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

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**Abstract**

Security forces are one of the main targets of political violence. This article examines the effect of their casualties on electoral outcomes. Between two general elections in 2015, Turkey experienced a series of attacks that killed 153 members of its security forces. Based on the as-if random assignment of their funerals across the country, I estimate that government vote share increases in the funeral places of security force terror victims. However, in the localities with recurring funerals, it decreases by a similar percentage. These non-linear changes provide strong evidence for the rally theory.

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# Introduction

Terror attacks are a problem in many countries.[1] The attacks might persist if violence helps radical groups gain concessions from governments (Pape, 2003, 2005), and there are worrying signs for the future. 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 hand, security forces are indeed one of the main targets in terrorist and guerrilla campaigns (Gibbs, 2018). How does the public react to the political violence against their security forces? If voters are sensitive to this specific type of violence, their electoral behaviour might affect the way governments approach violent groups. However, despite the existing evidence with regard to political violence against security forces, we know very little about its electoral consequences.

State funerals might be one reason why security force casualties are remarkably effective in gaining concessions from governments. 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 funeral.

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[1] According to the Global Terrorism Database (LaFree & Dugan, 2007), the last decade saw one or more terror attacks in over three quarters of all the countries in the world.

This article examines the effect that security force casualties in terror attacks have on vote choice in elections. Specifically, it analyses whether and how government vote share differs in districts that receive casualties of local townsmen from the 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 funeral 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 one of the major premises in the literature. 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 *multiple* casualties that government vote share *decreases*. 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 a national crisis (Brody, 1991; Mueller, 1973).

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 a distinct target of political violence. While they have been one of the main targets for much of the known history of terror attacks, civilians and civilian casualties remain the focus of the public and academic debate. Empirically, with a clear identification strategy, this article provides strong evidence for the rally theory, demonstrating how the electoral effects of casualties are different between the initial and repeated failures of governments to prevent the killing of security force members.

## Casualties and Elections

Casualties are the most important information cue about an armed conflict. For the majority of people away from conflict zones, loss of lives[2] are 'salient, visible, and accountable measures of cost' (Gartner & Segura, 2008, p. 95). As such, the public evaluates the success or failure of a country's involvement in a conflict, first and foremost, with the number of its 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 these increases, the closer the 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 terror 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;

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

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 the former US President George W. 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. Senators (Kriner & Shen, 2007) and congressmen (Grose & Oppenheimer, 2007) from the Republican party, which was in control of the government during the Iraq War, suffered electoral losses for casualties among their constituents. In contrast, 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).[3]

With regard to terrorism, there is more evidence that casualties affect electoral outcomes. Public support for right-wing parties increases 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 an 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 terror threat (Getmansky & Zeitzoff, 2014). Then again, both Bali (2007) and Montalvo (2011) find

[3]Perhaps the only notable exception to all these findings in the US comes from a cross national study, where Koch (2011) reports that wartime casualties *increase* the incumbent vote share.

that the 2004 Madrid train bombings led to a significant decrease in the government vote share in the Spanish general election 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 on the left-wing of the ideological spectrum (Williams et al., 2013).

These terrorism studies either focus on civilian casualties or look at casualties in general, leaving the security force casualties under-researched. Despite all we know about casualties and elections, it is puzzling how little of the existing evidence comes specifically 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 the governing parties but positively with that of the right-wing parties.

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). Indeed, 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.

This study helps fill these two dimensions of the research gap. On the one hand, like Kibris (2011), it focuses on security force casualties and uses the rotation of workplaces among the security personnel as an identification strategy. On the other hand, it provides a rigorous test for the main assumptions of the ‘rally ’round the flag effect’, including the assumption of non-linear public behaviour, with data from towns at elections held less than five months apart.

## 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, to where the public turns to form their opinion about a conflict in general and especially about their governments' handling of that conflict (Russett, 1990).

Although the rally theory is developed over the observations of public support for US Presidents in times of war, the rally effect is a 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 public support for government would increase in localities that experience a casualty.

H1: Government vote share increases in localities with 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 terror attacks, after which the rally effects start to fade away. Therefore, I expect that when localities experience multiple security force casualties, public opinion would change direction.

H2: Government vote share decreases in localities with multiple security force casualties.

# Data and Design

This study provides evidence from Turkey—one of the hardest-hit countries in the recent history of terror attacks. In fact, it has long been a target of Kurdish groups among others, and in about three decades, almost 8,000 members of the Turkish security forces died in terror attacks (TGNA, 2013). Figure 1 visualises the monthly number of security force casualties in the last decade.

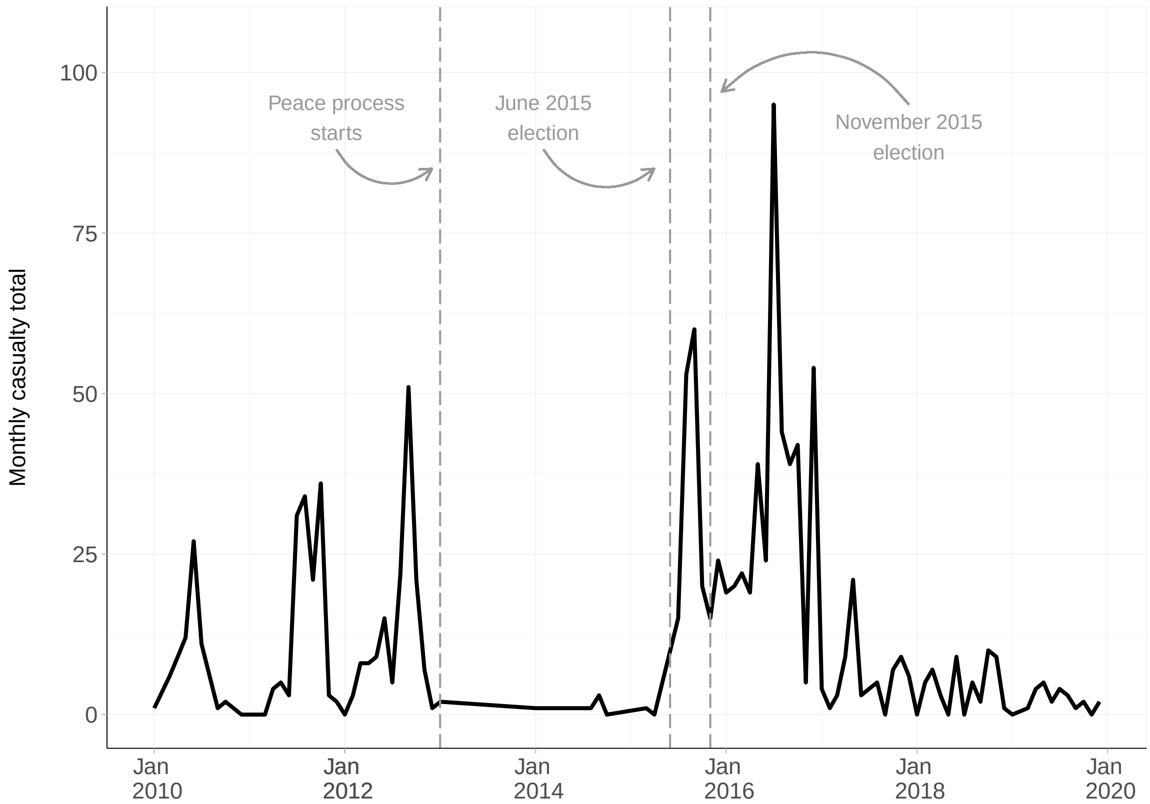


Figure 1: Recent trends in security force casualties in Turkey, 2010–2020. Political violence resumed in between the two elections in 2015. *Source*: UCDP Georeferenced Event Dataset (Pettersson & Öberg, 2020).

The 7 June 2015 general election took place amid a strained but nevertheless ongoing peace process, when the governing 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.[4] By the time the election was repeated on 1 November 2015, a further 153 security personnel had been killed in rapidly escalating terror attacks. Kemahlıoğlu (2015) and Sayarı (2016) provide detailed accounts of this series of events.

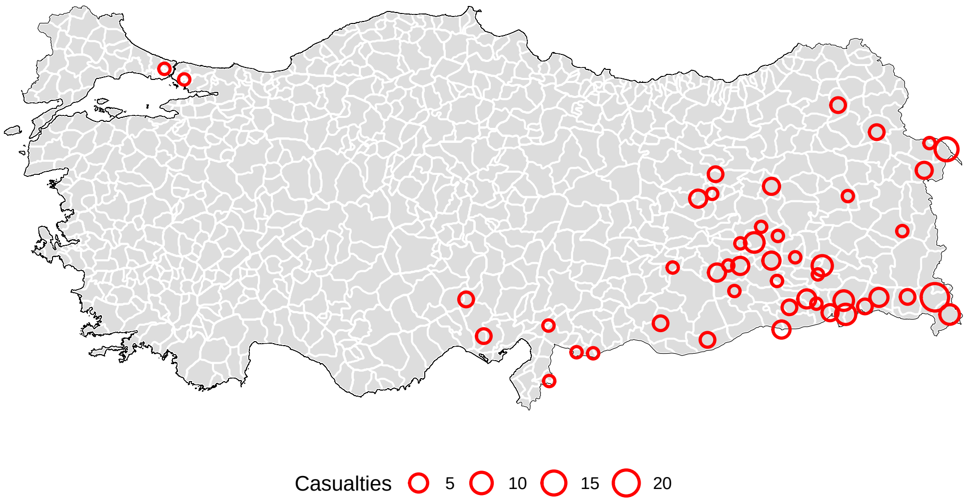


Figure 2: Districts of terror attacks with one or more security force casualties. The death places were concentrated in south-east Turkey.

Figure 2 marks the 47 districts[5] 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. Within a day or so after

[4]Yet a large majority of casualties occurred in attacks by the Kurdistan Workers' Party (PKK)—a separatist organisation that uses terrorist tactics. The only exceptions were the five casualties inflicted by the Islamic State of Iraq and Syria (ISIS; 4) or the Free Syrian Army (FSA; 1). The results reported below are not sensitive to excluding the latter group of casualties from the analysis. See Table S9 for further details. All tables numbered with the prefix $S$ are in the online Supporting Information.

[5]At the time, there were 970 districts (*ilçe*; the unit of observation and analysis in this study), nested in 81 provinces (*il*; the clustering variable in regression analyses) in Turkey.

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 the political parties, the bureaucracy, and the government alike. 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.

As Figure 3 shows, the funeral places of these casualties were scattered across the whole country. This is because the Turkish security force personnel serve anywhere except in their own 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 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 flag-draped coffins.

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 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 from the 5 June (pre-test) and 1 November (post-test) elections and (b) the funeral districts of the terror victims among the Turkish security forces.

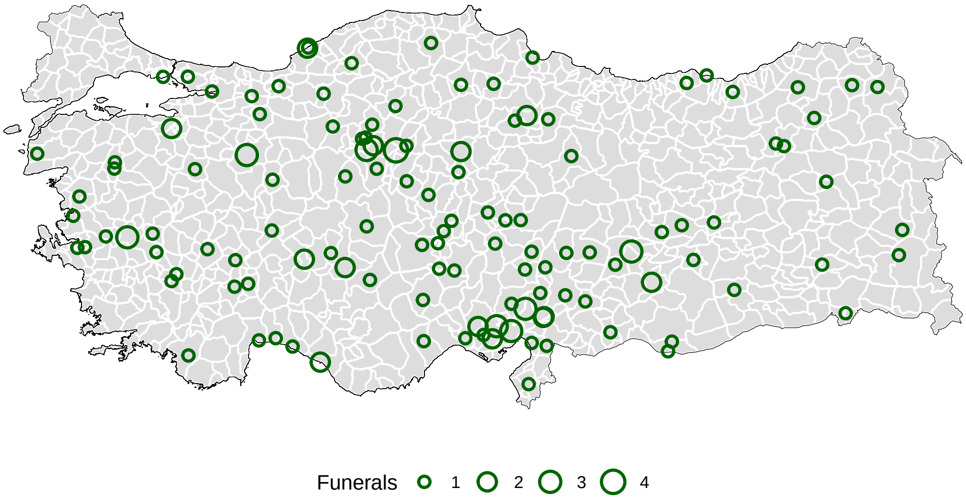


Figure 3: Treatment districts. The funeral places were distributed as-if randomly across Turkey.

The data on voting results comes from the Turkish Statistical Institute (TurkStat). The data on casualties originates from the UCDP Georeferenced Event Dataset (Pettersson & Öberg, 2020), which I validated against the news reports in the Turkish media. *Treatment* is coded as 1 for the 123 districts that had at least one funeral in between the two 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 it possible to distinguish between the effect of the initial and repeated casualties—a key assumption of the rally theory but one that has been largely 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 groups 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 at the end of 2014, as reported by the TurkStat. The motivation for this control strategy is the fact that age and gender strongly predict who serves in the Turkish security forces. The compulsory military service is for male citizens only, after turning 20 (Yildirim & Erdinç, 2007). Similarly, police officers are almost exclusively male (Ekşi, 2017), with the majority recruited in their early 20s as well (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 indeed a predictor of the treatment status. Once it is controlled for, however, these checks suggest that the assignment to the treatment groups is not correlated with a number of other pre-treatment district characteristics.

# 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 doubled in 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 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

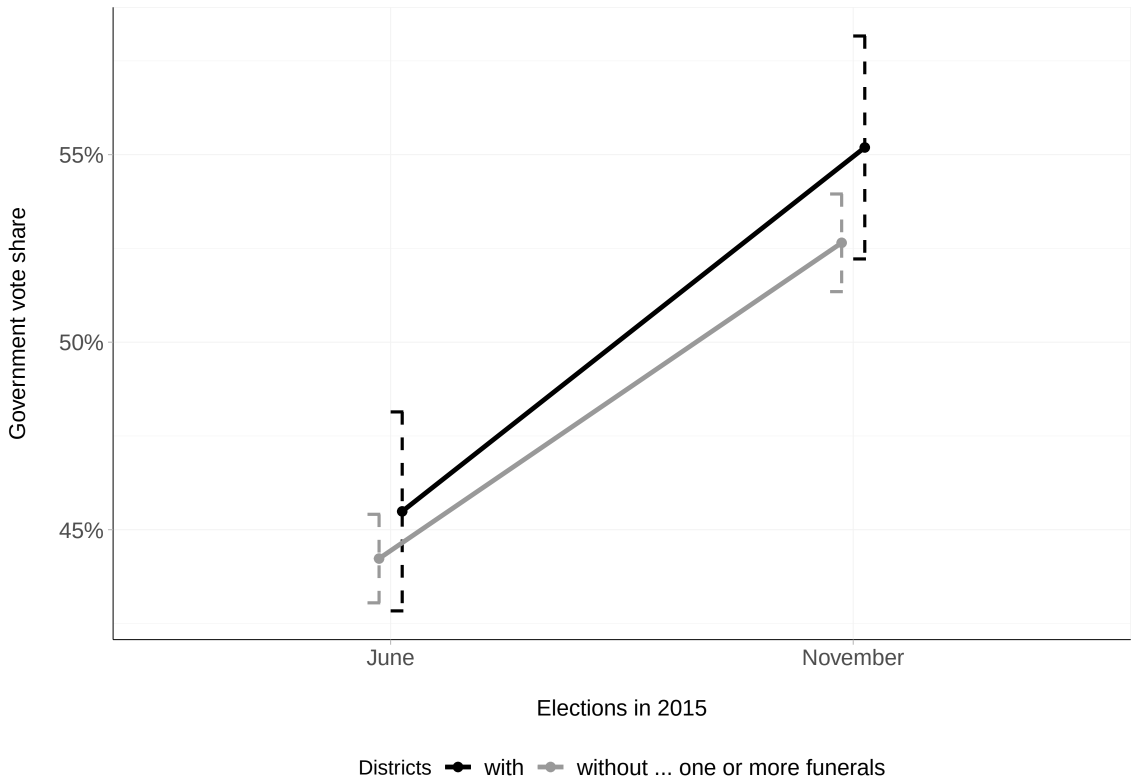


Figure 4: Government vote share in the 2015 elections. Compared to the election in June, the difference between the treatment and control districts was twice as large in November. *Note*: Error bars represent 95% confidence intervals.

level of provinces. In the first two models, which do not include *Multiple Treatment*, the coefficients for *Treatment* inform us about the same comparison as 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 just over 1 percentage point. This is slightly smaller than, yet comparable with, the simple difference of the group means in Figure 4.

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 government vote share. These estimates are slightly higher than

Table 1: Regression models of government vote share

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Treatment | 1.028* | 1.089** | 1.257** | 1.261** |
| | (0.412) | (0.365) | (0.470) | (0.407) |
| Multiple Treatment | | | –1.471* | –1.121* |
| | | | (0.716) | (0.510) |
| Pre-test | ✓ | ✓ | ✓ | ✓ |
| Recruitment Pool | ✓ | ✓ | ✓ | ✓ |
| Controls | ✗ | ✓ | ✗ | ✓ |
| Constant | 4.590*** | 17.003*** | 4.578*** | 17.072*** |
| | (0.878) | (4.681) | (0.875) | (4.697) |
| N | 970 | 970 | 970 | 970 |
| Clusters | 81 | 81 | 81 | 81 |
| $R^2$ | 0.960 | 0.969 | 0.960 | 0.970 |

*Notes*: All models are OLS regressions. Standard errors are in parentheses, clustered at the province level. *Controls* refer to seven variables: *Non-terror Funeral*, *Attack District*, *Kurdish District*, *AKP District*, *Higher Education*, *Electoral Margin*, and *Turnout*. See the Supporting Information for the complete results (Table S3) and for further details on the underlying data and variables.

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

in the preceding models, indicating that the government vote share increased by about 1.3 percentage points in the districts with only one funeral in between the two elections. This provides support for the first hypothesis.

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 decreased the electoral support for the Turkish government—by 1.1 to 1.5 percentage points, depending on the model specification. In other words, the rally effect changed direction in the districts with repeated casualties. Hence there is support for the second hypothesis as well.

These results are robust to rigorous tests, reported in the online Supporting Information. With regard to the comparability of treatment and control groups, Table S5 shows that the results do not change if the data is weighted with entropy balancing, which creates perfectly balanced samples with respect to the treatment assignment. In re-consideration of the treatment coding, the results replicate in two alternative schemes as well, designed to isolate the effect of single casualties (Table S6) and detect quadratic relationships (Table S7). Finally, further tests rule out the possibility that differences in treatment timing (Table S8), treatment source (Table S9), or turnout (Table S10) could have driven the differences in the government vote share.

# Conclusion

We know that governments are more likely to make concessions to violence *against security forces*, but we do not know why. Assuming that governments are concerned about public opinion, 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 study tackles these challenges with data from Turkey, where political violence resumed between two general elections held in less than five months apart, targeting the security forces as well as civilians. The security force victims of the resulting attacks were distributed 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 funeral 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 hometown, but this rally reverses 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 incumbents. 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 would not only avoid the punishment that the existing evidence attributes to the increasing number of casualties. It would also bring in rewards in localities with single casualties, and governments could catch the rally effect behind them. It is the latter aspect that this article adds to our knowledge.

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**Supporting Information for**

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

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# A Data

This study is based on a district-level dataset, with 970 observations. The motivation for choosing districts as the level of observation and analysis is the fact that the funerals for security force casualties take place at this level, often in the courtyard of the biggest mosque in the district centres.

The dataset has 31 variables, which fall under three main components: election results, security force casualties, and district characteristics. The first and the last come mostly from the Turkish Statistical Institute (TurkStat, http://www.turkstat.gov.tr), unless otherwise stated below. The component on security force casualties originates from the UCDP Georeferenced Event Dataset (Pettersson & Öberg, 2020).

## A.1 Election results

The data on election results comes from the TurkStat website. There were no changes in the district borders between the two elections in 2015. Hence, scraping the results for the 7 June and 1 November 2015 elections from the TurkStat website, I then merged the relevant variables together for each district.

## A.2 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 in the period under analysis.

An alternative source is the UCDP Georeferenced Event Dataset (Pettersson & Öberg, 2020), which records individual events of organised violence as reported in the international media. Based on the relevant records in this dataset, I then 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 in 2015. The aim of this additional step was twofold: (a) to validate the existing observations in the original dataset and (b) to code new variables of interest for this study.

This resulted in 153 observations of security force casualties in terror attacks among the military and police forces, excluding the village guards—paramilitaries recruited to protect their own village. Five of these casualties were missing in the UCDP Georeferenced Event Dataset, version 20.1.

## A.3 District characteristics

The dataset also includes a number of variables on district characteristics. Most importantly, these include *Recruitment Pool*, which is, as discussed in the main text, an important control for the likely unequal probabilities of being assigned to the treatment groups among districts with high or low numbers of people in the security forces in the first place.

## A.4 Variables and descriptive statistics

Table S1 presents the descriptive statistics of the variables used for the analysis in the main text, where *Post-test* is the dependent variable.

Table S1: Descriptive statistics

| | Mean | SD | Median | Minimum | Maximum |
|---|---|---|---|---|---|
| Post-test | 52.97 | 19.00 | 54.70 | 2.00 | 95.90 |
| Treatment | 0.13 | 0.33 | 0.00 | 0.00 | 1.00 |
| Multiple Treatment | 0.02 | 0.15 | 0.00 | 0.00 | 1.00 |
| Pre-test | 44.39 | 17.18 | 45.60 | 1.20 | 90.70 |
| Recruitment Pool | 6.57 | 10.85 | 2.25 | 0.09 | 88.25 |
| Non-terror Funeral | 0.04 | 0.19 | 0.00 | 0.00 | 1.00 |
| Attack District | 0.05 | 0.21 | 0.00 | 0.00 | 1.00 |
| Kurdish District | 0.18 | 0.39 | 0.00 | 0.00 | 1.00 |
| AKP District | 0.63 | 0.48 | 1.00 | 0.00 | 1.00 |
| 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 |

*Post-test.* A variable measuring the support for the governing Justice and Development Party (AKP) in the 1 November 2015 election, calculated by dividing the number of votes cast for the AKP by the total number of valid votes cast in each district. This is the dependent variable in the main text.

Note that there are different dependent variables for further analyses in this Supporting Information, and therefore *Post-test* might refer to different quantities in some tables. For example, in Tables S13 to S15, *Post-test* refers to the vote shares of the three main opposition parties in the 1 November 2015 election.

*Treatment.* A binary variable coded as 1 for districts with *one or more* funerals between 7 June and 1 November 2015 for members of security forces killed in terror attacks. Out of the 970 districts in Turkey, 123 had at least one funeral within this time frame between the 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 members of security forces killed in terror attacks. Out of the 123 treated districts, 21 were treated multiple times.

*Pre-test.* A variable measuring the support for the governing AKP in the 7 June 2015 election, calculated by dividing the number of votes cast for the AKP by the total number of valid votes cast in each district.

Note that *Pre-test* might refer to different quantities in some tables in this Supporting Information. For example, in Tables S13 to S15, *Pre-test* refers to the vote shares of the three main opposition parties in the 7 June 2015 election.

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

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

*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 occurred in 47 districts.

*Kurdish District.* 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.

*AKP District.* A binary variable coded as 1 for districts won by the AKP in the 2014 Turkish *local* elections.

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

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

Note that, as a rule, provinces are the electoral districts in the general elections in Turkey. For the elections under analysis, the only exceptions were the three largest provinces, which were divided into smaller electoral districts due to their size: İstanbul had 3 electoral districts while Ankara and İzmir had two each. Confusion may arise as *electoral* and *administrative* districts are different units. The latter is the unit of observation and analysis in this study.

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

Note that this variable is labelled as *Pre-test* in Table S10, which presents the regression models of turnout in the 1 November 2015 election (*Post-test*).

### A.5 Randomisation checks

Table S2 presents randomisation checks for both *Treatment* and *Multiple Treatment*, showing that the assignment of casualties was uncorrelated with several *pre-treatment* district characteristics, except for the number of male residents in their twenties. The estimates for *Recruitment Pool* are positive and statistically significant in all models. This means that the probability of districts to receive casualties was not identical: as it stands to reason, the districts with high numbers of potential security force recruits were more likely to be treated with funerals. However, once *Recruitment Pool* is controlled for, we see that the treatment and control districts become comparable in terms of pre-treatment characteristics.

Table S2: Regression models of treatment allocation

| | Treatment | | Multiple Treatment | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Recruitment Pool | 0.007* | 0.007* | 0.003* | 0.003* |
| | (0.003) | (0.003) | (0.001) | (0.001) |
| Pre-test | | 0.001 | | 0.000 |
| | | (0.001) | | (0.000) |
| Kurdish District | | –0.008 | | –0.011 |
| | | (0.040) | | (0.018) |
| AKP District | | –0.011 | | –0.008 |
| | | (0.028) | | (0.010) |
| Higher Education | | 0.000 | | 0.001 |
| | | (0.003) | | (0.001) |
| Electoral Margin | | 0.001 | | 0.001 |
| | | (0.002) | | (0.001) |
| Turnout | | –0.001 | | –0.001 |
| | | (0.003) | | (0.001) |
| Constant | 0.080*** | 0.106 | 0.001 | 0.079 |
| | (0.013) | (0.301) | (0.006) | (0.103) |
| N | 970 | 970 | 970 | 970 |
| Clusters | 81 | 81 | 81 | 81 |
| $R^2$ | 0.054 | 0.058 | 0.056 | 0.060 |

*Notes*: All models are OLS regressions. Standard errors are in parentheses, clustered at the province level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

## B Complete Table

For reasons of brevity and space, the regression table in the main text (Table 1) reports only a summary of the results. The complete results are available in Table S3.

Table S3: Main regression models, completing Table 1

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Treatment | 1.028* | 1.089** | 1.257** | 1.261** |
| | (0.412) | (0.365) | (0.470) | (0.407) |
| Multiple Treatment | | | –1.471* | –1.121* |
| | | | (0.716) | (0.510) |
| Pre-test | 1.084*** | 1.061*** | 1.084*** | 1.061*** |
| | (0.016) | (0.016) | (0.016) | (0.015) |
| Recruitment Pool | 0.020 | 0.051** | 0.023 | 0.053** |
| | (0.015) | (0.016) | (0.016) | (0.017) |
| Non-terror Funeral | | –0.523 | | –0.502 |
| | | (0.405) | | (0.397) |
| Attack District | | –0.970 | | –1.006 |
| | | (0.976) | | (0.979) |
| Kurdish District | | 3.293*** | | 3.288*** |
| | | (0.764) | | (0.755) |
| AKP District | | 2.075*** | | 2.068*** |
| | | (0.316) | | (0.316) |
| Higher Education | | –0.120** | | –0.119** |
| | | (0.036) | | (0.036) |
| Electoral Margin | | 0.017 | | 0.018 |
| | | (0.034) | | (0.034) |
| Turnout | | –0.148** | | –0.149** |
| | | (0.052) | | (0.052) |
| Constant | 4.590*** | 17.003*** | 4.578*** | 17.072*** |
| | (0.878) | (4.681) | (0.875) | (4.697) |
| N | 970 | 970 | 970 | 970 |
| Clusters | 81 | 81 | 81 | 81 |
| $R^2$ | 0.960 | 0.969 | 0.960 | 0.970 |

*Notes*: All models are OLS regressions. Standard errors are in parentheses, clustered at the province level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

# C Robustness Checks

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

## C.1 Entropy balancing

Could the imbalances between the treatment and control districts be driving the results? The entropy balancing method offers an opportunity to remove these imbalances completely (Hainmueller, 2012). Table S4 presents the mean values of the control variables used in the main text, before and after entropy balancing. It shows that this process has been successful—the procedure achieves a perfect balance.

Table S4: Treatment and control means, 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 |
| AKP District | 0.65 | 0.63 | 0.65 | 0.65 |
| 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 |

With the weights obtained from this balancing procedure, the regression models in Table S5 estimate the effects of *Treatment* and *Multiple Treatment* on the government vote share. Note that this exercise still 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. According to the second model, while the government vote share increases in the funeral places of terror victims, this effect reverses in the towns with repeated casualties. The magnitude of these changes are very similar to each other—about 1.1 to 1.2 percentage points.

Table S5: Regression models based on entropy balancing

| | (1) | | (2) | |
|---|---|---|---|---|
| | Coefficient | Std. Error | Coefficient | Std. Error |
| Treatment | 0.960* | (0.417) | 1.160* | (0.478) |
| Multiple Treatment | | | –1.154* | (0.586) |
| Pre-test | 1.090*** | (0.014) | 1.089*** | (0.014) |
| Constant | 4.639*** | (0.624) | 4.709*** | (0.623) |
| N | 970 | | 970 | |
| $R^2$ | 0.951 | | 0.951 | |

*Notes*: All models are OLS regressions. The data is adjusted with the entropy balancing weights. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

## C.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* (districts with *one or more* casualties) and *Multiple Treatment* (districts with *more than one* casualty). Table S6 provides an alternative way to test the effect of initial casualties: 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 relevant hypothesis is robust as the results point to an increase in government vote share, by about 1.2 to 1.3 percentage points, in districts with a single casualty.

Table S6: Regression models with single treatment

| | All Districts Included | | Excluding the Multiply-Treated | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Single Treatment | 1.266** | 1.255** | 1.237* | 1.236** |
| | (0.470) | (0.404) | (0.473) | (0.412) |
| Pre-test | 1.084*** | 1.061*** | 1.084*** | 1.061*** |
| | (0.016) | (0.015) | (0.016) | (0.016) |
| Recruitment Pool | 0.022 | 0.053** | 0.027 | 0.056** |
| | (0.015) | (0.016) | (0.018) | (0.018) |
| Non-terror Funeral | | –0.495 | | –0.378 |
| | | (0.394) | | (0.417) |
| Attack District | | –1.012 | | –1.045 |
| | | (0.977) | | (0.983) |
| Kurdish District | | 3.287*** | | 3.332*** |
| | | (0.753) | | (0.755) |
| AKP District | | 2.067*** | | 2.094*** |
| | | (0.316) | | (0.325) |
| Higher Education | | –0.119** | | –0.118** |
| | | (0.036) | | (0.037) |
| Electoral Margin | | 0.018 | | 0.017 |
| | | (0.034) | | (0.034) |
| Turnout | | –0.149** | | –0.148** |
| | | (0.052) | | (0.052) |
| Constant | 4.579*** | 17.084*** | 4.573*** | 16.933*** |
| | (0.875) | (4.686) | (0.880) | (4.709) |
| N | 970 | 970 | 949 | 949 |
| Clusters | 81 | 81 | 81 | 81 |
| $R^2$ | 0.960 | 0.970 | 0.959 | 0.969 |

*Notes*: All models are OLS regressions. Standard errors are in parentheses, clustered at the province level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

## C.3 Quadratic treatment

This subsection provides an alternative test for the claim that security force casualties have a non-linear effect on government vote share. The models in Table S7 include an untransformed count variable *Treatments* (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 with multiple casualties.

Table S7: Regression models with quadratic treatment

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Treatments | 0.459 | 0.570* | 1.639* | 1.522** |
| | (0.260) | (0.229) | (0.650) | (0.544) |
| Treatments Squared | | | –0.583* | –0.472* |
| | | | (0.282) | (0.215) |
| Pre-test | 1.085*** | 1.061*** | 1.084*** | 1.061*** |
| | (0.016) | (0.016) | (0.016) | (0.016) |
| Recruitment Pool | 0.022 | 0.052** | 0.022 | 0.052** |
| | (0.016) | (0.017) | (0.016) | (0.016) |
| Non-terror Funeral | | –0.503 | | –0.465 |
| | | (0.410) | | (0.396) |
| Attack District | | –0.961 | | –0.986 |
| | | (0.977) | | (0.978) |
| Kurdish District | | 3.293*** | | 3.294*** |
| | | (0.773) | | (0.761) |
| AKP District | | 2.078*** | | 2.071*** |
| | | (0.317) | | (0.316) |
| Higher Education | | –0.121** | | –0.118** |
| | | (0.037) | | (0.036) |
| Electoral Margin | | 0.017 | | 0.017 |
| | | (0.034) | | (0.034) |
| Turnout | | –0.148** | | –0.148** |
| | | (0.052) | | (0.052) |
| Constant | 4.605*** | 17.022*** | 4.592*** | 17.007*** |
| | (0.880) | (4.683) | (0.878) | (4.683) |
| N | 970 | 970 | 970 | 970 |
| Clusters | 81 | 81 | 81 | 81 |
| $R^2$ | 0.959 | 0.969 | 0.960 | 0.969 |

*Notes*: All models are OLS regressions. Standard errors are in parentheses, clustered at the province level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

## C.4 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 differences in government vote share were 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 2015 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 differences in government vote share were not driven by the heterogeneity in treatment timing.

Table S8: Regression models with treatment timing

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Treatment | 0.671 | 1.828** | 0.387 | 1.474** |
| | (0.728) | (0.541) | (0.679) | (0.493) |
| Timing (Mean) | 0.006 | –0.012 | | |
| | (0.012) | (0.009) | | |
| Timing (Minimum) | | | 0.011 | –0.007 |
| | | | (0.012) | (0.009) |
| Pre-test | 1.084*** | 1.061*** | 1.084*** | 1.061*** |
| | (0.016) | (0.016) | (0.016) | (0.016) |
| Recruitment Pool | 0.020 | 0.051** | 0.020 | 0.051** |
| | (0.015) | (0.016) | (0.015) | (0.016) |
| Non-terror Funeral | | –0.481 | | –0.511 |
| | | (0.408) | | (0.408) |
| Attack District | | –0.961 | | –0.960 |
| | | (0.977) | | (0.978) |
| Kurdish District | | 3.303*** | | 3.298*** |
| | | (0.765) | | (0.766) |
| AKP District | | 2.091*** | | 2.084*** |
| | | (0.315) | | (0.314) |
| Higher Education | | –0.121** | | –0.120** |
| | | (0.036) | | (0.036) |
| Electoral Margin | | 0.017 | | 0.017 |
| | | (0.034) | | (0.034) |
| Turnout | | –0.148** | | –0.148** |
| | | (0.052) | | (0.052) |
| Constant | 4.589*** | 17.010*** | 4.588*** | 17.002*** |
| | (0.878) | (4.681) | (0.877) | (4.682) |
| N | 970 | 970 | 970 | 970 |
| Clusters | 81 | 81 | 81 | 81 |
| $R^2$ | 0.960 | 0.969 | 0.960 | 0.969 |

*Notes*: All models are OLS regressions. Standard errors are in parentheses, clustered at the province level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

### C.5 Treatment source

As discussed in the main text, there was also a differentiation in the source of the treatment—while 148 casualties occurred in attacks by the Kurdistan Workers' Party (PKK), the remaining five were inflicted by the Islamic State of Iraq and Syria (ISIS; 4) or the Free Syrian Army (FSA; 1). All five exceptions led to funerals in districts that were treated only once. In other words, no district was treated by multiple sources of political violence.

Could the differences in government vote share be driven by the heterogeneity in treatment source? The robustness check in this subsection suggests not. The regression models in Table S9 are based on a subset of the data, where casualties by the ISIS and FSA are excluded. The results remain the same as in the main text.

Table S9: Regression models with PKK-inflicted treatment only

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Treatment | 0.833* | 0.908** | 1.038* | 1.059** |
| | (0.390) | (0.330) | (0.426) | (0.362) |
| Multiple Treatment | | | –1.262* | –0.938* |
| | | | (0.632) | (0.466) |
| Pre-test | 1.083*** | 1.061*** | 1.083*** | 1.061*** |
| | (0.016) | (0.015) | (0.016) | (0.015) |
| Recruitment Pool | 0.021 | 0.051** | 0.023 | 0.053** |
| | (0.015) | (0.016) | (0.016) | (0.016) |
| Non-terror Funeral | | –0.471 | | –0.454 |
| | | (0.394) | | (0.387) |
| Attack District | | –0.920 | | –0.951 |
| | | (0.971) | | (0.973) |
| Kurdish District | | 3.217*** | | 3.212*** |
| | | (0.722) | | (0.716) |
| AKP District | | 2.048*** | | 2.042*** |
| | | (0.314) | | (0.314) |
| Higher Education | | –0.116** | | –0.115** |
| | | (0.035) | | (0.035) |
| Electoral Margin | | 0.020 | | 0.020 |
| | | (0.034) | | (0.034) |
| Turnout | | –0.141** | | –0.142** |
| | | (0.052) | | (0.052) |
| Constant | 4.628*** | 16.407*** | 4.619*** | 16.475*** |
| | (0.878) | (4.677) | (0.875) | (4.692) |
| N | 965 | 965 | 965 | 965 |
| Clusters | 81 | 81 | 81 | 81 |
| $R^2$ | 0.961 | 0.970 | 0.961 | 0.970 |

*Notes*: All models are OLS regressions. Standard errors are in parentheses, clustered at the province level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

## C.6 Turnout

Differences in turnout could have affected 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 in the data. Table S10 presents four regression models of turnout, where the dependent variable is the district-level turnout in the November 2015 election. Here *Pre-test* is the turnout in the June 2015 election. While *Treatment* is significant at the 5% level in the first model, this disappears in models with controls variables and/or *Multiple Treatment*.

Table S10: Regression models of electoral turnout

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Treatment | 0.505* | 0.363 | 0.531 | 0.394 |
| | (0.249) | (0.220) | (0.269) | (0.248) |
| Multiple Treatment | | | –0.163 | –0.200 |
| | | | (0.354) | (0.356) |
| Pre-test | 0.853*** | 0.833*** | 0.853*** | 0.833*** |
| | (0.039) | (0.030) | (0.039) | (0.030) |
| Recruitment Pool | 0.025** | 0.027** | 0.025** | 0.027** |
| | (0.008) | (0.008) | (0.009) | (0.008) |
| Non-terror Funeral | | 0.335 | | 0.339 |
| | | (0.247) | | (0.245) |
| Attack District | | –0.473 | | –0.479 |
| | | (0.439) | | (0.436) |
| Kurdish District | | –2.170*** | | –2.170*** |
| | | (0.631) | | (0.632) |
| AKP District | | 1.168*** | | 1.166*** |
| | | (0.197) | | (0.197) |
| Higher Education | | –0.027 | | –0.027 |
| | | (0.031) | | (0.031) |
| Electoral Margin | | –0.066** | | –0.066** |
| | | (0.021) | | (0.021) |
| Constant | 12.791*** | 14.688*** | 12.796*** | 14.697*** |
| | (3.437) | (2.632) | (3.440) | (2.635) |
| N | 970 | 970 | 970 | 970 |
| Clusters | 81 | 81 | 81 | 81 |
| $R^2$ | 0.706 | 0.781 | 0.706 | 0.781 |

*Notes*: All models are OLS regressions. Standard errors are in parentheses, clustered at the province level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

# D Further Analyses

This section provides further analyses of the data, in addition to those reported in the main text.

## D.1 Government strongholds

A plausible hypothesis is that the effect of security force casualties on a party's vote share depends upon the pre-existing strength of that party in a given district. Specifically, governments might be better positioned to rally the townspeople behind them in districts where they are already strong. However, the data does not support this hypothesis.

Table S11 includes interactions between *Treatment* or *Multiple Treatment* on the one hand, and *Pre-test* on the other—measuring the pre-existing government strength in terms of the electoral baseline in the June 2015 election. As an alternative, Table S12 presents regression models where the interactions are with *AKP District* (districts where the governing AKP won the local elections in 2014) instead.

Out of the eight coefficients of interest that these tables have, only one is statistically significant, which points to the opposite direction of the above hypothesis—suggesting that the negative effect of receiving more than one casualty was particularly strong in the districts where the AKP was in local government. The remaining coefficients are substantively small and statistically insignificant. They also have inconsistent signs.

Table S11: Regression models with interaction terms, constructed with *Pre-test*

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Treatment | 0.774 | 2.096 | 1.256** | 1.262** |
| | (1.675) | (1.374) | (0.471) | (0.407) |
| Multiple Treatment | | | –3.791* | –0.232 |
| | | | (1.848) | (1.010) |
| Treatment × Pre-test | 0.006 | –0.022 | | |
| | (0.035) | (0.029) | | |
| Multiple Treatment × Pre-test | | | 0.056 | –0.021 |
| | | | (0.040) | (0.022) |
| Pre-test | 1.084*** | 1.063*** | 1.083*** | 1.061*** |
| | (0.016) | (0.017) | (0.016) | (0.016) |
| Recruitment Pool | 0.020 | 0.050** | 0.023 | 0.053** |
| | (0.015) | (0.016) | (0.016) | (0.016) |
| Non-terror Funeral | | –0.564 | | –0.517 |
| | | (0.396) | | (0.399) |
| Attack District | | –0.997 | | –1.006 |
| | | (0.976) | | (0.979) |
| Kurdish District | | 3.331*** | | 3.299*** |
| | | (0.757) | | (0.754) |
| AKP District | | 2.085*** | | 2.068*** |
| | | (0.315) | | (0.315) |
| Higher Education | | –0.119** | | –0.119** |
| | | (0.036) | | (0.036) |
| Electoral Margin | | 0.018 | | 0.018 |
| | | (0.034) | | (0.034) |
| Turnout | | –0.146** | | –0.148** |
| | | (0.052) | | (0.052) |
| Constant | 4.612*** | 16.732*** | 4.605*** | 17.017*** |
| | (0.898) | (4.720) | (0.882) | (4.695) |
| N | 970 | 970 | 970 | 970 |
| Clusters | 81 | 81 | 81 | 81 |
| $R^2$ | 0.960 | 0.969 | 0.960 | 0.970 |

*Notes*: All models are OLS regressions. Standard errors are in parentheses, clustered at the province level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table S12: Regression models with interaction terms, constructed with *AKP District*

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Treatment | 0.644 | 1.157* | 1.274** | 1.259** |
| | (0.557) | (0.525) | (0.440) | (0.407) |
| Multiple Treatment | | | –1.296 | –0.383 |
| | | | (0.764) | (0.505) |
| Treatment × AKP District | 0.654 | –0.106 | | |
| | (0.797) | (0.699) | | |
| Multiple Treatment × AKP District | | | –0.064 | –1.287* |
| | | | (0.775) | (0.641) |
| Pre-test | 1.049*** | 1.061*** | 1.049*** | 1.060*** |
| | (0.017) | (0.016) | (0.017) | (0.015) |
| Recruitment Pool | 0.013 | 0.051** | 0.016 | 0.053** |
| | (0.015) | (0.016) | (0.016) | (0.017) |
| Non-terror Funeral | | –0.526 | | –0.493 |
| | | (0.400) | | (0.386) |
| Attack District | | –0.973 | | –1.011 |
| | | (0.976) | | (0.979) |
| Kurdish District | | 3.297*** | | 3.295*** |
| | | (0.762) | | (0.752) |
| AKP District | 2.159*** | 2.089*** | 2.236*** | 2.101*** |
| | (0.386) | (0.324) | (0.395) | (0.325) |
| Higher Education | | –0.120** | | –0.120** |
| | | (0.036) | | (0.036) |
| Electoral Margin | | 0.017 | | 0.018 |
| | | (0.034) | | (0.034) |
| Turnout | | –0.148** | | –0.149** |
| | | (0.052) | | (0.052) |
| Constant | 4.813*** | 16.999*** | 4.756*** | 17.064*** |
| | (0.846) | (4.684) | (0.838) | (4.703) |
| N | 970 | 970 | 970 | 970 |
| Clusters | 81 | 81 | 81 | 81 |
| $R^2$ | 0.962 | 0.969 | 0.962 | 0.970 |

*Notes*: All models are OLS regressions. Standard errors are in parentheses, clustered at the province level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

## D.2 Other parties

Do security force casualties affect the electoral prospects of non-government parties as well? The 2015 elections returned the same four parties to the Turkish parliament in November as in June: the conservative AKP 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).

Figure S1 visualises the overall ideological stances of these parties, based on expert evaluations in 2014 (Figure S1a) or party manifestos in 2015 (Figure S1b), where higher values indicate stances further to the right.

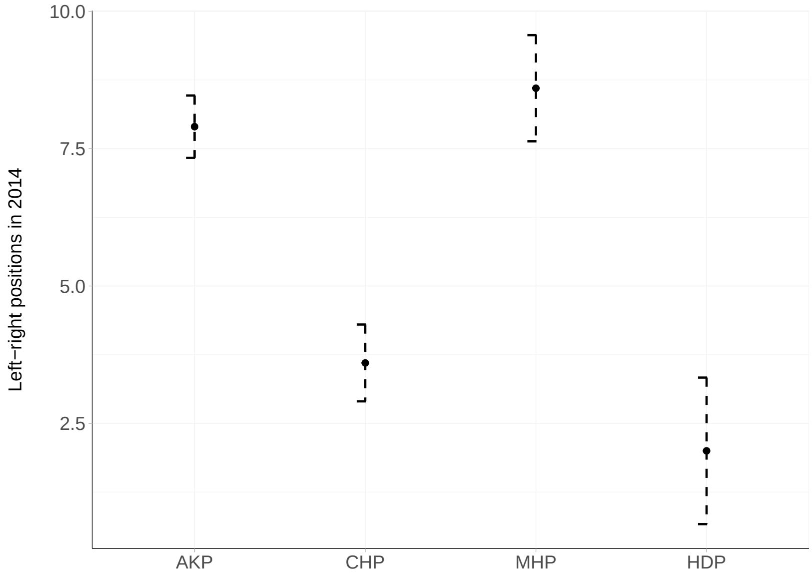
Tables S13 to S15 replicate the regression models in the main text for the three parties in opposition. The results show that, when considered individually, these parties were affected neither by an initial terror casualty nor by repeated casualties. The estimates for *Treatment* and *Multiple Treatment* are relatively small, and they are not statistically significant.

The same result applies to the right-wing parties as a group, as presented in Table S16. Here the pre- and post-test variables are calculated as the district-wise sum of vote shares of the three right-wing parties—the AKP, MHP, and the Felicity Party (SP)—with more than one per cent of the vote in either of the elections.

Finally, Table S17 presents alternative regression models, adjusted with entropy balancing weights. These models return null results as well: there is no evidence that casualties affect the vote share of other parties individually, or that of right-wing parties together.

These null results are in line with the assumption that rally effects are non-partisan. Accordingly, 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 or ideology but because they represent the country at a given point in time. Nevertheless, the results here are at odds with one of the main findings in the existing literature, that there is a positive relationship between casualties in terror attacks and public support for right-wing parties (Berrebi & Klor, 2006, 2008; Gould & Klor, 2010; Kibris, 2011).

(a) CHES left-right position




(b) MARPOR rile score

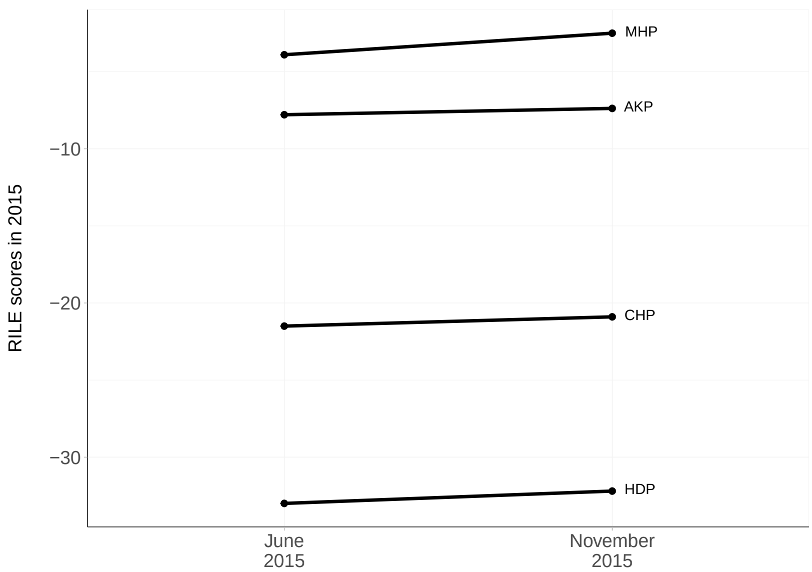



Figure S1: Ideological stances of the four parties represented in the Turkish parliament after the 2015 elections. *Notes*: Higher values indicate stances further to the right in both figures. Error bars in the top figure represent standard deviations. *Sources*: Chapel Hill Expert Survey (CHES; Polk et al., 2017) and Manifesto Project (MARPOR; Volkens et al., 2020).

Table S13: Regression models of CHP vote share

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Treatment | –0.145 | –0.119 | –0.116 | –0.077 |
| | (0.190) | (0.207) | (0.212) | (0.225) |
| Multiple Treatment | | | –0.183 | –0.276 |
| | | | (0.357) | (0.419) |
| Pre-test | 1.029*** | 1.027*** | 1.029*** | 1.027*** |
| | (0.010) | (0.014) | (0.010) | (0.014) |
| Recruitment Pool | 0.018** | –0.004 | 0.018** | –0.003 |
| | (0.006) | (0.010) | (0.006) | (0.010) |
| Non-terror Funeral | | 0.781* | | 0.786* |
| | | (0.355) | | (0.353) |
| Attack District | | 0.423 | | 0.414 |
| | | (0.475) | | (0.475) |
| Kurdish District | | 1.126* | | 1.125* |
| | | (0.515) | | (0.514) |
| AKP District | | –0.443* | | –0.445* |
| | | (0.208) | | (0.208) |
| Higher Education | | 0.121*** | | 0.121*** |
| | | (0.025) | | (0.025) |
| Electoral Margin | | 0.059* | | 0.059* |
| | | (0.023) | | (0.023) |
| Turnout | | 0.026 | | 0.026 |
| | | (0.026) | | (0.026) |
| Constant | –0.694** | –3.852 | –0.697** | –3.840 |
| | (0.213) | (2.211) | (0.213) | (2.214) |
| N | 970 | 970 | 970 | 970 |
| Clusters | 81 | 81 | 81 | 81 |
| $R^2$ | 0.978 | 0.980 | 0.978 | 0.980 |

*Notes*: All models are OLS regressions. Standard errors are in parentheses, clustered at the province level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table S14: Regression models of MHP vote share

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Treatment | –0.053 | 0.021 | –0.228 | –0.140 |
| | (0.337) | (0.288) | (0.345) | (0.300) |
| Multiple Treatment | | | 1.177 | 1.101 |
| | | | (0.903) | (0.839) |
| Pre-test | 0.726*** | 0.723*** | 0.724*** | 0.722*** |
| | (0.026) | (0.033) | (0.026) | (0.033) |
| Recruitment Pool | 0.016* | –0.002 | 0.014 | –0.005 |
| | (0.008) | (0.010) | (0.009) | (0.010) |
| Non-terror Funeral | | –0.187 | | –0.205 |
| | | (0.362) | | (0.362) |
| Attack District | | –0.062 | | –0.030 |
| | | (0.422) | | (0.433) |
| Kurdish District | | –0.389 | | –0.405 |
| | | (0.523) | | (0.516) |
| AKP District | | –1.299*** | | –1.288*** |
| | | (0.315) | | (0.313) |
| Higher Education | | 0.040 | | 0.039 |
| | | (0.028) | | (0.027) |
| Electoral Margin | | –0.095** | | –0.096** |
| | | (0.034) | | (0.034) |
| Turnout | | 0.050 | | 0.051 |
| | | (0.036) | | (0.036) |
| Constant | –0.382 | –3.452 | –0.343 | –3.476 |
| | (0.345) | (2.986) | (0.329) | (2.969) |
| N | 970 | 970 | 970 | 970 |
| Clusters | 81 | 81 | 81 | 81 |
| $R^2$ | 0.871 | 0.887 | 0.871 | 0.888 |

*Notes*: All models are OLS regressions. Standard errors are in parentheses, clustered at the province level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table S15: Regression models of HDP vote share

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Treatment | –0.374 | –0.217 | –0.367 | –0.233 |
| | (0.208) | (0.230) | (0.228) | (0.263) |
| Multiple Treatment | | | –0.046 | 0.103 |
| | | | (0.548) | (0.449) |
| Pre-test | 0.906*** | 0.932*** | 0.906*** | 0.932*** |
| | (0.013) | (0.017) | (0.013) | (0.017) |
| Recruitment Pool | –0.007 | –0.025*** | –0.007 | –0.025*** |
| | (0.007) | (0.007) | (0.007) | (0.007) |
| Non-terror Funeral | | –0.018 | | –0.020 |
| | | (0.436) | | (0.435) |
| Attack District | | 2.003* | | 2.006* |
| | | (0.827) | | (0.829) |
| Kurdish District | | –2.863** | | –2.864** |
| | | (0.901) | | (0.900) |
| AKP District | | –0.676** | | –0.675** |
| | | (0.200) | | (0.201) |
| Higher Education | | 0.001 | | 0.001 |
| | | (0.016) | | (0.016) |
| Electoral Margin | | 0.016 | | 0.016 |
| | | (0.028) | | (0.028) |
| Turnout | | 0.153*** | | 0.153*** |
| | | (0.039) | | (0.039) |
| Constant | –0.740*** | –13.297*** | –0.741*** | –13.300*** |
| | (0.115) | (3.377) | (0.116) | (3.379) |
| N | 970 | 970 | 970 | 970 |
| Clusters | 81 | 81 | 81 | 81 |
| $R^2$ | 0.986 | 0.989 | 0.986 | 0.989 |

*Notes*: All models are OLS regressions. Standard errors are in parentheses, clustered at the province level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table S16: Regression models of right-wing vote share

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Treatment | 0.125 | 0.028 | 0.347 | 0.168 |
| | (0.407) | (0.354) | (0.432) | (0.376) |
| Multiple Treatment | | | –1.447 | –0.926 |
| | | | (0.967) | (0.628) |
| Pre-test | 0.946*** | 0.965*** | 0.946*** | 0.966*** |
| | (0.016) | (0.016) | (0.016) | (0.016) |
| Recruitment Pool | 0.027 | 0.075*** | 0.030* | 0.076*** |
| | (0.015) | (0.013) | (0.015) | (0.013) |
| Non-terror Funeral | | –0.870 | | –0.854 |
| | | (0.566) | | (0.570) |
| Attack District | | –1.210 | | –1.237 |
| | | (0.894) | | (0.897) |
| Kurdish District | | 5.114*** | | 5.117*** |
| | | (0.898) | | (0.900) |
| AKP District | | 1.366*** | | 1.355*** |
| | | (0.348) | | (0.348) |
| Higher Education | | –0.185*** | | –0.184*** |
| | | (0.046) | | (0.046) |
| Electoral Margin | | –0.127* | | –0.127* |
| | | (0.055) | | (0.054) |
| Turnout | | –0.174* | | –0.175* |
| | | (0.071) | | (0.071) |
| Constant | 5.525*** | 19.103** | 5.495*** | 19.117** |
| | (1.207) | (6.300) | (1.201) | (6.320) |
| N | 970 | 970 | 970 | 970 |
| Clusters | 81 | 81 | 81 | 81 |
| $R^2$ | 0.959 | 0.973 | 0.959 | 0.973 |

*Notes*: All models are OLS regressions. Standard errors are in parentheses, clustered at the province level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table S17: Regression models of non-government party vote share, based on entropy balancing

| | CHP | MHP | HDP | RW |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Treatment | –0.184 | –0.059 | –0.254 | 0.480 |
| | (0.209) | (0.300) | (0.260) | (0.466) |
| Multiple Treatment | 0.044 | 1.431 | –0.210 | –1.090 |
| | (0.347) | (0.798) | (0.496) | (1.020) |
| Pre-test | 1.030*** | 0.702*** | 0.886*** | 0.926*** |
| | (0.007) | (0.023) | (0.014) | (0.013) |
| Constant | –0.451** | 0.086 | –0.722*** | 7.087*** |
| | (0.150) | (0.391) | (0.174) | (0.857) |
| N | 970 | 970 | 970 | 970 |
| $R^2$ | 0.981 | 0.841 | 0.983 | 0.953 |

*Notes*: All models are OLS regressions. The data is adjusted with the entropy balancing weights. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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