Appendix

ANNEX A. PROTEST EVENTS: IDENTIFICATION, CODING, AND RELIABILITY

To identify and code protest events, we instructed six research assistants proficient with one or more languages of the country cases. Following previous studies, coders were first asked to identify relevant coding units in newspaper articles, with the help of a dedicated keyword search on Factiva and Lexis-Nexis (Berkhout et al. 2015). We opted for the printed press because the comparative design covering eleven European countries made accessibility a primary concern, and thus the national press preferable to other sources such as agency dispatches and police reports (Hutter 2014). In the Hungarian case, *Népszabadság* would have been the most coherent choice in comparative perspective, but the newspaper ceased publication in 2016 under mounting government pressure. The Orbán government has attacked freedom of the press and colonised the media landscape since 2010 (Bajomi-Lázár 2013; Bátorfy and Urbán 2020). At the time of data gathering, there were no reliable or independent information sources to draw from outside of the internet, hence our decision to rely on two online news portals (i.e. Index and the website of the HVG weekly magazine) providing information on domestic affairs on a daily basis.

Since we wanted to employ sources that were as comparable as possible, we opted for one quality newspaper per country. Following previous examples, we chose the main liberal outlet in each country: these are considered particularly suited for comparative studies because they mirror the debates in a detailed manner and influence the editorial decisions of a wide range of other news organisations (Kriesi et al. 2012). To control for possible biases due to news outlet selection, we used the FACTIVA archives to compare the number of relevant articles in our target outlets with the ones of other mainstream quality newspapers in each country, for a sample period of six months. The results illustrate that the quantitative difference in the coverage of far-right protest mobilisations across quality papers is marginal (below 10 per cent), which is in line with the findings of previous studies (Koopmans 2004).

We used the standard definition of a protest event as a collective, public action, organised by a far-right collective actor with the explicit purpose of expressing critique or dissent (Hutter 2014). Subsequently, coders were asked to perform the same search on websites, browsing news and/or press release section, and coding all protest events described therein. Finally, coders were asked to code protest events according to 23 variables, including action repertoires (Table 1) and issue focus (Table 2). The full codebook with detailed definition of each variable is available upon request.

Since multiple researchers were involved in the coding, we ran reliability tests to check for inter-coder consistency (Berkhout et al. 2015). To test for selection bias, we asked coders to select the relevant articles/press releases within a broader sample whereby we included a number of false positives. To test for description bias, we then asked coders to code the relevant articles for the 23 variables included in the dataset. These tests yielded a strong consistency regarding both the selection/identification of events and their description. The Cronbach alpha for selection bias (computed on a sample of 15 articles and 10 web posts) was 0.985. The Cronbach alphas for description bias (computed on a sample of ten articles) were 0.998, 0.995, 0.992, 0.879, and 0.987, with an average of 0.970.

The tables below report metadata about the sources used for coding, and the main descriptive statistics for the protest event dataset. In addition, we included a comparison between the data produced in our project, and other publicly available comparative datasets on protest mobilisation.

Table A1. Main collective actors, newspapers, and websites used for data collection

Country	***Main actor***	***Newspaper***	***Website***
Bulgaria	VMRO	*Dnevnik*	www.vmro.bg
Estonia	EKRE	*Postimees*	www.ekre.ee
France	Les Identitaires	*Le Monde*	www.les-identitaires.com www.generation-identitaire.com www.bloc-identitaire.com
Germany	NPD (until 2014) PEGIDA (from 2015)	*Süddeutsche Zeitung*	www.npd.de www.facebook.com/pegidaevofficial
Greece	Golden Dawn	*Kathimerini*	www.xryshaygh.com
Hungary	Jobbik	*Heti Világgazdaság* *Index*	www.jobbik.hu
Italy	CasaPound Italia	*Il Corriere della Sera*	www.casapounditalia.org
Poland	Ruch Narodowy	*Gazeta Wyborcza*	www.ruchnarodowy.net
Slovakia	Kotleba – □udová Strana Na□e Slovensko	*SME*	www.naseslovensko.net
Sweden	Nordiska Motståndsrörelsen	*Dagens Nyheter*	www.nordfront.se
United Kingdom	EDL (until 2014) Britain First (from 2015)	*The Guardian*	www.englishdefenceleague.org.uk www.britainfirst.org

Table A2. Main collective actors included in the analysis

Country	Main group	Ideology	Year of Foundation	MPs or EMPs
Bulgaria	VMRO	Radical right	1999	2008 and 2014-2018
Estonia	EKRE	Radical right	2006	2008-2010; 2015-2018
France	Les Identitaires	Radical right	2003	-
Germany	PEGIDA	Radical right	2014	-
Germany	NPD	Extreme right	1964	2014-2018
Greece	Golden Dawn	Extreme right	1985	2012-2018
Hungary	Jobbik	Radical right	2003	2009-2018
Italy	CasaPound Italia	Extreme right	2003	-
Poland	Ruch Narodowy	Extreme right	2008	2015-2018
Slovakia	Kotleba – Ľudová strana Naše Slovensko	Extreme right	1995	2016-2018
Sweden	Nordiska Motståndsrörelsen	Extreme right	1997	-
UK	English Defence League	Radical right	2009	-
UK	Britain First	Radical right	2015	-

Table A3. Protest events by country

Country	***Protest events***	***%***
Bulgaria	264	5.45
Estonia	92	1.90
France	603	12.45
Germany	455	9.39
Greece	614	12.67
Hungary	201	4.15
Italy	1397	28.83
Poland	453	9.35
Slovakia	226	4.66
Sweden	339	7.00
United Kingdom	201	4.15
Total	*4845*	*100*

To test for potential sources of bias due to the political leanings and journalistic practices of the selected news sources, we looked at whether the same list of keywords would yield significantly different findings if applied to other quality newspapers. For a subsample of countries for which additional news sources were available in the Factiva web archives, we compared the overall number of articles produced by the keywords applied to two alternative quality newspapers. The results for a sample period of 12 months (May 2019-May2020) show that, while different quality newspapers might have diverging political leanings, this does not substantially affect the visibility of far-right collective actors, at least in terms of mentions.

Table A4. Media coverage of far-right groups in different newspapers

Name actor	***Newspaper 1***	***No.***	***Newspaper 2***	***No.***	***% Diff***
CasaPound Italia	*La Repubblica*	188	*Corriere della Sera*	240	12
EDL	*The Guardian*	48	*The Times*	47	1
Britain First	*The Guardian*	46	*The Times*	49	3
Les Identitaires	*Le Monde*	60	*Le Figaro*	71	8
PEGIDA	*Süddeutsche Zeitung*	163	*Die Zeit*	135	9
NPD	*Süddeutsche Zeitung*	167	*Die Zeit*	120	16
Ruch Narodowy	*Gazeta Wyborzca*	87	*Fakt*	73	9
EKRE	*Postimees*	90	*DELFI*	74	9
VMRO	*Dnevnik*	554	*24 Chasa*	632	7

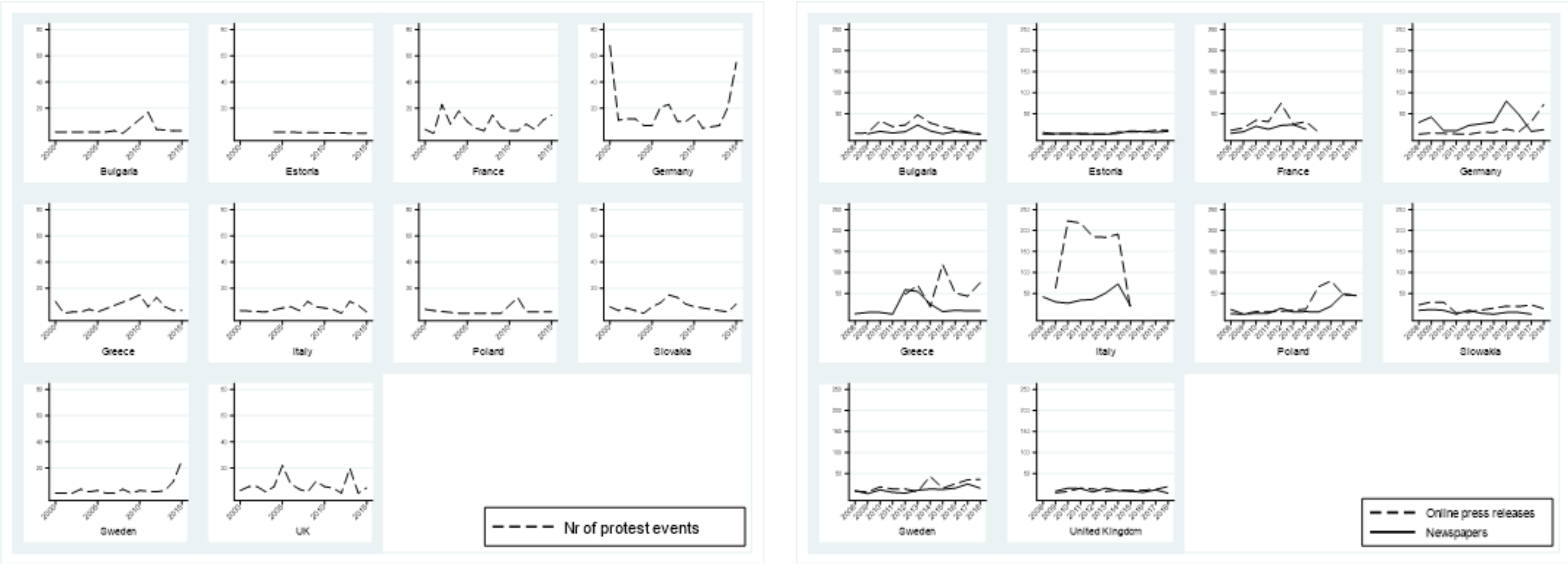
While no existing dataset focuses specifically on the far right, the archive by the Observatory for Political Conflict and Democracy (PolDem) allows for a comparison on a subset of the data, as it houses a large stock of comparative data on protest events and issue-specific public contestation covering a wide range of European countries over a long period of time. We focus on the poldem-protest_30 dataset (Kriesi et al. 2020a), which stores protest events in 30 European countries over the period 2000-2015. Since the dataset covers all issues of protest and does not include a variable for far-right collective actors, we selected protest events coded as 'xenophobic', and then excluded those that were promoted by mainstream political actors. From our data, we excluded all protest events derived from far-right collective actors' websites, limiting the comparison to newspapers data only. While we assume that this offers good grounds for comparison with far-right protest mobilisation, important differences exist between the two datasets, notably concerning the source of data (English language news wires vs. national quality newspapers), sampling strategy, and the string used to extract the data (general string vs. organisation names).

The figures below illustrate the advantages and disadvantages of respective designs, showing that the two data collection strategies produce slightly dissimilar data, notably with respect to countries like Germany and Italy. Our goal is not to assess which strategy performs best, but we believe that these divergences can be explained by the sampling technique adopted in the PolDem dataset, and the actor-based approach used in our own. A closer look at the data shows that, if our approach certainly reduces the bias of sampling over the total amount of protests reported, it underestimates the weight of spontaneous protests that could not be attributed to any specific actors (as confirmed by the large share of xenophobic protest events which did not have a 'sponsoring' actor in the PolDem dataset).

Table A5. Protest events by country (PolDem data vs. FARPE data, newspapers only)

	POLDEM Data		***FARPE Data***	
Country	***No. protests***	***%***	***No. protests***	***%***
Bulgaria	37	3.94	68	3.39
Estonia	3	0.32	44	2.19
France	137	14.62	151	7.53
Germany	290	30.95	315	15.70
Greece	79	8.43	187	9.32
Hungary	44	4.7	201	10.02
Italy	64	6.83	601	29.96
Poland	29	3.09	167	8.33
Slovakia	85	9.07	58	2.89
Sweden	62	6.62	120	5.98
United Kingdom	107	11.42	94	4.69
Total	*937*	*100*	*2006*	*100*

Figure A1. Cross-country and overtime distribution of protest events, PolDem data (left) and FARPE data (right)



Annex B. Description of the dependent variable and choice of model specification

Histogram of the dependent variable (*mobtot*) showing that OLS regression is not appropriate for count data and checked whether the mean and variance are the same as in a Poisson distribution. Since the variance of *mobtot* is nearly four times larger than the mean, its distribution displays signs of *overdispersion*, that is, greater variance than might be expected in a Poisson distribution. Since the goodness-of-fit test statistic for a Poisson regression indicates that the model is inappropriate, we opted for negative binomial regression – which is supported by the likelihood ratio test of overdispersion parameter alpha.

We then declared the panel structure of the data in the full model (supported by the likelihood-ratio test comparing the panel estimator with the pooled estimator). The final model includes random effects based on Hausman test (we run the full models using standard country fixed-effects specification – excluding time-invariant predictors – and the results are not substantially different from those presented above).

Figure B1. Distribution of the dependent variable (*mobtot*)

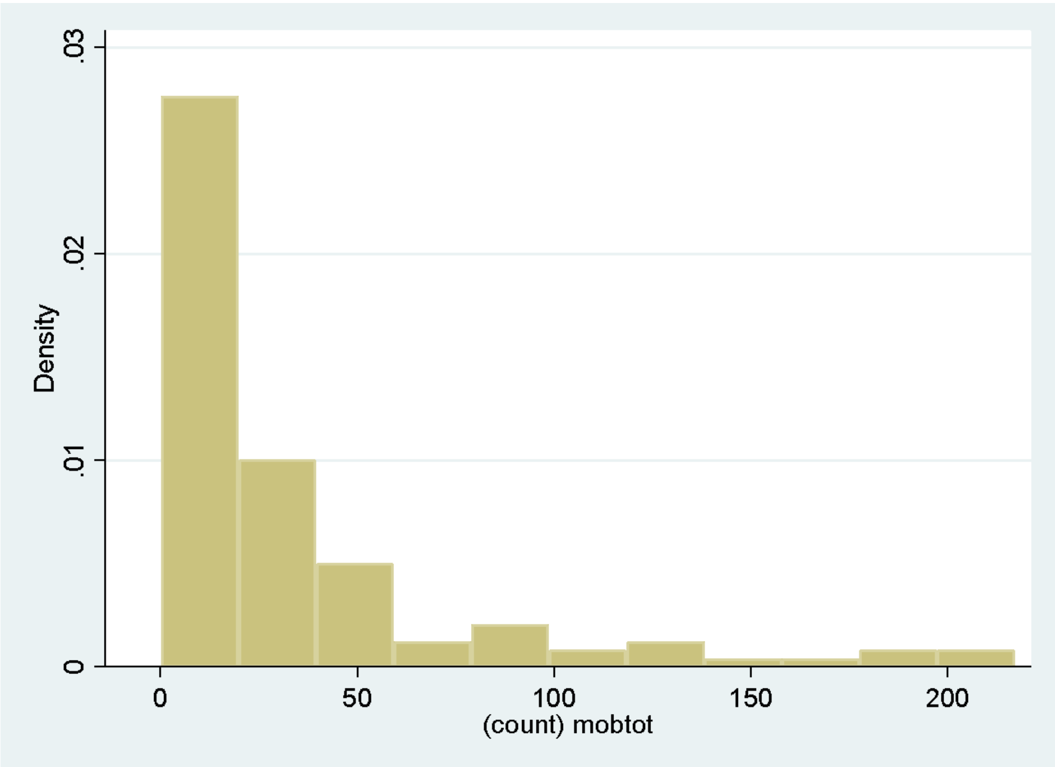


Table B1. Test for Poisson distribution of the dependent variable (*mobtot*) with goodness of fit

```
. summarize mobtot, detail

                       (count) mobtot
-------------------------------------------------------------
      Percentiles      Smallest
 1%            0              0
 5%            0              0
10%            2              0       Obs                 121
25%            6              0       Sum of Wgt.         121

50%           16                      Mean           34.01653
                        Largest       Std. Dev.      45.82103
75%           42            181
90%           96            193       Variance       2099.566
95%          138            209       Skewness       2.237711
99%          209            217       Kurtosis       7.776141

         Deviance goodness-of-fit =  2728.093
         Prob > chi2(105)         =    0.0000

         Pearson goodness-of-fit  =  2688.105
         Prob > chi2(105)         =    0.0000
```

Table B2. Likelihood-ratio test of alpha for negative binomial distribution

```
LR test of alpha=0: chibar2(01) = 2248.81              Prob >= chibar2 = 0.000
```

Table B3. Likelihood-ratio test on panel structure of the data (panel vs. pooled estimator)

```
LR test vs. pooled: chibar2(01) = 35.01                Prob >= chibar2 = 0.000
```

Table B4. Hausman test for random vs. fixed effects

```
    Test:  Ho:  difference in coefficients not systematic

                 chi2(14) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =        8.64
                Prob>chi2 =      0.8531
                (V_b-V_B is not positive definite)
```

ANNEX C. DESCRIPTIVE STATISTICS

Table C1. Descriptive statistics of dependent and independent variables

Variable	**Acronym**	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Total mobilization by year	mobtot	121	34.01	45.81	0.00	217.00
Economic Performance Index	griev_epi_s	121	0.00	1.00	-2.54	1.86
Inflow of Migrants	griev_migf~s	121	0.00	1.00	-0.62	5.04
Satisfaction with democracy	griev_satd~s	121	0.00	1.00	-1.99	1.86
Ban on far right parties	dos_ban_s	121	0.00	1.00	-1.23	1.00
Counter-mobilization	dos_ctrm~n_s	121	0.00	1.00	-0.88	2.23
Government L-R orientation	pos_lrgov_s	121	0.00	1.00	-2.51	1.78
Divided party control	pos_conse~_s	121	0.00	1.00	-2.00	2.75
Far-right network	res_coordt~s	121	0.00	1.00	-1.02	2.03
Elected officials	res_mps_s	121	0.00	1.00	-0.55	2.91
Organizational form	res_orgform	121	1.69	0.62	1.00	3.00
Ideology	res_ideology	121	1.52	0.50	1.00	2.00
Exposure	res_exposu~s	121	0.00	1.00	-1.31	3.11
Area	area	121	1.55	0.50	1.00	2.00

Figure C1. Cross-national and overtime variation in *counter-mobilisation* variable (yearly percentage of events facing reaction)

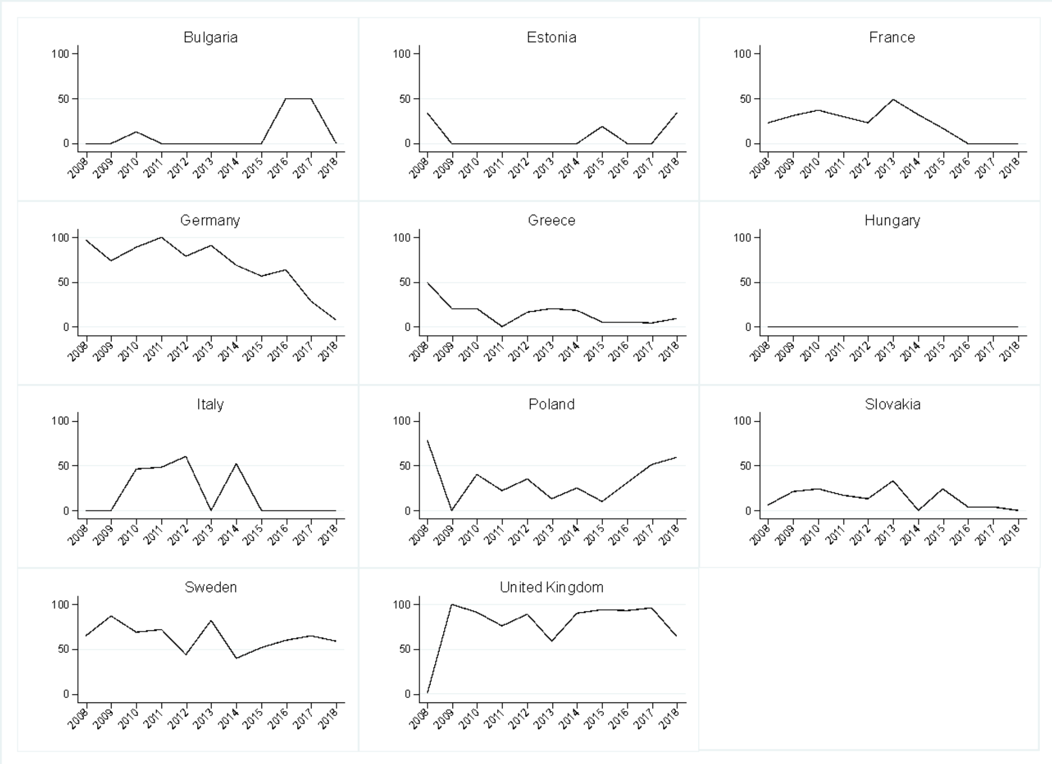


Figure C2. Cross-national and overtime variation in *network* variable (yearly percentage of joint events)

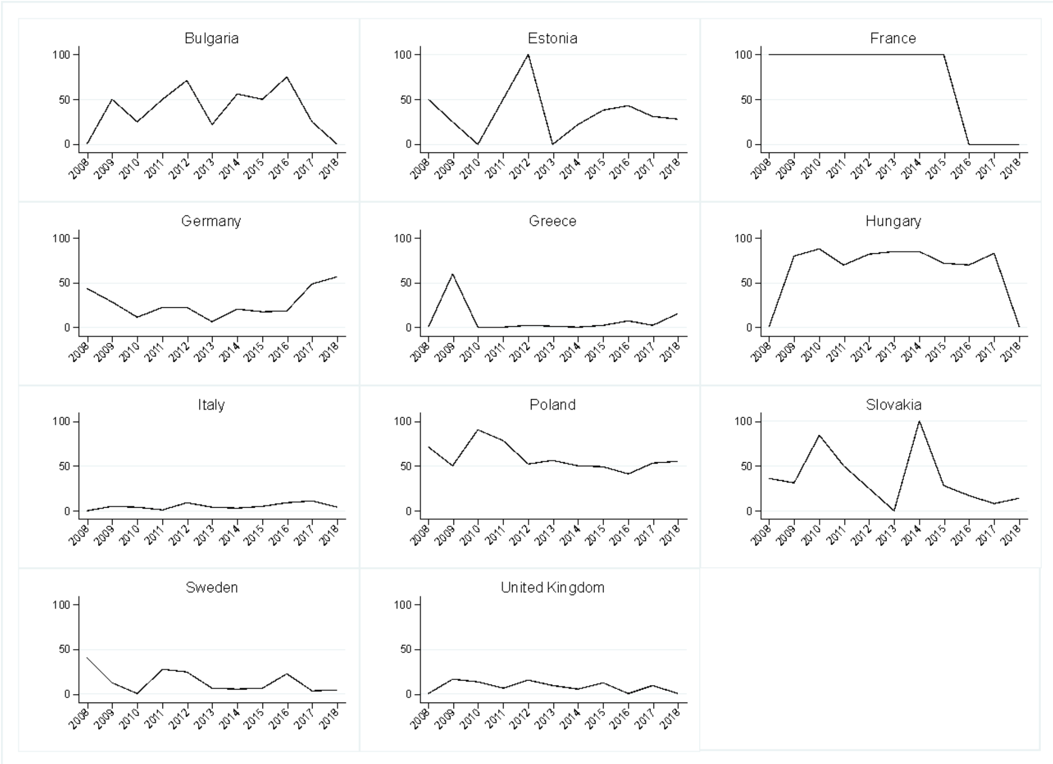


Figure C3. Cross-national and overtime variation in *representation* variable (percentage of elected officials)

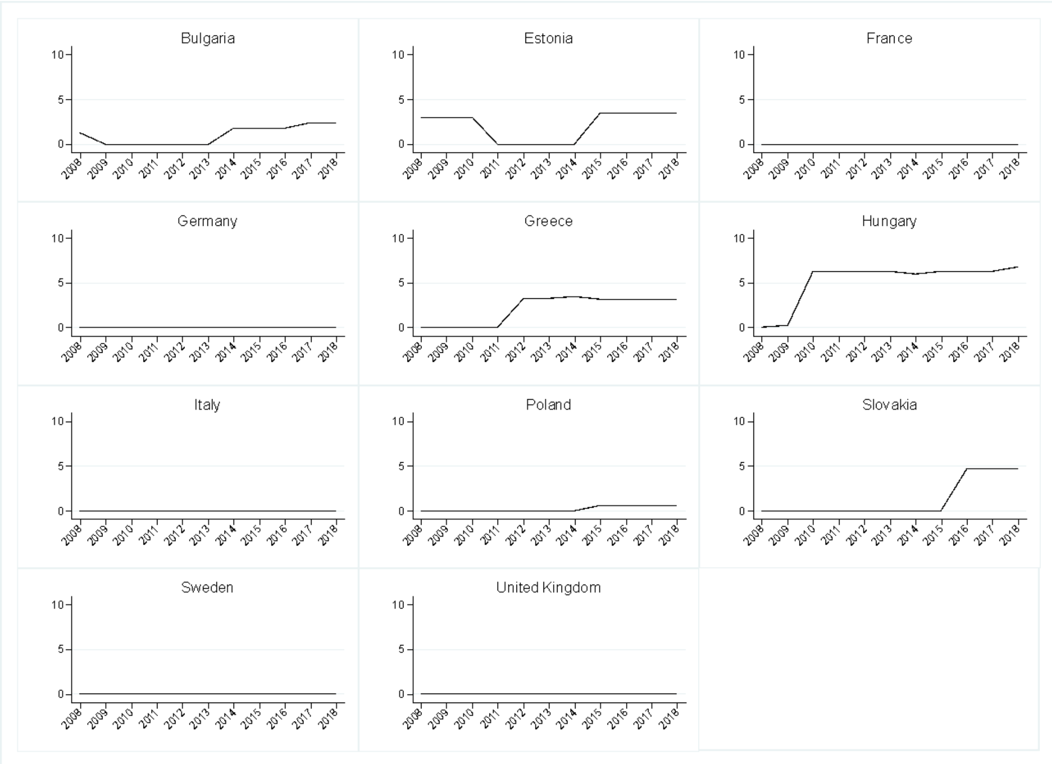
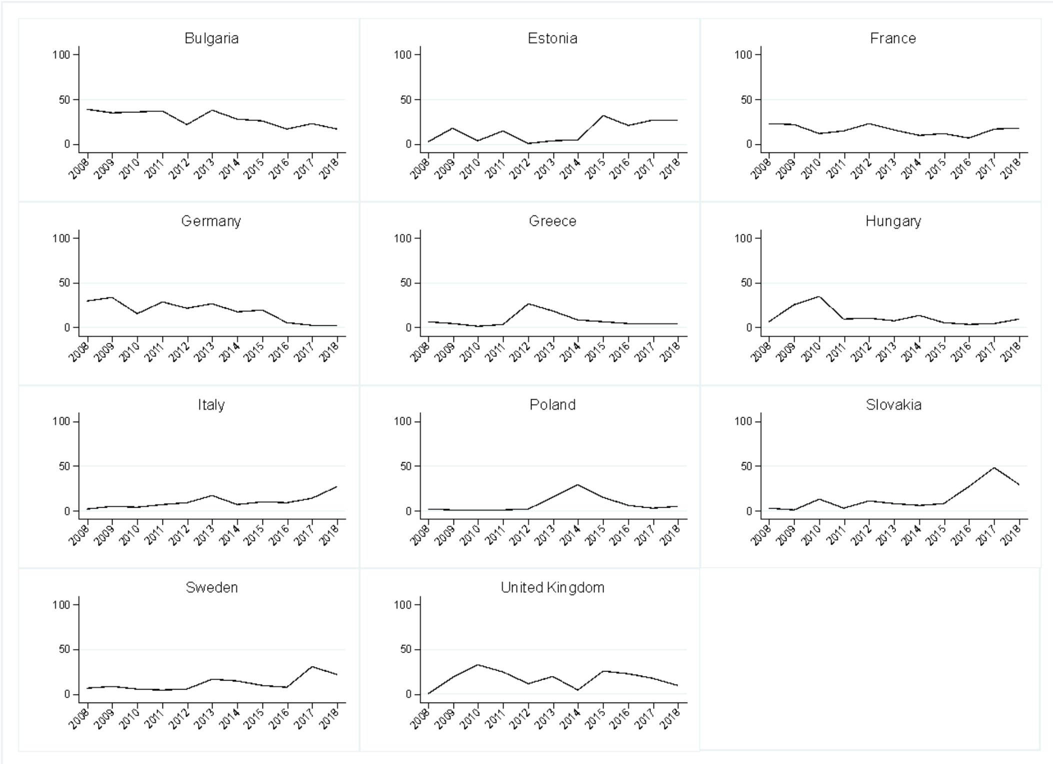


Figure C4. Cross-national and overtime variation in *exposure* variable (Google Trends figures)



ANNEX D. ROBUSTNESS OF RESULTS

Results of the negative binomial regression are unlikely to be robust with OLS due to the small N and low number of degrees of freedom, but they are consistent with Poisson specification.

Table D1. Poisson regression specification

```
Iteration 0:   log likelihood = -1515.2998
Iteration 1:   log likelihood = -1222.6053
Iteration 2:   log likelihood = -1214.2857
Iteration 3:   log likelihood = -1214.2564
Iteration 4:   log likelihood = -1214.2564

Conditional fixed-effects Poisson regression    Number of obs     =        121
Group variable: countrycode                     Number of groups  =         11

                                                Obs per group:
                                                              min =         11
                                                              avg =       11.0
                                                              max =         11

                                                Wald chi2(14)     =     505.54
Log likelihood  = -1214.2564                    Prob > chi2       =     0.0000
```

mobtot	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
griev_epi_s	-.0657432	.0327381	-2.01	0.045	-.1299087	-.0015777
griev_migflow_s	.3399808	.043859	7.75	0.000	.2540186	.4259429
griev_idnat_s	-.0667295	.0320363	-2.08	0.037	-.1295195	-.0039395
griev_satdemo_s	.4265612	.0584991	7.29	0.000	.3119051	.5412174
dos_ban_s	-.1709207	.0386085	-4.43	0.000	-.246592	-.0952494
dos_ctrmob_gen_s	.2483047	.0419259	5.92	0.000	.1661315	.3304779
pos_lrgov_s	-.0244809	.0223572	-1.09	0.274	-.0683002	.0193385
pos_consensus_s	.1154412	.0299412	3.86	0.000	.0567574	.1741249
res_coordtot_s	.3746011	.0378691	9.89	0.000	.3003791	.4488231
res_mps_s	.5515906	.043075	12.81	0.000	.4671652	.6360161
res_orgform						
2	.2445137	.0492228	4.97	0.000	.1480388	.3409886
3	.2872634	.1749835	1.64	0.101	-.055698	.6302248
res_ideology	-.6210654	.1355895	-4.58	0.000	-.886816	-.3553149
res_exposure_s	.0348326	.0265017	1.31	0.189	-.0171097	.0867749

We also investigated possible problems of endogeneity in the form of reverse causality. To check whether some independent variables affect the dependent variables (or the other way around), we plotted a matrix of the correlations, which shows that most of the independent variables are not highly correlated. We first run the model by omitting variables that display high correlations with other factors: *satisfaction with democracy* correlates with *counter-mobilisation* (-0.67), *Economic Performance Index* (=0.49) and *migration inflow* (-0.41). *Migration inflow* also correlates with *ban on parties* (0.41) and *counter-mobilisation* (0.42), and *share of MPs/MEPs* and *ban on parties* (-0.47). Models omitting *satisfaction with democracy*, *migration inflow*, and *ban on parties* are not substantially different from those presented above.

Table D2. Correlation matrix

	mobtot	gri~pi_s	grie~w_s	grie~t_s	grie~o_s	dos_ba~s	dos~en_s	pos_lr~s	pos_c~_s	res_~t_s	res_m~_s	res_or~m	res_id~y	res_ex~s
mobtot	1.0000													
griev_epi_s	-0.1252	1.0000												
griev_migf~s	0.1451	0.3097	1.0000											
griev_idna~s	-0.1723	-0.2489	-0.2215	1.0000										
griev_satd~s	0.2126	-0.4905	-0.4131	0.1360	1.0000									
dos_ban_s	0.1689	0.2912	0.4199	-0.1520	-0.3456	1.0000								
dos_ctrm~n_s	-0.1635	0.2845	0.4248	0.1509	-0.6736	0.4148	1.0000							
pos_lrgov_s	-0.1954	0.1450	0.0672	0.2652	-0.2564	0.0445	0.2377	1.0000						
pos_conse~_s	0.1364	-0.0776	0.0575	0.1053	0.0127	-0.0914	0.0630	0.0623	1.0000					
res_coordt~s	-0.1437	0.0815	-0.1660	-0.1390	0.0525	0.0369	-0.1443	0.0191	-0.3322	1.0000				
res_mps_s	-0.0568	-0.0094	-0.3057	0.0034	0.3604	-0.4691	-0.3721	0.0338	-0.0385	0.1449	1.0000			
res_orgform	-0.0234	0.1193	-0.1644	-0.1043	0.2292	-0.3487	-0.1479	-0.0148	-0.0053	-0.0781	0.3907	1.0000		
res_ideology	0.3509	-0.1842	0.0105	-0.3409	-0.0475	0.2538	0.1284	-0.2761	0.2576	-0.3033	-0.2468	-0.0198	1.0000	
res_exposu~s	-0.1282	0.0821	0.0191	0.0648	0.0441	-0.0419	0.1081	0.0411	0.0704	-0.0501	0.0864	0.1775	-0.2214	1.0000

Furthermore, we also checked for possible problems of reverse causality for specific variables: the *share of MPs/MEPs*, the *size of network*, and the extent of *counter-mobilisation*, which could also be a result of increased mobilisation. We reproduced the models without each (and all three items). The significance of other coefficients are not substantially different from those in the full model.

Finally, to assess the impact of the unequal distribution of observations across country cases on our regression coefficient estimates, we compared the results for the negative binomial regression by systematically excluding country cases displaying very high (Italy) or very low numbers of events (Estonia), and checked robustness excluding cases in Western (France) and Eastern Europe (Hungary). The results show that the impact is limited and that there is no change in the significance levels of our main predictors.

Table D3. Regression coefficients, excluding Italy (full model)

mobtot	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
griev_epi_s	-.0949231	.1062345	-0.89	0.372	-.303139	.1132928
griev_migflow_s	.4224356	.1133738	3.73	0.000	.200227	.6446442
griev_satdemo_s	-.0694073	.2096542	-0.33	0.741	-.480322	.3415075
dos_ban_s	.0854622	.1221931	0.70	0.484	-.1540318	.3249562
dos_ctrmob_gen_s	.3027249	.1306063	2.32	0.020	.0467413	.5587084
pos_lrgov_s	-.1242454	.0927188	-1.34	0.180	-.3059709	.05748
pos_consensus_s	.2268642	.0999492	2.27	0.023	.0309673	.4227612
res_coordtot_s	.4692924	.1025841	4.57	0.000	.2682311	.6703536
res_mps_s	.3318701	.1199617	2.77	0.006	.0967494	.5669907
res_orgform						
2	.2708279	.2544141	1.06	0.287	-.2278146	.7694703
3	.1735922	.3744099	0.46	0.643	-.5602377	.9074221
res_ideology	-.3224498	.3530219	-0.91	0.361	-1.01436	.3694605
res_exposure_s	.1528411	.0869509	1.76	0.079	-.0175795	.3232617
area						
Western Europe	.7003815	.387317	1.81	0.071	-.0587459	1.459509
population	-.0139599	.0076907	-1.82	0.069	-.0290333	.0011135
_cons	.7443464	.6277122	1.19	0.236	-.4859469	1.97464
/ln_r	1.066748	.5847876			-.0794148	2.212911
/ln_s	3.386369	.7181498			1.978822	4.793917
r	2.905914	1.699342			.9236567	9.142286
s	29.55845	21.22739			7.234214	120.7735

LR test vs. pooled: chibar2(01) = 12.59 Prob >= chibar2 = 0.000

Table D4. Regression coefficients, excluding Hungary (full model)

mobtot	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
griev_epi_s	-.0601678	.1256961	-0.48	0.632	-.3065277	.1861921
griev_migflow_s	.386813	.1157204	3.34	0.001	.1600052	.6136209
griev_satdemo_s	-.031405	.2043604	-0.15	0.878	-.4319441	.3691341
dos_ban_s	-.0101808	.1295205	-0.08	0.937	-.2640363	.2436746
dos_ctrmob_gen_s	.2699456	.1188578	2.27	0.023	.0369886	.5029026
pos_lrgov_s	-.1317858	.0900443	-1.46	0.143	-.3082693	.0446978
pos_consensus_s	.1905945	.1015224	1.88	0.060	-.0083857	.3895748
res_coordtot_s	.4344127	.1201065	3.62	0.000	.1990083	.6698171
res_mps_s	.4390298	.1944861	2.26	0.024	.057844	.8202155
res_orgform						
2	.2112036	.2377767	0.89	0.374	-.2548301	.6772373
3	.3578766	.3767464	0.95	0.342	-.3805327	1.096286
res_ideology	-.2962669	.348287	-0.85	0.395	-.9788969	.3863631
res_exposure_s	.1516483	.1003924	1.51	0.131	-.0451172	.3484137
area						
Western Europe	.6891691	.4291542	1.61	0.108	-.1519577	1.530296
population	-.0095171	.0080732	-1.18	0.238	-.0253403	.0063062
_cons	.728159	.6631273	1.10	0.272	-.5715466	2.027865
/ln_r	.3692041	.4978499			-.6065637	1.344972
/ln_s	2.736334	.6699348			1.423286	4.049382
r	1.446583	.7201811			.5452212	3.838079
s	15.43031	10.3373			4.150736	57.36199

LR test vs. pooled: chibar2(01) = 31.91 Prob >= chibar2 = 0.000

Table D5. Regression coefficients, excluding France (full model)

Log likelihood = -457.69582 Prob > chi2 = 0.0009

mobtot	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
griev_epi_s	-.0050194	.1056009	-0.05	0.962	-.2119933	.2019545
griev_migflow_s	.3389801	.1202741	2.82	0.005	.1032473	.5747129
griev_satdemo_s	.1177598	.198512	0.59	0.553	-.2713166	.5068361
dos_ban_s	.0323012	.1218555	0.27	0.791	-.2065312	.2711336
dos_ctrmob_gen_s	.2251855	.1237753	1.82	0.069	-.0174096	.4677805
pos_lrgov_s	-.1255185	.0937959	-1.34	0.181	-.3093551	.058318
pos_consensus_s	.165911	.0913593	1.82	0.069	-.0131499	.3449719
res_coordtot_s	.3680944	.1167432	3.15	0.002	.1392819	.5969069
res_mps_s	.3154957	.1232145	2.56	0.010	.0739998	.5569917
res_orgform						
2	.0161277	.2420649	0.07	0.947	-.4583108	.4905662
3	.0328752	.380662	0.09	0.931	-.7132086	.7789591
res_ideology	-.2985872	.3253837	-0.92	0.359	-.9363275	.3391531
res_exposure_s	.1767701	.0864573	2.04	0.041	.0073169	.3462232
area						
Western Europe	.8579862	.4260226	2.01	0.044	.0229973	1.692975
population	-.0063765	.0077843	-0.82	0.413	-.0216335	.0088806
_cons	.6874824	.5764871	1.19	0.233	-.4424115	1.817376
/ln_r	.4734225	.490609			-.4881534	1.434998
/ln_s	2.789568	.6412798			1.532683	4.046454
r	1.60548	.7876627			.6137587	4.199638
s	16.27399	10.43618			4.630584	57.19427

LR test vs. pooled: chibar2(01) = 28.63 Prob >= chibar2 = 0.000

Table D6. Regression coefficients, excluding Estonia (full model)

mobtot	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
griev_epi_s	-.1022159	.1118368	-0.91	0.361	-.321412	.1169801
griev_migflow_s	.3901221	.1169155	3.34	0.001	.1609721	.6192722
griev_satdemo_s	.1076966	.2058656	0.52	0.601	-.2957925	.5111857
dos_ban_s	.0701738	.121898	0.58	0.565	-.1687418	.3090894
dos_ctrmob_gen_s	.3070051	.1280225	2.40	0.016	.0560856	.5579247
pos_lrgov_s	-.0815279	.0957578	-0.85	0.395	-.2692098	.106154
pos_consensus_s	.2042407	.0975002	2.09	0.036	.0131438	.3953376
res_coordtot_s	.4197299	.1154177	3.64	0.000	.1935154	.6459445
res_mps_s	.3948192	.1261542	3.13	0.002	.1475616	.6420769
res_orgform						
2	.1837113	.2476028	0.74	0.458	-.3015812	.6690038
3	-.7385369	.7430972	-0.99	0.320	-2.194981	.7179069
res_ideology	-.1734369	.3408723	-0.51	0.611	-.8415344	.4946606
res_exposure_s	.0877848	.0898422	0.98	0.329	-.0883026	.2638723
area						
Western Europe	.720154	.4069869	1.77	0.077	-.0775257	1.517834
population	-.0083207	.0073845	-1.13	0.260	-.022794	.0061526
_cons	.3699864	.6345022	0.58	0.560	-.8736151	1.613588
/ln_r	.5762331	.5041742			-.4119301	1.564396
/ln_s	3.129629	.6534759			1.84884	4.410419
r	1.779323	.8970888			.6623706	4.779789
s	22.8655	14.94205			6.352446	82.3039

LR test vs. pooled: chibar2(01) = 26.92 Prob >= chibar2 = 0.000

Table D7. Regression coefficients with separate items for the share of verbal/contentious reactions (full model)

Log likelihood = -497.62753 Prob > chi2 = 0.0000

mobtot	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
griev_epi_s	-.1104862	.103097	-1.07	0.284	-.3125526	.0915801
griev_migflow_s	.4035004	.1101405	3.66	0.000	.1876291	.6193718
griev_satdemo_s	-.0064764	.1925057	-0.03	0.973	-.3837806	.3708279
dos_ban_s	.0814227	.119769	0.68	0.497	-.1533201	.3161655
dos_ctrmob_cont_s	.17569	.1157002	1.52	0.129	-.0510782	.4024581
dos_ctrmob_verb_s	.2419591	.0671057	3.61	0.000	.1104345	.3734838
pos_lrgov_s	-.1176422	.0832701	-1.41	0.158	-.2808486	.0455642
pos_consensus_s	.2162185	.0941935	2.30	0.022	.0316027	.4008344
res_coordtot_s	.4426068	.1028272	4.30	0.000	.2410692	.6441444
res_mps_s	.3432823	.1203035	2.85	0.004	.1074919	.5790728
res_orgform						
2	.2743885	.2160112	1.27	0.204	-.1489857	.6977627
3	-.0112482	.3910387	-0.03	0.977	-.7776699	.7551735
res_ideology	-.2023808	.3210547	-0.63	0.528	-.8316363	.4268748
res_exposure_s	.1281347	.0831576	1.54	0.123	-.0348512	.2911206
area						
Western Europe	.6584041	.3890241	1.69	0.091	-.1040692	1.420877
population	-.0085646	.0075681	-1.13	0.258	-.0233977	.0062685
_cons	.504615	.5849079	0.86	0.388	-.6417833	1.651013
/ln_r	.5993841	.474203			-.3300368	1.528805
/ln_s	2.980834	.6093107			1.786607	4.175061
r	1.820997	.8635223			.7188973	4.612661
s	19.70424	12.00601			5.969165	65.04381

LR test vs. pooled: chibar2(01) = 35.08 Prob >= chibar2 = 0.000

Table D8. Regression coefficients controlling for migration crisis effect, excluding the year 2015 (full model)

mobtot	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
griev_epi_s	-.069901	.1085079	-0.64	0.519	-.2825726	.1427705
griev_migflow_s	.3748711	.1586706	2.36	0.018	.0638824	.6858598
griev_satdemo_s	.0962775	.2215476	0.43	0.664	-.3379478	.5305028
dos_ban_s	.073662	.1211206	0.61	0.543	-.1637299	.311054
dos_ctrmob_gen_s	.285903	.1266638	2.26	0.024	.0376465	.5341594
pos_lrgov_s	-.1141803	.0922983	-1.24	0.216	-.2950816	.0667211
pos_consensus_s	.1961285	.1004423	1.95	0.051	-.0007347	.3929918
res_coordtot_s	.4914656	.1067961	4.60	0.000	.282149	.7007822
res_mps_s	.3547271	.1264731	2.80	0.005	.1068445	.6026098
res_orgform						
2	.1740236	.2478274	0.70	0.483	-.3117091	.6597563
3	.1559155	.3946925	0.40	0.693	-.6176675	.9294986
res_ideology	-.2718382	.3590149	-0.76	0.449	-.9754946	.4318181
res_exposure_s	.1543045	.0882646	1.75	0.080	-.0186911	.3273
area						
Western Europe	.9950933	.4215864	2.36	0.018	.1687991	1.821388
population	-.0107289	.0078824	-1.36	0.173	-.0261782	.0047204
_cons	.4701332	.6198371	0.76	0.448	-.7447251	1.684991
/ln_r	.626069	.4886299			-.3316279	1.583766
/ln_s	3.08464	.6346134			1.84082	4.328459
r	1.870244	.9138571			.7177543	4.873274
s	21.85959	13.87239			6.301706	75.82736

LR test vs. pooled: chibar2(01) = 29.36 Prob >= chibar2 = 0.000

. restore

Table D9. Regression coefficients controlling for migration crisis effect, excluding the year 2016 (full model)

mobtot	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
griev_epi_s	-.0475438	.1112539	-0.43	0.669	-.2655975	.1705099
griev_migflow_s	.3690466	.1336368	2.76	0.006	.1071233	.63097
griev_satdemo_s	.0899456	.2071209	0.43	0.664	-.3160039	.4958951
dos_ban_s	.0734325	.1253763	0.59	0.558	-.1723006	.3191656
dos_ctrmob_gen_s	.3000396	.132548	2.26	0.024	.0402503	.5598289
pos_lrgov_s	-.1005366	.0926011	-1.09	0.278	-.2820314	.0809582
pos_consensus_s	.2032474	.0982516	2.07	0.039	.0106779	.395817
res_coordtot_s	.4313115	.1071651	4.02	0.000	.2212718	.6413512
res_mps_s	.3288852	.12808	2.57	0.010	.077853	.5799175
res_orgform						
2	.1773236	.2540776	0.70	0.485	-.3206593	.6753065
3	.0674453	.4026747	0.17	0.867	-.7217826	.8566732
res_ideology	-.2177346	.368287	-0.59	0.554	-.9395639	.5040947
res_exposure_s	.1266365	.0901358	1.40	0.160	-.0500263	.3032993
area						
Western Europe	.6941816	.4002148	1.73	0.083	-.0902249	1.478588
population	-.0089975	.0077309	-1.16	0.244	-.0241498	.0061548
_cons	.4570207	.6824289	0.67	0.503	-.8805154	1.794557
/ln_r	.6510926	.5097035			-.3479078	1.650093
/ln_s	3.188747	.6669907			1.881469	4.496025
r	1.917635	.9774252			.706164	5.207465
s	24.25801	16.17987			6.56314	89.65998

LR test vs. pooled: chibar2(01) = 24.29 Prob >= chibar2 = 0.000

Table D10. Regression coefficients controlling for migration crisis effect, excluding the years 2015 and 2016 (full model)

mobtot	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
griev_epi_s	-.0217431	.1183164	-0.18	0.854	-.2536389	.2101527
griev_migflow_s	.2812646	.2110608	1.33	0.183	-.1324071	.6949362
griev_satdemo_s	.1685209	.2299565	0.73	0.464	-.2821855	.6192273
dos_ban_s	.1154351	.1297015	0.89	0.373	-.1387751	.3696454
dos_ctrmob_gen_s	.3131929	.1369011	2.29	0.022	.0448716	.5815142
pos_lrgov_s	-.0896875	.1002997	-0.89	0.371	-.2862713	.1068964
pos_consensus_s	.1742504	.1030161	1.69	0.091	-.0276575	.3761583
res_coordtot_s	.4558881	.1121315	4.07	0.000	.2361145	.6756617
res_mps_s	.3256314	.1347384	2.42	0.016	.0615489	.5897139
res_orgform						
2	.1360724	.2771716	0.49	0.623	-.407174	.6793187
3	-.0277676	.4292375	-0.06	0.948	-.8690576	.8135223
res_ideology	-.2671198	.4131099	-0.65	0.518	-1.0768	.5425608
res_exposure_s	.128207	.0935955	1.37	0.171	-.0552369	.3116508
area						
Western Europe	.8965781	.4304542	2.08	0.037	.0529034	1.740253
population	-.0084273	.0084172	-1.00	0.317	-.0249247	.0080701
_cons	.4014751	.752036	0.53	0.593	-1.072488	1.875439
/ln_r	.8079806	.5517079			-.2733469	1.889308
/ln_s	3.401058	.7189163			1.992008	4.810108
r	2.243373	1.237687			.7608288	6.614791
s	29.99582	21.56448			7.330238	122.7449

LR test vs. pooled: chibar2(01) = 19.54 Prob >= chibar2 = 0.000

. restore

Table D11. Regression coefficients excluding data from websites (full model)

Log likelihood = -390.82294 Prob > chi2 = 0.0000

mobtot	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
griev_epi_s	-.0651718	.1077828	-0.60	0.545	-.2764222	.1460787
griev_migflow_s	.5529837	.1267203	4.36	0.000	.3046164	.8013509
griev_satdemo_s	.1192006	.2055336	0.58	0.562	-.2836379	.5220391
dos_ban_s	-.1559994	.148963	-1.05	0.295	-.4479614	.1359627
dos_ctrmob_gen_s	.7075107	.1335934	5.30	0.000	.4456724	.969349
pos_lrgov_s	-.108023	.0890903	-1.21	0.225	-.2826367	.0665908
pos_consensus_s	.0732728	.0947846	0.77	0.439	-.1125017	.2590473
res_coordtot_s	.4929235	.1088603	4.53	0.000	.2795613	.7062857
res_mps_s	.1658363	.1173343	1.41	0.158	-.0641347	.3958072
res_orgform						
2	.2706369	.2281237	1.19	0.235	-.1764773	.7177511
3	.0845778	.3864453	0.22	0.827	-.672841	.8419966
res_ideology	-.2661075	.3070489	-0.87	0.386	-.8679123	.3356974
res_exposure_s	.2284877	.0912876	2.50	0.012	.0495672	.4074081
area						
Western Europe	.2567543	.4430676	0.58	0.562	-.6116423	1.125151
population	-.0208117	.0087375	-2.38	0.017	-.0379368	-.0036866
_cons	.9548155	.5775295	1.65	0.098	-.1771216	2.086753
/ln_r	.6801513	.4976063			-.2951392	1.655442
/ln_s	2.522602	.6092121			1.328568	3.716636
r	1.974176	.9823627			.744428	5.235392
s	12.46098	7.591377			3.775634	41.1258

LR test vs. pooled: chibar2(01) = 30.05 Prob >= chibar2 = 0.000

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