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

Revised Version: November 20, 2020

Abstract

We study the role of perceived threats from other cultures induced by terrorist attacks and by a criminal event on public discourse and voters' support for radical right parties. We first develop a rule which allocates Twitter users in Germany to electoral districts and then 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 dates of the exogenous events we estimate constituency-level shifts in similarity to party language. We find that following these events Twitter text becomes on average more similar to that of the main radical right party, AfD, while the opposite happens for other parties. Regressing estimated shifts in similarity on changes in vote shares between federal elections we find a significant association. Our results point to the role of perceived threats from other cultures on the success of nationalist parties.

Word count: 9,903

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 in the second half of the 2010s an unprecedented sequence of religiously motivated terrorist attacks, 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 have influenced public opinion and the support for radical right parties using data from Germany.

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 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.

We surmise that events increasing the perception of threats from other cultures

[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).

[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).

such as jihadist attacks and large scale crimes may have shifted voters' attitudes towards those affirmed by the party most vehemently opposed to immigration, and eventually may have had an effect on electoral outcomes.

Our main contribution with respect to the existing research on the topic is the use of Twitter data and several textual analyses to study attitude changes and their drivers. Several studies have used survey data to study the connection between terrorism and attitudes towards immigration (Legewie 2013; Böhmelt et al. 2020; Giani 2020). The advantage of Twitter data and textual analyses over surveys is the possibility of inferring changes in views from the evolution in 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 this way, we can improve the understanding of the drivers of radical right support.

In the empirical part, we first download the tweets posted by the official national Twitter accounts of the seven main German parties to reveal discussion topics and how they have changed using basic content analysis techniques. We then geolocalize 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 content posted by parties and the content posted 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 these events. We also fit a topic model and conduct sentiment analyses to understand the drivers of the changes in similarity that we observe.

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. 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 seems plausible that the increasing similarity between German Twitter users' and AfD's language is driven by users changing theirs to become more similar to the AfD's. To rule out effects of issue salience and agenda-setting, we show that the frequency of users' tweets about immigration and Islam, the two core topics in AfD's tweets, diverges over time from the share of news articles mentioning the same topics, and that the increasing frequency of these tweets is associated with worsening sentiment. We interpret this as evidence that changes in similarity between German users and parties capture changes in attitudes towards immigration and Islam among the public.

We further find that standard economic variables do not explain the estimated change in language similarity after an event. These changes, however, are significantly correlated with the difference in vote shares obtained by parties between the two elections.

A few contributions stem from our results. First, we 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 cultures which arise as a consequence of terrorist and crime events. We also contribute to the literature on the effects of terrorism and crime on public opinion (Finseraas et al. 2011; Legewie 2013; Böhmelt et al. 2020; Ferrín et al. 2020; Giani 2020) by using language measures from social media content to capture changes in attitudes. Finally, we contribute to the methodology of social science research based on Twitter data, by providing a strategy to geo-locate Twitter users to geographic units using following patterns and then using textual similarity to measure attitudes and preferences at the level of these units.

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

The surge of jihadist terrorism that hit Western democracies in the last few decades has significantly stressed inter-group relations and influenced politics. 9/11 increased negative attitudes towards Muslims (Skitka et al. 2004; Schüller 2016), the number of anti-Muslim hate crimes in the U.S. (Gould and Klor 2016), and broader discrimination (McConnell and Rasul 2020).

In Europe, the political debate that ensued terrorist attacks was largely centered around immigration policy and government attitudes towards ethnic and religious minorities. Terrorism increased concerns about immigration and minorities in European public opinion, a pattern consistently observed after events occurred on domestic territory or abroad (Echebarria-Echabe and Fernández-Guede 2006; Finseraas et al. 2011; Legewie 2013; Ferrín et al. 2020; Böhmelt et al. 2020). Attacks increased security fears (Giani 2020) and, in some cases, ethnic segregation in cities (Gautier et al. 2009).

The effects of terrorist attacks on public opinion resulted in electoral losses for incumbents (Montalvo 2011), rewards for right-wing parties (Kibris 2011; Getmansky and Zeitzoff 2014), and polarization of the electorate (Berrebi and Klor 2008). These findings also connect to a literature on crime and attitudes, which shows that exposure to crimes can increase discrimination towards a minority group, if the latter is perceived as associated to criminal activity (Mobasseri 2019).

Given the increasingly pervasive role of the Internet in social life, a natural question is whether changes in attitudes induced by terrorism and crime can be reflected in online 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, so that tweets allow to track individual attitudes at high frequency (Curini et al. 2015). Another reason for the relevance of social media in this context is that they can be platforms for spreading hate speech and discriminatory messages, which often translate in offline behavior, including acts of violence against minorities (Müller and Schwarz 2020; Müller and Schwarz forthcoming).

Our empirical strategy bridges these strands of the literature by using Twitter data to analyze changes in attitudes as reflected in the differences between social media language of users and parties and by analyzing at how 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), *BÜNDNIS 90/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.[3]

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

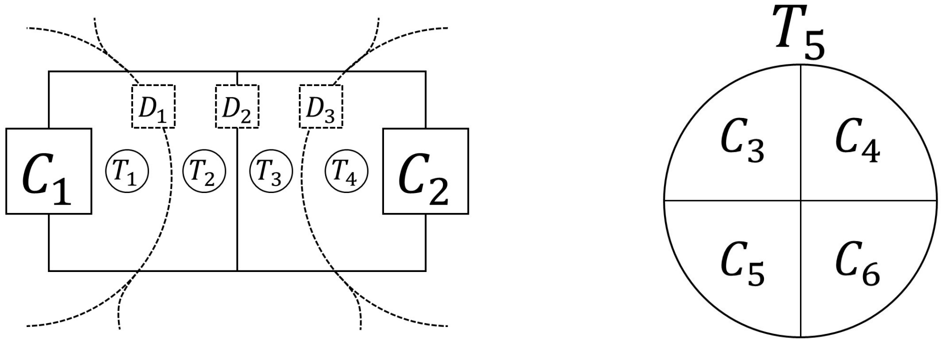
[3] We exclude the party leaders' and representatives' personal accounts in order to assess comparable accounts for all parties.

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

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.



(a) Case 1

(b) Case 2

Figure 1: Sampling Rule

The 299 German electoral constituencies[4] 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,[5] 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 C_1) that contains parts of one or more districts (dashed boundaries in Figure 1, such as D_1 or 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,

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

[5]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.

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 5,231 landmark Twitter accounts, around ten per town in our sample. Appendix A 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 825,551 users following any landmark, this strategy produces a sample of 178,271 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.[6]

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 have an impact.

[6]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).

Table 1: Sample Comparison: Constituencies

	All Constituencies			East Only		
Sample:	In	Out	Diff.	In	Out	Diff.
AfD						
Second Vote 2013 (%)	4.73	4.81	0.08	5.85	5.90	0.04
	(1.09)	(1.22)	(0.23)	(1.12)	(1.64)	(0.52)
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.)	8.26	8.86	0.60	16.68	18.25	1.57
	(4.77)	(5.90)	(1.01)	(4.49)	(4.11)	(1.95)
Structural Variables (2013)						
Population Density (km^2)	552	278	-274	279	106	-172
	(732)	(305)	(145)	(380)	(79)	(157)
Foreigners (%)	8.57	6.23	-2.34	2.68	1.98	-0.70
	(4.84)	(3.45)	(0.98)	(1.23)	(0.79)	(0.52)
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 $\geq$ 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.

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 ($\rho \simeq 0.75$).

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.[7] 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-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. 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.[8] 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.[9]

Of course, this evidence does not exclude the possibility of a right-wing bias in

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

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

[9]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.

Table 2: Sample Comparison: Users

	User in Sample (%)			AfD Voters (%)		
Age:	Male	Female	Total	Male	Female	Total
≤ 18	13.68	5.19	18.86	2.85	1.69	4.54
19–29	15.29	9.50	24.80	5.27	3.17	8.44
30–39	12.16	5.25	17.41	9.23	5.44	14.67
≥ 40	31.24	7.69	38.93	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.

our sample. AfD has supporters of young age and there is still a chance that 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, 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.

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 does not show signs of overproportional 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

Table 3: Twitter Accounts of Major German Parties

Party	Party Account	# tweets	# Followers	Joined
AFD	@AfD	18,600	130,000	Sep-12
Bündnis 90/ Die Grünen	@Die_Gruenen	18,000	441,000	Apr-08
CDU	@CDU	16,300	274,000	Feb-09
CSU	@CSU	14,800	186,000	Feb-09
Die Linke	@dieLinke	24,500	254,000	Jun-09
FDP	@fdp	10,900	331,000	May-09
SPD	@spdde	32,200	354,000	Mar-09

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

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.

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

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)

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.

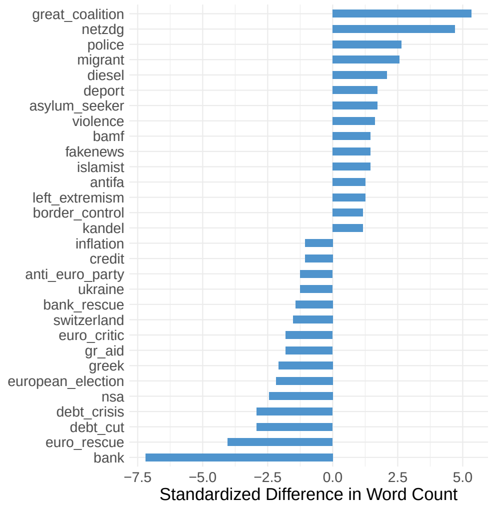
To ease exposition, we will from now on use the term *events* referring both to terrorist attacks and the non-terrorist crime incident just described.

Tweets and Content

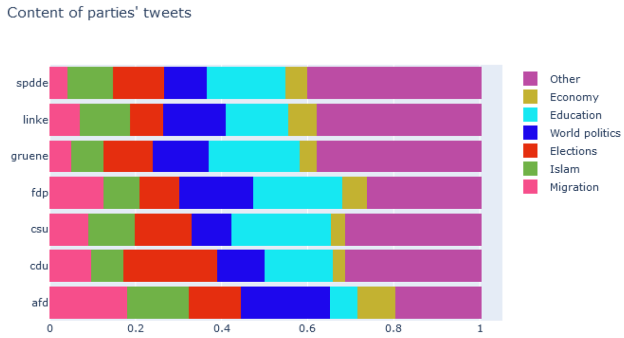
Before proceeding with our main analysis of the eleven events, we provide some information about the tweets we collected. For political parties, if the language used on Twitter is representative of the party position, we would expect to see strong differences in language across very different parties, 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



(a) AfD: Before and After July 2015



(b) LDA Topic Analysis

Figure 2: Descriptive Content Analysis

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). 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 the LDA model on our entire corpus of parties' and public's tweets, selecting the number of topics based on the lowest perplexity score. We find that the best number of topics is 16: immigration, Islam, elections, soccer, economy, world politics, education, arts (music and film), digital, cities, spare time, house, mobility, social networks, information, and interviews (more details in Appendix B). 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.

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. 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)[10], we end up with 752 documents for each party and 752 documents for each constituency in our sample.[11]

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:

$$\cos \theta_{cp_t} = \frac{\overrightarrow{c_t}\,\overrightarrow{p_t}}{\left\|\overrightarrow{c_t}\right\| \left\|\overrightarrow{p_t}\right\|}$$

This is the dependent variable used in our empirical analysis. In Appendix D we perform two validation exercises, a comparison with human evaluation, and correlations with electoral results at the national level and with regular polling data, finding that textual similarity is consistently correlated with measures of party support.

[10] 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.

[11] 752 is the maximum possible amount of documents for a given constituency in case the users posted tweets every single day.

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 over time (Bliese and Lang 2016).

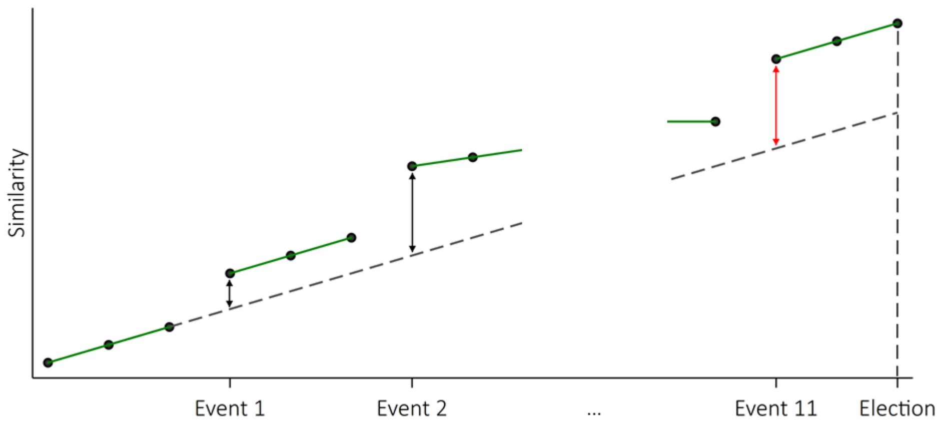


Figure 3: Discontinuous Growth Model: Simple Visualization

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

$$
\begin{aligned}
simil_{it}^{p} = \pi_{0i}^{p} + \pi_{1i}^{p} Time_t + \pi_2^{p} Time_t^2 + \pi_3^{p} Year_t \\
+ \sum_{k=1}^{11} \left[\pi_{4,ki}^{p} E_{kt} + \pi_{5,ki}^{p} Reset_{kt} + \pi_{6,k}^{p} Reset_{kt}^2 \right] + \epsilon_{it}^{p}
\end{aligned} \tag{1}
$$

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

$$
\begin{aligned}
\pi_{0i}^{p} &= \pi_0^{p} + r_{0i}^{p}, \\
\pi_{1i}^{p} &= \pi_1^{p} + r_{1i}^{p}, \\
\pi_{4,ki}^{p} &= \pi_{4,k}^{p} + r_{4,ki}^{p} \; \forall \; k \; \in \{1, \ldots, 11\}, \\
\pi_{5,ki}^{p} &= \pi_{5,k}^{p} + r_{5,ki}^{p} \; \forall \; k \; \in \{1, \ldots, 11\}
\end{aligned} \tag{2}
$$

and error terms and random coefficients are independently distributed as

$$
\epsilon_{ti}^{p} \sim N(0, \sigma_p^2), \quad \mathbf{r_i^P} \sim N(\mathbf{0}, \mathbf{\Sigma_p}), \quad \epsilon_{ti}^{p} \perp\!\!\!\perp \mathbf{r_i^P}
$$

$\mathbf{\Sigma_p}$ is a diagonal matrix, that is random coefficients are assumed to be jointly independently and identically distributed.

$simil^p_{it}$ 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[12]; r^p_{1i} are the random coefficients allowing for between-constituencies differences in time trend[13]; $Year$ is a dummy equal to 1 in 2016 and 0 elsewhere.[14] 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 $\pi^p_{4,ki} = \pi^p_{4k} + r^p_{4,ki}$ 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 in the absence of any event. $Reset_{kt}$ and $Reset^2_{kt}$ 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.[15] The associated parameters $\pi^p_{5ki} = \pi^p_{5k} + r^p_{5ki}$ indicate the degree to which the event alters the slope π^p_{1i} of time within constituencies after event k, while the parameter π^p_{6k} indicates the extent to which the event alters the quadratic effect of time estimated by π^p_2.

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,

---

[12]A series of Log-Likelihood Ratio tests indicate that the inclusion of a quadratic effect of Time 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.

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

[14]We estimate only one year dummy due to high multicollinearity.

[15]For an illustration of the coding of the variables see Table E.1 in appendix E.

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 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 ($\pi^p_{4,11i}$). 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

$$\Delta vote_{ip} = \alpha + \beta\, \pi^p_{4,11i} + \upsilon_{ip} \tag{3}$$

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, wile 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.

Who moves: the Parties or 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 $k = 1, \ldots, 11$ and different parties p we show the estimated coefficients $\pi^p_{4,k}$ (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). 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.

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.[16] 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

[16]See Foreign Policy (22.10.2015).

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.

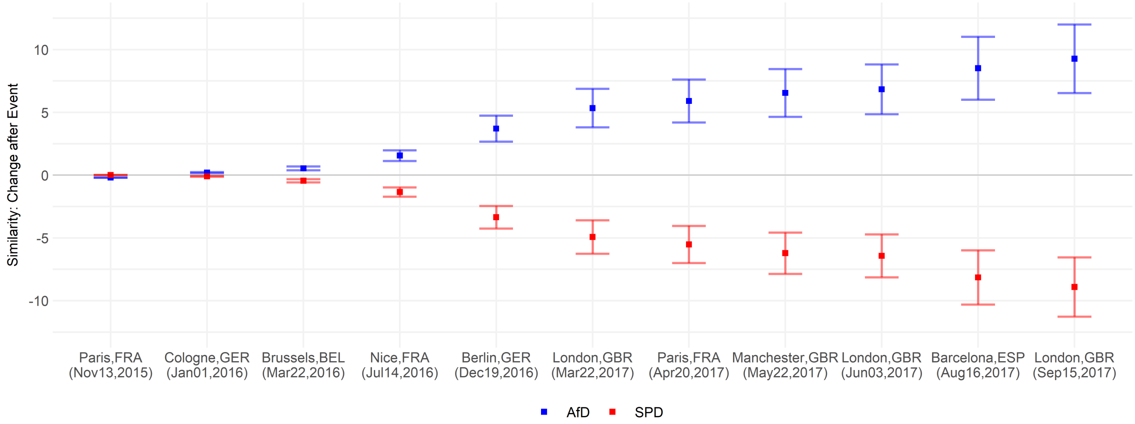
Shifts in Similarity and Votes

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.

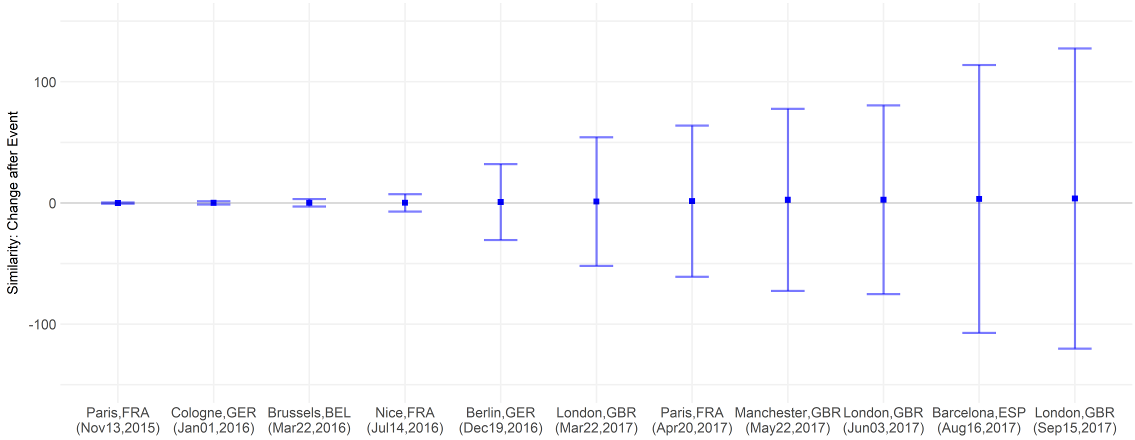
Results are presented in Table 5. The dependent variable is the change in vote share from 2013 to 2017 across parties and constituencies. The independent variable are the shifts in similarity to parties across parties and constituencies: $\pi^p_{4,11i}$ for all constituencies i and all parties p. Remember 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 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.

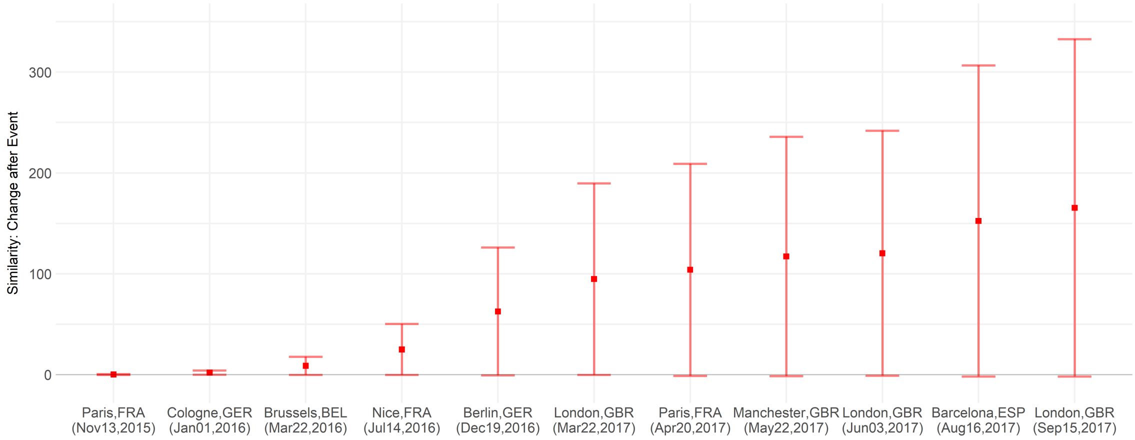
Although our events are exogenous to any local characteristic, one would still like to know which local characteristics amplify or dampen similarity shifts at the time



(a) Shifts in Similarity: AfD and SPD



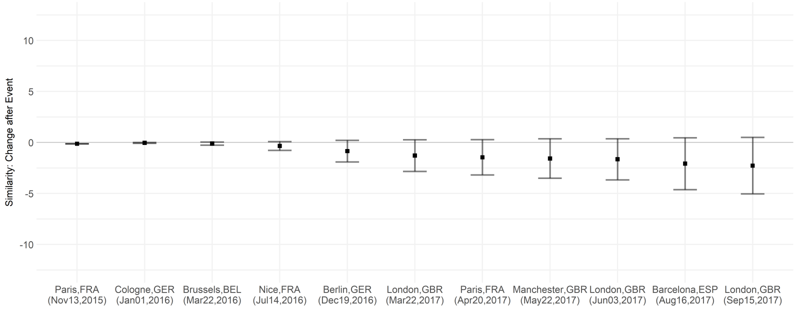
(b) Within-party Shifts in Similarity: AfD



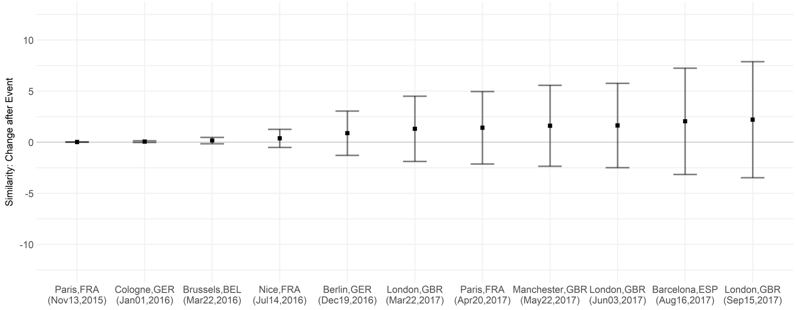
(c) Within-party Shifts in Similarity: SPD

Figure 4: Shifts in Similarity: AfD vs SPD

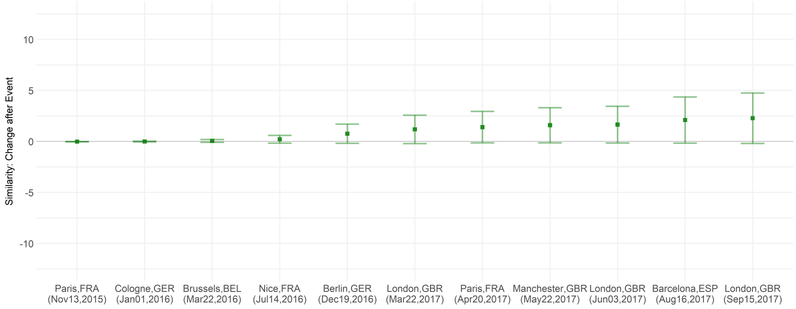
Notes: Subfigure 4a shows estimated coefficients $\pi^{p}_{4,k}$ (fixed component, see Equation 1) for parties AfD and SPD. Subfigures 4b and 4c show point estimates of event specific shifts in intercept, similar to $\pi^{p}_{4,ki}$ in Equation 2, as part of the within-party discontinuous growth model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



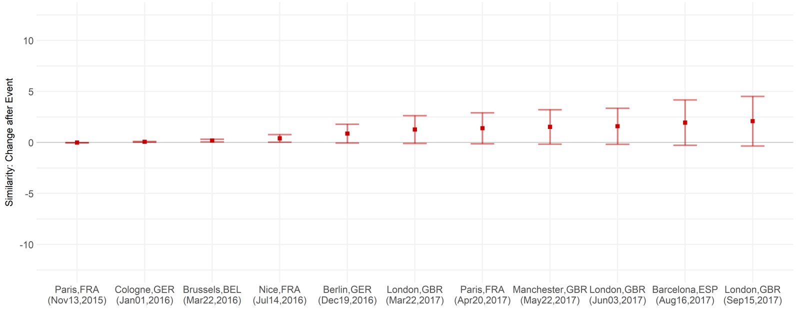
(a) CDU



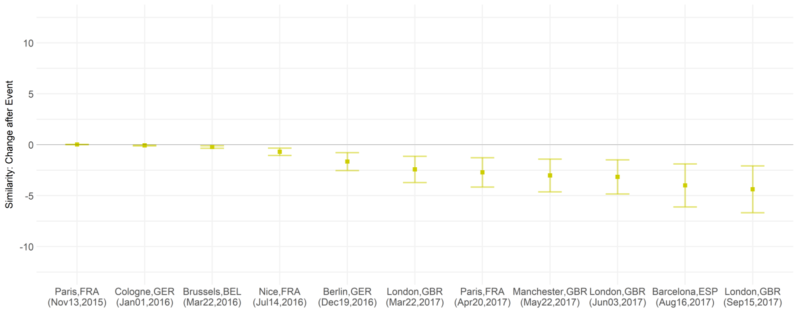
(b) CSU



(c) The Greens



(d) The Left



(e) FDP

Figure 5: Shifts in Similarity: other Parties

Notes: Estimated coefficients $\pi^{p}_{4,k}$ (fixed component, see Equation 1) for parties CDU, CSU, The Greens, The Left, and FDP. Confidence interval corresponds to the 95 percent significance level.

Table 5: Electoral Effect: Votes on Shifts in Similarity

	Δ Vote Share
Shift in Similarity	0.0055
	(0.0001)
Constant	0.0033
	(0.0001)
Observations	1410
R^2	0.234

Notes: ΔVote 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.

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 the them to be correlated with the size of reaction to events. Results are reported in Table F.4 in Appendix F.

Discussion

Alternative events

In order to be consistent with our hypothesis, language shifts of users relative to parties should capture attitudes changes. Therefore, they should not be observed after generically salient, but politically-unrelated, events. To check for 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). The findings are 1 or 2 orders of magnitude smaller or non-significant.

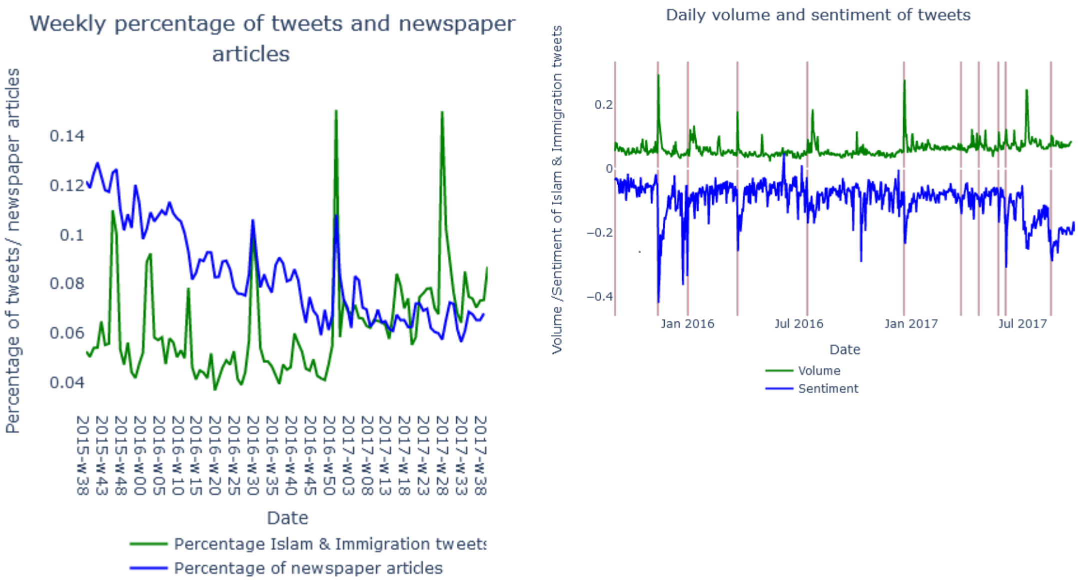
Similarity and attitudes

We have shown that the events we considered are associated with increases in similarity to AfD. In principle this may be due to the increase in salience of terrorism in the public discussion. If users kept tweeting about terrorism in the aftermath of an attack and AfD used to tweet frequently about terrorism in general, we could observe a shift in similarity driven by the changed topic of discussion. Similarly, the patterns in similarity we observe could reflect agenda-setting effects: if the public debate was primarily concerned with issues connected with the attacks, we could capture changes in the topics of discussion among the German public. For our argument to hold, the shifts in similarity need not be driven by a natural change in the topics discussed, given the information context, but rather by a change in the way topics are discussed. To this purpose, we use the LDA introduced previously.

First, we show that the frequency of tweets on Islam and immigration diverges from the coverage of these topics in the press. We consider the share of the public's tweets containing Islam and immigration topics and compare it to the share of German newspaper articles containing the same topics, retrieved from the Factiva database (see Appendix B). Figure 6a shows that while media outlets tend to mention Islam and immigration more in the week an event happens, the proportion of articles mentioning them decreases over time, whereas the proportion of tweets in which Islam and immigration topics appear increases. This suggests that the discussion of "AfD issues" is not due to the increased salience of these issues in the media environment.

Second, we show that the increase in frequency of these tweets comes with a more negative sentiment towards the topics of Islam and immigration. We run a sentiment analysis on the tweets on Islam and immigration, using a set of hand-coded tweets and supervised learning (details in Appendix B).[17] Figure 6b shows that tweets on Islam and immigration have a negative sentiment, which spikes at the time of events

[17] In our classification, 1 = positive sentiment, 0 = neutral, -1 = negative sentiment



(a) Salience in Public and Media (b) Sentiment in Public

Figure 6: Salience and Sentiment towards Immigration and Islam

and trends downwards after them. These results combined suggest that the increase in similarity with AfD is driven by increasing concerns and worsening attitudes towards immigration and Islam among Twitter users.

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 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 elicit perceptions of threats and hostility from a different culture and religion. The findings suggest that these concerns have been sparked by the events we study, possibly moving the political leaning of Twitter users towards the party which emphasized threats from immigration and multiculturalism the most. This interpretation is corroborated by a sentiment analysis in which we show that the events induce an increase in the amount of tweets mentioning immigration and Islam and by a more negative sentiment.

Although one should be cautious in interpreting our results as causal, the evidence suggests that it is not the online behavior of parties what drives our findings, which are consistent with the channels we hypothesize.

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 online behavior and political outcomes, confirming the relevance of social media text as a measure of attitudes. 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.

Our empirical analysis is limited to a single country. However, given the concurrent surge of radical right and terrorism in several Western democracies, we believe these results could be relevant in other settings. Moreover, the combination of exogenous real world events and geo-referenced social media data is 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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Terrorist Attacks, Cultural Incidents and the Vote for Radical Parties: Analyzing Text from Twitter

Online Appendices

A Appendix: Data

Landmarks

The final goal of our data collection process was to obtain a set of Twitter users allocated within German constituencies. The data section in the main part explained how we chose cities and towns in constituencies. For each of these towns, we manually obtained a set of landmarks Twitter accounts for which the key requirement is a high chance of being followed by local residents, but at the same time a low probability to be followed by non-residents. Remember here that with resident we include constituency area surrounding a city or town. For each city, the procedure started by searching for that specific town name in the Twitter search bar. Then, each result was individually assessed. We used direct and location search of the town name to find accounts that could represent landmarks. We employed a conservative stance, meaning that if an account gave reason for doubt it was not considered. Common sets of accounts which occurred frequently across cities and towns were:

- accounts by the city administration, which usually provide information on local events, regulations, or conditions (e.g. weather stations, traffic news)
- accounts by the local law enforcement agencies, fire departments, and other emergency facilities
- local business accounts of shops (but not larger shopping centers), markets, cinemas, barber shops, coffee shops, restaurants, bars, and similar facilities.
- leisure activities, such as bicycle, hiking, or running groups, as well as organized local sport activities (e.g. gymnastic clubs) excluding sport teams with a potentially wide-spread fan bases
- local news media and radio stations. Here, a more critical assessment was applied by including information provided on websites into the decision process. For example, small-scale local newspaper usually provide information on the

towns in which they are sold. It was assessed whether this set of towns lay within (but not beyond) the constituency it was supposed to cover. A similar case is represented by local radio station, which tend to provide information on their local coverage area.

In order to be included, the user had to follow at least 3 landmark accounts. As described in the main text, this strategy could potentially lead to the inclusion of users which follow such accounts from several cities, for instance if an active Twitter user commuted over far distances or moved from one place to another. In case our allocation rule located a user in more than one constituency, the user was dropped from the sample.

Users

Employing the above described strategy lead first to a set of 825,551 users who follow at least one landmark. 217,179 of those were eliminated because the followed landmarks in more than one constituency. Of the remaining users, 334,081 users follow only one landmark and 96,020 follow only two landmarks, resulting in another sample reduction of 430,101 users who follow less than thee landmarks.

Predicted User Characteristics

We use a Machine Learning algorithm described in Wang et al. (2019) and implemented in the `m3inference` library available in Python. The algorithm uses a multimodal deep neural architecture for joint classification of age, gender, and organization-status of Twitter users by looking at their username, screen name, provided biography, and profile image. We use this pre-trained deep neural model to predict the age, gender, and organization status of the users in our sample.

When the probability of the model prediction is below 0.75, we consider the prediction as missing. For instance, if the model predicts that a user is a man with 0.70 probability, we do not assign the user to any gender as the model prediction is not that certain. In the case of gender, we were not able to predict it with reasonable certainty for just 0.06% of our users. We find that 73% of our users are male. As for age, we adopt the same 0.75 probability threshold to infer it.

B Appendix: Tweets and Content

Parties' Tweets

In the following we provide the details on how the word comparison graphs are created. We first compute the following log-odds-ratio for each word[18] w in the tweets of a party:

$$log\ or_w = log\left[\frac{f_{i,w}}{1 - f_{i,w}}\right] - log\left[\frac{f_{j,w}}{1 - f_{j,w}}\right]$$

where $f_{i,w}$ is the frequency of a word w in document i.[19] This ratio identifies words which are most likely to appear in a party's tweets and at the same time least likely in another party's tweets, thus allowing us to identify what one party is most concerned about but the other one is not. We then rank them from highest to lowest and take the raw difference of occurrences for each word between documents and standardize it (Figure 2a). This allows to read one unit in the graph as one standard deviation of differences in occurrences. We further categorize the resulting list. Some of these words naturally occur mainly in one of the parties' tweets but not in another, such as the names of politicians and party specific congresses. Since we are mainly interested in identifying the words with political relevance we manually categorize each word, such that we know whether it is about a political topic or about something else, like the name of a politician, the reference to an event or non-identifiable junk.

After obtaining a categorized list still ordered by the ratio shown above (whose usefulness for a ranking were discussed), we plot the standardizes raw difference (which we expect to be easier to read compared to a log-odds ratio) for the top and

[18]With the term "word", we actually mean a "token" after pre-processing the tweets, as explained below in appendix section C.

[19]We use the log normalization to make the odds-ratios symmetric across documents.

bottom 15 words of our ranking.[20]

Latent Dirichlet Allocation (LDA)

Using the pre-processed text that we use for the doc2vec model, we fit the LDA model on our entire corpus of parties' and public's tweets. We explore models with different possible number of topics and then select the one with the lowest perplexity score. We find that the best number of topics is 16: immigration, Islam, elections, soccer, economy, World politcs, education, arts (music and film), digital, cities, spare time, house, mobility, social networks, information, and interviews. We report in Table B.1 the most descriptive words of each topic. We classify a tweet as discussing a certain topic if the model returns a probability higher than 0.90.

Salience of Topics: Immigration and Islam

In order to understand whether the increasing interest in Islam and immigration is driven by natural conversation or by media, we collect from the digital news database Factiva the weekly number of German newspaper articles that contain keywords related to immigration ("*migration*", "*wander*", "*flüchtling*", and "*asyl*") and Islam ("*Islam*" and "*muslim*").

Sentiment towards Topics: Immigration and Islam

We also conduct a sentiment analysis to investigate whether, beyond talking more about Islam and immigration, German users also develop more negative attitudes toward these topics. An increase in the negativity would indicate that we do not observe a simple national tendency towards talking more about core AfD message but rather a shift in opinions towards AfD attitudes.

We manually classify a random sample of 2000 users' tweets about Islam and immigration in three classes: negative, neutral, and positive. We train different clas-

[20] All phrases and words in Figure 2 are translated from German into English.

sifiers with the `sklearn` library in Python and find that the best one is a Ridge classifier with 9 cross-fold validation for model evaluation. This classifier reaches an accuracy score of 73%. We then look at the coefficients of each feature (i.e., word) in order to understand the most indicative feature of each class. We identify the following words for negative tweets: `kriminell` (criminal), `illegal_einwand` (illegal immigration), `kippah`, `islamist_gefahrd` (islamist_danger), `koran`, `migrant`, `illegal`, `stopislam`, `massenmigration` (mass migration), `islamisier`, `armutsmigration` (poverty migration), `islamist`. Tweets containing these words always have negative sentiment.

We hence go back to our sample of not-classified tweets and classify tweets containing these words as having a negative sentiment. These are the words for neutral tweets: `unterschied` (difference), `littlewiseh`, `kommentar` (comment), `muench` (Munich), `lauft` (running), `fussball`, `centrum`, `weltbank_unterwandert` (world bank infiltrate), `bergwand` (mountain wall). These are the words for positive tweets: `menschenrecht` (human rights), `europa`, `brauch zuwander` (need immigrants), `prophet`, `islam wert` (Islam value), `ramadan`, `rechtsstaat` (rule of law), `nichtohnemeinkopftuch` (not without a headscarf), `verabschiedet` (adopted). We hence classify the non-classified tweets containing these words as having neutral/positive sentiment. In this way, we have a much bigger sample of classified tweets for our classifier model to learn. We hence re-train a new set of classifiers on this large sample and find that this time the best one is a Bernoulli classifier, which reaches an accuracy of 93.6%.

Who tweets about Islam and immigration?

After showing that, over time, German users tend to discuss more core AfD messages related to Islam and immigration, and with increasingly negative attitudes, we analzye who drives this conversation. We select those tweets that our LDA model classifies as discussing Islam or immigration with a confidence higher than 0.90. Next, we identify the top 5% users who post the highest number of these tweets.

The tweets of these 231 "prolific" users represent 17% of the total Islam-immigration tweets. Then, we manually read the description in these users Twitter account as well as a few tweets and classify them in seven categories: AfD politicians (excluding the official party account), politicians by other parties (excluding the official party accounts), media, users who are openly racists, users who are clearly against racism, Muslims, and general public. We report in Figure B.1 below the number of tweets that these categories post. The vertical bars represent the days of the events. We observe that the general public always posts the majority of the Islam-immigration tweets. Consistent with the LDA analysis, we observe a positive trend as well as that these tweets peak around the days of the event. We observe a peak of tweets by the general public on July 7th, 2017, consistent with the findings of the LDA analysis. Also, we observe a peak of tweets by Muslims on April 17, 2017. We manually read these tweets and found out that these tweets are about the fact that Mirza Masroor Ahmad, the leader of the worldwide Ahmadiyya Muslim Community, visited Germany.

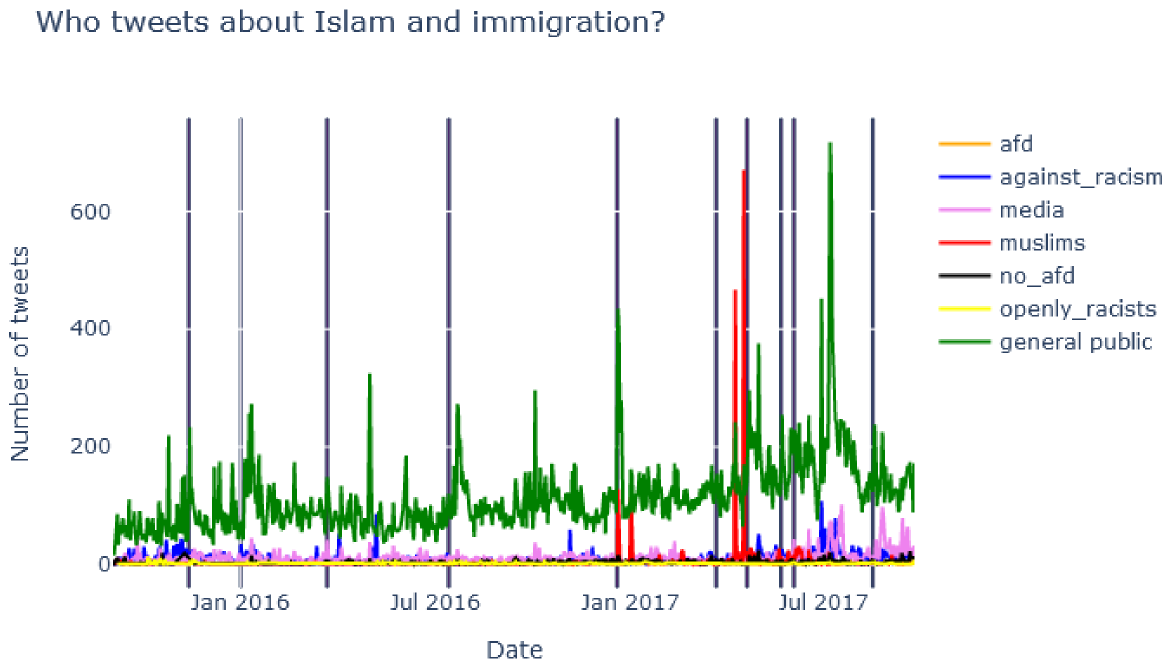

Figure B.1: Daily Tweets about Islam and Immigration by most Prolific Users

Furthermore, we identify, within each constituency, the Twitter users who discuss immigration and Islam. We find that the mean of users within a constituency discussing these topics is 0.43 and the standard deviation is 0.12, indicating that patterns in word similarity are due to a broad range of individuals and that there is large variance across constituencies.Figure B.2 provides a visualization.

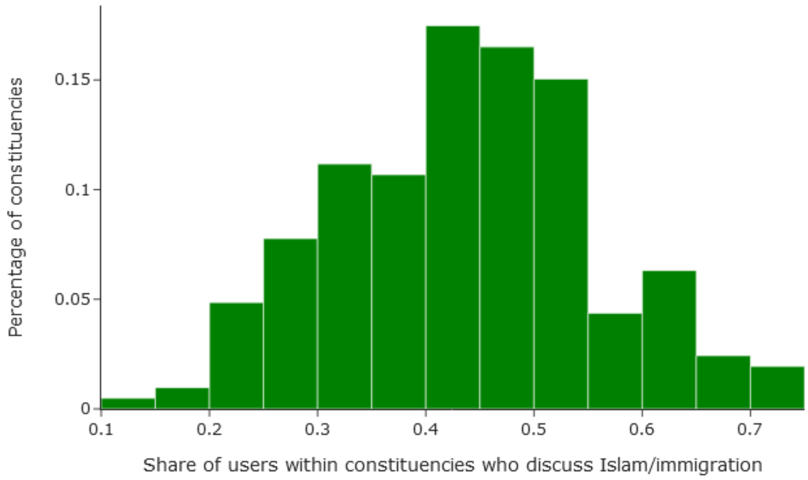

Figure B.2: Variation in Salience of Islam and Immigration Topics

Summarizing, the compound of LDA, sentiment, and most prolific users analyses reveal four key findings. First, over time, the general public tends to discuss more two core AfD topics such as Islam and immigration. Second, this discussion seems to be natural and not driven by medias or politicians. Third, the discussion shows an upward trend and it peaks around the days of the events. Fourth, there is also an increasingly negative attitude when discussing these topics. We believe that these findings provide some explanations about the similarity trend toward AfD that we observe in our data.

Table B.1: LDA: Most Descriptive Words for each Topic

immigration
zuwander, fluchen, fluchtling, asyl, migration, polizei, einwander, asyl, asylrecht, asylunterkunft, asylrechtverscharf, asylbewerb, fluchtling, syri, pegid, verletzen, gewalt, angreifen

islam
islam, jihad, muslim, minarett, burka, scheiss, polit, hass, terror, angst, welt, gewalt, opf, anschlag, gesellschaft, medi, land, freiheit

elections
wahl, btw, polit, merkel, partei, deutschland, vote, schulz, bundestag, herr, wahlkampf, gewahlt, bundestagswahl, land, ergebnis

soccer
fussball, tor, fan, bundesliga, saison, punkt, spielen, vfb, platz, team, gewinnen, fan, bvb, borussia_dortmund, mannschaft

world politics
trump, turkei, deutschland, europa, erdogan, eu, usa, merkel, land,polit, welt,russland, brexit

environment
schul, deutschland, stadt, fordern, zukunft, bildung, land, thema, ford, studi, polit, wirtschaft, arbeit, bildung

arts (music and film)
liv, ticket, film, konzert, feiern, party, musik, festival, band, album, cinema, kunst

digital
digital, digitalisi, zukunft, twitt, digitalisier, facebook, fb, googl, follow, youtub, retweet, stream, follow, onlin, blog

cities
dusseldorf, koln, berlin, stuttgart, leipzig, mainz, munch, frankfurt, bay, nuremberg, hanov

spare_time
urlaub, bier, leck, schlaf, kaffe, haus, trink, kuch, freund, wein, pizza,, vegan, fruhstuck, schmecken, rezept, heiss, koch

house
haus,geburstag,freund,feiern,family,katz,hund, haus, freund, bett, schlaf, sitzen, katz, bleib, arbeit, geburtstag, hund, weihnacht

mobility
auto, bahn, fahrt, fahr, zug, bus, flug, flucht, flugzeug, autobahn, richtung, sbahn, bahnhof

social networks
appl, updat, android, ios, test, microsoft, app, twitt, gewinn, retweet, facebook, stream, eur, tweet, youtub, cool, follow, liv, gewinnspiel, schauen, instagram, onlin

information
schreib, les,versteh,artikel, lern, artikel, versteh, fall, antwort, text, buch

interview
gest, thomas, buch, gluckwunsch, gast, guest, interview, gesprach, gluckwunsch

C Appendix: Text Processing Details

As discussed in the main text, we compute similarity between the tweets of the parties and the tweets of each constituency by transforming the two groups of tweets into vectors using doc2vec, a deep learning model that we describe below. We then measure similarity as the cosine similarity between the two vectors. Before proceeding with doc2vec, we pre-process tweets. In the following paragraphs we provide details on these steps.

Text Preprocessing

Text pre-processing is necessary to reduce the computational time necessary to run the doc2vec model. Computational time is more than directly proportional to vocabulary size, namely the number of words in our corpus of tweets. With pre-processing we reduce the number of words, and hence computational time, without losing relevant information. We follow standard procedures in text pre-processing with different libraries in Python. First we lower-case all words and tokenize the text, i.e., we break streams of text into single words, called "tokens". We do this using "word_tokenize" from the Python module NLTK. Next, we eliminate punctuation and stopwords, namely words that recur very frequently in our corpus and have little meaning. The dictionary of stopwords we use is the one in NLTK. We also remove all tokens that consist of non-alphanumeric characters only, and remove emoticons, links, @, and # symbols. Then, we perform "stemming", which implies conflating the variant forms of a word into a common representation, the stem. For instance, the words "ate" and "eating" are both reduced to the common stem "eat". Stemming relies on existing dictionaries: we use the German Stemmer in the Python module "gensim". Finally, we perform collocations, namely, we identify combinations of two words that have a higher probability of occurring together than separately. For instance, the tokens "angela" and "merkel" have higher chances of co-occuring as the bigram "angela merkel" than separately. In this case, collocations transform the two separate tokens into just one: "angela_merkel". We used

BigramCollocationFinder in NLTK. We then use the pre-processed tweets to train the doc2vec model.

doc2vec

After pre-processing our tweets, we create two "documents", each at daily frequency: a party- and a constituency- document. The party document is the text of all the tweets the party posted on a certain day. A constituency document is the text of all the tweets that all the users in our sample 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,[21] we end up with 752 documents for each party and 752 documents for each constituency in our sample.[22]

We use doc2vec (Le and Mikolov 2014), an unsupervised deep learning algorithm that learns how to represent each document with a unique vector, and which is a generalization of Word2Vec. In order to understand doc2vec it is necessary to first understand how Word2Vec works. Word2Vec (Mikolov et al. 2013) is an unsupervised deep learning algorithm that learns how to represent each word as a vector, depending on the surrounding (context) words. It takes as input a large vocabulary of words, trains a neural network language model with a single hidden layer, and produces a vector space, where each word is represented as a vector in this space. Word vectors, also called word embeddings, are positioned in the vector space such that words with similar semantic meaning are located in close proximity to one another. The model is trained using stochastic gradient descent with back propagation. When the algorithm converges, it represents words as word embed-

[21] As stated in the main text, 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 we emphasize that the empirical method chosen is not sensitive to the exact day.

[22] 752 is the maximum possible amount for a constituency whose users posted tweets every single day.

dings, namely meaningful real-valued vectors of configurable dimension (usually, 300 dimensions).

doc2vec (Le and Mikolov 2014) is an extension of Word2Vec which learns to represent not just individual words, but entire documents. By treating each document as a word token, the same Word2Vec methodology is used to learn document embeddings (Bhatia et al. 2016). As in Word2Vec, training happens through back propagation through several iterations. Each iteration of the algorithm is called an "epoch", and its purpose is to increase the quality of the output vectors. This type of document embedding allows to represent texts as dense fixed-length feature vectors, taking into account their semantic and syntactic structure.

We use the Distributed Bag of Words (DBOW) model and a freely available implementation of the doc2vec algorithm included in the gensim Python module, whose implementation requires the following hyperparameters:

- Size: the dimensionality of the vector representing the document. We set it to 300.
- Window size: The maximum distance between the current and predicted word within a sentence. We set it to 15.
- Epochs: Number of iterations over the corpus to train the algorithm. We set it to 300.
- Min_count: Ignores all words with total frequency lower than this. We set it to 20.
- Sub-sampling: The threshold for configuring which higher-frequency words are randomly down-sampled: useful range is $(0, 10^{-5})$. We set it to 10^{-3}.
- Negative: The number of "noise words" that should be drawn. We set it to 5.

With the resulting measures, we compute the cosine similarity described in the main text.

D Appendix: Validation

In order to control whether the computed similarity is indeed a valid measurement for how close public opinion is to the various parties, in this section we perform two validation experiments. These experiments first perform a basic but intuitive check by comparing the performance of doc2vec in assessing how close two documents of texts are, with the assessment by a human reader. Then, we focus on the German public and use public opinion and electoral data and observe that they also are correlated with our measure of similarity.

Human Reader

At the end of this section (Table D.2 – Table D.5) we present tweets of German parties and constituencies from four different days, together with the computed language similarity, which were assessed by a native German who first read both the tweets within a constituency and the corresponding party tweet on a given day and then judged between high or low similarity. The answers confirm the high and low text similarity computed by the doc2vec algorithm. This validation is only on a basic level, and is no proof of a valid similarity, but it presents a first transparent way to assess the quality of our measurement.

Votes and Polls

To further control the validity of the results of our doc2vec model, we compute the correlation between our measure of similarity and a) the results of the 2017 federal election at constituency level, and b) poll data provided by Infratest Dimap (2018) at state level.

For the election outcomes, we merge the tweets posted in the 30 days before the election within electoral constituencies and then apply the doc2vec algorithm. We repeat this 15 days before the election as a robustness check. The reason for merging texts over 30 days is to produce a sufficient amount of text for both parties

Table D.1: Validation: Measured Similarity

	ΔVote Share		Poll
	(1)	(2)	(3)
Similarity:			
15 days before Election	0.0982		
	(0.0164)		
30 days before Election		0.126	
		(0.0186)	
2015 to 2017			0.0679
			(0.0218)
N	1122	1200	454
R^2	0.020	0.031	0.684

Notes: ΔVote Share refers to the difference in electoral results between 2017 and 2013. The independent variable, similarity, is the measured similarity in the specified period. We merge text 15 and 30 days before the election. For polls, it corresponds to the day the poll was conducted. In estimations of electoral outcomes (1) and (2) standard errors are clustered on constituency level. Poll refers to poll surveys at state level conducted between 2015 and 2017. In estimation of poll results (3) standard errors are clustered at state level and party fixed effects are included. Standard errors in parentheses.

and constituencies as not all parties posted tweets in the days immediately before the election. For the analysis of poll data, since poll surveys are conducted at state level, we merge the tweets of all the constituencies in a given state on the day of the poll.

We then perform two regression analyses: one with the change in vote share from 2013 to 2017 for all parties as the dependent variable, and one with the poll results as the dependent variable.[23] In both cases, we regress the dependent variables on the measured similarity. We cluster standard errors on the lowest aggregate for the units of observation, i.e. electoral constituency level or state level, respectively. For the regression on poll results in levels we include party fixed effects to control for variations in levels of party support. Results are presented in Table D.1. We observe a positive correlation in all analyses. This analysis offers further support for the fact that our computed similarity captures the public mood across states and electoral borders.

[23]Each observation is party-constituency (in case change in vote share is the electoral outcome as dependent variable) or party-state-date (in case the poll results at state level on a given day is the dependent variable).

Table D.2: Example Tweets

Party Tweet (The Greens)
Raus aus der #Kohle , rein in die #Erneuerbaren ! Die #Klimaziele erreichen wir nur ohne Kohle. #endegelaende pic.twitter.com/4EPzxY4biB

Constituency Tweets
'Wie ging die Woche für Dich aus? Hast Du Deine geplanten Vorhaben verwirklicht? Was motiviert Dich....und was... https://t.co/Sl5Ku6mwkJ'
'24+24 kg Oberkörper Finisher https://t.co/3dZG8P3qiz'
'RT @dg_4und20: Chuck Norris ruft für sein eigenes Land an. #ESC2016 #esc #esc16 #eurovision'
'Österreich und Georgien nach vorne!! #aut #geo #ESC #esc2016 #eurovision
'Das erste Lied das sich "anders" anhört und mit fast dezenter Bühnenshow , Franz Ferdinand meets Moby... like. #geo #Esc2016 #esc'
'So, Italien bringt was fürs Auge ... Ach die singt auch? Gar nicht mitbekommen. #esc'
'Überschwemmung im Teletubbie Land #italy #esc'
'Ich habe bei dem Song immer das Gefühl jemand müsste von 33 auf 45umin umschalten #slothofgermany #ger #esc'
'Das erste Lied das sich "anders" anhört und mit fast dezenter Bühnenshow, Franz Ferdinand meets Moby... like. #geo#Esc2016
@z3ktus er ist doch Longboard-Rider, da gehört das zum Style oder es hat ihn eben einfach hingefetzt #Lat #esc'
'Oh, Harald Glööökler macht jetzt Bühnenshows ... Naja Hauptsache es lenkt nicht vom eigentlichen Liedbeitrag ab #rus #esc'
'Ich höre nur "let it go, let it goho"... #frozen #cro #esc
'Jetzt singt Morticia Adams schon für Serbia #srb #esc #Eurovision'
'Ich so: "Jaaa, endlich Rocker !!" ...und dann spielen die Jungs so BonJovi meets David Guetta #schade #cyp #Eurovision'
'Das ist der Franzose. nein ! DOCH !! Oh!!! #fra #esc'
'Bei dieser Frisur weiß man wenigsten woher der Wind wehte #ltu #esc
'Ah ja. Für Leute die man auffordern muss die Folie zu entfernen BEVOR man die TK-Pizza in den Ofen schiebt :D https://t.co/lnpTeYardK
'Klar doch, meine sind alle aus Vollgummi :D https://t.co/FOYVJmTjOJ
'Schöne Pfingsten ;) https://t.co/skomZukepg'
'PISA! Noch Fragen? Kinder sind doch aus Vollgummi :D https://t.co/yolVgyeK1C'

Computed Similarity: -0.22
Assessed Similarity: Low

Table D.3: Example Tweets

Party Tweet (AfD)
#AfD #Pazderski: „NO!”-Tattoos-“ Wie dämlich geht’s eigentlich noch? https://www.alternativefuer.de/pazderski-no-tattoos-wie-daemlich-gehts-eigentlich-noch/-
Constituency Tweets
’Neue Version der #IMSWARE APP HelpDesk veröffentlicht - Apple iOS https://t.co/omGbOiM8tI’, ’hat einen Runtastic Lauf über 3,63 km in 41m 56s mit der #Runtastic PRO App absolviert: https://t.co/g4ajk5FlBH’, ’@hassanscorner willst du Schalke siegen sehen , musst du Mittwoch ins Stadion gehen ..... yes WE can.... Wird aber schwer’ ’So wird es auch am mittwoch sein @s04 @hassanscorner @Sky_Dirk https://t.co/VgihbV5cgK’
Computed Similarity: -0.19 **Assessed Similarity: Low**

Table D.4: Example Tweets

Party Tweets (CSU)
Um 19.10 Uhr: @CSU -Chef Horst #Seehofer im ZDF-Sommerinterview! Einschalten lohnt sich! #CSUtvTipp #berlindirekt pic.twitter.com/ZP4DqkMW7Xpic.twitter.com/ZP4DqkMW7X
#Seehofer: Amoklauf in München aber auch die Attentate in Würzburg & Ansbach haben sich in unsere Herzen eingebrannt pic.twitter.com/zlZpgcpuDDpic.twitter.com/zlZpgcpuDD
#Seehofer auf der Trauerfeier: #Sicherheit ist das höchste Gut einer Demokratie, die oberste Pflicht des Staates.
#Seehofer auf der Trauerfeier: Menschen in unserem Land haben ein Recht darauf, dass wir entschlossen gegen jede Form von Gewalt vorgehen.
Constituency Tweets
'Die #SPD-Kandidaten haben alle 'nen recht deutlichen Schatten. #agh16"'
'Bevor ein Bayer Bundeskanzler wird gehört Bayern zu Österreich. #Seehofer #csu'
'Flüchtlingskrise: Seehofer distanziert sich scharf von Merkels "Wir schaffen das" https://t.co/SE4HRDiOTw'
'die französischen muslime verweigern den muslimischen attentätern die letzte ehre... ...gut so... ein klares... https://t.co/BqZTYsLVFZ'
'Eine Muslimin betete heute bei der Trauerfeier in München: "Allah, beschütze diese schöne Stadt und ihre Bewohner'
'Das #Sommerinterview mit Horst #Seehofer fand ich gut. Aber einen eigenen #Kanzlerkandidaten der #CSU kann ich mir nicht vorstellen.'
'@tagesschau: Seehofer: Ein bisschen zurückrudern, ein bisschen nachlegen https://t.co/vwW36uoYZK #CSU #Flüchtlinge'
'Horst Seehofer gegen Angela Merkel: Er kann einfach nicht anders'
'Es gibt Krawatten, mit denen würde ich mir nach einem Unfall nicht mal das Bein abbinden'
'Der Münchner Attentäter war lt. @NDRinfo "kein Rechtsextremist". Halt bloß ein ganz gewöhnlicher Hitler-Fan.'
'Wir müssten uns mal erlauben,in der Türkei eine deutsche Demo abzuhalten. Es ist einfach unfassbar was wir hier alles gestatten. #koeln3107'
'Ich versuche mal zu schlafen. Kann grade nichts tun und nur hoffen, dass die Einheimischen gestern Recht hatten.#Kreta #Waldbrand'
'Warum überträgt der Ereigniskanal Phoenix nicht die Trauerfeier in München? Schwer zu verstehen!'
'Wer für Erdogan auf d Straße geht unterstützt #Terror gegenüber Andersdenkenden #ARDSommerinterview'
'Wer hat Gauck und Merkel zur Trauerfeier eingeladen? Ist diese Inszenierung nicht erbärmlich?'
'Woher haben die Leute eigentlich immer Holzlatten und Eisenstangen? Flüchtlinge verprügeln Security-Mitarbeiter'
'@welt Wo wohnen bitte all diese Menschen?Was bietet die AfD denn für Lösungen?Und der München-Attentäter war AfD-Fan. https://t.co/rq9HfqKXhH'
Computed Similarity: 0.17
Assessed Similarity: High

Table D.5: Example Tweets

Party Tweet (The Greens)
'Kommt alle am Wochenende zu den Menschenketten gegen #Rassismus ! http://www.gruene.de/menschenkettehttp://www. gruene.de/menschenkette #HandInHand pic.twitter.com/h4oSMNXs9ipic.twitter.com/h4oSMNXs9i'
Constituency Tweets
'Bahnhöfe: Licht am Ende der Brücke aus Berliner Abendblatt: Licht am Ende der BrückeNach langem Hin und Her w... https://t.co/yPf71k2PaL'
'@Schmidtlepp Barcodes, der Kitt von Weltreichen.'
'Bus + Straßenverkehr: Den meisten Falschparkern fehlt das Unrechtsbewusstsein... https://t.co/728xdipm32'
'@spdberlin danke liebe SPD für eine Regenwanderschaft. Veranstaltung so gut organisiert wie die Bildungspolitik!'
'@UlrichSchulte Donť mess with "polizeilichen Befugnissen"! https://t.co/MVxQYaMpaO'
'#EnthemmteMitte zeigt: Antisemitismus,Antiziganismus, Homophobie; Verschwörungstheorien sind Probleme aller Parteien https://t.co/0yCLplvj55'
'Es gibt übrigens immer noch keine Neuigkeiten von Frank. Danke für euren Support. https://t.co/jneDmOmZL3'
'Die gute Nachricht: #EheFürAlle finden inzwischen alle gut. Die schlechte Nachricht: #KüssenVerboten #EnthemmteMitte https://t.co/Rt6pbwJfWE'
'#HandinHand gegen Rassismus! Komm zur Menschenkette in Berlin'
'#HandinHand gegen Rassismus! Komm zur Menschenkette in Bochum, Berlin, Hamburg, München und Leipzig https://t.co/qMkcOyFOOi via @campact'
'HTW_Berlin: @miauzus @rbb24 Die HTW Berlin wird den Lehrauftrag von Wolfgang Hebold sofort beenden.Wir dulden weder Rassismus noch Fremdenfeindlichkeit'
'Das neue Berlin wird aus Europaletten und Überseecontainern errichtet.'
'Potsdam: Öffentlicher Nahverkehr in Potsdam Der Herr der Schienen, aus \xa0PNN https://t.co/HYUcXsd3jD'
'Russland führt Hooligan-EM-Tabelle an, England auf Platz 2, Deutschland nur dritter #hooligans #em2016'
'S-Bahn: Hohe Hürden für S-Bahn bis Rangsdorf, aus\xa0MAZ https://t.co/my2m0XtueO'
'Schön, dass jemand den Rassismus erkennt: https://t.co/2p2J0XFnwE'
'Schutzblechen'
'@Tagesspiegel @spdberlin und Staatssekretär für Bildung war glatt entgangen, dass man in Schulen nicht wahlkämpft... https://t.co/CwAhBlcZ4j'
'U-Bahn Wegen Graffiti-Schäden fahren Züge mit weniger Waggons'
'Es ist übrigens auch #Rassismus, mich als Rassistin zu beschimpfen, nur weil ich blond bin und blaue Augen habe.'
Computed Similarity: 0.55 **Assessed Similarity: High**

E Appendix: Discontinuous Growth Model

Variables considered include:

1. *Time*: The first variable represents the linear time trend found in a typical growth model.

2. $Time^2$: Similar to before with a quadratic time trend.

3. E: Event specific change in intercept variable coded 0 prior to the event and 1 after the event, until the next event occurrs.

4. *Reset*: Event specific change in slope variable coded 0 at the period of which the event first occurs and increases with each subsequent period until the next event.

5. $Reset^2$: Similar to before with a quadratic change variable.

For analyzing multiple events, we simply introduce multiple variables for events and changes. The following table offers an overview on the coding of variables:

Table E.1: Coding of Time Variables - Multiple Events

$Time$	$Time^2$	E_1	E_2	$Reset_1$	$Reset_1^2$	$Reset_2$	$Reset_2^2$
0	0	0	0	0	0	0	0
1	1	0	0	0	0	0	0
2	4	0	0	0	0	0	0
3	9	0	0	0	0	0	0
4	16	0	0	0	0	0	0
5	25	1	0	0	0	0	0
6	36	1	0	1	1	0	0
7	49	1	0	2	4	0	0
8	64	1	0	3	9	0	0
9	81	1	0	4	16	0	0
10	100	0	1	0	0	0	0
11	121	0	1	0	0	1	1
12	144	0	1	0	0	2	4
13	169	0	1	0	0	3	9
14	196	0	1	0	0	4	16

Notes: the first event occurs in period 5, the second event in period 10.

F Appendix: Results

The following tables complement the choice of the functional form of the discontinuous growth model (DGM) introduced in equation 1 in the main text, as well as results visualized and discussed in the main text.

Table F.1 shows the results of likelihood ratio tests for the null hypothesis of having a better fit by only including a linear time trend into the discontinuous growth models for each party, compared to the alternative of adding also a quadratic term (no event variables included). As one can see, the null hypothesis is rejected in all cases at the 90 percent significance level, and for most cases even at the 99 percent significance level. We thus include the quadratic time trend in the DGM for all parties.

Table F.2 shows the full list of estimated coefficients for the DGM for each party.

Table F.3 shows the estimated coefficients for the within-party discontinous growth models for AfD and SPD, visualized in Figure 4b and Figure 4c in the main text.

Table F.4 shows an investigation at the potential determinants of the heterogeneity in estimated random coefficients of the main DGM. The explanatory variables used corresponds to a set used by Franz et al. (2018) to explain the electoral success of the AfD after the 2017 general election. Notice that the optimal set of explanatory variables may vary across parties, but for the sake of comparison we used the same explanatory variables in each regression.[24] As discussed in the main text, we do not find any significant relationship of these variables with the magnitude of the estimated random coefficients.

Table F.5 shows the results of estimating the discontinuous growth model on a set of placebo events, namely:

[24]Notice that the only variation in the set of explanatory variables is caused by the CSU not existing in the eastern part of Germany, hence the East indicator is excluded.

Table F.1: Likelihood Ratio Test Results: Linear vs Quadratic Time Trend

Party	Likelihood Ratio Test Statistic	p-Value
AfD	804.49	<0.01
CDU	498.4	<0.01
CSU	3.53	0.06
FDP	35.31	<0.01
SPD	56.46	<0.01
The Greens	238.91	<0.01
The Left	3.8	0.05

Notes: Test results refer to a likelihood ratio test for the null hypothesis of a better fit using only a linear time trend in equation 1 versus the alternative of adding a quadratic term.

- the *DFB Pokal Finale* (German soccer league final) on May 21, 2016
- the match Germany vs. Italy in the UEFA Euro league 2016 on July 02, 2016
- the match Germany vs. France in the UEFA Euro league 2016 on July 07, 2016
- the *DFB Pokal Finale* (German soccer league final) on May 27, 2017

Table F.2: Discontinuous Growth Model Results

	AfD	CDU	CSU	FDP	The Greens	The Left	SPD
Time	0.000162	-0.000167	-0.000045	-0.000728	0.000635	-0.000111	-0.001485
	(0.000199)	(0.000202)	(0.000413)	(0.000167)	(0.000180)	(0.000176)	(0.000172)
$Time^2$	-0.000017	0.000004	-0.000004	0.000009	-0.000005	-0.000004	0.000018
	(0.000003)	(0.000003)	(0.000006)	(0.000002)	(0.000003)	(0.000002)	(0.000002)
$Event_1$	-0.189245	-0.129344	0.015701	0.021558	-0.020901	-0.015322	0.011962
	(0.004852)	(0.005022)	(0.010167)	(0.004345)	(0.004446)	(0.004474)	(0.004337)
$Event_2$	0.200228	-0.036637	0.057938	-0.071373	-0.003188	0.063699	-0.096552
	(0.020061)	(0.020331)	(0.041784)	(0.016965)	(0.018157)	(0.017830)	(0.017397)
$Event_3$	0.544867	-0.112406	0.159906	-0.226041	0.057046	0.184897	-0.444325
	(0.075773)	(0.076876)	(0.157436)	(0.063891)	(0.068505)	(0.067287)	(0.065530)
$Event_4$	1.562768	-0.340869	0.378014	-0.691941	0.216601	0.405414	-1.346470
	(0.216918)	(0.220021)	(0.450713)	(0.182824)	(0.196064)	(0.192559)	(0.187527)
$Event_5$	3.710215	-0.847889	0.878455	-1.653615	0.758808	0.866092	-3.354696
	(0.532342)	(0.539945)	(1.106049)	(0.448660)	(0.481144)	(0.472546)	(0.460194)
$Event_6$	5.344926	-1.286950	1.309918	-2.423111	1.185146	1.267024	-4.923720
	(0.783015)	(0.794199)	(1.626826)	(0.659919)	(0.707705)	(0.695055)	(0.676887)
$Event_7$	5.913527	-1.457644	1.418320	-2.713813	1.403728	1.395900	-5.517458
	(0.871035)	(0.883477)	(1.809691)	(0.734102)	(0.787261)	(0.773187)	(0.752976)
$Event_8$	6.554457	-1.572828	1.607238	-3.016718	1.594557	1.525893	-6.213154
	(0.973610)	(0.987517)	(2.022825)	(0.820552)	(0.879971)	(0.864241)	(0.841650)
$Event_9$	6.841765	-1.647187	1.637697	-3.158336	1.652775	1.586773	-6.426340
	(1.013526)	(1.028003)	(2.105733)	(0.854192)	(0.916047)	(0.899671)	(0.876155)
$Event_{10}$	8.525083	-2.076569	2.043185	-3.993125	2.100466	1.942572	-8.143523
	(1.277501)	(1.295749)	(2.654166)	(1.076668)	(1.154633)	(1.133992)	(1.104351)
$Event_{11}$	9.276724	-2.273887	2.205123	-4.376092	2.282414	2.087538	-8.912369
	(1.393212)	(1.413113)	(2.894580)	(1.174189)	(1.259216)	(1.236705)	(1.204379)
$Reset_1$	0.005987	0.007958	-0.000962	-0.002376	0.001379	0.005159	-0.001407
	(0.000399)	(0.000403)	(0.000822)	(0.000340)	(0.000363)	(0.000357)	(0.000348)
$Reset_2$	0.003424	-0.001545	-0.000230	-0.001467	-0.001857	0.002149	-0.002578
	(0.000501)	(0.000508)	(0.001040)	(0.000423)	(0.000453)	(0.000445)	(0.000433)
$Reset_3$	0.003903	-0.001965	0.000731	-0.003270	0.000060	0.001800	-0.005859
	(0.000928)	(0.000942)	(0.001929)	(0.000783)	(0.000839)	(0.000824)	(0.000803)
$Reset_4$	0.010319	-0.002964	0.002050	-0.004997	0.003663	0.002237	-0.009772
	(0.001559)	(0.001581)	(0.003239)	(0.001314)	(0.001409)	(0.001384)	(0.001348)
$Reset_5$	0.015100	-0.005738	0.003973	-0.007197	0.006585	0.004192	-0.015143
	(0.002446)	(0.002481)	(0.005082)	(0.002062)	(0.002211)	(0.002171)	(0.002115)
$Reset_6$	0.009798	-0.001697	-0.001753	-0.011161	0.013461	-0.000711	-0.022276
	(0.003046)	(0.003090)	(0.006325)	(0.002568)	(0.002754)	(0.002705)	(0.002634)
$Reset_7$	0.017491	0.005055	0.004213	-0.010487	0.005747	-0.002687	-0.019454
	(0.003181)	(0.003227)	(0.006608)	(0.002682)	(0.002875)	(0.002824)	(0.002750)
$Reset_8$	0.020368	-0.011068	-0.010721	-0.023622	0.003075	0.001506	0.010854
	(0.004246)	(0.004309)	(0.008804)	(0.003578)	(0.003837)	(0.003769)	(0.003670)
$Reset_9$	0.020834	-0.006731	0.004702	-0.010329	0.004244	0.004030	-0.022386
	(0.003367)	(0.003415)	(0.006994)	(0.002837)	(0.003043)	(0.002988)	(0.002910)
$Reset_{10}$	0.025353	-0.007087	0.003990	-0.013292	0.004995	0.004525	-0.026293
	(0.003839)	(0.003894)	(0.007981)	(0.003237)	(0.003470)	(0.003409)	(0.003319)
$Reset_{11}$	0.016587	-0.020151	-0.001945	-0.038246	0.006985	0.007723	-0.021844
	(0.005272)	(0.005352)	(0.010917)	(0.004443)	(0.004765)	(0.004680)	(0.004557)
$Reset_1^2$	0.000072	-0.000228	0.000047	0.000026	-0.000013	-0.000076	-0.000024
	(0.000007)	(0.000007)	(0.000015)	(0.000006)	(0.000007)	(0.000007)	(0.000006)
$Reset_2^2$	0.000015	0.000012	0.000015	-0.000005	0.000034	-0.000014	-0.000019
	(0.000003)	(0.000003)	(0.000007)	(0.000003)	(0.000003)	(0.000003)	(0.000003)
$Reset_3^2$	0.000054	-0.000001	0.000011	-0.000005	0.000016	-0.000003	-0.000017
	(0.000003)	(0.000003)	(0.000006)	(0.000002)	(0.000003)	(0.000003)	(0.000003)
$Reset_4^2$	0.000018	-0.000003	0.000007	-0.000006	-0.000002	0.000004	-0.000018
	(0.000003)	(0.000003)	(0.000006)	(0.000002)	(0.000003)	(0.000002)	(0.000002)
$Reset_5^2$	0.000025	0.000013	0.000004	-0.000014	-0.000015	-0.000003	-0.000025
	(0.000003)	(0.000003)	(0.000007)	(0.000003)	(0.000003)	(0.000003)	(0.000003)
$Reset_6^2$	0.000407	-0.000224	0.000229	0.000047	-0.000229	0.000161	0.000061
	(0.000026)	(0.000026)	(0.000053)	(0.000022)	(0.000023)	(0.000023)	(0.000022)
$Reset_7^2$	0.000095	-0.000452	-0.000004	0.000014	0.000003	0.000228	-0.000074
	(0.000020)	(0.000020)	(0.000041)	(0.000017)	(0.000018)	(0.000018)	(0.000017)
$Reset_8^2$	0.000340	0.000600	0.001190	0.001004	0.000181	0.000086	-0.004121
	(0.000235)	(0.000238)	(0.000484)	(0.000198)	(0.000212)	(0.000208)	(0.000203)
$Reset_9^2$	0.000026	0.000018	0.000008	-0.000019	0.000029	0.000011	-0.000011
	(0.000004)	(0.000004)	(0.000008)	(0.000003)	(0.000003)	(0.000003)	(0.000003)
$Reset_{10}^2$	-0.000037	0.000005	0.000025	0.000016	0.000082	0.000008	0.000026
	(0.000024)	(0.000024)	(0.000049)	(0.000020)	(0.000021)	(0.000021)	(0.000020)
$Reset_{11}^2$	0.001113	0.001619	0.000146	0.002983	-0.000228	-0.000078	-0.000315
	(0.000375)	(0.000381)	(0.000769)	(0.000316)	(0.000339)	(0.000333)	(0.000324)
2016 FE	0.018115	-0.009527	0.021905	0.010483	0.039278	-0.000681	-0.003011
	(0.004464)	(0.004531)	(0.009240)	(0.003763)	(0.004035)	(0.003963)	(0.003859)
Constant	0.339869	0.308465	0.342375	0.341589	0.313398	0.315637	0.341546
	(0.004271)	(0.004681)	(0.009660)	(0.004398)	(0.004401)	(0.004248)	(0.004301)

Notes: Maximum likelihood estimation results for the discontinuous growth models for all parties, corresponding to the visualizations in Figure 4a and 5 in the main part of this work. All estimates refer to the fixed component (see Equation 1). Standard errors in parentheses.

Table F.3: Within Party Discontinuous Growth Model Results

	AfD	SPD
$Time$	0.0004	0.1392
	(0.1109)	(0.0764)
$Time^2$	-0.0005	-0.0160
	(0.012)	(0.0083)
$Event_1$	-0.0418	0.2072
	(0.2675)	(0.1767)
$Event_2$	0.0682	2.0552
	(0.7055)	(1.0742)
$Event_3$	0.1759	8.7424
	(1.5794)	(4.5511)
$Event_4$	0.1690	25.0055
	(3.6542)	(12.9016)
$Event_5$	0.7395	62.6707
	(15.9836)	(32.3396)
$Event_6$	1.2022	94.8064
	(27.0927)	(48.4635)
$Event_7$	1.4875	104.0130
	(31.8545)	(53.6669)
$Event_8$	2.6329	117.2648
	(38.3479)	(60.5441)
$Event_9$	2.7083	120.3558
	(39.7186)	(61.9692)
$Event_{10}$	3.3465	152.4504
	(56.3852)	(78.7396)
$Event_{11}$	3.6832	165.4034
	(63.1671)	(85.335)
$Reset_1$	0.0022	0.1654
	(0.4125)	(0.1058)
$Reset_2$	-0.1088	0.3764
	(0.3044)	(0.1953)
$Reset_3$	-0.0604	0.7611
	(0.3078)	(0.3904)
$Reset_4$	0.0237	1.2772
	(0.4223)	(0.6549)
$Reset_5$	0.0556	1.9982
	(0.8837)	(1.0366)
$Reset_6$	0.1266	1.5474
	(1.1684)	(1.2789)
$Reset_7$	0.8230	2.4962
	(1.2509)	(1.3395)
$Reset_9$	-0.0051	2.6525
	(1.3842)	(1.434)
$Reset_{10}$	-0.0155	3.2267
	(1.6656)	(1.6245)
$Reset_{11}$	0.0128	3.2459
	(1.7438)	(1.6821)
$Reset_1^2$	0.0422	0.0140
	(0.1913)	(0.0144)
$Reset_2^2$	0.0393	0.0148
	(0.0789)	(0.0089)
$Reset_3^2$	0.0096	0.0167
	(0.0282)	(0.0084)
$Reset_4^2$	0.0004	0.0156
	(0.0121)	(0.0083)
$Reset_5^2$	-0.0013	0.0172
	(0.0145)	(0.0087)
$Reset_6^2$	-0.0273	0.2277
	(0.0789)	(0.0543)
$Reset_7^2$	-0.1432	0.0397
	(0.0434)	(0.0299)
$Reset_9^2$	0.0068	0.0262
	(0.0131)	(0.0091)
$Reset_{10}^2$	0.0289	-0.0142
	(0.0789)	(0.0543)
$Reset_{11}^2$	0.0012	0.0161
	(0.012)	(0.0083)
2016($Indic.$)	-0.0013	0.0119
	(0.2509)	(0.1102)
$Constant$	0.0094	-0.1426
	(0.2174)	(0.1498)

Notes: Maximum likelihood estimation results for the within party discontinuous growth models for AfD and SPD, corresponding to the visualizations in Figure 4b and 4c in the main part of this work. All estimates refer to the fixed component (see Equation 1). Standard errors in parentheses.

Table F.4: Investigating Heterogeneity in Similarity Shifts

	AfD	CDU	CSU	The Greens	FDP	The Left	SPD
Age (60+)	0.0022122	51.1747484	-125489.7868742	-8766.6535638	72743.7089376	-9792.6924703	-15354.5388120
	(0.0121911)	(6938.0194877)	(491750.7892094)	(12420.4736911)	(38529.9661859)	(29977.9750216)	(28130.5437664)
Foreign Population (%)	0.0124456	5873.1746362	79573.8775716	15391.7027338	67223.0366473	37045.5308537	44778.4574321
	(0.0066914)	(3420.5202578)	(201275.0109139)	(7508.0630055)	(21310.2609544)	(15345.6608591)	(16055.7232721)
Disp. Income	-0.0000001	-3.7347076	-164.9010464	-5.8987972	-6.1200128	-36.7268198	-13.8832227
	(0.0000156)	(9.2232669)	(464.1942303)	(20.2664350)	(59.8243501)	(40.2715064)	(43.6774774)
Craftsmen Firms	-0.0133125	-7357.5429122	337815.1214307	7415.7543561	-24275.4408765	-29598.6794297	-42342.8325180
	(0.0251708)	(14318.8443025)	(439884.0204702)	(24554.3509301)	(84868.0123836)	(59152.8394599)	(73715.8999581)
Unemployment 2017	-0.0049659	-637.4080882	12105.3757402	-11065.8254812	-35300.6166897	14116.4094368	9391.8118688
	(0.0156749)	(8540.7355020)	(1231364.1709440)	(16589.5667102)	(57797.5907796)	(35668.5143569)	(41478.2322127)
High Education	-0.0000124	949.9912207	7377.5375312	7746.5665897	13813.0136895	4851.0197936	6434.4261924
	(0.0043920)	(2501.7087028)	(129829.7443088)	(5187.7531368)	(15012.5907699)	(10433.8544573)	(11484.9847720)
Manufacturing	-0.0015647	-963.0767100	-116062.1108746	-5324.1737990	-15097.0013567	-3174.6908814	-7866.4465776
	(0.0026639)	(1457.1421643)	(78007.0936129)	(3228.2363919)	(10813.0378866)	(8000.4583130)	(7365.7990198)
East	0.1247000	48558.7730236		209490.3121783	342580.3780608	380964.7025934	557562.8899178
	(0.0989498)	(52833.6164016)		(108870.8217799)	(346231.0152097)	(265349.0183427)	(283792.1967533)
Observations	235	199	36	235	235	235	235
R^2	0.028	0.052	0.119	0.104	0.080	0.082	0.112

Notes: Dependent variable is the shift in similarity to the specified parties after the last event. To improve readability dependent variable re-scaled by factor 10^8. Constant included. Amount of craftsmen firms per 1,000 inhabitants. Standard errors in parentheses and calculated using bootstrapping.

Table F.5: Discontinuous Growth Model Placebo Results

	AfD	CDU	CSU	FDP	SPD	The Greens	The Left
$Time$	-0.00109299	-0.00024009	-0.00003017	-0.00001322	-0.00003148	-0.00007141	0.00018055
	(0.00001735)	(0.00001624)	(0.00001465)	(0.00001503)	(0.00001510)	(0.00001569)	(0.00001545)
$Time^2$	0.00000130	0.00000046	-0.00000001	0.00000004	0.00000003	0.00000003	-0.00000024
	(0.00000003)	(0.00000003)	(0.00000002)	(0.00000002)	(0.00000003)	(0.00000003)	(0.00000003)
$Event_1$	0.11412411	0.04290170	0.01236712	0.02097155	-0.00136163	0.02528588	-0.01228253
	(0.00459503)	(0.00420001)	(0.00386641)	(0.00401562)	(0.00395419)	(0.00415956)	(0.00399120)
$Event_2$	0.14609481	0.04621330	0.00461153	-0.00153713	-0.20381707	0.00709182	-0.05378382
	(0.00860598)	(0.00820386)	(0.00721285)	(0.00745994)	(0.00763849)	(0.00790238)	(0.00785762)
$Event_3$	0.07639631	0.00917228	0.00758684	-0.02514460	-0.01089685	-0.00586923	-0.02974085
	(0.00296233)	(0.00303621)	(0.00319083)	(0.00307298)	(0.00321217)	(0.00319051)	(0.00313019)
$Event_4$	0.14580175	-0.01709263	0.01776192	-0.01658928	-0.01630931	0.01898061	0.00841205
	(0.00650709)	(0.00617692)	(0.00590024)	(0.00596182)	(0.00589090)	(0.00599740)	(0.00608145)
$Reset_1$	-0.00046094	-0.00277214	-0.00093517	-0.00213474	0.00006406	-0.00520722	-0.00094135
	(0.00044938)	(0.00041927)	(0.00036382)	(0.00037436)	(0.00038254)	(0.00039851)	(0.00039217)
$Reset_2$	-0.00994331	-0.09316505	-0.00186426	0.00846266	0.19485989	0.00318851	-0.02150679
	(0.00991183)	(0.00918251)	(0.00791841)	(0.00817086)	(0.00835700)	(0.00873663)	(0.00858608)
$Reset_3$	0.00041633	-0.00001589	-0.00003661	0.00023916	0.00012688	0.00010387	0.00012870
	(0.00002558)	(0.00002409)	(0.00002258)	(0.00002276)	(0.00002309)	(0.00002369)	(0.00002329)
$Reset_4$	-0.00080838	0.00001458	0.00002020	0.00048768	0.00053531	-0.00005005	-0.00004751
	(0.00009888)	(0.00009221)	(0.00008168)	(0.00008441)	(0.00008536)	(0.00008841)	(0.00008771)
$Reset_1^2$	0.00002137	0.00006718	0.00002621	0.00003746	-0.00000399	0.00013270	0.00003988
	(0.00001045)	(0.00000968)	(0.00000835)	(0.00000861)	(0.00000881)	(0.00000921)	(0.00000905)
$Reset_2^2$	0.00210620	0.02232141	0.00008960	-0.00095048	-0.03600088	-0.00026573	0.00981162
	(0.00237618)	(0.00220134)	(0.00189829)	(0.00195881)	(0.00200344)	(0.00209445)	(0.00205748)
$Reset_3^2$	-0.00000054	-0.00000021	0.00000020	-0.00000061	-0.00000034	-0.00000002	-0.00000022
	(0.00000007)	(0.00000006)	(0.00000005)	(0.00000006)	(0.00000006)	(0.00000006)	(0.00000006)
$Reset_4^2$	0.00000090	-0.00000512	-0.00000053	-0.00000670	-0.00000635	0.00000062	-0.00000023
	(0.00000076)	(0.00000071)	(0.00000061)	(0.00000063)	(0.00000064)	(0.00000067)	(0.00000066)
2016($Indic.$)	0.06356423	0.04217572	0.00238353	-0.00561187	0.00391214	-0.00234029	-0.00648141
	(0.00148501)	(0.00137715)	(0.00118996)	(0.00122760)	(0.00125514)	(0.00131160)	(0.00128867)
$Constant$	0.34439464	0.29375516	0.32473689	0.33315647	0.32419949	0.33104793	0.30430820
	(0.00349739)	(0.00330935)	(0.00359221)	(0.00369874)	(0.00359160)	(0.00363571)	(0.00353777)

Notes: Maximum likelihood estimation results for the discontinuous growth models for all parties. All estimates refer to the fixed component (see Equation 1). Standard errors in parentheses.

F.1 Appendix: Additional results

F.1.1 Alternative models

In this section we estimate models that account for possible autocorrelation in the daily constituency-to-party similarity. Table F.6 reports estimates from a DGM with a one-day lag of the dependent variable. This specification is demanding and for some parties the model doesn't converge. Table F.7 instead reports estimates from dynamic panel models with constituency fixed effects, lag of the dependent variable and autocorrelated error term.

Table F.6: Discontinuous Growth Model with lagged dependent variable

	AfD	CSU	FDP	SPD
$Simil_{t-1}$	0.3371421	0.1176873	0.1529277	0.106056
	(0.0047926)	(0.0210816)	(0.0081633)	(0.0086043)
$Time$	0.0003473	-7.58E-06	-0.0007003	-0.0015109
	(0.0001974)	(0.0004264)	(0.0001725)	(0.000178)
$Time^2$	-0.0000159	-3.73E-06	8.51E-06	0.0000183
	(2.73E-06)	(5.90E-06)	(2.39E-06)	(2.46E-06)
$Event_1$	-0.1193006	0.0126869	0.0191251	0.0109588
	(0.0044962)	(0.0098879)	(0.0040292)	(0.0041103)
$Event_2$	0.1708947	0.0485004	-0.0665478	-0.0987865
	(0.0193439)	(0.0419064)	(0.0169192)	(0.0174597)
$Event_3$	0.4919678	0.143052	-0.2174231	-0.4516273
	(0.0739104)	(0.159672)	(0.0645813)	(0.0666201)
$Event_4$	1.40807	0.3498179	-0.6580425	-1.363032
	(0.2121193)	(0.4582433)	(0.1853222)	(0.1911758)
$Event_5$	3.356182	0.8144245	-1.581551	-3.39922
	(0.5212352)	(1.125992)	(0.4553852)	(0.4697706)
$Event_6$	4.850779	1.213857	-2.320257	-4.995182
	(0.7669845)	(1.656841)	(0.6700857)	(0.6912546)
$Event_7$	5.375379	1.318826	-2.596283	-5.592466
	(0.853285)	(1.84326)	(0.7454839)	(0.7690365)
$Event_8$	5.96429	1.491135	-2.887625	-6.301349
	(0.9538598)	(2.060535)	(0.8333529)	(0.8596803)
$Event_9$	6.224859	1.524111	-3.024527	-6.51202
	(0.9929998)	(2.145068)	(0.8675487)	(0.8949596)
$Event_{10}$	7.775521	1.899874	-3.823139	-8.254774
	(1.251849)	(2.704225)	(1.093697)	(1.128254)
$Event_{11}$	8.465221	2.061745	-4.182664	-9.028893
	(1.365322)	(2.949343)	(1.192836)	(1.230524)
$Reset_1$	0.0047884	-0.0007426	-0.002184	-0.001506
	(0.0003761)	(0.0008112)	(0.0003283)	(0.0003395)
$Reset_2$	0.0030046	0.0000128	-0.0013431	-0.0026157
	(0.000486)	(0.0010496)	(0.0004245)	(0.0004381)
$Reset_3$	0.0043315	0.0007854	-0.0030038	-0.005878
	(0.0009077)	(0.0019609)	(0.0007931)	(0.0008181)
$Reset_4$	0.0094436	0.0019487	-0.0047666	-0.0099054
	(0.0015267)	(0.003298)	(0.0013339)	(0.001376)
$Reset_5$	0.0140646	0.0038286	-0.0068574	-0.0153469
	(0.0023968)	(0.0051773)	(0.002094)	(0.0021602)
$Reset_6$	0.0118355	-0.0013206	-0.0105862	-0.0222368
	(0.0029802)	(0.0064343)	(0.0026037)	(0.0026864)
$Reset_7$	0.016651	0.0037662	-0.0100268	-0.0200067
	(0.0031148)	(0.0067265)	(0.0027214)	(0.0028071)
$Reset_8$	0.020951	-0.0075443	-0.0226665	0.0127355
	(0.004106)	(0.0088423)	(0.0035871)	(0.0037009)
$Reset_9$	0.0193835	0.0043548	-0.0098324	-0.0227649
	(0.0033007)	(0.00713)	(0.0028837)	(0.0029748)
$Reset_{10}$	0.0230479	0.0042815	-0.0121848	-0.0262558
	(0.0037602)	(0.0081191)	(0.0032854)	(0.003389)
$Reset_{11}$	0.0171967	-0.0043572	-0.0366362	-0.0238347
	(0.0050909)	(0.0109399)	(0.0044475)	(0.0045873)
$Reset_1^2$	0.0000436	0.0000401	0.000024	-0.00002
	(7.02E-06)	(0.0000151)	(6.20E-06)	(6.39E-06)
$Reset_2^2$	0.0000161	0.0000117	-5.82E-06	-0.0000195
	(3.29E-06)	(7.11E-06)	(2.88E-06)	(2.97E-06)
$Reset_3^2$	0.0000392	9.55E-06	-5.92E-06	-0.0000178
	(2.84E-06)	(6.14E-06)	(2.48E-06)	(2.56E-06)
$Reset_4^2$	0.0000168	5.99E-06	-6.43E-06	-0.0000184
	(2.75E-06)	(5.95E-06)	(2.41E-06)	(2.48E-06)
$Reset_5^2$	0.0000211	1.83E-06	-0.0000134	-0.000025
	(3.29E-06)	(7.12E-06)	(2.89E-06)	(2.97E-06)
$Reset_6^2$	0.0002615	0.0002054	0.0000448	0.0000566
	(0.0000243)	(0.000052)	(0.0000213)	(0.0000218)
$Reset_7^2$	0.0000724	5.32E-06	0.0000122	-0.0000608
	(0.000019)	(0.0000408)	(0.0000167)	(0.0000171)
$Reset_8^2$	0.0000873	0.0008988	0.0010066	-0.0043316
	(0.000222)	(0.0004759)	(0.0001939)	(0.0002)
$Reset_9^2$	0.0000212	8.15E-06	-0.0000181	-9.87E-06
	(3.58E-06)	(7.71E-06)	(3.13E-06)	(3.23E-06)
$Reset_{10}^2$	-0.0000213	7.38E-06	-3.11E-06	0.0000163
	(0.0000224)	(0.0000494)	(0.0000196)	(0.0000202)
$Reset_{11}^2$	0.0007594	0.0003918	0.0028911	-0.000102
	(0.0003545)	(0.0007564)	(0.0003096)	(0.0003194)
2016($Indic.$)	0.0125078	0.0196468	0.0097336	-0.0024743
	(0.0042258)	(0.0090942)	(0.0036913)	(0.0038075)
$Constant$	0.2220574	0.3012208	0.2896693	0.3078506
	(0.0037276)	(0.0118441)	(0.0047442)	(0.0049001)

Notes: Maximum likelihood estimation results for the discontinuous growth models with 1-day lag of similarity. All estimates refer to the fixed component (see Equation 1). Standard errors in parentheses

Table F.7: Dynamic panel model with AR(1) disturbance

	(1) AfD	(2) CDU	(3) CSU	(4) SPD	(5) FDP	(6) The Left	(7) The Greens
$Simil_{t-1}$	0.5918520***	0.4356406***	0.4630511***	0.4478441***	0.4886256***	0.4299732***	0.4439785***
	(0.0019526)	(0.0023736)	(0.0054028)	(0.0021550)	(0.0021073)	(0.0021787)	(0.0021641)
$Time$	0.0005214***	0.0001746	-0.0003318	-0.0009135***	-0.0004085***	0.0002064	0.0006769***
	(0.0001581)	(0.0001793)	(0.0003606)	(0.0001499)	(0.0001447)	(0.0001582)	(0.0001608)
$Time^2$	-0.0000151***	-0.0000002	0.0000020	0.0000111***	0.0000049**	-0.0000062***	-0.0000066***
	(0.0000022)	(0.0000025)	(0.0000050)	(0.0000021)	(0.0000020)	(0.0000022)	(0.0000022)
$Event_1$	-0.0709102***	-0.0783019***	0.0029542	0.0089571***	0.0131886***	0.0021817	-0.0112367***
	(0.0035654)	(0.0040068)	(0.0080547)	(0.0033492)	(0.0032341)	(0.0035247)	(0.0035800)
$Event_2$	0.1461328***	-0.0100562	0.0012981	-0.0615602***	-0.0388719***	0.0607336***	0.0102269
	(0.0152644)	(0.0172805)	(0.0347879)	(0.0144602)	(0.0139604)	(0.0152486)	(0.0154928)
$Event_3$	0.4548978***	-0.0099343	-0.0247451	-0.2748935***	-0.1240759**	0.2122723***	0.1167259**
	(0.0585796)	(0.0663513)	(0.1335559)	(0.0555088)	(0.0535848)	(0.0585485)	(0.0594937)
$Event_4$	1.2944503***	-0.0157953	-0.1144733	-0.8271335***	-0.3788309**	0.5495078***	0.3926003**
	(0.1683502)	(0.1907182)	(0.3838412)	(0.1595387)	(0.1540059)	(0.1682856)	(0.1710106)
$Event_5$	3.1046734***	-0.0212970	-0.3044621	-2.0587970***	-0.9079168**	1.2719570***	1.1178421***
	(0.4139845)	(0.4690297)	(0.9439102)	(0.3923311)	(0.3787203)	(0.4138578)	(0.4205692)
$Event_6$	4.5037825***	-0.0441901	-0.4360328	-3.0215282***	-1.3314169**	1.8736915***	1.7163320***
	(0.6093073)	(0.6903422)	(1.3892681)	(0.5774425)	(0.5574096)	(0.6091357)	(0.6190175)
$Event_7$	4.9957210***	-0.0548574	-0.5094289	-3.3760938***	-1.4920697**	2.0737374***	1.9483445***
	(0.6779041)	(0.7680672)	(1.5456750)	(0.6424556)	(0.6201653)	(0.6777175)	(0.6887136)
$Event_8$	5.5524069***	0.0228443	-0.5586146	-3.8279667***	-1.6548673**	2.2927846***	2.1916303***
	(0.7578501)	(0.8586521)	(1.7279623)	(0.7182216)	(0.6933032)	(0.7576451)	(0.7699398)
$Event_9$	5.7953754***	-0.0380256	-0.5983351	-3.9300263***	-1.7359310**	2.3915808***	2.2768857***
	(0.7889608)	(0.8939021)	(1.7988959)	(0.7477090)	(0.7217651)	(0.7887492)	(0.8015490)
$Event_{10}$	7.2577953***	-0.0409155	-0.7759509	-4.9986590***	-2.1975428**	2.9775516***	2.8855302***
	(0.9947260)	(1.1270499)	(2.2680639)	(0.9427191)	(0.9100088)	(0.9944696)	(1.0106107)
$Event_{11}$	7.9115448***	-0.0413989	-0.8381206	-5.4557931***	-2.3981279**	3.2430659***	3.1355302***
	(1.0849320)	(1.2292605)	(2.4737390)	(1.0282127)	(0.9925348)	(1.0846554)	(1.1022618)
$Reset_1$	0.0040159***	0.0046392***	-0.0005983	-0.0011759***	-0.0014553***	0.0027466***	0.0010742***
	(0.0002921)	(0.0003313)	(0.0006648)	(0.0002765)	(0.0002670)	(0.0002918)	(0.0002963)
$Reset_2$	0.0028596***	-0.0005931	-0.0008162	-0.0015674***	-0.0007604**	0.0019171***	-0.0004303
	(0.0003843)	(0.0004353)	(0.0008759)	(0.0003642)	(0.0003516)	(0.0003841)	(0.0003903)
$Reset_3$	0.0045401***	-0.0002973	-0.0009677	-0.0035608***	-0.0017472***	0.0024504***	0.0012468*
	(0.0007204)	(0.0008161)	(0.0016424)	(0.0006827)	(0.0006590)	(0.0007201)	(0.0007318)
$Reset_4$	0.0088624***	-0.0003152	-0.0011392	-0.0059837***	-0.0027104**	0.0034776***	0.0041514***
	(0.0012128)	(0.0013741)	(0.0027652)	(0.0011494)	(0.0011095)	(0.0012125)	(0.0012321)
$Reset_5$	0.0132981***	-0.0010424	-0.0013508	-0.0092662***	-0.0039764**	0.0060970***	0.0074780***
	(0.0019047)	(0.0021581)	(0.0043427)	(0.0018051)	(0.0017425)	(0.0019042)	(0.0019351)
$Reset_6$	0.0132692***	0.0018926	-0.0056895	-0.0134392***	-0.0062212***	0.0033677	0.0101683***
	(0.0023685)	(0.0026830)	(0.0053971)	(0.0022445)	(0.0021665)	(0.0023672)	(0.0024057)
$Reset_7$	0.0164871***	0.0058315**	-0.0024801	-0.0134565***	-0.0056963**	0.0026825	0.0071359***
	(0.0024754)	(0.0028044)	(0.0056421)	(0.0023457)	(0.0022644)	(0.0024743)	(0.0025145)
$Reset_8$	0.0212769***	-0.0210963***	-0.0110518	0.0175147***	-0.0159866***	0.0069855**	0.0056361*
	(0.0033233)	(0.0037503)	(0.0075394)	(0.0031443)	(0.0030354)	(0.0033063)	(0.0033578)
$Reset_9$	0.0183691***	-0.0007029	-0.0025387	-0.0143970***	-0.0057611**	0.0071114***	0.0069910***
	(0.0026236)	(0.0029727)	(0.0059818)	(0.0024864)	(0.0024001)	(0.0026229)	(0.0026655)
$Reset_{10}$	0.0213229***	-0.0003689	-0.0023288	-0.0153975***	-0.0067961**	0.0084809***	0.0079909***
	(0.0029888)	(0.0033863)	(0.0068116)	(0.0028325)	(0.0027342)	(0.0029877)	(0.0030361)
$Reset_{11}$	0.0130692***	-0.0117924**	-0.0143565	-0.0187559***	-0.0271844***	0.0045403	0.0123027***
	(0.0041712)	(0.0046948)	(0.0094302)	(0.0039414)	(0.0038062)	(0.0041389)	(0.0042016)
$Reset_1^2$	0.0000205***	-0.0001227***	0.0000184	-0.0000070	0.0000174***	-0.0000308***	-0.0000048
	(0.0000055)	(0.0000063)	(0.0000126)	(0.0000052)	(0.0000050)	(0.0000055)	(0.0000056)
$Reset_2^2$	0.0000144***	0.0000102***	0.0000044	-0.0000118***	-0.0000030	-0.0000036	0.0000229***
	(0.0000026)	(0.0000029)	(0.0000059)	(0.0000025)	(0.0000024)	(0.0000026)	(0.0000026)
$Reset_3^2$	0.0000290***	0.0000019	0.0000022	-0.0000107***	-0.0000032	0.0000017	0.0000130***
	(0.0000023)	(0.0000026)	(0.0000051)	(0.0000021)	(0.0000021)	(0.0000023)	(0.0000023)
$Reset_4^2$	0.0000155***	0.0000009	-0.0000007	-0.0000111***	-0.0000038*	0.0000068***	0.0000028
	(0.0000022)	(0.0000025)	(0.0000050)	(0.0000021)	(0.0000020)	(0.0000022)	(0.0000022)
$Reset_5^2$	0.0000189***	0.0000100***	-0.0000028	-0.0000151***	-0.0000073***	0.0000012	-0.0000096***
	(0.0000026)	(0.0000029)	(0.0000059)	(0.0000025)	(0.0000024)	(0.0000026)	(0.0000026)
$Reset_6^2$	0.0001623***	-0.0001329***	0.0001361***	0.0000261	0.0000288	0.0001139***	-0.0000897***
	(0.0000193)	(0.0000217)	(0.0000435)	(0.0000182)	(0.0000176)	(0.0000191)	(0.0000194)
$Reset_7^2$	0.0000463***	-0.0002806***	0.0000045	0.0000056	0.0000055	0.0001483***	0.0000137
	(0.0000151)	(0.0000170)	(0.0000340)	(0.0000143)	(0.0000138)	(0.0000150)	(0.0000152)
$Reset_8^2$	-0.0000677	0.0015908***	0.0007007*	-0.0037343***	0.0008760***	-0.0000553	0.0001687
	(0.0001852)	(0.0002076)	(0.0004170)	(0.0001747)	(0.0001687)	(0.0001829)	(0.0001855)
$Reset_9^2$	0.0000186***	0.0000123***	0.0000023	0.0000016	-0.0000090***	0.0000114***	0.0000193***
	(0.0000028)	(0.0000032)	(0.0000064)	(0.0000027)	(0.0000026)	(0.0000028)	(0.0000029)
$Reset_{10}^2$	-0.0000080	-0.0000004	-0.0000267	-0.0000058	-0.0000122	-0.0000078	0.0000491***
	(0.0000178)	(0.0000201)	(0.0000400)	(0.0000168)	(0.0000162)	(0.0000177)	(0.0000180)
$Reset_{11}^2$	0.0010502***	0.0014645***	0.0007688	0.0003906	0.0024839***	0.0005111*	-0.0003445
	(0.0003038)	(0.0003386)	(0.0006793)	(0.0002860)	(0.0002762)	(0.0002982)	(0.0003023)
2016(*Indic.*)	0.0076044**	-0.0043519	0.0154257**	-0.0003302	0.0051644*	0.0041819	0.0302855***
	(0.0033286)	(0.0037593)	(0.0075490)	(0.0031492)	(0.0030409)	(0.0033148)	(0.0033674)
Constant	0.1345638***	0.1690951***	0.1884460***	0.1907090***	0.1758700***	0.1767166***	0.1691310***
	(0.0032582)	(0.0035029)	(0.0073757)	(0.0030697)	(0.0029690)	(0.0031053)	(0.0031291)
Observations	171,587	144,587	27,000	171,587	171,587	171,587	171,587
Number of constituencies	235	199	36	235	235	235	235

Notes: Results from fixed-effects dynamic panel models with 1-day lag of similarity and auto-regressive disturbance. Standard errors in parentheses