Fear-Anger Contests:

Governmental and Populist Politics of Emotion

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Online Supporting Information

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A. Twitter Data

As the section on "Data and Methods" in the main paper explains, much of our data consists of tweets from political actors, news media, and society more broadly. In the main paper, this is limited to our two observation periods: September 2015 – June 2017 for the Brexit referendum and February 2015 – March 2017 for the election of Donald Trump (see Figure 2 in the main paper). To enable further work, we have collected data more widely, for the entire period from 1 January 2015 to 31 December 2020 (Figure A1).

	UK Case (01/2015 - 12/2020)		US Case (01/2015 - 12/2020)	
	Remain	*Leave*	*Democrats*	*Republicans*
Political Actors	76,674	44,428	158,321	131,842
News Media	344,822		3,168,452	
Society	409,567		6,329,915	

Figure A1: Overview of the collected tweets by case (full time period, 01/2015-12/2020)

We rely on the official Twitter API to download tweets from online archives.

In what follows, we describe our procedure to generate Twitter datasets for each entity. To enable others to replicate our procedure and create similar lists and datasets for other countries and cases, we explain the procedure in detail. For a synopsis of what we call the root list approach, see Figure A2.

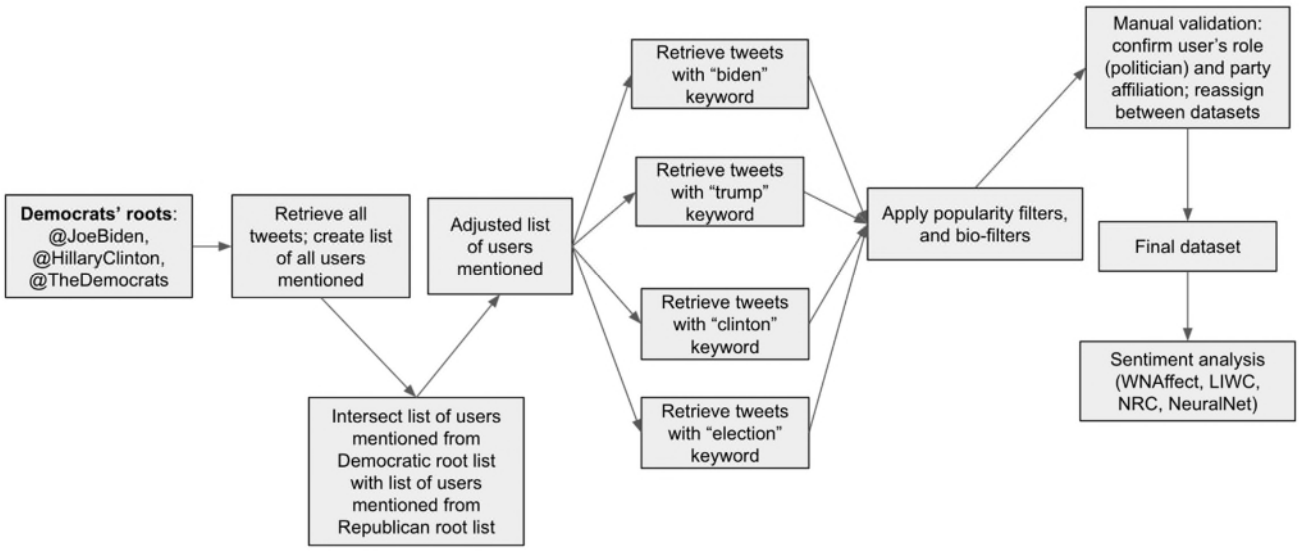


Figure A2: Synopsis of the root list approach

In following this procedure, we do not apply a language filter. Instead, we translate non-English tweets into English via Google Translate before conducting data coding and sentiment analysis.

Political Actors

The entity "political actors" includes politicians and their parties (US case) or political campaigns (UK case). For convenience, in what follows we sometimes use the terms "politicians" or "parties."

Before one can retrieve tweets from political actors, one needs lists of relevant user names. Unfortunately, no such lists are readily available. One option would be to rely on members of parliament as a proxy. In our case, however, this would exclude key players from the analysis. In the US, Donald Trump would be missing from the list during the 2016 presidential campaign because, at the time, he did not hold elected public office. In the UK, the influential populist leader Nigel Farage would be missing during the 2016 Brexit campaign because, at that time, he was Member of the European rather than the British parliament.

For this research, we obtain reliable lists of political actors by implementing the following procedure:

1. Create root lists of key players (Figure A2) and retrieve their tweets.
   a) Select the twitter accounts of two or three well-known key players for each party or campaign.
      For the US case, we select the accounts of each party, as well as its presidential candidate.
      For the UK case, we select two key accounts for each campaign (Figure A3).
   b) For the accounts on each list, retrieve all tweets containing select keywords.
      For the US case, we use the following keywords 'election', 'trump', 'clinton', 'biden'.
      For the UK case, we use the key-word 'brexit'.
   c) In addition to the text of the tweets, we collect date-stamp, tweet ID, user ID, username, number of favourites, number of tweets, number of followers, bio, users mentioned, hashtags used.

<table>
<tr><th colspan="2">UK case</th><th colspan="2">US case</th></tr>
<tr><th>Remain</th><th>Leave</th><th>Republicans</th><th>Democrats</th></tr>
<tr><td>@remain_eu
(Remain EU Official Account)</td><td>@LeaveEUOfficial
(Leave.EU Official Account)</td><td>@GOP
(Republican Party Official Account)</td><td>@TheDemocrats
(Official Democratic Party Account)</td></tr>
<tr><td rowspan="2">@Remain_Labour (Labour Remain Official Account)</td><td rowspan="2">@vote_leave
(voteleavetakecontrol.org Official Account)</td><td>@realDonaldTrump
(Donald Trump Personal Account)</td><td>@HillaryClinton
(2016 Democratic Candidate)</td></tr>
<tr><td>@POTUS
(US President Institutional Account)</td><td>@JoeBiden
(2020 Democratic Candidate)</td></tr>
</table>

Figure A3: Root lists

2. Identify Twitter users mentioned by key players. Intersect the lists.
   a) Extract all user names mentioned in the tweets of the key players on the root list.
      Like Barberá, Jost [1], we follow the intuition is that users who have similar political stances are likely to follow or otherwise interact with each other. In our case, we expect that Twitter users are more likely to mention others when they agree with them. For example, politicians are likely to mention politicians from their own party, or close to their party.
   b) Intersect user names on extended lists generated from root lists, to identify cross-listings.
      Politicians mention politicians from other parties, or close to other parties, often in negative ways. For example, Trump mentions "crooked" Hilary Clinton. Hence, we find Clinton not only on the Democratic list (where she appears more often) but also on the Republican list.

c) Retain user names on the extended list that mentions them more often.

For example, Hilary Clinton appears more often on the Democratic than on the Republican list. Assign her to the Democratic list, and remove her from the Republican list.

d) Remove any repetitive entries.

For example, Hilary Clinton appears many times. She should appear only once.

3. Retrieve tweets and apply filters.

a) Retrieve the tweets for all user accounts on each extended list.

We use a battery of Python libraries (snscrape, tweepy, pandas), as well as loop and sleeping functions, to collect the same information as for tweets from the root list (1c).

b) Select only influential twitter accounts.

We follow Barberá, Jost [1] in selecting only those accounts where users have sent at least 100 tweets and have a minimum of 3,000 followers.

c) Exploit twitter bios to identify political actors.

We search twitter bios for the following keywords (Figure A4).

UK case	US case
'Politician', 'politician', 'Candidate', 'candidate', 'Prime Minister', 'Chancellor of the Exchequer', 'MP', 'Member of Parliament', 'UKHouseofLords', 'UKHouseofCommons', 'Minister', 'Secretary', 'secretary', 'Leader', 'leader'	'President', 'president', 'Politician', 'politician', 'Candidate', 'candidate', 'Congressman', 'congressman', 'Congresswoman', 'congresswoman', 'Senator', 'senator', 'governor', 'Governor'

Figure A4: Bio filters for politicians

Political user accounts sometimes switch sides. For example, the UK government supported Remain/Leave before/after the EU referendum; similarly, the US administration changed between Democrats/Republicans with the inauguration of Donald Trump. We account for such "switches" by placing tweets from these user accounts on one side of the political divide until the referendum/election, and on the other side thereafter.

Figure A5 lists the political actors, as well as their party and level, for the UK case.

Remain		
Political operatives and campaigns		
Name	**Party**	**Level**
remain_eu	Other	UK
Remain_Labour	Labour	UK
UKLabour	Labour	UK
PeoplesMomentum	Labour	UK
WelshLabour	Labour	Wales
lewishamlabour	Labour	England
yorkshirelabour	Labour	England
andrew_harrop	Labour	UK
johnmcternan	Labour	UK
TheGreenParty	Green	UK
BHGreens	Green	England
Amelia_Womack	Green	England
duncanhames	Lib Dem	UK
jameschappers	Other	UK
kenblackwell	Other	Other
BridgfordMark	Other	England
Joanna13071726	Other	England
Senior politicians and related organizations		
Name	**Party**	**Level**

Leave		
Political operatives and campaigns		
Name	**Party**	**Level**
LeaveEUOfficial	Other	UK
vote_leave	Other	UK
Vote_LeaveMedia	Other	UK
BetterOffOut	Other	UK
BrendanChilton	Labour	England
OwenPaterson	Conservative	UK
PaulGoodmanCH	Conservative	UK
calvinrobinson	Conservative	England
Nigel_Farage	UKIP	UK
_HenryBolton	UKIP	UK
Lrihendry	Other	Other
RaoulRuparel	Other	UK
WorkersPartyGB	Other	UK
asabenn	Other	UK
bhatti_saqib	Other	UK
maturefinancier	Other	Other
Senior politicians and related organizations		
Name	**Party**	**Level**
10DowningStreet	Conservative	UK

jeremycorbyn	Labour	UK
Keir_Starmer	Labour	England
Ed_Miliband	Labour	UK
George_Osborne	Labour	UK
fmwales	Labour	Wales
MattWestern_	Labour	UK
johnprescott	Labour	UK
vaughangething	Labour	Wales
David_Cameron	Conservative	UK
PhilipHammondUK	Conservative	UK
Jeremy_Hunt	Conservative	UK
DavidGauke	Conservative	UK
WilliamJHague	Conservative	UK
BrandonLewis	Conservative	Northern Ireland
JustineGreening	Conservative	UK
MattHancock	Conservative	UK
PennyMordaunt	Conservative	UK
theresecoffey	Conservative	UK
trussliz	Conservative	UK
DHSCgovuk	Conservative	UK
nick_clegg	Lib Dems	UK
timfarron	Lib Dems	UK
vincecable	Lib Dems	UK
EdwardJDavey	Lib Dem	UK
EP_President	Other	EU
EUCouncil	Other	EU
EUCouncilPress	Other	EU
EU_Commission	Other	EU
eucopresident	Other	EU
LeoVaradkar	Other	Other
FabianPicardo	Other	Other
A_Gurria	Other	Other
PScotlandCSG	Other	Other
NicolaSturgeon	SNP	Scotland
AlexSalmond	SNP	Scotland
Lawmakers and candidates		
Name	**Party**	**Level**
Alison_McGovern	Labour	England
angelaeagle	Labour	England
AngelaRayner	Labour	England
angelasmithmp	Labour	England
AnnelieseDodds	Labour	England
BarryGardiner	Labour	England
BarrySheerman	Labour	England
BenPBradshaw	Labour	England
Bill_Esterson	Labour	England
bphillipsonMP	Labour	England
CarolineFlint	Labour	England
CatMcKinnell	Labour	England
ClaudiaWebbe	Labour	England
coyleneil	Labour	England
darrenpjones	Labour	England
DavidLammy	Labour	England
DawnButlerBrent	Labour	England
Debbie_abrahams	Labour	England
DerbyChrisW	Labour	England
DrRosena	Labour	England
EmilyThornberry	Labour	England
FloEshalomi	Labour	England
gareth_snell	Labour	England

cabinetofficeuk	Conservative	UK
theresa_may	Conservative	UK
BorisJohnson	Conservative	UK
LiamFox	Conservative	UK
michaelgove	Conservative	UK
pritipatel	Conservative	UK
sajidjavid	Conservative	UK
DominicRaab	Conservative	UK
GavinWilliamson	Conservative	UK
DCMS	Conservative	UK
DFID_UK	Conservative	UK
GregHands	Conservative	UK
MPIainDS	Conservative	UK
Jacob_Rees_Mogg	Conservative	UK
JohnSwinney	SNP	Scotland
AndrewScheer	Other	Other
SecPompeo	Other	Other
TurnbullMalcolm	Other	Other
winstonpeters	Other	Other
Lawmakers and candidates		
Name	**Party**	**Level**
ABridgen	Conservative	England
AlecShelbrooke	Conservative	England
amandamilling	Conservative	England
andreajenkyns	Conservative	England
andrealeadsom	Conservative	England
Andrew4Pendle	Conservative	England
AndrewRosindell	Conservative	England
annietrev	Conservative	England
AnthonyMangnal1	Conservative	England
BBradley_Mans	Conservative	England
bernardjenkin	Conservative	England
BillCashMP	Conservative	England
CGreenUK	Conservative	England
cmackinlay	Conservative	England
CrispinBlunt	Conservative	England
CSkidmoreUK	Conservative	England
danny__kruger	Conservative	England
DehennaDavison	Conservative	England
DKShrewsbury	Conservative	England
DouglasCarswell	Conservative	England
EdwardLeighMP	Conservative	England
EstherMcVey1	Conservative	England
gaganmohindra	Conservative	England
garystreeterSWD	Conservative	England
GavinBarwell	Conservative	England
geraldhowarth	Conservative	England
griffitha	Conservative	England
HeatherWheeler	Conservative	England
HenrySmithUK	Conservative	England
HuwMerriman	Conservative	England
iainastewart	Conservative	England
JackieDP	Conservative	England
JamesCleverly	Conservative	England
JamesDuddridge	Conservative	England
JohnGlenUK	Conservative	England
joymorrissey	Conservative	England
karlmccartney	Conservative	England
KemiBadenoch	Conservative	England
KwasiKwarteng	Conservative	England

GarethThomasMP	Labour	England
GwynneMP	Labour	England
HackneyAbbott	Labour	England
hammersmithandy	Labour	England
HarrietHarman	Labour	England
helenhayes_	Labour	England
hilarybennmp	Labour	England
JamesFrith	Labour	England
JamieFonzarelli	Labour	England
JanetDaby	Labour	England
JeffSmithetc	Labour	England
JennyChapman	Labour	England
jessphillips	Labour	England
johnmcdonnellMP	Labour	England
JonAshworth	Labour	England
JonCruddas_1	Labour	England
JulieForBurnley	Labour	England
KarlTurnerMP	Labour	England
KateGreenSU	Labour	England
KateOsborneMP	Labour	England
KerryMP	Labour	England
khalid4PB	Labour	England
labourlewis	Labour	England
LauraPidcock	Labour	England
leicesterliz	Labour	England
LilianGreenwood	Labour	England
lisanandy	Labour	England
LucyMPowell	Labour	England
margarethodge	Labour	England
MarshadeCordova	Labour	England
meaglemp	Labour	England
MikeGapes	Labour	England
MikeHillMP	Labour	England
mtpennycook	Labour	England
NavPMishra	Labour	England
NazShahBfd	Labour	England
patmcfaddenmp	Labour	England
peterkyle	Labour	England
RachaelMaskell	Labour	England
RachelReevesMP	Labour	England
RichardBurgon	Labour	England
RLong_Bailey	Labour	England
RosieDuffield1	Labour	England
RupaHuq	Labour	England
rushanaraali	Labour	England
RuthCadbury	Labour	England
SeemaMalhotra1	Labour	England
Siobhain_Mc	Labour	England
stellacreasy	Labour	England
StephenMorganMP	Labour	England
ThangamMP	Labour	England
TracyBrabin	Labour	England
wesstreeting	Labour	England
YvetteCooperMP	Labour	England
AlbertOwen2020	Labour	Wales
AlexDaviesJones	Labour	Wales
AnnaMcMorrin	Labour	Wales
GeraintDaviesMP	Labour	Wales
JoStevensLabour	Labour	Wales
KevinBrennanMP	Labour	Wales

Lee4NED	Conservative	England
lrobertsonTewks	Conservative	England
lucyallan	Conservative	England
MarcusFysh	Conservative	England
mariacaulfield	Conservative	England
MarkPawsey	Conservative	England
MartinVickers	Conservative	England
Michael4MDNP	Conservative	England
Mike_Fabricant	Conservative	England
nadams	Conservative	England
nadhimzahawi	Conservative	England
NadineDorries	Conservative	England
neil_parish	Conservative	England
paulbristow79	Conservative	England
PeterBoneUK	Conservative	England
RishiSunak	Conservative	England
robertcourts	Conservative	England
Royston_Smith	Conservative	England
SayeedaWarsi	Conservative	England
scullyp	Conservative	England
sherylImurray	Conservative	England
SimonClarkeMP	Conservative	England
SteveBakerHW	Conservative	England
SteveBarclay	Conservative	England
stevedouble	Conservative	England
SuellaBraverman	Conservative	England
timloughton	Conservative	England
Tobias_Ellwood	Conservative	England
tomhunt1988	Conservative	England
VotePursglove	Conservative	England
William_Wragg	Conservative	England
willquince	Conservative	England
AndrewRTDavies	Conservative	Wales
GutoAberconwy	Conservative	Wales
JonesyFay	Conservative	Wales
JGray	Conservative	Scotland
IoWBobSeely	Conservative	Other
CommonsLeader	Conservative	UK
EmmaLewellBuck	Labour	England
IanLaveryMP	Labour	England
LisaForbes_	Labour	England
RogerGodsiff	Labour	England
Steph_Peacock	Labour	England
frankfieldteam	Labour	England
jon_trickett	Labour	England
MaryWimbury	Labour	Wales
PaulGirvanMP	DUP	Northern Ireland
eastantrimmp	DUP	Northern Ireland
GRobinsonDUP	DUP	Northern Ireland
MichelleDewbs	Brexit Party	England
BrexitAlex	Brexit Party	EU
drdavidbull	Brexit Party	EU
JamesJimCarver	UKIP	EU
JonathanArnott	UKIP	EU
JimAllister	Other	Northern Ireland

Local and municipal politicians

Name	Party	Level
ARMilani_	Labour	England
BradenDavy	Conservative	Scotland
ShaunBaileyUK	Conservative	England

KevinPascoe	Labour	Wales
NickTorfaen	Labour	Wales
RhonddaBryant	Labour	Wales
SDoughtyMP	Labour	Wales
SKinnock	Labour	Wales
ToniaAntoniazzi	Labour	Wales
IanMurrayMP	Labour	Scotland
PaulJSweeney	Labour	Scotland
LabourLordsUK	Labour	UK
derekvaughan	Labour	EU
JohnHowarth1958	Labour	EU
SebDance	Labour	EU
AlokSharma_RDG	Conservative	England
CPhilpOfficial	Conservative	England
DamianCollins	Conservative	England
DamianGreen	Conservative	England
edvaizey	Conservative	England
GregClarkMP	Conservative	England
hbaldwin	Conservative	England
heidiallen75	Conservative	England
JDjanogly	Conservative	England
JohnnyMercerUK	Conservative	England
JoJohnsonUK	Conservative	England
MPritchardUK	Conservative	England
RobertBuckland	Conservative	England
Sandbach	Conservative	England
Simon4NDorset	Conservative	England
TomTugendhat	Conservative	England
nigelmp	Conservative	Wales
AndrewBowie_MP	Conservative	Scotland
Douglas4Moray	Conservative	Scotland
RuthDavidsonMSP	Conservative	Scotland
SHKMEP	Conservative	EU
AngusMacNeilSNP	SNP	Scotland
AngusRobertson	SNP	Scotland
joannaccherry	SNP	Scotland
PeterGrantMP	SNP	Scotland
PeteWishart	SNP	Scotland
StewartHosieSNP	SNP	Scotland
LaylaMoran	Lib Dem	England
LizWebsterLD	Lib Dem	England
SamGyimah	Lib Dem	England
sarahjolney1	Lib Dem	England
Wera_Hobhouse	Lib Dem	England
CarolineLucas	Green	England
Lord_Bilimoria	Other	England
HoCpetitions	Other	UK
MiRo_SPD	Other	EU
TonoEPP	Other	EU
Local and municipal politicians		
Name	**Party**	**Level**
AndrewHWestern	Labour	England
CllrTomHayes	Labour	England
JohnEdwards33	Labour	England
MuradQureshiLDN	Labour	England
RachelEden	Labour	England
SakinaZS	Labour	England
SanchiaAlasia	Labour	England
SeemaChandwani	Labour	England
tshep42	Labour	England

ZacGoldsmith	Conservative	England
davidkurten	UKIP	England

SiobhanBenita	Lib Dem	England			
stevebeasant	Lib Dem	England			
andree_frieze	Green	England			

Figure A5: UK – Political actors, as well as their party and level

Figure A6 lists the political actors, as well as their party and level, for the US case.

Democratic Party	
Political operatives and campaigns	
Name	**Level**
AmandaRenteria	Federal
Ann_OLeary	Federal
AnniesListTX	State
AshantiGholar	Federal
BenJealous	Federal
BrianCDeese	Federal
BrynneCraig	Federal
CAPAC	Federal
CollectivePAC	Federal
DNCWomen	Federal
DPGChair	Federal
JenGranholm	Federal
JessicaPost	State
MoElleithee	Federal
MoveOn	Federal
OpalVadhan	Federal
QJames	Federal
SarahRiggsAmico	Federal
Schriock1	Federal
TeamJoe	Federal
TheDemocrats	Federal
TrainDems	Federal
Zac_Petkanas	Federal
arenasummit	Federal
davidaxelrod	Federal
donnabrazile	Federal
finneyk	Federal
harrisonjaime	Federal
lgbt_dems	Federal
Senior politicians and related organizations	
Name	**Level**
AndyBeshearKY	State
BarackObama	Federal
BernieSanders	Federal
BillClinton	Federal
CommerceGov	Federal
DemGovs	State
DevalPatrick	State
FairfaxJustin	State
FredHubbell	State

Republican Party	
Political operatives and campaigns	
Name	**Level**
AugustPfluger	Federal
BillHagertyTN	Federal
CLewandowski_	Federal
Citizens4Trump	Federal
Citizens_United	Federal
DanScavino	Federal
David_Bossie	Federal
EricTrump	Federal
GOPconvention	Federal
JaRonSmith45	Federal
KarlRove	Federal
KayColesJames	Federal
MainStreetSarah	Federal
MattWolking	State
NRSC	Federal
Paduch	Federal
PressSec	Federal
SarahHuckabee	Federal
SarahPalinUSA	Federal
SheriffClarke	Federal
StarParker	Federal
TommyHicksGOP	Federal
TrumpWarRoom	Federal
VoteTrumpMAGA	Federal
WalshFreedom	Federal
billpostmus	Federal
bobvanderplaats	Federal
cindymccain	Federal
club4growth	Federal
gophawaii	State
hogangidley45	Federal
jimryun	Federal
kimguilfoyle	Federal
mercedesschlapp	Federal
michaelglassner	Federal
mowers	Federal
officialOKGOP	State
rajshah	Federal
seanspicer	Federal
tperkins	Federal
Senior politicians and related organizations	

GavinNewsom	State
GinaRaimondo	State
GovAndyBeshear	State
GovEvers	State
GovHowardDean	State
GovJanetMills	State
GovMLG	State
GovMarkDayton	State
GovMurphy	State
GovPeterShumlin	State
GovPritzker	State
GovRaimondo	State
GovSisolak	State
GovTimWalz	State
GovWhitmer	State
GovernorBullock	State
GovernorVA	State
HillaryClinton	Federal
JBPritzker	State
JanetMillsforME	State
JayInslee	State
JerryBrownGov	Federal
JoeBiden	Federal
JohnFetterman	State
JulianaforLG	State
KamalaHarris	Federal
KateBrownForOR	Federal
LincolnChafee	State
LouisianaGov	State
LupeValdez	State
MarkBegich	State
MartinOMalley	State
NYGovCuomo	State
NedLamont	State
OregonGovBrown	State
PhilMurphyNJ	State
RalphNortham	State
RichCordray	State
RoyCooperNC	State
SteveSisolak	State
TerryMcAuliffe	State
TomWolfPA	State

Name	Level
AmbJohnBolton	Federal
AsaHutchinson	State
BillLeeTN	State
BobbyJindal	State
BrianKempGA	State
ChrisSununu	State
CommerceGov	Federal
DanPatrick	State
DanielCameronAG	State
DougBurgum	State
DougForDakota	State
EricGreitens	State
GeorgeHWBush	Federal
GovBillLee	State
GovBrewer	State
GovDunleavy	State
GovHerbert	State
GovKemp	State
GovMattBevin	State
GovMikeDeWine	State
GovMikeHuckabee	State
GovPenceIN	State
GovRicketts	State
GovRonDeSantis	State
GovStitt	State
GovWalker	State
GovernorPataki	State
GovernorPerry	State
GovernorSununu	State
GregAbbott_TX	State
HHSGov	Federal
IAGovernor	State
Interior	Federal
JebBush	Federal
JimJusticeWV	State
KimReynoldsIA	State
LarryHogan	State
LtGovNunez	State
MikeDeWine	State
Mike_Pence	Federal
MittRomney	Federal
NC_Governor	State

Tony4WI	State
USCIS	Federal
USDOL	Federal
andrewcuomo	State
chuckschumer	Federal
dg4az	State
gretchenwhitmer	State
jay4ma	State
peggyflanagan	State
ricardorossello	State
staceyabrams	State
Lawmakers and candidates	
Name	**Level**
SMurphyCongress	Federal
SarahEMcBride	State
SenBillNelson	Federal
SenBlumenthal	Federal
SenBobCasey	Federal
SenCortezMasto	Federal
SenDonnelly	Federal
SenDuckworth	Federal
SenEvanBayh	Federal
SenFeinstein	Federal
SenGillibrand	Federal
SenJeffMerkley	Federal
SenSanders	Federal
SenSchumer	Federal
SenSherrodBrown	Federal
SenWarren	Federal
Sen_JoeManchin	Federal
SenateDems	Federal
SenatorBaldwin	Federal
SenatorBarb	Federal
SenatorCardin	Federal
SenatorReid	Federal
SenatorTester	Federal
SheldonforRI	Federal
SherrodBrown	Federal
StevenHorsford	Federal
SusieLeeNV	Federal
TeamHeinrich	Federal

NikkiHaley	Federal
POTUS	Federal
PamBondi	State
PatMcCroryNC	State
PhilBryantMS	State
RickSantorum	Federal
RonDeSantisFL	State
Schwarzenegger	State
ScottWalker	State
ScottforFlorida	State
SecretaryPerry	Federal
SpencerJCox	State
TSA	Federal
TrumpInaugural	Federal
USCIS	Federal
USDOL	Federal
US_FDA	Federal
VP	Federal
WVGovernor	State
WalkerStapleton	State
WhiteHouse	Federal
WhiteHouse45	Federal
auctnr1	Federal
dougducey	State
gov_gilmore	State
govkristinoem	State
henrymcmaster	State
marcorubio	Federal
mikeparson	State
realDonaldTrump	Federal
senorrinhatch	Federal
senrobportman	Federal
tatereeves	State
tedcruz	Federal
Lawmakers and candidates	
Name	**Level**
ARSenMissyIrvin	State
Bethvanduyne	Federal
BillyPrempeh	Federal
Buddy_Carter	Federal
BurgessOwens	Federal
ByronDonalds	State
CapitoforWV	Federal

TeamKCP	State
Ted_Strickland	State
TheOtherMandela	State
Tim_Walz	Federal
TinaSmithMN	Federal
TomCarperforDE	Federal
TulsiGabbard	Federal
XavierBecerra	Federal
YasmineTaeb	State
YvannaCancela	State
amyklobuchar	Federal
brianschatz	Federal
ericswalwell	Federal
ewarren	Federal
golden4congress	Federal
gracenapolitano	Federal
hiral4congress	Federal
jamie_raskin	Federal
jaredpolis	Federal
jdunnington	State
joekennedy	Federal
jontester	Federal
karlabigham	State
kyrstensinema	Federal
loriberman	Federal
lucymcbath	Federal
Mazieforhawai	Federal
maziehirono	Federal
mddems	State
ossoff	Federal
repjohnlewis	Federal
russfeingold	Federal
sethmoulton	Federal
stabenow	Federal
tammybaldwin	Federal
vgescobar	Federal
vingopal	State
wendydavis	Federal
Wildforcongress	Federal
xjelliott	Federal
Local and municipal politicians	
Name	**Level**
AftabPureval	Sub-State

CarolMillerWV	Federal
Casper4Colorado	Federal
CongressmanJVD	Federal
CoryGardner	Federal
CynthiaMLummis	Federal
DHarshbargerTN1	Federal
DainesforMT	Federal
DanCrenshawTX	Federal
DarrellIssa	Federal
DaveBratVA7th	Federal
DebbieLesko	State
DonJBacon	Federal
DrPaulGosar	Federal
EliseStefanik	Federal
FischbachMN7	Federal
GregPenceIN	Federal
HawleyMO	Federal
JacobsNY27	Federal
JamesComer	Federal
JayWebberNJ	State
JeffFlake	Federal
JerryMoran	Federal
JimHagedornMN	Federal
JimInhofe	Federal
JimPressOffice	Federal
JimRenacci	Federal
Jim_Banks	Federal
JoeWMiller	Federal
JohnCornyn	Federal
JohnnyIsakson	Federal
JohnsonLeads	Federal
JudgeJohnCarter	Federal
KLoeffler	Federal
KarinHousley	State
Kat_Cammack	Federal
KristiNoem	Federal
Lancegooden	State
LewisForMN	Federal
LindseyGrahamSC	Federal
MNJeffJohnson	State
MarkHarrisNC9	Federal
MarkKirk	Federal
MarkMeadows	Federal

DavidPepper	Sub-State	MarkSanford	Federal
FrankScottJr	Sub-State	MattForMontana	Federal
MayorSRB	Sub-State	MichelleSteelCA	Federal
SteveBenjaminSC	Sub-State	MikeCrapo	Federal
polkdems	Sub-State	Miller_Congress	Federal
rubendiazjr	Sub-State	NMalliotakis	Federal
		NancyMace	Federal
		NickForVA	Federal
		PatToomey	Federal
		RandPaul	Federal
		RandyFeenstra	Federal
		RepAmata	Federal
		RepAnnWagner	Federal
		RepChrisStewart	Federal
		RepHagan	Federal
		RepJimBanks	Federal
		RepLizCheney	Federal
		RepMarkMeadows	Federal
		RepMattGaetz	Federal
		RepRiggleman	Federal
		RepRonEstes	Federal
		RepStefanik	Federal
		RepTimBurchett	Federal
		RepTimmons	Federal
		RepTomGraves	Federal
		RichHudson	Federal
		RichforGA	Federal
		RogerMarshallMD	Federal
		RonnyJacksonTX	Federal
		RosLehtinen	Federal
		RussFulcher	Federal
		ScottRTipton	Federal
		Scotttaylorva	Federal
		SeanParnellUSA	Federal
		SenDanCoats	Federal
		SenDanSullivan	Federal
		SenDeanHeller	Federal
		SenFrankNiceley	Federal
		SenJohnBarrasso	Federal
		SenJohnHoeven	Federal
		SenJohnKennedy	Federal
		SenJohnMcCain	Federal
		SenMikeLee	Federal

		SenPatRoberts	Federal
		SenRickScott	Federal
		SenShelby	Federal
		SenThomTillis	Federal
		SenTomCotton	Federal
		SenToomey	Federal
		SenateGOP	Federal
		SenatorBraun	Federal
		SenatorCollins	Federal
		SenatorDole	Federal
		SenatorFischer	Federal
		SenatorIsakson	Federal
		SenatorRounds	Federal
		SenatorWicker	Federal
		SteveChabot	Federal
		StewartforUtah	Federal
		TTuberville	Federal
		TeamCornyn	Federal
		ThomTillis	Federal
		Tiffany_Shedd	Federal
		ToddYoungIN	Federal
		TomCottonAR	Federal
		TomTiffanyWI	Federal
		TonyGonzales4TX	Federal
		Upson4WV	State
		VanDrewForNJ	Federal
		VoteMarsha	Federal
		WVGOP	State
		WesleyHuntTX	Federal
		YoungForIowa	Federal
		YoungKimCA	Federal
		anitere_flores	State
		bradwenstrup	Federal
		bradyfortexas	Federal
		braun4indiana	Federal
		brettguthrie	Federal
		claudiatenney	Federal
		hinsonashley	Federal
		jameslankford	Federal
		jdanbishop	Federal
		johnthune	Federal
		joniernst	Federal
		justinamash	Federal

		kevincramer	Federal
		kimKBaltimore	Federal
		laurenboebert	Federal
		leezeldin	Federal
		mattgaetz	Federal
		michaelcburgess	Federal
		millermeeks	Federal
		repdonyoung	Federal
		repgregwalden	Federal
		replouiegohmert	Federal
		sendavidperdue	Federal
		senjudiciary	Federal
		stevestivers	Federal
		tommcclintock	Federal
		Local and municipal politicians	
		Name	**Level**
		JoeBorelliNYC	Sub-state
		NNVP_Lizer	Sub-state

Figure A6: US – Political actors, as well as their party and level

News Media

The extended lists generated via Step 2 of the procedure outlined above do not only contain political actors but also journalists as well as newspapers, TV stations, magazines and so on. This enables us to exploit the procedure also for sampling media users and retrieving their tweets. In Step 2b-d, we intersect media users the same way we intersect political actors. For example, Fox News appears more often on the Republican than on the Democratic list. We assign it to the Republican list. CNN appears more often on the Democratic list. We assign it to the Democratic list. In Step 3, we rely on bio filters to identify news media (Figure A9).

While we have created separate lists for governmental- and populist-leaning news media, we are less interested in this for the purposes of our paper, so have merged all media tweets into case-specific datasets. Since the media lists contain a number of "private journalists" (e.g. bloggers), we do not reproduce them here.

UK case	US case
'Newspaper', 'newspaper', 'Magazine', 'magazine', 'Media', 'media', 'TV', 'tv', 'Radio', 'radio', 'Broadcast', 'broadcast', 'Journalist', 'journalist', 'News', 'news', 'anchor', 'editor', 'columnist', 'theguardian', 'BBC', 'BBCNews', 'BBCPolitics', 'BBCWorld', 'SkyNews', 'Telegraph', 'SkyNewsPolitics', 'thetimes', 'Daily_Express', 'TheSun', 'DailyMirror'	'Newspaper', 'newspaper', 'Magazine', 'magazine', 'Media', 'media', 'TV', 'tv', 'Radio', 'radio', 'Broadcast', 'broadcast', 'Journalist', 'journalist', 'News', 'news', 'anchor', 'editor', 'columnist', 'ABC', 'CNN', 'washingtonpost', 'thehill', 'MSNBC', 'nytimes', 'Reuters', 'AP', 'USATODAY', 'latimes', 'FoxNews'

Figure A9: Bio filters for news media

Society

In addition to the datasets of tweets from political actors and news media, we need a dataset of tweets from society. To begin with, we rely on snscrape to retrieve tweets containing the same keywords that we also use for political actors and news media (listed above under 1b). We use timing parameters to retrieve only tweets written during our observation period. We use geographical parameters to ensure that tweets retrieved are from the countries under analysis.[1] Given the enormous amounts of tweets mentioning President Trump, we have gathered a sample of 40% of those tweets. Snscrape retrieves tweets based on randomized tweet IDs, so we may safely assume that the sample is representative. Subsequently, we rely on tweepy to extrapolate relevant information (listed above under 1c) from the tweets retrieved via snscrape. Finally, we remove any username that is already contained in our datasets of political actors and news media from the society dataset, in order to avoid overlap with the datasets described in the last two sections.

Data retrieval and management

To retrieve Twitter data, we use the standard search API. When requesting developer access, we stated our intentions and specified what we were going to do in our research. After a review, Twitter granted us access on 21 October 2020. We have retrieved data in three periods: late October 2020; late December 2020; and early January 2021. Thereby, we have scraped most the tweets of interest before the attack on the US Capitol on 6 January 2021 and subsequent ban of several political actors (including Donald Trump).

Following good practice for data protection, as well as Twitter's terms and conditions, we have stored tweets from political actors and news media, as well as society, on an encrypted and password-protected drive at all times. We have retrieved tweets only from publicly available user accounts and show results at the aggregate level, via tables and figures, without ever showing individual-level behaviour. For our dataset of tweets from society, we have removed all user names and retained only the anonymous users IDs.

[1] We identify the coordinates of the centre of the country on Google maps and apply a radius approximating the size of the country. For the radius, we take the distance from the centre of the country to the country's furthest border.

The procedure has a number of further applications, including but not limited to the following:

- Media classification

  The data generating process outlined above enables us not only to create reliable lists of political actors for each party or campaign, but also to generate lists of news media that are close to specific political parties. While lists of news media are readily available, it remains a challenge to measure the proximity between media and political parties [2]. The procedure outlined above provides comparative counts of how often specific media are mentioned by specified political actors. For example, we find MSBC more often mentioned by Democrats, and Fox News by Republicans. We also find CNN more often mentioned by Republicans. The latter appears counterintuitive because CNN is deemed liberal. However, a sentiment analysis of the valence of Republican tweets mentioning CNN would likely reveal that Republicans are largely negative whereas Democrats are largely positive about CNN. While all of this could be relevant for estimating ideological positionality, we have refrained from doing so in the main paper where we have merged news media into country-specific lists. It shall remain for future research, or other researchers, to exploit our procedure for media classification.

- Political polarization

  In creating our Twitter datasets, we have found only limited evidence for the existence of echo chambers. Despite some echo effects, we have found that politicians from one side tweet about politicians from the opposite side. They also refer to media that are closer to the opposite side, although typically in negative ways. This is in line with previous findings by Barberá, Jost [1], but our dataset could be exploited further to study the emotional valence of communications across political divides. There may not be homophily in the sense of an echo chamber, yet there could be homophily in the sense of speaking positively and communicating respectfully only about entities in one's own ideological camp. In these ways, the procedure may offer an opportunity for nuanced research on polarization.

B. Validation Samples

Figure B1 provides an extended sample of tweets for the UK case, complementing Table 4 in the paper.

UK Case: Extended sample of fearful/angry (blue/red) tweets					
Date	**Username**	**Entity (Affiliation)**	**Text**	**Anger (NeuralNet)**	**Fear (NeuralNet)**
26/03/2016	Debbie_abrahams	Politician (Remain)	Brexit would increase terrorist threat to UK, says ex-minister	0.00133	0.95661
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
14/06/2016	angelaeagle	Politician (Remain)	Brexit fears wipe £100bn off FTSE 100 in four days - business live	0.00024	0.99413
29/06/2016	NazShahBfd	Politician (Remain)	UK entering 'unchartered territory' of Islamophobia after Brexit vote	0.00048	0.99244
30/03/2017	AngusRobertson	Politician (Remain)	Must Read: 'Be very afraid, the Brexit nightmare is truly upon us' by @iainmacwhirter in @heraldscotland	0.00052	0.96082
10/06/2016	labourlewis	Politician (Remain)	Irritation and anger' may lead to Brexit, says influential psycholo-gist	0.97208	0.01978
17/08/2016	remain_eu	Campaign (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
09/11/2016	ClaudiaWebbe	Politician (Remain)	Micheal Moore at NBC: "Michigan, Ohio & Pennsylvania are #Brexit states of US, with an angry working class" True or false? #ElectionNight	0.83302	0.05700
26/11/2016	AngusMac-NeilSNP	Politician (Remain)	Indeed - those who voted #Brexit from anger may yet be a lot angrier.	0.86789	0.01705
27/03/2017	[Local politician]	Politician (Remain)	Nick Clegg tells EU march there is a 'perpetual sense of anger' over Brexit	0.93453	0.01598
25/02/2016	AndrewRosindell	Politician (Leave)	Project Fear and remain camp really are taking it too far. Des-perate times call for desperate measures #brexit	0.00019	0.98868
04/03/2016	LeaveEUOfficial	Campaign (Leave)	Project fear in overdrive as No10 is accused of recruiting France to scare us over Calais migrants	0.00000	0.99934
21/06/2016	HenrySmithUK	Politician (Leave)	Forget Project Fear. Be positive. Choose dynamism. Choose Brexit | via @telegraphnews	0.00004	0.99860
15/06/2016	SteveBakerHW	Politician (Leave)	WATCH: @DCBMEP does some myth-busting in "Taking the Fear out of Brexit"	0.00004	0.99437
19/12/2016	LeaveEUOfficial	Campaign (Leave)	“Let us not be frightened to death of tariffs: they may be con-sumed in currency fluctuation and some small tariff may not be disaster”.	0.00002	0.99248
24/10/2015	LeaveEUOfficial	Campaign (Leave)	What scottish referendum taught us: Pride, Hope, Anger are key. We shall succeed! @Telegraph #LeaveEU #Brexit	0.95491	0.02493
26/10/2015	vote_leave	Campaign (Leave)	Why the Government's ploy to get legal recognition from UN for EU deal is meaningless #voteleave #euref	0.67431	0.07644
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
07/11/2016	Nigel_Farage	Politician (Leave)	If the establishment betray the British people on Brexit then we will see huge political anger.	0.98310	0.00545
18/11/2016	LeaveEUOfficial	Campaign (Leave)	Raving europhile Lord Kerr sparked anger today after he said the UK needed immigration because British people were "too bloody stupid"!	0.98004	0.00214

20/03/2016	business	News Media	The coming week will offer an insight into whether pound traders fear #Brexit vote	0.00013	0.99650
23/12/2015	[Journalist]	News 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
29/03/2016	RT_com	News Media	Project Fear: RT unravels the latest scare tactics to keep Britain in the EU #Brexit	0.00006	0.99757
27/05/2016	CityAM	News Media	Project Fear? What Project Fear? #Brexit #Remain #EUref	0.00044	0.99841
28/05/2016	timesredbox	News Media	Bananas! Underpants! Graphs! FEAR! Have you had enough of the Brexit debate?	0.00058	0.99316
14/02/2016	Independent	News Media	David Cameron's approval ratings have slumped amid Brexit anger	0.98129	0.00885
05/06/2016	Telegraph	News Media	British voters succumbing to 'impulse, irritation and anger' - and it may lead to Brexit ...	0.97595	0.01265
06/06/2016	[Journalist]	News Media	The amount of yelling and aggression is making this a debate I'm not sure I want to be part of. #Brexit	0.96210	0.01148
23/06/2016	business	News Media	There's an anger that connects #Brexit, Trump and Le Pen	0.96528	0.00513
31/03/2017	TheNewEuropean	News Media	Stay angry. Fight #Brexit (buy #theneweuropean)	0.95719	0.00577
04/03/2016	private citizen	Society	These EU politicians can only use fear tactics about voting for a #Brexit, I'm voting to leave because of the positive benefits.	0.00031	0.98934
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
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
13/08/2016	private citizen	Society	I c #bbcnews r still tryin 2 scare brits about #Brexit Did they not get the message,the ppl dont blieve ur scaremongering lies #skynews	0.00032	0.99522
24/10/2016	private citizen	Society	Constitutional crisis after #Brexit now inevitable. So called “project fear" yet again proved to be “Project Fact".	0.00116	0.98440
23/06/2016	private citizen	Society	LEAVE LEAVE LEAVE LEAVE LEAVE #Brexit	0.71437	0.01342
24/06/2016	private citizen	Society	‘I don't understand the anger’: how the Europeans in London see Brexit	0.99534	0.00074
24/06/2016	private citizen	Society	Not sure whether I’m more angry, sad, disappointed or fearful #EUref #Brexit	0.95068	0.01047
07/09/2016	private citizen	Society	BREXIT AND THE NHS CORBYN FFS ITS REALLY NOT THAT HARD #PMQs	0.78910	0.02732
03/05/2017	private citizen	Society	Brexit shall be a most Bitter & Ugly divorce .... #Eurozone #UK .	0.82839	0.01452

Figure B1: UK – Sample tweets. Tweets high in fear/anger coded in blue/red.

Figure B2 provides an extended sample of tweets for the US case, complementing Table 5 in the paper.

US Case: Extended sample of fearful/angry (blue/red) tweets					
Date	**Username**	**Entity (Affiliation)**	**Text**	**Anger (NeuralNet)**	**Fear (NeuralNet)**
09/12/2015	donnabrazile	Politician (Democrat)	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!	0.00004	0.98251
09/05/2016	davidaxelrod	Politician (Democrat)	This is what both conservative and Democratic strategists fear: That Trump may etch-a-sketch his way to the middle.	0.00065	0.98357
29/07/2016	jamie_raskin	Politician (Democrat)	FDR: Nothing to fear but fear itself. Trump: nothing but fear. -- @HillaryClinton #DemsInPhilly	0.00034	0.98593
04/09/2016	MoveOn	Campaign (Democrat)	We'll be hearing from Muslim attendees on their thoughts of Donald Trump, how Islamophobia has impacted them, and more!	0.00042	0.99184
11/10/2016	JBPritzker	Politician (Democrat)	Trump is now directly quoting Russian disinformation. This is frightening.	0.00041	0.98937
22/07/2016	HillaryClinton	Politician (Democrat)	Every 👈 time 👈 @realDonaldTrump 👈 makes 👈 you 👈 mad 👈 chip 👈 in👈 $1.	0.90417	0.00754
01/09/2016	[Political operative]	Campaign (Democrat)	This election is OUR last chance. For many who are angry tonight, VOLUNTEER & VOTE.	0.88775	0.02273
26/09/2016	MariaEDurazo	Politician (Democrat)	In an Arizona county, anger at Trump spurs Latinos to vote	0.92497	0.03263
01/10/2016	TheDemocrats	Political Party (Democrat)	If Trump made you angry this week, there's only one thing to do about it.	0.83290	0.01682
17/10/2016	MoveOn	Campaign (Democrat)	"@realDonaldTrump's words don't make me sick anymore. They make me furious." - @SenWarren	0.88741	0.03810
22/03/2016	realDonaldTrump	Politician (Republican)	Obama, and all others, have been so weak, and so politically correct, that terror groups are forming and getting stronger! Shame.	0.00053	0.98411
10/06/2016	WalshFreedom	Politician (Republican)	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.	0.00011	0.98220
25/08/2016	realDonaldTrump	Politician (Republican)	Just watched recap of #CrookedHillary's speech. Very short and lies. She is the only one fear-mongering!	0.00104	0.98428
02/09/2016	Citizens4Trump	Politician (Republican)	Fears of Cheating, False Polls Could Spell Election Day Trouble	0.00003	0.99749
09/02/2017	[Local politician]	Politician (Republican)	In a nutshell - Dems: Collective amnesia of themselves & zombie-like fears of #Trump ushering Armageddon #MAGA	0.00134	0.98224
24/07/2015	SenFrankNiceley	Politician (Republican)	#Trump has become the vehicle for average folks to vent anger to DC. #IfYouDontFixItWeWill #MakeDCListen #GOP2016	0.85607	0.00421
17/08/2015	bradyfortexas	Politician (Republican)	I'm as angry as you about Clinton's email fiasco. She thinks she's above the law. I will fight for accountability.	0.97359	0.00146
04/05/2016	WalshFreedom	Politician (Republican)	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	0.78232	0.01174
26/06/2016	realDonaldTrump	Politician (Republican)	Clinton is trying to wash away her bad judgement call on BREXIT with big dollar ads. Disgraceful!	0.72547	0.02354
27/06/2016	VoteTrumpMAGA	Campaign (Republican)	Micro-aggression? LOL #MAGA #Trump #Trump2016 #StopHillary #trumptrain #AmericaFirst #GOP #ImWithYou #ImWithTrump	0.81843	0.03400

21/11/2015	[Journalist]	News Media	“I don’t want to reveal fears…I don’t like revealing my fears” @realDonaldTrump #ABC2020	0.00002	0.99924
14/03/2016	[Journalist]	News Media	Hillary Clinton: "Donald Trump is running a cynical campaign of hate and fear."	0.00029	0.99715
19/07/2016	NYDailyNews	News Media	Fear itself: Donald Trump’s apocalypse now	0.00017	0.99676
25/08/2016	DailyCaller	News Media	Trump Responds To Clinton By Accusing Her Of ‘Race-Baiting’ And ‘Fear-Mongering’	0.00009	0.99702
10/11/2016	denverpost	News Media	At suicide hotlines, the first 24 hours of Trump’s America have been full of fear	0.00005	0.99882
21/01/2016	wyffnews4	News Media	Clinton on anger: 'You have got to do something'	0.99496	0.00099
20/02/2016	FoxNews	News Media	@SenatorTimScott: “There’s no doubt @realDonaldTrump has done a good job harnessing the anger and frustration.”	0.99616	0.00037
27/02/2016	dallasnews	News Media	@realDonaldTrump didn’t invent populist anger, but plays it like an instrument	0.99160	0.00087
27/03/2016	DailyCaller	News Media	Trump Aide: People Are Angrier Over Trump’s RTs Than Illegals Murdering Americans [VIDEO]	0.99355	0.00186
12/11/2016	Slate	News Media	You don’t need to fit your Trump anxiety into five stages of grief. Rage all you want	0.99268	0.00251
08/03/2015	private citizen	Society	Tremble in fear, #GOP. @HillaryClinton is coming and @billclinton is coming with her!	0.00014	0.98941
06/01/2016	private citizen	Society	I smell fear and panic in @HillaryClinton camp!	0.00007	0.99402
07/05/2016	private citizen	Society	Blindly follow Trump over the cliff. #Fascism #Racism #Nazism #xenophobia	0.00018	0.99567
01/11/2016	private citizen	Society	😨😱💀👹 @ The Purge: Election Year at Halloween Horror Nights	0.00142	0.98616
17/11/2016	private citizen	Society	Gunna write a paper for history on how/why trump won the election: spoiler alert, it wasn't racism, sexism, hate or fear	0.00182	0.98552
10/09/2015	private citizen	Society	@realDonaldTrump my blood is boiling right now. Controlling my temper right now. Grr	0.98266	0.00633
11/03/2016	private citizen	Society	Trump: "People at my rallies have anger... They love their country." Right! Muslims have anger bc US gov is bombing their counties.	0.98026	0.00554
31/07/2016	private citizen	Society	"This whole election feels like someone's continually punching my pussy" yeessss!	0.78622	0.03290
31/07/2016	private citizen	Society	Donald Trump’s slander of Captain Humayun Khan’s family is horrifying, even for Trump! Get angry! Stay angry! #Vote!	0.97407	0.00765
27/01/2017	private citizen	Society	How would I describe @realDonaldTrump..... #Racist, #Fascist, #Xenophobic, #Nazi, etc..!! 😠😠😠😠😠😠😠😠😠😠😠😠😠	0.97294	0.00336

Figure B2: US – Sample tweets. Tweets high in fear/anger coded in blue/red.

C. Polling Data

We rely on Wikipedia [3], Wikipedia [4], Wikipedia [5] to retrieve opinion polls measuring citizen support for Republicans/Democrats (US) and Leave/Remain (UK). We have thus compiled 148 polls (73 for the UK case; 75 for the US case) into a csv file. We create a timestamp for each poll. For polls conducted over a period of more than one day, we use the last day for the timestamp. For validation purposes, we follow the hyperlinks given on Wikipedia and check the accuracy of data reported. Having checked 10% of the polls, we find that they are accurate except for minute rounding issues.

We present the polling results visually in Figure D1 and Figure D2 further below.

D. GDELT News Data

To add another dimension of validation, we consider another data source besides Twitter. For this purpose, we turn to online newspapers, which have been shown to contain political sentiment and emotion [2]. In contrast to Twitter data, news articles are characterised by a coarser temporal granularity and expected to contain less subjective, more formal language [6].

Retrieving online news data from as far back as 2015 is challenging due to restricted availability and paywalls. Putting emphasis on inexpensive reproducibility and broad coverage, we choose the Global Database of Events, Language, and Tone (GDELT; see www.gdeltproject.org). GDELT uses computational methods to extract events from online news and blogs. Entries contain information on date, location, themes and, importantly for us, sentiment. GDELT has been criticized for being recall-optimized, resulting in broad coverage with duplicate entries [7]. It is used rarely for its intended purpose, the analysis of political conflicts and natural disasters [8]. For the purposes of our study, however, its broad coverage may present an advantage.

The partitioned GDELT Global Knowledge Graph (GKG) allows us to analyze as many as 176,409,767 news items accessible through Google BigQuery. For each country covered by our analysis, we formulate a database query (see below). Each query parses 10.4 TB of data. Queries filter on location and theme, and aggregate items by week and word count. While the GKG does not contain the original text of news items, it records the word count for each article and a range of sentiment values.

When comparing the time series presented in Figures D1 and D2 with Figures 5 and 8 in the main text, it is striking that the trajectories for the news database GDELT seem almost entirely unrelated to the trajectories for Twitter media. Since it is impossible for us to analyse directly the original media items contained in GDELT's Global Knowledge Graph (GKG), we put greater trust in our Twitter datasets. With hindsight, we find ourselves compelled to admit that others may have been right in their scepticism about GDELT [7, 8].

We have retrieved GDELT news data from Google BigQuery with the query below.

```
SELECT EXTRACT(WEEK FROM TIMESTAMP(PARSE_DATE('%Y%m%d',SUBSTR(CAST(DATE as
STRING),0,8)))) as WEEK,
EXTRACT(YEAR FROM TIMESTAMP(PARSE_DATE('%Y%m%d',SUBSTR(CAST(DATE as STRING),0,8))))
as YEAR,
MIN(CAST(TIMESTAMP(PARSE_DATE('%Y%m%d',SUBSTR(CAST(DATE as STRING),0,8))) as
STRING)) DATE_TIME,
COUNT(GKGRECORDID) mentions,
SUM(CAST(REGEXP_EXTRACT(GCAM, r'wc:(\d+)') AS FLOAT64)) as word_count,
SUM(CAST(REGEXP_EXTRACT(GCAM, r'c15.198:(\d+)') AS FLOAT64)) fear_c15_198_wnaffect,
SUM(CAST(REGEXP_EXTRACT(GCAM, r'c9.898:(\d+)') AS FLOAT64)) fear_c9_898_thesaurus,
SUM(CAST(REGEXP_EXTRACT(GCAM, r'c15.15:(\d+)') AS FLOAT64)) anger_c15_15_wnaffect,
SUM(CAST(REGEXP_EXTRACT(GCAM, r'c15.81:(\d+)') AS FLOAT64)) disgust_c15_81_wnaf-
fect,
SUM(CAST(REGEXP_EXTRACT(GCAM, r'c5.32:(\d+)') AS FLOAT64)) anger_c5_32_liwc,
SUM(CAST(REGEXP_EXTRACT(GCAM, r'c5.33:(\d+)') AS FLOAT64))  anxiety_c5_33_liwc,
SUM(CAST(REGEXP_EXTRACT(GCAM, r'c8.3:(\d+)') AS FLOAT64))  anxiety_c8_3_martindale,
SUM(CAST(REGEXP_EXTRACT(GCAM, r'c15.22:(\d+)') AS FLOAT64)) anxiety_c15_22_wnaf-
fect,
FROM gdelt-bq.gdeltv2.gkg_partitioned
WHERE _PARTITIONTIME BETWEEN TIMESTAMP('2015-02-17') AND TIMESTAMP('2015-02-17')
AND
(LOWER(V2Locations) like '%united states of america%' OR LOWER(V2Locations) like
'%usa%' OR LOWER(V2Locations) like '%us%') AND
(LOWER(V2Themes) like '%elec%' OR LOWER(V2Themes) like '%gov%' OR LOWER(V2Themes)
like '%econ%' OR LOWER(V2Themes) like '%polit%' OR LOWER(V2Themes) like '%soc%')
GROUP BY WEEK, YEAR
```

The only parameters changed between cases are the "V2Location" parameters.

Figure D1. UK – GDELT Time series, aggregated by weeks (NeuralNet). We use a t-test for testing the population correlation coefficient at α = 5%, ensuring significant effect strength.

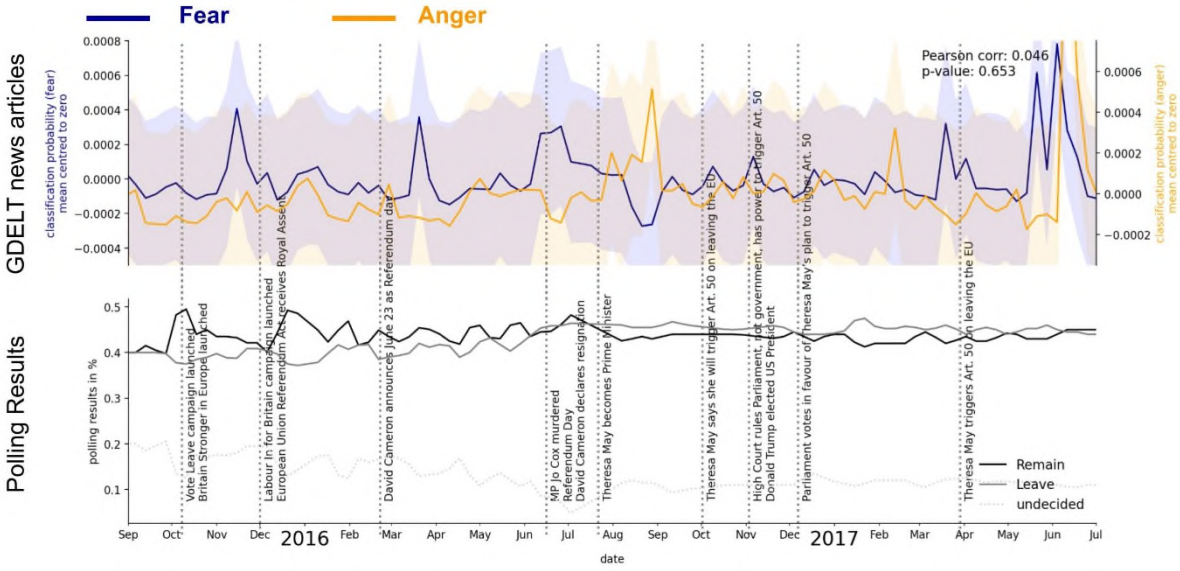
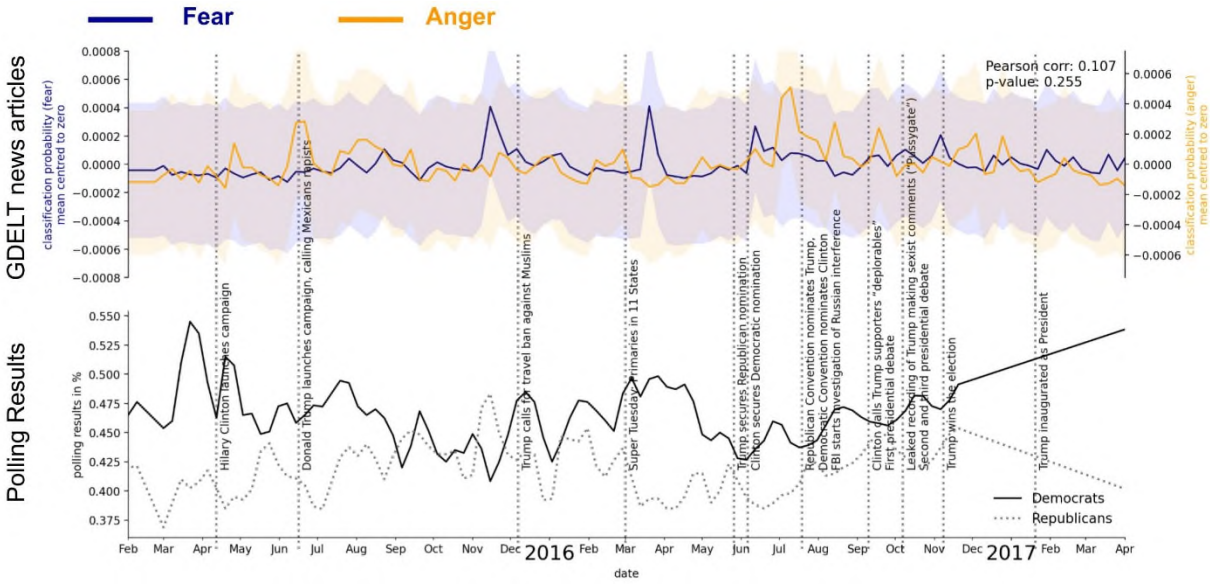


Figure D2. US – GDELT Time series, aggregated by weeks (NeuralNet). We use a t-test for testing the population correlation coefficient at α = 5%, ensuring significant effect strength.



E. Pearson correlations

Correlations are for Sept 2015 – June 2017 (UK case) and Feb 2015 – March 2017 (US case).

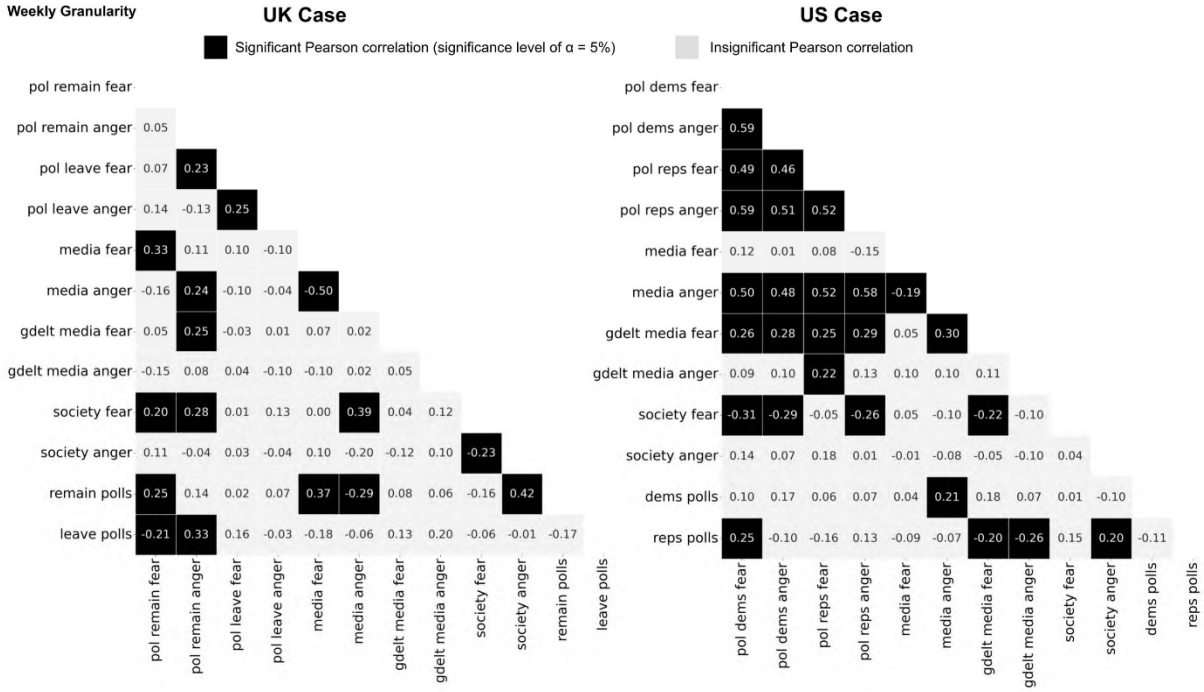


Figure E1. Pearson correlations across the first derivatives of time series (weekly granularity)

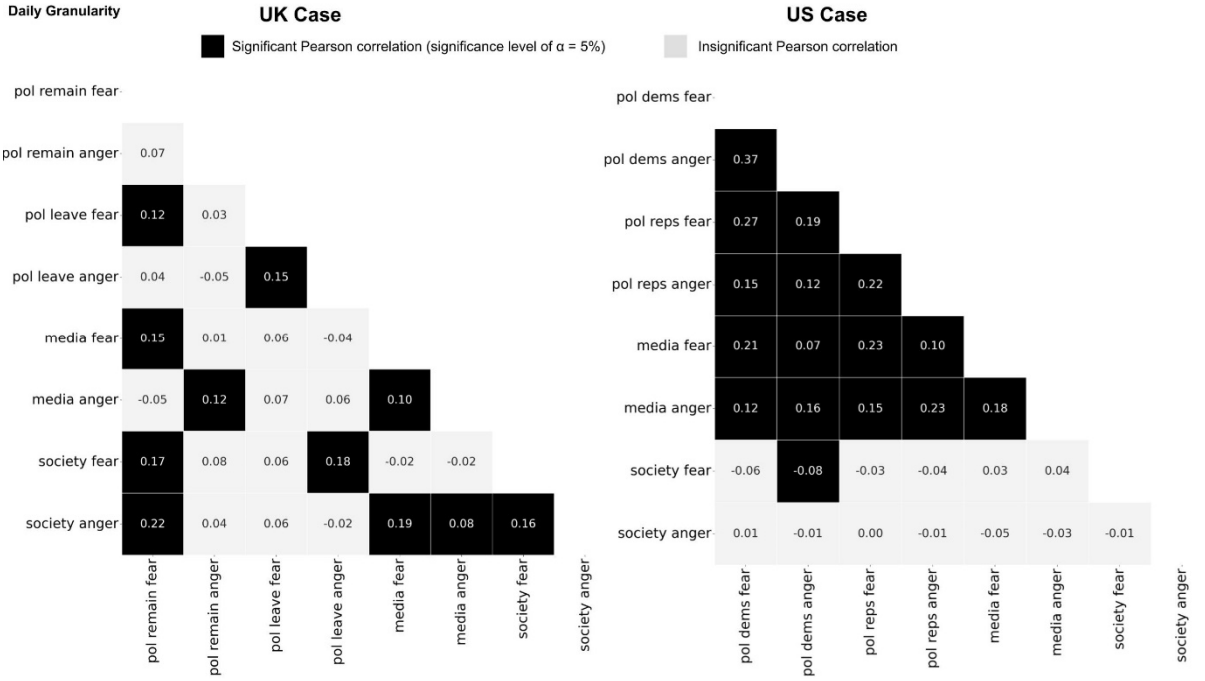


Figure E2. Pearson correlations across the first derivatives of time series (daily granularity)

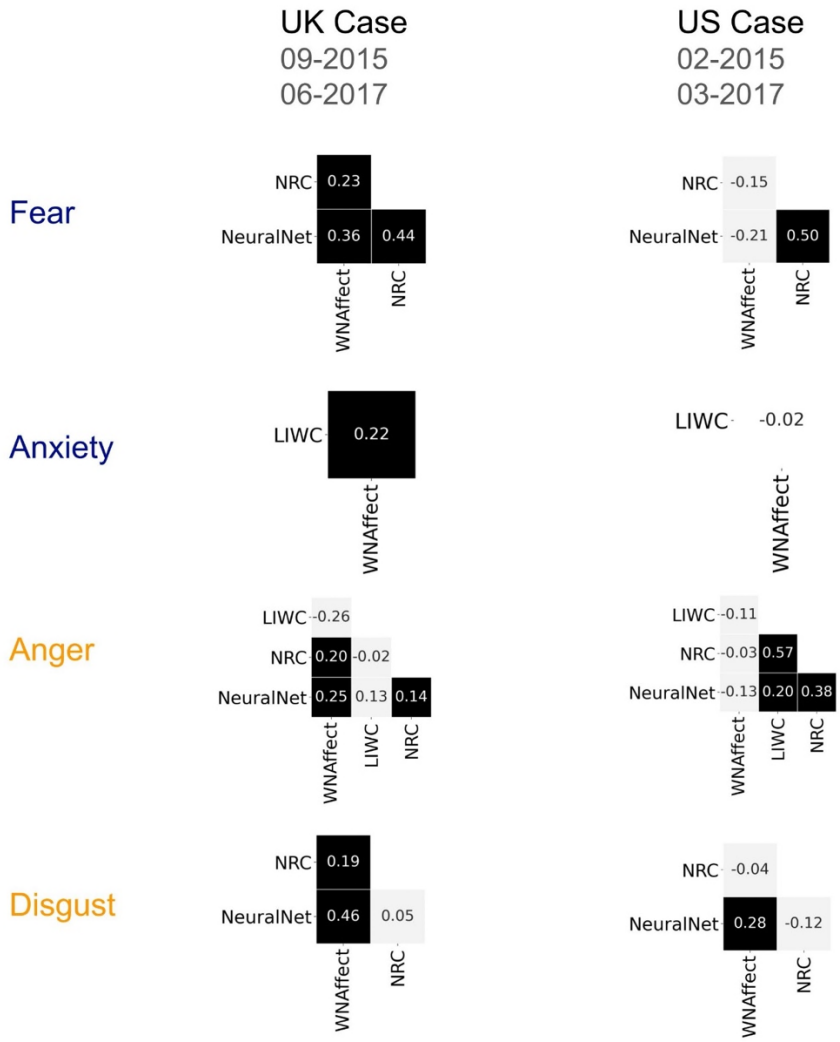


Figure E3. Pearson correlations across emotion classifiers (direct correlations)

F. Results with Daily Granularity

In the main paper, we aggregate and analyse data at a weekly granularity, steering clear of shorter (daily) and longer (monthly) intervals. Aggregation into short temporal intervals (e.g. days) may result in an overly noisy time series. On the contrary, very long temporal intervals (e.g. months) may wash out insightful, short-term fluctuations. Social media has indeed shown to be relatively fast, suggesting a more granular analysis, but diffusion does not necessarily happen within days but often within weeks or months [9]. This, sustained changes in fear and anger levels become visible over weeks rather than days; and only sustained changes really matter in strategic political contexts such as referendum campaigns or presidential elections. Yet we acknowledge that, given notoriously short attention spans on social media, assuming faster response times would seem conventional. We therefore follow Barberá, Casas [10] in conducting a parallel analysis with daily granularity. The results point in the same direction as those in the paper, except that the negative correlations presented in Figure 5 of the paper do not show in an analysis with daily granularity.

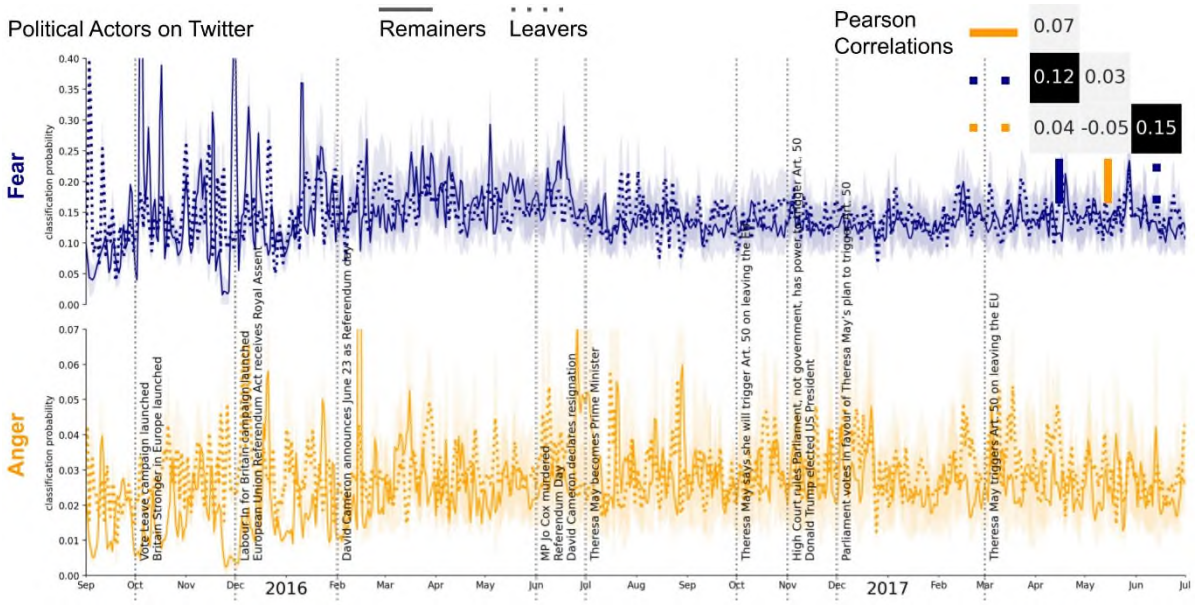


Figure F1. UK – time series and correlations for fear/anger from political actors (daily granularity)

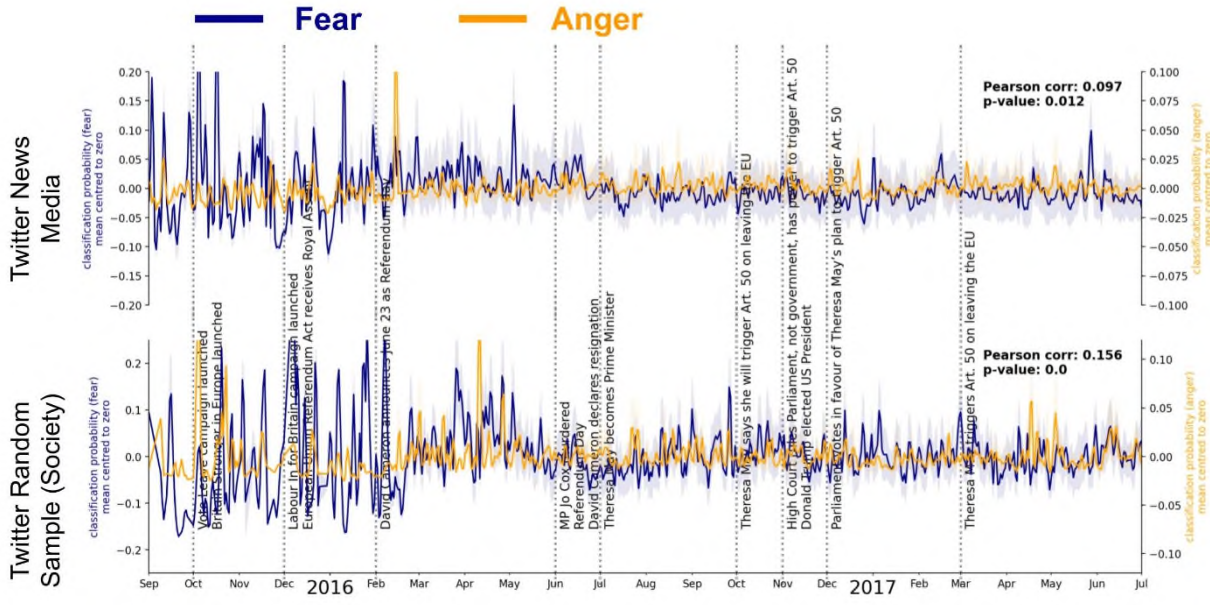


Figure F2. UK – overview of time series, aggregated by days.

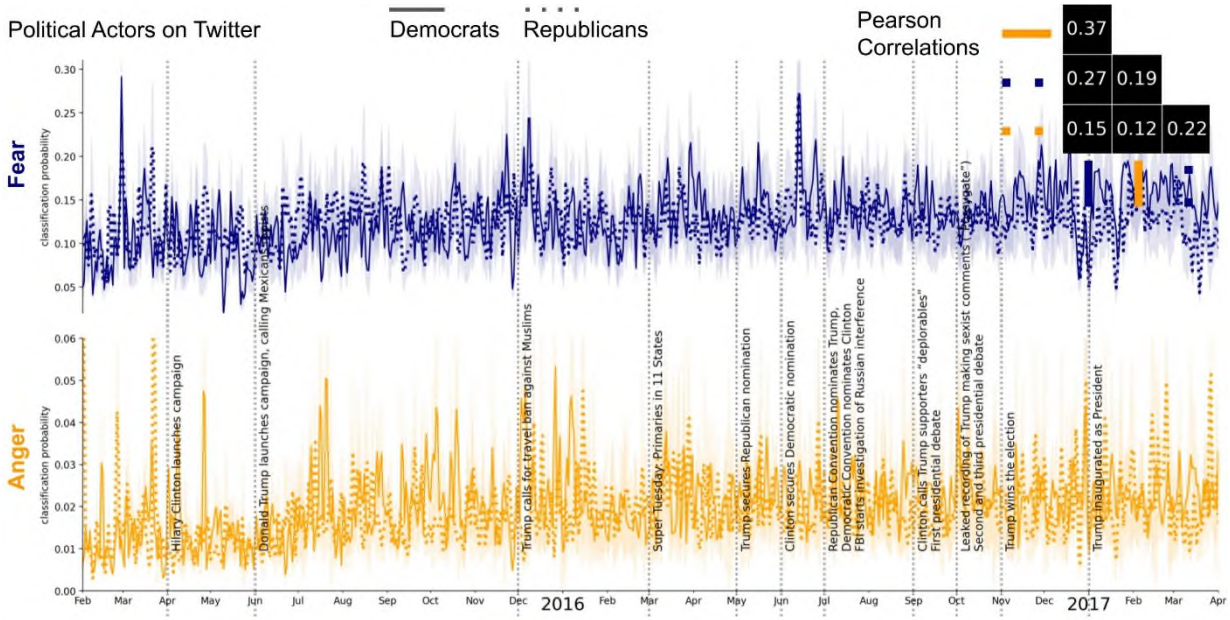


Figure F3. US – time series and correlations for fear/anger from political actors (daily granularity)

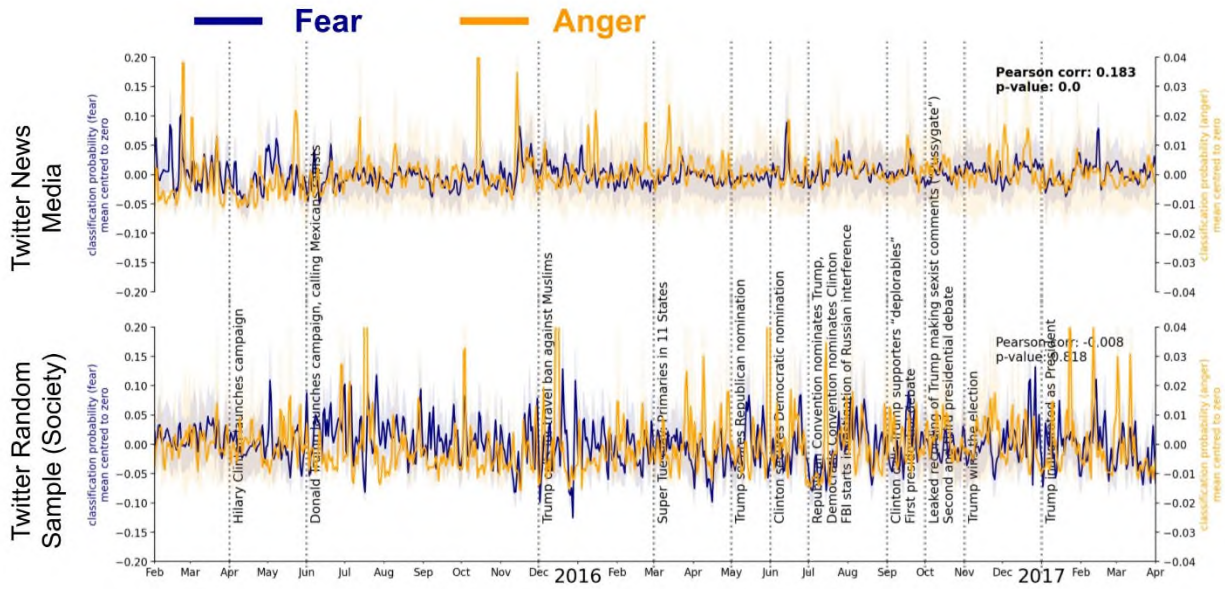


Figure F4. US – overview of time series, aggregated by days.

G. Granger Causality

Originally, we expected to find emotional "cascades" from "senders" via "amplifiers" to "receivers." We theorized that governmental actors send fear signals, news media amplify them, and citizens receive them, leading to greater support for governmental actors; whereas populist actors send anger signals, news media amplify them, and citizens receive them, leading to greater support for populist actors. We further expected that fluctuations in fear and anger signals emitted by political actors should precede fluctuations in fear or anger content in news media; these, in turn, should precede fluctuations in citizen support for the political actors in question. We aggregated opinion poll data and examined if there is the expected sequence of fear and anger signals percolating through the news and translating into citizen support for governmental and populist actors, respectively.

To do so, we calculated Granger causality between time series. Granger causality is a statistical hypothesis test quantifying the degree to which one time series holds informative value for forecasting another [11]. Intuitively, it measures whether predicting variable Y based on its own history and on the history of another variable X is more accurate than predicting Y only autoregressively, based on its own history. It is worth noting that two variables X and Y may reveal Granger causality when they are driven or confounded by a third, omitted variable Z; therefore, there is dispute as to whether Granger causality allows for causal claims [12].

To mitigate potential regular or seasonal trends in our time series, we take the first derivative of the time series. We verified stationarity using the Augmented Dickey-Fuller [13] and KPSS test [14], imposing a significance level of α=5%. Next, we identified the optimal time lag between the time series X and Y based on the Bayesian [15] information criteria on a Vector Autoregression Model (VAR).

We follow recent studies in political communication by Barberá, Casas [10] and Gilardi, Gessler [16].

Using the same model and the identified time lag, we measure Granger causality between time series based on an F-test using Statsmodels [17] and imposing a significance level of α = 5%. The results are presented below, for weekly (Figure G1) and daily granularity (Figure G2). For ease of interpretation, we have colour-coded all those cells where the model predicts Granger causality.

The figures show the results from Granger causality tests for all intersections between time series. Cells encased with an orange box are those where we would expect a positive result, given our original theoretical expectation that fear and anger signals cascade from politicians via news media to society. However, this expectation stands confirmed only in few cases. While many Granger causality tests across time series are positive, this is rarely the case where we would expect it. Indeed, there is as much Granger causality below the diagonal line as there is above. All cells where we have theoretical expectations are above the diagonal line. Below the diagonal line, many cells relate to time series predicting each other in a way that is opposite to our model expectations, for example politicians following rather than leading the media [10, 16].

There is some very limited indication that, after one to four weeks, society receives anger and fear signals from politicians and media in ways that might be consistent with theoretical expectations. In the UK, fear signals emitted by Remain politicians predict Remain polls by four weeks. Fear in Twitter media predicts fear in Twitter society and Remain polls by two weeks. Anger in Twitter media predicts anger in Twitter society by one week. In the US, fear signals emitted by Democratic politicians predict fear in Twitter media, as well as fear in Twitter society, by one week.

However, we should have little or no confidence in this. More often than not, Granger tests fail to confirm theoretical expectations. Indeed, the most interesting finding is accidental. It seems that, in the USA, average time lags are much shorter. This applies not only to weekly but also to daily granularity, the results of which we report in Figure G2 despite lower relevance for our theory.

Figure G1: Results of Granger causality tests (weekly granularity)

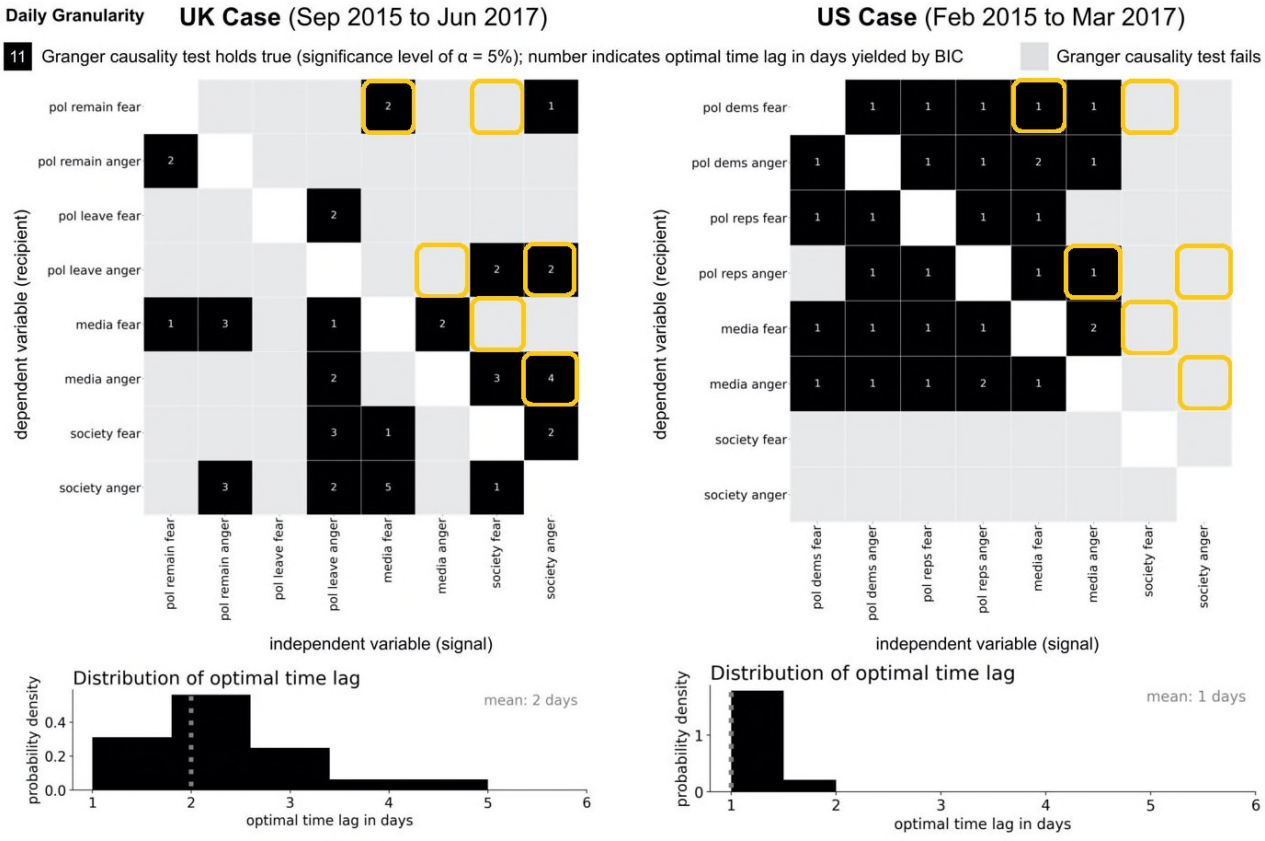


Figure G2: Results of Granger causality test (daily granularity)

Any communication cascade could be either real or imaginary, that is, it could be either measurable in the data or it could be in the strategic calculus of politicians and their advisers.

Since it is technically challenging to track cascading along systems of time series, we would not rule out that some form of cascading takes place even though we are unable to demonstrate it. However, our expectations in this regard have failed so clearly that we consider it probable that, effectively, there is no communication cascade. More likely, political actors, media and citizens both lead and follow each other [1, 16].

Any communication cascade could be either real or imaginary, that is, it could be either measurable in the data or it could be in the strategic calculus of politicians and their advisers. To the extent that governmental politicians hope to gain support from fomenting fear, and populist politicians from spreading anger, failure to disconfirm the null hypothesis about “cascading” has its own relevance. If the communication cascade does not exist or if it does not work, then this takes away any strategic incentive for political operatives to engage in fear mongering, or anger mongering for that matter.

Populist politicians may think they can capitalize on anger and governmental politicians on fear, but we do not find any such payoff. True, anger and fear signals sometimes ripple from political actors to news media and further to society, but we do not find anything to indicate a systematic mechanism translating fear/anger signals into actual polling support. If this is so, and if politicians and their advisors take it to heart, it can give much needed relief to highly polarized societies. In the absence of a communication cascade, there is no incentive for political hacks to beat the emotional drum.

H. Timelines

Brexit timeline. Main source: Walker [18]

2015	
October 8	*Vote Leave* campaign launched
October 12	*Britain Stronger in Europe* launched
December 1	*Labour In for Britain* campaign launched
December 17	*European Union Referendum Act* receives Royal Assent
2016	
February 22	David Cameron announces June 23 as Referendum day
June 16	MP Jo Cox murdered
June 23	Referendum day
June 24	David Cameron declares resignation
July 13	Theresa May becomes Prime Minister
October 2	Theresa May says she will trigger Art. 50 on leaving the EU
November 3	High Court rules Parliament, not government, has power to trigger Art. 50
November 8	Donald Trump elected US President
December 7	Parliament votes in favour of Theresa May's plan to trigger Art. 50
2017	
March 29	Theresa May triggers Art. 50 on leaving the EU

Trump timeline. Main source: Stracqualursi [19]

2015	
April 12	Hilary Clinton launches campaign
June 16	Donald Trump launches campaign, calling Mexicans rapists
December 7	Trump calls for travel ban against Muslims
2016	
March 1	Super Tuesday: Primaries in 11 States
May 26	Trump secures Republican nomination
June 6	Clinton secures Democratic nomination
July 19	Republican Convention nominates Trump
July 26	Democratic Convention nominates Clinton
July 31	FBI starts investigation of Russian interference
September 10	Clinton calls Trump supporters “deplorables”
September 26	First presidential debate
October 7	Leaked recording of Trump making sexist comments (“Pussygate”)
October 9	Second presidential debate
October 19	Third presidential debate
November 8	Trump wins the election
2017	
January 20	Trump inaugurated as President

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