Terrorist Attacks, Cultural Incidents, and the Vote for Radical Parties: Analyzing Text from Twitter

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Abstract. We study the role of perceived threats from other cultures induced by terrorist attacks and criminal events on public discourse and support for radical right parties. We develop a rule which allocates Twitter users to electoral districts in Germany and use a machine learning method to compute measures of textual similarity between the tweets they produce and tweets by accounts of the main German parties. Using the exogenous timing of attacks, we find that, after an event, Twitter language becomes on average more similar to that of the main radical right party, AfD. The result is driven by a larger share of tweets discussing immigrants and Muslims, common AfD topics, and by a more negative sentiment of these tweets. Shifts in language similarity are correlated with changes in vote shares between federal elections. These results point to the role of perceived threats from minorities on the success of nationalist parties.

Replication Material. The data, code, and any additional materials required to replicate all analyses in this article are available on the *American Journal of Political Science Dataverse* within the Harvard Dataverse Network, at: https://doi.org/10.7910/DVN/VA00ZI

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In the past decade changes in global trends have accompanied the rise of protectionist and culturally conservative politicians generally opposed to the free circulation of goods and people resulting, in several Western democracies, in an improved electoral performance by nationalist and radical right parties. The intensification of migration and refugee flows (Eurostat 2019) has made immigration policy a politically crucial issue, and one on which nationalist parties have built their fortunes.

Concurrently, Europe has faced an unprecedented sequence of religiously motivated terrorist attacks in the second half of the 2010s, which have made the defense of national borders an even more salient political issue. Radical right parties have framed some of their anti-immigration stances as policies designed to provide security against the threat posed by foreigners.[1]

In this paper we investigate the extent to which perceived threats associated with terrorist attacks and culturally salient crimes can influence public opinion discourse and the support for radical right parties, using data from Germany.

Germany is a relevant case-study for radical right voting and its connection to terrorism fears. In the period running from the 2013 to the 2017 Federal elections (*Bundestag* elections), several jihadist attacks occurred in Western Europe and in Germany. Moreover, in the midst of the refugee crisis, criminal acts perpetrated in Germany by men of reported Arab and Middle Eastern origin generated widespread concerns and fueled a political debate over the consequences of the government's immigration policies. Members of the radical right party AfD (*Alternative für*

[1] For instance, Matteo Salvini, leader of the League in Italy, said "the risk of terrorism is incredibly high […] we ask for a tight control of all our borders and the suspension of any further landing on our coasts" (Corriere Della Sera 28.03.2018)

Deutschland) pointed to the open border policy as posing a security threat for the German population.[2] In the 2017 Federal election, AfD entered for the first time the lower house of Parliament by almost tripling its vote share.

Our argument is that attacks and crimes which the public can attribute to members of specific ethnic or religious groups can induce a perception of threat arising from these groups. People more strongly affected by these shocks can in turn support parties whose narrative is focused on the dangers of multiculturalism. This maybe because the perception of threat from other groups worsens attitudes towards the compatibility between such groups and the hosting society (Echebarria-Echabeand Fernández-Guede 2006; Legewie 2013) and because shocking events increase the salience of public safety and counter-measures in the political debate (Böhmelt et al.2020; Giani 2020). Our main novelty is the use of Twitter data and textual analyses to study public opinion movements and their drivers. The empirical advantage of Twitter data is the possibility of tracking changes in views and public discourse from the evolution of the language of users relative to that of political actors, and to do this almost in real time. This allows to investigate how such changes are influenced by specific events.

In our empirical analysis, we download the tweets posted by the official national Twitter accounts of the seven main German parties to identify their discussion topics using topic modeling. We then geolocate a sample of more than 178,000 Twitter users and collect all their available tweets to obtain a panel dataset at the electoral constituency level and at daily frequency. Using a natural language processing algorithm (doc2vec), we compute a daily measure of similarity between the

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[2] Among many others, the former leader of the party, Alexander Gauland, openly advocated the closing of German borders by all means (Zeit Online 24.02.2017)

language used by parties and the language used by Twitter users in a given constituency. We use this measure of similarity to infer the alignment of Twitter users with national parties. Then, we use time variation in text similarity and the exogenous timing of a set of terrorist attacks and a criminal event to estimate a discontinuous growth model (Bliese and Lang 2016). This allows comparing the predicted similarity in the presence and in the absence of events.

We find that following these events the tweets posted in German constituencies become, on average, more similar to AfD's tweets and less similar to other parties' tweets, most notably, to the main center-left party. To rule out the possibility of capturing a strategic language change by AfD, we conduct a within-party analysis of tweets over time and find no evidence that party accounts change their language in the aftermath of our events. Hence, it is plausible that the increasing similarity between German Twitter users' and AfD's language is driven by users changing theirs to become more similar to AfD's. We use our topic model and sentiment analysis to complement the results on similarity and clarify the mechanisms. We show that the frequency of users' tweets about immigration and Islam, the two core topics in AfD's account, increases after events and over time, while the share of German news articles mentioning the same topics trends downward in the same period. This seems to suggest that the general public changes its language independently of agenda setting by the media.

This pattern is in part consistent with shifts in public discourse due to the salience of terrorist attacks, especially in the immediate aftermath of events. We further investigate whether these events also have an impact on the public's attitudes in the medium run. We show that the increasing frequency of Islam and immigration tweets is associated with worsening sentiment: German users not only tweet more about these topics, but they do so with a more negative tone. Differently, the sentiment of newspaper articles discussing Islam and immigration remains stable overtime. This could be interpreted as users in our sample expressing worse attitudes towards immigrants and Muslim minorities, in a way that is consistent with the narrative offered by AfD and independent from agenda setting. While ultimately we cannot fully ascribe our findings to shifting attitudes, we observe parallel behavioral change in terms of votes. The estimated changes in language similarity after an event are significantly correlated with the difference in vote shares obtained by parties between the two elections. We further find that standard economic variables do not explain these estimated changes in language similarity.

The results speak to the literature on the roots of radical right support (Colantone and Stanig 2018; Ballard-Rosa et al. 2018; Inglehart and Norris 2016) by emphasizing the role of perceived threats from other groups and cultures. Our contribution is also methodological, as we provide a novel strategy to geo-locate Twitter users to geographic units and conduct textual analysis at the level of these units.[3]

The structure of the paper is the following: we first discuss the related literature, describe the data and present descriptive statistics of tweets and users in our sample. Then, we introduce our measurement and empirical strategy and present and discuss our main results before concluding.

Terrorism, public opinion, and social media

It is well acknowledged that violence and terrorism can substantially affect political behavior in electoral democracies. Terrorist attacks are shocking and deeply traumatic events and voters can react to them (or to their threat) by mobilizing electorally (Balcells and Torrats-Espinosa 2018),

[3] See Mitts (2019) for another approach.

punishing the incumbent government (Montalvo 2011) or rewarding parties who maintain a hard line towards the perpetrators (Kibris 2011; Getmansky and Zeitzoff 2014), possibly contributing to political polarization (Berrebi and Klor 2008).

When terrorism is ethnically or religiously motivated, its impact can also extend to inter-group relations: 9/11 attacks worsened attitudes towards Muslims and foreigners (Skitka et al. 2004; Schüller 2016), and raised anti-Muslim hate crimes (Gould and Klor 2016) and broader discrimination towards non-white groups (Mc-Connell and Rasul 2020). More generally, research has shown that terrorism consistently leads to more negative attitudes towards out-groups and to the adoption of more authoritarian values (Echebarria-Echabe and Fernández-Guede 2006).[4] As a consequence, these effects translate into different policy preferences, especially in the domains of immigration and multiculturalism: attacks lead individuals to be more supportive of restrictive immigration policies (Finseraas et al. 2011) and display more negative views about immigrant groups and their impact on society (Legewie 2013; Ferrín et al. 2020). By increasing concerns about immigration, terrorism also makes the latter a more salient issue for the public (Böhmelt et al. 2020).

Although terrorist attacks are highly disruptive events, inter-group attitudes can be affected also by less deadly and more circumscribed illegal acts, if information from media or stereotypes facilitate attribution to a given ethnic, racial or religious community. For instance, geographic exposure to violent crimes is found to increase discrimination (Mobasseri 2019), and local crime news can increase support for political parties opposing immigrant integration (Couttenier et al. 2019). Therefore, it is plausible to expect that criminal events that can be associated with a specific

[4] Although some studies rule out increases in ethnic prejudice, see Giani (2020)

cultural minority will have a similar effect on behavior than terrorist attacks, the more so the more shocking it is to the public opinion.

Given the increasingly pervasive role of the Internet in social life, a natural question is whether changes in the topics and tone of public discourse induced by terrorism and crime can be detected in online behavior and whether these changes correlate with offline behavior. Users of social media like Twitter can comment news and communicate their views on politics and current events from their accounts in real time, allowing to track individual attitudes at high frequency (Curini et al.2015). Past literature shows a correlation between language used in social media and offline behavior. For instance, anti-refugees Facebook comments (Müller and Schwarz forthcoming) and Donald Trump's tweets about Islam (Müller and Schwarz2020) can predict offline hate crimes.

Our approach draws on these insights and uses Twitter data to analyze changes in public discourse as reflected in the differences between social media language of users and parties and analyzes whether such changes can predict voting behavior.

Data

Parties

We analyze the tweets of parties that won seats in the federal parliament (Bundestag)in 2017: *Alternative für Deutschland* (AfD, Alternative for Germany), *BÜNDNIS90/DIE GRÜNEN* (The Greens), *Christlich Demokratische Union Deutschlands* (CDU, Christian Democratic Union for Germany), *Christlich-Soziale Union in Bayern* (CSU, Christian Social Union in Bavaria), *Die Linke* (The Left), *Freie Demokratische Partei* (FDP, Free Democratic Party), and

Sozialdemokratische Partei Deutschlands (SPD, Social Democratic Party of Germany). For each party, we consider the main, national-level Twitter account.[5]

Electoral and Structural Data

The Federal Returning Officer of Germany (Der Bundeswahlleiter 2017b) publishes the election results of federal elections of each electoral constituency. We use the votes for the party list for the federal elections in 2013 and 2017. Furthermore, for each constituency Der Bundeswahlleiter (2017a) publishes a set of aggregate structural (economic and demographic) variables. Since electoral constituencies do not follow the borders of (NUTS-3) administrative districts, these statistics are published for federal election years only.

Along with electoral results we use polling data at the state level from Infratest Dimap (2018), which every Sunday asks more than 1,000 eligible voters which party they would vote for if there were a General Election the following Sunday. Thus, this data reflects the current mood of the electorate. For our purposes, these polls offer the possibility to validate our measure of similarity and provide evidence for our claim that it reflects the alignment of political views to a given party.

Twitter Users

[5] We exclude the party leaders' and representatives' personal accounts in order to assess comparable accounts for all parties.

We construct a sample of German Twitter users which encompasses most German electoral constituencies. We start from a complete list of towns belonging to each constituency provided by the Federal Returning Officer. The first challenge is to identify where Twitter users live, i.e. the town where they are most likely registered to vote. Twitter users can voluntarily choose to publish any location they wish on their profile and there is no reliable way to double check the provided information. Hence, using the locations provided by users would lead to four possible outcomes: missing addresses, reported correct addresses, reported incorrect addresses, and reported fantasy addresses (e.g. Disneyland). Excluding the latter is straightforward, but there is no simple method to verify whether the location a user provides is her real place of residency or not. For this reason, we construct a rule that allocates users to a constituency, whether or not they provide information on their location.

The 299 German electoral constituencies[6] are drawn with the goal of equalizing population across them. Thus, electoral borders in general do not follow a common structure, but are drawn over towns and districts. By the end of 2017 there existed 401 districts and district-free cities,[7] which correspond to the NUTS-3 classification of the European Union. For a given constituency, our approach first identifies the largest towns within each district of the given constituency. Here we face two possible situations (as shown in Figure 1).

The first, standard, case deals with a constituency (a square in Figure 1 with solid boundaries, such as $C1$) that contains parts of one or more districts (dashed boundaries in Figure 1, such as $D1$ or

[6] This number refers to constituencies for the general election of 2017.

[7] District-free cities are of considerable population size to have their own administration, while cities and towns belonging to districts share parts of the administration.

[FIGURE 1 ABOUT HERE]

*D*2). In this case we consider the largest towns in the respective districts belonging to the constituency (here, *T*1 as the largest town of district *D*1 within constituency *C*1, and *T*2 as the largest town of district *D*2 within constituency *C*1). Because one district can overlap with several constituencies (here *D*2 is part of *C*1, *C*2 as well as other non-labeled areas), the chosen towns are not necessarily the largest towns in their districts (*T*3 and *T*2 both belong to district *D*2, and *T*3 might be larger than *T*2. Nevertheless *T*2 is the largest town within *D*2 that is still part of *C*1). By choosing towns not only with respect to size, but with respect to size *and* districts, we gain a larger geographical spread which purposely stretches our sample of towns into more rural areas.

The second case concerns multiple constituencies (*C*3 to *C*6) which are entirely located within a district-free city (*T*5). For instance, the city of Berlin is divided into eleven constituencies. In these cases we merge all constituencies of a given city using averages weighted by population for structural and electoral variables. Our final sample comprises 261 constituencies, either original or artificially merged, in which the rule described above produces a sample of 493 towns. For constituencies belonging to case 1 (Figure 1a), our rule usually includes two or three towns, depending on how many districts intersect a constituency.

For each town, we manually identify the Twitter accounts of their landmarks. These are public or commercial accounts which can be clearly located in a given town and are likely to be followed by residents. Examples are small-scale shops, town halls, police stations, fire departments or theaters. We do not consider sport clubs, TV stations or newspapers, because non-local residents are likely to follow them too. For example, following a famous soccer club or a well-established newspaper is not a reliable source to infer where a user lives. Similarly, the catchment area of possible landmarks in constituencies outside of towns is much less clear than for landmarks within a town. For example, large shopping centers might attract people from relatively far away towns and using them can lead to wrong attributions to a constituency. This strategy produced a sample of 5,512 landmark Twitter accounts, around ten per town in our sample. Appendix A (p.2) provides more details about how the list of landmarks was generated.

Having identified local landmarks, we use the Twitter API to retrieve their followers. We eliminate those users who follow less than three landmarks in the same constituency or follow landmarks in more than one constituency: i.e., we assume that people who follow at least three landmarks of a certain constituency and no landmarks of another constituency live there. After retrieving 982,358 users following any landmark, this strategy produces a sample of 189,368 located Twitter users. This sampling procedure has the advantage of limiting the risk of including non-human users (bots) in our sample, which instead may significantly influence the political debate on social media: bots are very unlikely to follow accounts of facilities at a very local level, such as our landmarks (Ferrara et al. 2016).

For the users in our sample, we download all available tweets. Twitter limits the access to roughly the latest 3,200 tweets, but since only 128 users in the sample tweeted more than this, we consider the influence of this limit negligible and conclude that we use essentially all the tweets that the users in our sample posted. Importantly, this set includes quote-tweets, namely a comment or reply to an original tweet. Since Twitter API does not return the original quoted tweet but the comment only, we can consider quote-tweets as a normal tweet. We also include retweets in our sample. Theoretically, a retweet without any comment indicates personal interest in and agreement with the message of the retweeted tweet (Metaxas et al. 2015). Hence, we consider retweets as the highest form of agreement and similarity to someone’s message, which we purposely want to capture.[8]

Possible Sources of Bias

Our data could present three possible sources of bias.

First, we can retrieve Twitter users in only 235 constituencies out of the 261. This is due to the fact that for some constituencies we could not geo-localize a sufficient large number of users. Bias would arise if the constituencies in our sample were either more or less supportive of AfD than those that we do not observe at the beginning of our observation period. However, by comparing electoral results we find no such evidence. Table 1 shows no significant difference in the support for AfD at the beginning of our observation period, as measured by AfD votes in 2013(the only data point available before our analysis starts). Hence, our constituencies should have similar probabilities of increasing in support to AfD as out-sample constituencies. We also find no difference regarding the 2017 vote or the differences between the two elections. This holds also if we just analyze constituencies in East Germany, where AfD draws higher support on average.

We also analyze a set of pre-sample period structural variables collected for the federal election of 2013, which can be correlates of AfD support (Franz et al. 2018). We can see that there exist only few and moderately significant differences between observed and unobserved constituencies. Constituencies in our sample have a slightly higher share of foreigners and show a slightly lower share of older people. However, given the low magnitudes of these numbers, this is unlikely to

[8] Empirically, retweets represent 27% of our sample of total tweets. Around 14% stem from media outlets, and less than 1% from politicians (0.03% from AfD politicians).

have an impact. Electoral and structural differences combined and significance levels aside, these differences suggest that our sample consists of constituencies with *lower* potential support for right-wing supporters than Germany overall.

The second possible source of bias is due to the fact that, within the constituencies that we observe, we have more landmarks, and hence more Twitter users, in large cities than in smaller towns. This is due to the fact that there are more facilities that qualify as landmarks in larger cities. This sampling issue would bias our results if users in larger cities would support AfD differently than users in smaller cities. However, since support for AfD is highest in rural areas with low population density, we believe that the bias would likely be against the inference of a non-zero effect and therefore our estimates should represent a lower bound. Furthermore, we observe a high correlation between the percentage of total population residing in a city, and both the percentage of users in our sample from that city ($\rho \simeq 0{:}9$), as well as the percentage of tweets posted from the users located in that city ($\rho \simeq 0{:}75$).

[TABLE 1 ABOUT HERE]

Finally, a third source of bias could arise from the fact that a Twitter user (in our sample) likely differs from a representative German voter. The exact number of active German Twitter users is unknown; different sources estimate it between 2 and 5 million users over a population of about 83 million.[9] There is clearly a self-selection mechanism in our sample. To investigate this issue, we use a machine learning algorithm described in Wang et al. (2019), which employs a multimodal deep neural architecture for joint classification of age, gender, and organization-status of Twitter users by looking at their username, screen name, biography, and profile image. We use this pre-

[9] In the United States this figure is about three times larger.

trained model to predict the age, gender, and organization status of the users in our sample. Details on this procedure can be found in Appendix A (p.3), together with a discussion of ethical concerns about the use of algorithms to classify humans. Then, in Table 2, we compare our predicted age and gender shares with the representative electoral statistics for the 2017 federal election, which provides party-specific gender and age ratios for voters.[10] While more than 70% of AfD voters are 40 years or older, based on our model, this is true for less than 40% of our users. Gender ratios are more closely aligned, but show also large differences within age groups. We conclude that while older people are over-represented among AfD supporters, younger people are over-represented in our sample, and thus we have no reason to believe that the users in our sample consist of mainly right-wing supporters.[11]

[TABLE 2 ABOUT HERE]

Of course, this evidence does not exclude the possibility of a right-wing bias in our sample. AfD has supporters of young age and a large share of Twitter users belong to this group. However, Table 3 clearly shows that, based on the pattern of its followers, AfD is not as popular as other parties on Twitter overall. For instance, while The Greens, a left-wing party, posted roughly the same amount of tweets and retweets as AfD (although over a longer period of time), it has more than three times as many followers. In fact, AfD is the party with the fewest followers on Twitter,

[10] The representative electoral statistics are not a survey, but are constructed from a sample of official ballot papers indicating the gender and age group of a voter before the vote is cast.

[11] To make sure that the results are not driven by few prolific users, we also compute the Gini coefficient on the top decile of users, which is 0.41.

although it exceeded three of those parties in vote share. We believe that this represents strong evidence that Twitter users are not overly supportive of AfD.

[TABLE 3 ABOUT HERE]

The bottom line is that (i) our sample of constituencies does not show significantly higher initial or final support for AfD, (ii) the demographic profile of Twitter users in our sample is different from the one of a representative supporter of a right-wing populist party, and (iii) the German Twitter users does not show signs of over-proportional support for the right-wing party. Hence, a representative Twitter user in our sample is more likely to be more moderate or liberal in political beliefs than a potential AfD voter. Therefore, we surmise that although we will not be able to identify an effect for the German electorate as a whole, our method will most likely underestimate it. If there is an effect in the population of Twitter users, there should be an even stronger effect in the German population.

Events

For our analysis we use eleven events, from the end of 2015 until close to the federal election in 2017. We choose these events because they represent large shocks to public opinion. Among the several events related to terrorism and crime reported in the media between 2015 and 2017, we look for a subset which satisfies three properties. First, they need to be plausibly exogenous to local conditions. Hence, we disregard very local incidents such as small-scale violence. Events happening in other countries are particularly appropriate to this goal. Second, they need to be large shocks, affecting public opinion not only in the area where they happened (i.e. town or district), but in the whole country and in other countries. Thus, we exclude some non-deadly attacks and relatively less important events. Third, we select events that plausibly highlight the salience of an external cultural threat: since jihadism was the alleged or clear motivation behind all the attacks of this period, we believe this presumption is realistic. The events we consider are listed in Table 4.

[TABLE 4 ABOUT HERE]

In addition, we include a non-terrorist event which shocked public opinion in Germany and across Europe and generated wide political and social reactions consistent with the idea of cultural threat. In December 31, 2015 and January 1, 2016 in the city of Cologne, during the New Year's Eve celebrations, several hundred women were subject to harassment and sexual assaults. According to the police, investigations on the perpetrators concentrated on North African and Syrian young men. Similar cases were later reported in other German cities.

To ease exposition, we will from now on use the term *events* referring both to terrorist attacks and the non-terrorist crime incident just described.

Tweets and Content

Before proceeding with our main analysis of the eleven events, we provide some information about the tweets we collected. For political parties, if the language used on Twitter is representative of the party position, we would expect to see strong differences in language across very different parties, and within a party across time in case a party substantially changes its position. Furthermore, as we are able to locate Twitter users within constituencies, we can analyze correlations between the language used in each constituency and electoral results.

Parties' Tweets

We first show how AfD's language changed over time. From July 2015, AfD turned from a fiscally conservative euro-skeptic party to an outright radical right party. Figure 2a shows a comparison of words that the party was most likely to use before and after this date, respectively. We compute the log-odds-ratios for all the words in AfD's tweets pre- and post-July 2015, identifying which words are more likely to appear before, and at the same time less likely to appear after that date. After ranking these words based on the log-odds-ratios, we compute and plot the standardized raw count difference for the top and bottom 15 words in the ranking (details in Appendix B, p.5). In figure 2a we see that the words with a negative score, thus used more before July 2015, are related to economic issues such as the European debt crisis and monetary policy. In contrast, words with a positive score relate more to crime, extremism, immigration policies, and refugees.

Considering now all the parties, we use a Latent Dirichlet Allocation (LDA) model to classify the content of parties and public tweets. After pre-processing, we fit a Guided LDA model on our entire corpus of parties' and public's tweets, with 16 topics: immigration, Islam, elections, soccer, world politics, education, economy, arts (music and film), cities, digital, spare time, house, mobility, social networks, information, and interviews (more details and reports on accuracy, precision, and recall relative to a human benchmark in Appendix B, p.6). Figure 2b shows that about 35% of the AfD tweets are about immigration or Islam, a share approximately double or more that of any other party.

[FIGURE 2 ABOUT HERE]

Similarity between Texts

We compute a daily similarity between the tweets of the parties and the tweets of each constituency by transforming the two groups of tweets into vectors with doc2vec, a deep learning technique. Details on pre-processing and the hyperparameters used are in Appendix C (p.11). Here we briefly summarize the method. For our analysis, we create for each day documents for each party and constituency. A party document is the text of all the tweets a party posted on a certain day. A constituency document is the text of all the tweets that all the users located in a given constituency posted on a certain day. Since we have 752 days in our observation period (from September 4th 2015 to September 24th, 2017)[12], we end up with 752 documents for each party and 752 documents for each constituency in our sample.[13]

Given these documents, we use doc2vec (Le and Mikolov 2014), an unsupervised deep learning algorithm that learns how to represent each document with a unique vector. We then measure similarity between party p and constituency c in day t as the cosine similarity between the two corresponding vectors:

$$cos\ \theta_{cpt} = \frac{\overrightarrow{c_t}\,\overrightarrow{p_t}}{||\overrightarrow{c_t}||\,||\overrightarrow{p_t}||}$$

This is the dependent variable used in our empirical analysis. In Appendix D (p.13) we perform two validation exercises, a comparison with human evaluation, and correlations with electoral

[12] July 2015 marked a turning point in the history of the AfD. We leave two months between the change in leadership of the AfD and the starting point of our analysis, but the empirical method is not sensitive to the exact day.

[13] 752 is the maximum possible amount of documents for a given constituency in case the users posted tweets every single day.

results at the national level and with regular polling data, finding that textual similarity is consistently correlated with measures of party support.

Empirical Strategy

We aim to identify the association between a set of events, their effect on textual similarity between constituencies' and parties' language and the support for parties in the following Federal election. Our analysis relies on the plausible assumption that this set of events represents exogenous shocks to public opinion whose occurrence is independent of local conditions. The size of the possible effect of a specific event, however, could differ across constituencies because of their different characteristics. In other words, the degree to which a constituency reacts to an event may not be uniform.

Our data is a panel with daily frequency. One way to study the effect of events on similarity is to compute the difference between the similarity prior to an event and the one after it happened. However, inference based on this value has drawbacks. First, there could be self-selection into tweeting: that is, people who use Twitter to comment terrorist attacks while they happen, or minutes after, may not be representative of the overall Twitter population of that constituency. Moreover, we could simply measure an immediate outrage, while what we are interested in is the deviations from pre-existing trends between the tweets of people and parties. That is, we want to investigate whether there exists a lasting positive or negative shift in language towards parties that occurs at the time of those events.

To measure this shift in similarity we use a discontinuous growth model (DGM) (Bliese and Lang 2016). This model examines the evolution of a time series punctuated by one or more discontinuities. Figure 3 shows a simple visualization of the model. It allows, at specified points in time, for a change in growth (slope) and level (intercept) of the time series of interest. In our case, after each event, both the time trend and the level of similarity to parties are allowed to shift. The change in trend and level is relative to a trend in the absence of any discontinuity. The DGM thus does not estimate the immediate reaction to an event, meant as a comparison with the level in the days before, but captures its effect on the evolution of similarity overtime (Bliese and Lang 2016).

An unconditional means model with random coefficients reveals that the proportion of total variance that occurs between constituencies ranges from 10.3% for AfD to 18% for FDP. Overlooking this fact and not allowing coefficients to vary across constituencies would lead to biased estimates and standard errors (Goldstein 2013). We thus allow for changes in intercept and time trend of similarity to vary across constituencies on the day of each event. Given the eleven events, we estimate party by party separately the discontinuous growth model using maximum likelihood

$$simil_{it}^{p} = \pi_{0i}^{p} + \pi_{1i}^{p} Time_t + \pi_{2}^{p} Time_t^2 + \pi_{3}^{p} Year_t + \sum_{k=1}^{11} [\pi_{4ki}^{p} E_{kt} + \pi_{5ki}^{p} Reset_{kt} + \pi_{6k}^{p} Reset_{kt}^{p}] + \epsilon_{it}^{p}$$

where p denotes the party and coefficients with subscript i consist of a fixed and a random component, that is

$$\pi_{oi}^{p} = \pi_{0}^{p} + r_{0i}^{p},$$

$$\pi_{1i}^{p} = \pi_{1}^{p} + r_{1i}^{p},$$

$$\pi^p_{4ki} = \pi^p_{4k} + r^p_{4ki} \ \forall k \in \{1, \dots, 11\},$$

$$\pi^p_{5ki} = \pi^p_{5k} + r^p_{5ki} \ \forall k \in \{1, \dots, 11\}$$

and error terms and random coefficients are independently distributed as

$$\epsilon^p_{ti} \sim N(0, \sigma^2_p), r^p_i \sim N(0, \Sigma_p), \epsilon^p_{ti} \perp r^p_i$$

$simil^p_{it}$ is the measured daily similarity to party p in constituency i in period t; $Time_t$ and $Time^2_t$ are a time and a quadratic time trend: their coefficients estimate how similarity would evolve in the absence of events;[14] r^p_{1i} are the random coefficients allowing for between-constituencies differences in time trend;[15] $Year$ is an indicator variable equal to 1 in 2016 and 0 elsewhere.[16] For $k = 1, \dots, 11$ E_{kt} is the event k indicator variable, coded 1 after an event has occurred until the next event occurs, and 0 otherwise: the associated parameter $\_\pi^p_{4ki} = \pi^p_{4k} + r^p_{4ki}$ estimates the extent to which the predicted value of this model on the day of event k differs from the predicted value in absence of *any* event, and is based on the trend prior to the first event. In other words, we are estimating the difference between predicted similarity after events and the predicted counterfactual

[14] A series of Log-Likelihood Ratio tests indicate that the inclusion of a quadratic effect of the time variable improves the fit of each party model (90 percent significance level for all parties, although for most parties we find a much higher significance level). Results are presented in Table F.1 in Appendix F (p.21).

[15] We omit the random coefficients of the quadratic term of *Time*, since models including these random coefficients do not converge.

[16] We estimate only one year indicator variable due to high multicollinearity.

in the absence of any event. $Reset_{kt}$ and $Reset_{kt}^2$ are event-specific variables coded 0 until the day event k occurs, then increasing day after day until the next even occurs, and switching back to 0 when the next event has happened.[17] The associated parameters $\pi_{5ki}^p = \pi_{5k}^p + r_{5ki}^p$ indicate the degree to which the event alters the coefficient π_{1i}^p of time within constituencies after event k, while the parameter π_{6k}^pindicates the extent to which the event alters the quadratic effect of time estimated by π_2^p.

Our modeling approach allows us to estimate separately deterministic time trends in the dependent variable and the effects of multiple shocks on levels and trends, while at the same time allowing for heterogeneity in a panel setting. Thus it has benefits in terms of flexibility. It differs from an ARIMA approach with fixed coefficients, but may allow for the possibility of autocorrelation. In Appendix F.1.1 (p.28) we estimate a version of the DGM which includes the lag of similarity as well as dynamic panel models with auto-correlated error terms. We find that our results are robust to these different specifications.

Next, we estimate the average effect on party votes of the changes in similarity induced by the last event occurred before the election $\pi_{4,11i}^p$. In other words, we ask whether the difference between predicted similarity to a party after eleven events happened, and the counterfactual similarity in case no event had happened, is correlated with the electoral outcome. We pool all parties together and estimate

[17] For an illustration of the coding of the variables see Table E.1 in Appendix E (p.19).

$$\Delta vote_{ip} = \alpha + \beta\pi^{p}_{4,11i} + v_{ip}$$

where $\Delta vote_{ip}$ is the difference in vote share for party p in constituency i between the general elections of 2017 and 2013 and $\pi^{p}_{4,11i}$ is the shift in similarity after the last event (11) for constituency i and party p.

Differently from papers that correlate party votes with economic variables such as unemployment, we correlate votes to change in language similarity. Note that, differently from variables such as unemployment that are fixed at the constituency level, our right-hand side variable can vary across parties within a constituency. Thus, while it would not be possible to use macroeconomic variables as independent variables when pooling all parties together (because independent variables do not vary within a constituency, while the dependent variable does), we can use $\pi^{p}_{4,11i}$thanks to its variation within a constituency.

As mentioned above, although events occur independently of local characteristics, their effect on similarity could depend on local conditions. We investigated whether a set of standard variables often considered in explaining the growth of populist parties (e.g. unemployment, share of employees working in manufacturing or foreign population) can explain the cross-constituencies heterogeneity but did not find any significant effect. Results are presented in Table F.4 in Appendix F (p.26).

Who moves: the Parties of the Public?

One natural concern with our empirical strategy comes from the specific measure of language similarity that we use. We could think of similarity as an equilibrium outcome generated by the interaction between two agents: the party account and the public. In interpreting our results, however, we treat the parties' language on social media as exogenous and assume that individuals are getting "closer" or "farther" from the language of different parties according to their shifting views. This assumption would be threatened if parties (AfD in particular) changed the language of their tweets as a consequence of what Twitter users say (Barberá et al.2019). Therefore we ask: do parties themselves significantly change their language when events happen? If so, what we argue to be a public shift closer to or farther from a party after specific events could be simply due to party language changing on those days.

To shed light on this issue we aggregate all the tweets that a certain party posts in a week. The weekly aggregation is useful for example to avoid noise due to party-specific daily events, as opposed to a longer term shift in language use. Then, using the same doc2vec, we compute the within-party change in language similarity relative to the week before. Finally, we use the DGM to see whether the within-party similarity changes around events. In case a party used significantly different language from one week to another in the weeks after an event, we would observe a downward shift in within-party similarity. If instead following an event the party keeps using very similar language, we would expect no change in the observed language similarity at the time.

Results

Shifts in Similarity

We start presenting our results in Figures 4 and 5. For $k = 1, \dots, 11$ and different parties p we show the estimated coefficients π_{4k}^{p} (fixed component) representing the difference between the predicted levels in absence of events and the predicted values produced by our model which incorporates discontinuities (all the parameter estimates are in Appendix F, Table F.2, p.22). Higher values imply higher predicted increase in similarity.

The parties shown in Figure 4 are AfD and, for comparison, the center-left party SPD. Figure 4a shows that changes in language similarity at events is positive and significant for AfD, negative and significant for the SPD.

Figures 4b and 4c show that, in response to events, AfD does not change its language, whereas SPD becomes somewhat more similar to itself. Combining these observations with the finding in Figure 4a – under the relatively weak assumption that the left-wing SPD did not adopt a right-wing language following these events– we conclude that the public shifted towards AfD in response to the events.

[FIGURE 4 ABOUT HERE]

We consider other parties in Figure 5. The results reveal an interesting, and partially unexpected, pattern. AfD is the party that gains the most as we observe increasingly positive similarity shifts at each event. CSU, the Bavarian ally of Angela Merkel's CDU, traditionally the most right-wing party before the emergence of AfD, also shows positive shifts in language similarity, although much smaller compared to AfD. This is consistent with the recent party history: the union of CDU and CSU was under enormous pressure during the peak of the refugee crisis around 2015. High-ranked CSU officials challenged Angela Merkel's leadership after she announced an open-border policy for asylum seekers, and started promoting closed borders and deportation.[18] Thus, observing a positive shift in language similarity for this party as for AfD is not surprising. We find insignificant shifts in the case of the two left parties, The Left or The Greens, and for the center-right party CDU. Only the economic liberal party FDP shows a significant negative shift. In general people appear to move farther away from relatively more centrist parties and closer to right-wing parties.

[FIGURE 5 ABOUT HERE]

Shifts in Similarity and Votes

We have found that the events we consider can affect changes in language similarity to parties. We now investigate whether these changes can predict electoral outcomes in the 2017 federal election.

Results are presented in Table 5. The dependent variable is the change in vote share from 2013 to 2017 across parties and constituencies. The independent variable are the shifts in similarity to parties across parties and constituencies: $\pi^{p}_{4,11i}$ for all constituencies i and all parties p. Remember that these shifts are constituency-specific in that we allowed for random coefficients (see Equation 2) As mentioned before, all events are exogenous to local conditions, which are usually measured

[18] See Foreign Policy (22.10.2015)

with standard macroeconomic variables. In other words we are not trying to assess which local characteristics explain electoral outcomes. Instead, we want to investigate whether our events have independent explanatory power for electoral outcomes, beyond other factors orthogonal to those events.

We start by running a single regression pooling together all parties. Results are presented in Table 5, showing a highly significant association between shifts in similarity induced by the events and changes in vote share. After the large differences presented in Figure 4a and in Figure 5, where AfD appears to be the party with the strongest upward shift, this should not be a surprise considering that AfD was the party with the largest increase in vote share. If however we estimate this model party by party, we do not find a significant correlation, possibly because of low sample size.

Although our events are exogenous to any local characteristic, one would still like to know which local characteristics amplify or dampen similarity shifts at the time of events. As explained before, identifying the right set of independent variables that could possibly be correlated with this effect is not obvious. We use the set of variables identified by Franz et al. (2018) but we do not find any of them to be correlated with the size of reaction to events. Results are reported in Table F.4 in Appendix F (p.26).

[TABLE 5 ABOUT HERE]

Discussion

Alternative Events

In principle, it may be possible to observe an increase in language similarity between users and parties after events which are not related to politics. To assess this possibility, we estimate our model on a set of events for which the connection to xenophobic platforms is arguably weaker: sport events. We choose four soccer tournament finals in Germany and repeat our analysis on these events (results and details in Appendix F, p.27). The findings are 1 or 2 orders of magnitude smaller or non-significant.

Similarity and Attitudes

What drives the textual similarity between Twitter users and AfD? Part of the mechanism could be an increase in salience of Jihadist threat in the public discussion. If in the aftermath of an attack users keep tweeting about terrorism and AfD frequently tweets about terrorism, we could observe a shift in similarity driven by a sudden change in the topic of public discussion. This explanation would be plausible, since terrorist attacks, and large-scale events like the ones in Cologne, can naturally monopolize the information environment and the public debate. Another explanation would be consistent with attitude change. To improve our understanding of mechanisms, we analyze changes in the volume and sentiment of tweets discussing topics typical of AfD - i.e., immigration and Islam. Details of these analyses are in Appendix B (p.6). Figure 6a shows that the topics of Islam and immigration are more frequent among German Twitter users in the week an attack occurs, which indicates that AfD topics become more salient after an event. Figure 6b shows that tweets on Islam and immigration have on average a negative sentiment, with downward spikes on the day of events and a downward trend.[19] An Augmented Dickey-Fuller (ADF) test shows that the Twitter sentiment time series is not-stationary (ADF statistics= -0.86, p=0.80), suggesting a shifting, and worsening sentiment toward Islam and immigration in the period under study. We also try to understand who drives the conversation. First, we investigate whether the trends in Twitter volume and sentiment that we observe are due to the agenda-setting behavior of newspapers. We perform the same analyses that we just described for the six most relevant German newspapers (see Appendix B, p.6). Figure 6a shows that the percentage of articles discussing Islam and immigration increases during the week an attack occurs. However, differently from what we observe for Twitter, the volume of newspaper articles decreases over time. This seems to indicate that while the media pay less attention to these topics, the general public discusses it moreover time, suggesting that the general public changes its discourse independently of agenda setting by newspapers. In Appendix B (p.8) we further show that the majority of Islam-immigration tweets are posted by the general public rather than by accounts of politicians or media outlets. Figure 6b also depicts the sentiment of these newspaper articles, which tends to remain stable over time (ADF statistics= -6.90, p<0.01). Thus, over time the public sentiment about Islam and immigration diverges from the media.

[FIGURE 6 ABOUT HERE]

These additional analyses reveal that a) over time, the general public tends to discuss more two core AfD topics such as Islam and immigration; b) this discussion is not driven by media or politicians; c) the volume of this discussion shows an upward trend over time; d) there is an

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[19] In our classification: -1 = negative, 0 = neutral, 1 = positive

increasingly negative sentiment when discussing these topics. We believe that these findings provide some explanations about the similarity trend toward AfD that we observe in our data.

Conclusions

The rise of radical right, populist parties is at the core of political and scholarly debate in Western democracies. In this paper we exploited the exogenous timing of terrorist and crime events to study their effects on the language used by German users on Twitter and ultimately on the support for the anti-immigration AfD. Using an allocation rule based on geographic landmarks and following patterns of local Twitter accounts to assign users to geographic constituencies, and a deep learning model, we showed that unexpected terrorist attacks and an important crime event shifted the language of peoples' tweets closer to that of AfD. The same constituencies shifted away from the center-left SPD, and, to a minor extent, from other centrist parties. We only find weak evidence of increases in similarity for other left-wing parties.

Our interpretation is that terrorist attacks and large-scale crimes attributed to immigrants constitute shocks that deeply affect public opinion. Consequently, they increase the frequency of discussion topics preferred by parties that emphasize the dangers of multiculturalism in their platform. Also, discussion about these topics become more negative over time. It remains an open question whether this dynamic can be attributed to changes in attitudes towards Muslims and immigrants among German Twitter users, although the deterioration of tweets' sentiment over time that we observe is suggestive of a possible process of attitudes change over the medium run, beyond the events' aftermath. Moreover, the evidence we provide suggests that online behavior of parties does not drive our findings.

Overall, these findings advance our understanding of the roots of radical right support, stressing the role of perceived threats elicited by terrorist events and culturally salient crimes. They also contribute to the literature on the effects of terrorism on public opinion and elections, by showing that attacks have an effect on the support for parties promoting isolationism and cultural conservatism. Moreover, they highlight a significant connection between measures of online behavior and political outcomes. Finally, they show the potential of using information from individual accounts' following patterns to locate geographically social media users and exploit cross-sectional variation in their distribution for empirical designs.

Even if our empirical analysis is limited to a single country, given the concurrent surge of radical right and terrorism in several Western democracies, we believe these results could be relevant in other settings. The combination of exogenous real world events and geo-referenced social media data is also a promising approach for other areas of social science. For instance, it might be possible to study how people react online and offline, in the short and medium term, to crime events happening in their proximity. Another possibility could be to bring the study of online behavior in the aftermath of terrorist events to areas where different ethnic or national groups co-exist and relate it to integration or discrimination outcomes. Exploring these ideas further is an exciting avenue for future research.

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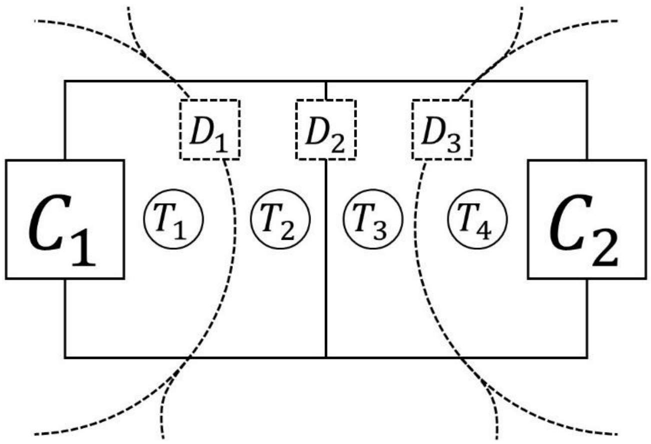
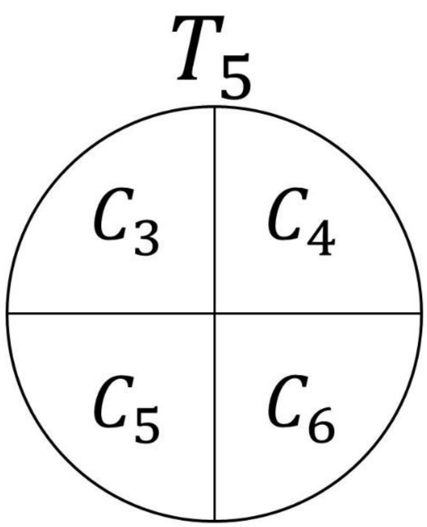
Figures and Tables

Figure 1: Sampling rule



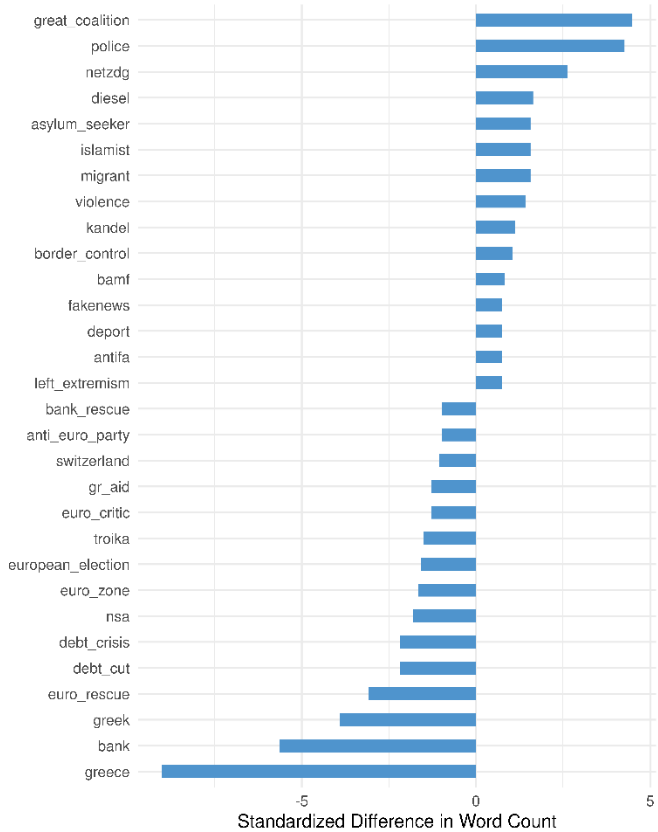
(a)Case 1



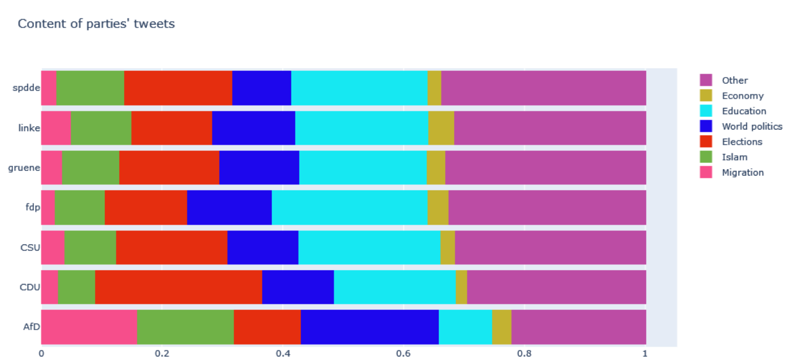
(b)Case 2

Notes: Figure 1 visualizes the sampling rules of towns (T) within districts (D) located in a single constituency (C) (case 1 in Subfigure a) and towns which consist of several constituencies within their boundaries (case 2 in Subfigure b).

Figure 2: Descriptive Content Analysis



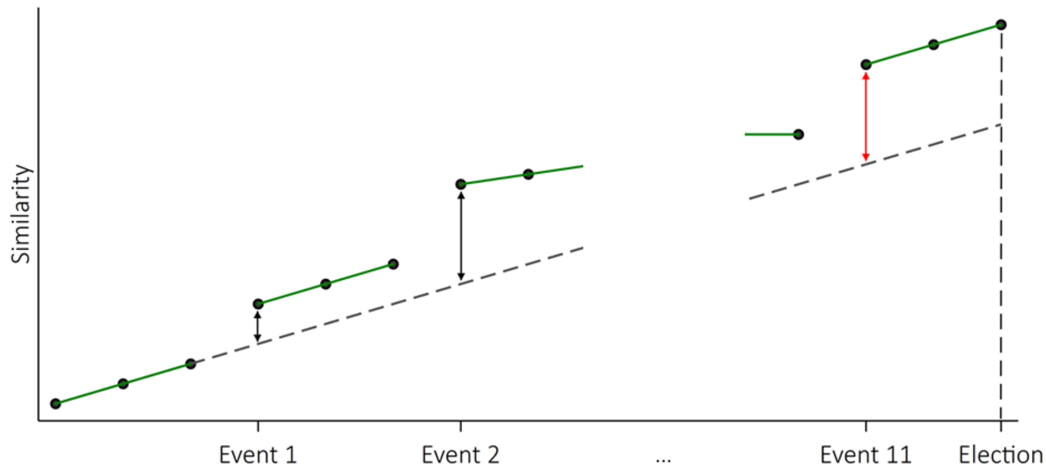
(a) AfD: Before and After July 2015



(b) LDA Topic Analysis

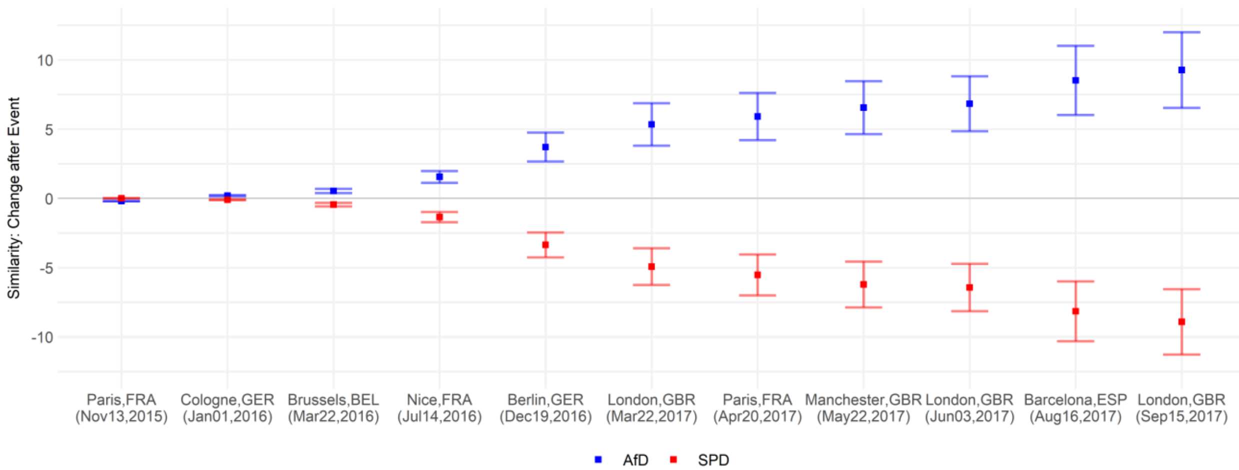
Notes: Figure 2 visualizes descriptive insights into the contents of tweets. Subfigure (a) shows a comparison of words that AfD was most likely to use before and after July 2015.Subfigure (b) shows the share of the most prevalent topics identified by the LDA model.

Figure 3: Discontinuous Growth Model: Simple Visualization

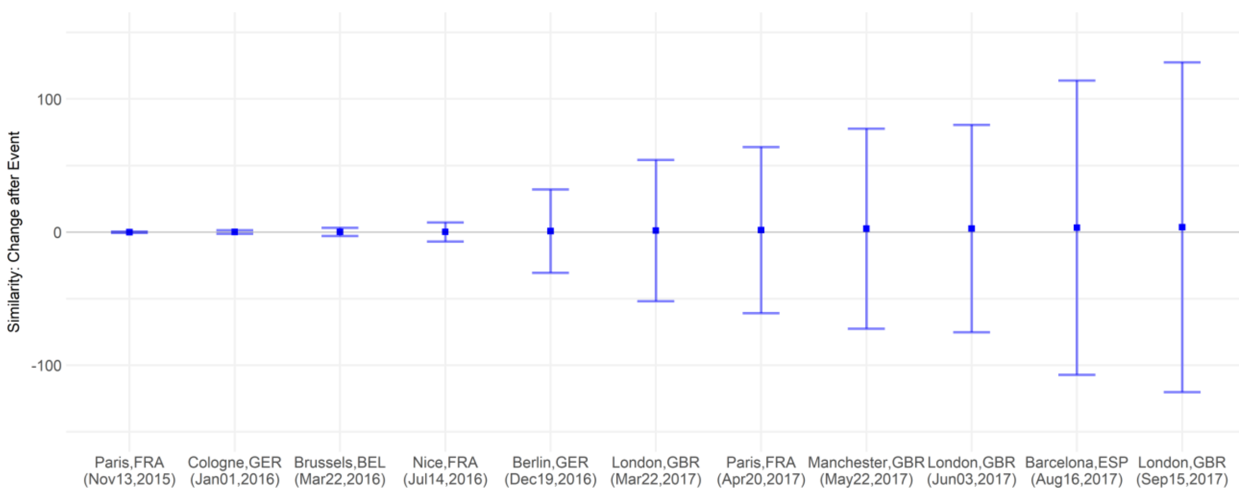


Notes: Figure3 shows a simple visualization of the discontinuous growth model, which allows, at specified points in time, for a change in growth (slope) and level (intercept) of the time series of interest.

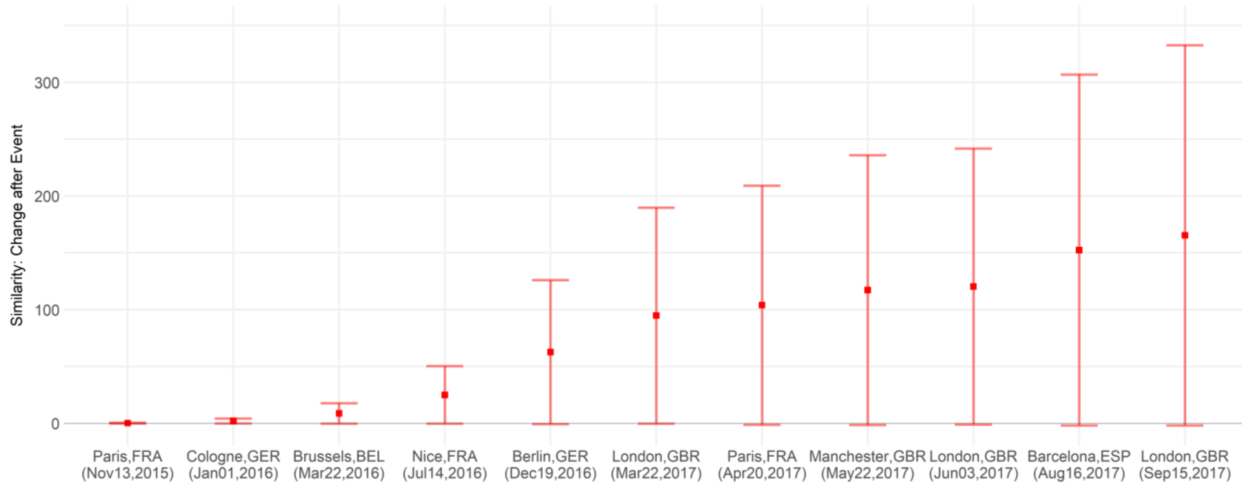
Figure 4: Shifts in Similarity: AfD vs SPD



(a) Shifts in Similarity: AfD vs SPD



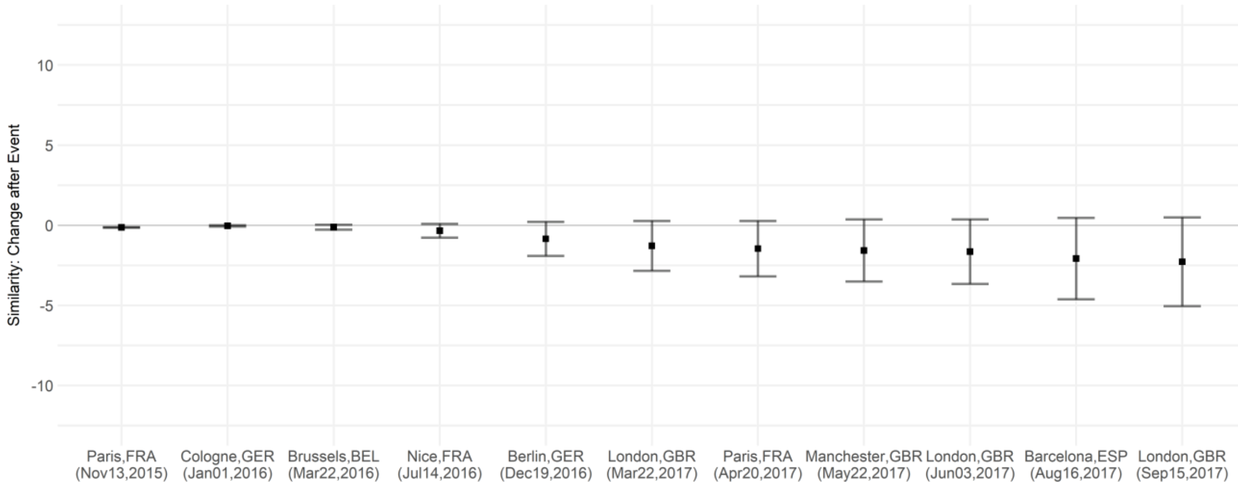
(b) Within-party Shifts in Similarity: AfD



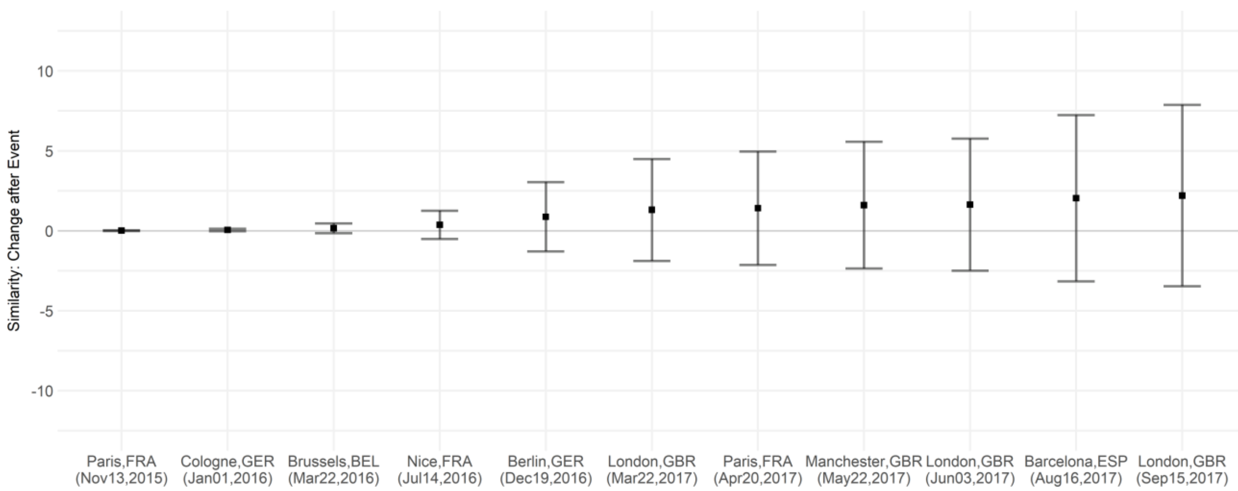
(c) Within-party Shifts in Similarity: SPD

Notes: Subfigure 4a shows estimated coefficients $\pi^{p}_{4,k}$ (fixed component, see Equation 1 and 2) of event specific shifts in intercept for parties AfD and SPD. Subfigures 4b and 4c show point estimates of event specific shifts in intercept, similar to $\pi^{p}_{4,k}$ in Equation 1 and 2, as part of the within-party discontinuous growth model estimated for AfD and SPD. Within-party similarity is calculated on a rolling weekly basis. Confidence interval corresponds to the 95 percent significance level.

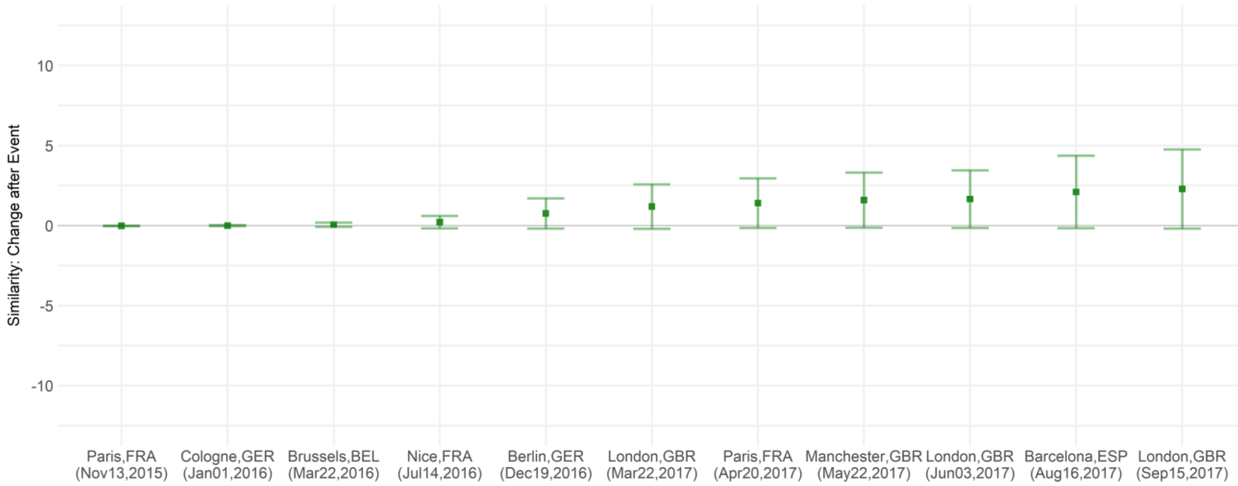
Figure 5: Shifts in Similarity: other Parties



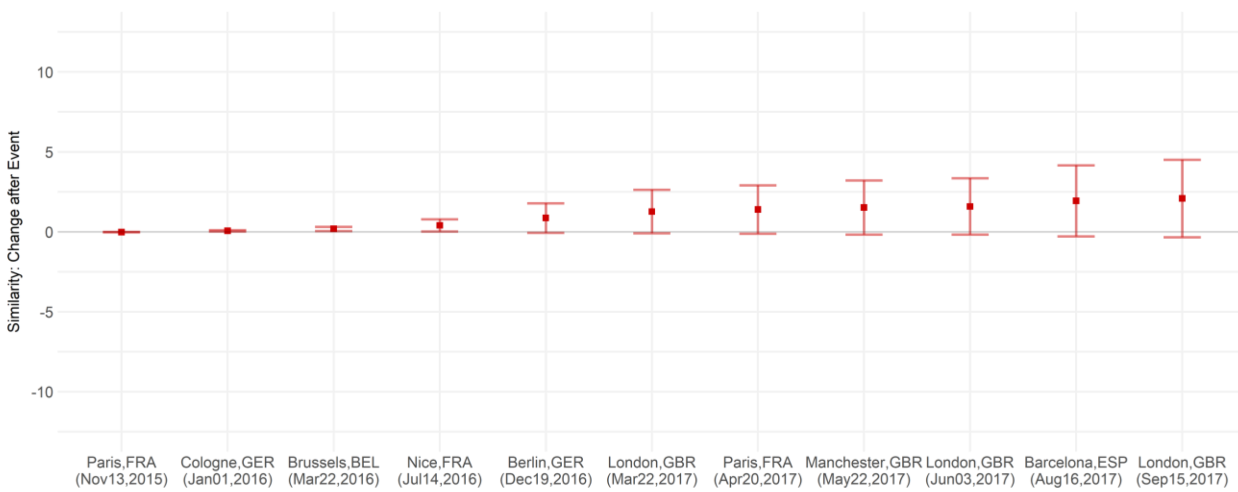
(a) CDU



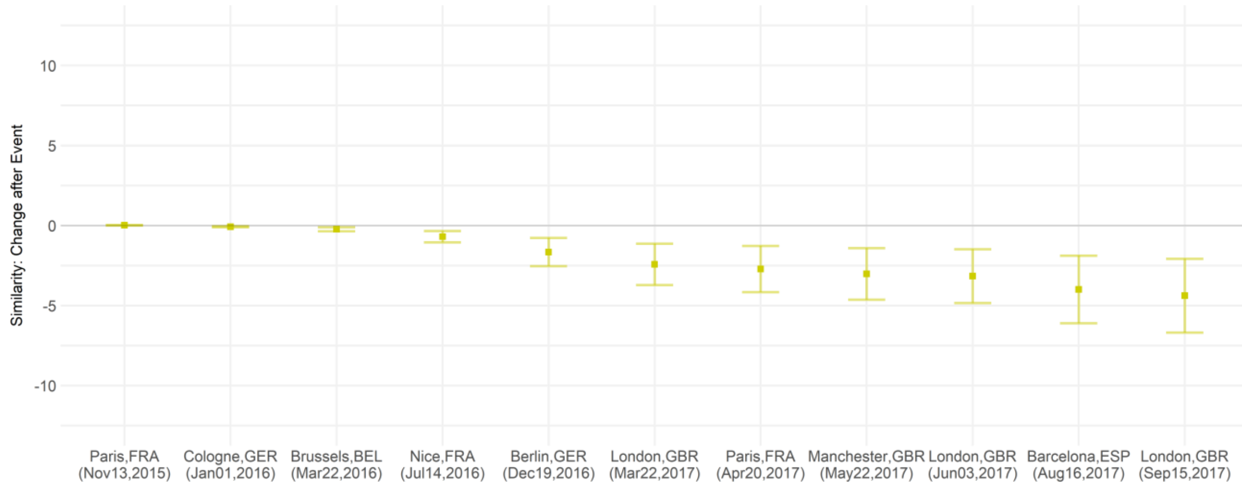
(b) CSU



(c) The Greens



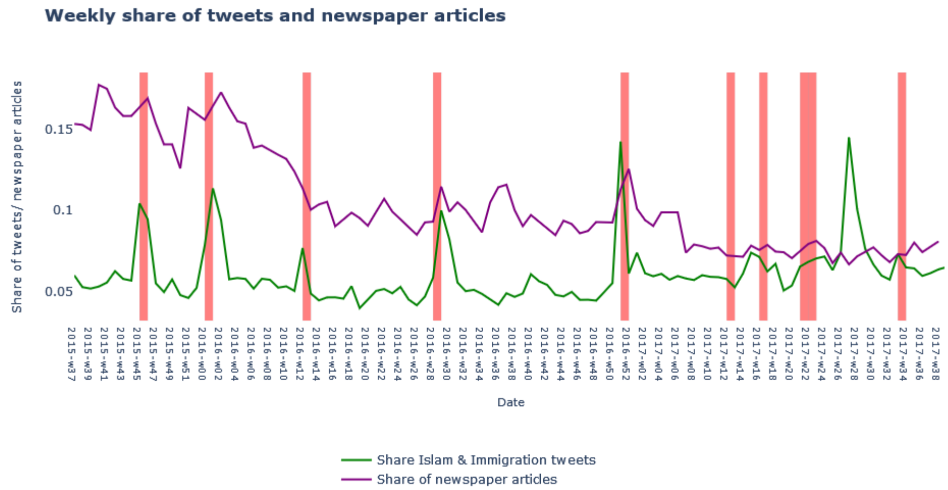
(d) The Left



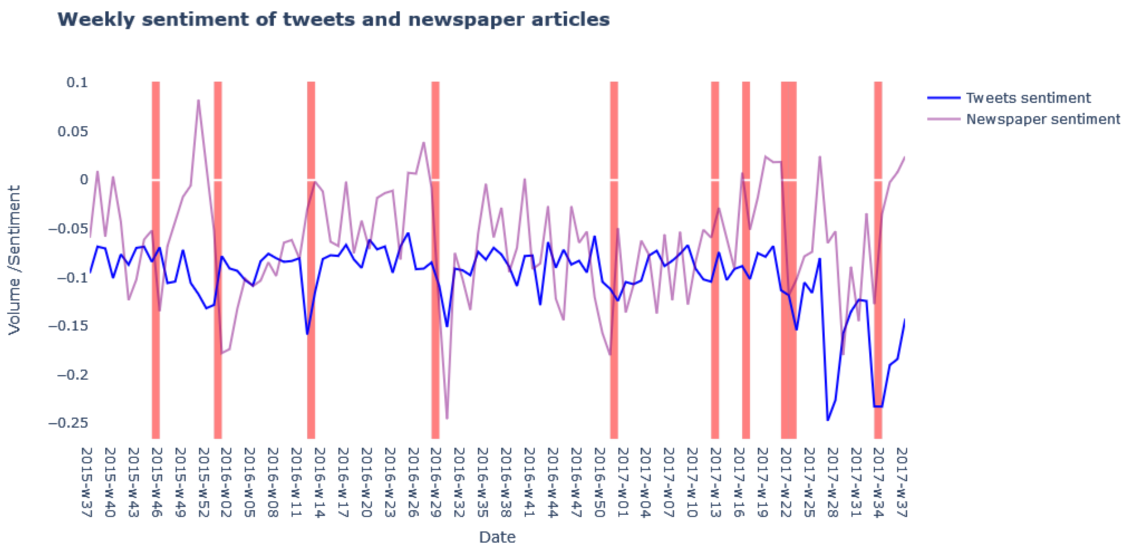
(e) FDP

Notes: : Subfigures 5a to 5e show estimated coefficients $\pi_{4,k}^{p}$ (fixed component, see Equation 1 and 2) of event specific shifts in intercept for parties CDU, CSU, The Greens, The Left, and FDP. Confidence interval corresponds to the 95 percent significance level.

Figure 6: Salience and Sentiment towards Immigration and Islam



(a) *Salience in Public and Media*



(b) *Sentiment in Public and Media*

Notes: Figure 6a shows that the salience evolution of the topics of Islam and immigration in tweets and newspaper articles over time. Figure 6b the sentiment evolution within tweets and newspapers with content on Islam and immigration. In both subfigures, red areas indicate occurrence of an event under consideration.

Table 1: Sample Comparison: Constituencies

	All Constituencies			East Only		
Sample:	In	Out	Diff.	In	Out	Diff.
AfD						
Second Vote 2013 (%)	4.69	4.81	0.12	5.84	5.90	0.06
	(1.08)	(1.22)	(0.23)	(1.13)	(1.64)	(0.53)
Second Vote 2017 (%)	12.99	13.67	0.68	22.54	24.15	1.61
	(5.41)	(6.71)	(1.15)	(5.12)	(5.65)	(2.27)
Δ Second Vote (pp.)	8.05	8.87	0.82	16.59	18.25	1.66
	(4.61)	(5.90)	(0.98)	(4.81)	(4.11)	(2.09)
Structural Variables (2013)						
Population Density (km^2)	552	278	-274	279	106	-172
	(732)	(305)	(145)	(380)	(79)	(157)
Foreigners (%)	8.44	6.23	-2.21	2.66	1.98	-0.68
	(4.51)	(3.45)	(0.91)	(1.19)	(0.79)	(0.51)
Net Migration (in 1000s)	2.55	1.28	-1.26	-0.67	-4.70	-4.03
	(5.11)	(4.54)	(1.05)	(5.97)	(0.57)	(2.46)
Age ≥ 60 (%)	26.78	28.05	1.27	30.14	31.03	0.90
	(2.51)	(2.44)	(0.52)	(2.44)	(2.18)	(1.06)
Manufacturing Employees (%)	33.09	33.74	0.64	28.67	33.45	4.78
	(9.52)	(8.86)	(1.96)	(8.36)	(4.33)	(3.51)
Unemployment Rate (%)	6.32	6.59	0.27	10.20	10.87	0.67
	(2.74)	(3.32)	(0.58)	(1.83)	(1.98)	(0.82)
Observations	235	26		41	6	

Notes: Table reports the mean for constituencies in and out of our sample together with a difference in means t-test between the two. Δ Second Vote refers to the difference in vote share from 2013 to 2017. Population density in absolute inhabitants per square kilometer. Standard deviation in parentheses for means and standard errors for differences.

Table 2: Sample Comparison: Users

	Users in Sample (%)			AfD Voters (%)		
Age:	Male	Female	Total	Male	Female	Total
≤ 18	13.68	5.19	18.87	2.85	1.69	4.54
19-29	15.28	9.50	24.77	5.27	3.17	8.44
30-39	12.17	5.25	17.42	9.23	5.44	14.67
≥ 40	31.25	7.68	38.94	46.37	27.86	74.23
Total	72.37	27.63	100	63.72	38.16	≈100

Notes: Table compares distribution of users for predicted age and gender groups to the distribution of AfD voters based on the electoral statistic for the same age and gender groups. Total sample size of users with non-missing predicted age and gender was 100,750. Total size of AfD voters in 2017 was 5,878,115. In case age groups used in the electoral statistic did not correspond to the predicted age groups, it was approximated assuming a uniform distribution within an age bracket and taking an average weighted by the share of overlap years. First row (≤ 18) for voting results includes only the age of 18 due to the minimum voting age in Germany. Voting total differs from 100 due to approximating and rounding.

Table 3:Twitter Accounts of Major German Parties

Party	Party Account	#Tweets	#Followers	Joined
AfD	@AfD	18,600	130,000	Sep-2012
Bündnis 90/ Die Grünen	@Die_Gruenen	18,000	441,000	Apr-2008
CDU	@CDU	16,300	274,000	Feb-2009
CSU	@CSU	14,800	186,000	Feb-2009
Die Linke	@dieLinke	24,500	254,000	Jun-2009
FDP	@fdp	10,900	331,000	May-2009
SPD	@spdde	32,200	354,000	Mar-2009

Notes: Retrieved February 11, 2019. Amount of tweets includes retweets.

Table 4: Terrorist Events

Date	City	Circumstance	Fatalities
November 13, 2015	Paris, France	Simultaneous attacks by groups of terrorists on several targets, including the *Bataclan* concert hall.	130
March 22, 2016	Brussels, Belgium	Coordinated bombings at several locations.	32
July 14, 2016	Nice, France	Truck driven at high speed over the crowd.	86
December 19, 2016	Berlin, Germany	Truck driven over the crowd in a Christmas market.	12
March 22, 2017	London, UK	Car driven over pedestrians.	5
April 20, 2017	Paris, France	Three policemen and another person shot by an attacker.	3
May 22, 2017	Manchester, UK	Suicide bombing after a concert at Manchester Arena.	22
June 3, 2017	London, UK	Car driven over pedestrians.	8
August 16 2017	Barcelona, Spain	Bombs detonated and a car driven over pedestrians.	16
September 15, 2017	London, UK	Bomb detonated at a train station.	0 (30 injured)

Notes: List of 10 terrorist events we include in our analysis, in addition to one non-terrorist event occurring in the night of December 31, 2015 to January 01, 2016.

Table 5: Electoral Effect: Votes on Shifts in Similarity

	Δ Vote Share
Shifts in Similarity	0.0054
	(0.0002)
Constant	0.0035
	(0.0002)
Observations	1361
R^2	0.232

Notes: Δ Vote Share refers to the difference in electoral results between 2017 and 2013. All standard errors are clustered on constituency level and calculated using bootstrapping. Standard errors in parentheses.