Online Social Networks and Media 32 (2022) 100240

Contents lists available at ScienceDirect

Online Social Networks and Media

journal homepage: www.journals.elsevier.com/online-social-networks-and-media

Fear-anger contests: Governmental and populist politics of emotion

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ARTICLE INFO

Keywords:
Populism
Fear
Anger
Sentiment analysis
Brexit
Trump

ABSTRACT

This article explores how political actors use the emotions of fear and anger in what we call fear-anger contests. Our theory distinguishes between governmental and populist actors and posits that, in a contest for media attention and the hearts and minds of citizens, populists pursue a politics of anger whereas governmental actors pursue a politics of fear. To evaluate the theory, we examine two episodes of contentious politics: the 2016 Brexit referendum and the election of Donald Trump in the same year. We rely on automated sentiment analysis, using machine learning and emotion dictionaries to examine a dataset of social media posts on Twitter. In the case of Brexit, we find a fear-anger contest between Remain (“Project Fear”) and Leave (“Project Anger”). In the case of the 2016 US presidential election, we find a negativity contest where both parties reinforce each other’s negative emotions.

1. Introduction

Populism is a contentious form of politics where anti-establishment politicians mobilise “the pure people” against “corrupt elites” [1]. Emotions run high when populist politicians and their parties arouse popular sentiment against established elites and their “betrayal” of whatever these parties and politicians present as the interest of the people. It stands to reason, therefore, that anger is the emotion most commonly expressed by populists [2].

Not everyone agrees, however. Some scholars present populism as fuelled primarily by anger [e.g. 3–5]. Pundits like Moore [6] and public intellectuals like Nussbaum [7] have turned this into accepted wisdom. For example, populists are supposed to foment fear of foreigners and exploit anxiety about loss of socioeconomic status [8,9]. Yet, the politics of fear is not a populist prerogative. On the contrary, establishment politicians from either side of the aisle routinely rely on fear to reach their policy objectives [10–12].

We suggest that, in a contest for media attention and the hearts and minds of citizens, populists tend to pursue a politics of anger and establishment politicians a politics of fear. The news media and citizens, at the aggregate level, tend to pivot either towards the establishment politics of fear or towards the populist politics of anger, which may have consequences for political outcomes. In this article, we explore such dances of fear and anger—what we call “fear-anger contests”— not only in theoretical depth but also empirically.

While populists are wont to denigrate their adversaries as the “establishment,” we prefer the term “governmental actors.” Governmentality is a poststructuralist perspective associated with Michel Foucault [13]. It is uncommon to rely on poststructuralism in an empirical study, yet we see good reason to do so in the present case. As we explain below, it has theoretical and analytical advantages to construct populism vs. governmentality as rival “thin-centred ideologies” [14] that transcend other common cleavages such as “left” vs. “right.”

In what follows, we theorize fear-anger contests and evaluate the theory in two prominent cases: the 2016 Brexit referendum and the 2016 election of Donald Trump. In the Brexit campaign, populists stoked anger against domestic elites and foreign forces. As a response, beleaguered establishment actors fomented fear of what might happen if populists were to win the referendum. One may wonder if the same applies in the election of Trump. As we shall see, the presidential campaign and its aftermath were indeed a fear-anger contest but, contrary to what our theory would lead us to expect, Democratic politicians relied more heavily not only on fear but also on anger than the Republicans led by Trump.

The Brexit referendum and election of Trump were periods of intense

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https://doi.org/10.1016/j.osnem.2022.100240
Received 28 June 2022; Received in revised form 15 November 2022; Accepted 17 November 2022
Available online 5 December 2022
2468-6964/

contestation and political crisis. We believe that the politics of negative emotions, like fear and anger, is most intense and observable in such episodes. This is not to rule out that the politics of fear and anger in "normal" times may follow similar patterns. It would be interesting to explore what happens when populists are in office, for example under Trump (2017–2020). However, it remains for future research to establish whether our theory applies more widely.

The article proceeds as follows. We first develop the theory and derive expectations. We then outline our research design, from cases to data and methods. We evaluate our theory and present the results of our analysis. Finally, we discuss our findings and conclude.

2. Theoretical framework

In developing our model of fear-anger contests, we rely on an eclectic mix of theories, ranging from the psycho-evolutionary theory of discrete emotions [15,16] to theories of cognitive appraisal [17,18] and the poststructuralist theory of governmentality [13].

2.1. Psycho-evolutionary and appraisal theory

Plutchik's psycho-evolutionary theory of discrete emotions [15,16] continues to be an important reference point, not least because it aligns with deeply ingrained patterns of human behaviour such as "fight" vs. "flight." According to Plutchik's theory, fear and anger are alternate responses to a real or perceived threat or danger. Fear, on the one hand, inhibits action or mandates escape towards safety ("flight"). Anger, on the other hand, invites disruptive action to remove an obstacle, for example by confronting an enemy seen as having caused the problem or standing in the way of its solution ("fight").

This suggests a negative relationship between levels of fear and anger experienced. Influential versions of appraisal theory, likewise, suggest a negative relationship. According to Smith and Ellsworth [17], angry people have a tendency to blame others and experience agency, whereas fearful people are less likely to blame others and, instead, experience disempowerment. This is because fear and anger are opposite ways of appraising a real or perceived threat or danger as either beyond or within people's control. Fear makes people risk-averse. They might try to escape the problem, put up with it, or submit to those in charge of addressing it. Anger, by contrast, makes people prone to take risks. They may wan to remove the threat or danger, and/or attack its perceived source [18,19].

Accordingly, it made sense for Plutchik [15,16] to class fear and anger as polar emotions. At the same time, fear and anger have important commonalities. Both are negative emotions, that is, people experience them as unpleasant (unlike positive emotions like enthusiasm or joy). Both fearful and angry people usually attribute the origin of their emotion to a source outside themselves. Accordingly, there could also be a mutually reinforcing relationship between fear and anger levels. Survey researchers have found such positive correlations, although Marcus et al. [20] caution that this may be owed to measurement issues.

Should we, therefore, expect a direct or an inverse relation between levels of fear and levels of anger? While we find the arguments of psycho-evolutionary and appraisal theory compelling, this is one of the empirical questions we shall evaluate.

2.2. Fear and anxiety, anger and disgust

In this article, we consider anxiety alongside fear, and disgust alongside anger. Plutchik, whose "wheel of emotions" [16] has influenced the operationalization of emotions not only in countless studies but also in authoritative machine-learning and dictionary-based sentiment analysis, fails to draw any distinction between fear and anxiety, while placing anger and disgust in close vicinity on the wheel of emotions. Shaver et al. [21] understand anxiety as a subcategory of fear, and disgust as a subcategory of anger. Hutcherson and Gross [22] view anger and disgust as distinct members of the same "family." Eadeh and Chang [23] find convergence between anger and disgust, as well as fear and anxiety. We follow these and other authors in considering anxiety alongside fear, and disgust alongside anger.

2.3. Governmentality vs. populism

Populists construe a political division between themselves and other actors, whom they disparage as "elite" or "establishment." The targets of populist attacks mirror this by construing a political division between themselves, as sharing a commonly held platform of respectable orientations, and populists who do not share that platform [24]. This amounts to a division that transcends common cleavages such as "left" vs. "right" or government vs. opposition. Norris and Inglehart [8] present it as a Manichaean struggle between liberal democracy (positive) and authoritarian populism (negative). We find this too normative. At the same time, we do not find it productive to present one side of the cleavage as the mere negation of the other (populism vs. anti-populism; establishment vs. anti-establishment). Instead, we rely on Foucault's poststructuralist theorizing [13] to construct governmentality as a "thin-centred ideology" that rivals populism as an opposing "thin-centred ideology" [14].

Governmentality, as per the term, is a mentality or rationality of governing [13]. It refers to the practice of, and perspective on, governing not as "command and control" but as "conduct of conduct" [25]. To govern human conduct, the "tactic" of governmental actors is to advance policy objectives not so much by imposition but rather through voluntary consent, entrenching disciplinary power and related disciplinary knowledge by shaping subjectivity rather than forcing people to act in ways that go against their will [26,27]. While politicians are not the only class of people involved in the conduct of conduct, there is no doubt that mainstream political actors, whether they find themselves in government or in opposition, commonly aim to influence subjects in order to gain their voluntary consent and participation.

This governmental disposition is precisely what populists rail against when mobilizing "the people" against "the elite." According to Mudde's definition [1], populism is "an ideology that considers society to be ultimately separated into two homogenous and antagonistic groups, 'the pure people' versus 'the corrupt elite'," demanding that politics should express the general will of the people. Mudde also calls populism a "thin-centred ideology," as opposed to more substantive political ideologies with fixed core ideas or normative commitments [14]. We suggest that governmentality is another thin-centred ideology that rivals populism, presenting society as ultimately separated between an enlightened elite and an ignorant people in need of disciplinary guidance.

As thin-centred ideologies, both populism and governmentality are compatible with a variety of ideologies (e.g. left and right, socialist and libertarian, etc.). Neither has a fixed ideological core. Indeed, we may find populist and governmental actors on either side of the aisle. We may also find populist and governmental actors in government and in opposition. Populist politicians may be in government, like Trump during his presidency, but continue to mobilize "the people" against "the elite." Oppositional actors, like most UK Labour politicians during the 2016 Brexit referendum campaign, can be more governmental than the government. Indeed, Prime Minister Cameron had called the referendum to accommodate populists in the governing Conservative party. Thus, "populist" does not equal "oppositional," nor does "governmental" equal "government." While most populists considered in this article are leaning towards the right, not all of them are. For example, there were Labour politicians supporting Leave. In short, the cleavage of governmentality vs. populism is orthogonal to conventional cleavages like left vs. right and government vs. opposition.

2.4. Who foments fear? Who stokes anger?

While the literature on emotions in politics is vast [28–31], our aim is relatively modest: exploring, in relation to populist and governmental actors, who is more prone to fomenting fear and who is more prone to stoking anger, as well as any linkages.

In the mid-2000s, Furedi [10] associated the politics of fear with established elites. This is confirmed by the findings of Albertson and Gadarian [12], who have conducted psychological experiments and other empirical research on the role of anxiety in governing democratic societies. It seems likely that fomenting fear comes natural to governmental actors because, when fear takes hold, people "rally around the flag" and "follow the leader," accepting that "there is no alternative" to the status quo, such as remaining in the EU, or risk-averse choices, such as (re-)electing established leaders. While Nussbaum [7] associates the politics of fear with right-wing populism, Furedi [11] has recently suggested that fear is typically an expression of governmental attitudes about risk, safety, etc.

Populists, on the other hand, mainly rely on anger [2], although they are of course no strangers to fear and other negative emotions [32]. Stoking anger comes natural to populists because populism is about disrupting established elites, and it takes anger to do so. Angry people do not accept that "there is no alternative" and see fearful people as misguided and part of the problem. When populists stir anti-elitist anger [33], this further increases the incentive for governmental actors to foment fear. This is so because fear makes people risk-averse and deferential. Governmental actors benefit from appealing to fear because, when people are fearful, they become more trusting towards authorities [12,34].

While governmental actors may propagate fear for a host of reasons, we believe they do so especially when populists try to mobilize followers based on anti-establishment anger. One way by which governmental actors may try to counter such anger is by claiming that populists are dangerous, discouraging citizens from supporting them and their causes.

2.5. Populist anger? Populist fear?

While anger and fear are not the only negative emotions associated with populism, they are the dominant ones [2]. As mentioned, we see reason to believe that populists rely on anger rather than fear, but the jury is out on whether this is actually the case.

Some associate populism with anger [35]. There is considerable evidence in support of this. A study of panel survey data from Spain finds that "anger, not fear, is the key emotion behind support for populism" [2]. Another survey-based study, on far-right voting in France after the 2015 Paris terrorist attacks, finds that "support is more likely built upon the public's anger rather than fear," and that "anger is associated with voting for the Front National, while fear is associated with voting against the Front National" [36]. A case study on the Tea Party Movement in the USA documents the politics of anger among right-wing Republican activists [37]. More recently, studies have associated Donald Trump with populist anger [38–40].

Others associate populism with fear. This ranges from public intellectuals like Moore [6] and Nussbaum [7] to academic scholars like Wodak [3] and Wojczewski [41]. Unlike those associating Trump with anger, Woodward [4] associates him with fear. The claim that populism thrives on fear has public appeal, and many will take it as a truism that populist politicians like Donald Trump and Nigel Farage, or populist news media like *Fox News* and the *Daily Mail*, foment fear. Yet, most academic work making such claims is qualitative and critical rather than quantitative and empirical. Wodak [3], for example, relies on critical discourse analysis. Wojczewski [41] applies critical securitization theory.

Widman presents a nuanced, middle-of-the-road suggestion. On the one hand he finds that, in normal times, populists tend to push negative emotions, including anger and fear [42]. During the COVID-19 public health emergency, on the other hand, Widman finds that other political actors have propagated negative emotions more than populists [43].

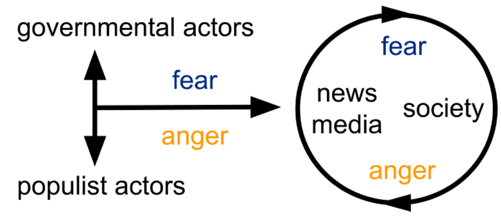

Fig. 1. Model of fear-anger contests.

2.6. Fear-anger contests

When governmental actors face intense contestation from populist actors, this leads to a battle for the hearts and minds of citizens. In that battle, populist actors express anger, hoping to garner media attention and societal support for themselves and their anti-establishment policies. Against this, governmental actors express fear, hoping to restore media attention and societal support for themselves and their policies. Governmental and populist actors thus compete for attention and support by fomenting fear and stoking anger, respectively.

In our model (Fig. 1), we consider three entities: *political actors, news media*, and *society*. For political actors, we distinguish between governmental and populist politicians as well as their platforms, such as political parties and referendum campaigns. We expect politicians to send fear and anger signals depending on circumstances and strategic rationale. In news media and society, however, we expect to find an inverse relationship between fear and anger because fear and anger are polar emotions. As explained in Section 2.1, we derive this expectation from psycho-evolutionary and appraisal theory, which suggest that it is difficult, although perhaps not impossible, for an individual to be fearful and angry at the same time. We expect to find the same at the aggregate level. When news media and society are more receptive to fear, we expect them to be less receptive to anger, and vice versa. We therefore expect levels of fear to rise when levels of anger subside, and vice versa

2.7. Theoretical expectations

A fear-anger contest is a constellation of contentious politics where political actors outdo each other in expressing fear and anger to rally support. News media and society are likely to amplify these negative emotions, although perhaps in uneven and selective ways. To explore whether the dynamics expected are actually at work, we formulate three hypotheses.

Hypothesis 1. Governmental actors use more fear-based rhetoric than populist actors.

This is in line with theoretical expectations, as outlined above. We do not expect to find, on the contrary, that populists use more fear-based rhetoric than governmental actors.

Hypothesis 2. Populist actors use more anger-based rhetoric than governmental actors.

This is also in line with theoretical expectations, as outlined above. As we will see, we find it confirmed in the case of Brexit but not in the case of Trump.

Hypothesis 3. There is a negative correlation between fear and anger in media and society.

Based on theoretical considerations, we expect this correlation to be negative. We find strong evidence for this in the case of Brexit, and weak evidence in the case of Trump.

Table 1
Overview of the number of tweets by case.

	UK Case (09/2015 - 06/2017)		US Case (02/2015 - 03/2017)	
	Remain	*Leave*	*Democrats*	*Republicans*
Political Actors	18,316 tweets	15,292 tweets	41,422 tweets	41,184 tweets
News Media	87,428 tweets		615,049 tweets	
Society	38,477 tweets		43,785 tweets	

leading the effort, but even key Republicans depicted a Trump presidency as a nightmare scenario [46]. In their presidential campaigns, both major parties relied heavily on negative emotions to get their messages across and gain votes [47].

Both cases are episodes of intense political contestation where we are likely to observe a fear-anger contest. They are comparable in that they fall into a similar timespan and involve a political establishment fighting back against a populist onslaught. In either case, the politics of anger called forth the politics of fear, and vice versa. Populist actors stoked anger against "Eurocrats in Brussels," "Washington swamp" and so on. Governmental actors fomented fear of nightmare scenarios like "Brexodus" and "Trumpism." While these similarities enable comparison, there is also interesting variation between the cases. While the UK case is about a popular referendum, the US case is about a national election. It will be useful, in future studies, to explore fear-anger contests in other contexts and periods.

Table 2
Brexit referendum: political actors.

		Lawmakers and electoral candidates		Senior politicians and related accounts		Political operatives and campaigns		Local and municipal politicians	
		Remain	*Leave*	*Remain*	*Leave*	*Remain*	*Leave*	*Remain*	*Leave*
N =		132	94	35	20	17	16	12	5
Party	Conservative Party	21	77	12	15	0	3	0	3
	Labour Party	95	8	8	0	8	0	9	1
	Liberal Democrats	5	0	4	0	1	0	2	0
	Green Party	1	0	0	0	3	0	1	0
	SNP	6	0	2	1	0	0	0	0
	Brexit Party	0	3	0	0	0	0	0	0
	UKIP	0	2	0	0	0	2	0	1
	DUP	0	3	0	0	0	0	0	0
	Other	4	1	9	4	5	10	0	0
Level	England	100	79	1	1	6	2	12	4
	Wales	13	4	2	0	1	0	0	1
	Scotland	11	1	2	1	0	0	0	0
	Northern Ireland	0	4	1	0	0	0	0	0
	UK (national)	2	1	20	14	9	12	0	0
	EU	6	4	5	0	0	0	0	0
	Other	0	1	4	4	1	2	0	0

3. Research design

To evaluate Hypotheses 1 and 2, we create lists of governmental and populist actors; measure the emotional content of their tweets; and investigate which political actors express more fear or anger. To evaluate Hypothesis 3, we create time series that allow us to correlate fear and anger levels, and establish whether these correlations are positive or negative; we rely on significance testing to ensure the validity of findings reported.

3.1. Cases

While we have collected data for the entire period from 1 January 2015 to 31 December 2020, we focus on two cases for a plausibility probe: the Brexit referendum (UK, September 2015 – June 2017) and the election of Donald Trump (USA, February 2015 – March 2017).[2]

Brexit referendum. On 23 June 2016, populist anger carried the day in the UK Brexit referendum. During the campaign, pundits like Forsyth [44] observed that London-based elites were relying on "Project Fear." Their playbook resembled the 2014 Scottish independence referendum, when London had warned Scottish voters against the dire consequences of separating from the United Kingdom ("Be careful what you wish for"). The strategy had worked back then, but backfired in 2016. Too many voters saw "Project Fear" as a ploy and gave free rein to their anti-EU and anti-elitist anger [45].

Election of Trump. On 8 November 2016, Donald Trump became the 45th US president on a tide of populist rage. Joe Walsh, a Republican politician, had tweeted in May: "Embrace the anger. Be the populism. We've had it with elites. Take that message forward Trump. It's your only hope." Understandably, therefore, during the presidential campaign, governmental actors fomented fear about what would happen if Trump's populism were to carry the day. Democrats were

3.2. Data

Social media have played an important role in the context of Brexit and Trump [48], as well as other political events in the same year, including the presidential election in Austria [49]. Given that political elites are a significant presence on Twitter [50] and that Twitter users are on average politically more attentive than, say, Facebook users [51, 52], we focus on tweets, which we accede through the Twitter API. We distinguish between three entities (political actors; news media; society) and generate Twitter datasets for each. For political actors, we distinguish between tweets from "Remainers" and Democrats on the one hand, and tweets from "Leavers" and Republicans on the other. See Table 1 for an overview.

3.2.1. Political actors

Before we can gather data for political actors, we face an obstacle: retrieving tweets on political or electoral campaigns presupposes suitable lists of user names, but no such lists are available. It would have been easy to rely on lists of MPs, but this would not have been suitable. In the UK and in the US, key players like Nigel Farage and Donald Trump would have been missing from such lists. Especially in the case of the EU referendum, both Labour and the Conservative Party had their share of governmental and populist actors.

[2] Tweet IDs for our social media data are available (see data statement).

Table 3
Election of Trump: political actors.

		Lawmakers and electoral candidates		Senior politicians and related accounts		Political operatives and campaigns		Local and municipal politicians	
		Democrats	*Republicans*	*Democrats*	*Republicans*	*Democrats*	*Republicans*	*Democrats*	*Republicans*
***N*=**		159	150	63	76	29	40	7	2
Level	Federal	135	140	13	26	27	37	0	0
	State	24	10	50	50	2	3	0	0
	Sub-state	0	0	0	0	0	0	7	2

To overcome this obstacle, we have developed an inductive data generating mechanism. To begin with, we select a couple of key players for each campaign or party.[3] We download all their tweets falling into the observation period and containing relevant keywords ("election," "Trump," "Clinton," "Brexit"). We retrieve all user names mentioned in the tweets of the key players, and download all their tweets (using the same keywords). We rely on user bios to filter the tweets for political actors associated with either party or campaign. For validation, we manually check all user names. First, we check if the filter has correctly identified political actors. Second, we check if the procedure has assigned them to the right ideological placement (Leave vs. Remain; Republicans vs Democrats).

Brexit referendum. Of the 196 political accounts for Remain, most are members of parliament and electoral candidates, mainly from Labour but also from the Conservative Party. There is a significant number of accounts held by campaigns and political operatives, senior politicians and related organizations, and local politicians. Similarly, of the 135 political accounts for Brexit, most are MPs and electoral candidates, mainly from the Conservative Party but also from Labour, Democratic Unionist Party, Brexit Party, and UK Independence Party. There is a significant number of accounts held by senior politicians, as well as political operatives and campaigns, and local politicians (Table 2).

Election of Trump. Of the 258 Democratic accounts, many are senior politicians including Washington elites and state governors, although most are Representatives and Senators, as well as electoral candidates, at federal and state level. There is also a significant number of political operators and campaigns including political action committees (PACs), as well as a few local and municipal politicians. Similarly, of the 268 Republican accounts, many are senior politicians, although most are parliamentarians and electoral candidates. There are also political operatives and campaigns, as well as local politicians (Table 3).

Having checked all individual accounts, we can confirm that, in both cases, key politicians known to us from the press, as well as other important political actors with influential Twitter accounts are all included. Given their limited relevance for our research, we find it acceptable that parliamentarians with less influential Twitter accounts and/or not mentioned in the campaign accounts and/or by the presidential candidates are not included. Instead, other key players relevant to the research—especially senior politicians and political operatives—are included (for further detail, see Supporting Information, Figs. A5–6). In short, our dataset selects on salience rather than exploring a predefined list of parliamentarians.

Fortunately, we completed our database before the massive Twitter ban in 2021, when many political users, including former President Donald Trump, lost their accounts.

3.2.2. News media and society

For tweets from news media, we follow the same procedure as outlined in the last section. We again rely on user bios to filter the tweets; but, instead of filtering the tweets for political actors, we filter them for journalists and other media accounts. We conduct manual validation to ensure that the user names collected actually represent news media.

For tweets from society, we download random tweets that contain our keywords and meet parameters of interest (time period, geographic location[4] etc.). We rely on the same keywords as for political actors and news media. To avoid overlap, we remove any user names contained in our lists of political actors and news media. The procedure relies on random selection, so we may safely assume that it is representative and sufficient for our analytical purposes, despite the rather limited number of tweets from society (Table 1).

3.3. Methods

For the sentiment analysis, we rely on a machine learning approach (neural networks, [53]) and three emotion dictionaries (WordNet Affect; LIWC; NRC) for robustness checks. For significance testing, we rely on statistical tests with a significance level of 5%.

3.3.1. Sentiment analysis

Sentiment analysis is a familiar yet challenging task of natural language processing measuring the polarity, often along a positive-negative axis, of opinionated pieces of text. In this study, we do not focus on a positive-negative axis but on emotion classification, which considers multiple, possibly continuous or discrete axes indicating the salience of different emotions. We consider two approaches to emotion classification: one machine learning approach [53] and three dictionary-based approaches [54–57]

For the machine learning approach, we rely on a pre-trained character-level recurrent neural network provided by Colnerič and Demšar [53]. "Pre-trained" refers to the model's internal parameters, which are not initialized randomly but have already been tuned to a particular dataset and task. "Recurrent" [58] refers to the model's internal architecture, which features a recursive module that can process input sequences of variable length.

To begin with, Colnerič and Demšar retrieve a large set of 73 million tweets. They filter the set for tweets containing emotional hashtags [56]. Relying primarily on Plutchik's wheel of emotions [16], they map the hashtags to different emotions. Thereby, they obtain ground-truth emotion labels for training a neural network. In comparison with several baseline models, Colnerič and Demšar obtain superior results with their model. Therefore, the model has found wide adaptation in the analysis of emotional tweets [e.g. 59–61].[5]

We do not fine-tune the pre-trained model any further. Instead, we simply apply it to predict emotion labels on the unlabelled tweets from our dataset. This is justified because our Twitter data correspond in type and style with the data Colnerič and Demšar [53] have used for training their model. As an input, we feed the model full-text tweets. The model

[3] UK case, Leave: @LeaveEUOfficial (campaign account); @vote_leave (campaign account). UK case, Remain: @remain_eu (campaign account); @Remain_Labour (campaign account). US case, Republicans: @GOP (party account); @realDonaldTrump (personal account). US case, Democrats: @TheDemocrats (party account); @HilaryClinton (2016 Democratic candidate).

[4] We identify the coordinates of the centre of the country on Google maps and apply a radius approximating the size of the country. To obtain the radius, we take the distance from the centre of the country to the country's furthest land border (excluding Alaska, in the United States).

[5] As per our research design, we do not have access to labelled, ground truth data. Therefore, we can evaluate the performance of our Machine Learning classifier only qualitatively, which we extensively do in the sections below, and by relying on emotion dictionaries for robustness checks.

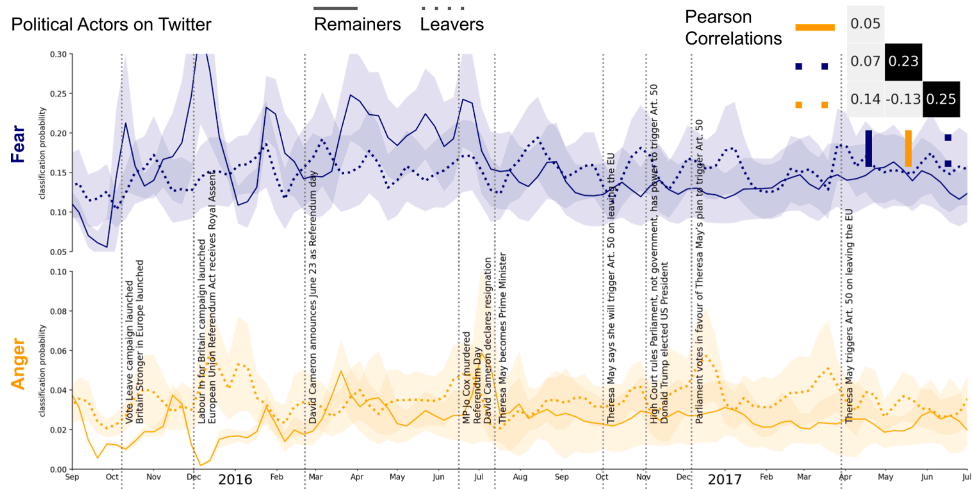

Fig. 2. Brexit referendum: time series and Pearson correlations for fear and anger expressed by political actors, measured with NeuralNet; significant correlations highlighted in black. Timeline of events derived from Walker [67].

itself handles all pre-processing, such as tokenization, and splits text into all its case-sensitive characters, including whitespaces and punctuations. As a "character-level" model, it considers a small "vocabulary" of 128 ASCII characters instead of a large vocabulary of words. This is advantageous for the data at hand: tweets contain many unknown (out-of-vocabulary) "words" from internet slang, different language expressions, and abbreviations [62].

While machine learning approaches outperform dictionary-based approaches in terms of classification accuracy, dictionary-based approaches have the advantage of being more transparent, easier to validate, and easier to communicate to non-technical audiences. Therefore, both approaches continue to compete. Dictionary-based approaches represent mappings between words and some kind of sentiment or emotion value. Given a text to be classified, the words contained in it are matched against the words in the dictionary. The words' corresponding sentiment values can be aggregated and used in various ways. Following Kiritchenko et al. [63] and Bostan and Klinger [64], we add all sentiment values per text and normalize by text length. Specifically, we rely on the following dictionaries: WordNet Affect [55], Linguistic Inquiry and Word Count [LIWC; 56], and the NRC Word-Emotion Association Lexicon [57]. Combined, the dictionaries cover all emotions of interest to our study: not only the polar opposites of fear and anger as defined by Plutchik [16] but also the closely related emotions of anxiety and disgust, adding further robustness.

Before applying the sentiment dictionaries, we pre-process the full-text tweets. First, we tokenize the text using the NLTK tokenizer [65]. Second, we lemmatize the tokens using the NLTK lemmatizer [65]. Regarding the automated pre-processing for application of the neural network, please refer to our explanation in the penultimate paragraph.

3.3.2. Significance testing

We validate our empirical findings by conducting statistical tests with a significance level of 5% throughout. For Hypotheses 1 and 2, we rely on t-tests. For Hypothesis 3, we rely on the population significance test for Pearson correlations [66].

Two-sided, unequal variances, independent t-test. To evaluate Hypotheses 1 and 2, we compute for each actor group and emotion classifier the distribution of all values measured for each emotion. Next, we rely on the *t*-test to determine if there is a significant difference in the mean emotion values between actor groups (governmental vs populist). Since the sample sets under comparison are of different size and variance, we resort to the unequal variance, independent *t*-test (Welch's *t*-test). When we observe p-values smaller than 5%, we reject the null hypothesis and conclude that both distributions feature unequal mean emotion values.

Pearson correlation with population significance test. To test Hypothesis 3, we use the Pearson correlation, which measures the bivariate directionality and strength of linear relationships between paired, continuous and Gaussian-distributed variables. The population correlation coefficient p provides a quantification of statistical significance and can be interpreted as the probability of observing a correlation despite the data being uncorrelated and the null hypothesis being true. We require p-values smaller than 5%. When reporting Pearson correlations between time series, we consider their first derivatives. This has the advantage of taking into account only differences relative to the overall trend.

3.3.3. Limitations

Before moving to the analysis section, we acknowledge three limitations. First, we rely on a machine learning classifier [53] that has been trained on tweets posted between 2008 and 2015, and apply it to political tweets from 2015 to 2017. Since the original training set tweets were not specifically focused on political topics, there is a risk of semantic change and domain shift. This prompts us to conduct robustness checks comparing the machine learning classifier against dictionary-based approaches. Second, we do not control for possible confounders. Given the complex interactions and forces driving fear-anger contests, we limit ourselves to studying correlations between the observed variables. Third, the Pearson correlation does not capture the possibility of time-lagged correlations. Instead, it measures how two continuous signals co-vary over time. Yet, applying the Pearson correlation to detrended, stationary time series is a common practice and has the benefit of high interpretability. Measuring time-lagged correlations requires more complex tools and metrics. One example is the Vector Autoregression (VAR) that we use for carrying out Granger causality tests. We report the results of these tests in the Supporting Information (Part G).

4. Analysis and results

In what follows, we rely on data visualization to present our analysis and results regarding the Brexit referendum in the UK and the election of Trump for US President. As we shall see, both cases present fear-anger contests, although the UK case conforms with theoretical expectations more closely than the US case. For each case, we begin with time series showing the strength of fear and anger expressed by governmental and populist political actors over time. In the top right, we show the strength of correlations between time series, highlighting significant results in

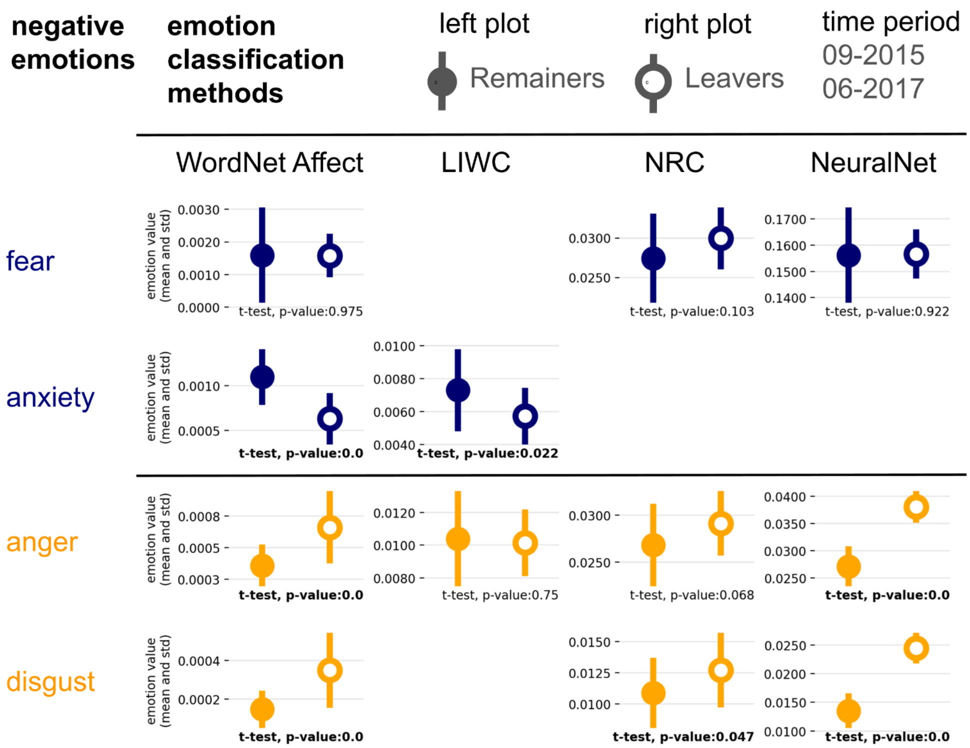

Fig. 3. Brexit referendum: fear/anxiety and anger/disgust in tweets from political actors as measured by different emotion classification methods. Significant results ($p < 5\%$) set in bold.

black (based on the population test). Next, we compare average levels of fear and anger among governmental and populist politicians, deploying t-tests and setting significant results in bold. Finally, we present time series for media and society, again highlighting significant results. In addition to evaluating Hypotheses 1–3, we offer case-specific observations and contemplate key events and turning points.

4.1. Brexit referendum

In the case of the 2016 UK Brexit referendum, we find a fear-anger contest between “Project Fear” (Remain) and “Project Anger” (Leave) that is closely aligned with theoretical expectations as expressed in Hypothesis 1, Hypothesis 2, and Hypothesis 3.

As a first approximation, consider Fig. 2. The figure refers to fear and anger expressed by governmental (Remain) and populist (Leave) political actors, starting one month before the launch of the referendum and ending a few months after the Prime Minister had triggered Article 50 on leaving the EU. During the referendum campaign, politicians in the Remain camp used more fear-based rhetoric than politicians in the Leave camp most of the time, supporting Hypothesis 1. Conversely, politicians in the Leave camp used more anger-based rhetoric than politicians in the Remain camp most of the time, supporting Hypothesis 2. The correlations between the usage of emotions in either campaign are insignificant or weak, suggesting that both sides followed their own emotional rationale (this does not concern Hypothesis 3, where we postulate negative correlations for news media and society).

In December 2015, at the launch of the “Labour In for Britain” campaign, there was a conspicuous spike of fear expressed by Remain politicians. Around the same time, Leave politicians expressed strong anger. From then on, Remain politicians continued to express more fear and Leave politicians more anger. Despite fluctuations, this was particularly the case in the run-up to referendum day (23 June 2016). Perhaps unsurprisingly, we observe a bout of anger among Remain politicians when their camp had lost.

After that, politicians in the Leave camp again expressed more anger than those in the Remain camp. Despite their victory in the referendum, it seems, Leave politicians were both angry and fearful: angry that establishment politicians were “dragging their heels” on Brexit,[6] and fearful of opportunistic elites failing to “deliver” Brexit. Accordingly, from July 2016, fear levels tended to be higher for politicians in the Leave than in the Remain camp, whereas during the referendum campaign the opposite had been the case.

We find a weak (0.23) but significant correlation between anger expressed by politicians in the Remain camp and fear expressed by politicians in the Leave camp. This suggests a contest where the response to anger on one side was fear on the other, and vice versa. We also find a weak (0.25) but significant correlation between fear and anger expressed by Leave politicians. These two correlations are significant but far from strong (unlike what we shall see in the US case), so we should probably take them with a grain of salt.

Overall, Fig. 2 lends support to Hypotheses 1 and 2. Especially during the run-up to the EU referendum on 23 June 2016, fear levels were higher among Remainers and anger levels among Leavers. The situation became less clear-cut after the referendum date when, arguably, Leavers were nervous that politicians might fail to deliver. Yet, we report results as found rather than succumbing to the temptation of redefining observation periods.

Fig. 3 further scrutinizes Hypotheses 1 and 2 by adding dictionary-based tools of emotion classification for robustness checks. We present results for all emotion classifiers deployed to compare average levels of discrete emotions in tweets from governmental and populist politicians. The classifiers measure fear and anxiety on the one hand, and anger and disgust on the other. We rely on the *t*-test for statistical significance testing.

For anxiety and disgust, theoretical expectations are confirmed

[6] There was only one time when anger was greater for Remain politicians for a month or more: around July 2016, when Theresa May was succeeding David Cameron as Prime Minister.

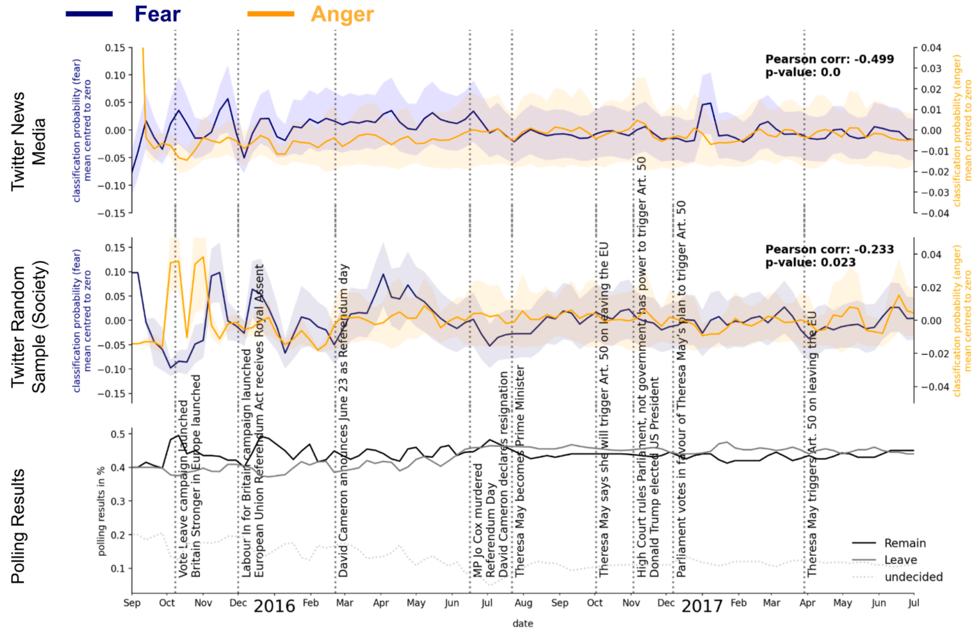

Fig. 4. Brexit referendum: time series and Pearson correlations for fear and anger expressed in news media and society, measured with NeuralNet; significant results ($p < 5\%$) set in bold.

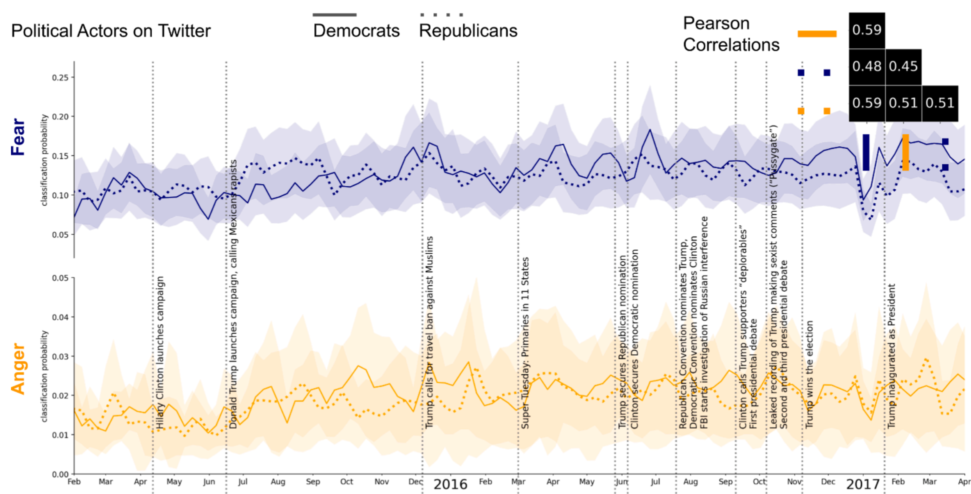

Fig. 5. Election of Trump: time series and Pearson correlations for fear and anger expressed by political actors, measured with NeuralNet; significant correlations highlighted in black. Timeline of events derived from Stracqualursi [69].

throughout the board. Governmental actors express more anxiety than populists, whereas populists express more disgust than governmental actors. While results for fear are not significant, results for anger confirm theoretical expectations for neural networks and WordNet Affect. Not a single significant result in Fig. 3 points in a direction opposite to Hypotheses 1 and 2.

As previously discussed, pundits have described the Remain Campaign as "Project Fear" and scholars have found some evidence in support [45]. Our findings confirm that the characterization of Remain as "Project Fear" was not without merit. Remain was dominated by anxiety, which may count as a subcategory of fear, whereas Leave was dominated by anger or even disgust, which may count as a subcategory of anger [21–23].

Fig. 4, finally, supports Hypothesis 3. For "Twitter News Media" and "Twitter Random Sample," we find a significant negative correlation between fear and anger. In either case, this indicates an inverse relationship whereby fear levels decline as anger levels rise, and vice versa. Before measuring correlations between time series, we take first derivatives to detrend the data and ensure stationarity. However, it is insightful to also consider trends within the time series. In the society sample, we see a crescendo of fear from February to April 2016, followed by a decline in May and June. This decline of fear in the final two months of the campaign may have contributed to the defeat of Remain, as it may have emboldened Brexit-leaning voters to vent their anger and vote Leave. For further background, we report results from opinion polls in the bottom panel (cf. Supporting Information, Part C).

4.2. Election of Trump

If the UK Brexit referendum presents a contest between "Project Fear" and "Project Anger" that closely aligns with theoretical expectations, then the election of Donald Trump presents another type of fear-anger contest that departs from some aspects of the model while conforming with others. To begin with, in Fig. 5, we find strong and

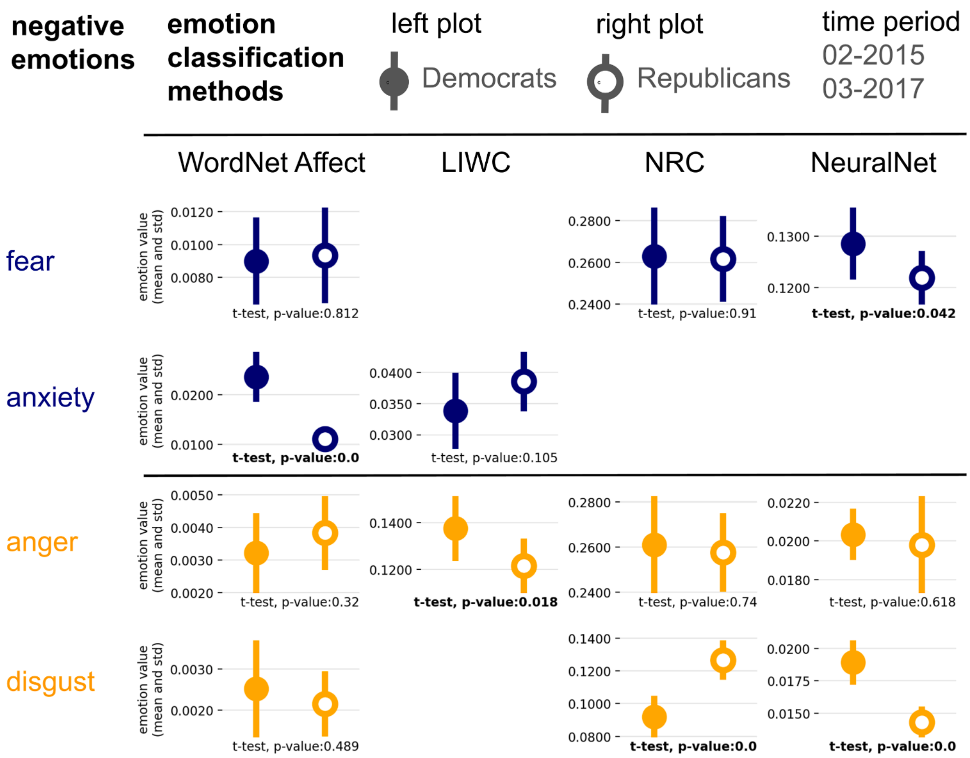

Fig. 6. Election of Trump: fear/anxiety and anger/disgust in tweets from political actors as measured by different emotion classification methods. Significant results ($p < 5\%$) set in bold.

significant positive correlations (0.45–0.59) between all of the time series. Even more than in the case of Brexit, this indicates a mutually reinforcing "negativity contest" in the way political actors express emotions, fuelling the notoriously acrimonious political culture of the United States with its elevated levels of political incivility on Twitter [68].

Further, as Fig. 5 shows, there was a neck-and-neck race between Democratic and Republican politicians when it came to expressing fear and anger, with either side sometimes in the lead. Among Democrats, anger levels shot up when Trump called for a travel ban against Muslims. Among Republicans, anger levels reached a peak when Clinton called Trump supporters "deplorables." Also among Republicans, fear levels reached an all-time low at the time of Trump's inauguration. Among Democrats, fear levels bounced back immediately afterwards and remained higher than among Republicans.

Fig. 6 presents a closer examination, adding dictionary-based tools of emotion classification for robustness and relying on t-tests for significance. In line with Hypothesis 1, Democrats rather than Republicans

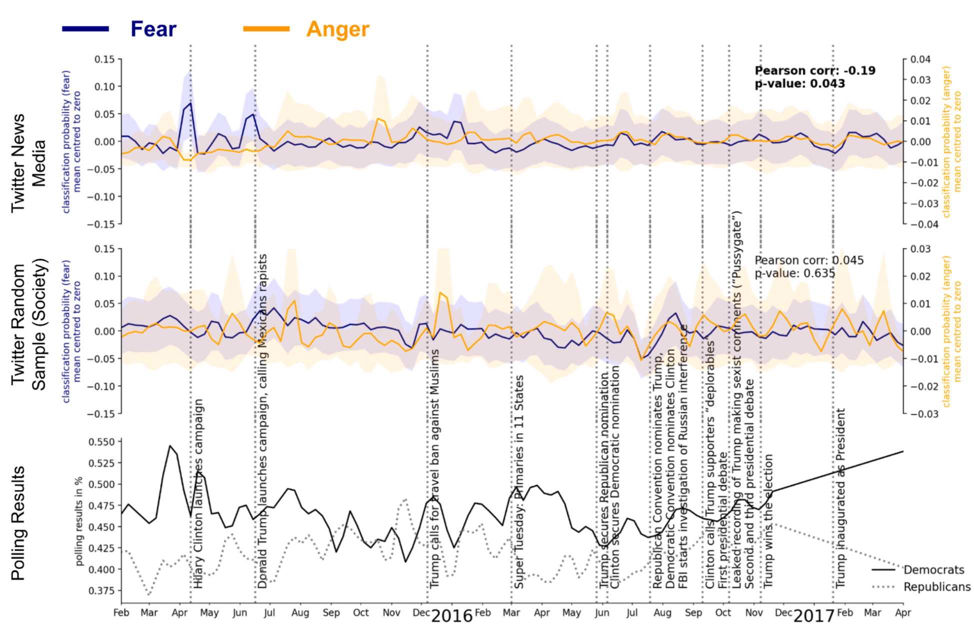

Fig. 7. Election of Trump: time series and Pearson correlations for fear and anger expressed in news media and society, measured with NeuralNet; significant results ($p < 5\%$) set in bold.

Table 4
Brexit referendum: sample of tweets high in fear/anger.

Date	Username	Entity (Affiliation)	Text	Anger (NeuralNet)	Fear (NeuralNet)	Dominant emotion
02/06/2016	AlokSharma_RDG	Politician (Remain)	@David_Cameron making case for #StrongerIn with passion: #Brexit would put #British jobs and exports at risk #skynews	0.00144	0.97059	Fear
14/06/2016	angelaeagle	Politician (Remain)	Brexit fears wipe £100bn off FTSE 100 in four days - business live	0.00024	0.99413	Fear
10/06/2016	labourlewis	Politician (Remain)	Irritation and anger' may lead to Brexit, says influential psychologist	0.97208	0.01978	Anger
17/08/2016	remain_eu	Politician (Remain)	the referendum angered people into a decision that they will end up regretting if it is to be carried out	0.97919	0.00516	Anger
04/03/2016	LeaveEUOfficial	Politician (Leave)	Project fear in overdrive as No10 is accused of recruiting France to scare us over Calais migrants	0.000000	0.99934	Fear
15/06/2016	SteveBakerHW	Politician (Leave)	WATCH: @DCBMEP does some myth-busting in "Taking the Fear out of Brexit"	0.00004	0.99437	Fear
03/06/2016	BorisJohnson	Politician (Leave)	Steelworkers should vote for Brexit. Mad that we can't cut steel energy costs because of EU rules (1/2) #VoteLeave #InOrOut	0.50725	0.10326	Anger
07/11/2016	Nigel_Farage	Politician (Leave)	If the establishment betray the British people on Brexit then we will see huge political anger.	0.9831	0.00545	Anger
23/12/2015	[Journalist]	Media	As Ed Miliband warned:"Threat of #Brexit is biggest hamper to UK growth in 2016. Many investors terrified UK may leave Europe"-@BloombergTV	0.00017	0.99579	Fear
29/03/2016	RT_com	Media	Project Fear: RT unravels the latest scare tactics to keep Britain in the EU #Brexit	0.00006	0.99757	Fear
05/06/2016	Telegraph	Media	British voters succumbing to 'impulse, irritation and anger' - and it may lead to Brexit ...	0.97595	0.01265	Anger
23/06/2016	business	Media	There's an anger that connects #Brexit, Trump and Le Pen	0.96528	0.00513	Anger
15/05/2016	private citizen	Society	Fears of #Brexit will add £115 to the average family holiday this year as the pound continues to lose value against the Euro. It is down 9%.	0.00035	0.98608	Fear
18/06/2016	private citizen	Society	The case to Remain is too weak to sell. Remainers are well aware of this, hence Project Fear. Vote #Brexit @UKIP	0.00103	0.99113	Fear
23/06/2016	private citizen	Society	LEAVE LEAVE LEAVE LEAVE LEAVE #Brexit	0.71437	0.01342	Anger
24/06/2016	private citizen	Society	'I don't understand the anger': how the Europeans in London see Brexit	0.99534	0.00074	Anger

lead on fear (NeuralNet) and anxiety (Wordnet Affect). Contrary to Hypothesis 2, however, Democrats also lead on anger (LIWC) and disgust (NeuralNet). While it is true that Republicans lead on Disgust (NRC), this is only one count and we have greater confidence in NeuralNet as the more advanced approach.

Whilst, in the case of Brexit, it seems fair to equate Remain with "Project Fear" and Leave with "Project Anger," in the case of Trump's election it seems that there was a general negativity contest, led by Democrats rather than Republicans. This is of course not to deny that there was mutual reinforcement between Democratic and Republican negativity, as suggested by the strong and significant positive correlations found in Fig. 5.

Fig. 7 shows (rather modest) support for Hypothesis 3 regarding an inverse correlation between fear and anger levels in news media and society. The fear-anger correlation for "News Media" is negative but weak (−0.19) and barely significant (0.04). The correlation for the society sample ("Twitter Random Sample") is even weaker and not at all significant. We concede that this seems insufficient for deriving any reliable inference.

5. Discussion

We have studied fear-anger contests between populists and their opponents in terms of a cleavage between governmentality and populism. We believe that, when it comes to episodes like the Brexit referendum or the election of Trump, among others, constructing a cleavage of populism vs. governmentality is more productive than trying to stick to conventional cleavages like "left" vs. "right" or government vs. opposition. On the one hand, constructing a cleavage of populism vs. governmentality is more informative than presenting one side as the mere negation of the other (establishment vs. anti-establishment, populism vs. anti-populism). On the other hand, it is more analytically neutral than extolling one side whilst denouncing the other (e.g. "liberal democracy" vs. "authoritarian populism," [8]).

As we have shown in the theory section, our analysis of fear-anger contests between populist and governmental actors is informed by, and can contribute to, existing scholarship on the use of emotions in political communication involving populists and their opponents. It speaks to ongoing discussions as to whether populists are prone to fear, anger, or both, and expands these discussions by asking the same questions about governmental actors.

Given the exploratory nature of our research, we have resorted to theory-driven case-study analysis. Such analysis is by necessity observational and aims to evaluate whether and to what extent our theory holds in a specified set of empirical instances. Causal claims may become possible at a later stage but, for now, we have relied on descriptive inference. To evaluate our theory, we have systematically collected a dataset of social media posts on Twitter. We then relied on automated sentiment analysis to examine this dataset, using a machine-learning approach as a benchmark and three dictionary-based approaches for robustness checks. We have applied significance tests to ensure the validity of findings.

We have conducted manual validation as an additional check. To evaluate whether and to what extent our findings are meaningful in light of our theory and hypotheses, we have read and analysed large numbers of tweets from our database. Given space constraints, we present only a small selection, retaining the user names of public figures and entities but suppressing them for all others (for larger samples, see Supporting Information, Part B).

In the case of the Brexit referendum (Table 4), we find that fearful tweets from Remain politicians tend to be of the kind expected, expressing fear about Brexit. Angry tweets from Remain politicians in some cases show anger about Brexit, but in other cases deplore populist anger as the reason for Brexit (that is, do not express anger but discuss

Table 5
Election of Trump: sample of tweets high in fear/anger.

Date	Username	Entity (Affiliation)	Anger coefficient	Fear coefficient	Dominant emotion	Text
09/12/2015	donnabrazile	Politician (Democrat)	0.00004	0.98251	Fear	The GOP likes to motivate its base by stoking their fears. But when they flirt with nominating a guy like Donald Trump, it stokes OUR fears!
11/10/2016	JBPritzker	Politician (Democrat)	0.00041	0.98937	Fear	Trump is now directly quoting Russian disinformation. This is frightening.
22/07/2016	HillaryClinton	Politician (Democrat)	0.90417	0.00754	Anger	Every time @realDonaldTrump makes you mad chip in$1.
01/10/2016	TheDemocrats	Politician (Democrat)	0.8329	0.01682	Anger	If Trump made you angry this week, there's only one thing to do about it.
22/03/2016	realDonaldTrump	Politician (Republican)	0.00053	0.98411	Fear	Obama, and all others, have been so weak, and so politically correct, that terror groups are forming and getting stronger! Shame.
10/06/2016	WalshFreedom	Politician (Republican)	0.00011	0.9822	Fear	Both political Parties are afraid of Trump. That's good. Very good. They should be scared. People are waking up. The jig is up. At last.
24/07/2015	SenFrankNiceley	Politician (Republican)	0.85607	0.00421	Anger	#Trump has become the vehicle for average folks to vent anger to DC. #IfYouDontFixItWeWill #MakeDCListen #GOP2016
04/05/2016	WalshFreedom	Politician (Republican)	0.78232	0.01174	Anger	Embrace the anger. Be the populism. We've had it w elites. We've had it w politicians.Take that message forward Trump. It's your only hope
19/07/2016	NYDailyNews	Media	0.00017	0.99676	Fear	Fear itself: Donald Trump's apocalypse now
25/08/2016	DailyCaller	Media	0.00009	0.99702	Fear	Trump Responds To Clinton By Accusing Her Of 'Race-Baiting' And 'Fear-Mongering'
27/02/2016	dallasnews	Media	0.9916	0.00087	Anger	@realDonaldTrump didn't invent populist anger, but plays it like an instrument
12/11/2016	Slate	Media	0.99268	0.00251	Anger	You don't need to fit your Trump anxiety into five stages of grief. Rage all you want
06/01/2016	private citizen	Society	0.00007	0.99402	Fear	I smell fear and panic in @HillaryClinton camp!
01/11/2016	private citizen	Society	0.00142	0.98616	Fear	@ The Purge: Election Year at halloween Horror Nights
11/03/2016	private citizen	Society	0.98026	0.00554	Anger	Trump: "People at my rallies have anger... They love their country." Right! Muslims have anger bc US gov is bombing their counties.
27/01/2017	private citizen	Society	0.97294	0.00336	Anger	How would I describe @realDonaldTrump..... #Racist, #Fascist, #Xenophobic, #Nazi, etc..!!

other people's anger). Similarly, tweets from Leave politicians that score high on fear often do not express fear as such but rather dismiss Remain as "Project Fear," whereas angry tweets from Leave politicians tend to embrace populist anger in the way envisaged by our theory. Remain- and Leave-leaning news media act as amplifiers of these emotions in the ways expected by our theory. The same applies to fear and anger expressed in tweets by private citizens.

In the case of Trump's election (Table 5), Democratic politicians often express fear of Trump, while also repeating the meme that populists stoke fear. At the same time, Democratic politicians express a considerable amount of anger about Trump and his movement. As with the Leave campaign, Republican politicians embrace populist anger while mocking the fear of the other side, more often than expressing fear as such. Liberal media express a considerable degree of anger and amplify anxiety about Trump and his "politics of fear," whereas media supporting Trump embrace populist anger while trying to expose liberal *angst*. Citizens leaning towards Clinton or Trump express similar sentiments in colloquial terms.[7]

Evidently, this clashes with conventional wisdom about Trump and associates uniquely fomenting fear and stoking anger [5]. Trump certainly did that, too; but it is worth remembering that, for all his rage about illegal immigration and "Washington swamp," Trump often framed ideas positively: "Make America Great Again;" "I will build a beautiful wall;" "We will win, win, win." For every tweet Trump sent in anger or fomenting fear (he did send many of these), it seems that his opponents sent more angry and fearful tweets than his supporters. In depicting Trump's populism as something to be feared and loathed, Trump's opponents may have ended up expressing more fear and loathing than his supporters [47] (incidentally, it seems that this may even have had mental health implications for liberal Americans after the Democratic defeat [70,71]).

Close inspection of our time series suggests that results would have been stronger with each case ending at or shortly after the election or referendum date. Nevertheless, we have retained our observation periods as originally set, since ex-post-facto adjustments would be bad practice. We have collected data not just for our observation periods but for the entire period from 1 January 2015 to 31 December 2020, enabling further research to explore the wider applicability of our theory (see Supporting Information, Part A).

6. Conclusion

We have explored two episodes where the expression of fear and anger played a crucial role in political contestation between governmental and populist actors and their followers: the 2016 UK Brexit referendum and the 2016 US presidential election. In the case of Brexit, we find a fear-anger contest that closely conforms with theoretical expectations. Especially during the referendum campaign, Remain politicians used more fear-based rhetoric (Hypothesis 1) whereas Leave politicians used more anger-based rhetoric (Hypothesis 2). We find an inverse relationship between levels of fear and anger in news media and society (Hypothesis 3). To put it colloquially: Remain approximates, if not "Project Fear" then "Project Anxiety," whereas Leave approximates "Project Anger" or even "Project Disgust."

We find another type of fear-anger contest in the case of Trump's election. Instead of a contest between "Project Anger" and "Project Fear," as in the case of Brexit, we find a general negativity contest led by Democrats but leading to a Republican victory. While both parties

[7] For formatting reasons, we were unable to reproduce emoticons in Table 5 so we present them here. Hilary Clinton (anger): "Every 👈 time 👈 @realDonaldTrump 👈 makes 👈 you 👈 mad 👈 chip 👈 in👈 $1." Private citizen (fear): "🎭🎃💀👹 @ The Purge: Election Year at Halloween Horror Nights." Private citizen (anger): "How would I describe @realDonaldTrump..... #Racist, #Fascist, #Xenophobic, #Nazi, etc..!! 😧😧😧😧😧😧😧😧😧😧😧😧."

reinforced each other's negative emotions, Democrats lead on both fear and anger. Although this failed to prevent Trump's victory, governmental actors persisted in depicting President Trump as a threat, for example to democracy or free trade. To counter this, Trump and his allies angrily denounced this as a "witch hunt." The continuation of fear-anger contests when populists are in power presents an interesting avenue for future research.

The question of which political actors rely more on fear or anger, and how fear and anger resonate in media and society, is of great salience in a time and age when political discourse is rife with emotions. Fear and anger are most prominent among these, ranging from anxiety about global calamities like climate change and COVID-19 to offence taking in the face of polarizing rhetoric about race and culture. This has been evident in the 2020 US presidential election, and it is destined to remain an issue. We call for further research exploring the interplay between the politics of fear and the politics of anger.

CRediT authorship contribution statement

Jörg Friedrichs: Conceptualization, Supervision, Validation. **Niklas Stoehr:** Methodology, Formal analysis, Visualization. **Giuliano Formisano:** Visualization, Data curation, Validation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Tweet IDs for the social media data used in this article are available at https://dataverse.harvard.edu/dataverse/fear-anger-contests.

Acknowledgements

Thanks are due to Marta Antonetti, Kalev Leetaru, Christoph Nguyen, Tao Li, Ilan Manor, Eric Kaufmann, Oliver Fläschner, Florian Schaffner and Micol Morellini for critical comments and helpful suggestions.

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