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A Deviations from the pre-analysis plan

Our study deviates from the pre-analysis plan in two main ways, which we detail below.

1. Upon presenting the work to colleagues and receiving their feedback, we decided to change the name of the second hypothesis. In the pre-analysis plan, it was titled "differentiation hypothesis", while in the current version of the paper it reads "distancing hypothesis", which we think reflects better the argument we put forward.

2. All the analyses that intend to provide evidence on the mechanism at play were thought of after knowing what the main effect was. These analyses were meant as exploratory in nature, whose goal was to provide in-depth understanding of the mechanism driving the main effect. This includes the qualitative analyses and the subsample analyses reported in the section on the mechanism, as well as the rationale for the implications of the mechanism found in the theoretical section. This also means that the second part of our distancing hypothesis, which refers to how effects should differ across politicians of different parties, was thought of post-hoc. Our pre-analysis plan included only the two main hypothesis, with no mention to the subsample analyses. Upon receiving peer feedback, we decided that including all theoretical reasoning together, regardless of it being pre-registered or not, made for a better reading and understanding of the paper than to have two separate theoretical sections—one, pre-registered, for the main effect; one, not pre-registered, for the mechanism and subsample analyses. We hope that this choice makes for a more straightforward understanding of the paper, without sacrificing transparency.

B Details on the original dictionary

This study applies a novel emotional dictionary (âĂIJed8âĂİ), that has been specifically created to measure discrete emotional language in political text, while taking into consideration German language specifics. It is specifically tailored to the political context and capable of measuring language associated with a wide range of different positive and negative emotions. Furthermore, contrary to many off-the-shelf dictionaries, the ed8 dictionary includes negation control. Similar to the augmented dictionary (Rauh 2018), the ed8 dictionary recognizes a variety of different negation patterns by including bigram negations, which are identified and replaced by markers in order for them not to be counted in the final emotional scores.

The dictionary has been created along a semi-automated two-step procedure. First, all terms have been manually reviewed and attributed, if suitable, into different emotional categories. From the total of 30,070 words included in the augmented dictionary, 19,091 terms have been categorized into one or more of the eight different emotional categories.

In a second step, we trained a word embeddings model using GoogleâĂŹs word2vec algorithm implemented in the R package rword2vec. Word embeddings are a method to analyze and understand words and their meaning (Mikolov et al. 2013). These models take into account the context in which words appear. Words are represented as a position in a multidimensional space, and the use of each word is predicted based on its contiguous words. The algorithm then turns each word into numerical values, which can be used to calculate distances between terms. More similar words are closer to one another, words with different meanings are more distant. Thus, based on these numerical values it easy to find words with semantic similarity which then can be used to expand an already existing dictionary.

To do so, the algorithm was locally trained on a large corpus of German political text, including parliamentary speeches, press releases and social media data from political parties in Germany, Austria, and Switzerland. We then used words that have been already attributed to one of the eight emotional categories to find synonyms and other words that have not yet been included in the dictionary. In this manner, we added 1491 terms (including inflections) to the previously identified 19091 terms. The ed8 dictionary now consists of a total number of 20,582 terms, which are attributed to one or several emotional categories.

The individual lists for each emotional category have comparable sizes among emotions of the same valence, i.e. all negative emotions have approximately similar lengths, and all positive emotions have approximately similar lengths. However, comparing negative categories to positive categories, lists for negative emotions are slightly longer. The list for anger includes 4,743 terms, for fear 4,024 terms, for disgust 4,216 terms, and for sadness 3,889 terms. The list for joy contains 2,800 terms, for enthusiasm 2,247 terms, for pride 3,063 terms, and for hope 2,526 terms. Thus, there is an overweight of negative words which, however, is closer to the real balance of positive and negative terms in German political language (see Rauh 2018).

As we refer in the main text, one of the reasons why we develop a new dictionary is to ensure its applicability to the German language. Many off-the-shelf dictionaries are tailored to the English language context and have been subsequently translated to other languages, often using automated machine-translation. This, however, makes them inept to process language specific grammar which in turn can lead to distorted results. To better illustrate this shortcoming of automatically translated dictionaries, we applied the German version of the âĂIJNRC Word-Emotion Association LexiconâĂİ (EmoLex, see Mohammad and Turney 2010)—a widely used emotional language dictionary available in over hundred languages—to the very short example sentence containing language with clear use of negative emotions.

Table 3: Results of coding an example sentence using the NRC EmoLex dictionary.

Example: âĂIJIch hasse die Regierung und diese ganzen Idioten!âĂIJ
(âĂIJI hate the government and all these idiots!âĂİ)

Anger	Anticipation	Disgust	Fear	Joy	Sadness	Surprise	Trust	Negative	Positive
0	0	0	0	0	0	0	0	0	0

As Table 3 shows, the EmoLex dictionary does not capture any of the clearly negative words in the sentence. While the infinitive form of hate and the singular form of idiot are included in the German version of the EmoLex, the first-person conjugation âĂIJhasseâĂİ

Table 4: Results of coding an example sentence using the ed8 dictionary.

Example: âĂIJIch hasse die Regierung und diese ganzen Idioten!âĂIJ
(âĂIJI hate the government and all these idiots!âĂİ)

Anger	Fear	Disgust	Sadness	Joy	Enthusiasm	Pride	Hope
2	1	1	1	0	0	0	0

(instead of âĂIJhassenâĂİ, to hate) and the plural form âĂIJIdiotenâĂİ are not. As shown in Table 4, the novel emotional dictionary applied in this study (âĂIJed8âĂİ) computes following output, which clearly shows the negatively charged language in the example sentence.

To validate the dictionary at hand, we have chosen crowd sourcing (or crowd coding) which is one of state-of-the-art methods used to code text in the social sciences (Benoit et al. 2016; Lehmann and Zobel 2018). Crowd sourcing refers to using the internet to distribute large amounts of small tasks to a very high number of workers around the world that receive financial rewards per task. Harvesting âĂIJthe wisdom of crowdsâĂİ offers new possibilities for researchers who want to quickly code large sections of political texts. It is very similar to manual coding, yet it is faster because several workers can work on the tasks simultaneously. However, one crucial difference is that crowd coders are no experts in the topic at hand. Instead, crowd coding is based on the assumption that judgement of many individuals taken together will eventually lead to a âĂIJtrueâĂİ answer (Benoit et al. 2016).

To conduct the validation process, we used a German crowd working platform called *Crowdguru*, which is similar to AmazonâĂŹs Mechanical Turk. While our study focuses on parliamentary speeches, we want to make sure that the validity of our dictionary travels beyond this specific data source. As such, following Rauh (Rauh 2018), we use data from different sources of political communication. Concretely, we selected 10,000 sentences coming from parliamentary speeches—drawn from the current legislative period of the German Bundestag, between October 2017 and June 2019—and Facebook posts taken from the official Facebook accounts of all German parties, during the same period[13]. The speeches and Facebook posts were subsequently collapsed into sentences, resulting in a total of 333,572 sentences in parliamentary speeches and 34,375 sentences in Facebook posts. From these sentences, 20 percent of the validation data (2000 sentences) were randomly selected. The remaining 80 percent were selected from pre-sampled data sets. Research on emotional language shows that emotional words only rarely occur in communication (Pennebaker, Mehl, and Niederhoffer 2003). Thus, randomly selecting sentences from the overall sample would most likely lead to a very low amount of emotionality, which would mean that from the 10,000 sentences only a few hundred sentences would include emotional language. Hence, we applied the ed8 dictionary to the overall sample of sentences and subsequently pre-sampled data sets for each emotion, including only sentences that have an emotional score above 0 for the respective emotion. This resulted

[13] While a replication of the main analyses of the paper on social media data would be interesting, it is unfortunately not possible because many state-level politicians could not be found in social media. Among the ones we could trace, many do not have a professional account, and their social media accounts (which have a very limited number of followers) include mostly posts about their daily life that have no connection to the political debate.

in eight data sets (one for each emotion) with sentences that have an emotional score that is greater than 0. From each of these eight pre-sampled data sets we subsequently selected 10 percent (1000 sentences) of the validation sample, resulting in 8000 sentences. Taken together with the 2000 sentences that were randomly chosen, this results in the total validation sample of 10,000 sentences.

To ensure valid and reliable data production, it is essential to build in several quality control measures. Similar to recent studies using crowd coding for data production (Benoit et al. 2016; Lehmann and Zobel 2018; Rudkowsky et al. 2018), the validation process included different tests before and during the coding process to assure a high quality of coding. First, coders had to finish a start quiz consisting of so-called âĂIJgold sentencesâĂİ. Gold sentences are sentences that are clearly associated with one specific emotion and therefore have a predefined unambiguous answer (Benoit et al. 2016). We used âĂIJartificiallyâĂİ constructed gold sentences to be able to manipulate the emotional strength. If the coder does not choose the predefined answer, the answer is counted as incorrect. In the start quiz, 80 percent of the answers had to be answered correctly in order to be admitted to the job. Ten crowd workers did not pass the start quiz and hence were not allowed to work on the task. During the coding process, the quality of the coders was assured using either gold sentences or âĂIJscreenersâĂİ. Screener sentences contain an exact instruction on how to label the sentence, which are designed to assure that coders carefully read the sentences. Based on the answers to the randomly chosen test question (gold sentence or screener) in each HIT, trust scores were calculated for each individual coder in regular intervals. Coders whose trust score fell below 60 percent were ejected from the job and their assignments added back to the HIT pool. However, only one crowd worker fell below the threshold of 60 percent and was subsequently removed from the task.

The crowd coded sentences serve as âĂIJtrueâĂİ answers and allow us to measure the accuracy of the ed8 dictionary. To do so, we calculate precision, recall, and F1 scores. Recall is the ratio of correctly predicted observations to the total amount of true observations. Recall scores therefore give the ratio of sentences correctly judged as âĂIJemotionalâĂİ (e.g. angry) by the dictionary to the total amount of sentences judged as âĂIJemotionalâĂİ (e.g. angry) by the human coders. Precision, on the other hand, is the ratio of correctly predicted observations to the total predicted observations. This means that precision is the ratio of correctly judged sentences by the dictionary to the total amount of retrieved sentences by the dictionary. The F1 score is defined as the harmonic mean of recall and precision:

$$F1 = 2 * (Recall * Precision)/(Recall + Precision)$$

For an initial comparison, we turned the continuous emotional scores computed by the dictionary to the same binary scale that the human coders produced. Table 5 shows the results for recall, precision and F1 scores.

As can be seen, for most emotions the ed8 dictionary attains good F1 scores around or above 0.5. In general, the ed8 dictionary attains very good recall scores which are, except for anger, higher than the precision scores. Our interpretation of this result is that the ed8 dictionary retrieves many of the sentences classified as emotional by human coders—meaning its classification is complete (due to the good recall scores)—yet, due

Table 5: Precision, recall, and F1 score for the ed8 dictionary.

	Actual	Predicted	Precision	Recall	F1 Score
Anger	4582	2768	0.78	0.47	0.59
Fear	1893	2778	0.44	0.65	0.53
Disgust	889	1823	0.33	0.67	0.44
Sadness	1919	2700	0.45	0.64	0.53
Joy	1427	1773	0.47	0.59	0.52
Enthusiasm	1990	2298	0.46	0.53	0.49
Pride	1563	2223	0.35	0.49	0.41
Hope	2873	2822	0.56	0.55	0.55

to lower precision values (especially for disgust and pride) it is necessary to treat these results with wariness. When it comes to anger, however, with a precision score of 0.78 it is reasonable to assume that the retrieved sentences can be trusted to a large extent.

However, it is important to compare the performance of the ed8 to other, off-the-shelve dictionaries that are often used in text analysis studies. To do so, we compare the ed8 dictionary to the commonly used LIWC dictionary (Linguistic Inquirer and Word Count, Tausczik and Pennebaker 2010) and the NRC EmoLex dictionary (Mohammad and Turney 2010). These lexica are among the few dictionaries available that not only include general categories for positive and negative tone but also categories for discrete emotions. The LIWC dictionary includes anger, anxiety (treated here as comparable to fear), and sadness. The NRC EmoLex dictionary includes anger, fear, disgust, sadness, joy, anticipation, surprise, and trust. Both dictionaries include a German lexicon versions. While the German version of the NRC EmoLex dictionary has been translated automatically using Google Translate, the German LIWC dictionary has been translated and adapted manually to the German language context (Meier et al. 2019). The precision, recall, and F1 scores for both dictionaries are shown in Table 4 and 5.

Table 6: Precision, recall, and F1 score for the NRC EmoLex dictionary.

	Actual	Predicted	Precision	Recall	F1 Score
Anger	4583	600	0.76	0.10	0.18
Fear	1893	780	0.32	0.13	0.19
Disgust	889	321	0.22	0.08	0.12
Sadness	1919	999	0.31	0.16	0.21
Joy	1773	694	0.32	0.15	0.21

Table 7: Precision, recall, and F1 score for the LIWC dictionary.

	Actual	Predicted	Precision	Recall	F1 Score
Anger	4583	1612	0.73	0.26	0.38
Fear	1893	809	0.40	0.17	0.24
Sadness	1919	977	0.48	0.24	0.32

The tables show that the novel ed8 dictionary substantially outperforms both the LIWC and NRC EmoLex. The highest F1 score for the NRC dictionary is 0.21, for the LIWC dictionary 0.38. Similarly, the individual scores for precision and recall for all emotions under scrutiny are lower than the respective scores for the ed8 dictionary (with the exception of the sadness precision score of the LIWC dictionary). The automatically translated German version of the NRC EmoLex dictionary shows the worst performance. In general, the recall scores for both dictionaries show substantially low values. These numbers indicate that the two off-the-shelve dictionary find only a fraction of the sentences that humans judge as emotional.

In this initial comparison we forced the continuous scale of the dictionaries into a binary variable. In the following, we check whether higher emotional scores of the dictionaries also correlate with higher emotionality as judged by human coders. Human coders were only faced with a binary decision (whether or not a given emotion was associated with a sentence). Nevertheless, we can construct a categorical variable based on the agreement/disagreement of the human coders. This means that instead of forcing the emotional scores of the dictionary into a binary variable, we turn the human judgment into a categorical variable, based on differences across human coding. Thus, human judgment was classified as âĂIJvery emotionalâĂİ (e.g. very angry) when four or five coders coded the sentence as associated with the respective emotion (e.g. anger). When two or three coders agreed on one emotion, the human judgment was categorized as âĂIJemotionalâĂİ (e.g. angry) and finally, when none or only one of the coders associated the sentence with the respective emotion the human code was categorized as âĂIJnot/slightly emotionalâĂİ (e.g. not/slightly angry). We would expect that the normalized emotional scores significantly increase from the lowest category (not/slightly emotional) to the highest (very emotional).

Figures 6 and 7 plot the normalized emotional scores and their 95% confidence intervals for all positive and negative emotions across three categories of human judgment, grouped by dictionary. These Figures show that the NRC EmoLex dictionary shows either no or only slight increase across the different categories of human judgement. Thus, the NRC cannot reliably distinguish among human judgements. In contrast, the ed8 and the LIWC dictionary exhibit clearly positive slopes across the scale of human judgment. However, the ed8 shows the best performance which discriminates the categories from âĂIJnot/slightlyâĂİ to âĂIJvery emotionalâĂİ in a statistically significant manner with comparably small confidence intervals. The LIWC dictionary shows greater uncertainty and does not discriminate significantly between âĂIJangryâĂİ and âĂIJvery angryâĂİ, as can be seen in the first panel of Figure 6.

Overall, the novel ed8 dictionary applied in this study outperforms widely used off-the-shelve dictionaries in several measures across all comparable emotions. It shows robust F1 scores and substantially improves the accuracy of automated text classification compared to other dictionaries.

To give readers a better understanding of how our approach works, the following exercise exemplifies how different emotional words are identified in the speeches. The marked words in the following paragraphs are recognized by the ed8 dictionary as âĂIJemotive wordsâĂİ and are assigned to at least one of the eight emotional categories. Each of the paragraphs stem from randomly selected speeches. The first paragraph has been taken from a speech on the topic of refugees (topic 7). As can be seen, the paragraph includes a number of negative words (red color) as well as positive words (green color). Table 8 indicates each identified emotive term and their assignment to different emotional

Figure 6: Comparing human judgement against normalized emotional scores (negative emotions).

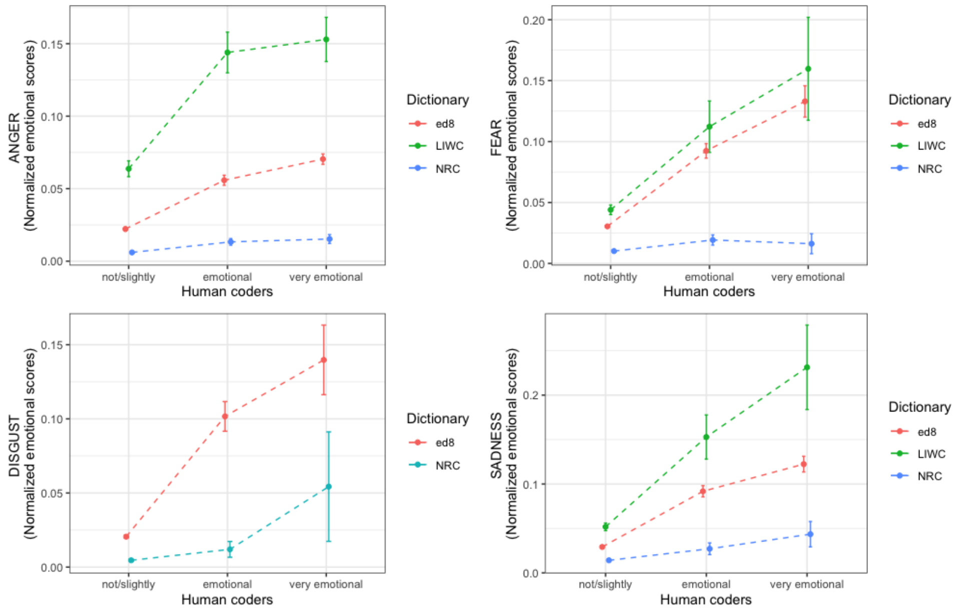


Figure 7: Comparing human judgement against normalized emotional scores (positive emotions).

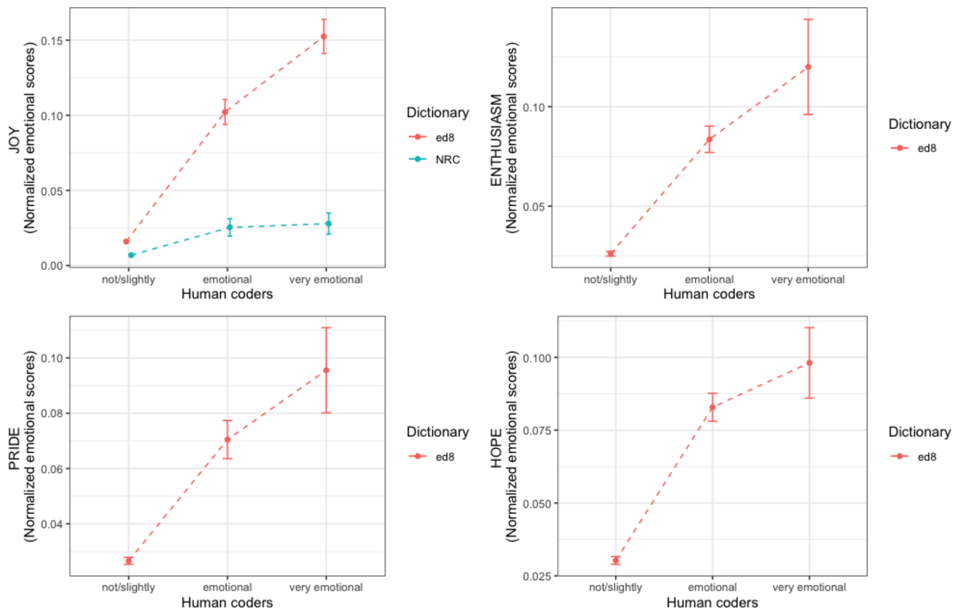


Table 8: Emotional score by each word in the example speech above.

	Anger	Fear	Disgust	Sadness	Joy	Enthusiasm	Pride	Hope
protect	0	0	0	0	0	1	0	1
relieve	0	0	0	0	0	0	0	1
murder	1	1	1	1	0	0	0	0
attack	0	1	0	1	0	0	0	0
danger	0	1	0	0	0	0	0	0
kill	1	1	1	1	0	0	0	0

categories.

"The AfD parliamentary group is calling for the consistent deportation of dangerous persons, Syrian returnees and Salafists in order to protect the citizens of Lower Saxony and also to relieve the burden on the local taxpayer. According to Die Welt, more than 600,000 Syrians had already returned to their homeland in 2017, and another 260,000 Syrians returned in 2018. Thus, Die Welt writes. Syria is ready for refugees to return, Syrian Foreign Minister al-Muallim tells United Nations. The AfD delegation that toured Syria in 2018 also believes that a safe life is possible there in large parts. The Bavarian Minister of the Interior is also of the same opinion. I said it before, but you, ladies and gentlemen, do not even want to deport the new Islamist threats living or residing here in Lower Saxony with an exclusively foreign citizenship, a citizenship that would make deportation possible. Instead, you want to hand out 70 points for murder if these individuals commit an attack. People who pose a danger must be deported, and before they kill, not when they have filled up their points account!"

(Speech by Jens Ahrends, AfD, 21.12.2018)

The second paragraph is taken from a speech on the topic of transportation (topic 6). As can be seen, fewer negative words are used in this paragraph. Nevertheless, the ed8 dictionary identified a number of terms associated with positive emotional appeals. Table 9 illustrates their assignment to different categories.

"Ladies and gentlemen, cooperative ventures like the one between Deutsche Post and RWTH Aachen University are also needed in other areas to enable the switch to new technologies. The federal government should also provide targeted support for climate-neutral vehicle fleets in order to open up the e-car premium to municipalities and certain companies. In addition, uniform standards for charging infrastructure are to be ensured. Ladies and gentlemen, the initiative of the five federal states was urgently needed and could also have been launched from North Rhine-Westphalia in recent years. In this respect, we are grateful that the North Rhine-Westphalia coalition and Minister President Armin Laschet have taken the first step here; because environmental friendliness alone is obviously not enough as an argument for buying electric cars. There is indeed a lack of suitability for everyday use, but also of affordability. Electric cars have to meet all these requirements."

(Speech by Klaus Voussem, CDU, 13.07.2017)

It is important to note that not all terms are necessarily âĂIJemotionalâĂİ terms, but rather words that hint towards the presence of a specific emotional appeal that might be appraised by humans as such. We chose this approach since previous research indi-

Table 9: Emotional score by each word in the example speech above.

	Anger	Fear	Disgust	Sadness	Joy	Enthusiasm	Pride	Hope
cooperative	0	0	0	0	0	0	0	1
initiative	0	0	0	0	0	1	0	0
grateful	0	0	0	0	1	0	1	0

cates that discrete emotions cannot only be measured by counting emotional words, such as emotion bearing adjectives. Instead, specific emotions are assumed to be expressed more implicitly and require more situational information (Wang et al. 2012). Since these words can be appraised and interpreted differently in varying contexts, some of the words are assigned to multiple categories. The robustness of this approach can be seen in Online Appendix B where we compare the accuracy of the ed8 dictionary to off-the-shelf dictionaries which are often applied in social science research.

C Examples of text scoring high on each emotion

C.1 Examples of speeches scoring high on anger

21.11.2018, Andre Poggenburg, AfD, Sachsen-Anhalt. “Dear Mrs von Angern, once again you have deliberately misrepresented the position of AfD. The AfD is concerned with real equality of opportunity rather than the imposition of quotas. That is the only correct approach. Take note that you and your left-wing political brethren are mentally courting a religion that has oppression and discrimination against women on its agenda. Against this background, all your alleged efforts to improve women’s opportunities and their equality are nothing but mockery, ridicule and hypocrisy. You should be ashamed of yourself in front of the women in this country."

22.06.2017, Kurt Wansner, CDU, Berlin. “[...] Whoever attacks the police attacks us all. The District Assembly condemns the feigning of an emergency and the targeted attack on police forces in Riga Street. The Assembly also condemns the serious interference with traffic the following night and the subsequent repeated attack on police officers. Violence by left-wingers, autonomists and supporters of the autonomous scene has reached a new level of insidiousness and brutality, which urgently needs to be stopped. The police are there to protect everyone. Whoever attacks the police attacks the whole of society. He attacks us all."

30.06.2017, Thomas Jung, AfD, Brandenburg. “Mr President, Mrs Johlige, it was really a low point from the left to defame us like this. Unlike you, we do not employ and have people who were in the RAF like you on the left. I only remind you of Inge Viett, who is now employed by the Left as a mass murderer. And on the other hand I say to you: These very people, these left-wing extremists, these leftists are attacking people. If you had experienced what has been described to me, where small children here in Potsdam were finally attacked by a lynch mob of you and your fellow-minded people, then you would simply keep quiet!"

C.2 Examples of speeches scoring high on fear

03.06.2016, Thomas HÃűse, The Left, Sachsen-Anhalt.“Mr President, honourable Members of Parliament. December, Berlin, truck: 55 injured, 12 dead. 1 January, Istanbul, firearm: 67 injured, 39 dead. 5 January, Gothenburg, explosives: one injured. February 3, Paris, machete: two injured. March 18, Paris. Firearm: one wounded, one dead. March 22nd, London, knife. Car: 41 injured, six dead. March 24, Grozny, firearms, explosives: 12 dead. April 3, Saint Petersburg, explosives: 51 wounded, 14 dead. April 7, Stockholm, firearms, truck: 15 injured, five dead. April 20, Paris, firearm, truck: 15 injured, two dead. 19 May, Milan, knife: three injured, two dead. May 22, Manchester, bomb: 59 injured, 23 dead. 3 June, London, knife, van: 48 injured, 11 dead. June 19, London, van 10 injured, 11 dead. Ladies and gentlemen! As a result of these attacks, which only cover the last six months, do the LEFT and the GREENS seriously believe that Europe, unlike Afghanistan, is a safe territory, or do they, in your words, offer a prospect of staying? That is completely absurd and unworldly."

18.11.2015, Bessin, AfD Brandenburg.“Mr President, honourable Members of Parliament. Dear guests! Violence prevails in our society, and not just since Friday .

There is violence in the family, violence in schools, violence is portrayed in the media, violence exists in social discourse and also in political debate. We have already heard a lot about violence and terror today. The cruelty of the terrorist attacks in Paris is hard to put into words. The motion that I have tabled, which is now to be discussed, aims to raise awareness of the facts about the increase in violence against political activists and to discuss this with all of you. However, as I can see from the agenda, the clan of SPD, CDU, Left and Greens has agreed not to discuss it with us. [...] But where does that come from, where does this potential for violence come from? It is not us who are rushing . I am surprised, Mr Woidke, that you are making yourself heard here. It is not us who are polemicizing against refugees and demonstrating against them - perhaps you should listen to us - but it is us who are protesting against the wrong refugee policy, which we believe the Chancellor and our state government are pursuing. And we have the right to express this opinion. Yes, we say out loud that we do not think this way of influx of foreign people is right, we clearly reject it.[...]"

C.3 Examples of speeches scoring high on disgust

12.10.2017, Heiner Garg, FDP, Schleswig-Holstein."Mr President, ladies and gentlemen. Ladies and gentlemen I find what you have just presented here disgusting. I find it really disgusting that you are making a mockery of the past we look back on, making a mockery of victims of that past. You can stand by that motion however you want. The debate on the substance, the debate on the substance has been conducted. I do not want to interfere in that. What you have just organized here is quite simply unworthy of this Parliament. It is not proper for a parliament to make fun of history in the way you have just made fun of it from the lectern."

19.12.2018, Ulrich Siegmund, AfD, Sachsen-Anhalt."Mr Grube, thank you for giving me the opportunity to deal with another topic in this context. At the beginning of your speech, you celebrated the Jusos adequately for their work. I would like to ask you what the SPD Group in Saxony-Anhalt, and also yourself, think about the current demand by the Young Socialists for late abortion to be legalized, that is to say, for a living baby to be killed by an injection of potassium into the heart and the body then to be taken out through the womb in an artificially induced birth lasting approximately 10 to 20 hours, so that this mother gives birth to a stillborn child. How do you feel about this disgusting and emotionally cold demand? That would interest me. Thank you."

C.4 Examples of speeches scoring high on sadness

21.01.2015, Ralf Stegner, SPD, Schleswig-Holstein."Mr President, ladies and gentlemen, it is a sad occasion on which we began today's plenary session with a minute's silence for the victims of terrorist violence in recent weeks. I am glad that we will continue it with a clear commitment by the Schleswig-Holstein Landtag to a peaceful, cosmopolitan and diverse society. Together we mourn all the victims of violence. Our special sympathy these days goes to the victims and relatives of the cruel attacks against the editors of the French satirical magazine Charlie Hebdo, the supermarket for kosher food in Paris and the murdered policeman. Once again, these were acts of terrorist violence that cannot be justified by anything. Violence is never right or acceptable, no matter what the aim, ideology, religion or worldview of the perpetrators."

21.01.2015, Daniel GÃijnther, CDU, Schleswig-Holstein."Mr President, ladies and gentlemen. Stunned, horrified and saddened by the barbaric murders of Paris. The brutality and cold-bloodedness of the murderers - this is what we see when we look at the pictures - shakes us again and again. 17 innocent people have lost their lives because terrorists have put their murderous and hateful plan into action, 17 people whose families and friends have to live on without them. They have our deepest sympathy. We mourn with our French neighbors. These heinous murders were a targeted attack on the very foundations of Europe: on freedom of expression and of the press, on our entire free democratic order and on our common values. In the midst of their grief, our French neighbors have sent an important and courageous signal: they will not bow to terrorists; they will not let themselves be brought to their knees by terrorist Islamists. The impressive demonstrations involving millions of people have sent out a common signal which has had an incredibly positive effect throughout Europe. That is why I think it is also a very good sign that we in the Schleswig-Holstein Landtag have today agreed on a joint motion on this issue. After all, it must be in our common interest and a common signal from all of us to counter these terrorists. I am very pleased about this signal. My sincere respect goes to the surviving journalists of "Charlie Hebdo". They have not allowed themselves to be intimidated by the terrorists and the barbaric attack on their editorial office."

23.02.2018, Anne Spiegel, GrÃijne, Rhineland-Palatinate."Mr President, ladies and gentlemen. Without need, no one decides to leave their home and family. Without need no one comes. But those in need shall be allowed to come. Many people are in such dire straits at home that they take the life-threatening flight across the Mediterranean. They seek protection in Europe. In the last few days alone, hundreds if not thousands have drowned in front of Fortress Europe. I am stunned when I see the pictures of this disaster and it makes me incredibly angry."

C.5 Examples of speeches scoring high on joy

29.03.2019, Bernd Heinemann, SPD, Schleswig-Holstein."Dear Sirs! Ladies and Gentlemen! A small addition from me: 62 years of the Treaty of Rome is a history of prosperity, equality, sustainability, peace, democracy, solidarity and freedom, not of envy, selfishness and isolation. Dear Alternative for Germany, we have a European Parliament. Yes, we have one, and we should have a bigger one. We also want more democracy in Europe. And yes, we have an anthem based on Friedrich Schiller's poem "An die Freude", set to music by Ludwig van Beethoven with the 9th Symphony. This anthem is indeed an expression of joy, and we have reason to rejoice."

28.02.2018, JÃijrgen Keck, FDP, BaWu."Mr President, ladies and gentlemen. It is already 15 years since the European Year of People with Disabilities was held - in 2003. The motto - as Minister Lucha suggested earlier - was: "Not about us without us". This still applies to us 15 years later. Thank you very much, Mrs Aeffner, for your active cooperation. I hope that you will be able to continue to contribute actively. In Baden-WÃijrttemberg, this was associated with the initiative "In the middle instead of on the outside". Even today, discussions, events and projects of the handicapped aid are still very much under this motto. It is a particular pleasure for me that we are today discussing the implementing law for the Federal Participation Act at its first reading. I would like to comment on this with: "What lasts long will finally be good.""

15.05.2019, JÃűrg Denninghoff, SPD, Rhineland-Palatinate. "Mr President, ladies and gentlemen, Mrs Schleicher-Rothmund. In the last two years, I have already had the opportunity to speak in plenary on the occasion of the Ombudsman's annual report, and this year is another great pleasure for me. I am even particularly pleased that now, after more than four decades, for the first time a woman is the Ombudsman of the Land of Rhineland-Palatinate."

C.6 Examples of speeches scoring high on enthusiasm

15.01.2015, Benedikt Lux, GrÃijne, Berlin. "Madam President, ladies and gentlemen. Dear Mr Herrmann! We naturally welcome your proposal to strengthen voluntary work with the voluntary fire brigade in Berlin. As you have said, the 1 400 or so volunteers are doing indispensable work for the city. They are also the backbone of the professional fire brigade with 3,600 people, and it would be impossible to imagine major events such as New Year's Eve without them. They ensure that dangers for Berliners are averted and help is provided in the event of fires, disasters, floods, etc. Therefore also from our side, from BÃijndnis 90/Die GrÃijnen: Many thanks to the helpers!"

24.05.2018, Wolfgang Aldag, GrÃijne, Sachsen-Anhalt. "[...]137 schools in Saxony-Anhalt received the award "School without racism School with courage". These schools are specifically committed to civil courage and a positive school climate. We, the Green parliamentary group in Saxony-Anhalt, think this is important and right; and we are not alone. Many representatives from this House support us. Many personalities from the fields of sport and music as well as representatives of the economy of this state stand as sponsors with their name and their conviction behind the project "School without racism School with courage". A large majority here in this House and a large majority in society support the work of the Courage Schools and stand firmly by their side. We will continue to do so[...]."

C.7 Examples of speeches scoring high on pride

7.03.2019, Harm Rykena, AfD, Niedersachsen. "Thank you very much. Madam President, ladies and gentlemen. With regard to this motion, it should be noted that all the political groups in the Lower Saxony State Parliament are in agreement and wish to give all possible support to the universities in Lower Saxony which are in the application procedure for the status of an Excellence University. We are all proud of the excellent work that has been and will be done at these universities during the application process. There is therefore no need for debate. That is why I do not want to go any further at this point and take up the time of the Landtag. Perhaps colleagues from the other groups will feel the same way. The AfD will be happy to agree to the motion. Thank you very much."

11.12.2018, Bernhard Braun, GrÃijne, Rhineland-Palatinate. "Mr President, ladies and gentlemen. I want to start by saying this because it has not yet been said today and I believe it must be said: The situation in Rhineland-Palatinate is good. The situation in Rhineland-Palatinate is actually very good. I believe that the situation in Rhineland-

Palatinate for the people of Rhineland-Palatinate has never been better. I believe that this is why we, as the government, as the groups that support the government, but also, of course, as the opposition, who make proposals in this budget, can be proud of this state of Rhineland-Palatinate. The people here are doing well, they are safe, they are well equipped, they have good education at their disposal, and they can be satisfied with it[...]"

23.03.2017, Heiko Sippel, SPD, Rhineland-Palatinate. “Madam President, ladies and gentlemen. A well-functioning constitutional state is the guarantor of democracy and freedom, of a high level of security, of the citizens' right to justice and of reliable framework conditions for society and the economy. Day after day, the judiciary in our country does an excellent job of meeting these high standards. For this, all judicial staff in the very different areas of responsibility deserve our thanks and recognition. Especially in times like these, when the rule of law and the validity of the law in many countries of the world are in question, we can be proud of the merits of our liberal democratic legal system[...]"

C.8 Examples of speeches scoring high on hope

13.10.2016, Wolfgang Reinhart, CDU, BaWu. “[...] All these changes - these are the issues of the future that must move us - are about our image of humanity. Do we see change only as an imposition from which we must protect employees, or do we trust in the freedom, talents, motivation, development and responsibility of the individual? Let us give this freedom room. Finally, the working world of the future will make possible what generations have dreamed of: a freer, more self-determined, more interesting and inspiring life. Let us seize this opportunity. Let us say yes to this future. Let us make Baden-WÃijrttemberg a model location for this new work, ladies and gentlemen."

29.01.2015, Ralf Seekatz, CDU, Rhineland-Palatinate. “Madam President, ladies and gentlemen. This year's theme is development policy under the motto "Our world, our dignity, our future". The aim of this EU Development Year 2015 is to inform and involve citizens about cooperation in the field of EU development aid via the individual Member States and - I think this is particularly important - to raise awareness of the benefits of development aid. With good development cooperation, a great deal can be achieved in terms of shaping globalization fairly, preserving the environment, but above all peace, freedom and democracy and human rights. The future of the people in developing countries, and thus also our own future, depends decisively on a good development policy. Promoting democracy and peace can only succeed if we have courage, hunger and disease in these countries under control."

23.05.2018, Heike Scharfenberger, SPD RLP. “Mr President, ladies and gentlemen. Mr President, ladies and gentlemen, the European Union is essentially an idea of human coexistence, of peace and freedom, of responsibility and social justice, of equal opportunities and humanity, of economic cooperation and joint progress. It is a historically unique [...]."

D Additional analyses

Table 10 shows how the emotions we use as dependent variables are correlated in our dataset.

Table 10: Correlations between the level of each emotion.

	Anger	Fear	Disgust	Sadness	Joy	Enthusiasm	Pride	Hope
Anger	1.0000							
Fear	0.6413	1.0000						
Disgust	0.5107	0.4950	1.0000					
Sadness	0.5797	0.6930	0.4701	1.0000				
Joy	-0.0740	-0.0766	-0.0497	-0.0626	1.0000			
Enthusiasm	-0.0376	0.0065	-0.0163	-0.0086	0.1193	1.0000		
Pride	-0.0656	-0.0542	-0.0378	-0.0457	0.5107	0.3109	1.0000	
Hope	-0.0403	0.0093	-0.0007	0.0017	0.1462	0.5564	0.3111	1.0000

Figure 8 shows the distribution of our eight outcome variables.

Figure 8: Distribution of the eight outcome variables used in the main analyses.

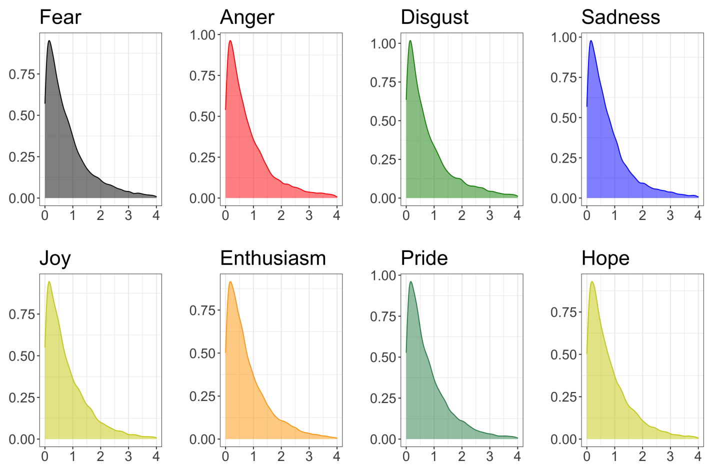


Table 11 shows the results of the main analyses shown in Figure 2 using unstandardized coefficients. For comparison, Table 12 reports the summary statistics of each outcome variable.

As noted in the main text, the analyses shown in Figure 2 make the assumption that all time-variant confounders that could affect the relations of interest are a function of the distance to the election. This assumption would be violated, for example, if there

Table 11: Results of the main analyses shown in in Figure 2 using unstandardized coefficients.

	(1) Anger	(2) Fear	(3) Disgust	(4) Sadness	(5) Neg emotions (PCA)	(6) Joy	(7) Enthusiasm	(8) Pride	(9) Hope	(10) Pos emotions (PCA)
After state election	0.000183	-0.00163	0.000596	-0.00162	-0.103	0.00666	0.00596	0.00443	0.00719	1.154
	(0.00134)	(0.00349)	(0.000734)	(0.00254)	(0.339)	(0.00184)	(0.00154)	(0.00161)	(0.00161)	(0.273)
Constant	0.00307	0.00585	0.000353	0.00532	-0.147	0.00565	0.00376	0.00666	0.00383	-0.645
	(0.00128)	(0.00346)	(0.000703)	(0.00252)	(0.335)	(0.00146)	(0.00132)	(0.00144)	(0.00143)	(0.243)
N	33948	33948	33948	33948	33948	33948	33948	33948	33948	33948

Standard errors in parentheses
All models include actor and month-to-election fixed effects.
Standard errors are clustered by actor.

Table 12: Summary statistics of the outcome variables in the control group.

Variable	Obs	Mean	Std. Dev.	Min	Max
Anger	14698	.003996	.004595	0	.05597
Fear	14698	.00505	.005667	0	.090909
Disgust	14698	.0016	.003246	0	.053097
Sadness	14698	.005154	.005212	0	.060606
Joy	14698	.010358	.007351	0	.105263
Enthusiasm	14698	.007119	.005625	0	.057554
Pride	14698	.008556	.006004	0	.063158
Hope	14698	.008525	.006308	0	.075269

was a longitudinal trend in the level of emotionality used by politicians. For this reason, in Figure 9 we relax this assumption. We replicate the analyses shown in Figure 2 adding controls for the calendar month of each speech. The results remain very similar.

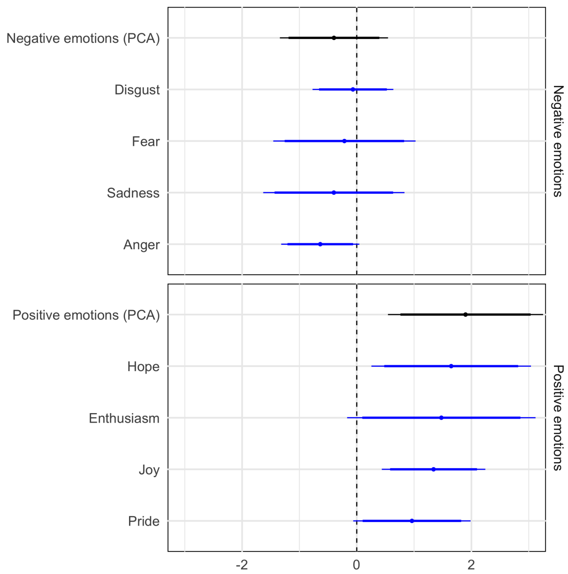
We also replicate the analyses depending on the government status of the MP's party. Concretely, we replicate the analyses for MPs whose party had been in government in the legislature leading up to the state election when AfD MPs first entered parliament; for MPs whose party was in government in the legislature that followed that election; and for MPs whose party was in government in both legislatures. The results, shown in Figure 10 show little heterogeneity across these categories. We then repeat this exercise for MPs of opposition parties. As with before, we replicate the analyses for MPs whose party had been in opposition in the legislature leading up to the state election when AfD MPs first entered parliament; for MPs whose party was in opposition in the legislature that followed that election; and for MPs whose party was in opposition in both legislatures.

Again, as shown in Figure 11, we find little evidence heterogeneity across the three categories. In all these six subsamples, the effects are very similar to the main ones shown in Figure 2. It is true that previous studies have found a difference in the emotional language used by government and opposition (Proksch et al. 2019). However, it should be noted that the analyses of Figure 11 do not focus on these descriptive differences, but rather on the possible heterogeneous effect of radical-right success on MPs of government and opposition parties. Previous research that also examined differences in effects for government and opposition parties found mixed results (Crabtree et al. 2020). Their study focused on economic performance with significant incumbency variation for the effect of inflation. However, when it comes to discussions of unemployment, their study, like ours, found no differential effects based on the government or opposition status of parties.

We also look for how the effects change based on the frequency of radical-right speeches. To do so, we split our sample into two subsamples: one comprising states where AfD politicians have a speech frequency above median; and one where AfD politicians have a speech frequency below median. As shown in Figure 12, the main result is replicated in both subsamples.

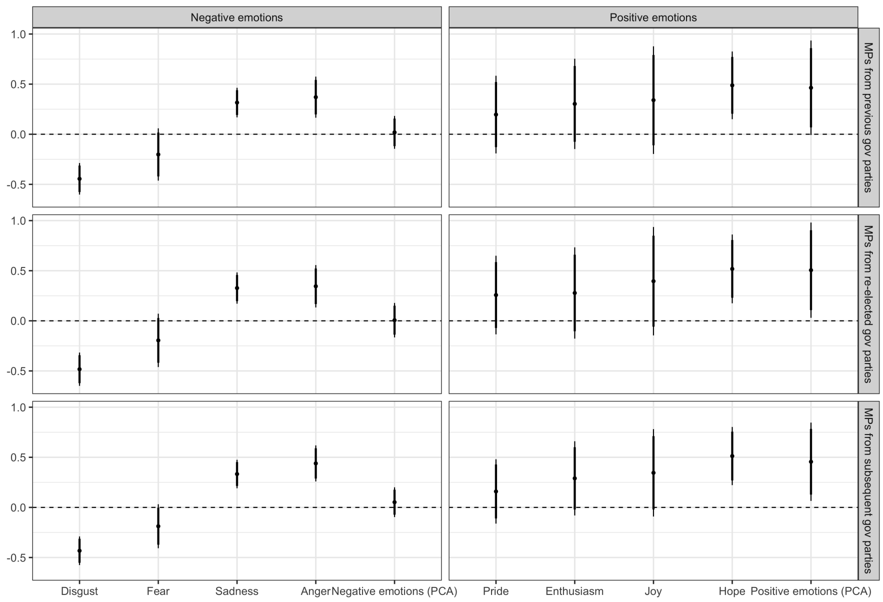
Because the analyses include actors from two legislatures, a potential concern is that not all MPs are re-elected. To make sure changes in the MPs that compose each state legislature are not driving the results, we replicate the analyses shown in Figure 2 using only MPs that were elected in both legislatures: before and after radical right politicians

Figure 9: Replication of the main analyses shown in Figure 2 controlling for calendar month.



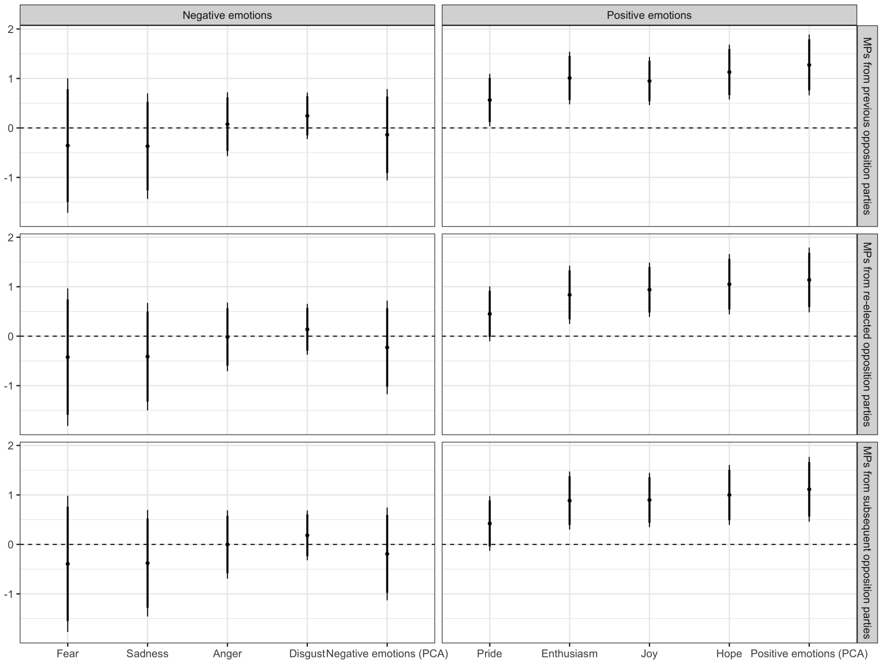
Notes: Thick lines represent 95% Confidence Intervals; thin lines represent 90% Confidence Intervals. All dependent variables are standardized. The models include actor-level and months-since-election fixed effects. Standard errors are clustered by actor.

Figure 10: Heterogeneous treatment effects on the government status of the MP's party.



Notes: Thick lines represent 95% Confidence Intervals; thin lines represent 90% Confidence Intervals. All dependent variables are standardized. The models include actor-level and months-since-election fixed effects. Standard errors are clustered by actor.

Figure 11: Heterogeneous treatment effects on the opposition status of the MP's party.



Notes: Thick lines represent 95% Confidence Intervals; thin lines represent 90% Confidence Intervals. All dependent variables are standardized. The models include actor-level and months-since-election fixed effects. Standard errors are clustered by actor.

entered parliament. These results, shown in Figure 13, are very similar to the main analyses.

In the main analyses shown in Figure 2, we remove speeches of length below 100 words. To make sure this decision is not driving the results, in Figure 14 we replicate the analyses without removing these speeches. The pattern remains similar to the one in Figure 2. The only difference is that the magnitude of the effects becomes smaller, as one should expect given that we include more data with no substantive interest, which should dilute the size of the overall effects.

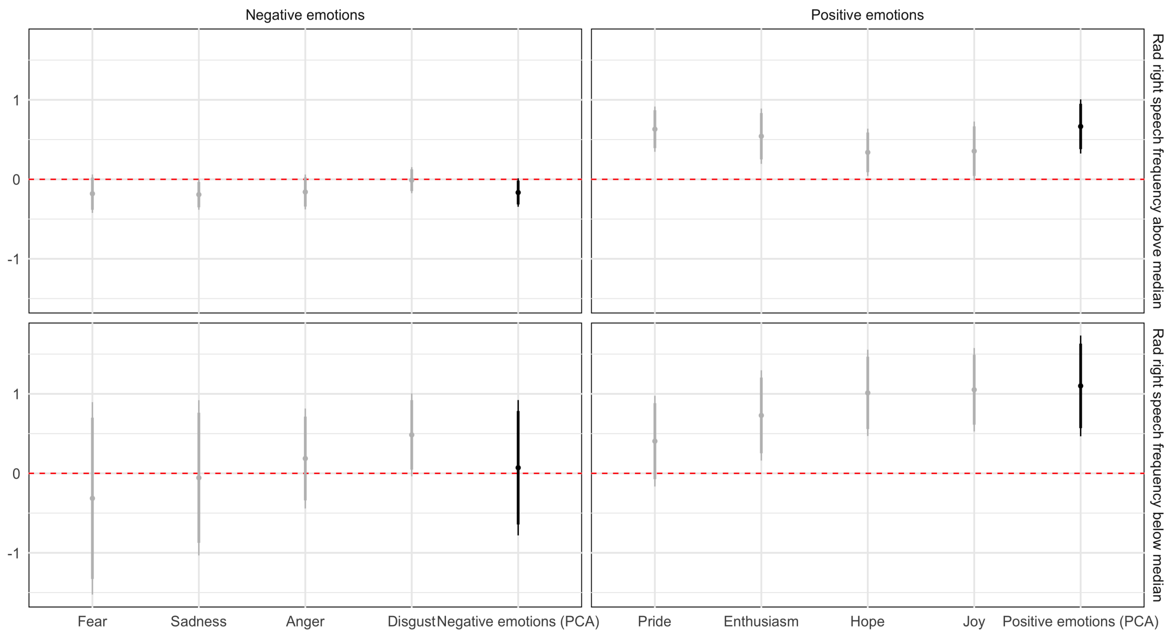
In the main analyses, the data are grouped by month-since-election. To make sure this aggregation is not driving the results, we replicate the analyses on a dataset that is aggregated by calendar date, instead of by month-since-election as in the main analyses shown in Figure 2. As with the main analyses, we include politician and month-since-election fixed effects. As Figure 15 shows, the results remain very similar.

We also replicate the analyses shown in Figure 2 with state fixed effects instead of politician fixed effects. As shown in Figure 16, the results remain very similar.

As shown in Figure 8, the distribution of the outcome variables is rather skewed. For this reason, we also replicate the analyses shown in Figure 2 with logged outcomes. Because many of our observations have a value of 0 in some outcome variable, we use the log of the value of each variable plus 1, so that no zero remains. As shown in Figure 17, the results remain very similar to the main ones, even if the effect on pride is no longer significant at traditional thresholds.

Tables 13 through 16 show the results of the PCA carried out to obtain the summary

Figure 12: Effect conditional on the frequency of speeches by AfD politicians.



Notes: Thick lines represent 95% Confidence Intervals; thin lines represent 90% Confidence Intervals. All dependent variables are standardized. The models include actor-level and months-since-election fixed effects. Standard errors are clustered by actor.

measures used in the analyses throughout the paper.

Table 13: Results of the PCA to obtain a summary measure for negative emotions (variable loadings).

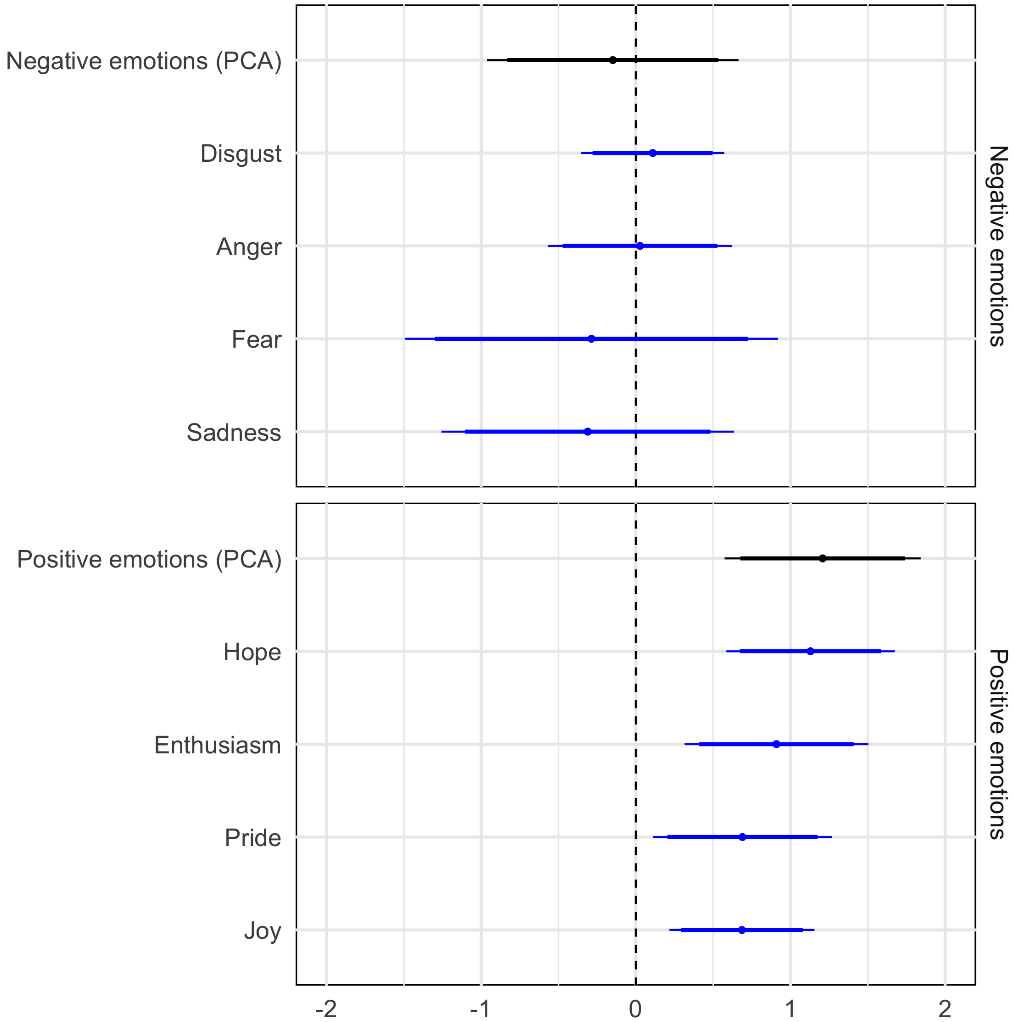
Variable	Comp 1	Comp 2	Comp 3	Comp 4
Anger	0.5077	-0.0607	-0.8217	0.2516
Fear	0.5294	-0.3122	0.1110	-0.7810
Disgust	0.4474	0.8698	0.2076	-0.0150
Sadness	0.5117	-0.3772	0.5190	0.5714

Table 14: Results of the PCA to obtain a summary measure for negative emotions (Eigenvalues).

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp 1	2.70303	2.12018	0.6758	0.6758
Comp 2	0.582852	0.164585	0.1457	0.8215
Comp 3	0.418267	0.122419	0.1046	0.9260
Comp 4	0.295849	—	0.0740	1.0000

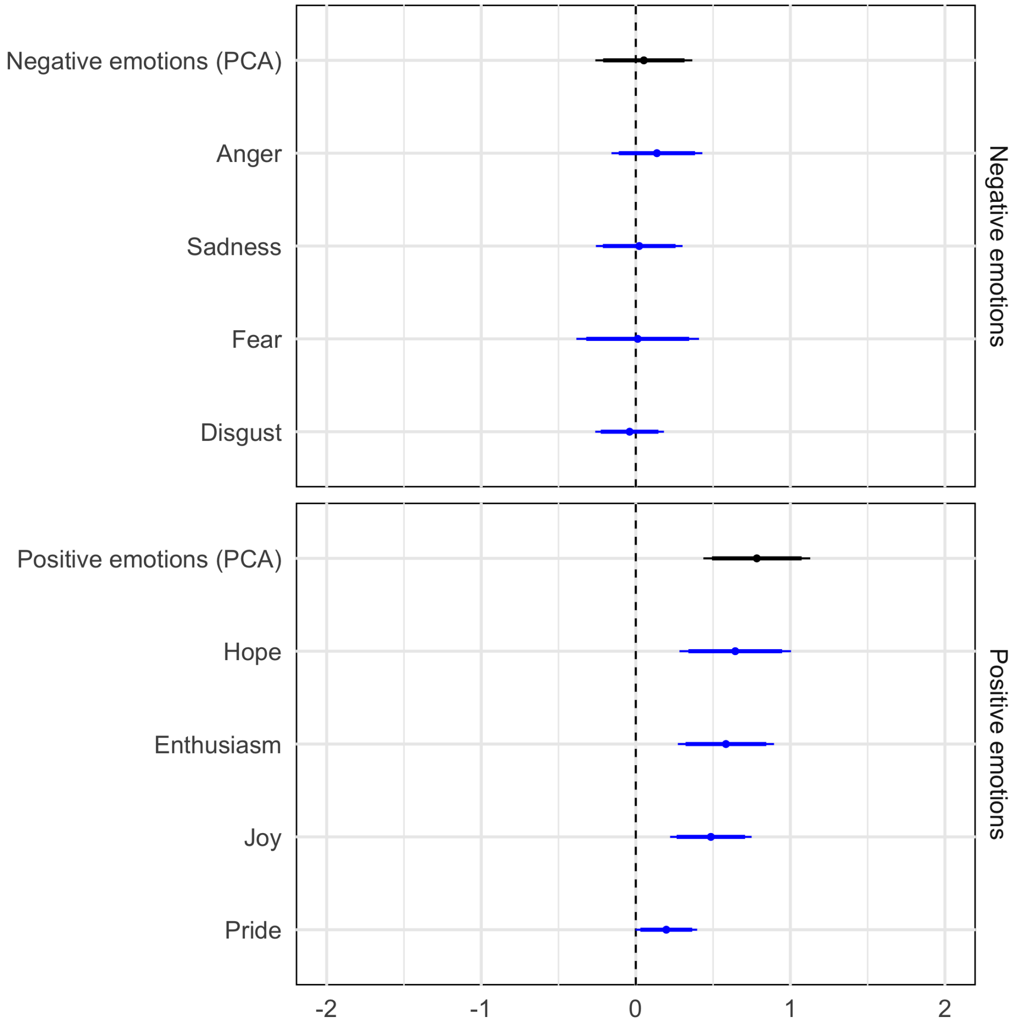
One possible criticism of our analyses is that the effect may simply be that of an election taking place, instead of the effect of AfD politicians entering parliament for the first time. In other words, one might argue that this increase in positive emotions effect

Figure 13: Replication of the main analyses shown in Figure 2 using only MPs that were re-elected.



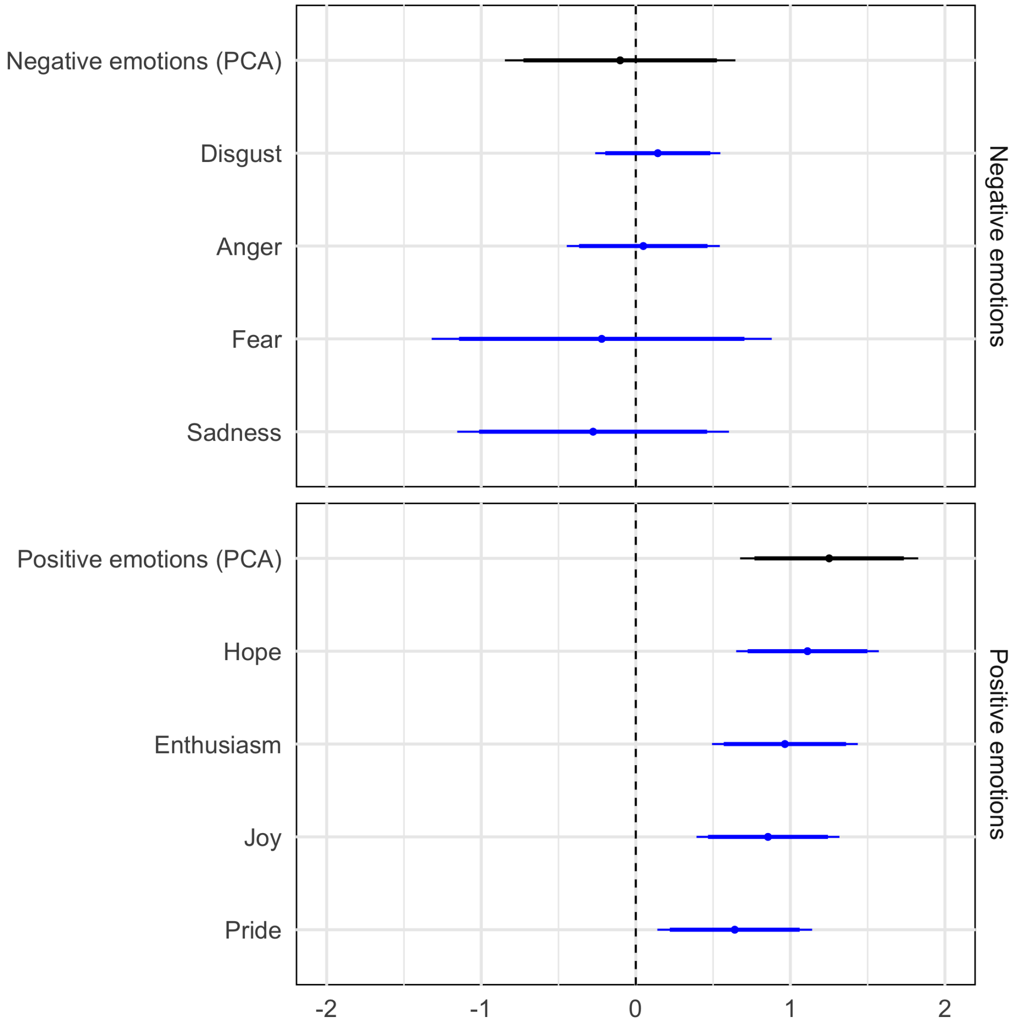
Notes: Thick lines represent 95% Confidence Intervals; thin lines represent 90% Confidence Intervals. All dependent variables are standardized. The models include actor-level and months-since-election fixed effects. Standard errors are clustered by actor.

Figure 14: Replication of the main analyses shown in Figure 2 without excluding speeches with less than 100 words.



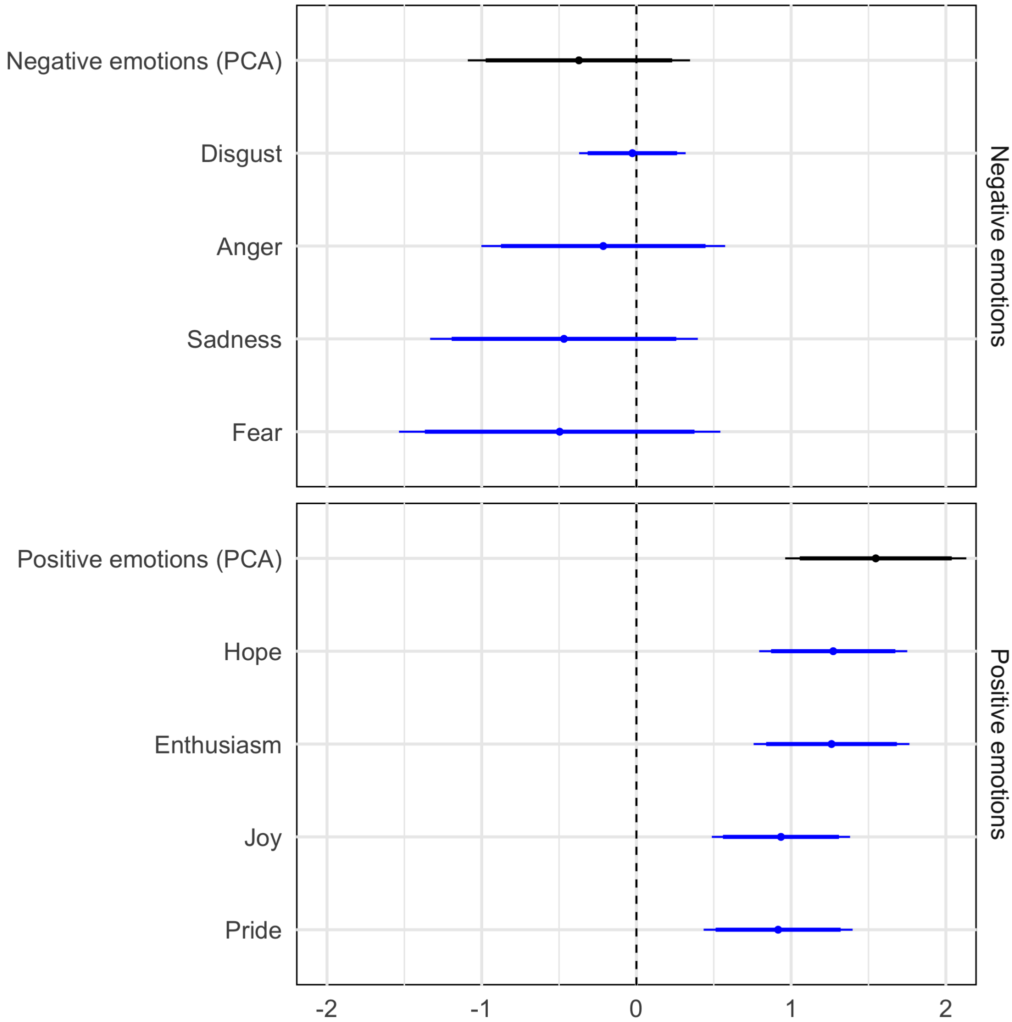
Notes: Thick lines represent 95% Confidence Intervals; thin lines represent 90% Confidence Intervals. All dependent variables are standardized. The models include actor-level and months-since-election fixed effects. Standard errors are clustered by actor.

Figure 15: Replication of the main analyses shown in Figure 2 without aggregating the data monthly.



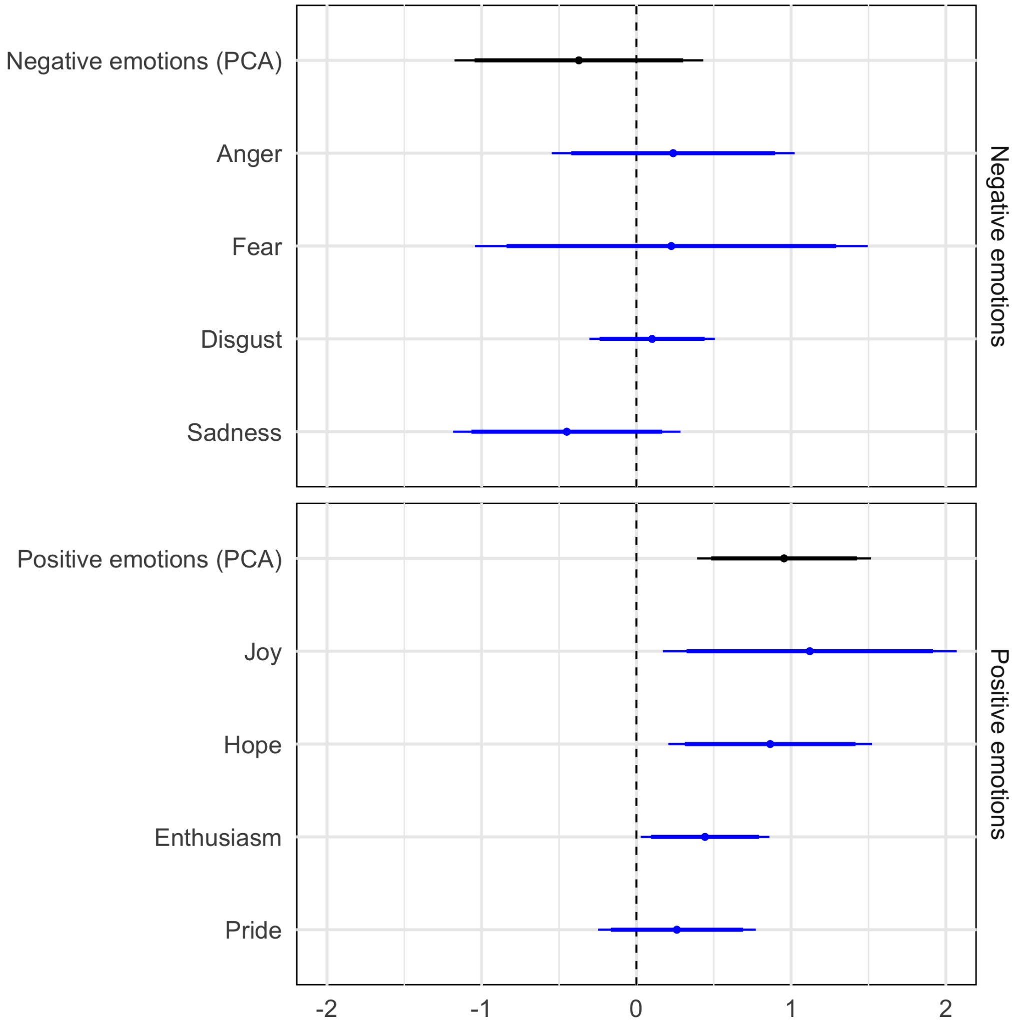
Notes: Thick lines represent 95% Confidence Intervals; thin lines represent 90% Confidence Intervals. All dependent variables are standardized. The models include actor-level and months-since-election fixed effects. Standard errors are clustered by actor.

Figure 16: Replication of the main analyses shown in Figure 2 with state fixed effects instead of politician fixed effects.



Notes: Thick lines represent 95% Confidence Intervals; thin lines represent 90% Confidence Intervals. All dependent variables are standardized. The models include actor-level and months-since-election fixed effects. Standard errors are clustered by actor.

Figure 17: Replication of the main analyses shown in Figure 2 with logged dependent variables.



Notes: Thick lines represent 95% Confidence Intervals; thin lines represent 90% Confidence Intervals. All dependent variables are standardized. The models include actor-level and months-since-election fixed effects. Standard errors are clustered by actor.

Table 15: Results of the PCA to obtain a summary measure for positive emotions(variable loadings).

Variable	Comp 1	Comp 2	Comp 3	Comp 4
Joy	0.4177	0.6496	0.5278	0.3534
Enthusiasm	0.5128	-0.4769	-0.2632	0.6636
Pride	0.5404	0.3840	-0.6365	-0.3941
Hope	0.5201	-0.4506	0.4970	-0.5286

Table 16: Results of the PCA to obtain a summary measure for positive emotions (Eigenvalues).

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp 1	1.98914	0.876214	0.4973	0.4973
Comp 2	1.11293	0.650727	0.2782	0.7755
Comp 3	0.462204	0.0264815	0.1156	0.89110
Comp 4	0.435722	—	0.1089	1.0000

happens after every election, regardless of radical-right politicians entering parliament or not. For this reason, we run a placebo test with the last state election that took place before AfD first entered a state parliament. This election was that of Hessen on September 22 2013. We believe that this election represents a good placebo test because it happened just before the temporal focus of our main analyses. Moreover, AfD did run for this election, but narrowly failed to make it to parliament. The party got 4.1 percent of the vote, narrowly missing the parliamentary threshold of 5 percent.

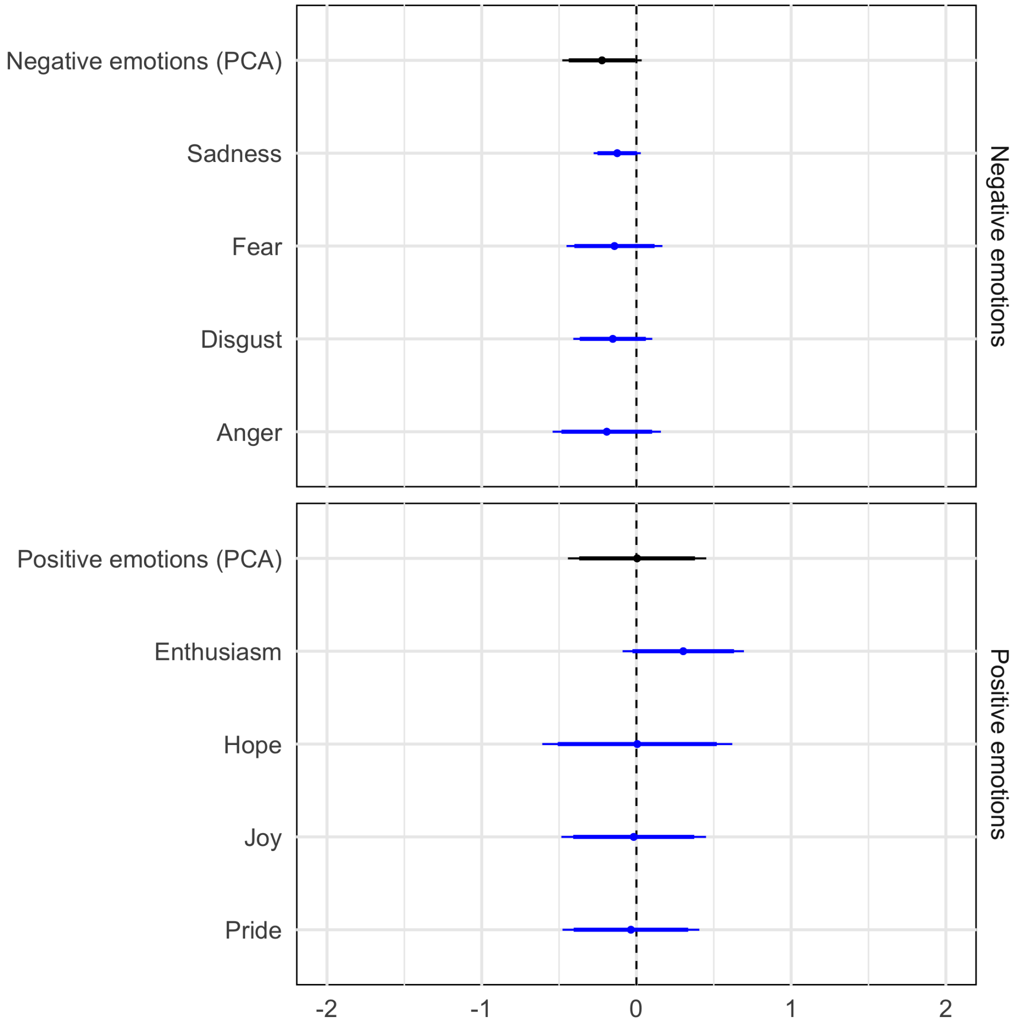
To check whether the same effect can be replicated when drawing upon this election, we collect data for one year prior to the sample used in our main analyses: January to December 2013. Then we replicate our main analyses on this sample.

The results of this exercise are shown in Figure 18. We find no evidence of an effect similar to the one reported in Figure 2, which represents our main analyses.

Another possible criticism of the main analyses shown in Figure 2 is that there may be spillover effects, by which an election in one state affects the behavior of MPs in another state. Previous research has hypothesized that the behavior of local politicians in Germany can have spillover effects (Zittel and Gschwend 2008). Indeed, some studies have found evidence of contagion across regional units (Guinjoan 2014). Should such contagion happen in our case, it could threaten the interpretation of our main findings.

To test for this possibility, we run a placebo test where we replicate the analyses of Figure 2, except that we use as the date of the treatment not the date of the election in the state itself, but the date of elections in other states. To do so, we run through the list of elections included in our sample and, for each election, we remove the state that actually had an election in that date. In some cases, more than one state had an election in the same date. In other cases still, states had election dates that were not exactly the same, but were very close. We remove states that fall under both categories. We end up with twelve dates that we use for the placebo tests: March 13 2016 (election in Baden Wurrtenberg, Rheinland Pfalz and Sachsen Anhalt); October 14 2018 (election in Bavaria); September 18 2016 (election in Berlin); September 14 2014 (election in

Figure 18: Placebo test using the state election in Hessen 2013.



Notes: Thick lines represent 95% Confidence Intervals; thin lines represent 90% Confidence Intervals. All dependent variables are standardized. The models include actor-level and months-since-election fixed effects. Standard errors are clustered by actor.

Brandenburg and Thuringen); May 10 2015 (election in Bremen); February 15 2015 (election in Hamburg); October 28 2018 (election in Hessen); September 4 2016 (election in Mecklenburg-Vorpommern and Saarland); October 15 2015 (election in Niedersachsen); May 14 2017 (election in Nordhein Westfalen); August 31 2014 (election in Sachsen); and May 7 2017 (election in Schleswig-Holstein).

The results of this exercise are shown in Figure 19. We find no clear evidence of a spillover effect. All coefficients are small, most fail to reach statistical significance, and some coefficients of one model go in the opposite direction of those from a different model.

Figure 20 presents a robustness check where we replicate the analyses after sequentially removing one all observations from each state.

As discussed in the text, the analyses shown in Figure 3 include the Greens as a mainstream party. To make sure this choice is not driving the results, we replicate the Figure excluding the Greens. This replication is shown in Figure 21. These results are very similar to the ones shown in Figure 3.

The analyses that compare the effects depending on the ideology of the MP's party, as shown in Figure 4 do not include the left-populist party The Left. To make sure this choice is not driving the results, Figure 22 replicates these analyses without removing these MPs. The effects remain stronger for left-wing MPs than for right-wing ones. The difference, however, is slightly smaller than the one shown in Figure 4—as one would expect given that there is no effect on MPs of the left-populist party The Left.

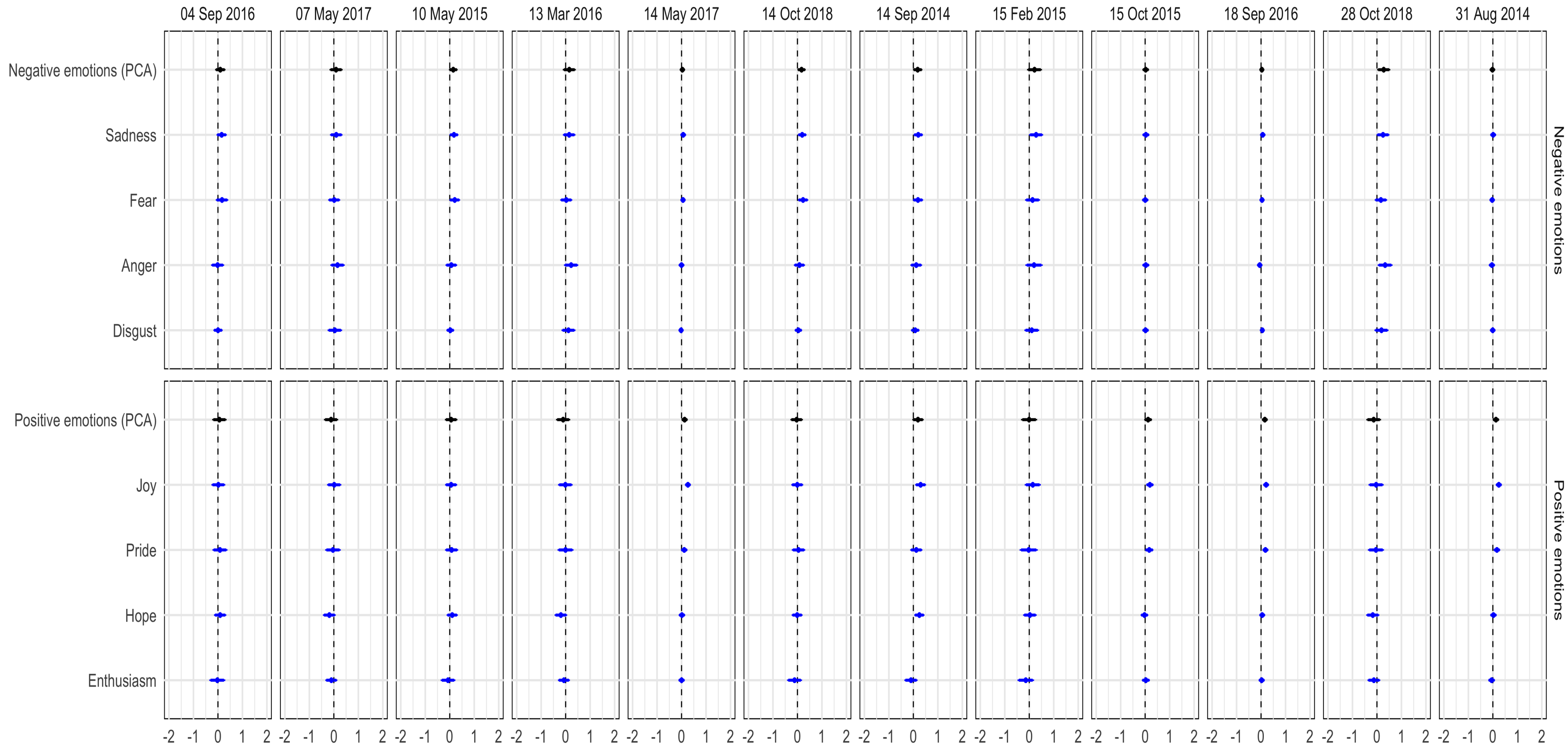
Alternative mechanism: Are the effects driven by a change in the issues that are debated?

Finally, we test for an alternative mechanism. It might be that the change in emotionality of the debate is a consequence of a change in the issues that are debated in state parliaments. If mainstream politicians attach different sets of emotions to different topics, the parliamentary entry of radical-right MPs could change the level of emotionality simply by increasing the frequency of discussion of issues that the remaining politicians are very positive about. Should this be the case, conditioning on how often radical-right politicians discuss a given issue, one should find no effect on the use of positive emotions. Rather, the effect should be driven simply by the fact that radical-right politicians discuss some issues more often than others.

In order to test this alternative mechanism, we need data on the main topic of each speech, and on the relative salience of each topic across time. To do so we rely on topic models, specifically structural topic models (STM) (Roberts, Stewart, and Tingley 2014). STM allows for the possibility of incorporating metadata, defined as additional information about each document. We are thus able to base the estimation of topic proportions on a number of different covariates. Since we assume that topic salience is strongly influenced by the political party of the speakers, we included the party variable as a topical prevalence factor. Furthermore, we assume that topic salience is a function of time, thus, adding the date variable as another topical prevalence factor.

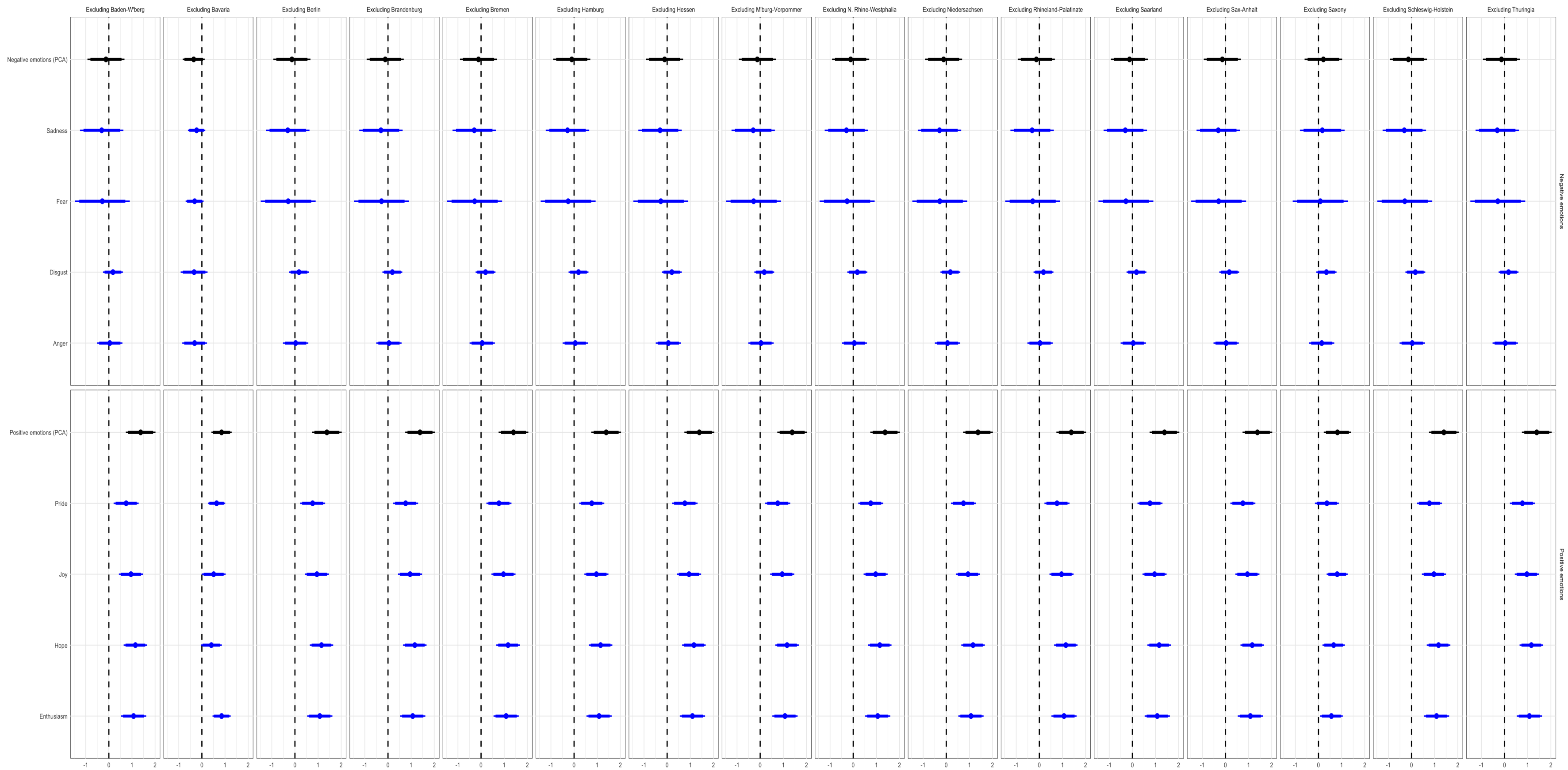
Before running the topic model, it is necessary to pre-process the text corpus. We used the inbuilt *textProcesser* function of the stm R package (Roberts, Stewart, and Tingley 2014). The pre-processing steps included the removal of German stopwords, numbers, and punctuation. All words have been reduced to their root form (stemming) and transformed

Figure 19: Placebo test using the dates of elections in other states.



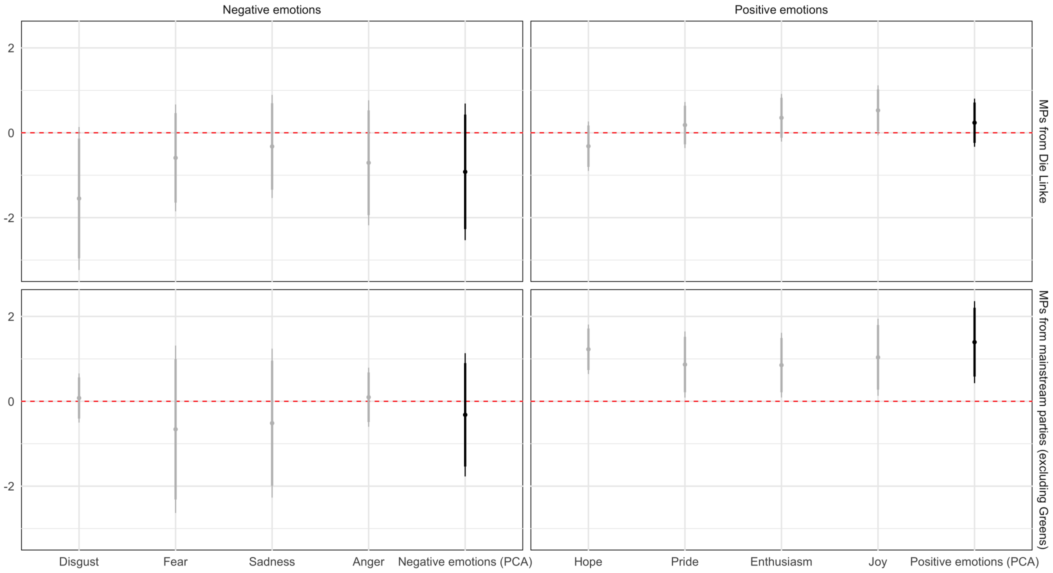
Notes: Thick lines represent 95% Confidence Intervals; thin lines represent 90% Confidence Intervals All dependent variables are standardized. The models include actor-level and months-since-election fixed effects. Standard errors are clustered by actor.

Figure 20: Results after removing one state at a time from the sample.



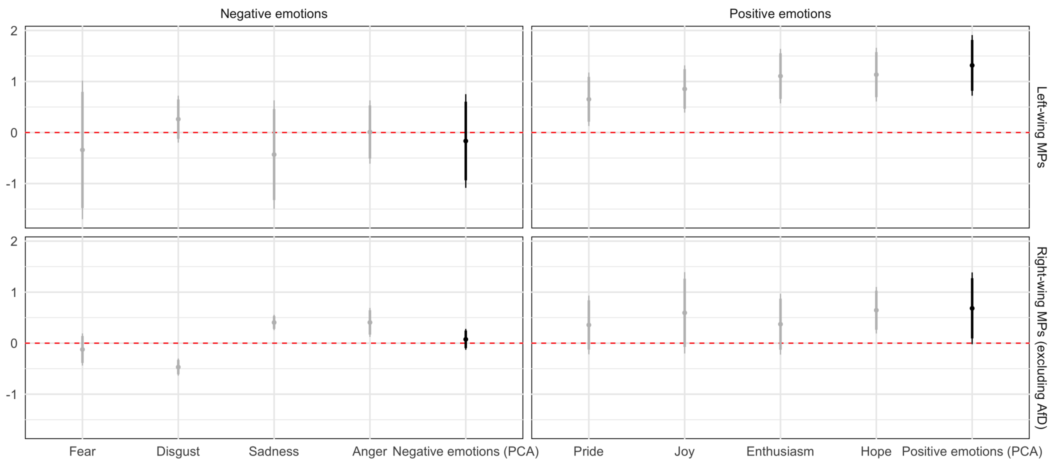
Notes: Thick lines represent 95% Confidence Intervals; thin lines represent 90% Confidence Intervals All dependent variables are standardized. The models include actor-level and months-since-election fixed effects. Standard errors are clustered by actor.

Figure 21: Who is more affected? Effect on radical left party Die Linke and remaining parties (excluding Greens).



Notes: Thick lines represent 95% Confidence Intervals; thin lines represent 90% Confidence Intervals. All dependent variables are standardized. The models include actor-level and months-since-election fixed effects. Standard errors are clustered by actor.

Figure 22: Effect conditional on the ideology of the MPs (without excluding MPs from The Left).



Notes: Thick lines represent 95% Confidence Intervals; thin lines represent 90% Confidence Intervals. All dependent variables are standardized. The models include actor-level and months-since-election fixed effects. Standard errors are clustered by actor.

Table 17: Details on the topic model.

Topic	FREX terms	Labels
1	beamtinnen, beamten, feuerwehr, polizei, polizistinnen	Police + Security
2	eeg, hektar, windkraftanlagen, windenergi, energien, erneuerbar	Alternative Energy + Agriculture + Environment
3	hochschulen, studierende, hochschul, universitÃďt, forschung	Research + University
4	untersuchungsausschus, gutachten, akten, staatsanwaltschaft, behÃűrd	Parliamentary Investigation
5	niedersÃďchsich, wolf, grÃijn, tier, tierschutz, lie	Animal + Animal Protection
6	lkw, bahn, pkw, hafen, maut, diesel	Transportation
7	flÃijchtling, asylbewerb, flÃijchtlingen, abschiebung, afghanistan	Refugees + Asylum
8	schÃijlerinnen, gymnasium, unterricht, schÃijler, schuljahr, gymnasium	School + Education
9	gesetzentwurf, Ãďnderung, beschlussempfehlung, anhÃűrung, Ãďnderungsantrag	Legislation + Law
10	glaub, find, kolleg, ding, diskutieren, ehrlich, versteh	Random words (topic removed)
11	brexit, russland, groÃ§britannien, europa, union, europÃďisch	European Union
12	schulden, ausgaben, schuldenbremse, milliarden, haushalt	Budget
13	staatsregierung, sport, engag, barrierefreiheit, behinderung	Volunteering + Sports + Integration
14	frauen, mÃďnner, ehe, geschlecht, mÃďdchen, gleichstellung	Gender equality
15	mindestlohn, arbeitnehm, wohnungsbau, wohnraum, mieten, wohnungen	Labour market + Housing
16	rundfunk, zdf, magdeburg, mdr, rundfunkÃďnderungsstaatsvertrag	Public Broadcaster + Media
17	digitalisierung, lÃďndlich, digital, wlan, industrie	Rural Areas + Economy
18	kinderarmut, erzieherinnen, kita, jugendhilfe, erzieh	Family + Children
19	datenschutz, videoÃijberwachung, vorratsdatenspeicherung, vollzug, Ãijberwachung	Data Privacy + Crime
20	patienten, pfegekamm, pflegekrÃďft, Ãďrzte, kliniken	Health
21	extremismus, antisemitismus, rassismus, islam, rechtsextremismus, linksextremismus	Extremism, Racism, Islam
22	anfrag, beantwortet, anfragen, drucksach, staatssekretÃďr	Procedural
23	bundesrat, lÃďnder, bundestag, lÃďndern, kompromiss, bund	Federalism

into lowercase letters. Using the prepDocuments function, we also removed very rare terms that appear in less than 50 speeches.

Another key parameter that needs to be determined before estimating the model is k, which represents the number of topics. There are no clear rules and no âĂIJrightâĂİ answer to the question of how many topics researchers should choose (Grimmer and Stewart 2013). We decided to run our topic model with 23 topics, based on the STMâĂŹs *searchK* function results (Roberts, Stewart, and Tingley 2014) and on the manual examination of the different topics. Having less than 23 topics resulted in the blending of substantially different issues into one combined cluster. On the other hand, having more than 23 topics did not result in more fine-grained topics that deal with substantially different issues. Among the 23 topics identified, one topic has been discarded because it consisted mainly of clusters of random word that are used in most speeches irrespective of the issue they draw upon.

We identified 22 topics, which are listed in Table 17 along with their respective FREX terms—words that appear frequently in one topic and less so in others. Among these topics, we assign the one with the highest θ value, representing the probability of a topic given the document, to each speech.[14]

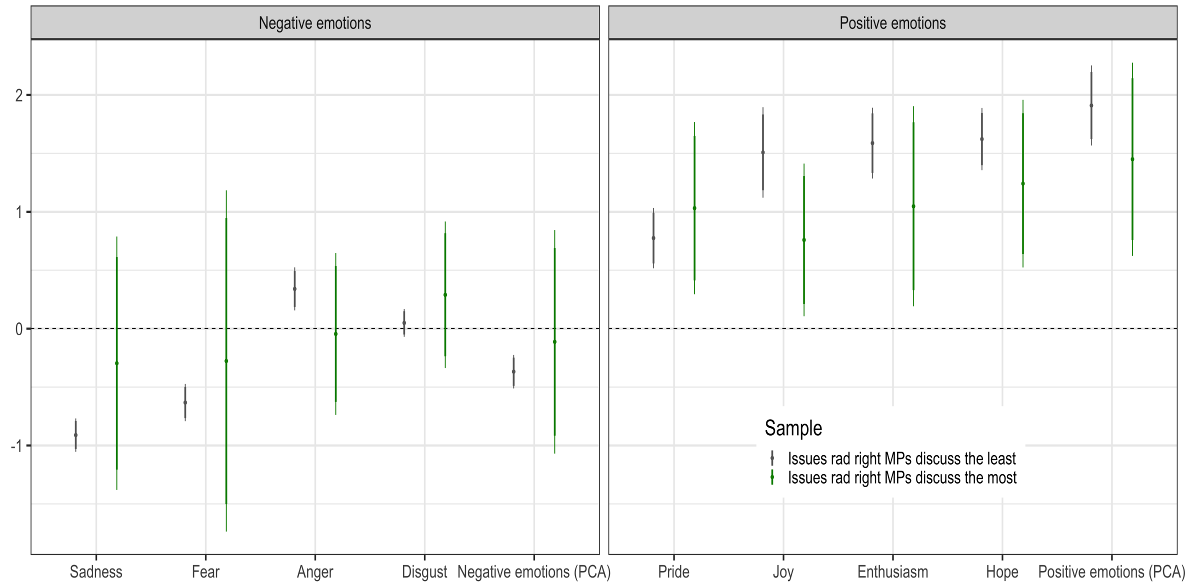
We can now look at whether there are differences in the level of emotionality of MPs as a consequence of radical-right success, conditional on how important the issue is for the radical right. To do so, we start with looking at the proportion of the total number of radical-right speeches that draw upon each specific issue. Then, we split our sample into two subsamples: one subsample including the eleven topics that the radical right discusses most often;[15] and one subsample including the eleven topics that the

[14]Each document receives k topic proportions, which in total add up to a value of one. The highest theta value represents the highest likelihood that a document is related to the respective topic.

[15]These issues are alternative energy, agriculture, and environment; budget; European Union; extremism, racism, and Islam; legislation and law; transportation; labor market and housing; procedural; refugees and asylum; school and education; and police and security.

radical right discusses least often.[16] Then, we replicate the main analyses in these two subsamples.

Figure 23: Effects conditional on how often radical right MPs debate the topic of the speech.



Notes: Thick lines represent 95% Confidence Intervals; thin lines represent 90% Confidence Intervals. All dependent variables are standardized. The models include actor-level and months-since-election fixed effects. Standard errors are clustered by actor.

The analyses, shown in Figure 23, suggest that the results are not being driven by radical-right politicians giving more importance to issues which the remaining politicians talk more positive about. While the effects seem slightly stronger on issues that radical-right politicians discuss least often, we find a clear increase in the use of positive emotions by the remaining politicians in both subsamples. This means that even when politicians discuss issues that are not very salient the radical-right MPs (research and university; parliamentary investigation; animals and animal protection; volunteering, sports, and integration; gender equality; public broadcasting and media; rural areas and economy; family and children; data privacy and crime; health; and federalism), they do so employing significantly more positive emotions than before the radical right was represented in parliament.

[16]These issues are research and university; parliamentary investigation; animals and animal protection; volunteering, sports, and integration; gender equality; public broadcasting and media; rural areas and economy; family and children; data privacy and crime; health; and federalism.

E Speeches that illustrate the arguments made in the section on the mechanism.

This appendix provides examples that support the claims made in the section providing qualitative evidence on the mechanism.

In the first place, we provide three examples of speeches calling out the radical-right rhetoric radical-right rhetoric as norm breaching and unnacceptable. For example, in her speech in November 30th 2016, Sabine WÃűlfe, MP for SPD (Social-Democratic Party) in the state of Baden-WÃijrttemberg referred to negative rhetoric as characteristic of MPs of the AfD, and proceeded to call such rhetoric shocking: "Dear Madam President, ladies and gentlemen. That was a typical AfD speech: full of insults, off-topic and with the usual claims of world conspiracy from social networks. One is so shocked that one is speechless.âĂİ

A second example can be found in the speech by Bernhard Lasotta, MP for the CDU (Christian Democrats) in the state of Baden-WÃijrttemberg, in May 9th 2018 by : "This is something new that we are experiencing here in the Landtag, that debates are being conducted with words and in fearful and aggressive tones, which in no way contribute to solving problems."

Another example comes from a speech by Andreas GlÃijck, MP for the FDP in Baden-WÃijrttemberg in November 23 2016: "If you pop things out like the moratorium issue, that's just pure populism. Either you don't know better, or—worse—you know better and just care about votes. I just say: "ugh" to your political style."

We then provide examples of speeches where MPs build a contrast between themselves or their party and the radical right, acting as enforcers of the norms breached by the radical right. One such example can be found in the speech by Uwe Schwarz, MP for the SPD in Niedersachsen, in December 11 2018: "They [AfD MPs] deliberately stir up discord and envy in the hope of being able to catch voices. You can be sure that you will not succeed. It will find the bitter resistance of all democratic groups and factions in this house. We, the SPD, will be at the forefront."

A second example can be found in the speech by Bjorn Fecker, Green MP in the state of Bremen, in January 25 2017. "I have listened to this [the AfD MPâĂŹs] speech from beginning to end and I can say that I actually went from one fainting spell to the next. I would like to give an example to show why we need to clearly distinguish ourselves from this speech. Mr HÃűcke [from AfD] referred to the handling of the memorial in Berlin, deliberately ambiguously spoke of a "memorial of shame" and in this context he made his demand for a "turnaround in memory policy". He directed his attack against Richard von WeizsÃďcker's speech. According to HÃűcke, he had given a speech against his own people when he spoke of "liberation day" in 1985. Statements such as those made by Mr HÃűcke and the ideology behind them are absolutely unacceptable in our country, and we will stand up against them together; they have no place here. "The second is the speech by Julia Willie Hamburg, MP for the Greens in Niedersachsen, in October 1 2019: "Mr. Wichmann, [your speech] is dishonest, dubious. That's not how we work in this house! Similar to the denunciation platform for teachers, you are only concerned with one thing here: intimidation of legal guardians or intimidation of the people who work every day to make our children self-confident and smart, educated and educated democratic people. We will not let you get away with that, dear colleagues."

We also provide examples of MPs using positive emotions to create this contrast. The speech by Cornelia LÃijddemann, MP for the Green party in Sachsen-Anhalt, in September 27 2018, provides a clear example. She starts her speech with using negative emotions such as sadness and anger to refer to the radical-right rhetoric: "I am sad and saddened, but also angry, by the instrumentalisation of this young person's death by right-wing, nationalist and ethnic movements." Then, the emotional tone of her speech changes as she refers to examples of how the people in her state—and her own party—stand by norms of tolerance and openness, against the radical-right discourse: "The vast majority of people in this state are tolerant and open. [âĂę] That, dear members of parliament, is the overwhelming majority in Saxony-Anhalt. That is the democratic Saxony-Anhalt, which we, as Alliance 90/The Greens, stand up for. And we stand on the side of these people. We Germans can be very proud of the democratic structures we have built up since the Second World War."

Another example can be found in the speech by Henning Homann, MP for the in Sachsen, in February 29 2016. Again, the speech starts with calling out the way the radical-right does politics: "[âĂę] To accuse the parties here in front of us of not doing so [putting forward proposals to effectively tackling the problems of the country] is bigotry. That is simple bigotry, and we will not let that pass. The fact that you end up re-electing a Secretary-General who thinks Mrs Merkel is a Stasi sleeper says more about you than it does about Mrs Merkel. You have finally said goodbye to serious politics, if you have ever pursued serious politics at all. When I listen to your words, I hear a very difficult relativisation. You shift the blame for the attacks in this country onto politics. There is no justification for violence. The argument that Mrs Merkel's refugee policy is to blame for the violence in this country is not valid. That is not acceptable. There is no relativisation of questioning the state's monopoly on the use of force and the dignity of human beings in this country. That must be clear to everyone in this country." Then, the speech immediately moves to a much more positive tone and clearly appeals to pride and hope, to build a contrast with the MP's view of what is needed in the country: "What we need in Saxony is now more than ever a culture of courage. Many thousands are already involved today - from the church, from the student body, many teachers from the cultural sector, many entrepreneurs, people from sport, many people in socio-culture. These many thousands of people are, I think, something like a new citizens' movement in Saxony. They are the decent Saxons. They are our figurehead. That is why these people need our support. It must be the central message of today that we bring these people out of the shadows into the light. These are the people we can be proud of. These are the people we are also happy when they are covered in the media."

Finally, we provide a clear example of politicians using emotional discourse to mobilize voters by using language associated with enthusiasm, as found in the speech by Henning Homann, MP for the SPD in Sachsen, on February 29 2016: "The conclusion that we must draw from this is that we must get the commitment to democracy and openness to the world out of its niche. It must not just be the concern of a few. We must mobilise the silent and perhaps sometimes somewhat hesitant majority in this country. We must mobilise them to stand up for democracy."

A further example can be found in the speeches of Jan Christoph Oetjen, MP for the FDP in Lower Saxony. On March 17, 2016, he said the following: "That is why we in this House, all democrats together, must take great care to distinguish ourselves on the one hand from those who spread such slogans, but on the other hand to deal with their issues or arguments. We must seek to engage with those who argue against foreigners and right-wing populists. That is the point, ladies and gentlemen. That is why it was such a fatal signal in Rhineland-Palatinate that the Prime Minister said: No, if the AfD is taking part in the debate, then I am not coming. That is precisely wrong! Go into the debate, seek a debate, expose it, make arguments! That is the path that we as democrats must take together against the right-wing populists." Here, he clearly tries to mobilize support, encouraging people to engage in debates and discussions.

Similarly, Katrin Budde, MP of the SPD in Saxony-Anhalt, appeals to enthusiasm to mobilize on April 07, 2017: "We must also fight to ensure that the values of our society - tolerance, openness and human rights - are protected from those who want to destroy them. [âĂę]" Then she continues her speech, first self-critical, but then she appeals to hope and calls for support: "[...] and perhaps, ladies and gentlemen, a little self-critical of this part of the plenary - we have been a little too complacent, we have taken many things for granted, and in doing so we have prepared the ground for Trump, Le Pen, the Brexit and the AfD. But the millions who are now taking to the streets for peace, democracy, solidarity and Europe are also giving us courage and hope again. That is why I believe we should support them with all our strength."

F Further details on the qualitative analyses

The qualitative analyses shown in the main text show how often politicians use each type of reaction to radical-right success and rhetoric. In coding these, we also coded the justification given for each of these reactions. Since these are not central to our argument, we detail them in this appendix.

We found that, in almost half the speeches in our random sample, politicians reacted to radical-right success and rhetoric by calling out the norm-breaching nature of its general way of doing politics. Table 18 shows the main justifications that politicians used for it.

Table 18: Main justifications for MPs to call out norm-breaching behavior by radical-right politicians in their general political style.

Justification	Absolute frequency	Proportion of total speeches in sample
Right-wing extremism, discrimination, anti-democratic, agitation, social division, against minorities	80	0.22
Un-constitutional, fraud, crimes	16	0.04
Populism: un-constructive, sensationalism, hypocritical, self-victimisation, fear-mongering, scapegoating	59	0.16
Lying, half-truths, disinformation	12	0.03
Fear-mongering, emotionalization, stirring up resentment	17	0.05

We also found evidence of politicians calling out the norm-breaching behavior of the radical right in their legislative behavior, specifically. Table 19 shows the main ways in which politicians justified doing so.

Table 19: Main justifications for MPs to call out norm-breaching behavior by radical-right politicians in their behavior in parliament.

Justification	Absolute frequency	Proportion of total speeches in sample
Hate speech, insulting or inhuman language, political agitation	27	0.08
Nazi rhetoric, racism, anti-democratic language, far-right rhetoric	14	0.04
Populism: un-constructive, sensationalism, hypocritical, self-victimisation, fear-mongering, scapegoating	50	0.14
Lying, half-truths, disinformation	20	0.06

Finally, we also find many instances of politicians making efforts to distance themselves and their party from the radical-right rhetoric and discourse. Table 20 shows the main ways in which they did so. It should be noted that all of them involve the use of positive emotional discourse to make a contrast with the radical right.

Table 20: Main justifications for MPs to contrast themselves and their party to the radical right.

Justification	Absolute frequency	Proportion of total speeches in sample
Praising the region / people in the region / volunteers in the region	20	0.06
Praising the EU	8	0.02
Emphasising democratic norms / rule of law / contrast between democratic parties and AfD	26	0.07
Call for tolerance and oppeness, anti-racism, anti-fascism	19	0.05
Praising own policies / work / achievements	39	0.11
Praising their own style of debating / doing politics (e.g. constructive, rational, etc.)	46	0.13

It should be noted that some speeches provide no explicit justification for their reaction, while others provide more than one. For this reason, the sum of the number of speeches using one specific justification for a reaction does not necessarily add up to the total number of speeches that include each of the reactions, as shown in Table 2. It should also be noted that we report the proportion that each justification represents of the whole sample of 361 speeches, not just of speeches that include each of reactions that each table refers to.