Rallies around the Flag-Draped Coffins: The Electoral Effects of Security Force Casualties in Terror Attacks*

Resul Umit†

A work in progress. Click here for the latest version, here for your comments.

July 18, 2018

Abstract

Security forces have recently become the main target of political violence. I examine a natural experiment in Turkey to understand the effect of their casualties on vote choice. Between two general elections in 2015, Turkey experienced a series of attacks that killed 157 members of the security forces. Based on an exogenous variation of their hometowns across the country, I estimate that the government vote share increases in the burial places of terror victims. However, in the towns with recurring casualties, the support decreases by a similar percentage, cancelling the immediate rally behind the government out. Opposition parties do not experience a significant change in their vote share. Distinguishing between the initial and repeated casualties in an experimental design, these results provide a causal evidence for the rally theory.

*I would like to thank Katrin Auel, Josip Glaurdić, Peter John, Elad Klein, Brian J. Phillips, Antje Schwennicke, and Guido Tiemann for their comments on the earlier versions of this article.

†University of Lucerne, Switzerland. Email: resul.umit@unilu.ch. Website: resulumit.com.

Introduction

Terrorism is a growing problem in many countries. The situation might continue to worsen if violence helps radical groups gain concessions from governments (Pape, 2003, 2005), and there are worrying sings. On the one hand, evidence shows violence can be effective provided that it is aimed primarily at military—rather than civilian—targets (Abrahms, 2006, 2012). On the other, security forces have recently become the main target in terrorist and guerilla campaigns (Gibbs, 2018; see also Figure 1). How does the public react to the political violence against their security forces? If voters are sensitive to this specific type of violence, their political behaviour might affect the way governments approach violent groups. However, despite the existing evidence and recent trends with regard to political violence against security forces, we know very little about its consequences.

State funerals might be one reason why security force casualties have remarkable consequences. In contrast to the private nature of funerals for civilian victims, combatant casualties are accorded public ceremonies, characterised by the national flag draping over the coffin. Designed to honour those who die while serving the nation, these spectacles nevertheless create physical and therefore emotional proximity to terror victims, indirectly exposing the locals to political violence. Similar exposures lead individuals to develop psychological distress and increased perception of threat (Canetti, Hall, Rapaport, & Wayne, 2013), which in turn influences their political attitudes (Canetti-Nisim, Halperin, Sharvit, & Hobfoll, 2009; Hirsch-Hoefler, Canetti, Rapaport, & Hobfoll, 2016). Therefore, terror attacks might affect political behaviour not only with the death of security forces but also with their burial.

This article explores whether security force casualties in terror attacks affect vote choice in elections. Specifically, it analyses how voting behaviour changes in districts that experience casualties of townsmen in Turkish security forces. Its design makes use of the facts that (a) Turkey had two general elections within a short period of time in 2015, (b) terror resumed in between these elections, leaving 157 members of the Turkish security forces dead, and (c) their burial places varied across the districts of Turkey due to the compulsory rotation of workplaces among the security personnel. The resulting *as-if* random assignment of casualties to districts is crucial to address the potentially endogenous relationship between terror attacks and vote choice—'a fundamental problem that arises in any attempt to quantify the effect of terrorism on the electorate's preferences' (Berrebi & Klor, 2008, p. 280; see also Getmansky & Zeitzoff, 2014).

The results contradict some major premises in the literature. First, I find that government vote share *increases* in the hometowns of terror casualties. This challenges the understanding that incumbents are punished for casualties of political violence (see, for example Gassebner, Jong-A-Pin, & Mierau, 2008, Kibris, 2011). It is only when districts receive additional casualties that the government vote share starts to decrease. Second, contrary to the thesis that right-wing parties gain when terror casualties (Berrebi & Klor, 2008) or threat (Getmansky & Zeitzoff, 2014) mounts, I find that *no party or party group other than the incumbent* experiences a significant change in their vote share as a result of casualties. Overall, these results are in line with the 'rally 'round the flag' effect—a temporary surge in support for the heads of state or government in reaction to national crisis (Brody, 1991; Mueller, 1973).

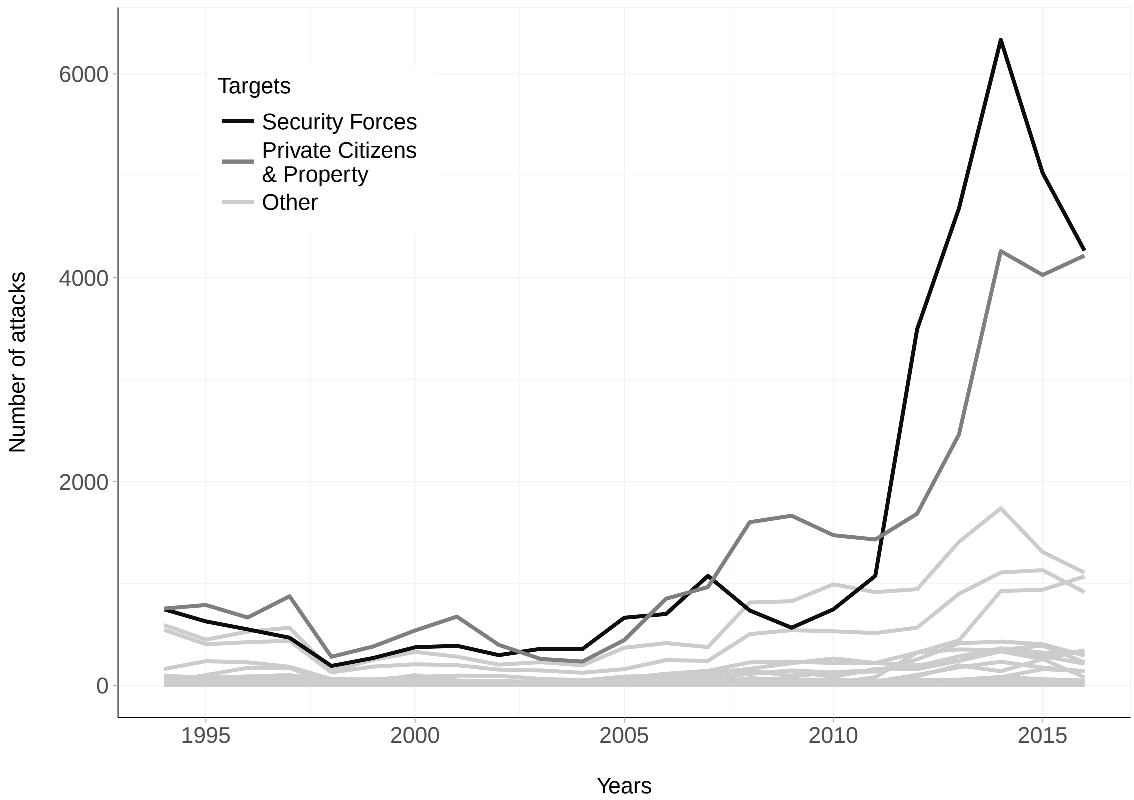

Figure 1: Trends in political violence by target. Security forces have become the main target of political violence in the last decade. *Note*: *Security Forces* consists of *Military* and *Police*, the original categories in the source—Global Terrorism Database (START, 2017).

This article extends the existing knowledge in at least two ways. First, the theoretical contribution of this article is to distinguish security force casualties in terror attacks. Much of what we know about the political effects of terrorism comes from studies of civilian casualties. In addition, its empirical contribution is the experimental verification of the differentiating effect between the initial and repeated failures of governments to prevent casualties on vote choice.

Casualties and Elections

Casualties are the most important information cue about an armed conflict. For the majority of the people away from conflict zones, loss of lives[1] are 'salient, visible, and accountable measures of cost' (Gartner & Segura, 2008, p. 95). As such, the public evaluates the success or failure of involving in a conflict, first and foremost, with the number of casualties (Burk, 1999). There is also a proximity effect below the national level: people might personally know the casualties (Moody, 2005), hear about local elites reacting to them (Brody, 1991), or learn about them in the local in addition to national media (Gartner & Segura, 2008)—the likelihood of all increases with the decreasing proximity of casualties to people.

As an easily quantifiable measure, casualties are also a subject for an influential literature on political behaviour, most notably in wars but also in terrorist attacks. With regard to wars, studies find that as the military deaths of a nation increase, the public support for involvement in a conflict decreases (Gartner, 2008; Gartner & Segura, 1998; Mueller, 1973), especially when the involvement is not perceived as successful or justified (Boettcher & Cobb, 2006; Gelpi, Feaver, & Reifler, 2006). It stands to reason, then, if voters punish those in charge or in favour of these costly involvements in the ballot box. For example, Karol and Miguel (2007) show that President Bush, seeking re-election in 2004, significantly underperformed in states that experienced higher shares of casualties in the Iraq War. There are similar reports from the Congressional elections in the US—a major focus of this strand of literature. Republican senators (Kriner & Shen, 2007) and

[1] Throughout the article, casualties refer to deaths only although the term technically includes also those wounded or lost in a conflict.

congressmen (Grose & Oppenheimer, 2007), who were in control of the government during the Iraq War, suffered electoral losses for increasing casualties among their constituents. To compare, the vote shares of Democrats remained unaffected (Grose & Oppenheimer, 2007). In the Vietnam War, there was a similar relationship between state-level casualties and the electoral fate of incumbent senators irrespective of their party (Gartner, Segura, & Barratt, 2004). Perhaps the only notable exception to these findings is from a cross national study, where Koch (2011) reports that casualties can increase the incumbent vote share.

With regard to terrorism, there is more evidence that casualties affect elections. Public support for right-wing parties increase as a result of civilian casualties in Israel (Berrebi & Klor, 2006), a finding that replicates in localities with casualties (Berrebi & Klor, 2008; Gould & Klor, 2010) or increased threat thereof (Getmansky & Zeitzoff, 2014). However, Israeli governments seem unaffected by casualties (Berrebi & Klor, 2006, 2008), and their vote share might even increase as a result of spreading terror threat (Getmansky & Zeitzoff, 2014). Then again, in Spain, both Bali (2007) and Montalvo (2011) find that the 2004 Madrid train bombings led to a significant decrease in the government vote share in the elections of that year. Similarly, cross-national analyses show that terror casualties decrease the probability of incumbent parties to stay in power (Gassebner et al., 2008), especially if they are from the left-wing (Williams, Koch, & Smith, 2013).

These studies focus either explicitly on civil casualties or casualties in general, leaving the combatant casualties under-researched. One exception is a study by Kibris (2011) who analyses Turkish security force casualties in the first half of 1990s. She finds that province-level casualties affected the election results—they correlated negatively with the vote share of governing parties but positively with that of right-wing parties. Yet how much her analysis can address the research gap around security force casualties is debatable because of three limitations with her research design. First, although Kibris (2011, p. 224) rightly suggests that large social gatherings like security force funerals can affect voters' political behaviour, due to lack of data her analysis is at a higher—province—level than where these gatherings happen. The article also excludes the south-east provinces from the study and fails to control for the fact that some units were not comparable across the elections as they were divided into smaller provinces during the time-frame (Kibris, 2011, pp. 229–230). Indeed, these could be the reasons why neither of her main findings are replicated in this study.

A second dimension of the research gap emerges as the literature 'cannot, at least in many instances, account for the presence or absence of a public opinion rally at the *outset* of a military conflict, before the public observes either the ultimate costs or outcome' (Groeling & Baum, 2008, p. 1065). Rarely is there an opportunity to put together a dataset with observations on casualties and short-term public opinion *at the local level*. As a result, studies time and again rely on typically high aggregation levels and/or lengthy periods between elections, making it impossible to differentiate how the public reacts to initial and repeated casualties. This is especially problematic as the theory suggests a non-linear public behaviour, known as the rally effect.

Rally Effect

Public perception of casualties may not be consistent over the course of a conflict. Studies particularly differentiate between the initial reaction to emerging conflicts and the political mood that follows in the later stages (Brody, 1991; Chowanietz, 2011; Mueller, 1973; Waltz, 1967). Specifically, Mueller (1973, p. 209) defines a 'rally 'round the flag effect', which causes a temporary surge in public support for US Presidents who involve in international conflicts. Some explain this surge in terms of a patriotic reflex, where the public unites behind the leader against a common enemy (Mueller, 1973). This might be one of the reasons why the immediate reaction to casualties is, if anything, a hardened determination among the public to fight back (Kull & Destler, 1999; Schwartz, 1994).

Others argue that rallies start among the political elite before spreading to the public through the media. Elites might avoid criticising the government if they lack the necessary information about what is happening (Brody, 1991) or what the public thinks (Hetherington & Nelson, 2003). In the aftermath of crises, when this lack of information is most severe, opinion leaders refrain from taking the risk of being wrong or sounding controversial (Zaller, 1994; Zaller & Chiu, 1996). In the absence of their criticism, there appears to be an unusual level of support for the government on the media, where the public turns to form their opinions about a conflict in general and especially about their governments' handling of that conflict (Russett, 1990).

Although, as a concept, it is often defined with regard to US Presidents in time of war, the rally effect is phenomenon that also applies to other executives in other crises, such as governments under terror attacks (see, for example, Chowanietz, 2011). Accordingly, be it as a result of a patriotic reflex or elite behaviour, I expect that the vote share of a government would increase in localities receiving a casualty.

H1 *Rally*: Government vote share increases in the localities that experience a security force casualty.

Rally effects are sensitive to repetition. On the one hand, the patriotic reflex weakens with new casualties (Mueller, 1973). On the other, elites become more confident to openly criticise the government. For example, Chowanietz (2011) finds that opposition parties hold back their criticism of the government for three consecutive terrorist attacks, after which the rally effects start to fade away. Therefore, I expect that when localities are treated with multiple security force casualties, the rally effect would change direction.

H2 *Repetition*: Government vote share decreases in the localities that experience multiple security force casualties.

Rally effects are also nonpartisan. The public rallies behind their governments (Chowanietz, 2011) or government institutions (Parker, 1995) as well as the President (Mueller, 1973) not because they represent a particular party but because they represent the country. This implies that any rally effect that we might observe should be strictly nonpartisan. As a result, I expect that no other party or party group would be electorally affected by security force casualties.

H3 *Nonpartisan*: Vote shares of other parties are not affected by security force casualties.

Data and Design

This study provides evidence from Turkey—one of the hardest-hit countries in the recent history of terrorism. In fact, it has long been a target of Kurdish groups among others, and in about three decades, terror attacks have killed over 7,500 members of the Turkish security forces alone (TBMM, 2013).[2] Yet the June 2015 general elections took place amid a strained but nevertheless ongoing peace process, when the Justice and Development Party (AKP) fell short of controlling a majority of the parliamentary seats for the first time in 13 years. With the Syrian Civil War spilling in through south-east Turkey—where the majority of the Kurdish population live—the country came under a double terrorist threat by both Kurdish and jihadist groups soon after the indecisive results. By the time the elections were repeated in November 2015, a further 157 security personnel had died in rapidly escalating terror attacks. Figure 2 demonstrates where these terror casualties occurred, systematically pointing to the south-eastern region of the country.

Whenever there are reports of a terror attack on security forces, districts across Turkey—no matter how far from the south-eastern region—brace themselves for receiving a casualty. This is because security force personnel serve anywhere but in their hometown, rotating among the other districts and provinces.[3] Indeed, Figure 3 shows that the

[2]The civilian death toll was at least 5,500 in the same period of time (TBMM, 2013).

[3]There were 970 districts (*ilçe*) in 81 provinces (*il*) in 2015. Confusion may arise as these administrative districts are not at the same time electoral districts. As a rule, provinces make up the latter. The only exceptions are Ankara, İstanbul, and İzmir—the three largest cities—which are divided into smaller electoral districts due to their size. Hence, the total number of electoral districts was 85 in the period under analysis.

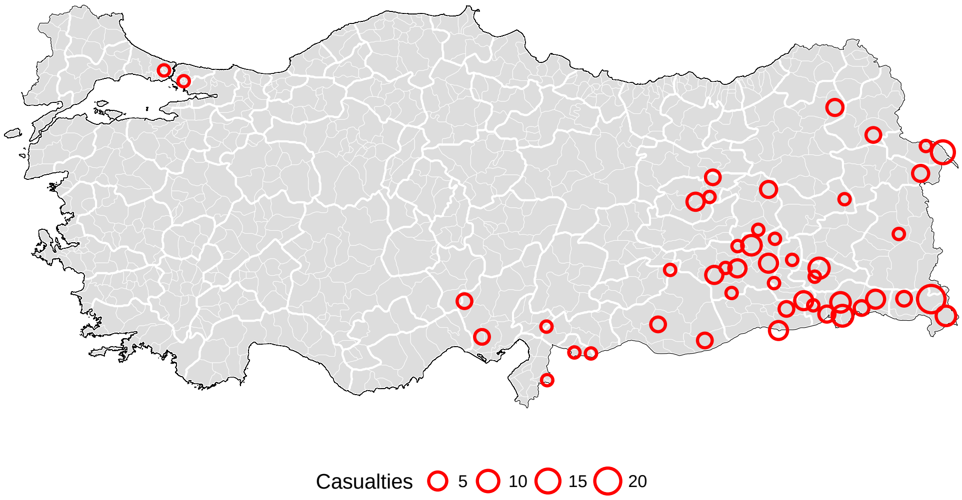

Figure 2: Districts of terror attacks with security force casualties. The death places concentrated in south-east Turkey.

157 casualties scattered across the country. Within a day or so after the deadly attacks, their flag-draped coffins arrive in their home districts, where a state funeral takes place. Fellow townspeople, typically in their thousands, attend these ceremonies with high-level representatives from bureaucracy and government alike. It is not unusual for the Prime Minister and cabinet ministers or even the President to be present during these funerals.

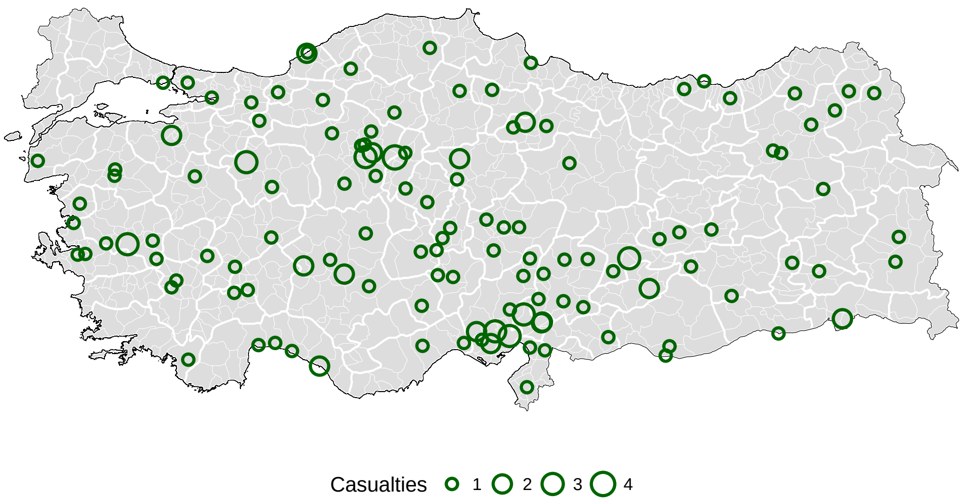

Figure 3: Treatment districts. The burial places distributed *as-if* randomly across Turkey.

Security forces killed in the line of duty are given similar state ceremonies elsewhere in the world as well. Yet, what makes the Turkish case special is the compulsory system of workplace rotation for the security forces. This setting offers a natural experiment, where districts are treated *as-if* randomly[4] with security force casualties in between the pre- and post-test of elections, making it possible to calculate the causal effect of terror casualties among security forces on the vote choice. Specifically, the analysis is based on two variables of interest: (a) district-level voting results at the 5 June (pre-test) as well as the 1 November (post-test) elections and (b) burial districts of the terror victims among the Turkish security forces. The data on election results comes from the Turkish Statistical Institute (TurkStat, http://www.turkstat.gov.tr), coded as the percentage of valid votes cast in the elections. For the data on security force casualties, I went through news archives, and coded *Treatment* as 1 for the 126 districts that received at least one casualty in between the elections. While 104 districts were treated only once, the remaining 22 districts were treated multiple times—they received two or more casualties (mean= 2.41, sd= 0.59). I coded *Multiple Treatment* as 1 for these districts to exploit the difference in treatment intensity. Hence it is possible to distinguish between the effect of initial and repeated casualties—a key element of the rally effect but one that has been unexplored so far.

[4]See Table S2 in the Supporting Information for randomisation checks.

Results

Figure 4 plots the average vote share that the Turkish government achieved in the two general elections of 2015. It shows that the treated and control districts were similar in terms of government vote share in the pre-test. Indeed, there was only a 0.6% difference in favour of the treated districts. This suggests, as we would expect from a random distribution, that there was a balance between the treatment and control groups with respect to their pre-test scores. In the post-test, however, this difference more than tripled, and the government vote share was 1.9% higher among the treated districts than among the control districts. Overall, the comparison of the average vote shares between the two elections suggests that security force casualties might have increased the electoral support for the government.

Table 1 presents a summary of ordinary least squares (OLS) regression estimates with clustered standard errors at the level of provinces. Controlling for the results in the June 2015 election in three models, it shows that government vote share indeed increased significantly in the districts that experienced security force casualties between the elections. Model 1, which additionally includes the pre-test results, estimates that the casualties led to a 1.2 percentage point increase. In other words, the difference apparent in Figure 4 is indeed statistically significant at the 0.01 level. These results confirm that, on average, government vote share increased in the localities that experience security force casualties.

The results could not be more different where a locality received terror casualties repeatedly. With *Multiple Treatment*, the estimates reveal what happens when there is

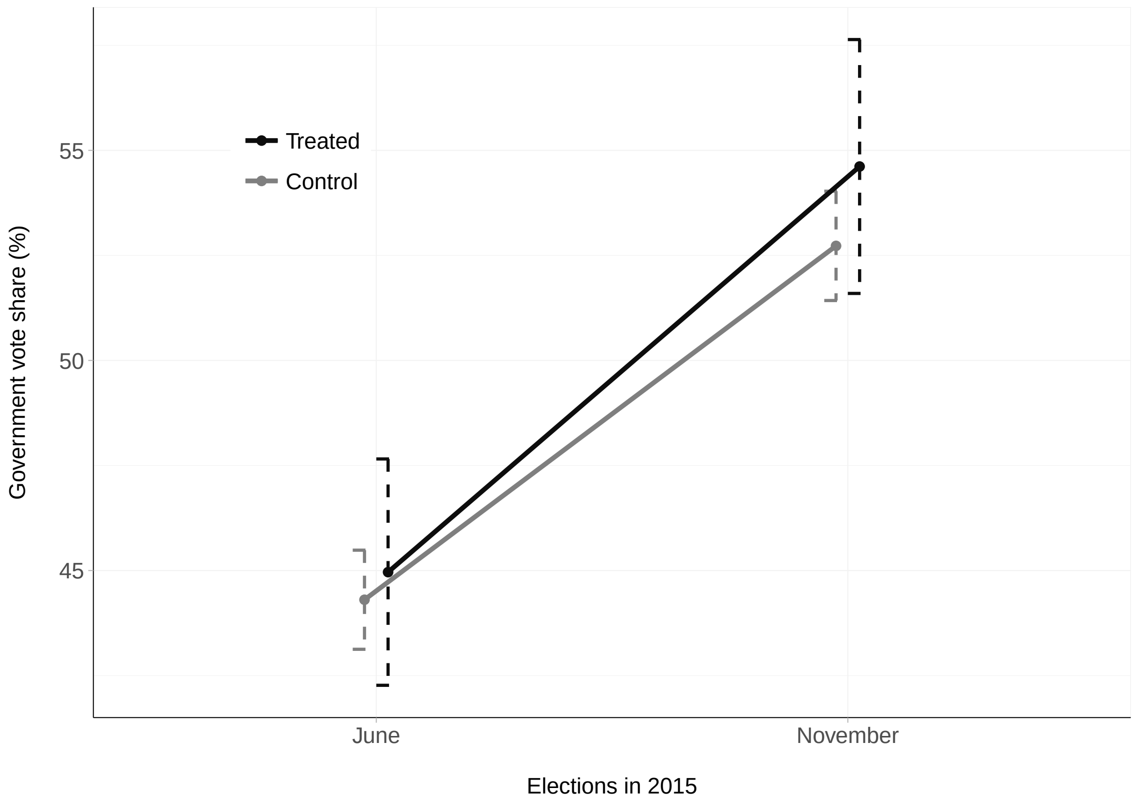

Figure 4: Change in government vote share. Compared to the control group of districts with no casualties (*Treatment*= 0), the average vote share of the government increased at a higher rate among the treated districts (*Treatment*= 1).

more than one—on average, 2.41—casualty, showing that this significantly decreases the electoral support for government. In fact, it cancels out the rally effect of having just one casualty: Model 3 estimates that repeated casualties led to a 1.3 percentage point decrease in government vote share in the towns that had already received a casualty before. At the same time, *Treatment* still points to a statistically significant, 1.2 percentage point increase. These results support the hypotheses on *Rally* as well as *Repetition* effects.

To explain these electoral results as a rally effect, they should be limited to the government, where individual parties in opposition or groups of parties in general remain unaffected. The 2015 elections returned the same four parties to the Turkish parliament

Table 1: Do casualties affect government vote share? —Yes.

Variables	(1)	(2)	(3)
Treatment	1.178**	1.420**	1.208**
	(0.418)	(0.483)	(0.431)
Multiple Treatment		–1.385*	–1.344*
		(0.665)	(0.633)
Pre-test	✓	✓	✓
Covariates	✗	✗	✓
Constant	4.772	4.796	2.083
	(0.834)	(0.837)	(0.775)
N	970	970	970
Clusters	81	81	81
R^2	0.960	0.960	0.966

Notes: Models include OLS coefficients with clustered standard errors in parentheses. See the Supporting Information for more on the data and variables, the descriptive statistics (Table S1), and for the complete table (Table S3). * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

in November as in June: the conservative AKP in government was accompanied by the social-democrat Republican People's Party (CHP), far-right Nationalist Action Party (MHP), and the left-wing Peoples' Democratic Party (HDP). Table 2 replicates the main model above—Model 3 of Table 1—for the right wing (*RW Parties*)[5] as well as for the three individual parties in opposition. The results show that they were affected neither by an initial terror casualty nor repeated casualties. The estimates from *Treatment* and *Multiple Treatment* are relatively small, and they are not statistically significant. Hence the results confirm the *Nonpartisan Hypothesis* as well.

[5]For *RW Parties*, the pre- post-test variables are calculated as the district-wise sum of shares for AKP, MHP, and the Felicity Party (SP)—the right wing parties with more than 1% nation-wide votes.

Table 2: Do casualties affect other parties' or party groups' vote share? —No.

Variables	(CHP)	(MHP)	(HDP)	(RW Parties)
Treatment	0.080	–0.207	0.303	0.073
	(0.211)	(0.315)	(0.266)	(0.436)
Multiple Treatment	–0.123	1.344	0.491	–1.271
	(0.392)	(0.873)	(0.602)	(0.718)
Pre-test	✓	✓	✓	✓
Covariates	✓	✓	✓	✓
Constant	–1.793***	0.500	–0.775***	0.974
	(0.376)	(0.611)	(0.184)	(1.262)
N	970	970	970	970
Clusters	81	81	81	81

Notes: This table replicates Model 3 of Table 1 for the opposition parties and the right wing party group. See the Supporting Information for the complete table (Table S4). * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Several other tests suggest that these results are robust. Most notably, the results do not change if the data is weighted with entropy balancing, which creates perfectly balanced samples with respect to *Treatment*. There is also no evidence that differences in turnout or treatment timing drive the change in government vote share. Given the space constraints here, these and other robustness checks are fully reported only in the Supporting Information.

Conclusion

Societies are experiencing a new trend in the threat they face as their security forces become the main target of political violence. We know that governments are more likely to make concessions to this specific type of violence, but we do not know why. Assuming that governments are concerned first and foremost about their public support, we need to understand the electoral effects of security force causalities in political violence if we want to solve this puzzle. Yet we cannot do so with the existing knowledge because it either does not distinguish between the targets of political violence or, when it does, it suffers from large casualty totals as well as from the endogenous relationship between targets and votes.

This article tackles these challenges with data from a natural experiment from Turkey, where political violence resumed between two general elections held in less than five months, targeting the security forces as well as the civilians. The security force victims of the resulting attacks assigned as-if randomly across the districts in the country, and their flag-draped coffins were the centre of public ceremonies in their hometowns. Hence the data provides us with two ultimate tests on public opinion in a short period of time, small casualty totals by localities, and most importantly, with an exogenous variation of burial places.

The results show that the public reacts significantly to political violence against security forces, but with a nuance: they rally behind their government after the initial terror victim from their town, but this effect disappears if the government fails to prevent further victims. This contradicts the existing studies that assume a linear relationship between the number of casualties and vote choice, debating whether casualties increase or decrease the support for government. It can do both.

These results might explain why governments are more likely to make concessions to stop violence against security forces. Once the members of security forces start falling victim to violence, preventing further casualties does not only avoid the punishment that the existing evidence attributes to the increasing number of casualties. It may also bring in rewards in localities with single casualties, and governments can catch the rally effect behind them. It is the latter aspect that this article adds to our knowledge.

References

Abrahms, M. (2006). Why terrorism does not work. *International Security*, *31*(2), 42–78.

Abrahms, M. (2012). The political effectiveness of terrorism revisited. *Comparative Political Studies*, *45*(3), 366–393.

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

Berrebi, C. & Klor, E. F. (2006). On terrorism and electoral outcomes: Theory and evidence from the Israeli-Palestinian conflict. *Journal of Conflict Resolution*, *50*(6), 899–925.

Berrebi, C. & Klor, E. F. (2008). Are voters sensitive to terrorism? Direct evidence from the Israeli electorate. *American Political Science Review*, *102*(03), 279–301.

Boettcher, W. A. & Cobb, M. D. (2006). Echoes of Vietnam? Casualty framing and public perceptions of success and failure in Iraq. *Journal of Conflict Resolution*, *50*(6), 831–854.

Brody, R. (1991). *Assessing the president: The media, elite opinion, and public support.* California: Stanford University Press.

Burk, J. (1999). Public support for peacekeeping in Lebanon and Somalia: Assessing the casualties hypothesis. *Political Science Quarterly*, *114*(1), 53–78.

Canetti-Nisim, D., Halperin, E., Sharvit, K., & Hobfoll, S. E. (2009). A new stress-based model of political extremism: Personal exposure to terrorism, psychological distress, and exclusionist political attitudes. *Journal of Conflict Resolution*, *53*(3), 363–389.

Canetti, D., Hall, B. J., Rapaport, C., & Wayne, C. (2013). Exposure to political violence and political extremism. *European Psychologist*, *18*(4), 263–272.

Chowanietz, C. (2011). Rallying around the flag or railing against the government? Political parties' reactions to terrorist acts. *Party Politics*, *17*(5), 673–698.

Gartner, S. S. (2008). The multiple effects of casualties on public support for war: An experimental approach. *American Political Science Review*, *102*(1), 95–106.

Gartner, S. S. & Segura, G. M. (1998). War, casualties, and public opinion. *Journal of Conflict Resolution*, *42*(3), 278–300.

Gartner, S. S. & Segura, G. M. (2008). All politics are still local: The Iraq War and the 2006 midterm elections. *PS: Political Science & Politics*, *41*(1), 95–100.

Gartner, S. S., Segura, G. M., & Barratt, B. A. (2004). War casualties, policy positions, and the fate of legislators. *Political Research Quarterly*, *57*(3), 467–477.

Gassebner, M., Jong-A-Pin, R., & Mierau, J. O. (2008). Terrorism and electoral accountability: One strike, you're out! *Economics Letters*, *100*(1), 126–129.

Gelpi, C., Feaver, P. D., & Reifler, J. (2006). Success matters: Casualty sensitivity and the war in Iraq. *International Security*, *30*(3), 7–46.

Getmansky, A. & Zeitzoff, T. (2014). Terrorism and voting: The effect of rocket threat on voting in Israeli elections. *American Political Science Review*, *108*(03), 588–604.

Gibbs, J. C. (2018). Terrorist attacks targeting the police: The connection to foreign military presence. *Police Practice and Research*, *19*(3), 222–240.

Gould, E. D. & Klor, E. F. (2010). Does terrorism work? *Quarterly Journal of Economics*, *125*(4), 1459–1510.

Groeling, T. & Baum, M. A. (2008). Crossing the water's edge: Elite rhetoric, media coverage, and the rally-round-the-flag phenomenon. *Journal of Politics*, *70*(4), 1065–1085.

Grose, C. R. & Oppenheimer, B. I. (2007). The Iraq war, partisanship, and candidate attributes: Variation in partisan swing in the 2006 US House elections. *Legislative Studies Quarterly*, *32*(4), 531–557.

Hetherington, M. J. & Nelson, M. (2003). Anatomy of a rally effect: George W. Bush and the war on terrorism. *PS: Political Science and Politics*, *36*(1), 37–42.

Hirsch-Hoefler, S., Canetti, D., Rapaport, C., & Hobfoll, S. E. (2016). Conflict will harden your heart: Exposure to violence, psychological distress, and peace barriers in Israel and Palestine. *British Journal of Political Science*, *46*(4), 845–859.

Karol, D. & Miguel, E. (2007). The electoral cost of war: Iraq casualties and the 2004 US presidential election. *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. T. (2011). Casualties and incumbents: Do the casualties from interstate conflicts affect incumbent party vote share? *British Journal of Political Science*, *41*(04), 795–817.

Kriner, D. L. & Shen, F. X. (2007). Iraq casualties and the 2006 Senate elections. *Legislative Studies Quarterly*, *32*(4), 507–530.

Kull, S. & Destler, I. M. (1999). *Misreading the public: The myth of a new isolationism*. Washington, DC: Brookings Institution Press.

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.

Moody, J. (2005). Fighting a hydra: A note on the network embeddedness of the war on terror. *Structure and Dynamics*, *1*(2), 1–5.

Mueller, J. E. (1973). *War, presidents, and public opinion*. New York: John Wiley & Sons.

Pape, R. A. (2003). The strategic logic of suicide terrorism. *American Political Science Review*, *97*(3), 343–361.

Pape, R. A. (2005). *Dying to win: The strategic logic of suicide terrorism*. New York: Random House.

Parker, S. L. (1995). Towards an understanding of "rally" effects: Public opinion in the Persian Gulf War. *Public Opinion Quarterly*, *59*(4), 526–546.

Russett, B. (1990). *Controlling the sword*. Cambridge: Harvard University Press.

Schwartz, B. C. (1994). *Casualties, public opinion, and U.S. military intervention: Implications for U.S. regional deterrence strategies*. Santa Monica: Rand.

START. (2017). Global terrorism database. Retrieved from https://www.start.umd.edu/gtd

TBMM. (2013). *Terör ve şiddet olayları kapsamında yaşam hakkı ihlallerini inceleme raporu*. İnsan Haklarını İnceleme Komisyonu. Ankara. Retrieved from https://www.tbmm.gov.tr

Waltz, K. (1967). Electoral punishment and foreign policy crises. In J. N. Rosenau (Ed.), *Domestic sources of foreign policy* (pp. 263–293). New York: Free Press.

Williams, L. K., Koch, M. T., & Smith, J. M. (2013). The political consequences of terrorism: Terror events, casualties, and government duration. *International Studies Perspectives*, *14*(3), 343–361.

Zaller, J. (1994). Elite leadership of mass opinion: New evidence from the Gulf War. In W. L. Bennett & D. L. Paletz (Eds.), *Taken by storm: The media, public opinion, and US foreign policy in the Gulf War* (pp. 82–101). Chicago: University of Chicago Press.

Zaller, J. & Chiu, D. (1996). Government's little helper: US press coverage of foreign policy crises, 1945–1991. *Political Communication*, *13*(4), 385–405.

SUPPORTING INFORMATION

"Rallies around the Flag-Draped Coffins: The Electoral Effects of Security Force Casualties in Terror Attacks"

Resul Umit

University of Lucerne

resul.umit@unilu.ch

S1 Data

There are three main components of the data: security force casualties, election results, and district characteristics. While the latter two originate from the Turkish Statistical Institute (TurkStat, http://www.turkstat.gov.tr), I compiled the data on security force casualties from three news archives. The resulting dataset, together with the code to replicate the analyses, will be publicly available upon publication of this article.

S1.1 Security force casualties

Security force casualties are officially named in Turkey; the General Staff of the Republic of Turkey announces military deaths while the General Directorate of Security are responsible for announcing police deaths. However, both institutions remove these statements from their websites soon after the incidents, and there is no official cumulative data on casualties. An alternative source is the Turkish media, which widely report on security force casualties in Turkey. To create this data component, I therefore searched the electronic archives of three major sources of Turkish news—two newspapers, Hürriyet and Cumhuriyet, as well as the Cihan News Agency—for the time period between the two general elections, 7 June to 1 November 2015. I coded the casualties among police and military forces including the guards—paramilitaries recruited to fight terror. This resulted in 195 observations. For each casualty, I then coded their (a) district of death, (b) district of burial, (c) cause of death, (d) age, and (e) gender.

S1.2 Election results

In the period under analysis, there were 970 *administrative districts* (*ilçe*) in 81 Turkish provinces (*il*). Provinces are at the same time *electoral districts* as a rule, but the three largest cities are divided into smaller districts due to their size: İstanbul has 3 electoral districts while Ankara and İzmir have two each. Therefore there are 85 electoral districts in Turkey. TurkStat provides election results at several levels, from ballot box to electoral districts. This analysis is based on the election results at the level of 970 administrative districts as the funerals of security forces take place at this level, often in the courtyard of the biggest Mosque at the centre of districts. The related variables of this data component include (a) the total number of valid votes cast and (b) the number of votes cast for each party in each district. There were no changes in district names or borders between the elections. Hence, scraping the results for the 7 June and 1 November elections from the

TurkStat website, I then simply merged these variables together. I then calculated the pre- and post-test results as vote shares in percentage points.

The final dataset is based on five parties, four of which passed the ten per cent electoral threshold to secure seats in the parliament on both occasions. Beside the governing AKP, the three other parties entering the parliament were the Republican People's Party (*Cumhuriyet Halk Partisi*, CHP), Nationalist Action Party (*Milliyetçi Hareket Partisi*, MHP), and the Peoples' Democratic Party (*Halkların Demokratik Partisi*, HDP). To calculate the right-wing vote share, I also considered the Felicity Party (*Saadet Partisi*, SP)—the only other party that had more than one per cent of the vote in either of the elections—in the same group with AKP and MHP.

S1.3 District characteristics

As district characteristics might predict the treatment assignment or the outcome, the data includes a related component. Most importantly, districts with different numbers of people serving in the security forces had different probabilities of being assigned to the treatment group. In the absence of the data as to from which districts the serving members of the security forces come, I use a proxy variable measuring the number of men in their 20s resident in each district. I assume there is a close correlation between the number of men in their 20s in a district and the number of security personnel from that district. Military service in Turkey is compulsory for male citizens turning 20. Female officers in the armed or police forces are a very small minority. For example, the percentage of women in police remains about 5.5% (TurkStat, 2016). Besides, the casualties in the dataset are all male with a median age of 26 (mean= 29.1, sd= 7.8, min= 20, max= 54).

Despite the relatively short period of time between the two general elections, controlling for the changes in district electorates might still increase the precision of the estimates. Hence I use the numbers of eligible voters in each election (available on the TurkStat website) to calculate *Electorate Change (%)* at the district level. Finally, considering that Kurdish rebels were one of the two groups responsible from security force casualties, Kurdish districts might react to treatments or to the elections in general differently. Because there are no statistics on the ethnic composition of districts or provinces in Turkey, here I rely on a study by Aydın (2004), who lists the predominantly Kurdish provinces, to control for this possibility.

S1.4 Variables and descriptive statistics

Table S1 presents the descriptive statistics of the variables used for the analysis reported in the main text.

Treatment. A binary variable coded as 1 if districts had *one or more* funerals between 7 June and 1 November 2015 for security forces killed in terror attacks. Out of the 970 districts in Turkey, 126 had at least one funeral within this time frame between two general elections.

Multiple Treatment. A binary variable coded as 1 if districts had *more than one* funeral between 7 June and 1 November 2015 for security forces killed in terror attacks. Out of the 126 treated districts, 22 were treated multiple times.

Table S1: Descriptive statistics

Variables	Mean	Std. Deviation	Minimum	Maximum
Treatment	0.13	0.34	0	1
Multiple Treatment	0.02	0.15	0	1
Non-Hostile Death	0.01	0.08	0	1
Casualty District	0.05	0.21	0	1
Kurdish Province	0.18	0.39	0	1
Males (20–29)	6,600.53	11,023.88	101	87,846
Electorate Change (%)	–0.32	1.76	–15.43	14.93
Pre-Test Results				
Government June (%)	44.39	17.18	1.20	90.70
CHP June (%)	21.12	15.07	0.20	77.10
MHP June (%)	17.36	9.05	0.40	50.10
HDP June (%)	12.40	23.12	0.10	97.40
Right Wing June (%)	63.77	21.97	2.00	97.00
Margins				
Government Margin (%)	6.08	6.72	0.07	51.91
CHP Margin (%)	8.43	7.09	0.07	32.64
MHP Margin (%)	17.36	9.05	0.40	50.10
HDP Margin (%)	11.44	9.41	0.14	77.57
Last Seat Margin (%)	4.74	5.16	0.07	32.64
Post-Test Results				
Government Nov (%)	52.97	19.00	2.00	95.90
CHP Nov (%)	21.15	15.71	0.40	79.50
MHP Nov (%)	12.32	7.01	0.20	41.50
HDP Nov (%)	10.40	21.10	0.00	95.80
Right Wing Nov (%)	65.29	20.94	3.30	98.40

Non-Hostile Death. A binary variable coded as 1 if districts had one or more funerals between 7 June and 1 November 2015 following a non-hostile death of a security personnel. There were 38 such cases, where the deaths were related to, for example, hearth attacks, traffic accidents, or lightning strikes.

Casualty District. A binary variable coded as 1 if districts had one or more terror attacks between 7 June and 1 November 2015 with one or more security force casualties. Out of the 970 districts in Turkey, terror attacks with security force casualties were limited to 47 districts.

Kurdish Province. A binary variable coded as 1 for districts in the predominantly Kurdish provinces (Aydın, 2004)—Adıyaman, Ağrı, Batman, Bingöl, Bitlis, Diyarbakır, Elazığ, Erzurum, Hakkari, Iğdır, Kars, Malatya, Mardin, Muş, Siirt, Tunceli, Van, Şanlıurfa, and Şırnak.

Males (20–29). A count variable measuring the number of male residents in their 20s in each district in 2015.

Electorate Change. A continuous variable measuring the percent difference in the number of eligible voters in the 1 November compared to the 7 June 2015 elections.

Pre-Test Results. A group of variables measuring the support for parties in the 7 June 2015 elections, calculated by dividing the votes cast for parties over the total number of valid votes in each district.

Margins. A group of variables measuring the electoral margins of the last seat in each district in the 7 June 2015 elections, calculated as the percentage of votes needed either to win or to defend the last seat.

Post-Test Results. A group of variables measuring the support for parties in the 1 November 2015 elections, calculated by dividing the votes cast for parties over the total number of valid votes in each district.

S2 Randomisation Check

Table S2 presents randomisation checks, showing that the random assignment of casualties was uncorrelated with all observable district characteristics but the number of resident males in their twenties. This means that the probability of districts receiving the treatment was not identical: as it stands to reason, districts with higher number of (potential) security force recruits were more likely to receive the treatment. This is why the models with covariate adjustments should be the preferred models to explain the effects of casualties on vote choice. Notice also that, Section S2 below provides robustness checks based on entropy balancing, which creates perfectly balanced samples with respect to *Treatment*.

Table S2: Randomisation check

	DV: Treatment		DV: Multiple Treatment	
Variables	(1)	(2)	(3)	(4)
Government June	0.000	–0.004	–0.000	0.002
	(0.001)	(0.010)	(0.000)	(0.003)
CHP June		0.005		0.003
		(0.006)		(0.002)
MHP June		0.004		0.004
		(0.009)		(0.004)
HDP June		0.006		0.003
		(0.006)		(0.002)
Right Wing June		0.010		0.001
		(0.011)		(0.003)
Turnout June		–0.003		–0.001
		(0.003)		(0.001)
Non-Hostile Death		0.359		0.239
		(0.199)		(0.176)
Casualty District		0.029		–0.017
		(0.041)		(0.022)
Kurdish Province		0.063		0.016
		(0.048)		(0.021)
Males (20–29)		0.000**		0.000*
		(0.000)		(0.000)
Electorate Change		0.008		–0.000
		(0.005)		(0.002)
Last Seat Margin		–0.002		0.000
		(0.002)		(0.001)
Constant	0.119***	–0.404	0.038**	–0.285
	(0.030)	(0.597)	(0.018)	(0.196)
N	970	970	970	970
Clusters	81	81	81	81
R^2	0.000	0.104	0.002	0.091

Notes: Models include OLS coefficients with clustered standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

S3 Complete Tables

For reasons of brevity and space, the regression tables in the main text report only summaries of the results. This section provides the complete versions of these tables.

Table S3: Complete version of Table 1

Variables	(1)	(2)	(3)
Treatment	1.178**	1.420**	1.208**
	(0.418)	(0.483)	(0.431)
Multiple Treatment		–1.385*	–1.344*
		(0.665)	(0.633)
Pre-test	1.082***	1.082***	1.118***
	(0.015)	(0.015)	(0.016)
Non-Hostile Death			–1.214
			(1.133)
Casualty District			–1.192
			(1.050)
Kurdish Province			4.324***
			(0.808)
Males (20–29)			0.000**
			(0.000)
Electorate Change (%)			0.115
			(0.090)
Government Margin			0.036
			(0.028)
Constant	4.772	4.796	2.083
	(0.834)	(0.837)	(0.775)
N	970	970	970
Clusters	81	81	81
R^2	0.960	0.960	0.966

Notes: Models include OLS coefficients with clustered standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table S4: Complete version of Table 2

	CHP			MHP			HDP			RW Parties		
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)			
Treatment	0.049	0.045	0.080	0.082	–0.141	–0.207	–0.387*	–0.442*	0.303	0.446	0.670	0.073
	(0.200)	(0.216)	(0.211)	(0.320)	(0.337)	(0.315)	(0.184)	(0.222)	(0.266)	(0.370)	(0.411)	(0.436)
Multiple		0.019	–0.123		1.299	1.344		0.317	0.491		–1.275	–1.271
Treatment		(0.335)	(0.392)		(0.813)	(0.873)		(0.661)	(0.602)		(0.892)	(0.718)
Pre-test	1.031***	1.031***	1.051***	0.723***	0.722***	0.712***	0.906***	0.906***	0.949***	0.932***	0.932***	0.995***
	(0.010)	(0.010)	(0.012)	(0.026)	(0.026)	(0.035)	(0.013)	(0.013)	(0.020)	(0.016)	(0.015)	(0.017)
Non-Hostile			–0.692			–0.325			0.099			–0.991
Death			(0.575)			(0.582)			(1.539)			(2.041)
Casualty			0.625			0.234			2.216*			–1.221
District			(0.507)			(0.437)			(0.954)			(0.999)
Kurdish			1.098*			–0.388			–3.775***			6.813***
Province			(0.542)			(0.600)			(1.017)			(0.969)
Males			0.000*			–0.000			–0.000**			0.000**
(20–29)			(0.000)			(0.000)			(0.000)			(0.000)
Electorate			0.048			0.174*			0.021			0.114
Change (%)			(0.045)			(0.074)			(0.060)			(0.105)
Margins			0.047*			0.052*			0.015			-0.121*
			(0.022)			(0.023)			(0.012)			(0.054)
Constant	–0.631**	–0.631**	–1.793***	–0.240	–0.226	0.500	–0.780***	–0.780***	–0.775***	5.766***	5.777***	0.974
	(0.209)	(0.209)	(0.376)	(0.350)	(0.340)	(0.611)	(0.113)	(0.113)	(0.184)	(1.137)	(1.135)	(1.262)
N	970	970	970	970	970	970	970	970	970	970	970	970
Clusters	81	81	81	81	81	81	81	81	81	81	81	81
R^2	0.978	0.978	0.979	0.870	0.871	0.877	0.986	0.986	0.988	0.960	0.960	0.966

Notes: Models include OLS coefficients with clustered standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

S4 Robustness Checks

This section provides a series of four checks on the robustness of the statistically significant results reported in the main text. The first of these checks reconsiders the hypotheses on *rally* and *repetition* effects, this time after entropy balancing—a propensity score weighting approach to create balanced samples with respect to treatments (Hainmueller, 2012). The remaining three checks are then based on models with and without the weights obtained from entropy balancing.

S4.1 Entropy balancing

Could the imbalances between the treatment and control districts be driving the results? Although we know (from the results in Table S2 in Section S2 above) that in all but one cases these differences are statistically insignificant, the entropy balancing method offers an opportunity to remove these imbalances completely. Table S5 presents the mean values of the covariates used in the main text, before and after entropy balancing. It shows that this process has been successful—the procedure achieves a perfect balance for all covariates.

With the weights obtained from this balancing procedure, Table S6 reconsiders the effects of *Treatment* and *Multiple Treatment* on the government vote share. Notice that this exercise follows the pre-test, post-test design used in the main text. The results are very similar to the ones reported in the main text as well—both in statistical and practical terms: while the government vote share increases in the burial places of terror

Table S5: Treatment and control groups before and after entropy balancing

	Before Matching		After Matching	
Variables	Treatment	Control	Treatment	Control
Non-Hostile Death	0.03	0.00	0.03	0.03
Casualty District	0.06	0.05	0.06	0.06
Kurdish Province	0.17	0.19	0.17	0.17
Males (20–29)	13048	5638	13048	13048
Electorate Change (%)	0.08	–0.38	0.08	0.08
Government Margin	5.63	6.14	5.63	5.63

Notes: This table presents the mean values of the covariates in the entropy balancing procedure.

victims by about 1.2 percentage points, this rally effect disappears in the towns with repeated casualties. The resulting decrease is about 1.4 percentage points.

S4.2 Turnout

Differences in turnout could affect the government vote share even if no one actually changed their position to rally behind or against the government between the two elections. However, there is little evidence of this happening in the data. Table S7 presents related OLS estimates for the effect of casualties on turnout, where the dependent variable is the district turnout in November 2015 and *Pre-test* is the turnout in the June 2015 election. While *Treatment* initially seems significant at the 5% level, this disappears once the models are adjusted with covariates (Model 3) or entropy balancing weights (Model 4). *Multiple Treatment*, on the other hand, is insignificant across the models (Models 2–4).

Table S6: Regression models based on entropy balancing

Variables	(1)	(2)
Treatment	0.952*	1.193**
	(0.398)	(0.458)
Multiple Treatment		–1.352*
		(0.589)
Pre-test	1.090***	1.087***
	(0.013)	(0.013)
Constant	4.670***	4.770***
	(0.587)	(0.582)
N	970	970
R^2	0.953	0.953

Notes: Models include OLS coefficients with standard errors in parentheses. The data is adjusted with the entropy balancing weights. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

S4.3 Treatment timing

The treatment timing was not homogeneous across the treated units—while the earliest funeral took place 117 days before the second election on 1 November 2015, the latest was only five days before this post-test. To check if the change in government vote share is driven by the heterogeneity in treatment timing, Table S8 introduces two new control variables: (a) the mean and (b) the minimum number of days between the funerals and the November election, considering that some districts received the treatment more than once. Because they are set to 0 for the untreated districts, these variables are equivalent of the interactions of time and treatment. Their coefficients are statistically insignificant

Table S7: Regression models of turnout

	Unweighted data			Weighted data
Variables	(1)	(2)	(3)	(4)
Treatment	0.605*	0.573*	0.428	0.373
	(0.240)	(0.274)	(0.243)	(0.227)
Multiple Treatment		0.184	–0.293	0.197
		(0.347)	(0.394)	(0.300)
Pre-test	0.860***	0.860***	0.834***	0.840***
	(0.040)	(0.040)	(0.034)	(0.037)
Non-Hostile Death			1.191	
			(0.712)	
Casualty District			–0.724	
			(0.467)	
Kurdish Province			–2.291***	
			(0.658)	
Males (20–29)			0.000***	
			(0.000)	
Electorate Change (%)			–0.144	
			(0.101)	
Last Seat Margin			–0.064**	
			(0.022)	
Constant	12.307***	12.318***	15.066***	14.213***
	(3.467)	(3.465)	(2.956)	(3.201)
N	970	970	970	970
Clusters	81	81	81	0
R^2	0.702	0.702	0.766	0.689

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

across the models with or without the entropy weights, indicating that the change in government vote share is unrelated to the treatment timing.

S4.4 Single casualty

In the main text, Table 1 distinguishes the effect of a single casualty by using the two treatment variables together in the same models (Models 2 and 3): *Treatment* (the districts with *one or more* casualties) and *Multiple Treatment* (the districts with *more than*

Table S8: Regression models with treatment timing

	Unweighted data		Weighted data	
Variables	(1)	(2)	(3)	(4)
Treatment	0.892	0.604	0.679	0.398
	(0.742)	(0.683)	(0.774)	(0.704)
Mean Days	0.005		0.005	
	(0.012)		(0.013)	
Minimum Days		0.010		0.010
		(0.012)		(0.012)
Pre-test	1.082***	1.082***	1.090***	1.089***
	(0.015)	(0.015)	(0.013)	(0.013)
Constant	4.774***	4.778***	4.676***	4.694***
	(0.834)	(0.835)	(0.585)	(0.583)
N	970	970	970	970
Clusters	81	81	0	0
R^2	0.960	0.960	0.953	0.953

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

one casualty). Table S9 provides an alternative way to test the *Rally Hypothesis*: coding *Single Treatment* as 1 for the districts that received only one casualty and 0 for all the others (including those with multiple casualties), it shows that the evidence for the hypothesis is robust. This is true, again, according to both the unweighted and weighted data.

Table S9: Regression models with *Single Treatment*

Variables	Unweighted data (1)	(2)	Weighted data (3)
Single Treatment	1.419**	1.214*	1.216**
	(0.483)	(0.430)	(0.455)
Pre-test	1.082***	1.118***	1.087***
	(0.015)	(0.016)	(0.013)
Non-Hostile Death		–1.249	
		(1.140)	
Casualty District		–1.190	
		(1.048)	
Kurdish Province		4.326***	
		(0.808)	
Males (20–29)		0.000**	
		(0.000)	
Electorate Change (%)		0.115	
		(0.090)	
Government Margin		0.036	
		(0.028)	
Constant	4.797***	2.081**	4.741***
	(0.828)	(0.774)	(0.574)
N	970	970	970
Clusters	81	81	0
R^2	0.960	0.966	0.953

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

References

Aydın, O. (2004). *Kürdistan'ın demografisi ve Kürdistan'da nüfus hareketleri*. Spånga: Apec Forlag.

Hainmueller, J. (2012). Entropy balancing for causal effects: A multivariate reweighting method to produce balanced samples in observational studies. *Political Analysis*, *20*(1), 25–46.

TurkStat. (2016). Cinsiyete göre polis sayıları ve cinsiyet oranı, 2003–2016. Retrieved from http://www.turkstat.gov.tr