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Terrorism and Voting: The Rise of Right-Wing Populism in Germany

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Terrorism and Voting: The Rise of Right-Wing Populism in Germany

Abstract

Can right-wing terrorism increase support for far-right populist parties, and if so, why? Exploiting quasi-random variation between successful and failed attacks across German municipalities, we find that successful attacks lead to significant increases in the vote share for the right-wing, populist Alternative für Deutschland (AfD) party. Our results are predominantly observable in state elections, though attacks that receive high media coverage increase the AfD vote share in Federal elections. These patterns hold even though most attacks are motivated by right-wing causes and target migrants. Using a longitudinal panel of individuals, we find successful terror leads individuals to prefer the AfD more and worry more about migration. Exploiting news reports, we find that successful attacks receive more media coverage from local and regional publishers and that this coverage focuses on Islam and terror. Overall, and in contrast to previous work, we find terrorism is politically consequential in Western, multi-party democratic systems.

JEL-Codes: D720, K420, L820.

Keywords: terrorism, populism, media, salience, voting.

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1. Introduction

Right-wing populist movements present a threat to liberal democracies around the world (Levitsky and Ziblatt [2019](#)). Whereas in the past, the threat was explicit — for example, through military rule, outright dictatorships, and fascist governments — today, it is more subtle, involving the gradual erosion of trust in democratic norms and institutions (Levitsky and Ziblatt [2019](#); Norris and Inglehart [2019](#)). Nevertheless, right-wing movements are thriving: In Western societies, for example, the vote share for right-wing authoritarian populist parties in national elections more than doubled from some 5 percent in the 1960s to more than 12 percent in the 2010s (Norris and Inglehart [2019](#)).

These developments have renewed academic interest to understand the causes of populism. A substantial literature has argued that the rise of right-wing populism in many countries can be attributed to such factors as economic insecurity and marginalization (Fetzer [2019](#); Guiso et al. [2017a](#), [2020](#); Bo' et al. [2023](#)), globalization and migration shocks (Rodrik [2018](#); Dustmann, Vasiljeva, and Piil Damm [2019](#)), cultural attitudes, identity, and education (Norris and Inglehart [2019](#); Gethin, Martínez-Toledano, and Piketty [2021](#); Bonomi, Gennaioli, and Tabellini [2021](#)) as well as shifts in party positions and changes in voter demographics and priorities (Danieli et al. [2022](#)).¹ Surprisingly, although this literature has examined the role of cultural conflict in explaining the rise of populism, the role of political conflict, and in particular terrorism, has received less attention, especially in the context of advanced, multi-party Western democracies. Given that many right-wing authoritarian movements emphasize security against (actual or perceived) threats and play on the politics of fear (Norris and Inglehart [2019](#)), the question arises as to whether acts of terror can actually shift the political landscape of a nation to the right: Can they, for example, mobilize voters, affect voter preferences and attitudes, and, ultimately, lead to differential voting behavior?

In this paper, we aim to answer these questions by identifying the causal impact of small, local terror attacks on the vote share for the right-wing, populist Alternative für Deutschland (henceforth AfD) party across German municipalities. We also provide an account as to

1. Although economics-based accounts of populism prevail, Margalit ([2019](#)) argues that this literature overstates the role of economic factors in explaining populism's success.

why terror increases support for the far-right, highlighting the role of factors such as voter mobilization, shifts in voter preferences, and media reporting. For identification, we rely on the success or failure of attacks². A balance test along a wide range of municipality characteristics reveals no significant social, economic, demographic, geographic, or political differences between municipalities hit with successful or failed attacks. This lends credence to our identifying assumption that, conditional on being attacked, the success of an attack is unrelated to municipality characteristics.³

We then compare the AfD vote share in Federal, European, and state elections between 2013 and 2021 in German municipalities targeted with successful and failed attacks since 2010⁴. Our baseline estimate suggests that the AfD experiences a 6 percentage point increase in state elections in municipalities hit with successful attacks, which represents an increase of some 37 percent relative to the sample mean. For attacks that receive high media coverage, we find very similar effects at the Federal level. Our baseline estimate is robust to a wide range of specifications and samples, placebo tests, and alternative statistical inference methods. We also find significant geographic spillovers: The AfD vote share in state elections in untargeted, neighboring municipalities also increases significantly, an effect that diminishes to zero with distance.

Our results are even more intriguing when one considers that nearly 75 percent of the attacks in our sample are both carried out by right-wing extremists and target foreigners, suggesting that the right-wing AfD benefits from right-wing attacks. To better understand why this is the case, the rest of our paper explores the mechanisms that drive our effects. In this respect, we report three main sets of results.

First, successful terror attacks lead to large, significant increases in voter turnout in state elections, in the order of some 16 percentage points. The AfD claims more than 30 percent of this mobilization, whereas the remaining 70 percent of the turnout effect is spread among other

2. In doing so, we follow Brodeur (2018) and Jones and Olken (2009): Brodeur (2018) exploits the success of attacks to identify employment effects in the USA while Jones and Olken (2009) use assassination attempts of political leaders to explain cross-country institutional change and conflict.

3. We also find no significant differences in attack characteristics, including attack motivation or weapon technologies, although, unsurprisingly, successful attacks are more deadly than failed attacks.

4. Our sample begins in 2010 because it is just a few years prior to the establishment of the AfD in 2013 and because Germany experienced a surge in terror attacks beginning in 2010.

political parties⁵ This differential capture of voters translates into a significant realignment of vote shares. Whereas the AfD increases its vote share by some 6 percentage points, other (mainstream) parties, including the center-right Christian Democratic Union (CDU) that led the Federal government from 2005 to 2021, experience either no effects or much smaller gains⁶

Second, the aggregate patterns in voting outcomes appear to be driven by changes in individual political attitudes and preferences. Using the restricted-use German Socio-Economic Panel (SOEP), we study the political preferences of the *same* person in time periods before and after an attack. We find that a person residing in a municipality hit with a successful attack identifies as more hard-right on the political spectrum and significantly prefers the AfD following an attack. They also report being increasingly worried about immigration and significantly more active in local politics. Interestingly, individual concerns about terrorism are not affected by successful attacks. Importantly, we find no significant differences in pre-attack social and economic characteristics or in political preferences between individuals residing in municipalities hit with successful or failed attacks. This confirms the view that successful attacks are politically impactful because they differentially affect voter preferences and not because they target different types of voters.

Using the SOEP, we document several heterogeneities in individual responses to successful terror. We find, for example, that individuals without pre-terror partisan affiliation are significantly more likely to prefer the AfD following a successful attack. In addition, we find that people that have prior political affiliation with the CDU, the ruling party from 2005 to 2021, the Left party, a traditional protest party, as well as Neo-Nazi fringe parties (the National Democratic Party and Die Republikaner), differentially prefer the AfD following successful attacks. These results indicate that voters migrate from across the political spectrum, including from two established parties, to the AfD. We also find that people who reported being politically inactive pre-attack go on to prefer the AfD significantly more following an attack, suggesting that terror leads to politically slanted mobilization. What is more, we find that individuals

5. These figures assume no voter migration and therefore represent an upper bound. As we explain later, we find evidence of voter migration. However, the magnitude of the relevant coefficients suggests that the baseline effect is explained equally by voter migration and political activation.

6. The SPD, the main rival of the ruling CDU, experiences a 3-point increase in response to terror, the only other party to increase its vote share. We report full results for the SPD and the CDU in Online Appendix H

without university education prefer the AfD differentially more in response to terror compared to those with university education, results in line with what Norris and Inglehart (2019) term the “authoritarian reflex”: the notion that groups in society who feel “left behind” by globalization may react defensively to shocks that undermine security — including terrorism — by adopting more extreme ideological positions.⁷

Third, we posit that a primary channel through which successful terror affects both voting outcomes and political preferences is media reporting which makes terror attacks salient to voters. Following Taylor and Thompson (1982), we argue that successful terror attacks are made salient in the media because they (a) attract differential attention compared to failed attacks and (b) disproportionately affect subsequent voting decisions because of that attention.⁸ To support these claims, we first examine whether successful attacks receive differential attention in the news media compared to failed attacks. Second, we test the extent to which high-coverage attacks explain our voting results. To conduct these exercises, we collect news stories from two sources: the Frankfurter Allgemeine Zeitung (FAZ), a national publisher in Germany that enjoys one of the highest circulation rates among all newspapers, and LexisNexis which collects stories from a range of local and regional publishers.

Using these newspaper reports, we find that, on average, successful attacks are no more *likely* than failed attacks to receive regional or local coverage. However, successful attacks receive significantly *more* local coverage than failed attacks.⁹ We also document significant differences in *tone* and *content* between local stories that cover successful attacks and local stories that cover failed attacks: Stories that cover successful terror have lower sentiment scores and use significantly different vocabulary, highlighting themes such as Islam and terror and playing down issues related to right-wing populism. These results are particularly noteworthy when one considers that the characteristics of successful and failed attacks, including the motivation behind the attack and the weapon technology employed, are not significantly different. These

7. This particular result is also (partially) in line with Gethin, Martínez-Toledano, and Piketty (2021) who document the gradual process of disconnection between the effects of both education and income on voting outcomes.

8. Bordalo, Gennaioli, and Shleifer (2013) apply this notion of salience to understand context-dependent choice of consumers.

9. We find no such patterns when examining national news coverage: Not only do attacks receive less coverage at the national level than at the local level, there is no differential coverage of successful attacks compared to failed attacks at the national level.

results suggest that local media coverage plays an important role in making successful attacks — and certain themes used to describe those attacks — salient.

Finally, to understand the extent to which media coverage drives our voting results, we re-run our baseline analysis in samples split according to the media coverage attacks receive. We find that the effect of successful terror on the AfD vote share in state elections nearly doubles for those attacks that receive the most media coverage (i.e., attacks that receive more coverage than the 75th percentile of the news coverage distribution). These same attacks also significantly increase the vote share of the AfD in Federal elections by some 4 percentage points, an effect that represents a 35 percent increase relative to the sample mean, very similar to our baseline effects for state elections. This result underscores the important role of the media in shaping political preferences and voting behavior.

Our paper contributes to a rich literature that documents the electoral consequences of terrorism. These papers, by and large, fall into three categories: The study of terrorism in Israel (Gould and Klor [2010]; Berrebi and Klor [2008]; Getmansky and Zeitzoff [2014]); in less stable, non-Western democracies (Rehman and Vanin [2017]; Kibris [2011]); or in cross-country settings which include a wide range of democracies (Jones and Olken [2009]; Rees and Smith [2022]; Larsen, Cutts, and Goodwin [2020]; Gassebner, Jong-A-Pin, and Mierau [2008]). The findings of these papers is mixed: Some find that incumbent politicians lose electoral support as a result of terror (Gassebner, Jong-A-Pin, and Mierau [2008]) while others do not (Koch and Tkach [2012]). Some find that terrorist attacks increase support for right-wing parties (Berrebi and Klor [2008]; Getmansky and Zeitzoff [2014]) and others find that right-wing parties shift to the left in response to terror (Gould and Klor [2010]). Our point of departure from this literature is twofold. First, we examine the effect of terrorism on far-right voting in the context of an advanced, multi-party Western democracy^{10,11}. Second, our analysis includes a full account of *why* terror influences

10. Although Israel has characteristics of a liberal democracy, scholars do not consider it comparable to Western liberal democracies for several reasons. These include security concerns — including the very high frequency of terrorist attacks (according to the GTD, all the countries in Western Europe combined experienced 3,891 terrorist attacks between 2000 and 2020 compared to 2,924 attacks only in Israel in that same period) — ethnic and religious divisions as well as territorial disputes (Dieckhoff [2016]; Neuberger [1989]). As such, some scholars refer to Israel as an “ethnic” democracy as distinct from liberal democracy (Smooha [1997]).

11. To our knowledge, Baccini et al. [2021] and Bali [2007] are the only other papers that examine the impact of terror on electoral outcomes in Western democracies. However, Baccini et al. [2021] do not find any effects and, perhaps because they study a two-party democratic system, do not examine the question of right-wing populism. Bali [2007] studies the effect of the 2004 Madrid bombing on electoral outcomes in Spain but does not benefit

political outcomes, a step not taken in most previous work. In this respect, we highlight the role of voter mobilization, shifting political attitudes, and media coverage.

Our paper also adds to the literature that explains the rise of populism. Especially in recent years, this has been the subject of focus by economists who have highlighted the important role that economic factors play in explaining the rise of populist movements. These include the role of economic insecurity and distress (Guiso et al. [2020](#); Guiso et al. [2017b](#); Bo' et al. [2023](#); Dehdari [2021](#)), globalization shocks (Rodrik [2018](#)) and government austerity (Fetzer [2019](#)). Scholars have increasingly paid attention to the importance of factors such as identity, education, and migration in generating a “cultural backlash” from which populist movements spring to power (Bonomi, Gennaioli, and Tabellini [2021](#); Gethin, Martínez-Toledano, and Piketty [2021](#); Norris and Inglehart [2019](#)). Although this literature has examined cultural conflicts, the role of violent conflict is surprisingly absent. We thus advance this literature by shedding light on the causal role of violence in explaining the rise of, or at least the added support for, right-wing populism.

Finally, by documenting differential newspaper reporting, our paper speaks to a broad literature that documents the important role of media — including radio, newspapers, and cable news — in shaping political outcomes (Strömberg [2004](#); Gentzkow, Shapiro, and Sinkinson [2011](#); DellaVigna and Kaplan [2007](#); Durante, Pinotti, and Tesei [2019](#))¹². It also adds to scholarship that illustrates the specific impact of media attention in amplifying terror's effects (Alfano and Görlach [2022](#); Brodeur [2018](#); Jetter [2017](#), [2019](#)).

The rest of the paper is organized as follows: Section [2](#) describes the institutional setting of our study, including details on terrorism in Germany, the establishment of the AfD, and the broader German political landscape. In Section [3](#), we provide sources and other relevant details regarding our data. Section [4](#) discusses and evaluates our identification strategy. In Section [5](#), we present our baseline estimating equation and results, while in Sections [6](#) to [9](#) we present evidence on mechanisms that drive our effects. Finally, we conclude in Section [10](#).

from exogenous variation and does not examine right-wing voting.

12. Refer to Gentzkow, Shapiro, and Sinkinson ([2011](#)) for an overview of the political science literature that documents the political effects of media.

2. Institutional Setting

2.1 *Terrorism in Germany*

Our data on terror attacks in Germany come from the Global Terror Database (GTD, 2018) collected by the University of Maryland, College Park.¹³ These data indicate that there have been 232 attacks in Germany between 2010 and 2020. These attacks are geographically widespread, taking place in all 16 Federal states, and are mostly small and non-deadly. The average population of targeted municipalities is around 155,000, and the attacks, on average, result in 1 injury and 0.2 casualties (see Table A.1 in the Online Appendix for further details).

A novel feature of this data is that it includes a variable that records whether an attack was successful. The code book to the GTD defines this variable as follows:

Success of a terrorist strike is defined according to the tangible effects of the attack.

Success is not judged in terms of the larger goals of the perpetrators. For example, a bomb that exploded in a building would be counted as a success even if it did not succeed in bringing the building down or inducing government repression.¹⁴

The GTD applies its definition of success to attacks that were actually executed. Plots or conspiracies that are *not* attempted are not included in the GTD. As the GTD code book explains, “for an event to be included in the GTD, the attackers must be “out of the door”, en route to execute the attack. Planning, reconnaissance, and acquiring supplies do not meet this threshold.” This alleviates an important endogeneity concern that attacks fail because of preemptive policing efforts.

We provide detailed descriptive information on terrorist attacks in Germany in Online Appendix A. As shown in that table, of the 232 attacks in our sample, 86 percent succeeded and 14 percent failed. What is more, the majority of the attacks in our sample are carried out by right-wing extremists and target migrants.

13. We describe these data further in the Supplemental Data Appendix and how we match them to German municipalities in Section 3.

14. An important exception are assassination attempts. As the GTD explains: “In order for an assassination to be successful, the target of the assassination must be killed. For example, even if an attack kills numerous people but not the target, it is an unsuccessful assassination.” Because the success/failure of assassinations is defined differently to other types of attacks, we omit assassinations from our analysis.

2.2 *The Alternative für Deutschland*

Norris and Inglehart (2019) classify the Alternative for Germany (AfD) as “authoritarian-populist” on the basis of political party positions along three dimensions: authoritarian values (security against threats, loyalty to strong leader), populist rhetoric (“*we the people*”) and conservative economic values (economic protectionism).

The AfD was established in 2013 as a single-issue party focused on the Euro crisis and the Greek bailout. The party quickly gathered public attention as it won 4.7 percent of the seats in parliament in the Federal elections later that same year and 7.1 percent of the European parliament elections in 2014 (Cantoni, Hagemeister, and Westcott 2019). Although established as a single-issue party, the AfD included many members that held hard-right, populist sentiments from its beginnings. Their voices eventually led the party to a turning point in 2015 when two of its members, Björn Höcke and Andreas Kalbitz, laid out the prominent “Erfurt Declaration” which founded the far-right faction of the AfD (*Der Flügel* or *The Wing*) (Cantoni, Hagemeister, and Westcott 2019). This document described the AfD as a “resistance movement against the further erosion of the identity of Germany” and, since then, the party, especially its far-right faction, has been increasingly characterized by racist, Islamophobic, xenophobic and anti-Semitic rhetoric, including downplaying Nazi crimes.¹⁵ One of its former members was also arrested as part of a 2022 attempt to overthrow the German government, execute the chancellor, and restore Germany’s imperial Reich.¹⁶ Nonetheless, support for the party has only increased. After its hard right turn in 2015, the party won as much as 16 percent of the vote in state elections. In 2017, the AfD was represented in the federal parliament for the first time and it continues to enjoy representation across various levels of government across the country. Figure B.1 in Online Appendix B shows the average vote share for the AfD between 2013 and 2021 across all elections. As shown, its average vote share has increased from less than 5 percent in 2013 to close to 16 percent in 2021 and it has fared significantly better in state elections than in Federal elections as shown in Figure B.2 in Online Appendix B.

15. See [this](#) news piece for further details. Accessed 4 April 2023.

16. See [this](#) story for further details. Accessed 4 April 2023.

2.3 The German Political Landscape

The AfD is situated on the far-right of the political spectrum in German politics. In addition to the AfD, this spectrum consists of five other established parties.

The two dominant parties are the center-right CDU, which ruled the German government between 2005 and 2021, and the left-leaning social democrats, the SPD. The other main party right of center in German politics is the economically liberal FDP. The left end of the political spectrum is populated by two parties, aside from the SPD: *Die Grünen* (the Greens) and the socialist *Die Linke* (the Left party). The Greens have their roots in the post-materialist movements of the 1970s and emphasize environmental sustainability and women's rights (Probst 2013). The Left party, on the other hand, is the successor of the East German Communist Party, which had ruled the German Democratic Republic (GDR) until its dissolution in 1990.

The German political landscape now comprises six major parties, as shown in Figure 1 where they are plotted according to a left-right score according to data collected by the Manifesto Project (Lehmann et al. 2022). As shown, the AfD is clearly the far-right party.

3. Data

The primary unit of observation in our study is the German municipality which we observe in different election years. In this section, we describe the main variables used in our analysis. The Supplemental Data Appendix contains further details.

Terror attacks: We collect information on terror attacks in Germany between 2010 and 2020 from the Global Terror Database (GTD, 2020) maintained by the University of Maryland, College Park. This is an open source database that documents information on terror attacks from around the world from 1970 to the present day. In the Supplemental Data Appendix, we provide additional details as to how the GTD collects these data as well as the criteria they employ to determine what events are included in the Database.

The GTD includes longitude and latitude coordinates of the city in which each attack took place which we use to map each attack onto a German municipality.¹⁷ This enables us to map

17. In the case of Berlin, we do not rely on these coordinates as they always point to central Berlin. Instead, we

the 232 attacks in our sample onto 124 unique municipalities. According to the GTD, over 50 percent of these attacks are motivated by right-wing causes.

Of the 124 municipalities targeted with an attack between 2010 and 2020, 33 were targeted more than once. We thus define a municipality as being hit with a successful attack if, at any point since 2010, it was hit with a successful attack, even if before or after that particular attack it was hit with a failed attack. A municipality is marked as being targeted with a failed attack if, at any point since 2010, it was targeted with one or more failed attacks but never with a successful attack. In our baseline analysis, the date of the first failed or first successful attack is the reference point from which we determine whether an election was pre- or post-attack. According to the GTD, 75 percent of these first attacks are carried out by right-wing extremists and 75 percent target foreigners.

Election data: In our analysis, we study election outcomes across the three most prominent elections in Germany: Federal elections; European Parliament elections; and elections across the 16 Federal states, the *Bundesländer*, that determine representation at the state level.

We obtain municipality level election results for the 2013, 2017 and 2021 Federal Elections and the 2014 and 2019 European Parliament elections in Germany from the Federal Returning Officer (*i.e.*, the *Bundeswahlleiter*).¹⁸ We obtain municipality election results for state elections that took place between 2013 and 2021 from the Regional Data Bank service of the German Federal Government.¹⁹ In all our analyses, we leverage information on the *second* vote (*i.e.*, *Zweitstimme*), which is the voters choice of political party, as opposed to the first vote (*i.e.*, *Erststimme*) which is the voter's direct choice of candidate. This is to avoid confounding our analyses with candidate-specific effects.

Municipality characteristics: We check for balance along a wide range of covariates in municipalities hit with successful or failed attacks. Information on all municipality characteristics is based on the description of the attack in order to locate in which of the 12 municipal districts, *Stadtbezirke*, of Berlin the attack is located.

18. These data can be accessed here: <https://www.bundeswahlleiter.de/en/>. Accessed 14 December 2022

19. Specifically, these data were taken from the *Statistische Ämter Des Bundes und Der Länder* which can be accessed here: <https://www.regionalstatistik.de/genesis/online/>. Accessed 14 December 2022

tics are taken from the Regional Data Bank service of the German Federal Government whose source is provided in Footnote [19](#).

SOEP Survey Data: The Germany Socio-Economic Panel (SOEP) is one of the largest and longest-running multidisciplinary household surveys worldwide. Every year since 1984, approximately 30,000 people in 15,000 households are interviewed for the SOEP. The SOEP contains survey questions on a wide range of social, political, demographic and economic issues. Crucially, the SOEP is a panel that tracks individuals and households over time. This enables us to study the political preferences and attitudes of the *same person* before and after experiencing a terror attack. We obtained access to the restricted-use SOEP data with municipality identifiers in order to link our data on successful/failed attacks to this survey data. The Supplemental Data Appendix contains further details on the exact formulation of the questions used in the SOEP and how we used them in our analysis [20](#).

Frankfurter Allgemeine Zeitung (FAZ): The FAZ is a prominent newspaper in Germany that enjoys some of the highest nationwide circulation. We obtain its newspaper data in order to test whether successful attacks receive differential coverage compared to failed attacks. Specifically, for each of the attacks in our sample, we obtain all news stories that mention the city of the attack on the particular day of the attack and for the 10 days that follow the attack. This provides us with a database of some 105,000 unique news stories [21](#). We employ three criteria to match stories to attacks: a neural-network based classification model trained on Austrian terror data and its coverage; matching based on key words; and, as a final step, we manually checked all remaining stories to rule out false positives [22](#). In the end, we are left with around 350 stories.

LexisNexis: We use LexisNexis in order to collect news stories from national, regional and local publishers across Germany. This provides us with a sample of some 80,000 stories.

20. We are thankful to the German Institute for Economic Research (the DIW) in Berlin for making our visit to the SOEP Data Center possible.

21. We thank the FAZ-Foundation for its financial support in helping us to procure these data.

22. Further details on the methods used to match stories to attacks can be found in the Supplementary Data Appendix.

For each of the attacks in our sample, we match them to stories from the LexisNexis data using the same three criteria we used for the FAZ data. Moreover, we identify all news stories from *local and regional* sources and exclude stories from national publishers. This leaves us with a sample of around 4,500 stories.

4. Establishing Balance

Our identification strategy relies on the assumption that the success of an attack is orthogonal to municipality characteristics. In this section, we test this assumption. We define the variable $SUCCESS_i$ as one if municipality i was hit at least once with a successful attack since 2010 and zero if it was hit with at least one failed attack (and no successful attack) in that same time period; the variable is undefined for municipalities that did not experience any attacks. We then regress a range of municipality characteristics measured in time periods *prior* to the attack on the success variable as shown in the following estimating equation²³

$$X_{i,t < t_{ATTACK}} = \beta_0 + \beta_1 SUCCESS_i + \epsilon_i \quad (1)$$

Our strategy is validated if our estimate for β_1 is indistinguishable from zero. We present our findings in Columns 1 and 2 of Panel A of Table 1. As shown, there are no differences between municipalities targeted with successful and failed attacks. This pattern holds for a wide range of socio-economic characteristics and underscores the random nature attack success²⁴

Importantly, success is uncorrelated with a number of key socio-economic variables which may act as confounders. For example, the 2015 Syrian refugee crisis in Germany sparked a wave of discontent in the country and it could be that the number of refugees in a municipality has a direct influence on both the likelihood of an attack's success and support for the radical right. As shown in Table 1, however, success is uncorrelated to refugee inflows, both in total and specifically from Syria. Another potential concern relates to the geographical location of attacks. Support for the far-right has traditionally been stronger in former East Germany and

23. The only exceptions are (1) whether a municipality is located in East/West Germany and the 1933 NSDAP vote share which are analyzed in the cross-section and (2) the number of days between an election and an attack, for which we include periods both before and after the attack.

24. We also find no difference in the size or presence of the police force. However, these data are only available as of 2019 for a select number of municipalities. For this reason, we do not include these measures in our analysis.

around a third of the attacks in our sample take place there, leaving open the possibility that characteristics specific to East Germany drive both right-wing voting and successful terror. The results in Table 1 however, make clear that success does not exhibit geographical selection. Finally, we find that success is uncorrelated with political characteristics, including the size of the eligible voting population, voter turnout and, crucially, the vote share of the AfD as well as the vote share for Hitler’s NSDAP party in 1933, the last democratic election of interwar Germany. This suggests that, in the absence of terror attacks, support for right-wing populism is not a pre-existing characteristic of municipalities targeted with successful attacks.

The differences between municipalities targeted with successful and failed attacks, presented in Table 1 stand in sharp contrast to those between municipalities targeted with attacks and those untargeted. This is demonstrated in Online Appendix C where we document systematic differences between targeted and untargeted municipalities. What is more, we find that these differences hold for municipalities targeted with *both* successful and failed attacks, suggesting that the municipalities hit with failed attacks are not just a random subset of untargeted German municipalities²⁵

In Panel B, we compare the characteristics of all the attacks in our sample²⁶ As shown, there is little distinguishable difference in weapon technologies or attack motivations, further underscoring the quasi-random nature of an attacks success²⁷

5. Terror and the AfD

5.1 Baseline Model

We model the AfD vote share in municipality i , in election e , in time period t as follows:

$$AfD_{i,e,t} = \beta_0 + \beta_1 [SUCCESS_i \times POST_{i,e,t} \times ELECTION_e] + \zeta \mathbf{X}_{i,e,t} + \lambda_{ie} + \alpha_t + \epsilon_{i,t} \quad (2)$$

25. Because municipalities hit with failed attacks demonstrate selection compared to untargeted municipalities, later in the paper we investigate whether failed attacks generate their own political effects.

26. We study patterns for all 232 attacks to (1) increase the sample size of this analysis and (2) establish the more general conclusion that successful and failed attacks resemble each other. Repeating this analysis using only the first attack in the 124 unique municipalities that experience an attack produces similar results.

27. We present balance results for the three most common weapon types used in attacks: explosives (which include incendiary devices), firearms and melee (hand) weapons.

As before, $SUCCESS_i$ is one if a municipality experienced one or more successful attacks and it is zero if it experienced one or more failed attacks (and no successful attacks). To isolate the effect of a terror attack on an election result, we interact the indicator $SUCCESS_i$ with an indicator $POST_{i,e,t}$ that is 0 for all elections e in years t that were held prior to the *first* attack in municipality i and 1 for all elections that were held after the first attack and with a categorical variable, $ELECTION_e$ that indicates a Federal, European Parliament or state election. The vector $\mathbf{X}_{i,e,t}$ includes all lower order terms of the triple interaction, but we omit the term $SUCCESS_i \times POST_{i,e,t}$ so that the coefficient of interest, β_1 , is interpreted as the total marginal effect of a successful attack, compared to failed attacks, before and after a given election.

Because we study Federal, European and state elections in the same model, we include election-type by municipality fixed effects, λ_{ie} , to filter out potentially confounding effects specific to each municipality that might vary across different election types. We also include year fixed effects, α_t to capture unobserved time heterogeneities and we cluster the standard errors, $\epsilon_{i,t}$, at the municipality level.

5.2 Baseline Results

We report the results in Table [2](#). In Column 1, we run the baseline model and find that the AfD vote share increases by some 6 percentage points in state elections, a 37 percent increase relative to the sample mean. In Columns 2 to 9, we undertake a number of robustness exercises which we describe in turn.

In Column 2, we include the interaction between an East/West Germany indicator and year dummies so as to control for any time varying factors specific to East/West Germany that might influence both the number of attacks and the rise of the AfD. This is especially important when one considers that the AfD has stronger support in former East Germany. In Column 3 we omit Berlin, a city-state that experienced some 25 percent of the attacks in the sample and which, in some ways, acts as an outlier. In Column 4, we interact an indicator for whether a municipality is classified as an urban district, a *kreisfreie Stadt*, with year dummies so as to control for potentially confounding effects of dense urban centers. In Column 5, we control for

the weapon used in the attack and in Column 6, we include the number of days between a given election and the date of the first attack so as to account for the wide variation in an attack's timing relative to an election. In Column 7, we omit the 33 municipalities that experienced more than one attack and in Column 8, we omit those attacks that were part of a larger, coordinated attack and thus had greater likelihood of success.²⁸ Finally, in Column 9, we include all municipality characteristics presented in Panel A of Table 1 as controls (except for political characteristics). Specifically, for each municipality, we measure the *pre-attack* mean of each characteristic and interact this measure with year dummies, thus allowing municipality characteristics other than terror to differentially affect the AfD vote share post-attack.

Across all these specifications and samples, we find consistent patterns: successful terror attacks lead to differential increases for the AfD in state elections. The coefficient of interest is stable across all columns and is precisely estimated. By contrast, we see no clear patterns for Federal or European Parliament elections. The coefficients are smaller, are not distinguishable from zero and display no clear sign. However, as we demonstrate in Section 8, successful terror attacks that receive high media coverage also have large, positive (and significant) effects on the AfD vote share in Federal elections.

A key institutional feature of Germany that helps explain why our effects are more pronounced at the state level compared to the Federal level is the distribution of power among Federal and state governments. Concerning terrorism, there are two policy areas where states play a larger role than the Federal government. The first is internal security which, according to Article 30 of the German constitution, is primarily organized and executed at the level of the federal state (Riedl 2018; Schnöckel 2018).²⁹ The second area is the issue of immigration and refugee settlement which, as we show later, terror increases worries about. Although asylum seekers are distributed across the Federal states according to formula, their distribution *within* states is a discretionary matter for states to determine.³⁰ Our results suggest, therefore, that at least a subset of voters is aware of the distribution of competencies between federal and state

28. The GTD counts a coordinated terror attack as successful even if one of its constituent attacks succeeded and the others failed.

29. This institutional feature of Germany is reflected in public expenditures on internal security: they are significantly higher at the state level (€14.619 billion in 2011) than they are at the federal level (€3.343 Billion in 2011) (Riedl 2018).

30. See [this](#) page of The Federal Office for Migration and Refugees for additional details. Accessed 4 April 2023

governments concerning internal security and asylum and vote accordingly in response to terror.

There are three pieces of evidence that support this view. First, as we demonstrate later, terror has a large, significant effect on voter turnout in state elections. By contrast, turnout in Federal and European elections is completely unaffected by terror. This suggests that terror has a *mobilizing* effect in state elections which benefits the AfD. Second, we compare the AfD vote share in municipalities targeted with successful terror attacks pre- and post-attack on a sample of municipalities that had both Federal and state elections on the *same* date. The intuition is to test whether terror attacks lead voters to vote differentially in state and Federal elections, even when those elections are held at the same time. Although this exercise considerably shrinks our sample, we find that the AfD vote share is higher in state elections than it is in Federal elections post-attack ($\hat{\beta} = 0.003$ with a p -value of 0.168). This increases our confidence that local acts of terror make state level policy more relevant for voters. Third, as we demonstrate in Online Appendix [L](#), local acts of terror lead the AfD to use different vocabulary in its election manifestos for *state* elections, demonstrating that, at least the AfD, campaigns differentially at the *state* level in response to terror.

5.3 Additional Robustness

In Online Appendix [D](#), we report results from four additional sets of robustness exercises which are briefly described in this section.

First, there is a growing literature addressing issues related to panel estimation with two-way fixed effects and staggered treatment. Because our setting involves a staggered, binary treatment variable, we carry out our baseline estimation using an alternative estimator from this literature proposed by Borusyak, Jaravel, and Spiess ([2021](#)). As shown in Appendix [D.1](#) there is little difference to our main result when using this alternative estimator.

Second, in Online Appendix [D.2](#) we repeat the baseline analysis using a “rolling window” approach in order to incorporate a larger number of attacks into the analysis. For the 91 municipalities that received one attack, the coding of the variables *SUCCESS* and *POST* remain unchanged. However, instead of dropping the 33 municipalities that received more than one attack as we did in Column 7 of Table [2](#), we now create a “rolling window” of time

around each municipality-attack, where each window is defined as the period of time between an election, an attack and the next election³¹. *SUCCESS* is now coded according to the attack in the window and *POST* is coded for each election in the window depending on whether the election was before or after the attack. The results are reported in Table D.2 and produce very similar results to those generated using the first attack only, alleviating concerns that municipalities hit with multiple attacks adversely affect our results. As mentioned in the Online Appendix, however, this approach has the disadvantage of making interpretation more difficult because of overlapping time-periods: the “post” period of one attack in a given municipality is the “pre” period for the subsequent attack. For this reason, we use only the first attack in our baseline analysis.

Third, given the relatively small size of our sample — 124 municipalities of which 11 are in the control group — we present our baseline result with alternative inference methods in Online Appendix D.3³². These include a permutation exercise in which the variable success is randomly permuted in order to generate a null distribution from which to estimate a p -value as well as wild cluster bootstrapping (Cameron, Gelbach, and Miller 2008). As shown, our baseline result is robust to alternative inference.

Fourth, we run our baseline model 124 times, each time omitting one municipality from the analysis to ensure that no outliers drive our result. As shown in Figure D.1 of Online Appendix D.4, the results are stable to this robustness exercise.

5.4 Effects of Successful and Failed Terror Attacks

Our baseline estimate identifies the effect of successful terror attacks *relative* to failed attacks. One may wonder, however, whether terror attacks, regardless of success, have an overall *level* effect on voting outcomes when compared to untargeted municipalities³³. We address this

31. In practice, the “pre” and “post” periods in each window can include more than one election. This is the case if there are no attacks between elections.

32. In addition to alternative inference, we undertake two additional exercises to address the small size of the control group. The first of these is the rolling window approach described above which increases the number of control municipalities to 20. Second, as described in the next subsection, we employ a propensity score matching method to increase the size of the control group to over 200 municipalities.

33. This is especially true when one considers that municipalities targeted with both successful *and* failed attacks are systematically different along a wide-range of socio-economic characteristics compared to untargeted municipalities, as demonstrated in Online Appendix C

question in this subsection by undertaking a propensity score matching exercise. Specifically, for each successfully targeted municipality, we identify its nearest neighbors on the basis of propensity scores from the sample of untargeted municipalities using all the municipality covariates presented in our balance table.³⁴ We then use these matched municipalities, which we refer to as *placebo fail*, to run a number of additional tests presented in Table 3.

In Columns 1 and 2 we check for balance in the AfD vote share between successfully targeted municipalities and placebo fail municipalities (Column 1) and failed municipalities compared to placebo fail (Column 2). As shown, there is no distinguishable difference in the AfD vote share between these municipalities, suggesting that the matching procedure worked well.

Next, we run our baseline analysis using these different municipality types. In Column 3, we estimate our baseline model in a sample that uses only successful targeted municipalities and untargeted municipalities matched via propensity scores (i.e., placebo fail). As shown, the coefficient is very similar to our baseline estimate, even as the size of the control group expands considerably to include just over 200 municipalities. In Column 4, we compare outcomes in municipalities that actually experienced failed attacks compared to placebo failed municipalities. As shown, the coefficient on state elections is two orders of magnitude smaller and is indistinguishable from zero. These results suggest that failed attacks do not generate their own effects and that our baseline is, in fact, driven by the success of terror attacks.

5.5 Attack Type Heterogeneity

We examine whether our baseline estimates display heterogeneous effects according to the motives of the attacker. In Figure 3, we estimate our baseline model in samples split by right-wing causes — all right-wing attacks and right-wing Neo-Nazi attacks — as well as on a sample of attacks that target foreigners. We also estimate the baseline effect on the sample of attacks that are non-right wing, including left-wing attacks and Islamist attacks. As shown, we find that the baseline attack is driven almost entirely by right-wing attacks and by attacks that target foreigners. This suggests that the AfD benefits from acts of terror which, by and large, are

34. Online Appendix E contains further details regarding the propensity score matching.

motivated by right-wing causes.³⁵

5.6 Geographic Spillovers

In Online Appendix G, we present evidence to suggest that successful terror has significant geographical spillover effects. Specifically, we investigate the impact of successful terror for municipalities within a radius of up to 80 kilometers from an attack. As shown, the coefficient of interest is around 50 percent smaller than the baseline but statistically significant for municipalities located between 25 and 50 kilometers from an attack. The qualitative effects persist beyond 50 kilometers, but are even smaller and are mostly indistinguishable from zero. For municipalities located 80 kilometers away, the effect diminishes to zero.

6. Terrorism and Turnout

We begin our investigation of channels by studying the effect of terror on voter turnout and on the vote share for other parties.³⁶ We estimate the same model presented in equation 2 and present the results for the triple interaction for state elections in Figure 2.³⁷

In Panel (a), we study the effect of terror on turnout as measured by the number of votes cast per eligible voter in a municipality. The coefficient in the first bar suggests that, following a successful attack, the number of eligible voters who participate in state elections increase by some 16 percentage points ($\beta = 0.1665$, p -value = 0.000), a 28 percent increase relative to the sample mean of turnout in state elections. Given that the eligible voting population does not differ between municipalities hit with successful or failed attacks (see Table 1), this result underscores the impact of successful terror on voter mobilization and not on the size of the

35. One concern is that these effects might not cleanly identify the motive of an attack because municipalities that received more than one attack might have experienced attacks with mixed motivations — say, a right-wing attack followed by a left-wing attack — making it difficult to identify the role of attack motive on the AfD vote share. To alleviate this concern, we re-generate Figure 3 in a sample of municipalities that were attacked only once, enabling us to cleanly identify effects according to motives. The revised plot is shown in Figure F.1 of Online Appendix F. As shown, right-wing attacks have an even larger effect in the sample of municipalities targeted with only one attack, reinforcing the view that right-wing terror has the strongest impact on the AfD vote share.

36. Though election data is available for years prior to 2013, we limit our sample to elections that took place as of 2013 so as to compare the effects of terror on turnout and other parties vote shares once the AfD had entered the political landscape in Germany.

37. Like the baseline results, the coefficients for Federal and European elections are much smaller, are not significant and display no clear patterns when studying turnout.

voting population. In the remaining bars, we study how these voters are distributed among the various parties in German politics. These coefficients thus measure the share of voters, and not the share of the vote, claimed by each party. As shown, the AfD captures captures fully a third of the increases in voter turnout, some 5 percentage points out of the 16 ($\beta = 0.050$, p -value = 0.000). With the exception of the FDP, which captures none of the increases in turnout, the other major parties in the German political landscape claim between 2 and 4 points of the 16 point increase.

In Panel (b) of Figure 2 we examine the extent to which these changes in turnout affect each party's performance as measured by the share of the vote they win. The AfD bar repeats the baseline effect while the remaining bars show the results for other parties. Aside from the SPD, which experiences a 3 percentage point increase in state elections as a result of terror, no other major party in Germany experiences a significant increase in vote shares in response to terror attacks.³⁸

7. Terrorism and Political Attitudes

In this section, we examine the extent to which successful terror affects the political attitudes and preferences of individuals. To do so, we use data from the German Socio-Economic Panel (SOEP), a panel of individuals and households observed over time. The advantage of a longitudinal study like this is that it enables us to study the political attitudes and preferences of the *same person* before and after an attack. We obtained access to the restricted-use SOEP data with municipality identifiers in order to link our data on successful/failed attacks to this survey data. We first establish that individuals residing in municipalities targeted with success and failed attacks are statistically indistinguishable. We then present evidence that suggests our AfD results are driven by voters migrating from across the political spectrum to the AfD as well as by the political activation of previously inactive persons. Finally, we demonstrate that our results display significant heterogeneous effects according to education and, to a lesser

38. The SPD result also appears somewhat robust: specifically, six of the 9 specifications in Table 2 return positive and significant results for the vote share of the SPD in state elections. However, the absolute magnitude of the coefficient is smaller for the SPD compared to the AfD. Given the sample mean for the SPD in state elections is larger for the SPD than it is for the AfD, the SPD effect is even smaller relative to the sample mean (15 percent increase relative to the sample mean compared to a 37 percent increase for the AfD). Nonetheless, this positive effect for the SPD might help explain some of the voter migration results which we present later in the paper.

extent, gender and age. This particular result is in line with recent scholarship that documents demographic factors that make individuals most prone to populist rhetoric and authoritarian values.

7.1 Balance in the SOEP

We begin by checking for balance across a range of pre-attack individual characteristics between people who live in municipalities that experience successful or failed attacks. For each person, we regress different individual characteristics on the variable, $SUCCESS_i$, defined as before. We present the results in Online Appendix II. As shown, there are very little distinguishable differences in socio-economic characteristics between people living in municipalities hit with successful or failed attacks. Moreover, we document no differences in people's pre-attack political attitudes and preferences. This increases our confidence that successful acts of terror lead to differences in voting outcomes because they affect political preferences and not because they target different types of people. Moreover, people do not report moving after experiencing a successful attack, suggesting that successful terror does not lead to geographical sorting.

7.2 Terrorism and Individual Political Attitudes

For each person, p , residing in municipality i surveyed in year t , we estimate the parameters of the following model:

$$y_{p,i,t} = \beta_0 + \beta_1 [SUCCESS_i \times POST_{i,t}] + \delta_p + \alpha_t + \epsilon_{m,t} \quad (3)$$

Where y captures responses to different survey questions. Success is 1 or 0 if an individual resides in a municipality that experiences a successful (1) or failed (0) attack. The variable $POST_{i,t}$ is now defined as 0 for all interviews that occurred prior to an attack and 1 for all interviews that occurred after an attack. Crucially, the model includes person fixed effects, δ_p , as well as year fixed effects α_t . Because treatment still varies at the level of the municipality, we cluster our standard errors at that level, denoted by $\epsilon_{m,t}$.

Table 4 presents our findings. The coefficients in Columns 1 and 2 indicate that, after successful attacks, individuals not only identify as more right-wing on a left-right political

ideology scale but as more hard-right. This ideological shift is also reflected in the partisan preferences individuals hold. In Columns 3 to 5, for example, we find that successful attacks lead people to identify more with the AfD, less with the CDU (though not quantitatively significant) and significantly more with the SPD, results that are directly in line with our aggregate results on vote shares. Although the coefficient for the SPD is larger than that of the AfD, the effect relative to the sample mean is much larger for the AfD than it is for the SPD, again in line with our baseline findings. Interestingly, the coefficient in Column 6 suggests that, following a successful attack, individuals participate significantly more in politics *at the local level*, patterns consistent with our findings that suggest terror matters primarily for state elections.

In Columns 7 and 8 we investigate the differential effects of terror on different social attitudes. In Column 7, for example, we find that terror significantly increases people's worries about immigration to Germany. By contrast, in Column 9 we find that successful terror has no effects on people's concerns about terrorism. While these results are interesting in their own right, they are broadly consistent with how both the news media and the AfD respond, in terms of the language they employ in their reporting and election documents, respectively (described in subsequent sections).

7.3 Heterogeneous Effects: Voter Migration and Political Activation

To what extent are these changes in political attitudes driven by voter migration — that is, committed partisans of one party leaving to support the AfD — and to what extent are they reflective of the political mobilization of politically inactive people who turn out to support the AfD? To investigate these questions, we test for heterogeneous effects along two dimensions: partisanship and political activity. Specifically, we estimate the parameters of the following two estimating equations:

$$\text{Prefer AfD}_{p,i,t} = \beta_0 + \beta_1 [SUCCESS_i \times POST_{i,t} \times PARTISAN_p] + \zeta \mathbf{X}_{p,i,t} + \delta_p + \alpha_t + \epsilon_{m,t} \quad (4)$$

$$\text{Prefer AfD}_{p,i,t} = \gamma_0 + \gamma_1 [SUCCESS_i \times POST_{i,t} \times ACTIVE_p] + \zeta \mathbf{X}_{p,i,t} + \delta_p + \alpha_t + \epsilon_{m,t} \quad (5)$$

In both models, the outcome is an indicator that is 1 if the preferred political party of person p in municipality i in time period t is the AfD and zero otherwise.

In equation 4, we identify the effects of terror on a persons likelihood to prefer the AfD for people with and without partisan commitments. The variable $PARTISAN_p$ is thus defined as 1 if, in all the surveys *prior* to an attack, a person prefers a particular party (i.e. the person is a committed partisan). It is zero if, in the surveys preceding an attack, an individual states more than one party as their preferred political party. For each major party, we thus identify its pre-terror committed partisans and investigate whether successful terror leads them to migrate from their preferred party to the AfD.

In equation 5, we investigate whether successful terror has differential effects for people who are politically active compared to those who are inactive. The variable $ACTIVE_p$ is thus defined as 1 if an individual reports participating in local politics frequently in all the surveys that *precede* an attack. It is defined as zero for individuals who, pre-attack, report their participation in local politics as seldom or never. Both estimating equations include all lower order terms, $X_{p,i,t}$, and all other terms are defined as before³⁹

We present our results in Table 5. In Columns 1 to 6, we find that, across the board, people who are *not* politically committed to a certain party all tend to prefer the AfD more after experiencing a successful attack. Moreover, people committed to the SPD (the main rival to the CDU), the FDP and the Greens show no increased preference for the AfD in response to terror, suggesting that voters do not migrate from these parties to the AfD. By contrast, people who are committed to the CDU prior to an attack display significant preference for the AfD after experiencing a successful attack, suggesting that voter migration from the the main ruling party to the AfD does, in fact, drive some of our results. Similar patterns are found for the Left party (Column 4): in fact, the coefficient is larger for committed partisans than it is for uncommitted partisans, suggesting that acts of terror lead to significant voter migration from the Left party to the AfD. Interestingly, we find some migration away from Germany's ultra-right parties into the AfD. Specifically, in Column 6, we find that individuals who, pre-attack, identify with parties such as the Neo-Nazi National Democratic Party (NPD) of Germany or the anti-immigration

39. In both equations, we omit $SUCCESS_i \times POST_{i,t}$ such that the triple interaction can be interpreted as total marginal effects and not differences.

Die Republikaner respond to terror by preferring the AfD. This suggests that voters from across the entire political spectrum respond to terror by shifting their preference to the AfD.

In Column 7, we present our estimate of γ_1 from equation 5. The coefficients indicate that politically inactive individuals significantly prefer the AfD following a successful attack whereas the opposite is true (though not statistically significant) for politically active people, suggesting that the political activation effects of terror have a partisan slant. Together, these results suggest that the strong demand for the AfD in response to terror appears to be driven both by voter migration from across the entire political spectrum as well as by the political activation of previously inactive people.

7.4 Heterogeneous Effects: Cultural Conflict

We investigate whether terror attacks exhibit heterogeneous effects on political attitudes along relevant dimensions of political conflict, including education, income and employment, gender and age. Specifically, we study three outcomes from the SOEP: whether a person prefers the AfD; whether they prefer the SPD; and whether they participate in local politics. For each outcome, we estimate β_1 from equation 3 in samples split by the relevant dimension of political conflict and plot the corresponding coefficients in Figure 4. We also estimate a model that includes a triple interaction, $SUCCESS_i \times POST_{i,t} \times COVARIATE_p$ (lower order terms included as well), and plot the coefficient on the triple interaction in order to understand whether the coefficients in the split samples are significantly different from one another.

We document clear heterogeneous effects along one dimension: education. Individuals without university education respond differentially to successful terror by preferring the AfD more; they show no increased preference for the SPD. For those with university education, the opposite is true: they differentially support the SPD in response to terror without showing any changes in preference for the AfD. In both cases, the differences between university and non-university educated are quantitatively significant. Interestingly, we also find that education helps drive our results on political participation. While individuals with and without education respond to terror by participating significantly more in local politics, the effect is significantly larger for higher-educated people. These patterns appear consistent with what Norris and

Inglehart (2019) term the “authoritarian reflex”: the notion that groups in society who feel “left behind” by globalization react defensively to shocks that undermine security — including terrorism — by adopting more extreme ideological positions. They are also consistent (at least partially) with Gethin, Martínez-Toledano, and Piketty (2021) who document the gradual process of disconnection between the effects of both education and income on voting outcomes.

7.5 *Timing of the Effect*

In Online Appendix J.1 we examine how people’s political preferences change over time in response to successful terror. To this purpose, we run an event-study regression in which a person’s preference for the AfD is used as the outcome. As shown, there are no pre-trends, suggesting that prior to an attack, AfD preferences are not increasing among people residing in successfully targeted municipalities. Following an attack, however, we observe clear, positive increases preferences for the AfD for people who experienced a successful attack compared to those who experienced a failed one.

8. Terrorism and Media

We posit that a primary channel through which successful terror affects both voting outcomes and political preferences is media reporting which makes successful attacks salient to voters. Following Taylor and Thompson (1982), we argue that successful terror attacks are made salient in the media because they (a) attract differential attention compared to failed attacks and (b) disproportionately affect subsequent voting decisions because of that attention. In this section, we support these claims with evidence first by documenting the extent to which successful attacks receive differential media coverage compared to failed attacks and second by investigating the impact of highly-covered attacks on the AfD vote share.

8.1 *Differential Media Coverage of Successful and Failed Attacks*

To test whether successful attacks receive more media coverage than failed attacks, we collect news stories from two sources: the Frankfurter Allgemeine Zeitung (FAZ), a prominent national publisher in Germany, and LexisNexis which collects stories from a range of publishers and

which includes regional and local news reports⁴⁰ For each terror attack in our sample, we first aggregate the number of stories that cover it in order to understand whether successful attacks are (a) more *likely* to receive coverage and/or (b) whether they receive greater *quantity* of coverage than failed attacks. Then, for each story that is linked to a terror attack in our sample, we analyze the extent to which success influences the *tone* of coverage, as measured by sentiment scores, and the *content* of coverage, as measured by the frequency of key words. Our results are presented in Table 6 In Columns 1 and 2, the unit of observation is the terror attack. In Columns 3 to 9, the unit of observation is the news story. Because we aim at estimating the difference in media coverage between successful and failed attacks — and not between successful and failed attacks before and after an election — we drop municipality and year fixed effects and replace them with state \times year fixed effects so that we can estimate the parameter of interest.

In Panel A, we present results from regional and local news reports collected from LexisNexis. In Column 1 we find that successful attacks are no more *likely* than failed attacks to receive coverage. However, in Column 2 we find that successful attacks, on average, receive differentially *more* coverage: compared the failed attacks, successful attacks receive around 8 more news reports among regional and local news sources (a 73 percent increase relative to the sample mean of 11 stories per attack). The results in Columns 1 and 2 thus suggest that successful attacks are salient in the news media because they are covered more intensively and not because failed attacks fail to receive coverage, results that are directly in line with Brodeur (2018). In Columns 3 and 4, we find that news stories that cover successful attacks have worse sentiments, both in the story title (though not quantitatively significant) and body, suggesting that success not only influences the quantity of coverage but the *tone* of coverage. Finally, we investigate the extent to which successful terror attacks influence the *content* of news reports as measured by the frequency of key words. Stories that cover successful attacks speak significantly less about right-wing populism and crime but significantly more about Islam, a result that is particularly noteworthy given that the majority of the attacks in our sample are motivated by right-wing causes and are targeted against migrants. We also find that news coverage at the

40. LexisNexis also includes stories from national outlets but we omit these so that our LexisNexis measures only local and regional coverage.

sub-national level uses words related to terrorism significantly more in response to successful attacks. This suggests that local and regional media coverage differentially label successful attacks as terrorist events and differentially highlight Islam when describing them.

The patterns for national coverage are different. As shown in Columns 1 and 2 of Panel B, successful attacks do not enjoy greater coverage at the national level, nor is the sentiment of a story (Columns 3 and 4) affected by an attacks success. National stories that cover successful attacks, compared to national stories that cover failed attacks, do, however, appear to highlight issues related to Islam and downplay crime, just like news coverage at the local and regional level. On the whole, however, not only do the attacks in our sample receive less coverage at the national level compared to the local level, successful attacks are no more salient than failed attacks in national reporting. Together, these results suggest that the regional and local news media play an important role in making successful attacks, and certain topics used to describe those attacks, salient⁴¹

8.2 High-Coverage Attacks and AfD Vote Share

We now examine how media coverage affects our baseline results. To conduct this test, we repeat our baseline analysis in samples split by the amount of media coverage that terrorist attacks receive. The results are presented in Figure 5. In Panel (a), we repeat our baseline analysis. Panel (b) shows the same parameters but in a sample of municipalities whose terror attacks (successful and failed) received more than the 75th percentile of news coverage. There are two noteworthy conclusions: first, the baseline effect on state elections nearly doubles, in line with the view that greater media coverage of successful attacks leads to stronger political effects. Second, there is now a positive, significant effect for Federal elections. The point estimate on Federal elections is around 4 percentage points which represents a 35 percent increase relative to the sample mean, very similar to our baseline effects for state elections. By contrast, in the sample of municipalities hit with low-coverage attacks, shown in Panel (c), the Federal election effect vanishes while the coefficient on state elections decreases by around 50 percent

41. In Online Appendix K we also test for differential coverage of successful attacks using Facebook data. Drawing on data from Müller and Schwarz (2021), we find that successful attacks lead to differentially more AfD Facebook users.

but remains statistically significant. Together, these results are consistent with previous research that demonstrates the important role of media coverage in shaping political outcomes (Gentzkow and Shapiro [2006](#); Gentzkow, Shapiro, and Sinkinson [2011](#); Strömberg [2004](#)). They are also in line with scholarship that illustrates the impact of media attention in amplifying terror's effects on educational and economic outcomes (Alfano and Görlach [2022](#); Brodeur [2018](#)).

9. Terrorism and Political Parties

In Online Appendix [L](#) we examine the language employed by political parties in their election manifestos in state elections in response to terror. To this purpose, we collect the election manifestos of all political parties in state elections from 2013 to 2021 and we also collect the 2009 Federal election manifesto of the CDU which we use as a reference to compare shifts in language. From each state-party manifesto, we identify the number of trigger words per 10,000 words related to topics such as migration, terrorism and crime^{[42](#)}. We then calculate the difference in the number of trigger words per 10,000 words between a given party's state election manifesto in a given year and the 2009 CDU Federal election manifesto and use this measure as our outcome variable.

We find that, in response to terror at the state level, the AfD uses differentially more trigger words related to issues like crime, immigrant naturalization and integration while all other parties either do not respond or respond in the opposite direction as the AfD, using less trigger words on these same subjects. Interestingly, the word terror receives no special mention, neither by the AfD nor by other parties. These results point to a clear ideological divide in the response to terror among the main political parties in Germany. They also highlight the relevance of state elections as the key political arena where political parties — or at least the AfD — campaign differentially in response to terror attacks^{[43](#)}.

42. We choose these trigger words on the basis of work by Detering [\(2019\)](#) who studies the rhetoric of the parliamentary right in Germany.

43. Of course, a state level analysis in a setting such as ours suffers from two important limitations: first, an analysis across the 16 German Federal states offers more limited cross-sectional variation. Second, aggregating (successful) attacks to the state level means that we lose our sharp identifying variation between successful and failed attacks. As such, we take these results as suggestive. Nonetheless, a state level analysis offers insights into how political parties respond to terror. And the results are broadly in line with the rest of the analysis that exploits much richer variation at the municipal and individual level.

10. Conclusion

Exploiting quasi-random variation in the success of terror attacks across German municipalities, we shed light on the extent to which local acts of terrorism influence the political landscape of a country. The picture that emerges is that terror has significant effects on political attitudes, preferences, and outcomes: following successful terror attacks, the vote share of the right-wing, populist Alternative für Deutschland (AfD) party, a relative newcomer to German politics, increases by some 6 percentage points in state elections. This effect is driven both by the mobilization of previously politically inactive individuals and by voters migrating from two mainstream parties to the AfD. Correspondingly, people's social attitudes shift to considerably more populist positions in response to successful acts of terror: people are increasingly worried about migration and are more likely to participate in local politics. We also found differential coverage of successful attacks in the news media and that high-coverage attacks (i) have even larger consequences for the AfD in state elections and (ii) significantly increase the vote share of the AfD in Federal elections. For its part, the AfD campaigns differentially in response to terror at the state level compared to other parties. Together, our results provide first evidence that acts of terror can lead to a broad shift in the political landscape of a nation by mobilizing voters, shifting their preferences, and realigning news reporting and the messaging of political parties in their campaign documents.

One striking feature of our results is that a right-wing, populist party like the AfD benefits from acts of terror which, by and large, were carried out by perpetrators motivated by right-wing extremist causes, including Neo-Nazi attacks, and who, by and large, targeted foreigners. This appears to be the result of the ability of the AfD to use acts of terror to support its own narrative. That the AfD speaks more about crime, integration, and immigrant naturalization rather than terrorism in response to successful attacks speaks to this point. Additionally, we found that news stories that cover successful attacks use significantly different vocabulary, highlighting such issues as terrorism and Islam and using fewer words related to right-wing populism. This result is particularly noteworthy when one considers that the characteristics of successful and failed attacks are indistinguishable. It also points to the influential role of the media in shaping human perceptions as well as political and social attitudes, preferences, and behaviors.

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11. Figures

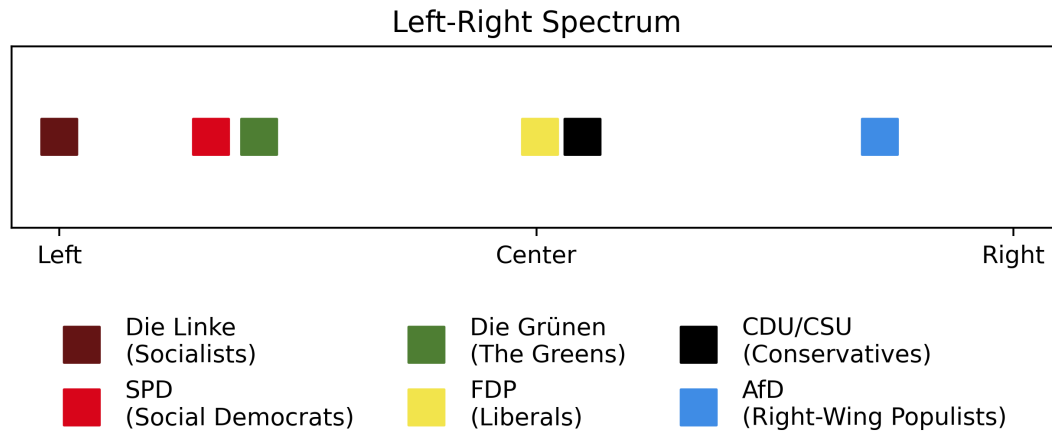


Figure 1
The Political Spectrum in Germany

Note: This figure shows the six major political parties in Germany according to their positions on a left-right policy scale using data from election manifestos from Lehmann et al. (2022). The dimensions used to map a party on the left-right scale include, among others, the extent to which a party favors traditional moral values; a party's preference for rigorous law enforcement; the degree to which a party upholds a positive memory of its nation's history. For a complete list of considered dimensions, see the code-book offered by Lehmann et al. (2022).

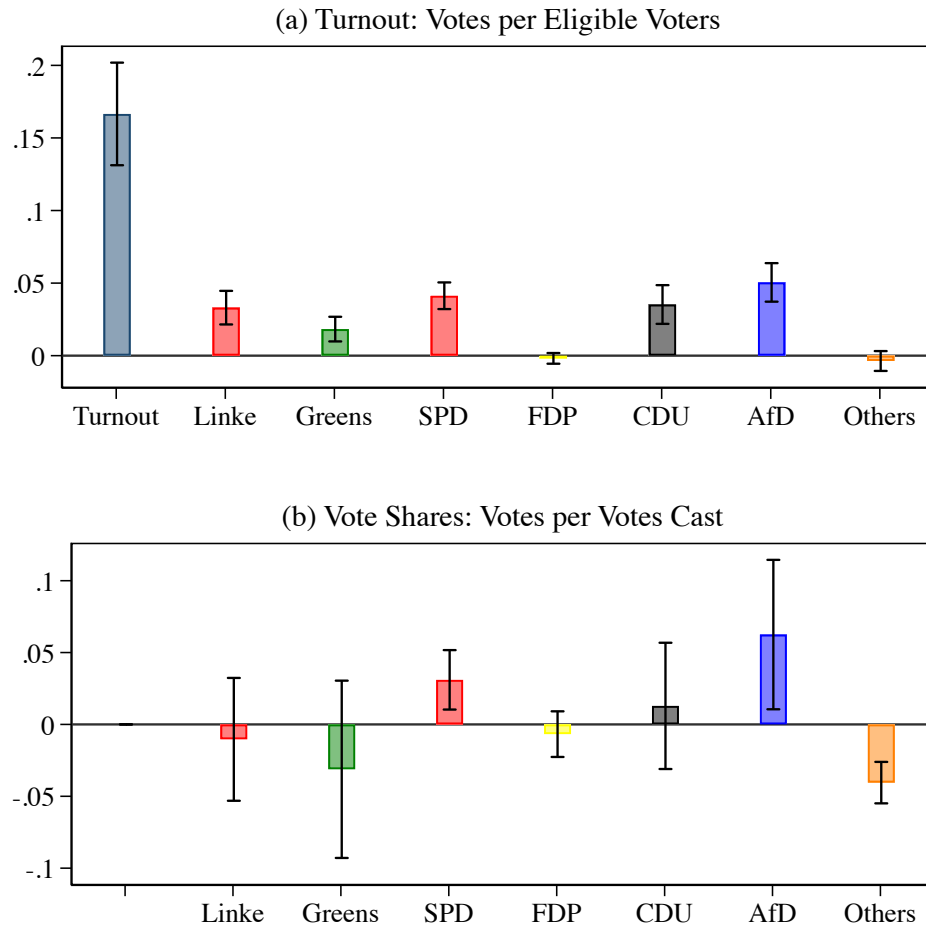


Figure 2
Terror, Turnout and Other Parties

Note: In Panel (a), we run our baseline regression specification using voter turnout, as measured by the number of votes cast per eligible voter, as the main outcome variable. We first study overall municipality turnout and then party-specific turnout as labeled along the x -axis. In Panel (b), we run the baseline when using party-specific vote shares as the outcome, again as labeled along the x -axis. For each regression, we report only the coefficient on the triple interaction between *SUCCESS*, *POST* and *STATE ELECTIONS*. All regressions include election-type by municipality fixed effects, year fixed effects, and all lower order interactions. Standard errors are clustered at the municipality and confidence intervals are drawn at 95%.

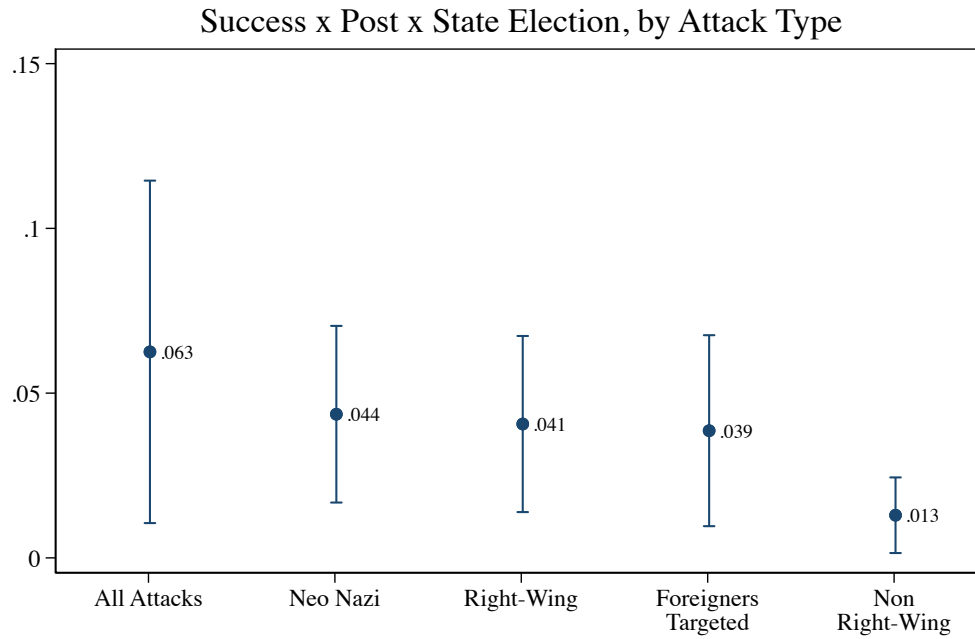


Figure 3
Heterogeneous effects according to attack type or target

Note: In this figure, we plot β_1 from our baseline estimating model as specified in equation [2](#) in samples split by attack type or attack target. Standard errors are clustered at the municipality and confidence intervals are drawn at 95%. Magnitude of the coefficients are noted next to each point estimate.

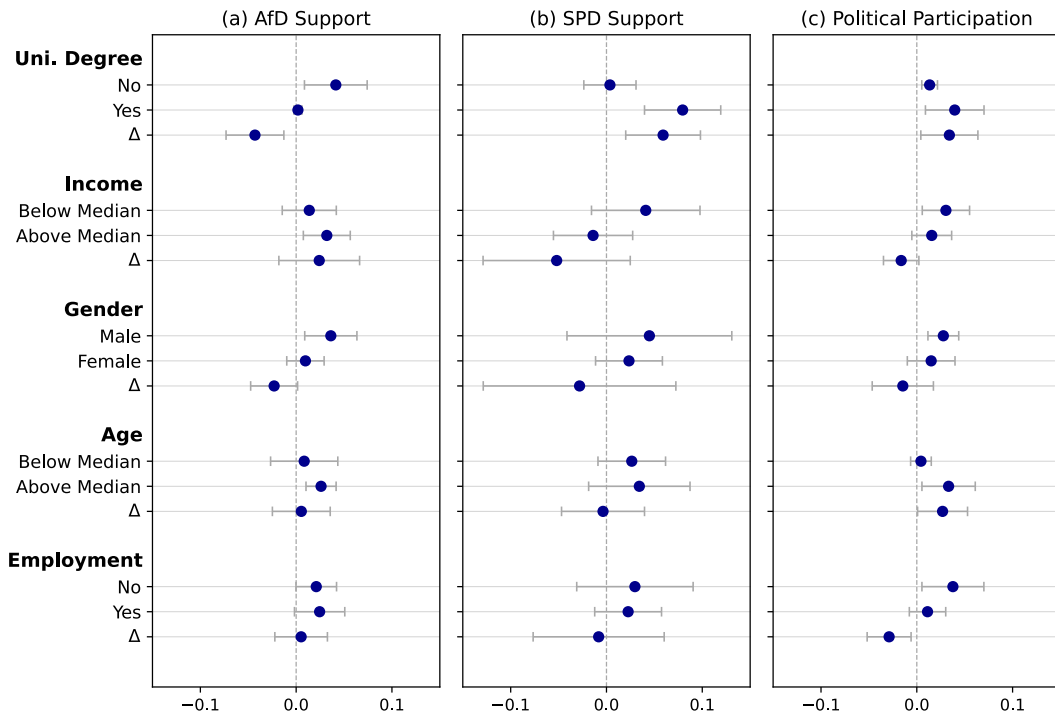


Figure 4
Political attitudes in samples split by various socio-economic variables

Note: The outcome in each panel is an indicator that is 1 if people prefer the AfD, the SPD or participate more in local politics, respectively, and 0 otherwise. For each outcome, we estimate the coefficient on $SUCCESS_i \times POST_{i,t}$ in samples split by the relevant covariates as labeled. Δ is the coefficient on the triple interaction when the outcome is regressed on $SUCCESS_i \times POST_{i,t} \times COVARIATE_p$. This model includes all lower order terms as well as person fixed effects and year fixed effects. Standard errors are clustered at the municipality and confidence intervals are drawn at 95%.

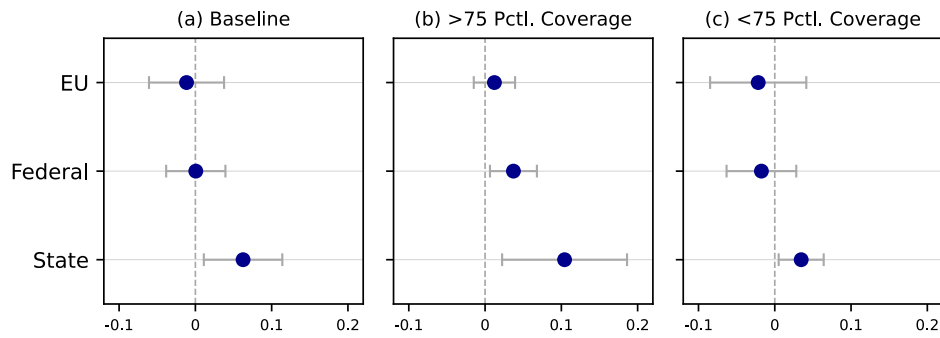


Figure 5
Baseline Effects of Terror on AfD Vote Share in Samples Split by Media Coverage

Note: Panel (a) presents our baseline estimate for $SUCCESS \times POST$ for European, Federal and State elections, respectively. Panels (b) and (c) reports the same coefficient but for samples split by the amount of media coverage attacks receive. Panel (b) is the sample of municipalities hit with terror attacks that receive more than 75th percentile news coverage while Panel (c) includes the sample of municipalities targeted with attacks that receive less than the 75th percentile of coverage.

12. Tables

Table 1
Characteristics in Successful v. Failed Municipalities and Attacks

Variable	(1) $\hat{\beta}$	(2) p-value $H_0 : \beta = 0$	(3) N
Panel A: Municipality Characteristics			
<i>Economic:</i>			
Per capita Income (000s)	1.427	0.284	411
Unemployed (000s)	-3.478	0.280	408
Employed (000s)	-24.401	0.345	405
Tax revenue (pc)	0.165	0.669	353
<i>Demographic:</i>			
Population (000s)	-62.891	0.313	423
Average age	0.409	0.615	401
Share men	-0.003	0.437	423
<i>Migration:</i>			
In-migration (000s)	-4.058	0.382	423
Out-migration (000s)	-4.143	0.328	423
Asylum seekers	-791.335	0.585	402
Asylum seekers, Syria	-28.494	0.908	397
<i>Education:</i>			
University eligible	58.139	0.747	402
No secondary education	-50.275	0.295	402
<i>Geographic:</i>			
Surface area (km ²)	-1.662	0.938	432
Forest area (ha)	-263.798	0.736	389
East Germany	-0.100	0.526	124
<i>Social Assistance:</i>			
Welfare recipients (pc)	-0.556	0.381	402
Welfare recipients (foreigners),(pc)	-0.000	0.928	386
<i>Road Accidents:</i>			
Traffic accidents	-247.482	0.413	432
Deadly accidents	-202.472	0.433	432
<i>Tourism:</i>			
Number of hotels	-6.770	0.713	410
Tourists (000s)	-69.541	0.872	374
<i>Health:</i>			
Number of hospitals	-0.337	0.852	393
Hospitals beds	-68.165	0.847	393
<i>Political:</i>			
Eligible voters (000s)	-31.778	0.374	431
Turnout	0.017	0.422	429
AfD Vote Share	-0.007	0.533	326
1933 NSDAP Vote Share	-0.004	0.870	121
Days b/w Attack and Election	1.55	0.995	916
Panel B: Attack Characteristics			
<i>Weapon Type:</i>			
Explosives	-0.052	0.488	232
Firearms	0.039	0.280	232
Melee	0.027	0.564	232
<i>Casualties:</i>			
Killed	0.204	0.027	232
Wounded	1.054	0.001	231
<i>Motivation:</i>			
Right-Wing	0.097	0.332	211
Neo-Nazi	0.061	0.543	211
Left-Wing	0.013	0.875	211
Islamist	-0.108	0.172	211

Notes: Panel A compares characteristics in municipalities targeted with successful v. failed attacks in the pre-attack period. Panel B compares characteristics of successful and failed attacks.

Table 2
Terror Attacks and AfD Vote Share

		Outcome: AfD Vote Share							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Baseline		East	Omit	Urban	Weapon	Attack	Omit	Omit	All
Model	× Year	× Year	Berlin	× Year	× Year	Timing	Multiple	Coordinated	Controls
Success × Post × Federal	0.0005 (0.0198)	0.0225 (0.0144)	0.0071 (0.0213)	-0.0068 (0.0169)	-0.0066 (0.0207)	0.0005 (0.0198)	0.0050 (0.0217)	0.0030 (0.0200)	0.0271 (0.0192)
Success × Post × European	-0.0116 (0.0251)	0.0226 (0.0177)	-0.0102 (0.0290)	-0.0166 (0.0208)	-0.0098 (0.0264)	-0.0116 (0.0251)	-0.0113 (0.0288)	-0.0104 (0.0253)	0.0066 (0.0211)
Success × Post × State	0.0625** (0.0263)	0.0501*** (0.0132)	0.0671*** (0.0255)	0.0589** (0.0228)	0.0335*** (0.0096)	0.0733** (0.0308)	0.0477*** (0.0151)	0.0715** (0.0307)	0.0482*** (0.0130)
<i>N</i>	734	734	664	734	723	734	534	664	511
Clusters	124	124	114	124	123	124	91	112	89
\bar{Y}_{State}	.17	.17	.19	.17	.18	.17	.19	.17	.19
[<i>S.D.</i>]	[.1]	[.1]	[.1]	[.1]	[.1]	[.1]	[.11]	[.1]	[.1]

Notes: The dependent variable is the vote share for the Alternative for Deutschland (AfD) party at the municipality level. Success is one if a municipality experienced a successful terror attack anytime after 2010 and 0 if it experienced a failed attack but not a successful attack in that same time period. Post is 1 if the first attack in a municipality occurred prior to an election and zero if it occurred after an election. Column 2 includes an indicator that is 1 if a municipality is located in East Germany and zero otherwise interacted with year dummies. In Column 3 we omit 10 of the 12 municipal districts, *Stadbezirke*, of Berlin targeted with attacks. In Column 4 we include an indicator for whether a municipality is an urban district interacted with year dummies and in Column 5 we interact the weapon used in the attack with year dummies. In Column 6 we control for the number of days between an attack and an election. In Column 7 we omit those municipalities targeted with more than one attack. In Column 8, we omit those municipalities that experienced coordinated attack with multiple attacks on the same day. In Column 9 we include mean values of all pre-attack municipality covariates presented in Table 1 interacted with year dummies. All regressions include election-type by municipality fixed effects, year fixed effects, and all lower order interactions. Standard errors (shown in parentheses) are clustered at the municipality level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3
Effects of Successful and Failed Attacks

	Balance Test		Baseline Estimate	
	(1) Success v. Placebo Fail	(2) Failed v. Placebo Fail	(3) Success v. Placebo Fail	(4) Failed v. Placebo Fail
Success	0.0090 (0.0066)			
Failed		0.0162 (0.0155)		
Success × Post × Federal			0.0132 (0.0085)	
Success × Post × European			-0.0033 (0.0132)	
Success × Post × State			0.0505*** (0.0161)	
Failed × Post × Federal				0.0107 (0.0184)
Failed × Post × European				0.0083 (0.0259)
Failed × Post × State				-0.0007 (0.0357)
<i>N</i>	1,993	1,334	1,828	1,214
Clusters	316	214	314	212
\bar{Y}_{State}	.14	.14	.17	.17
[<i>S.D.</i>]	[.083]	[.074]	[.091]	[.08]

Notes: The dependent variable is the vote share for the Alternative for Deutschland (AfD) party at the municipality level. The variable success is one if a municipality experienced a successful terror attack anytime after 2010 while the variable Failed is one if a municipality experienced a failed terror attack in that same time period. The counterfactual municipalities in this table are all derived via propensity score matching. Both Success and Failed are thus coded as 0 for municipalities that did not experience any terrorist attacks but that, on the basis of propensity score matching, resembled municipalities that experienced a successful attack (i.e. placebo fail). Post is 1 if the attack in a municipality occurred prior to an election and zero if it occurred after an election. The regressions in columns 3 and 4 include election-type by municipality fixed effects, year fixed effects, and all lower order interactions. Standard errors (shown in parentheses) are clustered at the municipality level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4
Terrorism and Individual Political Attitudes and Preferences using SOEP

Dependent Variable: Individual Attitudes and Preferences								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Identify Right-Wing	Identify Hard-Right	Prefer AfD	Prefer CDU	Prefer SPD	Participate Local Politics	Worried Immigration	Worried Terrorism
Success \times Post	0.0652*** (0.0206)	0.0438** (0.0179)	0.0234** (0.0104)	-0.00693 (0.0185)	0.0314* (0.0178)	0.0205*** (0.00693)	0.0361*** (0.0174)	0.00204 (0.0261)
N	4,572	4,572	13,279	13,279	13,279	14,298	29,610	9,587
Clusters	87	87	89	89	89	95	95	88
People in Sample	2,286	2,286	2,401	2,401	2,401	3,715	4,102	2,682
\bar{Y}	0.176	0.0956	0.0297	0.318	0.307	0.0254	0.289	0.84
[S.D]	[0.381]	[0.294]	[0.170]	[0.466]	[0.461]	[0.157]	[0.453]	[0.367]

Notes: The dependent variable is the attitude of a given person in a given municipality toward various political and social topics as measured in the SOEP survey. Success is one if a person's municipality experienced a successful terror attack anytime after 2010 and 0 if it experienced a failed attack. Post is 1 if the attack occurred prior to the individual being surveyed and zero if it occurred after the survey. All regressions include person fixed effects and year fixed effects. Standard errors (shown in parentheses) are clustered at the municipality level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5
Political Commitment, Political Activation and the AfD using SOEP

	Dependent Variable: Individual Prefer's AfD						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	CDU	SPD	FDP	Linke	Greens	Ultra Right	Politically Active
Success × Post × Non-partisan	0.0253* (0.0145)	0.0281*** (0.00895)	0.0230** (0.0109)	0.0230** (0.0110)	0.0257** (0.0125)	0.0219** (0.0106)	
Success × Post × Partisan	0.0166*** (0.00475)	0.0109 (0.0262)	0.0715 (0.0525)	0.0381** (0.0188)	0.00806 (0.00623)	0.267*** (0.125)	
Success × Post × Inactive							0.0259** (0.0115)
Success × Post × Active							-0.0116 (0.00868)
N	9,089	9,089	9,089	9,089	9,089	9,089	9,162
Clusters	76	76	76	76	76	76	76
People in Sample	1,591	1,591	1,591	1,591	1,591	1,591	1,647

Notes: The dependent variable is an indicator that is 1 if a person's preferred party is the AfD and zero otherwise as measured in the SOEP survey. Success is one if a person's municipality experienced a successful terror attack anytime after 2010 and 0 if it experienced a failed attack. Post is 1 if the attack occurred prior to the individual being surveyed and zero if it occurred after the survey. Partisan is a dummy that is 1 if a person's preferred political party pre-attack is always as stated in the column header. It is zero (i.e., non-partisan) if a person states more than one party as their preference in the pre-attack surveys. Active is an indicator that is 1 if a person participates in local politics on a regular basis pre-attack. It is zero (i.e., inactive) if a person seldomly or never participates in local politics pre-attack. All regressions include person fixed effects and year fixed effects. Standard errors (shown in parentheses) are clustered at the municipality level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6
Media Coverage of Successful Terror Attacks

	Articles		Sentiment		Topics				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Found	Count	Title	Body	Right-wing Populism	Migration	Crime	Islam	Terror
Panel A: LexisNexis									
Success	.0756 (.1754)	8.246** (4.015)	-.0339 (.0232)	-.0321** (.0145)	-.3467*** (.091)	-.1185 (.0995)	-.8085*** (.1641)	.6186*** (.0818)	.1895*** (.0684)
State × Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Publisher FE			✓	✓	✓	✓	✓	✓	✓
N	232	232	4,683	4,683	4,683	4,683	4,683	4,683	4,683
Clusters	124	124	1,303	1,303	1,303	1,303	1,303	1,303	1,303
\bar{Y}	0.642	11.125	-0.091	-0.114	0.544	0.440	1.162	0.314	0.607
Panel B: FAZ									
Success	.0241 (.1531)	-.017 (.3378)	-.0251 (.042)	.0338 (.029)	-.2848 (.212)	.1211 (.0963)	-.4963* (.2774)	.3178*** (.1052)	.1145 (.1023)
State × Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
N	186	186	338	338	338	338	338	338	338
\bar{Y}	0.457	0.828	-0.053	-0.105	0.715	0.576	1.229	0.298	0.515
Unit of Observation	Attack		Story						

Notes: Panel A presents results when using regional and local news sources collected via LexisNexis. Panel B presents the same results but using national news stories collected from the Frankfurter Allgemeine Zeitung (FAZ). In Columns 1 and 2 the individual terror attack is the unit of observation. In Columns 3 to 9, the news story is the observation. In both cases, Success is an indicator that is 1 for successful terror attacks (or stories that cover successful attacks) and 0 for failed attacks (or stories that cover failed attacks). Standard errors are shown in parentheses. In Panel A, they are clustered at the municipality level in Columns 1 and 2 and at the municipality × publisher level in Columns 3 to 9. In Panel B, robust standard errors are reported. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Online Appendix for Paper: *Terrorism and Voting: The Rise of Right-Wing Populism in Germany*

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A. Terrorism in Germany

Table A.1 provides detailed statistics related to the targets, weapons and attack types used in each of the 232 attacks in Germany between 2010 and 2020 while Figure A.1 illustrates the frequency and intensity—in terms of deaths and injuries—of these attacks.

As shown in Table A.1 the overall success rate of attacks in Germany stands at 86 percent. The majority of attacks are facility or infrastructure attacks. They constitute 62 percent of all attacks and have a very high success rate of 94 percent. The next most common type of attack is armed assault. These make up 21 percent of all attacks and have a success rate of around 80 percent. The next most common attack type are bombings and explosions; they make up 10 percent of the attacks but have a success rate of just 54 percent, the lowest among all attack types. Fifty percent of the attacks target private citizens and their property.

Panel A in Figure A.1 demonstrates that, with the exception of 2013, attacks occur in Germany in every year, though there is great variation across years with 2015 experiencing many attacks and 2010 and 2012 experiencing relatively few attacks. In Panel B we see that most attacks involve very little deaths and injuries.

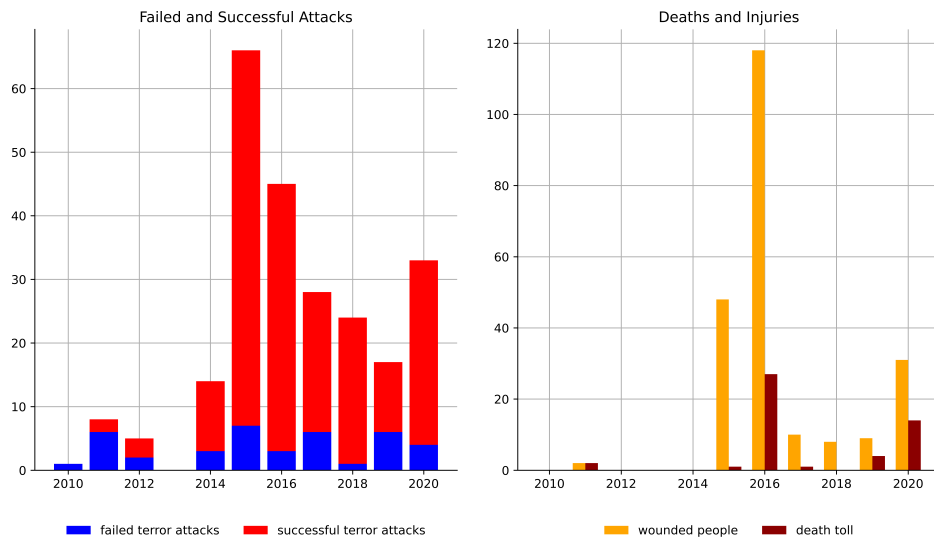


Figure A.1
Frequency and intensity of attacks

Table A.1
Terrorism summary statistics for Germany (2010 - 2020)

	Observations	Percentage	Attack success	If success (mean)	
				Wounded	Killed
<i>Attack Type</i>					
Armed Assault	48	0.21	0.79	2.32	0.87
Bombing/Explosion	24	0.10	0.54	1.54	0.08
Facility/Infrastructure Attack	143	0.62	0.94	0.24	0.00
Hijacking	1	0.00	1.00	0.00	1.00
Hostage Taking Barricade Incident	1	0.00	1.00	4.00	0.00
Unarmed Assault	13	0.06	0.77	7.44	1.20
Unknown	2	0.01	1.00	2.50	0.00
<i>Target Type</i>					
Business	26	0.11	0.92	1.54	0.50
Educational Institution	1	0.00	1.00	0.00	0.00
Government Diplomatic	9	0.04	0.89	0.00	0.00
Government General	20	0.09	0.75	0.20	0.07
Journalists & Media	2	0.01	1.00	2.00	0.00
Military	2	0.01	1.00	1.00	1.00
Police	10	0.04	0.90	0.22	0.11
Private Citizens & Property	116	0.50	0.87	1.65	0.30
Religious Figures/Institutions	22	0.09	0.86	0.16	0.05
Telecommunication	2	0.01	1.00	0.00	0.00
Transportation	20	0.09	0.75	0.00	0.00
Utilities	1	0.00	1.00	0.00	0.00
Violent Political Party	1	0.00	1.00	0.00	0.00
<i>Weapon Type</i>					
Explosives/Incendiary	178	0.77	0.85	0.48	0.02
Firearms	15	0.06	0.93	3.00	1.79
Melee	20	0.09	0.90	2.18	0.39
Other	2	0.01	0.50	1.00	0.00
Sabotage Equipment	3	0.01	1.00	0.00	0.00
Unknown	8	0.03	1.00	0.62	0.00
Vehicle	6	0.03	0.67	14.50	3.00
<i>Attack Motivation</i>					
Islamist	24	0.10	0.75	5.67	1.17
Left-wing	44	0.19	0.86	0.05	0.00
Others	27	0.12	0.93	0.20	0.04
Right-wing	116	0.50	0.87	0.70	0.13
Unknown	21	0.09	0.86	2.06	0.67
Total Attacks	232		0.86	1.09	0.23

B. The AfD in Germany

In this Online Appendix, we present descriptive statistics that show the AfD's rapid rise in German politics since its inception in 2013. Figure B.1 plots the average vote share for the AfD party across all elections since its establishment in 2013. As shown, the AfD has experienced a marked increase in the years since it was founded in every election, increasing its average vote share from less than 5 percent to some 15 percent.

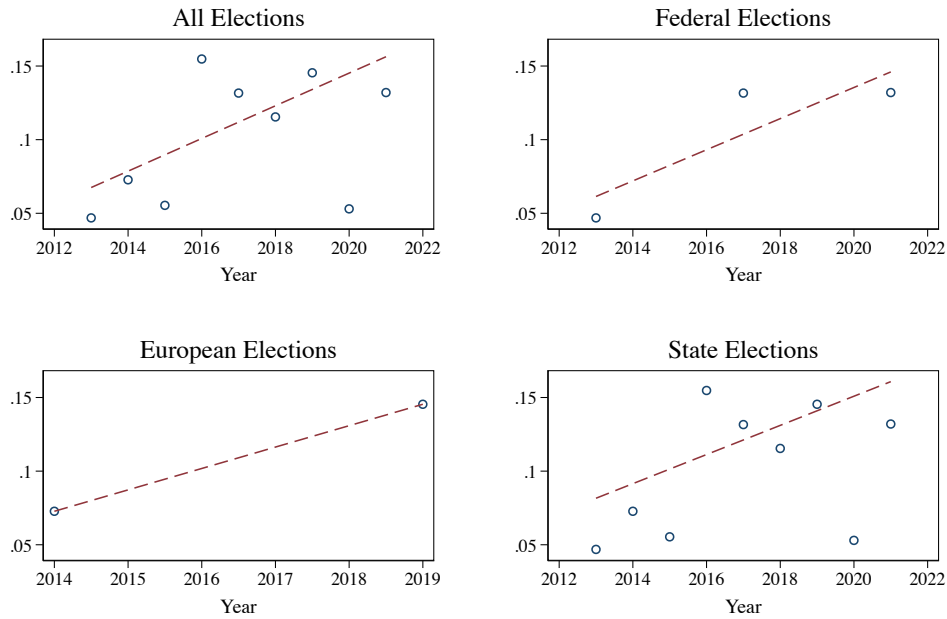


Figure B.1
Average AfD Vote Share Across All Elections in Germany

Figure B.2 overlays the distribution of the AfD vote share across German municipalities targeted with terror attacks for both Federal and state elections. As shown, the AfD has performed better in state elections compared to Federal ones. A t -test of equality of means reveals that the AfD vote share is 3.1 points higher in state elections than in Federal elections (p -value of 0.002).

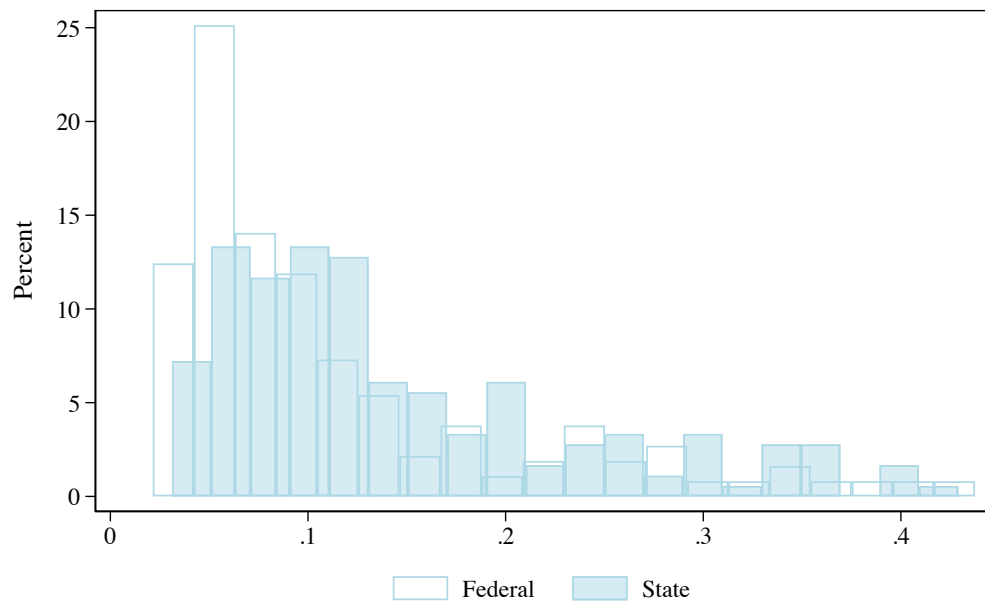


Figure B.2
Distribution of AfD Vote Share in Federal and State Elections in Targeted Municipalities

C. Targeted v. Untargeted Municipalities

In our main paper, we established that the success or failure of an attack is unrelated to municipality characteristics. In this Online Appendix, we demonstrate that municipalities targeted with attacks are not just a random subset drawn from the universe of municipalities in Germany. This is shown in Figure C.1. In Panel (a), for example, we see that targeted municipalities are systematically different to untargeted ones while in Panels (b) and (c), respectively, we see that these differences hold for municipalities targeted with *both* successful and failed attacks.

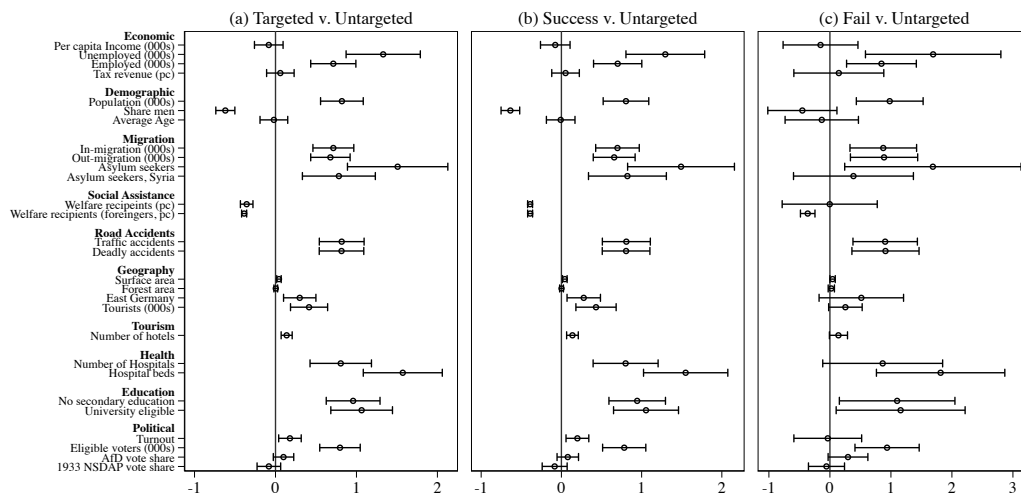


Figure C.1
Characteristics in Targeted and Untargeted Municipalities

Note: This figure presents characteristics in municipalities targeted with attacks (Panel (a)), successful attacks (Panel (b)) and failed attacks (Panel (c)). In each case, the comparison municipalities are those untargeted by any terrorist attack.

D. Additional Robustness

In this Online Appendix we present our baseline results using estimators that are robust to two-way fixed effects with staggered treatment. We also present our baseline estimate using a rolling window approach to incorporate a larger number of attacks into the analysis and not just the first attack in a given municipality. Finally, we demonstrate that our baseline estimation is robust to two alternative methods of statistical inference.

D.1 Heterogeneity Robust DiD with Staggered Treatment

In recent years, there has been a fast growing literature addressing the issues related to difference-in-differences estimations using two-way fixed effects (TWFE), in particular when treatment effects are heterogeneous and/or when treatment is staggered (De Chaisemartin and D’Haultfoeuille [2022]; De Chaisemartin and d’Haultfoeuille [2020]; Goodman-Bacon [2021]; Borusyak, Jaravel, and Spiess [2021]).

In our setting, the issue of a staggered, binary treatment takes on relevance. Because different municipalities are hit with attacks at different points in time, our baseline estimate may, in fact, be the result of “forbidden comparisons” (De Chaisemartin and D’Haultfoeuille [2022]; Borusyak, Jaravel, and Spiess [2021]), whereby groups that are treated early are compared to those that are treated later but receive different weights which might affect of overall estimate⁴⁴. In particular, those municipalities hit with attacks very early may receive negative weights compared to those who were attacked later. To the extent that the short- and long-run effects of terror are different, this may give rise to a biased estimator as more weight is given to the short-run effects of terror and a negative weight assigned to its long run effects.

This literature has not only identified the nature of the problem, but has also developed a range of heterogeneity-robust DID estimators (for a summary, see De Chaisemartin and D’Haultfoeuille [2022]). In this Online Appendix, we repeat our baseline model using one of these alternative estimators, `did_imputation`, put forward by Borusyak, Jaravel, and Spiess [2021]. This estimator estimates the effects of a binary treatment with staggered rollout allowing for arbitrary heterogeneity and dynamics of causal effects in manner that is more efficient to those proposed by other researchers⁴⁵.

Our results are shown in Table D.1. In Column 1, we report our baseline estimate as a marginal effect (rather than a total marginal effect) so as to make estimation with `did_imputation` comparable. As shown, successful attacks increase the AfD vote share by some 6 points in state elections compared to European elections. In Column 2, we report the results when using `did_imputation`. As explained in Borusyak, Jaravel, and Spiess [2021], this estimation is carried out in three steps. First, municipality and year fixed effects are fitted on a model that uses only untreated observations (i.e. those that were hit with failed attacks or successfully attacked municipalities prior to the attack). Second, these estimations are used to predict the untreated *potential outcomes* for treated units, including imputing non-treated potential outcomes where necessary. This enables the command to estimate the treatment effect $\tau = Y_{it,observed} - Y_{it,potential}$. Finally, the command calculates a weighted average of these

44. Goodman-Bacon [2021] provides an exposition of the various comparisons that make up an overall difference-in-difference estimator when treatment is staggered while Borusyak and Jaravel [2017] provide an intuitive explanation of “forbidden” comparisons or extrapolations involved in such cases.

45. The only difference is that using this alternative command, we report the marginal effect of successful terror on state elections compared to European elections rather than the *total* marginal effect of successful terror on state elections.

different treatment effects with weights corresponding to the estimation target⁴⁶

As shown, the differences, both in magnitude and precision, between Columns 1 and 2 are small and, if anything, the effect size using a heterogeneity robust DiD estimator is larger. This increases confidence that our baseline estimation using linear difference-in-difference is, in fact, unbiased.

Table D.1
Heterogeneity Robust DiD Estimation

	Coefficient on $SUCCESS \times POST \times STATE$ Election	
	(1) Baseline	(2) DiD Imputation
β	0.0741*** (0.0280)	
τ		0.0938*** (0.0022)
N	734	623
Clusters	124	105
Estimator	reghdfe	DID imputation

Notes: This table reports the coefficient of $SUCCESS \times POST \times STATE$ in a model that includes municipality and year fixed effects as well as municipality-by-election-type fixed effects. In Column 1, the coefficient, β , is estimated via using `reghdfe`. In Column 2, the coefficient, τ , is estimated using using the imputation estimator of Borusyak, Jaravel, and Spiess (2021). In both models, we report the marginal effect of successful terror on state elections relative to European elections. . * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

D.2 Rolling Window Approach

In our baseline analysis, we use the first attack in a given municipality as a reference from which we determine the variables *SUCCESS* and *POST*. In this Online Appendix, we reproduce Table 2, our baseline results, using a larger number of attacks in the sample and not just the first attack. For the 91 municipalities that received only one attack, the coding of *SUCCESS* and *POST* remain unchanged. For the 33 municipalities that received more than one attack, however, we now create a “rolling window” of time around each municipality-attack (or groups of attacks if there are no elections between them). *SUCCESS* is now coded according to the attack in the window and *POST* is coded for each election in the window depending on whether the election was before or after the attack. This analysis has the disadvantage, however, of making interpretation more complicated because of overlapping time-periods: the “post” period of one attack in a given municipality is the “pre” period for the subsequent attack in

46. With municipality fixed effects included in the model, imputation is not possible for units treated in all periods in the sample; this is the case for 63 municipality-years in our sample and this explains the difference in observations between Columns 1 and 2 of Table D.1

that same municipality. For this reason, we use only the first attack in our baseline analysis. Nevertheless, we present the results using a rolling window approach in Table [D.2](#) and, as shown, the results are rather similar to our baseline, alleviating concerns that municipalities hit with multiple attacks adversely affect our results.

Table D.2
Terror Attacks and AfD Vote Share Using a Rolling Window

	(1) Baseline Model	(2) East × Year	(3) Omit Berlin	(4) Urban × Year	(5) Weapon × Year	(6) Attack Timing	(7) Omit Multiple	(8) Omit Coordinated	(9) All Controls
Success × Post × Federal	0.0019 (0.0159)	0.0106 (0.0125)	0.0118 (0.0180)	-0.0053 (0.0138)	-0.0031 (0.0166)	0.0060 (0.0162)	0.0050 (0.0217)	0.0039 (0.0162)	0.0122 (0.0172)
Success × Post × European	-0.0184 (0.0222)	0.0028 (0.0183)	-0.0075 (0.0291)	-0.0251 (0.0190)	-0.0156 (0.0234)	-0.0154 (0.0220)	-0.0113 (0.0288)	-0.0166 (0.0223)	0.0104 (0.0206)
Success × Post × State	0.0571** (0.0252)	0.0436*** (0.0115)	0.0533** (0.0237)	0.0563** (0.0236)	0.0441 (0.0272)	0.0683** (0.0300)	0.0477*** (0.0151)	0.0588** (0.0266)	0.0436*** (0.0123)
<i>N</i>	787	787	693	787	776	787	534	711	549
Clusters	124	124	114	124	123	124	91	112	92
\bar{Y}_{State} [<i>S.D.</i>]	.16 [.099]	.16 [.099]	.18 [.1]	.16 [.099]	.17 [.1]	.16 [.099]	.19 [.11]	.16 [.1]	.18 [.1]

Notes: See notes of Table 2 * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

D.3 Alternative Inference

Our estimating sample involves 124 unique municipalities of which around 15 percent experienced a failed attack. Given this relatively small sample, we present our baseline estimate using alternative methods of statistical inference. Our results are shown in Table D.3. The table reports $\hat{\beta}$, the coefficient on the triple interaction for state elections from our baseline model. It then presents p -values from three different methods of inference: First, p -values based on analytically derived standard errors using clustered standard errors (as in our baseline approach). Second, p -values calculated using wild cluster bootstrapping as suggested by Cameron, Gelbach, and Miller (2008) and implemented via their `boottest` command in Stata with 10,000 replications. Third, p -values are estimated from permutation tests using Monte Carlo simulations with 10,000 permutations of the variable success in order to generate placebo coefficients and a null distribution from which to estimate the p -value. As shown, across all three methods of inference, the baseline estimate of successful terror is significantly distinguishable from zero.

Table D.3
Alternative inference

	(1)
$\hat{\beta}$	0.0625
N	734
Clusters	124
p -values:	
1. Analytical	.019
2. Wild Cluster Bootstrap	.034
3. Permutation Based	.000

Notes: 1. p -values are based on analytically derived standard errors using Stata's `vce(cluster)` command. 2. p -values are calculated as the two-tailed symmetric p -value using wild cluster bootstrapping following Cameron, Gelbach, and Miller (2008) and implemented via their `boottest` command in Stata with 10,000 replications. 3. p -values are calculated as two-tailed symmetric p -value based on 10,000 permutation placebo coefficients resulting from permuting success using Stata's `permute` command.

D.4 Dropping one Municipality at a Time

In this robustness exercise, we run our baseline model 124 times, each time omitting one municipality from the analysis so as to ensure no one municipality is adversely affecting our results. As shown in Figure D.1, the results are stable to this robustness check.

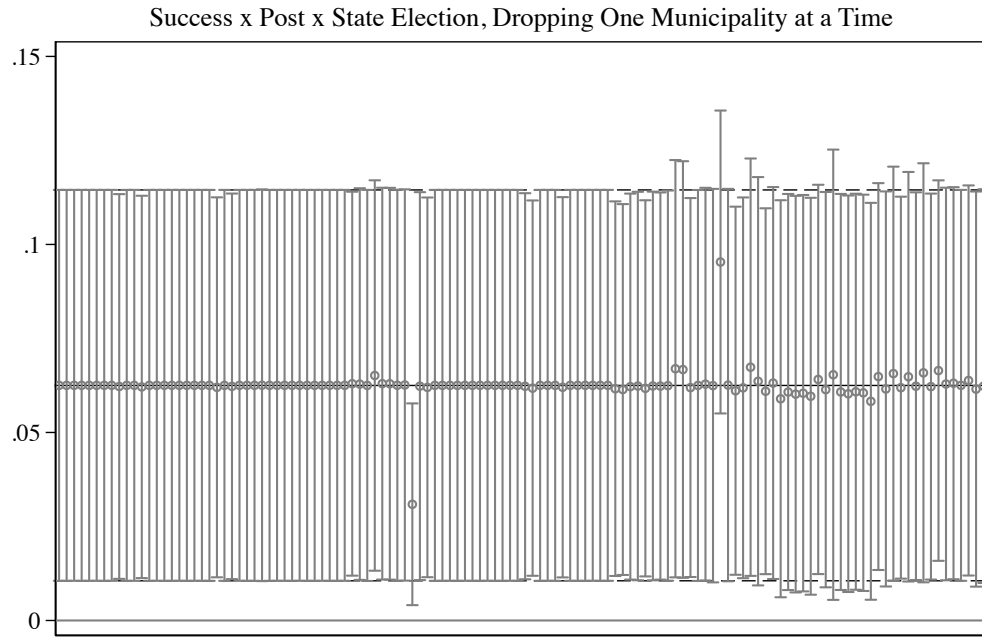


Figure D.1
Baseline model for $SUCCESS \times POST \times STATE$

Note: This Figure plots β_1 from our baseline estimating model 124 times, each time when a different municipality is dropped from the sample. The thick horizontal gray line is the baseline coefficient, with corresponding confidence intervals shown in thick dashed gray lines.

E. Propensity Score Matching

In this Online Appendix, we present details concerning our propensity score matching which we use to generate a counterfactual set of “placebo fail” municipalities. As mentioned in the main text, we use all the municipality covariates presented in our balance table in order to match untargeted counties to successfully targeted ones on the basis of propensity scores. We use nearest neighbor matching in order to identify each successfully targeted municipalities two nearest neighbors. We generate our propensity scores from the following probit regression, the results of which are presented in Table E.1

$$Pr(SUCCESS_i|X) = \Phi(\gamma_0 + \gamma X_i) \quad (6)$$

Table E.1
Propensity Score Matching Results

	(1) PrSuccess=1
Per capita Income (000s)	0.9592 (0.0364)
Employed (000s)	1.0000 (0.0000)
Unemployed (000s)	1.0001 (0.0001)
Tax revenue (pc)	1.0673 (0.1372)
Population (000s)	0.9909 (0.0104)
Average age	0.9649 (0.0188)
Share men	0.0000*** (0.0000)
In-migration (000s)	1.0002* (0.0001)
Out-migration (000s)	0.9997* (0.0001)
Foreigners (000s)	1.0000 (0.0000)
Asylum seekers	1.0001* (0.0000)
University eligible	0.9999 (0.0001)
No secondary education	0.9983* (0.0008)
Welfare recipients (pc)	0.8430 (0.1621)
Welfare recipients (foreigners),(pc)	0.0000*** (0.0000)
Traffic accidents	1.0030** (0.0011)
Deadly accidents	0.9984 (0.0011)
Surface area (km ²)	0.9917 (0.0054)
Total Farmland (Agricultural Use) in ha	1.0001 (0.0001)
Forest area (ha)	1.0001 (0.0001)
Number of hotels	0.9899* (0.0048)
Tourists (000s)	1.0001 (0.0003)
Number of hospitals	0.9661* (0.0158)
Hospitals beds	1.0003*** (0.0001)
N	10,967

Notes: See notes of Table 2. * $p < 0.1$, ** $p < 0.05$,
*** $p < 0.01$

F. Attack Heterogeneity Using Only First Attacks

In our main paper, we demonstrated that successful terror has the largest effects on state elections when those attacks are motivated by right-wing extremists. In this Online Appendix we reproduce Figure 3 using only the first attacks in a given municipality. The reason is that municipalities that received more than one attack might complicate the interpretation of Figure 3. A municipality, for example, targeted with several attacks of mixed motivations — say, a right-wing attack followed by a left-wing attack — would make it difficult to cleanly identify the effect of an attack’s motive on the AfD vote share. To alleviate this concern, we re-generate Figure 3 in a sample of municipalities that were attacked only once (i.e. dropping the 33 municipalities hit more than once), enabling us to cleanly identify effects according to motives. The revised plot is shown in Figure F.1. As shown, the baseline effect in this sample is about 25 percent smaller than the overall baseline (.0477 v. .0625). However, in this sample, the baseline effect is amplified for right-wing attacks⁴⁷. This confirms that right-wing terror has the strongest impacts on the AfD vote share.

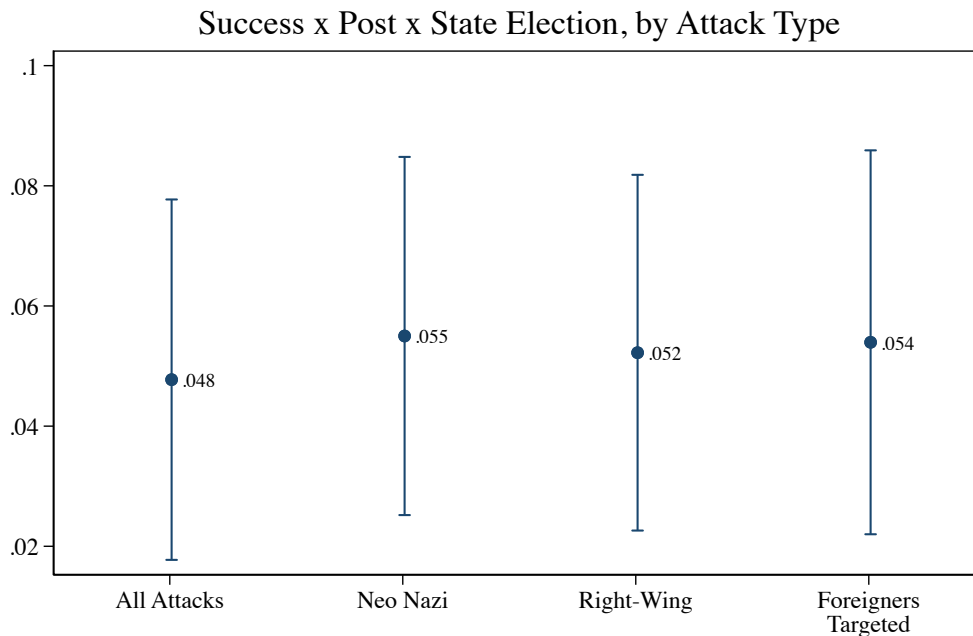


Figure F.1
Heterogeneous effects according to attack type or target

Note: This Figure plots β_1 from our baseline estimating model in samples split by attack type or attack target. All samples omit the 33 municipalities targeted by more than 1 terror attack. Confidence intervals are drawn at 95 percent.

47. There are not even a sufficient number of non-right wing attacks in this sample to estimate an effect.

G. Geographic Spillovers

In Figure [G.1](#) we investigate spillover effects. Specifically, we code untargeted municipalities within a radius of up to 80 kilometers of targeted municipalities as either success or failed depending on their distance to the nearest successful or failed attack. We then re-run our baseline estimating equation in samples of municipalities according to their distance to an actual attack and plot the coefficient of interest for state elections. Distance 0 shows our baseline effect and the coefficients for all other municipalities are plotted according to their distance to the targeted municipality. As shown, there are clear, local spillover effects: the coefficient is around 50 percent smaller than the baseline but statistically significant for municipalities located between 25 and 50 kilometers from an attack. The qualitative effects persist beyond 50 kilometers, but are even smaller and are mostly indistinguishable from zero. For municipalities located 80 kilometers away, the effect diminishes to zero.

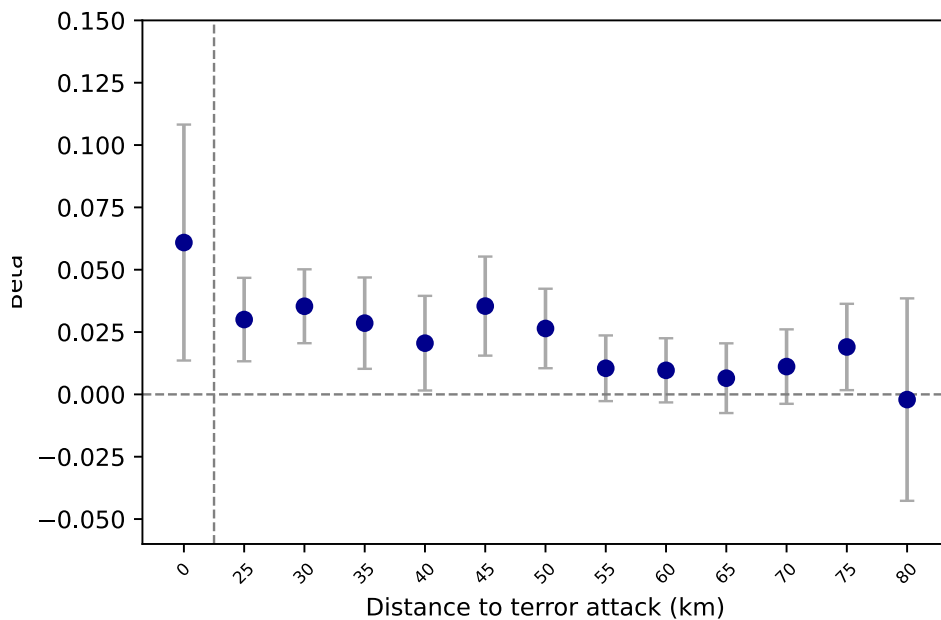


Figure G.1
Geographic Spillovers of Successful Terror

Note: This figure plots the coefficient on $SUCCESS \times POST \times STATE$ from our baseline estimating equation for all municipalities in Germany as a function of distance to a successful or failed attack. Untargeted municipalities are coded as having either a successful or failed attack according to their distance to the nearest successful or failed attack. The regressions all include municipality and year fixed effects as well as municipality by election-type fixed effects and include all lower order terms. Standard errors are clustered at the municipality and confidence intervals are drawn at 95%.

H. Terror and Vote Share for SPD and CDU

In this Online Appendix, we present our full baseline results using the vote share for the SPD and the CDU as the outcome. As shown in Table H.1, terror does lead to positive and significant increases for the SPD at the state level though the results are not nearly as large (relative to the mean) or as strong (losing precision in three of the nine specifications) as the baseline effects of terror on the AfD. By contrast, terror appears to have little to no relationship for the vote share of the CDU. At the Federal and European level, there is a weak negative effect of terror on the vote share for the CDU, but at the state level there are no clear or consistent patterns.

Table H.1
Terror Attacks and SPD and CDU Vote Share

	(1) Baseline Model	(2) East × Year	(3) Omit Berlin	(4) Urban × Year	(5) Weapon × Year	(6) Attack Timing	(7) Omit Multiple	(8) Omit Coordinated	(9) All Controls
<i>Panel A. SPD Vote Share</i>									
Success × Post × Federal	-0.000226 (0.0142)	0.00404 (0.0100)	0.00375 (0.0151)	-0.00728 (0.0112)	-0.00691 (0.0132)	-0.000478 (0.0145)	-0.00201 (0.0148)	-0.00100 (0.0141)	0.00633 (0.0137)
Success × Post × European	0.00701 (0.0139)	0.0202 (0.0163)	0.0124 (0.0148)	0.00372 (0.0145)	0.00970 (0.0143)	0.00701 (0.0139)	0.00962 (0.0162)	0.00777 (0.0139)	0.00453 (0.0122)
Success × Post × State	0.0310*** (0.0104)	0.0263*** (0.00701)	0.0355** (0.0152)	0.0122 (0.0132)	0.00595 (0.0160)	0.0155* (0.00896)	0.0238*** (0.00627)	0.0355*** (0.0127)	0.0380*** (0.0107)
\bar{Y}_{Pre} [S.D.]	0.20 [0.11]	0.20 [0.11]	0.20 [0.12]	0.20 [0.11]	0.20 [0.11]	0.20 [0.11]	0.21 [0.12]	0.21 [0.11]	0.21 [0.12]
<i>Panel B. CDU Vote Share</i>									
Success × Post × Federal	-0.0360* (0.0192)	-0.0472** (0.0182)	-0.0349 (0.0211)	-0.0313* (0.0186)	-0.0253 (0.0177)	-0.0363* (0.0188)	-0.0380* (0.0215)	-0.0366* (0.0194)	-0.0327 (0.0209)
Success × Post × European	-0.0211** (0.00982)	-0.0304* (0.0154)	-0.0198* (0.0110)	-0.0195* (0.0113)	-0.0239** (0.0100)	-0.0211** (0.00983)	-0.0259** (0.0112)	-0.0224** (0.00992)	-0.0173 (0.0120)
Success × Post × State	0.0129 (0.0222)	0.00436 (0.0209)	0.0144 (0.0250)	0.0232 (0.0322)	0.0233 (0.0352)	-0.00775 (0.0195)	-0.0259** (0.0103)	0.00422 (0.0204)	-0.0130 (0.0135)
\bar{Y}_{Pre} [S.D.]	0.30 [0.11]	0.30 [0.11]	0.31 [0.10]	0.30 [0.11]	0.30 [0.11]	0.30 [0.11]	0.31 [0.10]	0.29 [0.11]	0.31 [0.09]
N	776	776	706	776	761	776	568	702	549
Clusters	124	124	114	124	123	124	91	112	89

Notes: The dependent variable is the vote share for the Alternative for Deutschland (AfD) party at the municipality level. Success is one if a municipality experienced a successful terror attack anytime after 2010 and 0 if it experienced a failed attack but not a successful attack in that same time period. Post is 1 if the first attack in a municipality occurred prior to an election and zero if it occurred after an election. Column 2 includes an indicator that is 1 if a municipality is located in East Germany and zero otherwise interacted with year dummies. In Column 3 we omit 10 of the 12 municipal districts, *Stadtbezirke*, of Berlin targeted with attacks. In Column 4 we include an indicator for whether a municipality is an urban district interacted with year dummies and in Column 5 we interact the weapon used in the attack with year dummies. In Column 6 we control for the number of days between an attack and an election. In Column 7 we omit those municipalities targeted with more than one attack. In Column 8, we omit those municipalities that experienced coordinated attack with multiple attacks on the same day. In Column 9 we include mean values of all pre-attack municipality covariates presented in Table F.1 interacted with year dummies. All regressions include election-type by municipality fixed effects, year fixed effects, and all lower order interactions. Standard errors (shown in parentheses) are clustered at the municipality level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

I. Balance in the SOEP

In this Online Appendix, we test for balance across a range of pre-attack individual characteristics between people who live in municipalities that experience successful or failed attacks. For each person, we regress different individual characteristics on the variable, $SUCCESS_i$, defined as before. We present the results in Figure I.1. As shown, there are very little distinguishable differences in socio-economic characteristics between people living in municipalities hit with successful or failed attacks.⁴⁸ Moreover, we document no differences in people's pre-attack political attitudes and preferences. This increases our confidence that successful acts of terror lead to differences in voting outcomes because they affect political preferences and not because they target different types of people. Moreover, people do not report moving after experiencing a successful attack, suggesting that successful terror does not lead to geographical sorting.

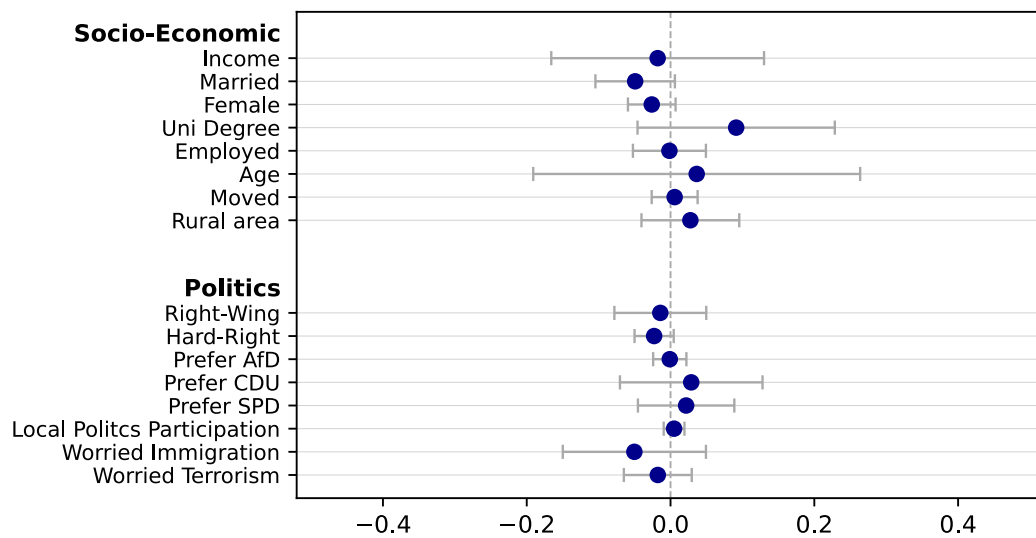


Figure I.1
Individual characteristics of people in successful v. failed municipalities

Note: This figure plots the differences in individual characteristics for people residing in municipalities that experienced successful attacks compared to those that experienced failed attacks. Specifically, it plots β from the following regression: $X_{p,t < t_{Attack}} = \beta_0 + \beta_1 SUCCESS_i + \epsilon_i$ where $X_{p,t < t_{Attack}}$ is a person p 's characteristic measured in the pre-terror time period. The only exceptions are (a) gender (the variable *Female*) which is regressed in the cross-section and (b) the variable *Moved* (which is 1 if a person reports moving after a terror attack and zero otherwise) for which we use the whole sample period. For time invariant characteristics (a person's sex or whether they moved residence) we measure the covariate in the year immediately before the attack. The regression that uses the dummy variable "moved" also uses all time periods in the sample in order to test whether individuals in successful or failed municipalities move differentially post-attack. Standard errors are clustered at the municipality and confidence intervals are drawn at 95%.

48. The only significant difference is marital status which has a coefficient with a p-value of 0.0823. Controlling for this one factor in the analysis does not make any difference to our results.

J. SOEP Event Study: Preferences for the AfD

Using the SOEP, we are also able to examine how people's political preferences change in response to successful terror over time. To this purpose, we run an event-study regression in which a person's preference for the AfD is used as the outcome. To increase statistical power, we group people's responses into two year bins. The results are shown in Figure J.1. As shown, there are no pre-trends, suggesting that prior to an attack, people do not display increasing preferences for the AfD in successfully targeted municipalities. By contrast, we observe clear, positive effects following an attack. Because we group the data into two year bins, our result suggests that the effect only becomes positive and significant two years following an attack. One plausible explanation for this delay is the fact that state elections occur every five years (except for the state of Bremen which is every four years), implying, on average, a two year gap between the terror attack and the first subsequent election. Moreover, there is evidence to suggest that voters decide which party to vote for in the final months of political campaigns (Le Pennec and Pons [2023](#)).

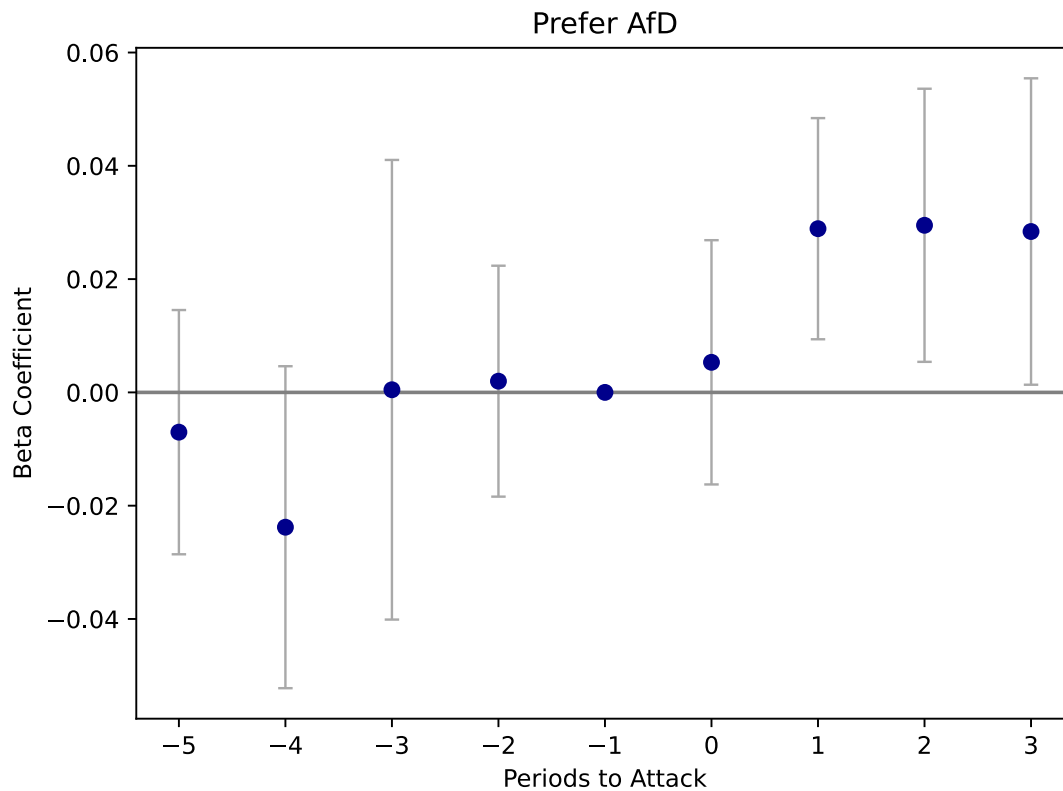


Figure J.1
Successful Terror and Preferences for the AfD

Note: This figure plots the coefficient on *SUCCESS* when it is interacted with time period dummies and regressed against an indicator that is 1 if a person reports preference for the AfD and zero otherwise. Responses are grouped into two year bins. Confidence intervals drawn at 95 percent and standard errors are clustered at the level of the municipality.

K. Terror and Social Media Posts

In this Online Appendix we examine whether successful terror leads to differential social media activity. To conduct this exercise, we rely on data from Müller and Schwarz (2021) who collect data on the number of AfD Facebook page users per population at the county level. We therefore assign municipalities hit with successful and failed attacks the outcome of their associated county. In order to estimate the parameter on the variable *SUCCESS*, the model omits municipality fixed effects and includes, instead, federal state \times year fixed effects. As shown in Table K.1, successful attacks leads to differentially more AfD Facebook users.

Table K.1
Social Media and Successful Terror

	(1) AfD Users
Success	0.255** (0.106)
<i>N</i>	10,101
Clusters	64

Notes: The outcome variable is the number of AfD Facebook users per 1,000 population. The model includes federal state \times year fixed effects so that we can estimate the parameter on *SUCCESS*. Standard errors are clustered at the municipality level.

* $p < 0.1$, ** $p < 0.05$,

*** $p < 0.01$

L. Terrorism and Political Parties

In this Online Appendix, we examine the language employed by political parties in their election manifestos in state elections in response to terror. We thus collect the election manifestos (i.e. the *Wahlprogramm*) of all political parties in state elections from 2013 to 2021 and we also collect the 2009 Federal election manifesto of the CDU which we use as a reference to compare shifts in language.⁴⁹ We digitize the text of all such manifestos in order to identify the number of trigger words per 10,000 words related to topics such as migration, terrorism and crime.⁵⁰ For each party, p , we calculate the difference in the number of trigger words per 10,000 words, ΔTW , between party p 's state election manifesto in year t and the 2009 CDU Federal election manifesto. We use this difference as the outcome of interest in the following estimating equation:

$$\Delta TW_{p_t-CDU_{2009}} = \pi_0 + \pi_1 \sum_s SUCCESS_{s,t-1} + \pi_2 Party_p + \pi_3 \left[\sum_s SUCCESS_{s,t-1} \times Party_p \right] + \alpha_t + \zeta_s + \epsilon_{s,t} \quad (7)$$

In this model, $\sum_s SUCCESS_{s,t-1}$ measures the total number of successful attacks in federal state s in the year prior to a state election in year t . The parameter π_1 thus captures the effect of terrorism at the state level on the number of trigger words a given party uses in comparison to the 2009 CDU. The model includes a dummy, $Party_p$, that is 1 for political party p and 0 for all other parties. The coefficient π_2 thus captures the *level* difference in trigger words used between the various parties and the 2009 CDU *regardless* of violence at the state level. The coefficient of interest, therefore, is π_3 . It captures, for each party, the additional effect on the number of trigger words used in its election manifestos at the state level as a result of terrorism. The model also includes year fixed effects, α_t , state fixed effects, ζ_s and its standard errors are clustered at the level of the state.⁵¹

Of course, a state level analysis in a setting such as ours suffers from two important limitations: first, analysis across the 16 German Federal states offers more limited cross sectional variation. Second, aggregating (successful) attacks to the state level means that we lose our sharp identifying variation between successful and failed attacks. As such, we interpret these findings with caution. Nonetheless, a state level analysis offers insights into how political parties respond to terror. And the results are broadly in line with the rest of the analysis that exploits much richer variation at the municipal and individual level.

We report our results in Figure L.1. Each patch reports our result for π_3 which we estimate for each party in samples split by trigger word.⁵² The patches are colored according to the sign of the coefficient (negative red, positive blue) and shaded according to precision (lightest 90 percent, darkest 99 percent). The patterns are clear. In response to terror at the state level, the AfD uses differentially more trigger words related to issues like crime, immigrant naturalization and integration. All other parties either do not respond or respond in the exact opposite direction as the AfD, using less trigger words on these same subjects. Interestingly, the word terror receives no special mention, neither by the AfD nor by other parties. These results

49. We collect the election manifestos from the non-profit organization *Abgeordnetenwatch* (Delegate Watch) which can be found here: <https://www.abgeordnetenwatch.de/>. In the few instances that *Abgeordnetenwatch* does not have a particular manifesto, we obtain it directly from the party's website.

50. We choose these trigger words on the basis of work by Detering (2019) who studies the rhetoric of the parliamentary right in Germany.

51. Because there are only 16 Federal states, we estimate the standard errors using nonparametric bootstrapping.

52. Specifically, for n parties and m trigger words, we run $n \times m$ regressions.

point to a clear ideological divide in the response to terror among the main political parties in Germany. They also highlight the relevance of state elections as the key political arena where political parties — or at least the AfD — campaign differentially in response to terror attacks.

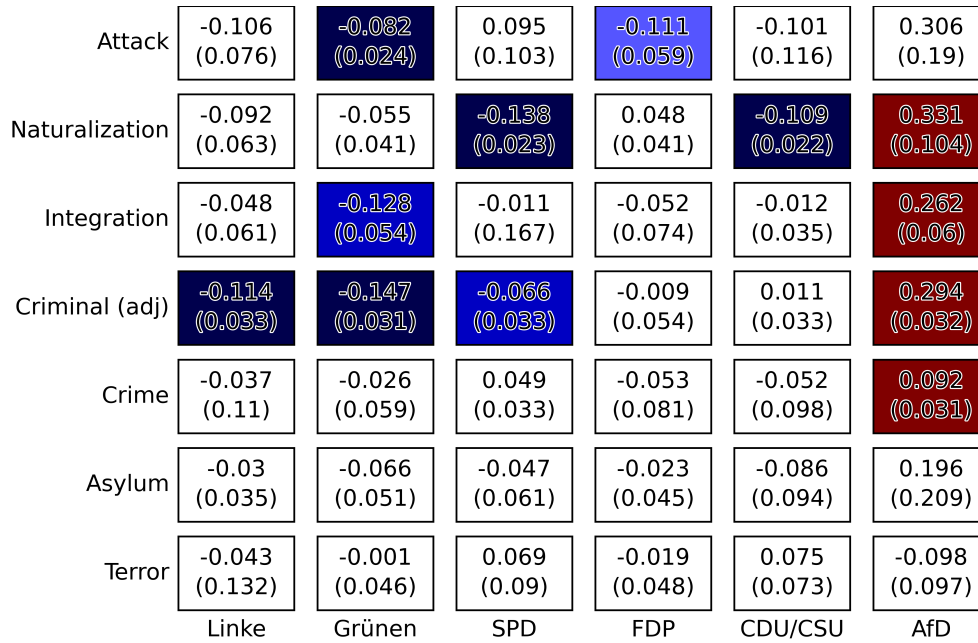


Figure L.1

Trigger words used by different parties in different states compared to 2009 CDU

Note: This figure plots π_3 from estimating equation (7). It measures the differences in each trigger word used by each party in its state level election manifesto in states with more or less acts of terror relative to the 2009 CDU Federal election manifesto. Colored patches indicate statistical significance for positive (red) and negative (blue) effects: lightest shade indicates precision at the 90 percent level and darkest shade indicates 99 percent significance.

Supplemental Data Appendix for Paper:
Terrorism and Voting:
The Rise of Right-Wing Populism in Germany

Navid Sabet* Marius Liebold Guido Friebe

This Version: September 1, 2023

Our paper aims at understanding the impact of terrorist attacks on right-wing voting in Germany. We compiled a new dataset from several different sources to carry out this study, which we describe more fully in this Appendix.

The Global Terror Database

We collect data on terror attacks in Germany between 2010 and 2020 from the Global Terror Database (GTD, 2020) which is maintained by the University of Maryland, College Park. This is an open source database that documents information on terror attacks from around the world from 1970 to the present day. The database is maintained through data collection efforts from public, unclassified materials including media articles and electronic news archives, existing datasets and secondary source materials such as legal documents and books.

For an event to be included in the GTD several criteria must be met. First, the incident must be intentional, it must entail some level of violence and it must be perpetrated by sub-national actors. In other words, the database does not include state-sponsored acts of terrorism. Second, two of the following criteria must also be met: (i) The act must be aimed at attaining a political, economic, religious, or social goal; (ii) there must be evidence of an intention to coerce, intimidate, or convey some other message to a larger audience beyond the immediate victims; and/or (iii) the incident must occur outside the context of legitimate warfare.

The GTD provides information with regard to the identity of the target and the motivation of the perpetrator(s), though the latter information is not always complete. We therefore complete this information by looking up each of the 232 attacks using our news data and the internet to obtain information on the identity of the perpetrator and the motives behind the attack. Doing so enables us to classify 211 of the 232 attacks. The majority of the attacks (116 of the 211, or 55 percent) are carried out in the name of right-wing extremist causes and 57 percent target non-Germans, in line with the example illustrated in Section 2 of the main manuscript. If, however, we consider only the 124 first attacks in each of the unique 124 municipalities targeted by an attack, the figures are considerably higher: 75 percent of these attacks are carried out by right-wing extremists and 75 percent target foreigners.

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NSADP Vote Share in 1933

Falter and Hänisch 1990 provide data on the *National Socialist German Workers' Party* (NSDAP) vote share for federal elections between 1920 and 1933 in interwar Germany. This source includes the major parties' municipality-level election results for cities and villages with more than 2000 inhabitants during the 1920s. As no common identifier exists between this source and the data provided by *the Bundeswahlleiter*, we have to match municipalities between the sources.

We use MLMATCH, a novel state-of-the-art EM framework introduced by Karapanagiotis and Liebald 2023 to link municipalities across sources. This framework uses a similarity encoder to translate pairs of entity records from both data sources to machine learning-compatible numeric data. When translating the data, the encoder accounts for a range of similarity concepts (e.g., Levenshtein, Jaro-Winkler, Euclidean, etc.). Moreover, aside from using various similarity functions on one pair of variables, it also allows us to account for many variable combinations. The encoders' output is fed to two layers of deep artificial neural networks, resulting in a matching probability for each potential combination of records from both sources.

In our setup, we use nine similarity functions when comparing the non-harmonized municipality names between the two sources. Aside from this, we rely on the networks' standard specifications. As illustrated by Column 1 of Table 1, we train the model on 80% of the manually labeled subsample. The subsample corresponds to the municipalities in which terror attacks occurred during our observation period and for which we could find a match between the data sources.

Table 1
Benchmark Performance

(1)	(2)	(3)	(4)	(5)	(6)
Dataset	Fraction	Accuracy	Precision	Recall	F1-Score
Training	0.8	99.7	98.7	93.8	96.2
Testing	0.2	98.4	100	96.9	98.4

Note: This table illustrates MLMatch's performance when matching historic municipalities from Falter and Hänisch 1990 with their current representations obtained from *the Bundeswahlleiter*. Column 1 indicates the dataset type underlying the performance evaluation. Column 2 indicates each dataset's fraction of the overall number of manually labeled municipalities. Columns 3 to 6 illustrate the corresponding performance metrics, including accuracy ($= \frac{TP+TN}{TP+TN+FP+FN}$), precision ($= \frac{TP}{TP+FP}$), recall ($= \frac{TP}{TP+FN}$), and the F-Score ($= 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}}$).

Columns 3 to 6 of Table 1 highlight the model's performance. When making predictions on the previously unseen testing data, the model does not lead to false positive matches, as indicated by a precision of 100. Moreover, the model likewise only makes very few false negative predictions, leading to a recall of 96.9 and a f1-score of 98.4.

News Coverage Data

We use news data from two sources. The first source, the *Frankfurter Allgemeine Zeitung* (FAZ), offers a country-wide and geographical unbiased news coverage. The FAZ is the second-largest national daily newspaper in Germany, measured in sales volumes. Unlike the tabloid press, the public considers the FAZ to sell high-quality journalism. The second data source is *LexisNexis*.

LexisNexis provides access to news articles from more than 1,000 newspapers through its on-line portal for academic research. Aside from a few more prominent news sources, LexisNexis predominantly covers local and regional newspapers, focusing on different geographic areas. The dataset construction is divided into three steps, outlined in the following.

Raw Data Collection & Transformation

For each terror attack in the GTD from our observation period in Germany, we collected news articles potentially covering the incident. We assume a news article to potentially cover a terror attack if it was published within the first ten days after the attack and if it included the name of the city of the attack. For *LexisNexis* data, we additionally established the criterion that a news article must incorporate at least one (case-insensitive) terror attack-related keyword (i.e., "Attacke", "Anschlag", or "Terror"). This additional condition reflects (opportunity) costs associated with obtaining *LexisNexis* data as the online portal only allows for semi-automated access. In total, we gathered approximately 105,000 news articles published by the *FAZ*, and 60,000 provided by *LexisNexis*.

Classification

Subsequently, to better identify news articles related to instances of terror, we implemented a three-step procedure. First, according to predictions by a classification model, we labeled the news articles as either related or unrelated to terrorism. In fact, we trained multiple classification models utilizing various classifier technologies and selected the best performing among them. Figure 2 summarizes the prediction quality of the models trained. As the MLP (Multilayer Perceptron) Classifier delivers the most robust results in terms of Accuracy (85.1 percent), we used this model for classifying the news articles. All models are trained on the same data, consisting manually labeled news articles collected from *LexisNexis* covering terror attacks in Austria and Switzerland between 2006 and 2018. The usage of Swiss and Austrian data is appropriate for two reasons. On the one hand, the language in Germany, Austria, and large parts of Switzerland, and thus of most news articles reporting on the incident, is the same. On the other hand, German newspapers frequently report on attacks in Germany's neighboring countries. We implemented the steps using the *scikit-learn* library for *Python*. Before we fit the model, we conducted preprocessing for both the training (372 news stories) and test data (94 reports). Specifically, we harmonized the spellings, performed lemmatization, and only kept lemmas representing adjectives, nouns, verbs, or institutions. During the preprocessing, we relied on the open-source software library *Spacy* and its associated *de_core_news_sm* pipeline, which comes pre-trained on German news data.

To minimize false-positive classifications, we establish a second condition for news articles to be considered terrorism-related. Articles must include at least one terrorism-related keyword. The list of valid keywords consists of the expressions "Terror", "Attacke", "Anschlag", "Bombe", "Messer", "Sprengstoff", "Blutbad", "Molotow", and "Attentat" in any style of writing. The third step guarantees that news articles labeled as related to terrorism indeed report on the terror attack of interest and not terrorism in general or a different incident. Accordingly, we manually check the classifications of all news articles previously labeled as terrorism-related. In summary, the implemented three-step procedure de facto eliminates false positive classifications and assignments. It, on the contrary, can not entirely rule out the existence of false-negative classifications. However, the confusion matrix of the trained MLP model (Figure 1) suggests that the problem of false-negative classifications is of minor relevance.

Table 2
Classification Model Performances

Model	Accuracy Score	Precision Score	Recall Score	F1 Score	Training Articles	Test Articles
SVC	0.606383	0.550000	0.536585	0.543210	372	94
KN	0.436170	0.436170	1.000000	0.607407	372	94
NB	0.765957	0.672727	0.902439	0.770833	372	94
DT	0.808511	0.810811	0.731707	0.769231	372	94
LR	0.808511	0.848485	0.682927	0.756757	372	94
RF	0.797872	0.958333	0.560976	0.707692	372	94
MLP	0.851064	0.813953	0.853659	0.833333	372	94

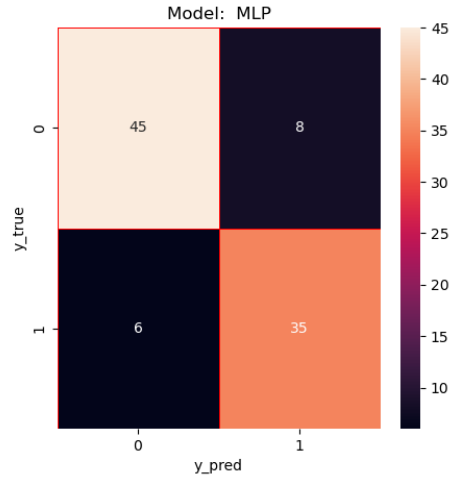


Figure 1
MLP Classification Confusion Matrix

Note: This figure plots the confusion matrix for the MLP classification model when evaluation the predictions of the test data.

Sentiment Analysis

When generating sentiment scores for news articles, we calculated the mean value of connotations associated with the words included in a report. The connotations capture the words' polarity (i.e., whether it has a positive or negative character), range between -1 (negative) and 1 (positive), and stem from the *SentiWS* word collection (Remus, Quasthoff, and Heyer 2010). For instance, whereas the term "hinterlistig" ("insidious") corresponds to a negative sentiment of -0.3187, "großzügig" ("generous") represents the positive score of 0.2077. The word collection contains sentiments of circa 3,500 base words and their 35,000 inflections.

SOEP Questions

We use data from the German Socio-Economic Panel (SOEP) which is a panel of individuals and households over time in order to study the political preferences and attitudes of the *same person* before and after an attack. We obtained access to the restricted-use SOEP data with municipality identifiers in order to link our data on successful/failed attacks to this survey data. Below, we provide details on the exact formulations of the survey questions used in the SOEP data and how we used them in our analysis.

Political attitude

We use variable *plh0004* to identify a person's position on the left-right political spectrum. Details are as follows:

Question:	In politics people sometimes talk of left and right. Where would you place yourself on a scale from 0 to 10 where 0 means the left and 10 means the right?
Answer Range:	An index from 0 (left) to 10 (right).
Usage:	We construct two binary variables using this measure. First, we generate a variable that is 1 if <i>plh0004</i> ≥ 6 and second, we construct an indicator that is 1 if <i>plh0004</i> ≥ 7 and 0 otherwise.

Party preferences

We use variable *plh0012_v6* to identify a person's political party preferences.

Question:	Which party do you lean toward?
Answer Range:	Categorical variable for all main parties in Germany.
Usage:	We construct multiple binary variables using this measure. First, we generate a variable that is 1 if <i>plh0012_v6</i> == <i>AfD</i> and 0 otherwise. Second, we construct an indicator that is 1 if <i>plh0012_v6</i> == <i>CDU</i> , <i>plh0012_v6</i> == <i>CSU</i> , or <i>plh0012_v6</i> == <i>CDU/CSU</i> and 0 otherwise. Subsequently, we repeat the exercise and label someone to prefer the social democrats if <i>plh0012_v6</i> == <i>SPD</i> , the left if <i>plh0012_v6</i> == <i>Die Linke</i> , the FDP if <i>plh0012_v6</i> == <i>FDP</i> , the green party if <i>plh0012_v6</i> == <i>Buendnis90/Gruene</i> . Moreover, we create a binary variable indicating ultra-rightwing party preferences that equals 1 if <i>plh0012_v6</i> == <i>NPD/Republikaner/DieRechte</i> and 0 otherwise.

Worried about migration to Germany

We use variable *plj0046* to identify people's concerns about migration to Germany.

Question:	How concerned are you about immigration to Germany.
Answer Range:	Range: 1 (very concerned), 2 (somewhat concerned), 3 (not concerned).
Usage:	We construct a binary variable that is 1 if a person is very concerned about migration to Germany and 0 otherwise.

Worried about (global) terrorism

We use variable *plh0039* to identify people's concerns about global terrorism.

Question:	How worried are you about global terrorism?
Answer Range:	1 (very concerned), 2 (somewhat concerned), 3 (not concerned at all).
Usage:	We construct a binary variable that is 1 if people are very concerned or somewhat concerned about global terrorism (i.e. $plh0039 == 1$ or $plh0039 == 2$) and 0 otherwise.

Political Participation

We use variable *pli0097_h* to identify people's participation in local political affairs.

Question:	Now some questions about your leisure time. Please indicate how often you take part in each activity: daily, at least once per week, at least once per month, seldom or never? (One of the listed activity reads out: Participating in political parties, municipal politics, citizens' initiatives)
Answer Range:	1 (daily), 2 (at least once a week), 3 (at least once a month), 4 (seldom), and 5 (never).
Usage:	We construct a binary variable that is 1 if people participate at least one time per month in local politics (i.e. $pli0097_h == 1$, $pli0097_h == 2$, or $pli0097_h == 3$) and 0 otherwise. Additionally, if a person residing in a municipality targeted by a terror attack has always participated in local political affairs according to the definition above before the attack, we label him/her politically active.

Other Variables

Variable	SOEP Label
Income	ijob1
Married	d11104
Female	d11102II
Uni Degree	bex8cert
Employed	e11102
Age	syear & birth_year
Moved	gkz
Rural area	kr_population & kr_area

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