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Discourse Networks of the Far Right: How Far-Right Actors become Mainstream in Public Debates

Appendices

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A Data Description and Public Debates across Time

Newspaper	Articles	Sentences total (average)	Cultural sentences	Contextual sentence groups	Period
Die Welt	95,217	411,0367 (43.16)	773,164	188,160	1999-2020
Junge Freiheit	26,038	101,1901 (38.86)	229,994	50,668	2000-2020
Sächsische Zeitung (Dresden)	15,995	655,886 (41.00)	140,141	33,904	2010-2020
Stuttgarter Zeitung	76,779	2,431,275 (31.66)	471,950	119,703	2010-2020
Süddeutsche Zeitung	131,156	546,2253 (41.64)	866,071	217,641	2000-2021
taz	175,231	6,009,181 (34.29)	1,297,490	319,852	1994-2020

Table 1: Newspaper Data Summary

Newspaper	Ideological orientation	Print issues*	Edition
Die Welt	Right-wing ***	464.924	Daily, national
Junge Freiheit	Radical-right ***	21,123	Weekly, national
Sächsische Zeitung (Dresden)	NA/Ambiguous	262.897	Daily, local
Stuttgarter Zeitung	NA/Ambiguous	204.601**	Daily, local
Süddeutsche Zeitung	Center-left ***	444.983	Daily, national
taz	Left-wing	57.123	Daily, national

Table 2: Newspaper characteristics

* Source: Informationsgemeinschaft zur Feststellung der Verbreitung von Werbeträgern (numbers from 1/2011). Note: ** Including Stuttgarter Nachrichten. *** SZ and Die Welt ideological classification according to Hallin and Mancini (2004, p. 27). Junge Freiheit according to Czymara and Bauer (2023).



Figure 6: Attention Towards Cultural Issues within German Mass Media

Note: Junge Freiheit covers cultural issues the most in around every third article. Die Welt and taz follow with increasing attention from around 10 % in 2000 up to 25 % in 2016. Comparatively, the SZ as well as both regional outlets the Sächsische Zeitung and the Stuttgarter Zeitung cover cultural issues the less. Yet, most attention towards the issue is captured in 2016 (14-15 %). Total amount of articles as unit of analysis.



Figure 7: Distribution of Number of Sentences

Note: N = 929,928. Distribution of number of sentences in the contextual sentence groups data set, excluded values with > 20 sentences. 70 % of the observations includes three or four newspaper sentences.

B Issue Dictionary

For conceptual simplicity in capturing the cultural issue in text, we developed a dictionary covering the sub-issues of Islam, migration, and nationalism.

Islam, migration, nationalism dictionary: islam*, mosl*, musl*, mosche*, kopft*, burka*, minaret*, scharia*, schura*, imam*, koran*, migra*, einwander*, flüchtling*, geflüchtete*, integration*, asyl*, abschieb*, einbürger*, überfremd*, rassis*, fremdenfeind*, multikult*, patriot*, nationalis*, identitär*, leitkultur, national* identität*, nazi*, völkisch*.

We validated our dictionary at the article level with N = 1,446 hand-coded articles by four different coders. Before the hand-coding, the researchers had several meetings with the coders to define more concretely the three concepts of interest: nationalism, migration and Islam. The meeting protocols created a more common understanding of what did and what did not belong to those concepts. Table 3 presents the performance of the Islam, migration and nationalism dictionaries *used* for the analysis. F1-scores reflect the balance of optimizing true positive texts identified while maintaining a few false positives and false negatives. Overall, the Islam and migration dictionaries implemented performed relatively well concerning the golden standard of hand-coding (0.91 and 0.81 respectively). The nationalism dictionary, in comparison, slightly under-performs with an F1-score of 0.65, which seems reasonable for such an abstract concept. Compared to migration and Islam dictionaries, there is a smaller amount of automated text analysis and existing dictionaries on the topics of nationalism and regional variation.

We also tested three different expansions of the dictionary. First, we surveyed student assistants to come up with further exclusive and broad terms for the three dictionaries. Second, we reviewed the literature and collected dictionaries on the three issues. Combinations with these three expansions show that the initial Islam and migration dictionaries already performed quite well.

TP	FN	FP	Dictionary	Recall	Precision	F1-score
227	213	28	Nationalism (used)	0.52	0.89	0.65
233	207	32	Nationalism review	0.53	0.88	0.66
318	122	206	Nationalism + review + survey broad	0.72	0.61	0.66
288	152	84	Nationalism + review + survey exclusive	0.65	0.77	0.71
267	19	33	Islam (used)	0.93	0.89	0.91
268	18	38	Islam review	0.94	0.88	0.91
277	9	54	Islam survey + review + broad	0.97	0.84	0.90
271	15	48	Islam survey + review + exclusive	0.95	0.85	0.90
284	34	100	Migration (used)	0.89	0.74	0.81
296	22	139	Migration review	0.93	0.68	0.79
304	14	241	Migration + review + survey broad	0.96	0.56	0.70
302	16	176	Migration + review + survey exclusive	0.95	0.63	0.76

Table 3: Dictionary performance vis-à-vis hand-coded articles

Table 4 displays the inter-coder reliability of the three sub-issues of interest based on the hand-coding. Therefore, a second student assistant coded 150 random articles for the second time. Articles can portray the three sub-issues at the same time, therefore, these are analysed separately. Overall, the inter-coder reliability of the coders is satisfyingly high in terms of Cohen's kappa ranging between 0.76 and 0.90. The positive rates indicate that the sub-issues were also prominent in the data in around 27 % of the articles, based on the first coder. Within the positive cases, where the sub-issues were present according to the first coder, the right positive rate or convergence with the second coder was above 0.83 across the three sub-issues.

Dimensions	Cohen's kappa	Ν	Positive rate	Right positive rate
Nationalism	0.762	150	0.333	0.854
Migration	0.846	150	0.280	0.833
Islam	0.897	150	0.207	0.903

Table 4: Dictionary hand-coding of articles and inter-code reliability

C Far-Right Actors Identification

To identify far-right actors within security reports by the Bundesverfassungsschutz, we first selected report pages handling the radical right based on the following regular expression: patriot*|nationalis*|identitär*|leitkultur*|national*\\s+identität*|nazi|nationalsoz*| nsdap|völkisch*|rechtsradikal*|rechtsextremis*|recht[-]radikal*| recht[-]extre mis*| anti(|[-])islam|rassistisch|anti(|[-])muslim*|muslimfeind*|islamfeind*.

We then divide the text into sentences and then captured name entities with the *de-pos-maxent* algorithm by OpenNLP. We inspect all occurrences including two following nouns, a noun + a number (for cases like "Wolfsbrigade 44"), or any pronoun. A student assistant then manually extracted the far-right actors and grouped different names for the same actors across time. We ran the collection of actors in a loop so that cases that were already in our data were not shown again in non-coded reports. This approach spared us increasingly more time as we coded more and more reports. According to a pre-test, we are able to capture 79% of the far-right actors in a report compared to a full manual reading. For the initial reports, when we coded all sentences identified with the name entity recognition, coding time lasted already half of the time of the manual reading approach. This optimization increased with the number of reports we coded.

We catalogued 559 unique far-right actors from 1995 to 2020. Regular expressions covering different names and name configurations were created for the far-right actors. In this step, we had to exclude certain actors whose names were too generic and would bias our analysis by capturing issues completely off-topic, e.g. Der Gegenangriff, Phoenix, Volkszorn. With the first far-right actor's list, we identified 90 actors appearing in our German media corpus. We validated appearances of these actors in a maximum of random 10 sentences by actor; for certain far-right actors with less than 10 appearances in our corpus, we inspected all cases. After the validation, we adapted many names and abbreviations, and we had to fully exclude further 15 actors due to wrong identification. These 15 actors' names were still too generic and were misclassifying many text identifications, e.g. Aktionsfront always captured Islamist groups abroad.

D Topic Model Selection and Sub-Issue Aggregation

First, to select an "optimal" topic model among the range of K-models (3, 4, 5, 6, 7, 8, 9, 10, 11, 13, 15, 17, 19, 21, 23, 25, 27, 29, 30, 32, 35, 38, 39, 40, 41, 42, 43, 44, 45, 46, 48, 50, 52, 55, 58, 60, 62, 65), we calculate standard parameters of performance (Figure 8). K-models 9, 17, 30, 35, 42, 52, and 60 show local optima in the performance parameters, especially concerning the exclusivity-semantic coherence trade-off (Roberts et al., 2019). Based on these K models selections, we select the three cases with a middle-size K (35, 42, 52) to reduce complexity and topic fragmentation and obtain more overarching sub-issues. However, the rest of the models indicate similar topic distributions in an aggregated manner in the case of lower Ks. Further topic models with higher K seem unnecessary in practical terms, since the performance of models with Ks > 50 reach an asymptote in the performance indicators.

In the second step, two research assistants within the research project labeled each of the sub-issues (k's) independently of each other based on the more common words for each topic across the three models (35, 42, 52). The independent task between student assistants aims to avoid contamination of subjective interpretations of the topics. We then compare the labels across coders to evaluate whether they classified or labelled the topics in a conceptually consistent manner. Across the three models, topic labels overlap from 90 % to 94 %, showing stability and consistency across the K-range. Based on discussions among the research group, we selected model K = 42 mostly based on face validity and confirmation of certain expectations in the exploration. In this model, the overlap of labels between the two student coders converges at 90 % (see STM replication script). The overlap is a product of similar labels with slightly different wording but consistent in terms of content. The overlap for each topic within the K model was decided by the researchers. Last, we compare our model K = 42

labeling and aggregation with a model with an extremely low but reasonable K in terms of performance (K = 9). Table 6 shows the cosine similarity between conceptually matched subissues between both models' outputs (see Jacobi et al., 2016 for a similar approach).



Figure 8: Topic models – parameter optimization

K	Topic Label	Sub-Issue	K	Topic Label	Sub-Issue
Topic			Topic		
1	Time Countryside	miscellaneous	22	Integration	Integration
2	Nazi Protest Dresden	Racism	23	Russian Nationalism	International
					politics
3	Racism US President	International	24	Refugee Health Family	Integration
		politics			
4	Refugees Labour Politics	Integration	25	Refugee Deportation	Asylum
5	French Politics	International	26	Israel-Palestine	International
		politics			politics
6	Film Drama	Miscellaneous	27	Islamism	Islamism
7	Global Illegal Migration	Migration	28	Terror Middle East	International politics
8	Refugee Sea Aid	Migration	29	Asylum Policies EU	Migration
9	City Country Description	Miscellaneous	30	City Media Names	Miscellaneous
10	National European	Europe	31	Merkel Migration	Migration
	Identities				
11	Racism Soccer	Racism	32	Art	Miscellaneous
12	Media Name	Miscellaneous	33	Patriotism	Nationalism
13	Months Name	Miscellaneous	34	Islamism Middle East	Islamism
14	Police and Refugees	Security	35	Asylum Assistance	Asylum
15	War Africa UN	International	36	Islam Headscarf	Islam
		politics			
16	Berlin City	Miscellaneous	37	Balkan Refugee	Migration
17	Turkey Politics	International	38	National socialism	Nazi
		politics			
18	Islamic International	Islamism	39	Migration	Migration
	Terror				
19	Taliban Afghanistan	Islamism	40	Far-right Racist	Racism
				Violence	
20	Islam and Christianity	Islam	41	Migration Kids	Migration
21	Judicial Process	Security	42	Time Media	miscellaneous

Table 5: Topic labels and sub-issue aggregation

Comparison K = 9 and K = 42 (aggregated)	Cosine similarity		
1. Refugee city			
Asylum aggr.	0.632		
2. Police, racism, AfD			
Security aggr.	0.629		
Racism aggr.	0.753		
3. USA, racism			
Racism aggr.	0.387		
International politics aggr.	0.481		
4. Integration, Germany, CDU			
Integration aggr.	0.796		
5. Europe, government, Israel			
Europe aggr.	0.478		
International politics aggr.	0.623		
6. Nazi, Germany, history			
Nationalism aggr.	0.662		
Nazi aggr.	0.704		
7. Islamism, Middle east			
Islamism aggr.	0.597		
International politics aggr.	0.610		
8. Asylum			
Asylum aggr.	0.531		
Migration aggr.	0.649		
Integration aggr.	0.433		
9. Islam, muslisms			
Islam	0.846		

Table 6: STM K = 9 and K = 42 aggregated model comparison

Note: See Jacobi et al. (2016) for an analogue methodological comparison.

In a last robustness check, we conduct an alpha-parameter sensibility analysis following Jacobi et al. (2016, p. 6). The alpha parameter in the STM estimator determines the flexibility of the number of topics that can appear within each document, in our case contextual sentence groups. Additional to the default in the main model (alpha = 50/k per k-model), we conduct a series of models with alpha = 5/k. A lower alpha implies that the model forces a higher concentration of topics per document during the optimization. This sensitivity analysis across models with different alpha-levels serves to examine the robustness of the topic models for text corpora with shorter texts, as is our case (see Figure 7).

We conducted the alpha sensitivity analysis based on a random sample of 5 % of the whole corpus (N = 46,388) for computational power reasons. We will then compare the topic distributions based on this random sample of the main model and the alpha-adjusted model. Across the range of topic models from K-models from K=3 to K=65 with alpha = 5/k, we observe the same pattern in the main performance parameters for the different alpha models (Figure 9). In terms of exclusivity, the pattern is very similar and converges more strongly once exclusivity reaches the asymptote. With regard to semantic coherence, the performance diverges between the two alpha models and stronger differences arise with k-values above 30. Consequently, we observe local optima in the semantic coherence of the alpha 5/k model to find a suitable model for comparison. We selected the K model 48 for a fair comparison due to its high level of sematic coherence. In the following, we compare the topic distribution between the two models with different alpha levels; (b) we compare a model using the full sample with a model using a 5% subset; and (c) due to the different parameter optimization of the models, we select different K values that force different number of

topics for each document. The models should, however, show high levels of convergence to reassure the stability of the main topic model that has been selected.



Figure 9: Model selection robustness check with alpha manipulation

Note: blue dotted lines indicate local optima of the model alpha = 50/k (as in Figure 8); red dotted lines indicate local optima of the model alpha = 5/k; and the black dotted line refers to a local optimum of both models.

Figure 10 depicts the correlation matrix between the main topic model and the alpha-sensitive model. First, we aggregate semantic topics into substantive sub-issues as in the main analysis. The 48 topics are aggregated into 12 substantive sub-issues. Second, the alpha-sensitive model presents more sub-issues due to its larger K-value. Third, as in the main analysis, we exclude irrelevant sub-issues, such as "miscellaneous", "mixed", "art" and "party actors". Overall, the results confirm the stability of our main model in the alpha sensitivity analysis. The main

model sub-issues asylum, international politics, Islam, Islamism, integration, Nazi, racism, and security strongly correlate with related sub-issues in the alpha = 5/k model. The sub-issues Europe, migration and nationalism have middle-size positive correlation with comparable sub-issues in the alpha = 5/k model. These results confirm the robustness of our main topic model.



Figure 10: Aggregated sub-issue correlations across different alpha-models

Note: sub-issues "miscellaneous", "mixed", "art" and "party actors" are excluded from the alpha = 5/k model. Blank squares indicate non-significant correlations; coloured squares indicate significant correlations at p < 0.01.

E Endogenous Issue Validation and Far-Right Actors

In the last validation step, we reverse engineer our issue definition procedure by reading 200 randomly selected group sentences including far-right actors and manually coding to what degree they belong to the 12 aggregated cultural sub-issues. A coder that was not involved in the issue labeling step read and manually categorized the group sentences by assigning 10 points across the 12 issues. In the following, we present the validation results. The validation results indicate middle size Spearman correlation estimates (Table 7). Overall, all statistically significant associations are positive.

	rho estimate	p-value
Miscellaneous	0.0154516	0.8280825
Asylum	0.3423244	0.0000007
Islam	0.1723078	0.0146953
Europe	0.1422688	0.0444728
Integration	-0.0401763	0.5721786
International politics	0.2766974	0.0000730
Islamism	0.2948477	0.0000225
Migration	0.2842591	0.0000452
Nationalism	0.0916880	0.1966142
Racism	0.1763859	0.0124735
Nazi	0.1685050	0.0170715
Security	0.4240469	0.0000000

Table 7: Spearman correlations

The Spearman correlation across the 200 documents, irrespective of the within-issue structure, results in a *rho* = 0.287 (p < 0.000; N = 2.400 for the 12 issues). Running 200 Spearman correlations within each document (N = 12 each), we obtain an average *rho* = 0.290

with 15.5 % of the correlation being significant at p < 0.10 level. Similarly, 200 Pearson's correlations result in an average correlation estimate of 0.443 with 27.4 % of the correlations being significant at p < 0.10 level. Considering the fact that we assigned 10 points across issues and we had aggregated many sub-issues beforehand, the validation results confirm the intuitive nature of the issues in our data.



Figure 11: Example visualization of two validated issues - Pearson's correlation

F Representative Texts for the Aggregated Sub-Issues

The following list shows a selection of representative texts from the aggregated sub-issues. Only the first 300 characters of each representative group sentences are displayed.

 Asylum: Bleiberecht abgelehnt; AUFENTHALT I Ahmed Siala ist mit seiner Klage für ein dauerhaftes Aufenthaltsrecht vor dem Verwaltungsgericht in Hannover gescheitert. Mit einer Abschiebung muss der Mann von Gazale Salame aber nach 28 Jahren in Deutschland trotzdem nicht [...]

- Europe: Das voluntaristische Konzept übersieht zudem, daß Nationenbildung immer von "objektiven" Faktoren wie gemeinsamer Herkunft, Kultur, Geschichte, Territorium und dem subjektiven Faktor – dem politischen Willen, eine Nation zu sein – gleichermaßen abhängt. Heute, im Zeitalter des Globalismus [...]
- integration: Patinnen f
 ür Familien und Frauen gesucht; Sozialdienst- Der Sozialdienst katholischer Frauen (SkF) sucht Patinnen f
 ür sein Projekt "Familienpatenschaften". Im Rahmen des Projekts f
 ür gefl
 üchtete Familien und Frauen in schwierigen Situationen sind seit M
 ärz 2011 insgesamt 68 Familien von 41 Patinnen [...]
- 4. *international politics*: Rebellen starten Gegenoffensive in Aleppo- Nach Beginn einer Offensive zur Befreiung des belagerten Aleppo rücken islamistische Rebellen gegen Regimetruppen nahe der syrischen Stadt vor. Die Aufständischen wollen den Ring aus Einheiten von Machthaber Baschar al-Assad durchbrechen [...]
- 5. Islam: Kopftuchverbot: Urteil stärkt Bundesländer; Referendarinnen müssen unverhüllt ins Gericht- Die Bundesländer dürfen Rechtsreferendarinnen das Tragen eines muslimischen Kopftuches im Gerichtssaal verbieten. Auch wenn solch ein Kopftuchverbot [...]
- 6. Islamism: Hinter der im Ausland geplanten Aktion stünden "dieselben Personen, die das Attentat auf Bali" sowie die jüngsten Anschläge auf den Philippinen organisiert hätten. Die indonesischen Behörden vermuten hinter den Explosionen auf Bali die Fundamentalistenorganisation Jemaah Islamiah. [...]
- 7. *migration*: Allerdings täuscht der Blick auf die vom Statistischen Bundesamt geführten Statistiken. Denn durch die hohe Zahl der Einbürgerungen vor allem seit Mitte der

neunziger Jahre ist die Zahl der Ausländer von knapp 7,5 auf derzeit rund 7,1 Millionen zurückgegangen.[...]

- miscellaneous: Hier werden die Weichen gestellt und vor allem im Mittelteil die Langsamkeit zelebriert. Ist gut, aber hätte Potenzial für etwas viel Grösseres gehabt. (outnow.ch) BHV, BS, DEL, FL, GÖ, H, HB, HH, HL, KI, LG, OL, OS, SN Home for Christmas Norwegen/Schweden/Deutschland 2010 [...]
- 9. *nationalism*: Kritische Stimmen wurden dagegen als "elitär" oder "politisch korrekt" denunziert, die angeblich die Sorgen und Nöte der "normalen Menschen" nicht verstünden. So wurden nach und nach rassistische Verrohung in "verständliche Emotion" umgedeutet und falsche Tatsachenbehauptungen [...]
- 10. Nazi: Eine Erbengemeinschaft der Kunstsammlerin Sophie Lissitzky-Küppers hatte das Bild, ein Frühwerk Klees, zurückgefordert. Die Erben gehen davon aus, dass die Nazis es 1937 widerrechtlich beschlagnahmt hatten. Das Bild wurde 1937 von den Nationalsozialisten als "entartet" diffamiert und beschlagnahmt [...]
- 11. racism: Spurensuche nach Brand dauert an. Gößweinstein: Flüchtlingsheim in Flammen aufgegangen. Gößweinstein Nach dem Brand in einer Flüchtlingsunterkunft im oberfränkischen Gößweinstein gibt es keine Hinweise auf einen Anschlag. Die Ursache für das Feuer sei noch unklar, sagte ein Polizeisprecher [...]
- security: Feuertod-Prozess wird neu aufgerollt Karlsruhe Fünf Jahre nach dem Feuertod des Asylbewerbers Oury Jalloh in einer Dessauer Polizeizelle muss der

Prozess gegen einen beteiligten Beamten neu verhandelt werden. Das Urteil mit dem Freispruch des Polizisten vom Dezember 2008 weise zahlreiche Lücken [...]



G Sub-Issues across Time by Far-Right Actor Mention

Figure 12: Sub-issues across time by far-right actor mention

H History of the Most Prevalent Far-Right Actors in Mass Media

The first group consists of political parties. This includes The German People's Union (DVU) which was an extreme rightwing party in the Federal Republic of Germany founded in 1987. The DVU entered state parliaments in Germany nine times and achieved 12.9 % of the votes in the state parliament of Saxony-Anhalt in 1998, marking the highest result of an extreme right-wing party at state level up to that time. In 2011 the DVU merged with the National Democratic Party of Germany (NPD) which was dissolved one year later. The NPD was founded in 1964 and was represented eleven times in seven German state parliaments until 2016 and narrowly missed entering the Bundestag in the 1969 Federal elections. In 2006, the NPD founded the women's organization Ring Nationaler Frauen (RNF). In contrast to the DVU, the NPD makes its extreme racist positions public and distinguishes itself from other right-wing parties, as it appeals to the neo-Nazi spectrum and has a direct programmatic and linguistic proximity to the NSDAP (Kailitz, 2004, p. 57). However, prohibition proceedings against the party before the Federal Constitutional Court were rejected due to its increasing insignificance in the political arena. Finally, the AfD founded in 2013 as an EU-sceptical party is the most central far-right party in contemporary Germany. In 2014, the AfD succeeded in entering the European parliament. It subsequently entered all German state parliaments and was, in the 2017 Bundestag elections, with 12.6 % of the vote the third strongest force. In 2015 the economic liberal wing of the party split off, while the rest of the party moved significantly to the right (Franzmann, 2014). "Der Flügel", the völkisch-nationalist wing of the party, has been officially dissolved after it has been classified as a suspected right-wing extremist case and observed by the Federal Office for the Protection of the Constitution in 2020. Since 2022 the entire party is classified as such.

The second group of far-right actors that were most visible in cultural debates since 1990s were the movement and terrorist organizations Kameradschaften, NSU and PEGIDA. Currently there are around 150 regional and national Kameradschaften according to the security reports in Germany. Kameradschaften emerged in the mid-1990s in Germany and are free associations in which activists are not listed by any association membership register (and therefore cannot be forbidden by the state). PEGIDA (Patriotische Europäer gegen die Islamisierung des Abendlandes) was founded in 2014 in Dresden and is a far-right political movement "against the Islamization of the occident". PEGIDA had its peak mobilization period with up to 25.000 participants at demonstrations in 2015 after the Charlie Hebdo attacks in France and in the context of the so-called "refugee crisis". Finally, one of the most extreme actors in Germany was the NSU (National Socialist Underground). The NSU was a neo-Nazi terrorist organization in Germany that formed around 1999 and committed 9 racist murders, 43 attempted murders, three bomb attacks and 15 robberies which did not come to light until 2011 (Quent, 2019). The third group of far-right actors includes alternative news media outlets, which have played a central role in expanding the far-right's reach in recent decades. A central alternative news medium and cultural actor of the contemporary far right in Germany is COMPACT. COMPACT is a monthly political magazine in Germany and often advocates the AfD and PEGIDA. Since December 2021, the Federal Office for the Protection of the Constitution has listed the magazine as a secured right-wing extremist.

I Illustrated Explanation of Text Network Procedures

In the following, we describe the methodological procedure of text network analysis in short steps. Table 8 summarizes the measurements of the discourse network analysis.

- Newspaper article data: we identify the contextual sentence groups within newspaper articles with the mentioned dictionaries. Grouped sentences are conformed by subsequently reported sentences of the cultural issues.
- 2. Topics and sub-issue aggregation: we identify the 42 topics from the structural topic models and aggregate prevalences into substantially relevant sub-issues.
- 3. Far-right mentions and co-occurrences: based on our far-right actor's dictionaries, we identify individual actors within contextual sentence groups with different sub-issue shares.
- 4. Co-occurrence networks: joint mentions of far-right actors within a contextual sentence group counts as a co-occurrence. In the actor network, co-occurrences count as network ties between at least two nodes.
- 5. Issue networks with topic similarity: based on the distribution of sub-issues (aggregated model topics, see Table 5), Manhattan distances between text units (contextual sentence groups) are calculated for all the cases of far-right mentions within text units. Manhattan distances are the sum of the differences across variables.¹ In other words, the sum of differences among the 11 substantial topics creates a theoretical maximum value of 11.

¹ We choose to implement Manhattan distances since these reflect more directly the sum of the differences between vector values (see Strauss & von Maltitz, 2017 on Manhattan distances' advantages). Manhattan distances are suitable for high-dimensional data (Aggarwal et al., 2001), which applies to the sub-issue share vectors that distribute topic shares adding to 1 between actor-sentences comparisons. Therefore, cosine distances accounting for different natural predominance within vectors are not explicitly necessary. To assess the robustness of the measure, we compare the overall Manhattan distance between actor-issues in the data with the cosine distance measure. For the simulation periodization used in the visualized networks, the measures correlate at the 0.93 level (p<.000). This test assures us about the stability of selecting Manhattan distances as a measure to assess sub-issue connections.

Discourse	Network	Measurement	Indicator
Туре	Mediated actor network	Co-occurrence of actors in contextual sentence groups in newspaper articles	Mediated and publicly perceived connection between actors
	Mediated issue network	Mediated connection of actors based on the issues they raise or they are associated with based on Manhattan distance scores (0=minimum distance to 11= maximum distance)	Mediated and publicly perceived connection between actors and issues
Statistics	Density	Cohesiveness in terms of the ratio of present connections from the maximum possible connection (number of observed ties divided by the number of all possible ties)	Mediated fragmentation or perceived cohesiveness of the debate, e.g. shared mentions or issue associations in newspaper articles
	Centralization	Concentration of connections and relative dominance of actors within the discourse network	Public debates on cultural issues are dominated by a few far-right actors because journalists refer to them jointly
	Average path length	Average distance between any two nodes in the largest connected component	Mediated connection paths between all far-right actors in the network across issues, reflecting the intensity of overall connections independent of central actors

Table 8: Summary indicators and measurements discourse network analysis



Figure 13: Data analysis and methodological procedure of network analysis



J Network Visualization, taz Sub-Sample 1994-2019

Figure 14: Actor networks over time - taz sample

Note: Analysis based on taz sample. The taz newspaper is the only one covering the whole period of study. Highlighted nodes and actor labels refer to the top three most relevant actors in term of connections within each network.

Figure 15: Issue networks over time - taz sample

Note: Analysis based on taz sample. The taz newspaper is the only one covering the whole period of study. Analysis included only connections surpassing the topic Manhattan similarity median by period. Highlighted nodes and actor labels refer to the top three most relevant actors in term of connections within each network.

K Issue-Networks Thresholding, Backbone Extraction Robustness and Random Graph Baselining

The issue-network analyses are based on median sub-issue Manhattan distances between the far-right actors. The issue-networks are defined by connections or edges with Manhattan distances between far-right actors below the edges' distance median for the respective network. The data generation process produces connections between all far-right actors within a period, since any combination entails a minimum similarity or maximum distance. Therefore, the median defines the cutting point (threshold) for an edge to count as such.

The median is a chosen threshold that can generate biases if the results are not stable. Therefore, we simulate the network-level estimates based on two further varying threshold levels belonging to the 40th and the 60th percentiles. The former is a stricter criterion to count edges as such, while the latter allows weaker connections to qualify as an edge. The approach is inspired by Mukerjee et al. (2018), although we adapt our simulation criteria to the data generation process of our network data. Figure 13 displays the centralization and density estimates for the public debates and the taz samples. The black lines depict the medianthreshold network estimates, while the grey lines depict the varying percentile thresholds. Overall, the results are robust to changing the threshold condition.

Figure 16: Issue networks trend and threshold robustness analysis

Note: The black line depicts the network-estimates based on the median threshold condition; the grey lines depict the estimates based on the 40th and 60th percentile threshols. The Pearson coefficient represents the overtime linear trend of the median-threshold estimates.

To control for the fact that such transformations may bias network-level estimates (see Mukerjee et al., 2022 on global thresholding), we perform a backbone extraction analysis after thresholding as a second robustness test. We implement a disparity filtering algorithm with local sparsification (see Coscia & Rossi, 2020; Neal, 2014). Local sparsification uses Jaccard coefficients to account for the overlapping "neighboring connections" between two nodes. The procedure then prioritizes edges of nodes that share many common neighbors to filter out

less stable connections (Neal, 2022). Figure 14 shows the estimates of the backbone extracted issue networks as described. The issue network results remain robust, and the same conclusion can be drawn: overall decrease in density and increase in centralization over time.

Figure 17: Issue networks trend and backbone extraction robustness analysis

As a last robustness check, we inspect random network graphs over time and adjust for centralization. Random graphs serve as a simulated random baseline to adjust for natural characteristics of certain networks, e.g. holding constant density and the number of actors. We make use of the Erdős–Rényi model (G(n,m)) to generate random graphs and hold the network density constant (see van Wijk et al., 2010). Centralization trend results remain robust.

Issue networks	Public Debates	<i>R</i> = 0.615	p = 0.009
	taz sample	R = 0.674	<i>p</i> = 0.000
Actor networks	Public Debates	<i>R</i> = 0.423	<i>p</i> = 0.091
	taz sample	R = 0.143	<i>p</i> = 0.514

Table 9: Centralization trends after adjusting for random graph deviation, Pearson correlations over time

Note: Pearson correlation over time on centralization trends from the deviation from simulated random network graphs. For each period simulation, density and number of actors are held constant. The Erdős–Rényi model (G(n,m)) from the R package igraph (Csardi & Nepusz, 2006) is implemented; random centralization values are subtracted from the empirical centralization. For the comparison between empirical and random graphs, we reduce the actor networks to bipartite connections in both cases.

L Average Path Length Complement

Certain network characteristics such as density are more sensitive to the data generation process (see Mukerjee et al., 2022). In the case of issue networks based on public debates in the media data, density is sensitive to the intensity of newspaper coverage of cultural debates. Therefore, we conduct a complementary analysis for both actor and issue networks by including average path length. Average path length reflects the average shortest distance between two far-right actors within the respective networks over time (Rubinov and Sporns, 2010). Average path length is less sensitive to the number of edges in the network because the measure accounts for the total path length between any two far-right actors over the total path length between any two far-right actors because of the high visibility of the former.

Since we found that the density of both actor and issue networks decreases over time, especially since 2010, we would expect the average path length to follow the opposite pattern. Figure 15 and Figure 16 show the average path length of the far-right actor and issue networks, respectively. Overall, the results show a positive trend over time for both measures - the opposite trend of the density analysis. In other words, the average path length analysis complements the density analysis: as density decreases, the path length between any two far-right actors in the network increases. Less dense networks imply longer paths. This fits our results in that far-right networks become larger and more diverse in terms of sub-issues over time. More central actors are holding the less dense network with larger paths together.

Last, in order to obtain robust estimates of average path length of the issue-networks, we simulate the two further thresholding levels (40th and 60th percentile) to define connecting edges. The different threshold filtering serves to test the stability of network measures with different cutting points for the median Manhattan distances defining far-right actors' issue connections. Figure 17 demonstrates the stability of the results for the two simulated thresholds. The Pearson coefficients reflect the increasing trend of average path length over time of the median-threshold networks.

Figure 18: Actor-network average path length

Sample = Public Debates • taz sample

Figure 19: Issue-network average path length

Figure 20: Issue-network average path length - threshold robustness analysis

Period start	Period end	Count	Total	Relative	Count	Total	Relative
				connection	taz	taz	connection taz
1994-01-01	1998-12-31	—	_	_	25	30991	0.081
1995-01-01	1999-12-31	—	_	_	28	30256	0.093
1996-01-01	2000-12-31	—	_	_	33	33790	0.098
1997-01-01	2001-12-31	_	_	_	30	41350	0.073
1998-01-01	2002-12-31	—	_	_	29	36252	0.080
1999-01-01	2003-12-31	_	_	_	18	40650	0.044
2000-01-01	2004-12-31	70	147639	0.047	26	49354	0.053
2001-01-01	2005-12-31	79	158130	0.050	30	51481	0.058
2002-01-01	2006-12-31	90	164237	0.055	41	53345	0.077
2003-01-01	2007-12-31	107	179954	0.059	47	65544	0.072
2004-01-01	2008-12-31	127	169813	0.075	62	66306	0.094
2005-01-01	2009-12-31	110	155616	0.071	64	62128	0.103
2006-01-01	2010-12-31	105	152984	0.069	69	61716	0.112
2007-01-01	2011-12-31	110	140860	0.078	73	58376	0.125
2008-01-01	2012-12-31	137	136646	0.100	94	59099	0.159
2009-01-01	2013-12-31	137	145933	0.094	96	61391	0.156
2010-01-01	2014-12-31	248	162570	0.153	153	66674	0.229
2011-01-01	2015-12-31	738	186724	0.395	446	77565	0.575
2012-01-01	2016-12-31	1191	212982	0.559	711	88440	0.804
2013-01-01	2017-12-31	1412	225027	0.627	847	92672	0.914
2014-01-01	2018-12-31	1664	234543	0.709	996	94773	1.051
2015-01-01	2019-12-31	1679	229037	0.733	1016	92082	1.103
2016-01-01	2020-12-31	1327	202630	0.655	798	81513	0.979

M Far-Right Network Development and AfD Test

Table 10: Actor network size relative to media debate size

Note: Relative number of actor relations. Relative basis is the number of contextual sentence groups (%). taz sample across time for comparability, since taz is the only newspaper covering the whole period since 1994.

Period start	Period end	Count	Total	Relative	Count	Total	Relative
				connection	taz	taz	connection taz
1994-01-01	1998-12-31	_	_	_	15	30991	0.048
1995-01-01	1999-12-31	_	_	—	14	30256	0.046
1996-01-01	2000-12-31	_	_	_	18	33790	0.053
1997-01-01	2001-12-31	_	_	_	21	41350	0.051
1998-01-01	2002-12-31	_	_	_	21	36252	0.058
1999-01-01	2003-12-31	_	_	_	41	40650	0.101
2000-01-01	2004-12-31	106	147639	0.072	42	49354	0.085
2001-01-01	2005-12-31	76	158130	0.048	40	51481	0.078
2002-01-01	2006-12-31	79	164237	0.048	44	53345	0.082
2003-01-01	2007-12-31	99	179954	0.055	57	65544	0.087
2004-01-01	2008-12-31	93	169813	0.055	57	66306	0.086
2005-01-01	2009-12-31	89	155616	0.057	55	62128	0.089
2006-01-01	2010-12-31	80	152984	0.052	52	61716	0.084
2007-01-01	2011-12-31	110	140860	0.078	74	58376	0.127
2008-01-01	2012-12-31	105	136646	0.077	48	59099	0.081
2009-01-01	2013-12-31	113	145933	0.077	71	61391	0.116
2010-01-01	2014-12-31	138	162570	0.085	77	66674	0.115
2011-01-01	2015-12-31	213	186724	0.114	162	77565	0.209
2012-01-01	2016-12-31	226	212982	0.106	224	88440	0.253
2013-01-01	2017-12-31	247	225027	0.110	189	92672	0.204
2014-01-01	2018-12-31	263	234543	0.112	205	94773	0.216
2015-01-01	2019-12-31	228	229037	0.100	208	92082	0.226
2016-01-01	2020-12-31	220	202630	0.109	186	81513	0.228

Table 11: Issue network size relative to media debate size

Note: Relative number of issue relations. Relative basis is the number of contextual sentence groups (%). taz sample across time for comparability, since taz is the only newspaper covering the whole period since 1994.

			Centraliz				Centraliz		Density
	Period	Central	ation w/o		Density	Centraliz	ation taz	Density	taz w/o
Period start	end	ization	AfD	Density	w/o AfD	ation taz	w/o AfD	taz	AfD
01.01.1994	31.12.1998	-	-	-	-	1.778	1.778	0.556	0.556
01.01.1995	31.12.1999	-	-	-	-	2.156	2.156	0.622	0.622
01.01.1996	31.12.2000	-	-	-	-	2.400	2.400	0.600	0.600
01.01.1997	31.12.2001	-	-	-	-	2.255	2.255	0.545	0.545
01.01.1998	31.12.2002	-	-	-	-	2.173	2.173	0.527	0.527
01.01.1999	31.12.2003	-	-	-	-	1.091	1.091	0.273	0.273
01.01.2000	31.12.2004	3.235	3.235	0.515	0.515	1.697	1.697	0.394	0.394
01.01.2001	31.12.2005	6.356	6.356	1.756	1.756	3.405	3.405	1.429	1.429
01.01.2002	31.12.2006	6.455	6.455	1.364	1.364	4.250	4.250	1.464	1.464
01.01.2003	31.12.2007	5.065	5.065	0.699	0.699	4.194	4.194	1.306	1.306
01.01.2004	31.12.2008	5.489	5.489	0.668	0.668	6.214	6.214	2.214	2.214
01.01.2005	31.12.2009	5.441	5.441	0.809	0.809	5.722	5.722	1.778	1.778
01.01.2006	31.12.2010	4.553	4.553	0.614	0.614	5.145	5.145	1.255	1.255
01.01.2007	31.12.2011	3.732	3.732	0.399	0.399	3.792	3.792	0.608	0.608
01.01.2008	31.12.2012	3.791	3.791	0.313	0.313	3.496	3.496	0.368	0.368
01.01.2009	31.12.2013	3.468	3.454	0.274	0.280	2.922	3.033	0.271	0.300
01.01.2010	31.12.2014	4.408	3.446	0.440	0.296	3.376	2.806	0.374	0.271
01.01.2011	31.12.2015	12.408	5.173	1.239	0.608	7.619	4.128	0.897	0.515
01.01.2012	31.12.2016	19.469	6.611	1.693	0.646	12.250	4.500	1.266	0.532
01.01.2013	31.12.2017	27.695	8.508	2.517	0.892	17.312	5.578	1.822	0.672
01.01.2014	31.12.2018	33.640	10.270	2.966	1.123	21.025	6.611	2.142	0.796
01.01.2015	31.12.2019	33.561	9.501	2.822	1.016	21.648	6.574	2.185	0.796
01.01.2016	31.12.2020	29.674	5.214	2.513	0.786	19.463	3.711	1.966	0.609

Table 12: Actor network measures - AfD difference

			Centraliz				Centraliz		Density
Period	Period	Centrali	ation w/o		Density	Centraliz	ation taz	Density	taz w/o
start	end	zation	AfD	Density	w/o AfD	ation taz	w/o AfD	taz	AfD
01.01.1994	31.12.1998	-	-	-	-	0.000	0.000	1.000	1.000
01.01.1995	31.12.1999	-	-	-	-	0.000	0.000	1.000	1.000
01.01.1996	31.12.2000	-	-	-	-	0.133	0.133	0.867	0.867
01.01.1997	31.12.2001	-	-	-	-	0.208	0.208	0.417	0.417
01.01.1998	31.12.2002	-	-	-	-	0.208	0.208	0.417	0.417
01.01.1999	31.12.2003	-	-	-	-	0.394	0.394	0.515	0.515
01.01.2000	31.12.2004	0.268	0.268	0.614	0.614	0.364	0.364	0.545	0.545
01.01.2001	31.12.2005	0.297	0.297	0.703	0.703	0.244	0.244	0.756	0.756
01.01.2002	31.12.2006	0.253	0.253	0.747	0.747	0.133	0.133	0.867	0.867
01.01.2003	31.12.2007	0.368	0.368	0.632	0.632	0.258	0.258	0.742	0.742
01.01.2004	31.12.2008	0.275	0.275	0.658	0.658	0.273	0.273	0.727	0.727
01.01.2005	31.12.2009	0.254	0.254	0.559	0.559	0.121	0.121	0.697	0.697
01.01.2006	31.12.2010	0.379	0.379	0.444	0.444	0.167	0.167	0.652	0.652
01.01.2007	31.12.2011	0.295	0.295	0.495	0.495	0.399	0.399	0.425	0.425
01.01.2008	31.12.2012	0.253	0.253	0.484	0.484	0.364	0.364	0.636	0.636
01.01.2009	31.12.2013	0.381	0.376	0.391	0.424	0.308	0.363	0.692	0.637
01.01.2010	31.12.2014	0.388	0.413	0.403	0.413	0.417	0.442	0.583	0.558
01.01.2011	31.12.2015	0.350	0.363	0.650	0.637	0.326	0.298	0.543	0.565
01.01.2012	31.12.2016	0.347	0.329	0.542	0.556	0.265	0.252	0.550	0.556
01.01.2013	31.12.2017	0.291	0.316	0.598	0.607	0.326	0.261	0.630	0.648
01.01.2014	31.12.2018	0.340	0.314	0.556	0.579	0.292	0.310	0.588	0.607
01.01.2015	31.12.2019	0.256	0.265	0.590	0.615	0.318	0.317	0.640	0.600
01.01.2016	31.12.2020	0.293	0.317	0.493	0.497	0.392	0.435	0.567	0.565

Table 13: Issue network measures - AfD difference

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