? Direct Evidence from the Israeli Electorate. *American Political Science Review 102*(3), 279–301.

Brodeur, A. (2018). The Effect of Terrorism on Employment and Consumer Sentiment: Evidence from Successful and Failed Terror Attacks. *American Economic Journal: Applied Economics 10*(4), 246–82.

Ferejohn, J. (1986). Incumbent Performance and Electoral Control. *Public choice 50*(1), 5–25.

Gassebner, M., R. Jong-A-Pin, and J. O. Mierau (2008). Terrorism and Electoral Accountability: One Strike, You're Out! *Economics Letters 100*(1), 126–129.

Gelpi, C., P. D. Feaver, and J. Reifler (2006). Success Matters: Casualty Sensitivity and the War in Iraq. *International Security 30*(3), 7–46.

Gould, E. D. and E. F. Klor (2010). Does Terrorism Work? *The Quarterly Journal of Economics 125*(4), 1459–1510.

Karol, D. and E. Miguel (2007). The Electoral Cost of War: Iraq Casualties and the 2004 US Presidential Election. *The Journal of Politics 69*(3), 633–648.

Kibris, A. (2011). Funerals and Elections: The Effects of Terrorism on Voting Behavior in Turkey. *Journal of Conflict Resolution 55*(2), 220–247.

Koch, M. and B. Tkach (2012). Deterring or Mobilizing? The Influence of Government Partisanship and Force on the Frequency, Lethality and Suicide Attacks of Terror Events. *Peace Economics, Peace Science and Public Policy 18*(2).

Leip, D. (2019). David Leip's Atlas of U.S. Presidential Elections, Datasets.

Merolla, J. L. and E. J. Zechmeister (2013). Evaluating Political Leaders in Times of Terror and Economic Threat: The Conditioning Influence of Politician Partisanship. *The Journal of Politics 75*(3), 599–612.

Montalvo, J. G. (2011). Voting After the Bombings: A Natural Experiment on the Effect of Terrorist Attacks on Democratic Elections. *Review of Economics and Statistics 93*(4), 1146–1154.

National Consortium for the Study of Terrorism and Responses to Terrorism (START) (2019). Global terrorism database.

Sood, G. and S. Laohaprapanon (2020). Vanderbilt TV News Abstracts.

Online Appendix A

Descriptive

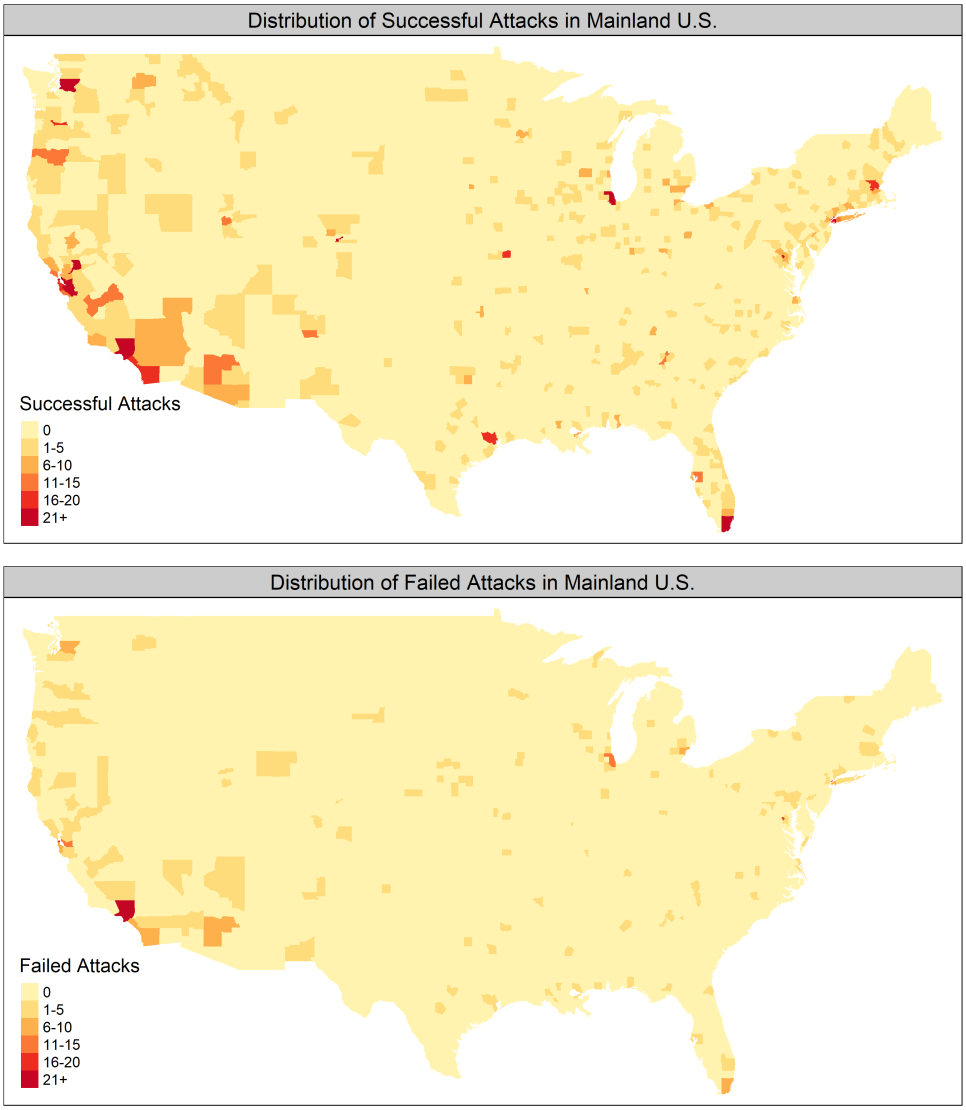

Figure A1: The Geography of Terrorist Attacks - County Level

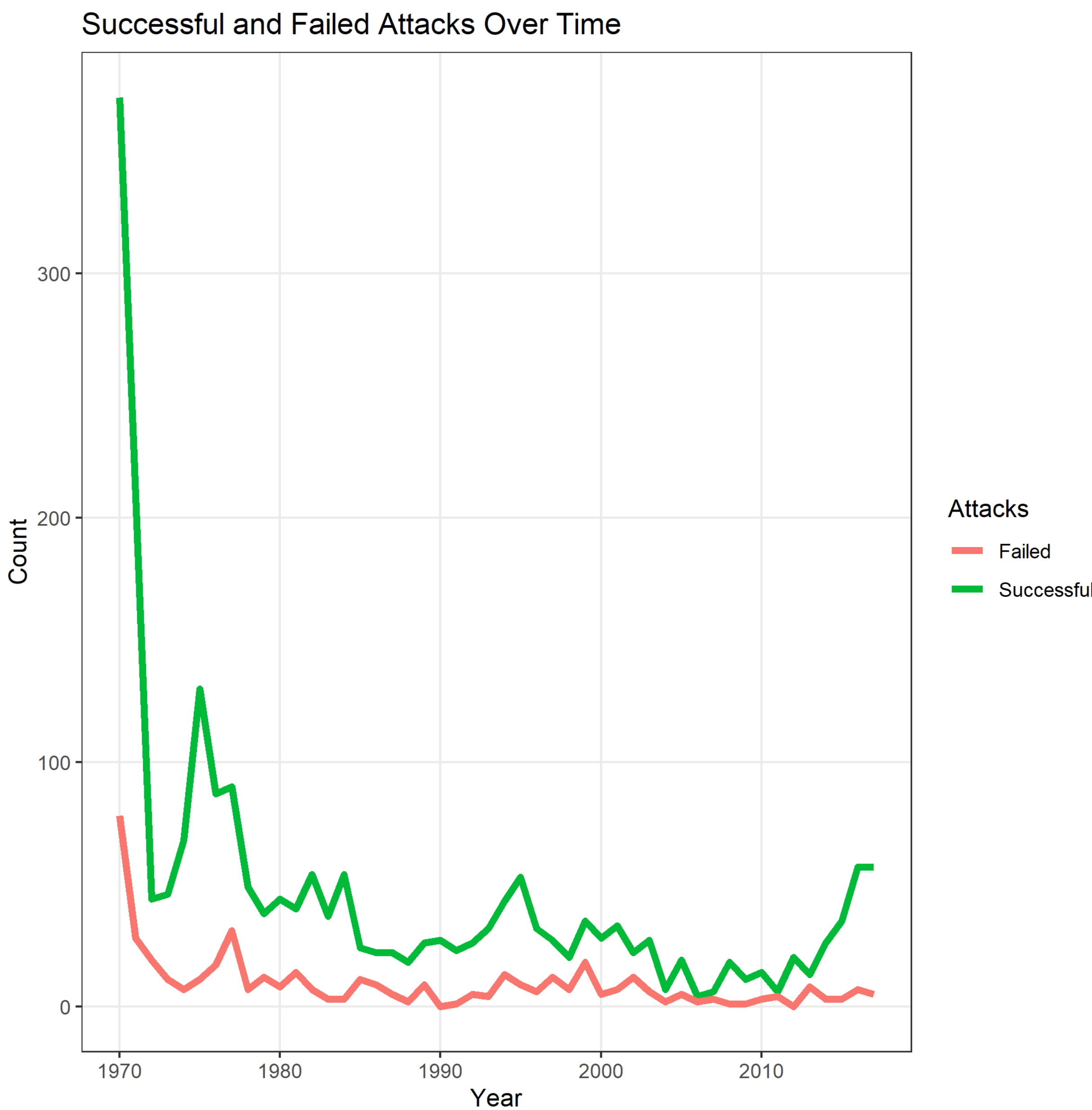

Figure A2: Successful and Failed Attacks Over Time

Table A1: GTD Summary Statistics

Category:	*Type*	*Count*	*Perc.*	*Perc. Success*
Attack Type	Bombing/Explosion	1216	46.08	78.78
	Facility/Infrastructure Attack	883	33.46	89.81
	Armed Assault	272	10.31	94.85
	Assassination	123	4.66	60.98
	Unarmed Assault	62	2.35	56.45
	Hostage Taking (Barricade Incident)	36	1.36	94.44
	Hostage Taking (Kidnapping)	23	0.87	95.65
	Hijacking	17	0.64	88.24
	Unknown	7	0.27	71.43
Target Type	Business	681	25.81	86.78
	Private Citizens & Property	348	13.19	84.77
	Government (General)	295	11.18	73.22
	Abortion Related	271	10.27	85.24
	Police	164	6.21	82.32
	Educational Institution	162	6.14	77.16
	Religious Figures/Institutions	149	5.65	89.26
	Government (Diplomatic)	138	5.23	77.54
	Military	133	5.04	85.71
	Utilities	69	2.61	92.75
	Airports & Aircraft	67	2.54	76.12
	Journalists & Media	60	2.27	80.00
	NGO	29	1.10	82.76
	Transportation	18	0.68	66.67
	Unknown	14	0.53	71.43
	Tourists	11	0.42	100.00
	Terrorists/Non-State Militia	8	0.30	87.50
	Violent Political Party	6	0.23	100.00
	Telecommunication	5	0.19	100.00
	Maritime	4	0.15	100.00
	Other	4	0.15	100.00
	Food or Water Supply	3	0.11	66.67
Weapon Type	Explosives	1228	46.53	78.01
	Incendiary	859	32.55	88.94
	Firearms	377	14.29	89.39
	Melee	49	1.86	97.96
	Unknown	42	1.59	88.10
	Biological	24	0.91	54.17
	Sabotage Equipment	19	0.72	94.74
	Other	17	0.64	11.76
	Chemical	11	0.42	72.73
	Vehicle (not vehicle-borne explosives)	7	0.27	100.00
	Fake Weapons	5	0.19	60.00
	Radiological	1	0.04	0.00
Operation	Lone wolf	477	0.20	79.45
	Multiple Attacks	410	0.17	80.24
	Logistics International	297	0.12	79.12
	Non-US Target	278	0.12	79.14
All Attacks		2639	100	83.18

Table A2: GTD Summary Statistics

Motive:	*Sub-motive*	*Count*	*Perc.*	*Perc. Success*
Anti-Abortion	All	277	0.10	85.92
Hatred	All	319	0.12	90.60
	Racial Animosity	180	0.56	90.00
	Islamophobia	36	0.11	94.44
	Anti-semitism	30	0.09	90.00
	Unknown	27	0.08	88.89
	Right Wing	19	0.06	94.74
	Religious	14	0.04	78.57
	Homophobia	4	0.01	100.00
	India	4	0.01	100.00
	Incel	3	0.01	100.00
	Other	2	0.01	100.00
Political	All	1818	0.69	81.41
	Left-Wing	401	0.22	78.30
	Unknown	207	0.11	78.74
	Puerto Rico	161	0.09	81.37
	Cuba	118	0.06	88.98
	Environmental	117	0.06	85.47
	Jewish Right Wing	113	0.06	77.88
	Black Nationalism	109	0.06	87.16
	Animal Rights	104	0.06	73.08
	Anti-war	83	0.05	85.54
	Islamist	56	0.03	85.71
	Chicano Activism	40	0.02	95.00
	Anti-Government	38	0.02	71.05
	Black Power	33	0.02	75.76
	Armenian	23	0.01	86.96
	Strike	22	0.01	100.00
	Palestine	22	0.01	45.45
	Croatia	21	0.01	85.71
	Communist	20	0.01	85.00
	Right Wing	15	0.01	73.33
	IRS	15	0.01	80.00
	Anti-Communism	13	0.01	84.62
	Desegregation	9	0.00	100.00
	Iran	8	0.00	100.00
	Anti-Police	7	0.00	100.00
	American Indian	6	0.00	100.00
	Russia	4	0.00	100.00
	Local Politics	4	0.00	75.00
	Haiti	4	0.00	100.00
	Regulation	3	0.00	66.67
	Gay Rights	3	0.00	100.00
	Libya	3	0.00	100.00
	Technology	3	0.00	100.00
	Anti-environment	3	0.00	100.00
	Taiwan	2	0.00	50.00
	Irish Republicanism	2	0.00	50.00
	India	2	0.00	100.00
	Serbia	2	0.00	100.00
	Mexico	2	0.00	50.00
	Trucking	2	0.00	0.00
	Other	18	0.01	88.89
Unknown	All	225	0.09	83.56

Note: Percent counts are of total for motives and within group for sub-motives. Sub-motives which occur only once are aggregated to "Other."

Balance Tests

To assess if counties where successful attacks take place are similar with respect to confounding variables to counties which experience no attacks, we collect data on a battery of controls. Data on employment, earnings, and several other economic indicators come from the Quarterly Census of Employment and Wages (QCEW), a Bureau of Labor Statistics (BLS) program which publishes near comprehensive data on establishments in the United States. Crime statistics are from the F.B.I. Uniform Crime Reporting Program.

Table A3: Bivariate Regressions of Potential Confounders on Successful Attack vs Failed Attack

Independent Variable:	*Dependent variable:*
	Successful vs Failed Attack
	(1)
(1) Log Jobs Per Capita	−0.105
	(0.299)
(2) Log Earnings Per Capita	−0.124
	(0.201)
(3) Log Population	0.214
	(0.183)
(4) Log Retirement Income Per Capita	0.397
	(0.224)
(5) Log Unemployment Insurance Per Capita	0.119
	(0.061)
(6) Log Officers Killed Per Capita	0.003
	(0.002)
(7) Log Murders Per Capita	0.003
	(0.004)
(8) Log Vehicle Thefts Per Capita	−0.004
	(0.005)
(9) Log Robberies Per Capita	0.004
	(0.005)
(10) Log Violent Crime Per Capita	0.003
	(0.005)
(11) Log Property Crime Per Capita	0.0003
	(0.004)
(12) Log Total Crime Per Capita	0.0002
	(0.004)
Year and County FEs	Yes
Observations	1,029
R^2	0.430 - 0.436

Notes: This table presents results from a series of bivariate regressions. We individually regress 12 potential confounding variables on if at least one attempted attack in a county was successful, among counties where at least one attack was attempted, to show if counties where attacks are successful differ from those where they fail. All independent variables are log transformed and all but regression (3) are divided by county population. All models also include county and year fixed effects, and use county clustered standard errors. $^*p<0.05$; $^{**}p<0.01$

News Coverage

Table A4

	Dependent variable:			
Panel A:	Broadcast Count	CBS Count	ABC Count	NBC Count
	(1)	(2)	(3)	(4)
Success	0.268*	0.141**	0.051	0.076
	(0.130)	(0.053)	(0.056)	(0.048)
Killed	0.072**	0.013**	0.035**	0.024**
	(0.009)	(0.003)	(0.003)	(0.003)
Non-terror Broadcasts	0.142*	0.046	0.052*	0.043
	(0.070)	(0.024)	(0.022)	(0.025)
R^2	0.645	0.545	0.689	0.645
Panel B:	Broadcasts Duration	CBS Duration	ABC Duration	NBC Duration
	(1)	(2)	(3)	(4)
Success	470.300*	161.839*	161.564*	146.898
	(223.140)	(78.024)	(72.645)	(75.743)
Killed	310.694**	74.552**	146.905**	89.237**
	(13.334)	(4.374)	(4.768)	(4.266)
Non-terror Broadcasts	97.762*	35.488*	36.786**	25.488
	(40.908)	(14.270)	(13.944)	(14.456)
R^2	0.838	0.783	0.878	0.816
Observations (Both Panels)	2,577	2,577	2,577	2,577

Notes: This table presents results for the effect of successful attacks on attack news coverage. In Panel A the outcome is the count of stories about the attack during the day of the attack or the following 10. In Panel B the outcome is the total duration of those stories about the attack in seconds. All models control for the number of people killed in the attack and the number of non-attack related broadcasts for the targeted city, during the same period. We further control for the categorical variables: attack type, attack weapon, and hand-coded motive; and we include fixed effects for the county, year, month, and Census Region-year of the attack. We report county-clustered standard errors. *p<0.05; **p<0.01

Online Appendix B

Different Model Specifications

We estimate the model in equation 1 using a binary indicator of if at least one successful terrorist attack took place in Table B1. Here we find that the occurrence of at least one successful attack in a county is associated with an increase of between 1.7 and 2.7 percent in the Republican two-party vote share, and that the increase is significant at $p < 0.05$ only with all attacks and the 9 month window.

Table B2 shows the model in equation 1 including potential confounders. Findings for executive elections are robust to the inclusion of these variables, and if anything, we find a significant effect even in the smallest window, in which we do not find any effect without controls. When studying House elections, coefficients remain not significant. On the contrary, turning to the Senate, we find a large and significant effect, when studying all attacks and those within a 3 month window. In each window and in each election type, estimates of the effect of terrorist attacks on the Republican two-party vote share are positive.

Table B1: Effect of Terrorist Attacks on the Republican Two-Party Vote Share in Presidential Elections, County-Election Year Level, Binary

	Republican Two-Party Vote Share			
Pre-Election Window:	All Attacks	9 months	6 months	3 months
	(1)	(2)	(3)	(4)
Attack	1.688**	2.650*	2.537	2.800
	(0.474)	(1.159)	(1.345)	(2.013)
Year Fixed Effects	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes
Treated County-Years	792	187	141	70
Observations	36,096	35,404	35,358	35,283
R^2	0.745	0.748	0.748	0.749

Notes: This table presents results for the model in equation 1 with Republican two-party vote share at the county-level in presidential elections as the outcome, and county clustered standard errors. The dependent variable can take values between 0 and 100. All models include county and year fixed effects. The sample of elections includes all presidential elections since and including the Election of 1972. Attack is a binary indicator of if at least one successful attack took place in a county in the period since the last election and before the election at time t. *p<0.05; **p<0.01

Table B2: Effect of Terrorist Attacks on the Republican Two-Party Vote Share in Presidential Elections, County-Election Year Level, with Controls

	Republican Two-Party Vote Share			
Pre-Election Windows:	All Attacks	9 months	6 months	3 months
	(1)	(2)	(3)	(4)
Attack Count	0.422**	1.808**	2.821**	3.568**
	(0.134)	(0.593)	(0.795)	(1.183)
Retirement Income	0.905	0.595	0.515	0.447
	(0.778)	(0.768)	(0.768)	(0.767)
Unemployment Insurance	−0.183	−0.172	−0.176	−0.177
	(0.156)	(0.156)	(0.156)	(0.156)
Murders	−0.035**	−0.035**	−0.035**	−0.035**
	(0.006)	(0.006)	(0.006)	(0.007)
Year Fixed Effects	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes
Number of Attacks	1874	260	174	77
Observations	32,775	32,146	32,104	32,043
R^2	0.759	0.760	0.760	0.760

Notes: This table presents results for the model in equation 1 including controls, with Republican two-party vote share at the county-level in presidential elections as the outcome, and county clustered standard errors. Controls are log transformed and divided by population. The dependent variable can take values between 0 and 100. All models include county and year fixed effects. *p<0.05; **p<0.01

Table B3: Effect of Terrorist Attacks on the Republican Two-Party Vote Share in Presidential Elections, with State-Election Year Fixed Effects

	Republican Two-Party Vote Share			
Pre-Election Window:	All Attacks	9 months	6 months	3 months
	(1)	(2)	(3)	(4)
Attack Count	0.313*	0.656	0.537	0.996
	(0.149)	(0.359)	(0.485)	(0.894)
Year Fixed Effects	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes
State-Election Fixed Effects	Yes	Yes	Yes	Yes
Number of Attacks	2033	311	218	97
Observations	36,095	35,403	35,357	35,282
R^2	0.873	0.874	0.874	0.875

Notes: This model includes state-election year fixed effects. The outcome is Republican two-party vote share in US presidential elections. *Attack Count* is a count of successful terrorist attacks that took place in a county in the period since the last election or 9 or 6 or 3 months before the election at time t. The unit of analysis is county-election. Standard errors are clustered by county. $^{*}p<0.05$; $^{**}p<0.01$

Table B4: Effect of Terrorist Attacks on the Republican Percentage Vote (including Third Parties) in Presidential Elections, County-Election Year Level

	Republican Percentage Vote			
Pre-Election Window:	All Attacks	9 months	6 months	3 months
	(1)	(2)	(3)	(4)
Attack Count	0.430**	1.462**	1.773**	1.843
	(0.136)	(0.471)	(0.643)	(1.124)
Year Fixed Effects	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes
Number of Attacks	2033	311	218	97
Observations	36,096	35,404	35,358	35,283
R^2	0.767	0.769	0.769	0.769

Notes: The outcome is Republican percentage vote of total in US presidential elections. *Attack Count* is a count of successful terrorist attacks that took place in a county in the period since the last election or 9 or 6 or 3 months before the election at time t. The unit of analysis is county-election. Standard errors are clustered by county. $^{*}p<0.05$; $^{**}p<0.01$

The Role of Incumbency

Table B5: Effect of Terrorist Attacks on the Republican Two-Party Vote Share in Presidential Elections, with Democrat incumbent, County-Election Year Level

	Republican Two-Party Vote Share			
Pre-Election Window:	All Attacks	9 months	6 months	3 months
	(1)	(2)	(3)	(4)
Attack Count	0.802*	0.446	−0.598	0.169
	(0.340)	(1.037)	(1.179)	(2.279)
Year Fixed Effects	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes
Number of Attacks	625	128	100	48
Observations	15,029	14,735	14,718	14,683
R^2	0.783	0.787	0.787	0.788

Notes: This table presents results for the model in equation 1 when the incumbent president is a Democrat. Republican two-party vote share at the county-level in presidential elections is the outcome, and standard errors are county clustered. *p<0.05; **p<0.01

Table B6: Effect of Terrorist Attacks on the Republican Two-Party Vote Share in Presidential Elections, with Republican incumbent, County-Election Year Level

	Republican Two-Party Vote Share			
Pre-Election Window:	All Attacks	9 months	6 months	3 months
	(1)	(2)	(3)	(4)
Attack Count	0.348**	1.783*	2.942**	3.446*
	(0.117)	(0.742)	(0.951)	(1.476)
Year Fixed Effects	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes
Number of Attacks	1408	183	118	49
Observations	21,067	20,669	20,640	20,600
R^2	0.770	0.772	0.772	0.772

Notes: This table presents results for the model in equation 1 when the incumbent president is a Republican. Republican two-party vote share at the county-level in presidential elections is the outcome, and standard errors are county clustered. $^{*}p<0.05$; $^{**}p<0.01$

With Motives

Table B7 presents estimates for model 3, which is equivalent to model 1, but with attack counts disaggregated for the four motives we code. The model is:

$$Y_{c,t} = \alpha_c + \gamma_t + \beta_1 Hatred_{c,t} + \beta_2 Abortion_{c,t} + \beta_3 Political_{c,t} + \beta_4 Unknown_{c,t} + \delta^\top \mathbf{Z}_{c,t} + \epsilon_{c,t} \quad (3)$$

where $Hatred_{c,t}$, $Abortion_{c,t}$, $Political_{c,t}$, and $Unknown_{c,t}$ are counts of successful attacks by motive, in county c during the period since the last election before the election during year t. $\mathbf{Z}_{c,t}$ is a vector of controls identified as potential confounders in table A3, and α_c and γ_t represent county and election year fixed effects, respectively.

Table B7: Effect of Terrorist Attacks by Motive on the Republican Two-Party Vote Share, County-Election Year Level, with Controls

	Republican Two-Party Vote Share		
Election Type:	Presidential Elections	House Elections	Senate Election
	(1)	(2)	(3)
Hatred Count	0.770**	−0.076	0.798
	(0.283)	(0.836)	(0.784)
Anti-Abortion Count	0.558	0.748	3.349**
	(0.289)	(1.183)	(0.979)
Political Count	0.393**	0.687	1.992*
	(0.119)	(0.421)	(0.885)
Unknown Count	−0.599	2.107	1.901
	(0.379)	(1.221)	(1.686)
Year Fixed Effects	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Hatred Attacks	227	78	54
Anti-Abortion Attacks	242	119	89
Political Attacks	1625	260	162
Unknown Attacks	168	50	28
Observations	32,775	29,636	20,087
R^2	0.759	0.653	0.623

Notes: This table presents results for the model in equation 3 with Republican two-party vote share at the county-level in each election as the outcome, and county clustered standard errors. Controls are log transformed and divided by population. *p<0.05; **p<0.01

Fatal Attacks

Table B8: Effect of Terrorist Attack Fatalities on the Republican Two-Party Vote Share in Presidential Elections, County-Election Year Level

	Republican Two-Party Vote Share			
Pre-Election Window:	All Attacks	9 months	6 months	3 months
	(1)	(2)	(3)	(4)
Fatalities	-0.003^{**}	-0.585^{**}	-0.594^{**}	1.715
	(0.001)	(0.073)	(0.076)	(5.292)
Year Fixed Effects	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes
Observations	36,096	35,404	35,358	35,283
R^2	0.745	0.748	0.748	0.749

Notes: The outcome is Republican two-party vote share in US presidential elections. *Fatalities* is a count of the total number of fatalities from terrorist attacks that took place in a county in the period since the last election or during the last 9 or 6 or 3 months before the election at time t. The unit of analysis is county-election. Standard errors are clustered by county. *p<0.05; **p<0.01

Pre and Post 9/11 Elections

Table B9: Effect of Terrorist Attacks on the Republican Two-Party Vote Share in Presidential Elections, County-Election Year Level, Pre 9/11 Elections

	Republican Two-Party Vote Share			
	All Attacks	9 months	6 months	3 months
	(1)	(2)	(3)	(4)
Attack Count	0.235**	1.173**	1.787**	1.422
	(0.080)	(0.336)	(0.539)	(0.799)
Year Fixed Effects	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes
Observations	24,068	23,549	23,515	23,466
R^2	0.809	0.811	0.811	0.811

Notes: The sample here is elections before September 11th, 2001. The outcome is Republican two-party vote share in US presidential elections. *Attack Count* is a count of successful terrorist attacks that took place in a county in the period since the last election or 9 or 6 or 3 months before the election at time t. The unit of analysis is county-election. Standard errors are clustered by county. *p<0.05; **p<0.01

Table B10: Effect of Terrorist Attacks on the Republican Two-Party Vote Share in Presidential Elections, County-Election Year Level, Post 9/11 Elections

	Republican Two-Party Vote Share			
	All Attacks	9 months	6 months	3 months
	(1)	(2)	(3)	(4)
Attack Count	-0.967^{**}	-1.532^{*}	-1.922^{*}	-3.995^{**}
	(0.359)	(0.706)	(0.797)	(1.123)
Year Fixed Effects	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes
Observations	12,028	11,855	11,843	11,817
R^2	0.939	0.940	0.940	0.940

Notes: The sample here is elections following September 11th, 2001. The outcome is Republican two-party vote share in US presidential elections. *Attack Count* is a count of successful terrorist attacks that took place in a county in the period since the last election or 9 or 6 or 3 months before the election at time t. The unit of analysis is county-election. Standard errors are clustered by county. *p<0.05; **p<0.01

Table B11: Effect of Terrorist Attacks on the Republican Two-Party Vote Share in Presidential Elections, County-Election Year Level, Pre 9/11 Elections, By Motive

	Republican Two-Party Vote Share			
	All Attacks	9 months	6 months	3 months
	(1)	(2)	(3)	(4)
Hatred Count	0.537	1.077**	1.056**	1.219**
	(0.361)	(0.151)	(0.210)	(0.199)
Abortion Count	−0.392	−0.725	−0.719	−1.115
	(0.301)	(0.574)	(0.630)	(0.909)
Political Count	0.259**	0.233**	0.245	0.199
	(0.069)	(0.087)	(0.171)	(0.163)
Unknown Count	−0.955**	−0.722	−0.693	−1.043
	(0.322)	(0.391)	(0.516)	(0.612)
Year Fixed Effects	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes
Observations	24,068	23,549	23,515	23,466
R^2	0.810	0.811	0.811	0.811

Notes: The sample here is elections before September 11th, 2001. The treatment is attack count disaggregated by motive. The outcome is Republican two-party vote share in US presidential elections. *Attack Count* is a count of successful terrorist attacks that took place in a county in the period since the last election or 9 or 6 or 3 months before the election at time t. The unit of analysis is county-election. Standard errors are clustered by county. *p<0.05; **p<0.01

Table B12: Attack Motive Counts - Pre-9/11

Motive:	*Sub-motive*	*Count*	*Perc.*	*Perc. Success*
Anti-Abortion	All	248	0.09	85.89
Hatred	All	219	0.08	89.50
	Racial Animosity	146	0.67	89.04
	Anti-semitism	20	0.09	90.00
	Unknown	20	0.09	90.00
	Right Wing	17	0.08	94.12
	Religious	10	0.05	90.00
	Other	3	0.01	100.00
	Islamophobia	3	0.01	66.67
Political	All	1565	0.59	81.85
	Left-Wing	391	0.25	78.52
	Unknown	181	0.12	80.66
	Puerto Rico	161	0.10	81.37
	Cuba	116	0.07	88.79
	Jewish Right Wing	113	0.07	77.88
	Black Nationalism	109	0.07	87.16
	Anti-war	83	0.05	85.54
	Animal Rights	67	0.04	68.66
	Environmental	52	0.03	88.46
	Chicano Activism	40	0.03	95.00
	Black Power	32	0.02	75.00
	Armenian	23	0.01	86.96
	Strike	22	0.01	100.00
	Palestine	22	0.01	45.45
	Croatia	21	0.01	85.71
	Communist	20	0.01	85.00
	IRS	14	0.01	78.57
	Other	13	0.01	84.62
	Anti-Communism	13	0.01	84.62
	Desegregation	9	0.01	100.00
	Iran	8	0.01	100.00
	Right Wing	7	0.00	71.43
	Islamist	7	0.00	85.71
	American Indian	6	0.00	100.00
	Local Politics	4	0.00	75.00
	Haiti	4	0.00	100.00
	Libya	3	0.00	100.00
	Russia	3	0.00	100.00
	Technology	3	0.00	100.00
	Anti-Government	3	0.00	100.00
	Anti-environment	3	0.00	100.00
	Taiwan	2	0.00	50.00
	Regulation	2	0.00	100.00
	Irish Republicanism	2	0.00	50.00
	Gay Rights	2	0.00	100.00
	India	2	0.00	100.00
	Serbia	2	0.00	100.00
Unknown	All	160	0.06	81.25

Note: Percent counts are of total for motives and within group for sub-motives. Sub-motives which occur only once are aggregated to "Other."

Table B13: Effect of Terrorist Attacks on the Republican Two-Party Vote Share in Presidential Elections, County-Election Year Level, Post 9/11 Elections, By Motive

	Republican Two-Party Vote Share			
	All Attacks	9 months	6 months	3 months
	(1)	(2)	(3)	(4)
Hatred Count	-3.038^{**}	-2.105^{**}	-2.673^{**}	-3.589^{*}
	(0.699)	(0.793)	(0.917)	(1.747)
Abortion Count	-1.110	-0.172	-2.169	
	(1.169)	(1.700)	(2.933)	(0.000)
Political Count	0.268	-0.138	0.873	0.024
	(0.360)	(1.290)	(1.221)	(1.414)
Unknown Count	-2.720^{**}	-3.065^{**}	-3.803^{**}	-3.659^{**}
	(0.859)	(1.052)	(0.904)	(1.137)
Year Fixed Effects	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes
Observations	12,028	11,855	11,843	11,817
R^2	0.939	0.940	0.940	0.940

Notes: The sample here is elections following September 11th, 2001. The treatment is attack count disaggregated by motive. The outcome is Republican two-party vote share in US presidential elections. *Attack Count* is a count of successful terrorist attacks that took place in a county in the period since the last election or 9 or 6 or 3 months before the election at time t. The unit of analysis is county-election. Standard errors are clustered by county. $^{*}p<0.05$; $^{**}p<0.01$

Table B14: Attack Motive Counts - Post-9/11

Motive:	*Sub-motive*	*Count*	*Perc.*	*Perc. Success*
Anti-Abortion	All	29	0.01	86.21
Hatred	All	100	0.04	93.00
	Racial Animosity	34	0.34	94.12
	Islamophobia	33	0.33	96.97
	Anti-semitism	10	0.10	90.00
	Unknown	7	0.07	85.71
	India	4	0.04	100.00
	Religious	4	0.04	50.00
	Incel	3	0.03	100.00
	Homophobia	3	0.03	100.00
	Right Wing	2	0.02	100.00
Political	All	253	0.10	78.66
	Environmental	65	0.26	83.08
	Islamist	49	0.19	85.71
	Animal Rights	37	0.15	81.08
	Anti-Government	35	0.14	68.57
	Unknown	26	0.10	65.38
	Other	12	0.05	83.33
	Left-Wing	10	0.04	70.00
	Right Wing	8	0.03	75.00
	Anti-Police	7	0.03	100.00
	Trucking	2	0.01	0.00
	Cuba	2	0.01	100.00
Unknown	All	65	0.02	89.23

Note: Percent counts are of total for motives and within group for sub-motives. Sub-motives which occur only once are aggregated to "Other."

Congressional Elections

Tables B15, B16, B17, B18 estimate model 1 using elections to the House and Senate, respectively. When studying elections to the House, we fail to replicate the finding of a significant positive association between attacks and the Republican vote share as in presidential elections. Indeed, while all estimates have large standard errors, the direction of each coefficient is in the opposite direction. When we turn our attention to the Senate, we similarly fail to replicate the presidential findings, with our estimates quite evenly dispersed around zero.

Table B15: Effect of Terrorist Attacks on the Republican Two-Party Vote Share in House Elections, County-Election Year Level

	Republican Two-Party Vote Share			
Pre-Election Window:	All Attacks	9 months	6 months	3 months
	(1)	(2)	(3)	(4)
Attack Count	−0.376	−0.786	−1.777	−1.741
	(0.440)	(0.854)	(1.095)	(1.771)
Year Fixed Effects	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes
Number of Attacks	538	203	142	71
Observations	37,442	37,169	37,115	37,056
R^2	0.613	0.612	0.612	0.612

Notes: This table presents results for the model in equation 1 with Republican two-party vote share at the county-level in House elections as the outcome, and county clustered standard errors. The dependent variable can take values between 0 and 100. All models include county and year fixed effects. The sample of elections includes all House elections since and including the Election of 1994. Attack Count is a count of successful terrorist attacks that took place in a county in the period since the last election and before the election at time t, and within the specified window. *p<0.05; **p<0.01

Table B16: Effect of Terrorist Attacks on the Republican Two-Party Vote Share in Senate Elections, County-Election Year Level

	Republican Two-Party Vote Share			
Pre-Election Window:	All Attacks	9 months	6 months	3 months
	(1)	(2)	(3)	(4)
Attack Count	0.676	−0.278	−0.968	1.585
	(0.650)	(1.145)	(1.018)	(1.854)
Year Fixed Effects	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes
Number of Attacks	341	125	90	45
Observations	25,553	25,372	25,331	25,294
R^2	0.607	0.607	0.607	0.607

Notes: This table presents results for the model in equation 1 with Republican two-party vote share at the county-level in Senate elections as the outcome, and county clustered standard errors. The dependent variable can take values between 0 and 100. All models include county and year fixed effects. The sample of elections includes all Senate elections since and including the Election of 1994. Attack Count is a count of successful terrorist attacks that took place in a county in the period since the last election and before the election at time t, and within the specified window. $^{*}p<0.05$; $^{**}p<0.01$

Table B17: Effect of Terrorist Attacks on the Republican Two-Party Vote Share in House Elections, County-Election Year Level, with Controls

	Republican Two-Party Vote Share			
Pre-Election Window:	All Attacks	9 months	6 months	3 months
	(1)	(2)	(3)	(4)
Attack Count	0.575	1.429	1.791	2.467
	(0.395)	(0.765)	(1.185)	(1.916)
Retirement Income	-9.198^{**}	-9.431^{**}	-9.498^{**}	-9.501^{**}
	(2.175)	(2.184)	(2.187)	(2.189)
Unemployment Insurance	-1.914^{**}	-1.906^{**}	-1.915^{**}	-1.916^{**}
	(0.360)	(0.360)	(0.361)	(0.361)
Murders	-0.030^{*}	-0.030^{*}	-0.030^{*}	-0.030^{*}
	(0.015)	(0.015)	(0.015)	(0.015)
Year Fixed Effects	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes
Number of Attacks	401	131	82	43
Observations	29,636	29,414	29,368	29,330
R^2	0.653	0.652	0.652	0.651

Notes: This table presents results for the model in equation 1 including controls, with Republican two-party vote share at the county-level in House elections as the outcome, and county clustered standard errors. Controls are log transformed and divided by population. The dependent variable can take values between 0 and 100. All models include county and year fixed effects. *p<0.05; **p<0.01

Table B18: Effect of Terrorist Attacks on the Republican Two-Party Vote Share in Senate Elections, County-Election Year Level, with Controls

	Republican Two-Party Vote Share			
Pre-Election Window:	All Attacks	9 months	6 months	3 months
	(1)	(2)	(3)	(4)
Attack Count	2.115**	1.533	1.542	3.892*
	(0.656)	(1.498)	(1.545)	(1.893)
Retirement Income	−5.216**	−5.476**	−5.684**	−5.683**
	(1.727)	(1.734)	(1.735)	(1.736)
Unemployment Insurance	−0.063	−0.086	−0.097	−0.104
	(0.313)	(0.315)	(0.316)	(0.316)
Murders	−0.027	−0.027	−0.027	−0.027
	(0.015)	(0.015)	(0.015)	(0.015)
Year Fixed Effects	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes
Number of Attacks	251	80	52	30
Observations	20,087	19,940	19,906	19,881
R^2	0.623	0.622	0.622	0.622

Notes: This table presents results for the model in equation 1 including controls, with Republican two-party vote share at the county-level in Senate elections as the outcome, and county clustered standard errors. Controls are log transformed and divided by population. The dependent variable can take values between 0 and 100. All models include county and year fixed effects. $^{*}p<0.05$; $^{**}p<0.01$

Online Appendix C

Different Model Specifications

Table C1: Effect of Successful Terrorist Attacks on the Republican Two-Party Vote Share in Presidential Elections, Attack Level, with State-Election Fixed Effects

	Republican Two-Party Vote Share			
Pre-Election Window:	All Attacks	9 months	6 months	3 months
	(1)	(2)	(3)	(4)
Success	−0.098	0.470	0.139	0.000
	(0.202)	(0.994)	(0.841)	
Year Fixed Effects	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes
State-Election Fixed Effects	Yes	Yes	Yes	Yes
Observations	2,455	341	243	106
R^2	0.979	0.993	0.998	1.000

Notes: This model includes state-election year fixed effects. The outcome is Republican two-party vote share in US presidential elections. *Success* is a binary indicator of if the attempted attack is successful or unsuccessful. The unit of analysis is the attempted attack. Standard errors are clustered by county.*p<0.05; **p<0.01

Table C2: Effect of Successful Terrorist Attacks on the Republican Percentage Vote (including Third Parties) in Presidential Elections, Attack Level

	Republican Percentage Vote			
Pre-Election Window:	All Attacks	9 months	6 months	3 months
	(1)	(2)	(3)	(4)
Success	−0.201	0.389	0.607	−0.569
	(0.251)	(1.000)	(0.899)	(0.447)
Year Fixed Effects	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes
Observations	2,455	341	243	106
R^2	0.943	0.973	0.985	0.995

Notes: The outcome is Republican percentage vote of total in US presidential elections. *Success* is a binary indicator of if the attempted attack is successful or unsuccessful. The unit of analysis is the attempted attack. Standard errors are clustered by county.$^{*}p<0.05$; $^{**}p<0.01$

The Role of Incumbency

Table C3: Effect of Successful Terrorist Attacks by Incumbency on the Republican Two-Party Vote Share in Presidential Elections, Attack Level

	Republican Two-Party Vote Share	
	Democrat Incumbent	Republican Incumbent
	(1)	(2)
Success	0.089	−0.113
	(0.376)	(0.279)
Year Fixed Effects	Yes	Yes
County Fixed Effects	Yes	Yes
Observations	776	1,679
R^2	0.972	0.957

Notes: This table presents results for the model in equation 2, with attempted attacks disaggregated by incumbency. Republican two-party vote share at the county-level in Presidential elections is the outcome, and standard errors are county clustered. $^*p<0.05$; $^{**}p<0.01$

With Motives

Fatal Attacks

Table C4: Effect of Successful Terrorist Attacks Fatalities on the Republican Two-Party Vote Share in Presidential Elections, Attack Level

	Republican Percentage Vote			
Pre-Election Window:	All Attacks	9 months	6 months	3 months
	(1)	(2)	(3)	(4)
Fatalities	0.001	−1.587	−1.817	−0.000
	(0.002)	(3.685)	(4.148)	(0.000)
Year Fixed Effects	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes
Observations	657	57	48	19
R^2	0.970	0.995	0.995	1.000

Notes: The outcome is Republican two-party vote share in US presidential elections. *Fatalities* is a count of the fatalities from a terrorist attack. Failed attacks are coded as 0, and successful attacks which do not produce fatalities are omitted, so as to maintain the counterfactual as the failed attack. Standard errors are clustered by county.*p<0.05; **p<0.01

Pre and Post 9/11 Elections

Table C5: Effect of Successful Terrorist Attacks on the Republican Two-Party Vote Share in Presidential Elections, Attack Level, Pre 9/11 Elections

	Republican Two-Party Vote Share			
Pre-Election Window:	All Attacks	9 months	6 months	3 months
	(1)	(2)	(3)	(4)
Success	−0.090	0.463	0.586	−0.610
	(0.225)	(1.035)	(1.000)	(0.482)
Year Fixed Effects	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes
Observations	2,090	262	180	83
R^2	0.948	0.973	0.981	0.997

Notes: The sample here is elections before September 11th, 2001. The outcome is Republican two-party vote share in US presidential elections. *Success* is a binary indicator of if the attempted attack is successful or unsuccessful. The unit of analysis is the attempted attack. Standard errors are clustered by county.*p<0.05; **p<0.01

Table C6: Effect of Successful Terrorist Attacks on the Republican Two-Party Vote Share in Presidential Elections, Attack Level, Post 9/11 Elections

	Republican Two-Party Vote Share			
Pre-Election Window:	All Attacks	9 months	6 months	3 months
	(1)	(2)	(3)	(4)
success	0.102	0.335	0.000	0.000
	(0.385)	(0.467)	(0.000)	(0.000)
Year Fixed Effects	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes
Observations	365	79	63	23
R^2	0.997	0.999	1.000	1.000

Notes: The sample here is elections following September 11th, 2001. The outcome is Republican two-party vote share in US presidential elections. *Success* is a binary indicator of if the attempted attack is successful or unsuccessful. The unit of analysis is the attempted attack. Standard errors are clustered by county.*p<0.05; **p<0.01

Congressional Elections

Table C7: Effect of Successful Terrorist Attacks on the Republican Two-Party Vote Share in House Elections, Attack Level

	Republican Two-Party Vote Share		
	All Attacks	9 months	6 months
	(1)	(2)	(3)
Success	0.266	−2.152	−2.329
	(1.027)	(1.897)	(2.199)
Year Fixed Effects	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes
Observations	633	244	168
R^2	0.959	0.990	0.995

Notes: This table presents results for the model in equation 2 with Republican two-party vote share at the county-level in House elections as the outcome, and county clustered standard errors. The dependent variable can take values between 0 and 100. All models include county and year fixed effects. The unit is the attempted attack, and the treatment "Success" is a binary indicator of if the attempted attack was successful or unsuccessful. *p<0.05; **p<0.01

Table C8: Effect of Successful Terrorist Attacks on the Republican Two-Party Vote Share in Senate Elections, Attack Level

	Republican Two-Party Vote Share		
	All Attacks	9 months	6 months
	(1)	(2)	(3)
Success	−1.147	−2.020	0.206
	(1.704)	(3.574)	(0.318)
Year Fixed Effects	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes
Observations	603	162	112
R^2	0.880	0.993	0.999

Notes: This table presents results for the model in equation 2 with Republican two-party vote share at the county-level in Senate elections as the outcome, and county clustered standard errors. The dependent variable can take values between 0 and 100. All models include county and year fixed effects. The unit is the attempted attack, and the treatment "Success" is a binary indicator of if the attempted attack was successful or unsuccessful. *p<0.05; **p<0.01