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

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**Abstract**

Security forces have recently become the main target of political violence again. This article examines the effect of their casualties on elections. Between two general elections in 2015, Turkey experienced a series of attacks that killed 153 members of the security forces. Based on the as-if random variation of their funerals across the country, I estimate that the government vote share increases in the burial places of terror victims. However, in the towns with recurring funerals, 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. These results provide strong evidence for the rally theory.

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# 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 guerrilla campaigns again (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 a perception of threat (Canetti et al., 2013), which in turn influence their political attitudes (Canetti-Nisim et al., 2009; Hirsch-Hoefler et al., 2016). Therefore, terror attacks might affect political behaviour not only with the death of security forces but also with their burial.

This article examines the effect of security force casualties in terror attacks on vote choice in elections. Specifically, it analyses whether and how aggregate voting behaviour differs in districts that receive 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 153 members of the Turkish security forces dead, and (c) their burial places varied across the districts of Turkey as a result of compulsory random assignment to and rotation of workplaces among the security personnel. Conditional on the number of personnel in service from each district, 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 et al., 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 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).

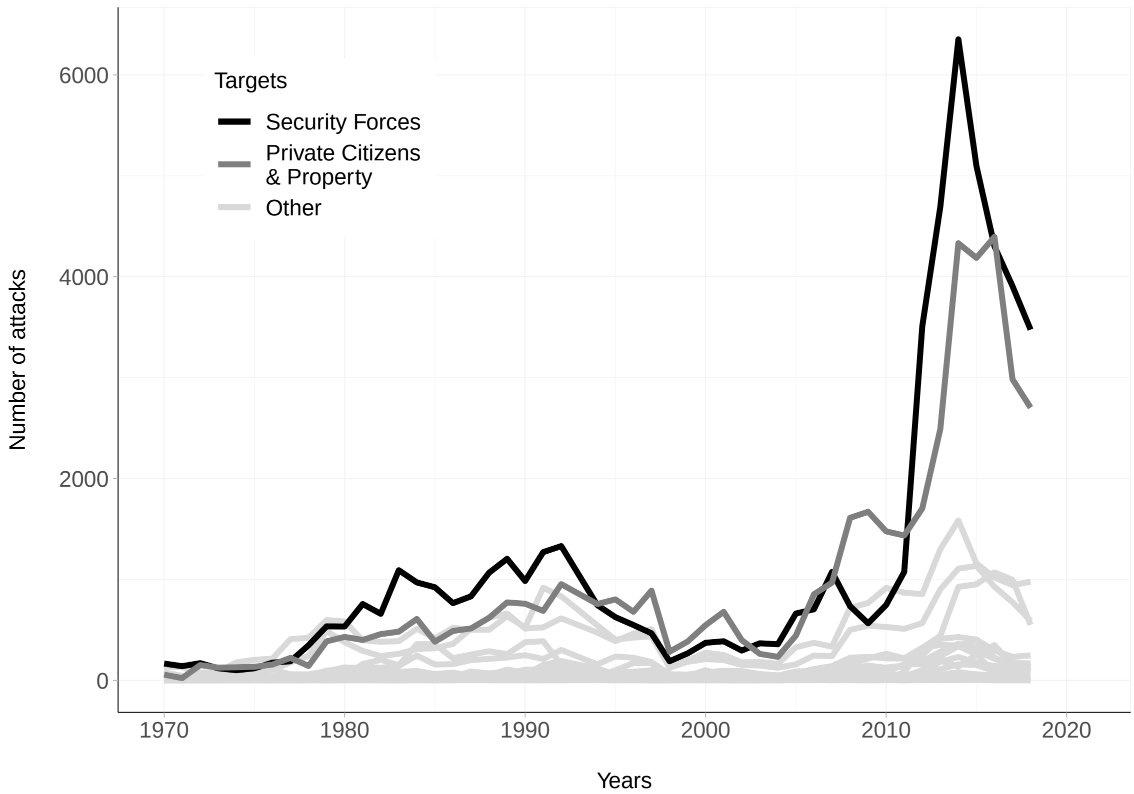


Figure 1: Trends in political violence by target. Security forces have become the main target of political violence again in the last decade. *Note*: *Security Forces* consists of *Military* and *Police*, the original categories in the source—Global Terrorism Database (LaFree & Dugan, 2007).

This article extends the existing knowledge in at least two ways. Theoretically, it contributes to the efforts to develop an understanding of security forces as distinct targets of political violence. While they have been the main target for much of the known history of terrorism, civilians and civilian casualties remain the focus of the related literature. Empirically, with a clear identification strategy, this article provides strong evidence for the rally theory, where the electoral effects of casualties differ not only from government to opposition parties but also from the initial to repeated failures of governments to prevent the killing of security forces.

# 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 distance 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 et al., 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 congressmen

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

(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 et al., 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 electoral outcomes. 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 et al., 2013).

These studies focus either explicitly on civilian casualties or casualties in general, leaving the combatant casualties under-researched. Despite all we know about casualties and elections, it is puzzling how little of the existing evidence comes from security force casualties in terror attacks. One exception is Kibris (2011), which is an analysis of Turkish security force casualties itself, in the first half of 1990s. It reports that province-level casualties correlate negatively with the vote share of governing parties but positively with that of right-wing parties. Neither of these main findings replicates in this study.[2]

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

[2] In addition to being a province-level analysis, Kibris (2011) excludes the south-east provinces in Turkey and does not control for the fact that some units were not comparable across the elections as they were divided into smaller provinces during the time-frame under analysis (Kibris, 2011, pp. 229–230). These potentially consequential choices could be among the reasons why neither of its main findings replicates here.

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 killed over 7,500 members of the Turkish security forces alone (TGNA, 2013).[3] 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 153 security personnel had been killed in rapidly escalating terror attacks. Figure 2 marks the 47 districts[4] where these terror casualties occurred, systematically pointing to the south-eastern region of the country.

In contrast, as Figure 3 shows, the burial places of these casualties are scattered across the country. This is because Turkish security force personnel serve anywhere but in their hometown, randomly assigned to and rotated among the other districts and provinces (Kibris, 2011, p. 223). Indeed, none of the 153 victims were serving in their home district at the time of their killing—instead, they were originally from 123 other districts unbeknown to the attackers, somewhere on average 715 kilometres away from

[3]The civilian death toll was at least 5,500 in the same period of time, 1981–2011 (TGNA, 2013). See Figure S1 for a visualisation of the number of security force casualties in the last decade. All figures and tables numbered with the prefix *S* are in the online Supporting Information.

[4]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.

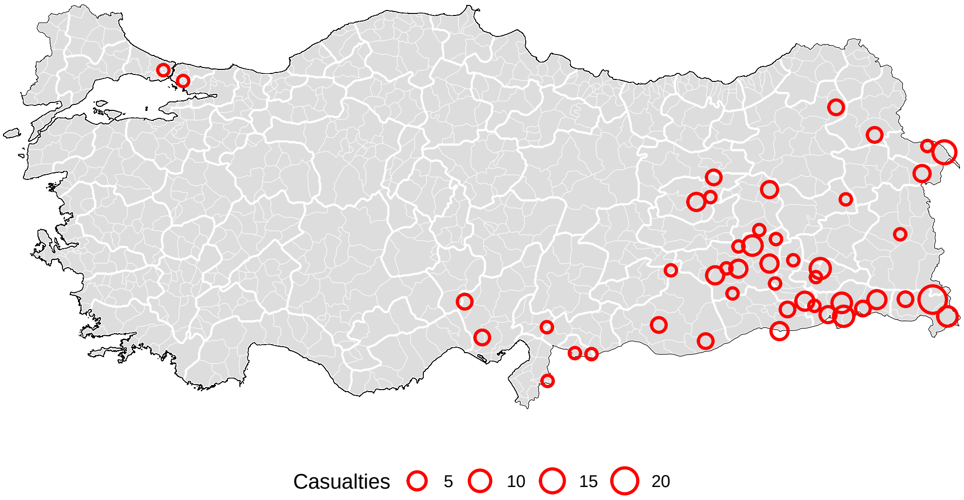


Figure 2: Districts of terror attacks with security force casualties. The death places are concentrated in south-east Turkey.

the attacks (sd = 362, median = 718, min = 46, max = 1576). In other words, terrorist groups might target security forces *in* specific districts in Turkey, but they cannot target *to* which districts their victims will be taken in coffins.

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. Within a day or so after the deadly attacks, flag-draped coffins arrive in home districts, where state funerals take place. Fellow townspeople, typically in their thousands, attend these ceremonies with high-level representatives from political parties, the 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. 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 random assignment and workplace rotation for the security forces.

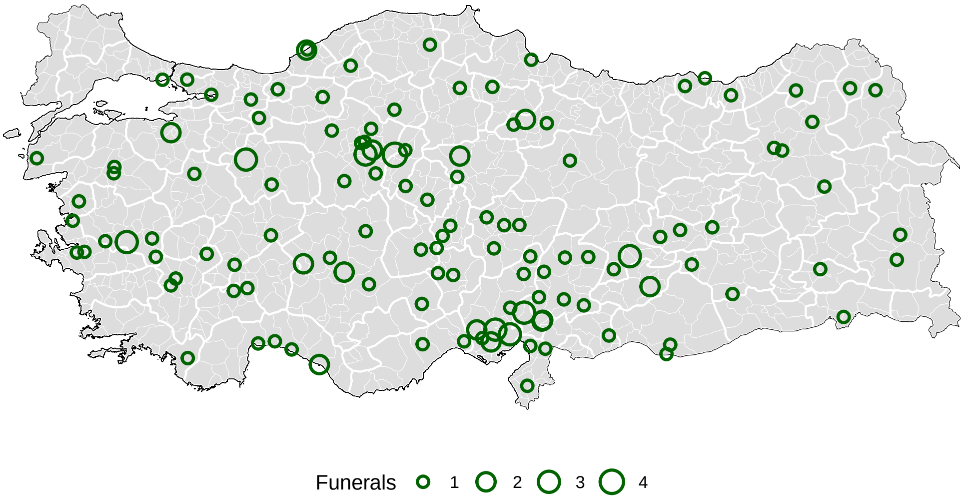


Figure 3: Treatment districts. The burial places are distributed as-if randomly across Turkey.

This is a favourable setting to estimate the causal effect of security force casualties in terror attacks on electoral outcomes—with the overall assumption that the districts are treated with funerals as-if randomly, and therefore that those with and without funerals are comparable, conditional on the number of security personnel in service from each district. Overall, 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), coded as the percentage of valid votes cast for the parties in each election. News archives are the source of the data on security force casualties, with *Treatment* coded as 1 for the 123 districts that had at least one funeral in between the elections. While 102 districts were treated only once, the remaining 21 districts were treated multiple times—they received two or more casualties (mean = 2.4, sd = 0.6, median = 2, min = 2, max = 4). I coded *Multiple Treatment* as 1 for these districts, making possible to distinguish between the effect of the initial and repeated casualties—a key element of the rally effect but one that has been unexplored so far.

The condition on the as-if random treatment is due to the likely consequential differences in the number of security personnel recruited from each district, requiring an adjustment for the increased probability of being assigned to the treatment group among the districts with more townsmen in service. In the absence of precise data on this variable, I use a proxy measure—*Recruitment Pool*, the number of men in their 20s from each district.[5] The motivation for this control strategy is the fact that age and gender strongly predicts who serves in the Turkish security forces. The compulsory military service is for male citizens only, after turning 20 (Yildirim & Erdinç, 2007). Police officers are also almost exclusively male as well (Ekşi, 2017), with most recruited in their early 20s (Caglar, 2004). This is reflected in the data, as all 153 casualties were male, with an average age of 28.9 (sd = 7.6, median = 26, min = 20, max = 54). Moreover, randomisation checks reported in Table S2 confirm that *Recruitment Pool* is a predictor of the treatment status.[6] Once it is controlled for, these checks suggest that the treatment assignment is

[5]The data for this variable comes from TurkStat, as measured at the end of 2014. Here the variable is specified in thousands.

[6]Correlation analyses show that the age bin 20–29 (i.e., number of men in their 20s) is a better predictor than other age bins—such as 20–24 or 25–29 on their own, or various other combinations of the bins in the original TurkStat data.

uncorrelated with a number of other district characteristics,[7] which are used as further controls in the regression analyses below.

## Results

Figure 4 plots the government vote share in the two general elections of 2015, by treatment status. It shows that the treated and control districts were separated by a 1.3 percentage point difference in favour of the treated districts in the pre-test. In the post-test, however, this difference is double the size, and the government vote share was 2.6 percentage points higher in the districts that received one or more casualties before the second election, compared to the control districts with no casualties. Overall, the comparison of the average vote shares suggests that security force casualties might have increased the electoral support for the government.

The results in Table 1 confirm that this is a statistically significant increase. These are ordinary least squares (OLS) regression models with standard errors clustered at the level of provinces. In the first two models, which do not include *Multiple Treatment*, the coefficients of *Treatment* inform us about the same comparison visualised in Figure 4—the differences between the government vote share in the districts with and without *one or more* funerals. After regression adjustments, the best estimates for the difference are

[7] These include indicators for the districts where casualties occurred and for the districts with predominantly Kurdish population as well as shares of district-level higher education attainment, electoral marginality, and turnout.

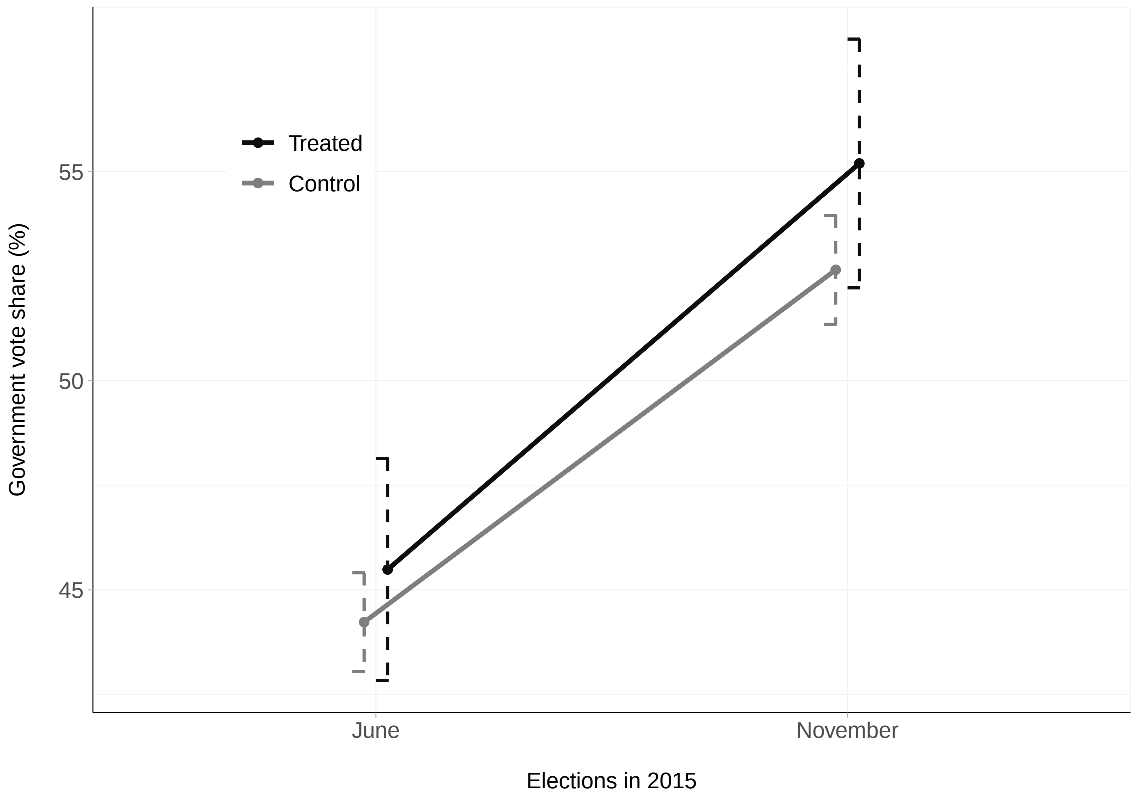


Figure 4: Change in government vote share. Compared to the control group of districts with no funerals (*Treatment*= 0), the average vote share of the government increased at a higher rate among the treated districts (*Treatment*= 1).

just over 1 percentage point. This is slightly smaller than, yet comparable with, the simple difference of group means above (2.6 *versus* 1.3).

What happens when *Multiple Treatment* is introduced into the analysis, as in Model 3 and 4? First, *Treatment* now estimates the effect of a *single* casualty, instead of *one or more* casualties, on vote share. These estimates are slightly higher than in the preceding models, indicating that the government vote share increased by about 1.2 percentage points in the districts with only one funeral in between the elections. This provides support for the rally hypothesis.

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

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Treatment | 1.028* | 1.048** | 1.257** | 1.240** |
| | (0.412) | (0.386) | (0.470) | (0.431) |
| Multiple Treatment | | | –1.471* | –1.246* |
| | | | (0.716) | (0.560) |
| Pre-test | ✓ | ✓ | ✓ | ✓ |
| Recruitment Pool | ✓ | ✓ | ✓ | ✓ |
| Other Covariates | ✗ | ✓ | ✗ | ✓ |
| Constant | 4.590*** | 16.188** | 4.578*** | 16.268*** |
| | (0.878) | (4.740) | (0.875) | (4.758) |
| N | 970 | 970 | 970 | 970 |
| Clusters | 81 | 81 | 81 | 81 |
| $R^2$ | 0.960 | 0.968 | 0.960 | 0.968 |

*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). * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Second, the effect of *more than one* casualty is now captured by *Multiple Treatment*. In contrast to the previous scenario, the results show that multiple casualties significantly decreased the electoral support for the Turkish government—by 1.2 to 1.5 percentage points, depending on the model specifications. In other words, repeated casualties reverse the rally effect that emerge after just one casualty. Hence there is support for the repetition hypothesis as well.

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 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 ($RW$)[8] 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. The results confirm the nonpartisan hypothesis.

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

| | CHP | MHP | HDP | RW |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Treatment | –0.064 | –0.148 | –0.233 | 0.163 |
| | (0.224) | (0.322) | (0.264) | (0.371) |
| Multiple Treatment | –0.240 | 1.255 | 0.186 | –1.025 |
| | (0.429) | (0.908) | (0.455) | (0.618) |
| Pre-test | ✓ | ✓ | ✓ | ✓ |
| Recruitment Pool | ✓ | ✓ | ✓ | ✓ |
| Other Covariates | ✓ | ✓ | ✓ | ✓ |
| Constant | –4.549* | –5.896 | –14.233*** | 19.448** |
| | (2.258) | (3.078) | (3.460) | (6.295) |
| N | 970 | 970 | 970 | 970 |
| Clusters | 81 | 81 | 81 | 81 |
| $R^2$ | 0.980 | 0.881 | 0.989 | 0.972 |

*Notes*: This table runs Model 4 of Table 1 for the opposition parties (Models 1–3) and the group of right wing parties (Model 4). See Table S4 to Table S7 for the complete results. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

[8] For right wing 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.

These main results are robust to rigorous tests, reported in the online Supporting Information. With regard to the comparability of treatment and control groups, Tables S9 and S10 show that the substantive results do not change if the data is weighted with entropy balancing, which creates perfectly balanced samples with respect to *Treatment*. In re-consideration of the treatment coding, the results replicate in two alternative schemes, designed to isolate the effect of single casualties (Table S11) and detect quadratic relationships (Table S12). Finally, further tests also rule out the possibility that differences in turnout (Table S13) or treatment timing (Table S14) could have driven the change in the government vote share.

## Conclusion

Societies are experiencing a reoccurring 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 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 does 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.

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SUPPORTING INFORMATION

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

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# A Casualty trends in Turkey

As mentioned in the main text, following a relatively calm period of two and a half years, Turkey experienced a surge in political violence soon after the June 2015 elections. Figure S1, based on data compiled by the International Crisis Group (www.crisisgroup.org), visualises the resulting Turkish security force casualties for much of the last decade.

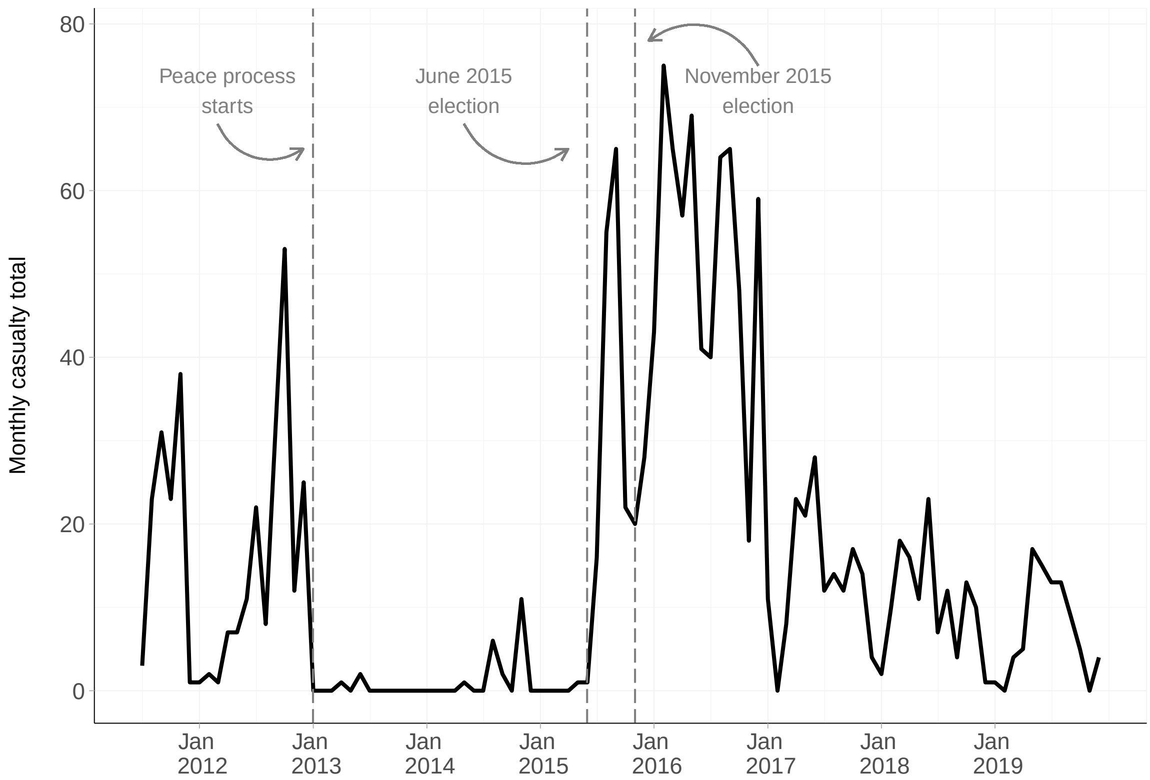


Figure S1: Recent trends in security force casualties in Turkey. Political violence resumes in between two elections in 2015. *Source*: International Crisis Group.

# B Data

There are three main components of the data: security force casualties, election results, and district characteristics. While the latter two originate mostly 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.

## B.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 military and police forces, excluding the village guards—paramilitaries recruited to protect their own village. This resulted in 153 observations. For each casualty, I then coded their (a) district of killing, (b) district of burial, and (c) date of burial.

## B.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.

## B.3 District characteristics

The dataset also includes a number of variables on district characteristics, to adjust the regression estimates accordingly. Most importantly, these include *Recruitment Pool*, which is, as discussed in the main text, an important control for the likely equal probabilities of being assigned to the treatment group among districts with high or low number of people in security forces in the first place. All characteristics are measured pre-treatment.

## B.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 for districts with *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, 123 had at least one funeral within this time frame between two general elections.

*Multiple Treatment.* A binary variable coded as 1 for districts with *more than one* funeral between 7 June and 1 November 2015 for security forces killed in terror attacks. Out of the 123 treated districts, 21 were treated multiple times.

*Recruitment Pool.* A count variable measuring the number of male residents in their 20s in each district at the end of 2014.

Table S1: Descriptive statistics

| | Mean | SD | Median | Minimum | Maximum |
|---|---|---|---|---|---|
| Treatment | 0.13 | 0.33 | 0 | 0 | 1 |
| Multiple Treatment | 0.02 | 0.15 | 0 | 0 | 1 |
| Recruitment Pool | 6.57 | 10.85 | 2.25 | 0.09 | 88.25 |
| Non-terror Funeral | 0.04 | 0.19 | 0 | 0 | 1 |
| Attack District | 0.05 | 0.21 | 0 | 0 | 1 |
| Kurdish District | 0.18 | 0.39 | 0 | 0 | 1 |
| Higher Education | 7.27 | 4.34 | 6.23 | 1.46 | 36.85 |
| Electoral Margin | 4.74 | 5.16 | 2.86 | 0.07 | 32.64 |
| Turnout | 85.59 | 4.23 | 86.20 | 67.00 | 98.80 |
| *Pre-Test* | | | | | |
| AKP (Jun) | 44.39 | 17.18 | 45.60 | 1.20 | 90.70 |
| CHP (Jun) | 21.12 | 15.07 | 19.15 | 0.20 | 77.10 |
| MHP (Jun) | 17.36 | 9.05 | 17.60 | 0.40 | 50.10 |
| HDP (Jun) | 12.40 | 23.12 | 2.00 | 0.10 | 97.40 |
| RW (Jun) | 63.77 | 21.97 | 68.00 | 2.00 | 97.00 |
| *Post-Test* | | | | | |
| AKP (Nov) | 52.97 | 19.00 | 54.70 | 2.00 | 95.90 |
| CHP (Nov) | 21.15 | 15.71 | 18.90 | 0.40 | 79.50 |
| MHP (Nov) | 12.32 | 7.01 | 12.10 | 0.20 | 41.50 |
| HDP (Nov) | 10.40 | 21.10 | 1.20 | 0.00 | 95.80 |
| RW (Nov) | 65.29 | 20.94 | 69.80 | 3.30 | 98.40 |

*Non-terror Funeral.* State funerals are held not only for the terror victims among the security forces, but also for those who die from other causes during their service. There were 42 such cases, where the deaths were related to, for example, hearth attacks, traffic accidents, or lightning strikes. This variable is coded as 1 for the 36 districts where their funerals took place.

*Attack District.* A binary variable coded as 1 for districts with one or more terror attacks between 7 June and 1 November 2015 that resulted in 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.

*Higher Education.* A variable measuring the share of district population with university education at the end of 2014.

*Turnout.* A variable measuring the percentage of eligible voters who cast a ballot in each district in the 7 June 2015 elections.

*Electoral Margin.* A variable measuring the electoral marginality of the last seat in each province (i.e., electoral district) in the 7 June 2015 elections, calculated as the percentage of votes needed either to win or to defend the last seat.

*Pre-Test.* 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.

*Post-Test.* 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.

# C 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. The estimates for *Recruitment Pool* are positive and statistically significant. 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. However, once *Recruitment Pool* is controlled for, as in every regression model in this analysis, we see that the treatment and control districts become comparable in terms of other characteristics. Notice also that, Section E below provides robustness checks based on entropy balancing, which creates perfectly balanced samples with respect to *Treatment*.

Table S2: Randomisation check

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Recruitment Pool | 0.007* | 0.007* | 0.008** | 0.008* |
| | (0.003) | (0.003) | (0.003) | (0.003) |
| AKP (Jun) | | 0.001 | –0.001 | –0.004 |
| | | (0.001) | (0.010) | (0.009) |
| CHP (Jun) | | | 0.004 | 0.005 |
| | | | (0.006) | (0.006) |
| MHP (Jun) | | | 0.006 | 0.004 |
| | | | (0.009) | (0.009) |
| HDP (Jun) | | | 0.006 | 0.006 |
| | | | (0.006) | (0.006) |
| RW (Jun) | | | 0.007 | 0.010 |
| | | | (0.010) | (0.010) |
| Non-terror Funeral | | | | 0.142 |
| | | | | (0.077) |
| Attack District | | | | –0.046 |
| | | | | (0.039) |
| Kurdish District | | | | 0.065 |
| | | | | (0.047) |
| Higher Education | | | | –0.000 |
| | | | | (0.003) |
| Electoral Margin | | | | –0.002 |
| | | | | (0.002) |
| Turnout | | | | –0.002 |
| | | | | (0.003) |
| Constant | 0.080*** | 0.026 | –0.547 | –0.454 |
| | (0.013) | (0.032) | (0.565) | (0.622) |
| N | 970 | 970 | 970 | 970 |
| $R^2$ | 0.054 | 0.057 | 0.098 | 0.108 |

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

# D 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 results for AKP—the governing party

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Treatment | 1.028* | 1.048** | 1.257** | 1.240** |
| | (0.412) | (0.386) | (0.470) | (0.431) |
| Multiple Treatment | | | –1.471* | –1.246* |
| | | | (0.716) | (0.560) |
| Pre-test | 1.084*** | 1.093*** | 1.084*** | 1.093*** |
| | (0.016) | (0.015) | (0.016) | (0.015) |
| Recruitment Pool | 0.020 | 0.061*** | 0.023 | 0.063*** |
| | (0.015) | (0.015) | (0.016) | (0.016) |
| Non-terror Funeral | | –0.479 | | –0.455 |
| | | (0.413) | | (0.407) |
| Attack District | | –1.146 | | –1.186 |
| | | (1.001) | | (1.005) |
| Kurdish District | | 3.366*** | | 3.359*** |
| | | (0.775) | | (0.765) |
| Higher Education | | –0.135*** | | –0.134*** |
| | | (0.036) | | (0.036) |
| Electoral Margin | | 0.026 | | 0.027 |
| | | (0.035) | | (0.035) |
| Turnout | | –0.140** | | –0.141** |
| | | (0.052) | | (0.053) |
| Constant | 4.590*** | 16.188** | 4.578*** | 16.268*** |
| | (0.878) | (4.740) | (0.875) | (4.758) |
| N | 970 | 970 | 970 | 970 |
| Clusters | 81 | 81 | 81 | 81 |
| $R^2$ | 0.960 | 0.968 | 0.960 | 0.968 |

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

Table S4: Complete results for CHP

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Treatment | –0.145 | –0.101 | –0.116 | –0.064 |
| | (0.190) | (0.206) | (0.212) | (0.224) |
| Multiple Treatment | | | –0.183 | –0.240 |
| | | | (0.357) | (0.429) |
| Pre-test | 1.029*** | 1.033*** | 1.029*** | 1.033*** |
| | (0.010) | (0.013) | (0.010) | (0.013) |
| Recruitment Pool | 0.018** | –0.005 | 0.018** | –0.004 |
| | (0.006) | (0.009) | (0.006) | (0.009) |
| Non-terror Funeral | | 0.742* | | 0.747* |
| | | (0.361) | | (0.358) |
| Attack District | | 0.559 | | 0.552 |
| | | (0.472) | | (0.472) |
| Kurdish District | | 1.316* | | 1.316* |
| | | (0.501) | | (0.500) |
| Higher Education | | 0.123*** | | 0.123*** |
| | | (0.025) | | (0.025) |
| Electoral Margin | | 0.059* | | 0.059* |
| | | (0.024) | | (0.024) |
| Turnout | | 0.029 | | 0.029 |
| | | (0.026) | | (0.026) |
| Constant | –0.694** | –4.557* | –0.697** | –4.549* |
| | (0.213) | (2.257) | (0.213) | (2.258) |
| N | 970 | 970 | 970 | 970 |
| Clusters | 81 | 81 | 81 | 81 |
| $R^2$ | 0.978 | 0.980 | 0.978 | 0.980 |

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

Table S5: Complete results for MHP

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Treatment | –0.053 | 0.036 | –0.228 | –0.148 |
| | (0.337) | (0.312) | (0.345) | (0.322) |
| Multiple Treatment | | | 1.177 | 1.255 |
| | | | (0.903) | (0.908) |
| Pre-test | 0.726*** | 0.718*** | 0.724*** | 0.717*** |
| | (0.026) | (0.036) | (0.026) | (0.035) |
| Recruitment Pool | 0.016* | –0.009 | 0.014 | –0.012 |
| | (0.008) | (0.009) | (0.009) | (0.009) |
| Non-terror Funeral | | –0.309 | | –0.327 |
| | | (0.368) | | (0.373) |
| Attack District | | 0.267 | | 0.300 |
| | | (0.443) | | (0.456) |
| Kurdish District | | –0.139 | | –0.159 |
| | | (0.576) | | (0.567) |
| Higher Education | | 0.075** | | 0.074** |
| | | (0.025) | | (0.025) |
| Electoral Margin | | –0.097** | | –0.097** |
| | | (0.035) | | (0.035) |
| Turnout | | 0.067 | | 0.068 |
| | | (0.037) | | (0.036) |
| Constant | –0.382 | –5.892 | –0.343 | –5.896 |
| | (0.345) | (3.088) | (0.329) | (3.078) |
| N | 970 | 970 | 970 | 970 |
| Clusters | 81 | 81 | 81 | 81 |
| $R^2$ | 0.871 | 0.880 | 0.871 | 0.881 |

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

Table S6: Complete results for HDP

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Treatment | –0.374 | –0.204 | –0.367 | –0.233 |
| | (0.208) | (0.231) | (0.228) | (0.264) |
| Multiple Treatment | | | –0.046 | 0.186 |
| | | | (0.548) | (0.455) |
| Pre-test | 0.906*** | 0.939*** | 0.906*** | 0.939*** |
| | (0.013) | (0.017) | (0.013) | (0.017) |
| Recruitment Pool | –0.007 | –0.030*** | –0.007 | –0.031*** |
| | (0.007) | (0.007) | (0.007) | (0.007) |
| Non-terror Funeral | | –0.044 | | –0.047 |
| | | (0.436) | | (0.434) |
| Attack District | | 2.065* | | 2.070* |
| | | (0.843) | | (0.845) |
| Kurdish District | | –3.001** | | –3.002** |
| | | (0.908) | | (0.907) |
| Higher Education | | 0.022 | | 0.021 |
| | | (0.015) | | (0.015) |
| Electoral Margin | | 0.013 | | 0.013 |
| | | (0.028) | | (0.028) |
| Turnout | | 0.157*** | | 0.157*** |
| | | (0.039) | | (0.039) |
| Constant | –0.740*** | –14.230*** | –0.741*** | –14.233*** |
| N | 970 | 970 | 970 | 970 |
| Clusters | 81 | 81 | 81 | 81 |
| $R^2$ | 0.986 | 0.989 | 0.986 | 0.989 |

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

Table S7: Complete results for right-wing parties together

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Treatment | 0.205 | 0.007 | 0.420 | 0.163 |
| | (0.402) | (0.345) | (0.431) | (0.371) |
| Multiple Treatment | | | –1.395 | –1.025 |
| | | | (0.972) | (0.618) |
| Pre-test | 0.935*** | 0.971*** | 0.935*** | 0.971*** |
| | (0.016) | (0.015) | (0.016) | (0.015) |
| Recruitment Pool | 0.026 | 0.083*** | 0.029* | 0.085*** |
| | (0.015) | (0.014) | (0.014) | (0.013) |
| Non-terror Funeral | | –0.823 | | –0.805 |
| | | (0.555) | | (0.560) |
| Attack District | | –1.265 | | –1.295 |
| | | (0.916) | | (0.918) |
| Kurdish District | | 5.276*** | | 5.277*** |
| | | (0.918) | | (0.921) |
| Higher Education | | –0.206*** | | –0.205*** |
| | | (0.047) | | (0.047) |
| Electoral Margin | | –0.127* | | –0.127* |
| | | (0.055) | | (0.055) |
| Turnout | | –0.180* | | –0.180* |
| | | (0.071) | | (0.071) |
| Constant | 5.479*** | 19.429** | 5.450*** | 19.448** |
| | (1.182) | (6.274) | (1.176) | (6.295) |
| N | 970 | 970 | 970 | 970 |
| Clusters | 81 | 81 | 81 | 81 |
| $R^2$ | 0.958 | 0.972 | 0.958 | 0.972 |

*Notes*: Models include OLS coefficients with clustered standard errors in parentheses. The dependent variable is the right-wing vote share in each district—the total vote share achieved by three parties, AKP, MHP, and SP. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

# E Robustness Checks

This section provides a series of five checks on the robustness of the statistically significant results reported in the main text.

## E.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 C above) that in all but one cases these differences are statistically insignificant, the entropy balancing method offers an opportunity to remove these imbalances completely (Hainmueller, 2012). Table S8 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.

Table S8: Treatment and control groups before and after entropy balancing

| | Before Matching | | After Matching | |
|---|---|---|---|---|
| | Treatment | Control | Treatment | Control |
| Recruitment Pool | 13.17 | 5.61 | 13.17 | 13.17 |
| Non-terror Funeral | 0.10 | 0.03 | 0.10 | 0.10 |
| Attack District | 0.04 | 0.05 | 0.04 | 0.04 |
| Kurdish District | 0.15 | 0.19 | 0.15 | 0.15 |
| Higher Education | 8.42 | 7.10 | 8.42 | 8.42 |
| Electoral Margin | 4.27 | 4.81 | 4.27 | 4.27 |
| Turnout | 85.63 | 85.58 | 85.63 | 85.63 |

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

With the weights obtained from this balancing procedure, Table S9 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 victims by about 1.2 percentage points, this rally effect disappears in the towns with repeated casualties. The resulting decrease is again about 1.42 percentage points.

Table S9: Regression models based on entropy balancing, for AKP—the governing party

| | (1) | | (2) | |
|---|---|---|---|---|
| | Coefficient | Std. Error | Coefficient | Std. Error |
| Treatment | 0.969* | 0.418 | 1.168* | 0.478 |
| Multiple Treatment | | | –1.152* | 0.585 |
| Pre-test | 1.090*** | 0.014 | 1.089*** | 0.014 |
| Constant | 4.619*** | 0.622 | 4.689*** | 0.622 |
| N | 970 | | 970 | |
| $R^2$ | 0.951 | | 0.951 | |

*Notes*: Models include results from OLS regressions. The data is adjusted with the entropy balancing weights. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Based on the same weighted data from entropy balancing, Table S10 presents the results for the three opposition parties and the right-wing group. Confirming what has been reported in the main text, these models return null results: there is no evidence that casualties affect the vote share of other parties individually, or that of right-wing parties together. In contrast to the results from the analysis of the government vote share, here the coefficients for *Treatment* and *Multiple Treatment* are not only small, but also statistically insignificant.

Table S10: Regression models based on entropy balancing, for other parties

| | CHP | MHP | HDP | RW |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Treatment | –0.186 | –0.065 | –0.259 | 0.554 |
| | (0.209) | (0.300) | (0.260) | (0.465) |
| Multiple Treatment | 0.043 | 1.430 | –0.209 | –1.047 |
| | (0.347) | (0.798) | (0.497) | (1.013) |
| Pre-test | 1.031*** | 0.703*** | 0.887*** | 0.916*** |
| | (0.007) | (0.023) | (0.014) | (0.013) |
| N | 970 | 970 | 970 | 970 |
| $R^2$ | 0.981 | 0.841 | 0.983 | 0.952 |

*Notes*: Models include results from OLS regressions. The data is adjusted with the entropy balancing weights. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

## E.2 Single treatment

In the main text, Table 1 distinguishes the effect of the initial from repeated casualties by including the two binary variables together in the same regression models (Models 3 and 4): *Treatment* (the districts with *one or more* casualties) and *Multiple Treatment* (the districts with *more than one* casualty). Table S11 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.

Table S11: Regression models with *Single Treatment*

| | All Districts Included | | Excluding the Multiply-Treated | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Single Treatment | 1.266** | 1.240** | 1.237* | 1.215** |
| | (0.470) | (0.428) | (0.473) | (0.435) |
| Pre-test | 1.084*** | 1.093*** | 1.084*** | 1.094*** |
| | (0.016) | (0.015) | (0.016) | (0.015) |
| Recruitment Pool | 0.022 | 0.063*** | 0.027 | 0.066*** |
| | (0.015) | (0.015) | (0.018) | (0.017) |
| Non-terror Funeral | | –0.455 | | –0.367 |
| | | (0.405) | | (0.432) |
| Attack District | | –1.186 | | –1.218 |
| | | (1.003) | | (1.009) |
| Kurdish District | | 3.359*** | | 3.409*** |
| | | (0.764) | | (0.768) |
| Higher Education | | –0.134*** | | –0.132*** |
| | | (0.036) | | (0.038) |
| Electoral Margin | | 0.027 | | 0.026 |
| | | (0.035) | | (0.035) |
| Turnout | | –0.141** | | –0.139** |
| | | (0.052) | | (0.053) |
| Constant | 4.579*** | 16.268*** | 4.573*** | 16.058** |
| | (0.875) | (4.744) | (0.880) | (4.758) |
| N | 970 | 970 | 949 | 949 |
| Clusters | 81 | 81 | 81 | 81 |
| $R^2$ | 0.960 | 0.968 | 0.959 | 0.967 |

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

## E.3 Quadratic treatment

This subsection provides an alternative test for the overall hypothesis that the effect of casualties on electoral outcomes is a non-linear effect. The models in Table S12 include an untransformed count variable *Treatments* (the number of funerals in each district). In addition, Models 3 and 4 include the square of the same variable, *Treatments Squared*, allowing for non-linearity tests. As both variables are statistically significant, with the former being positive and the latter negative, the results confirm that the effect is indeed non-linear: the initially positive effect turns into negative as the number of casualties increases.

Table S12: Regression models with *Treatments Squared*

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Treatments | 0.459 | 0.522* | 1.639* | 1.532* |
| | (0.260) | (0.244) | (0.650) | (0.592) |
| Treatments Squared | | | –0.583* | –0.488* |
| | | | (0.282) | (0.245) |
| Pre-test | 1.085*** | 1.094*** | 1.084*** | 1.104*** |
| | (0.016) | (0.015) | (0.016) | (0.015) |
| Recruitment Pool | 0.022 | 0.062*** | 0.022 | 0.059*** |
| | (0.016) | (0.016) | (0.016) | (0.015) |
| Non-terror Funeral | | –0.452 | | –0.550 |
| | | (0.417) | | (0.437) |
| Attack District | | –1.140 | | –1.336 |
| | | (1.001) | | (1.053) |
| Kurdish District | | 3.365*** | | 3.841*** |
| | | (0.782) | | (0.787) |
| Higher Education | | –0.137*** | | –0.133*** |
| | | (0.037) | | (0.039) |
| Electoral Margin | | 0.026 | | 0.032 |
| | | (0.035) | | (0.035) |
| Turnout | | –0.140** | | |
| | | (0.052) | | |
| Constant | 4.605*** | 16.212*** | 4.592*** | 3.630*** |
| | (0.880) | (4.741) | (0.878) | (0.925) |
| N | 970 | 970 | 970 | 970 |
| Clusters | 81 | 81 | 81 | 81 |
| $R^2$ | 0.959 | 0.967 | 0.960 | 0.967 |

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

## E.4 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 S13 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 in modes with covariates and/or *Multiple Treatment.*

Table S13: Regression models of turnout

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Treatment | 0.505* | 0.370 | 0.531 | 0.419 |
| | (0.249) | (0.230) | (0.269) | (0.255) |
| Multiple Treatment | | | –0.163 | –0.320 |
| | | | (0.354) | (0.398) |
| Pre-test | 0.853*** | 0.818*** | 0.853*** | 0.818*** |
| | (0.039) | (0.032) | (0.039) | (0.032) |
| Recruitment Pool | 0.025** | 0.033*** | 0.025** | 0.033*** |
| | (0.008) | (0.008) | (0.009) | (0.008) |
| Non-terror Funeral | | 0.453 | | 0.459 |
| | | (0.276) | | (0.275) |
| Attack District | | –0.777 | | –0.787 |
| | | (0.474) | | (0.472) |
| Kurdish District | | –2.450*** | | –2.451*** |
| | | (0.658) | | (0.659) |
| Higher Education | | –0.059 | | –0.059 |
| | | (0.030) | | (0.030) |
| Electoral Margin | | –0.064** | | –0.064** |
| | | (0.023) | | (0.023) |
| Constant | 12.791*** | 16.962*** | 12.796*** | 16.971*** |
| | (3.437) | (2.848) | (3.440) | (2.851) |
| N | 970 | 970 | 970 | 970 |
| Clusters | 81 | 81 | 81 | 0 |
| $R^2$ | 0.706 | 0.765 | 0.706 | 0.765 |

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

### E.5 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 whether the change in government vote share is driven by the heterogeneity in treatment timing, Table S14 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 across the models, indicating that the change in government vote share is unrelated to the treatment timing.

Table S14: Regression models with treatment timing

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Treatment | 0.671 | 1.402* | 0.387 | 1.086* |
| | (0.728) | (0.591) | (0.679) | (0.544) |
| Timing (Mean) | 0.006 | –0.006 | | |
| | (0.012) | (0.009) | | |
| Timing (Minimum) | | | 0.011 | –0.001 |
| | | | (0.012) | (0.009) |
| Pre-test | 1.084*** | 1.093*** | 1.084*** | 1.093*** |
| | (0.016) | (0.015) | (0.016) | (0.015) |
| Recruitment Pool | 0.020 | 0.061*** | 0.020 | 0.061*** |
| | (0.015) | (0.015) | (0.015) | (0.015) |
| Non-terror Funeral | | –0.458 | | –0.477 |
| | | (0.417) | | (0.416) |
| Attack District | | –1.142 | | –1.145 |
| | | (1.002) | | (1.003) |
| Kurdish District | | 3.371*** | | 3.366*** |
| | | (0.775) | | (0.775) |
| Higher Education | | –0.136*** | | –0.136*** |
| | | (0.036) | | (0.036) |
| Electoral Margin | | 0.026 | | 0.026 |
| | | (0.035) | | (0.035) |
| Turnout | | –0.140** | | –0.140** |
| | | (0.052) | | (0.052) |
| Constant | 4.589*** | 16.189** | 4.588*** | 16.188** |
| | (0.878) | (4.742) | (0.877) | (4.744) |
| N | 970 | 970 | 970 | 970 |
| Clusters | 81 | 81 | 81 | 81 |
| $R^2$ | 0.960 | 0.968 | 0.960 | 0.968 |

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

# References

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