Online Appendix File for:
Disproportionality in Media Representations of Campaign Negativity

1. Coding of the Newspaper Statements

All of the campaign coverage in eight newspapers (*Der Standard, Die Presse, Salzburger Nachrichten*, *Kurier, Kleine Zeitung*, *Kronen Zeitung, Österreich, Heute*) during the 6-week period before election day was coded at the sentence level. The coded elements include political actors (parties and individuals) as the subject and object of each statement, and the "topic" of the statement, alongside the valence of statements that reflects the relationship between the actors (e.g., negative). The following provides examples of how sentences were coded:

Negative statements ("attack") example (1):		
"Die ÖVP hat eine wahlkampftaugliche Berufsbezeichnung für Werner Faymann gefunden: "Lügenkanzler" nannte ihn Innenministerin Johanna Mikl-Leitner am Dienstag bei einer Pressekonferenz – in Anlehnung an ein Thema, das eigentlich schon ausdebattiert schien: Kein Mensch denke derzeit daran, dass Frauenpensionsalter früher als geplant – nämlich stufenweise ab 2024 – an jenes der Männer anzugleichen, versicherte Mikl-Leitner." [*Österreich, August 21, 2013]*		
Subject actor	**Relations**	**Object actor**
Johanna Mikl-Leitner (ÖVP)	negative ("attack")	*Werner Faymann (SPÖ)*
English translation: *"The ÖVP has found a campaign-suitable job title for Werner Faymann [SPÖ]: "Lying chancellor", he was called by Minister of the Interior Johanna Mikl-Leitner [ÖVP] on Tuesday during a press conference – with regard to an issue that seemed to have been covered: Mikl-Leitner assured that nobody is currently thinking about equalizing the pension age for women to that of men – stepwise, starting in 2024."*		

Negative statements ("attack") example (2):		
"Aus dem ÖVP-Arbeitnehmerverbund (ÖAAB) kommt von Generalsekretär August Wöginger scharfe Kritik an der Ankündigung [Rudolf] Hundstorfers für 2014: „Das kann der Sozialminister nicht einhalten." [*Österreich, August 20, 2013]*		
Subject actor	**Relations**	**Object actor**
August Wöginger (ÖVP)	negative ("attack")	*Rudolf Hundstorfer (SPÖ)*
English translation: *"General secretary August Wöginger [ÖVP] voices harsh criticism on behalf of the ÖVP Labor Union (ÖAAB) regarding the announcement of [Rudolf] Hundstorfer [SPÖ] for 2014 - The Minister of Social Affairs cannot keep that promise."*		

2. Data preparation

The reasons for building party-by-party matrices rather than individual-by-individual matrices are essentially threefold. One, a number of interactions in the news reports and in the press releases do not feature an individual attacker or target but are clearly relevant to the question at hand. Two, as we subset the attack network by issue area, the data is quite sparse, particularly in the comparatively minor issue areas. The sparsity problem would be massively exacerbated by running an individual-level analysis, as only a tiny fraction of the individual actors are ever featured in issue-specific attack dyads in the press releases or the media. Three, conceptually, the party seems like the correct unit of analysis as issue ownership is clearly a party-level indicator. This is all the more true as most of the individual attack interactions are structured by party affiliations.

We construct issue-specific attack networks as the issue ownership indicator varies by issue area, i.e. a given node (party) in the network is the issue owner for some of the interactions while it is not on other interactions. One might reasonably question whether these issue-specific interaction networks constitute a valid representation of party behavior. Specifically, one may wonder to what extent parties engage in cross-issue interactions and what effect this may have on our analysis. While such patterns of cross-network interactions could not be captured in our models, we would suggest that the incentives to react to an attack ordinarily trump parties' preference not to address an issue which they might otherwise downplay in their campaign communication. This is to say that if a non-issue-owning party is being attacked over its environmental policies, it is still likely that this party would defend its policy proposals in the issue area rather than counter-attack in a different policy area.

3. Construction of the issue ownership measures

We rely on evidence that was collected using a two-step procedure, where respondents were first asked to indicate important issues before naming the most competent party, as this provides us with data on all issue areas included in this study. For two of the issues we can validate this approach with more direct measures. Respondents were asked what party promotes the best policy solutions in the areas of immigration and unemployment, where the latter should capture competence perceptions in the area of welfare reasonably well. In both cases the most frequently named party is the same as for the indirect measure -- FPÖ in case of immigration, and SPÖ in case of welfare.

In general, given that we study issue ownership patterns on fairly broadly construed issue dimensions and given that we are only interested in aggregate public perceptions, the survey evidence paints a fairly accurate picture of public competence ascriptions. Indeed, an analysis of party manifestos yields a similar picture, where the environmentalist GRÜNE devote a greater share of their manifesto to environmentalist issues than any other party, the right-wing populist FPÖ devotes a greater share of their manifesto to immigration issues, and so on. Therefore, the observed ownership structures are well aligned with salience perceptions among parties. Moreover, issue ownership perceptions on these broad issues are fairly stable across elections. When considering similar evidence from a post-election survey that was collected on the occasion of the 2008 Austrian national election, we find that the structure of issue ownerships is nearly identical between the two elections. The only exception is the ÖVP, which is perceived as most competent on economic issues in 2008, whereas the SPÖ owns the issue in 2013.

4. Descriptive statistics of attach networks by issue area and by newspapers

Table S1. Descriptive statistics of attack statements per parties, by topic

	Budget	**Economy**	**Environment**	**Immigration**	**Welfare**
Total attacks	193	466	36	93	154
Unique attacks	15	24	9	12	22
Average attacks	5.361	12.944	1	2.583	4.278
(SD)	21.142	33.520	2.125	4.837	7.440
Maximum attacks	123	173	9	17	29
Minimum attacks	0	0	0	0	0

*Note: Cell entries are the number of attack statements among political parties in the media (across all newspapers) in the five issue areas. "Total attacks" refers to the total number of attack statements in an issue area. "Unique attacks" presents the number of non-absent attack relations (out of a possible 6 * 6 - 6 = 30), i.e. ignoring repetitive attacks among party nodes. Average attacks and the standard deviation (SD) refer to the average number of attacks per party dyad. Minimum and maximum attacks refer to the minimum and maximum number of attacks per party dyad.*

Table S2. *Descriptive statistics of attack statements per parties, by newspapers*

	Der Standard	***Die Presse***	***Salzburger Nachrichten***	***Kronen***
Total attacks	252	335	144	482
Unique attacks	26	28	21	25
Average attacks	7	9.306	4	13.389
(SD)	12.981	18.416	8.509	20.288
Maximum attacks	66	81	37	93
Minimum attacks	0	0	0	0

	Österreich	***Heute***	***Kurier***	***Kleine***
Total attacks	650	197	421	242
Unique attacks	29	24	25	26
Average attacks	18.056	5.472	11.694	6.722
(SD)	28.391	9.254	21.756	11.423
Maximum attacks	134	46	90	43
Minimum attacks	0	0	0	0

Note: Cell entries are the number of attack statements among political parties in the media (across all issue areas) in the eight newspapers.

5. Sample Goodness-of-fit (*gof*) Assessment

In this section, we provide MCMC-diagnostics and sample goodness of fit assessments for the valued ERGM specifications. The MCMC diagnostics present a trace of the sampled output and a density estimate for each variable in the chain per each issue area, where normal-like distributions of the MCMC chains indicate the successful mixing of the proposed algorithm for the MCMC sample estimates. The Goodness of fit diagnostics, presented in Figures S6 to S10, simulate a number of global networks ($N = 1{,}000$ for the current analysis), and compare each of the model statistics from the observed network with the distribution of the same statistics from the simulated networks. All of the figures suggest that our model specifications re-produce the characteristics of the networks being modeled well.

Figure S1. MCMC-diagnostics plot, model "Budget"

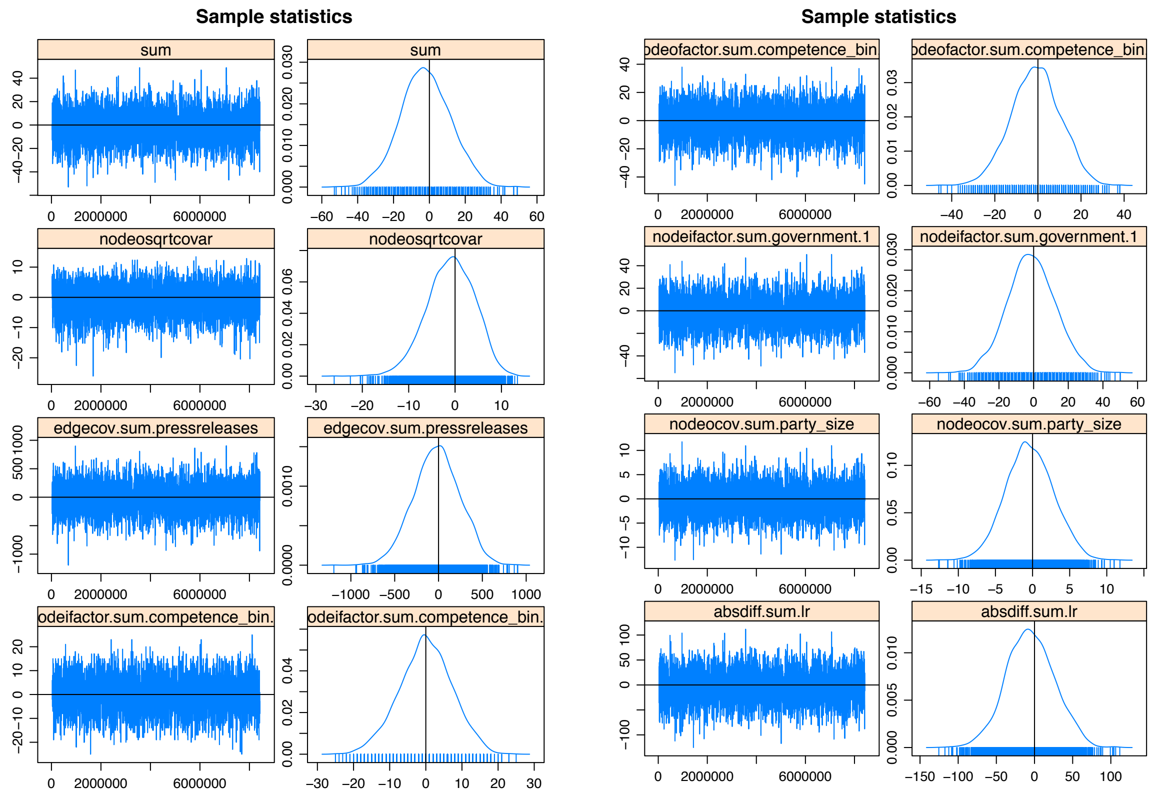


Figure S2. MCMC-diagnostics plot, model "Economy"

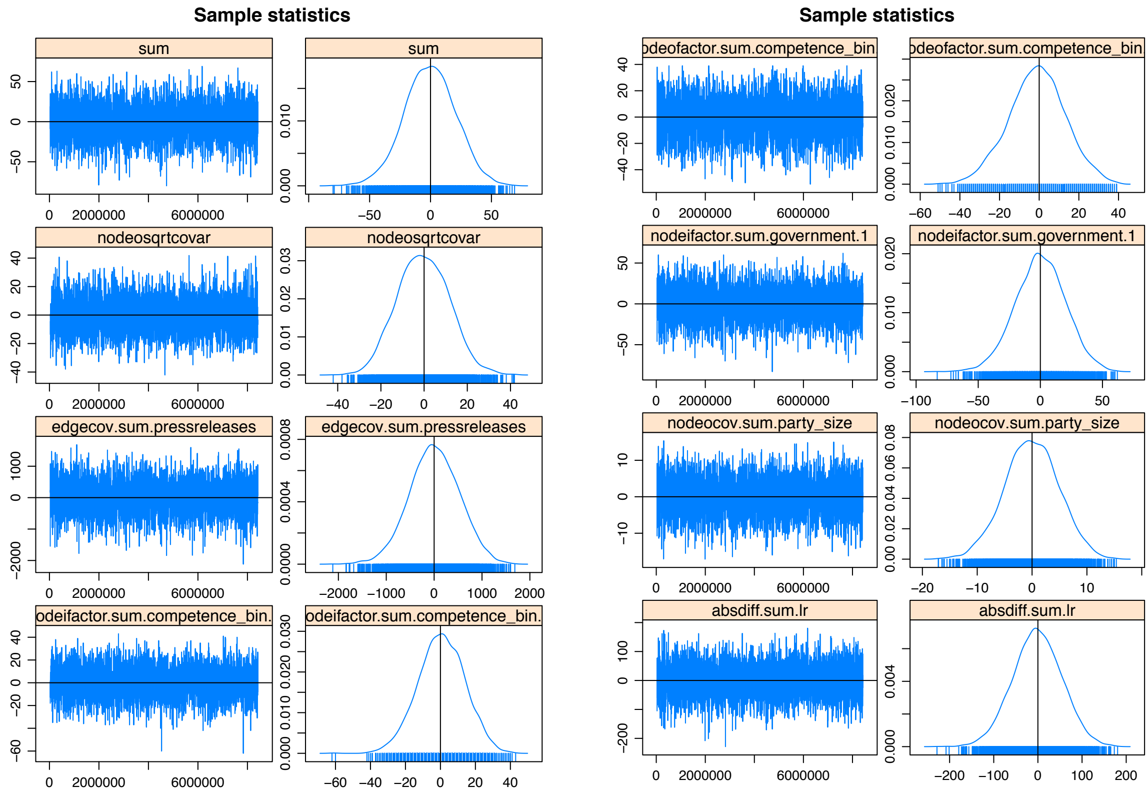


Figure S3. MCMC-diagnostics plot, model "Environment"

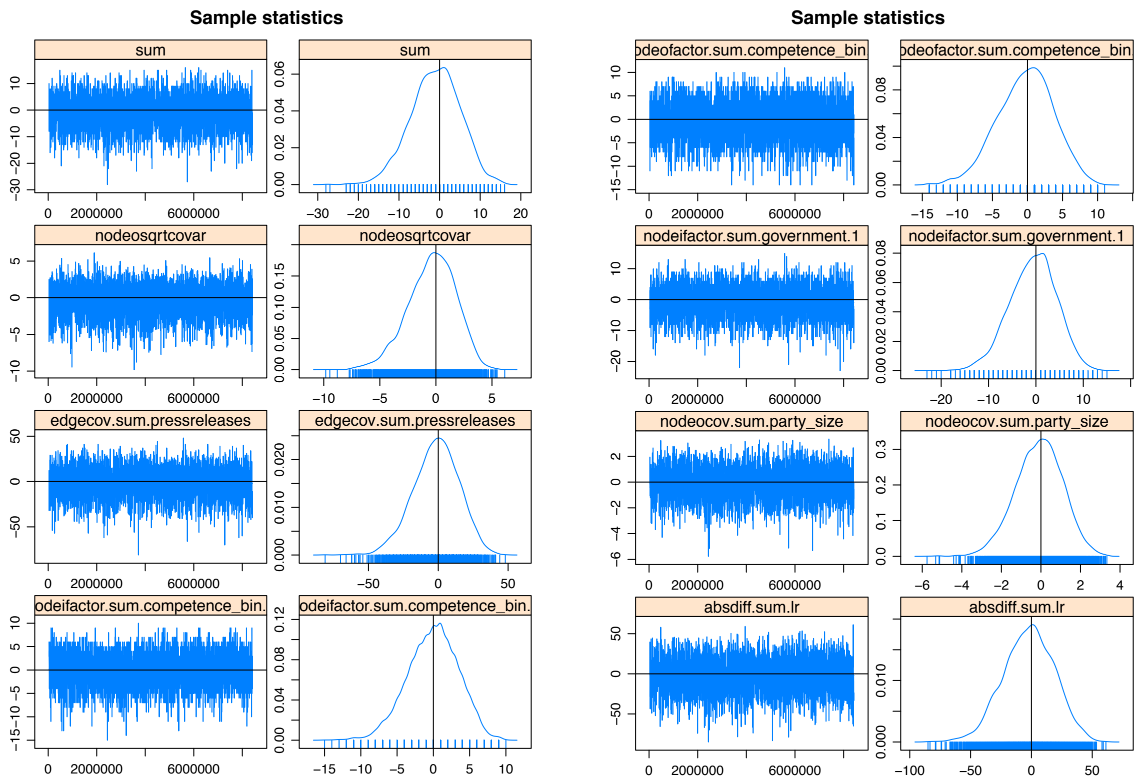


Figure S4. MCMC-diagnostics plot, model "Immigration"

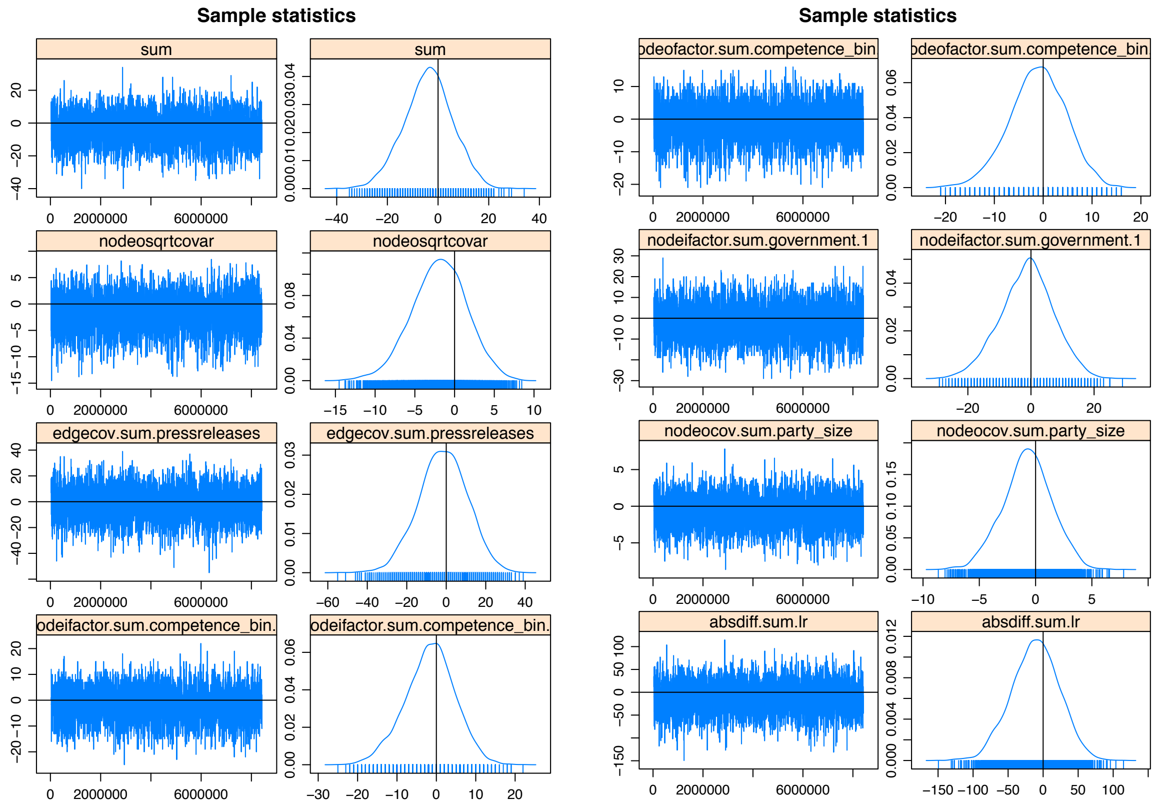


Figure S5. MCMC-diagnostics plot, model "Welfare"

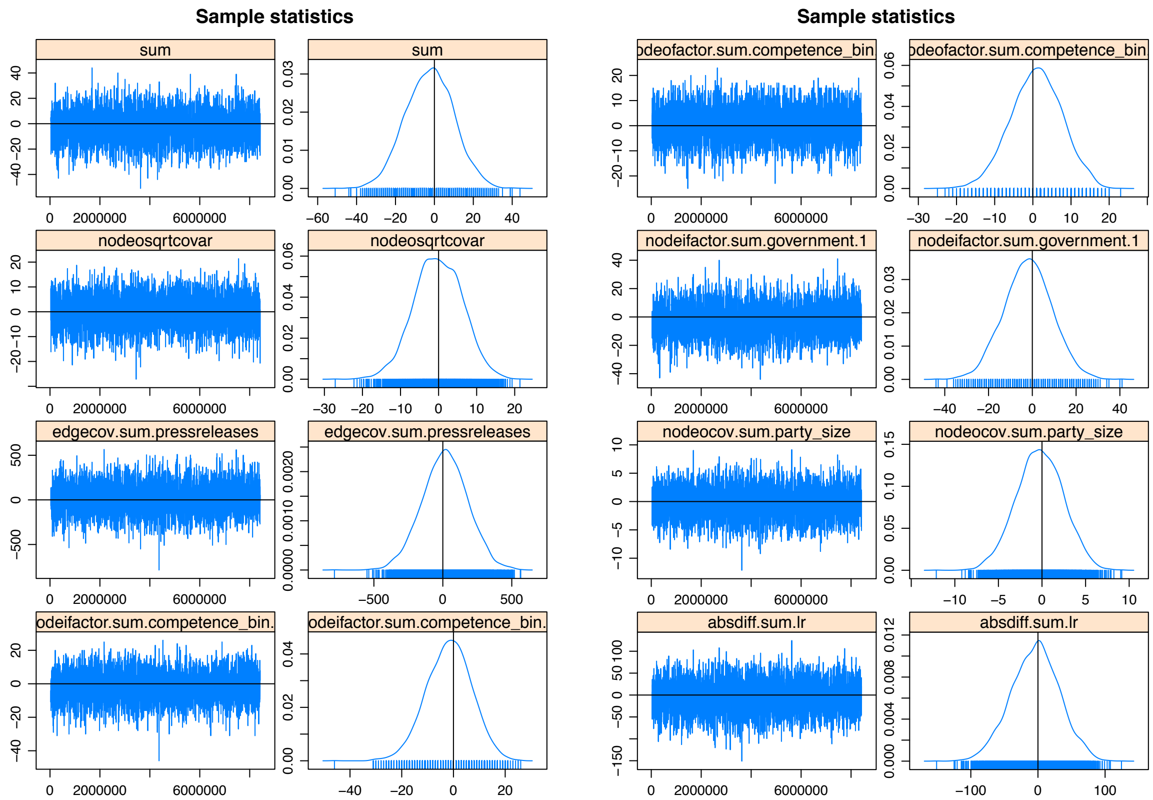


Figure S6. Sample Goodness-of-fit (gof) plot, model "Budget"

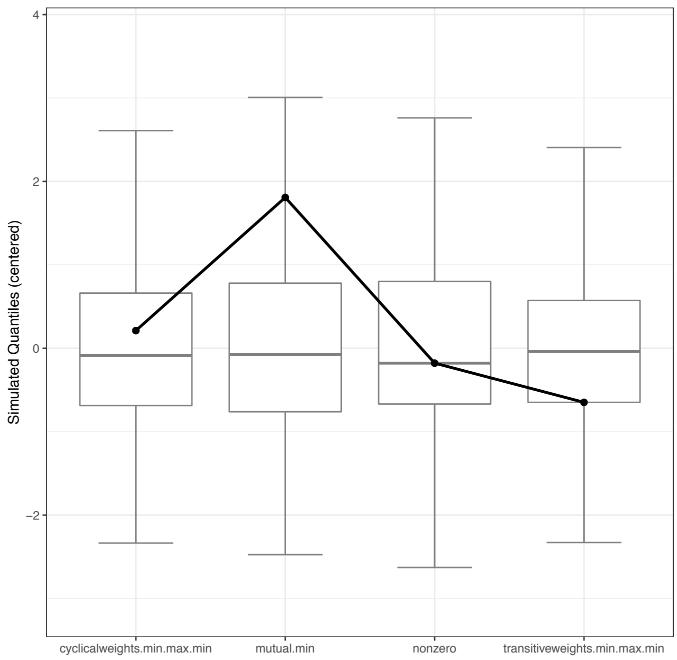


Figure S7. Sample Goodness-of-fit (gof) plot, model "Economy"

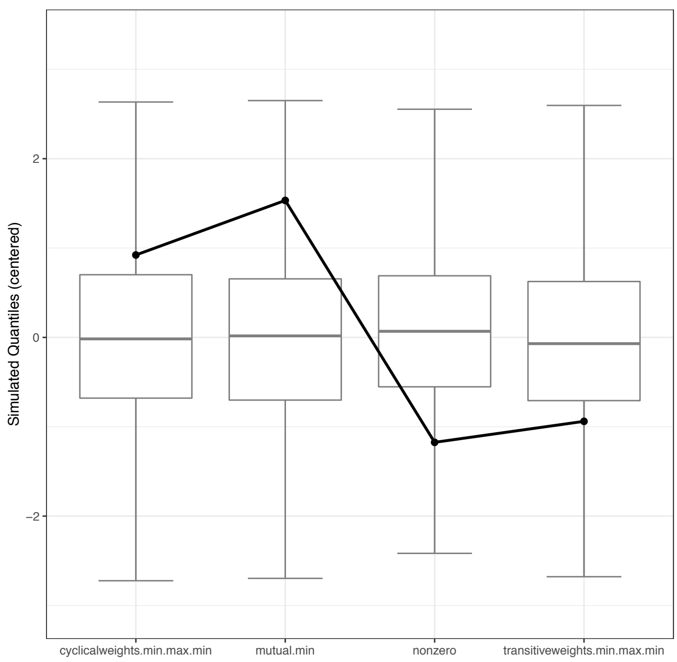


Figure S8. Sample Goodness-of-fit (gof) plot, model "Environment"

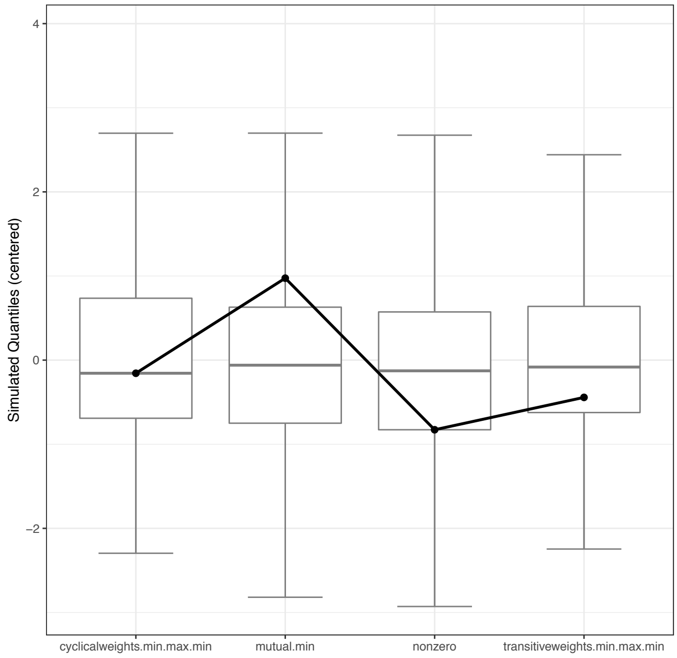


Figure S9. Sample Goodness-of-fit (gof) plot, model "Immigration"

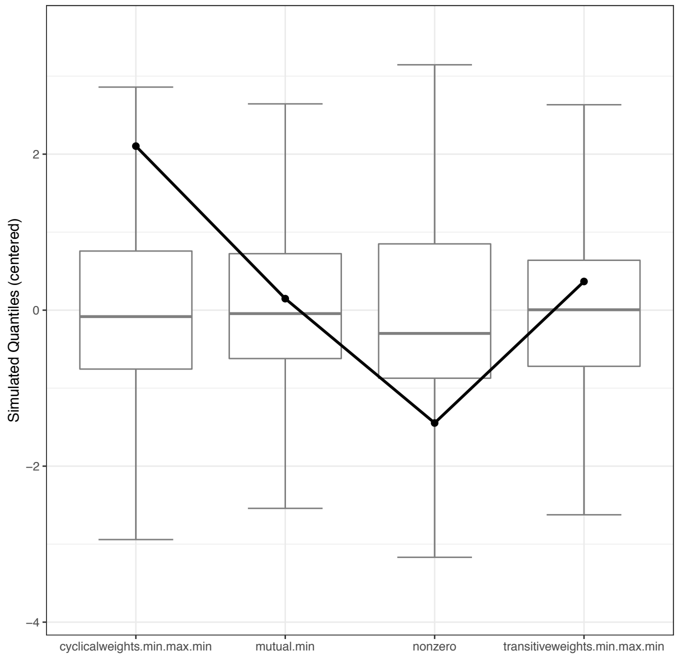
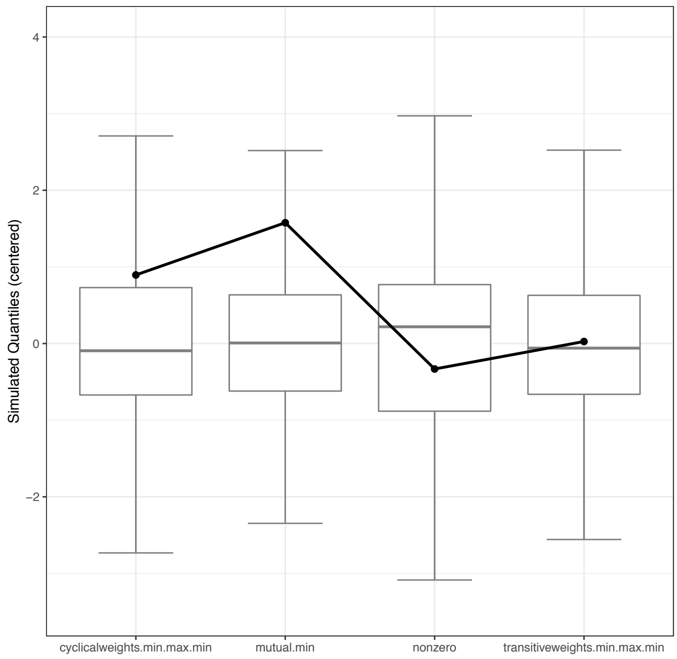


Figure S10. Sample Goodness-of-fit (gof) plot, model "Welfare"



Note: The *gof* plot presents the distribution of auxiliary network statistics from the observed network (thick bold line) against the simulated networks (presented as a series of box plots, using 1,000 simulations), where auxiliary network statistics are model terms that are not explicitly modeled in our model specification (presented in Table 1 of the manuscript). The result suggests that our models correctly reproduce the global properties of the network statistics that are not explicitly modeled.

5. Models with issue ownership as a continuous indicator, replication of Table 1.

Since our models (Table 1 in the manuscript) utilize a binary, or rather a binarized issue ownership measure, there is a worry that this measure is too coarse to represent public perceptions of issue ownership in a multi-party system, although such an operationalization is common in the literature. To get a better sense of the variability of the party-issue associations and their varying degree of contestedness, we estimated a set of models where we replace the binary factor – one party owns an issue – with a metric measure based on the survey responses. In this case, we take all party mentions for an issue and calculate the share of responses naming the various parties as most competent.

With this metric measure of issue ownership, the substantive conclusions remain unchanged. Regardless of whether only one party is clearly associated with an issue (e.g., 82.7 percent of the respondents label the green party as most competent in the area of the environment) or whether an issue is more contested (e.g., 47.5 percent of the respondents consider the SPÖ most competent on economic matters, compared to 32.6 percent naming the ÖVP), there is a strong and positive effect of issue ownership on the propensity of being featured in the media. We have refrained from replacing the results in the main text with these results as we are concerned that party identification has too great of an effect on a continuous, survey-based measure of issue ownership. As partisans are much more likely to name their preferred party as most competent, a continuous measure would naturally rank the large parties somewhat too highly, and we have no reliable way to partial out such an influence in the continuous measure of issue ownership (even though we also control for the effect of party size in the model).

Table S3. Models with issue ownership as a continuous measure, replication of Table 1.

	Budget	**Economy**	**Environment**	**Immigration**	**Welfare**
Sum	-2.23**	0.31	-8.75***	-1.59*	-1.49*
	(0.84)	(0.41)	(2.15)	(0.78)	(0.70)
Individual heterogeneity	-0.91	-0.62**	-0.87	-2.02***	-0.31
	(0.47)	(0.22)	(0.96)	(0.59)	(0.46)
Objective attacks	0.04	0.03***	-0.05	0.16	-0.00
	(0.03)	(0.01)	(0.21)	(0.18)	(0.02)
Issue owner (Target)	9.35***	3.47***	5.14***	2.94***	1.40
	(2.20)	(0.73)	(0.99)	(0.78)	(0.80)
Issue owner (Attacker)	5.21	-0.22	3.22***	2.85*	2.42**
	(2.95)	(0.82)	(0.97)	(1.21)	(0.83)
Incumbent (Target)	0.82	1.67***	2.36*	0.63	1.15**
	(1.19)	(0.33)	(0.94)	(0.33)	(0.40)
Party size	-3.13	2.14	23.74***	9.71***	8.21***
	(2.86)	(1.61)	(5.79)	(2.25)	(2.35)
Ideological distance	0.14	0.09	0.48**	-0.01	0.09
	(0.13)	(0.05)	(0.17)	(0.09)	(0.07)
AIC	-1153.14	-2787.09	-69.32	-249.70	-459.60
BIC	-1141.93	-2775.89	-58.11	-238.49	-448.39
Log Likelihood	584.57	1401.55	42.66	132.85	237.80

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Note: A proportion-based issue ownership indicator is being used. Standard errors in parentheses. AIC for null model is defined as zero in valued ERGM.

6. Models Controlling for Possible Overdispersions, Replication of Table 1.

Since descriptive statistics of our issue network suggests a highly imbalanced distribution of attacks across parties, our reference distribution in Table 1 – the Poisson distribution – may be biased due to overdispersion. We estimated identical models as the ones presented in the main text with controls for possible overdispersion of the data (using fractional moments in intercept term specification), as presented in Table S4 below. The substantive conclusions remain unchanged.

Table S4. Models controlling for possible overdispersion, replication of Table 1.

	Budget	**Economy**	**Environment**	**Immigration**	**Welfare**
Sum (fractional moment)	-2.08^{*}	-1.70	-3.84^{***}	-2.61^{**}	-1.46
	(0.81)	(1.07)	(0.78)	(0.88)	(0.98)
Individual heterogeneity	0.05	0.27	0.48	-0.77	-0.13
	(0.64)	(0.54)	(0.77)	(0.78)	(0.63)
Objective attacks	0.13^{***}	0.05^{***}	0.18	0.16	0.02
	(0.04)	(0.01)	(0.18)	(0.18)	(0.01)
Issue owner (Target)	0.71^{*}	-0.21	1.11^{*}	1.02^{*}	0.48^{*}
	(0.34)	(0.17)	(0.48)	(0.43)	(0.22)
Issue owner (Attacker)	0.10	0.26	0.93^{**}	0.61^{*}	0.30
	(0.66)	(0.17)	(0.31)	(0.26)	(0.24)
Incumbent (Target)	0.94^{*}	1.68^{***}	0.49	0.84^{*}	1.07^{***}
	(0.42)	(0.22)	(0.55)	(0.34)	(0.24)
Party size	4.12^{*}	5.72^{**}	4.34^{*}	6.73^{***}	5.96^{***}
	(1.85)	(1.80)	(1.93)	(1.91)	(1.62)
Ideological distance	-0.04	0.08	0.05	0.05	0.05
	(0.11)	(0.05)	(0.09)	(0.08)	(0.06)
AIC	-1138.68	-2769.46	-61.92	-252.46	-454.44
BIC	-1127.47	-2758.25	-50.71	-241.25	-443.23
Log Likelihood	577.34	1392.73	38.96	134.23	235.22

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Note: Standard errors in parentheses. AIC for null model is defined as zero in valued ERGM.

7. Jackknifing Media Outlets

Here, we additionally present an robustness check involving jackknifing media outputs. This analysis is intended to check whether the results are driven by the misrepresentation in one newspaper. Specifically, we omit one media outlet at a time, and re-estimate the model reported in Table 1 of the manuscript. Since we have 8 newspapers, this involves 8 batches of replicated results. Next, we summarize the results based on Rubin's rule, where averaged parameter estimates and pooled SEs are reported in Table S2.[1] Therefore, the results in Table S2 represent the average coefficients across 8 batches while taking the variations in coefficients across each batch due to the omission of outlets (i.e., variations in disproportionality across news outlets) into account. As can be seen in Table S2, the impact of issue ownership (using a binary indicator), especially attacks *targeting* the issue owner ("Target" variable) is consistent with the results reported in the main manuscript. Attacks originating *from* the issue owner ("Attacker" variable) were somewhat inconsistent, suggesting that each news outlet may have a disproportionate propensity to feature attacks originating from the issue owner.

Table S5. Jackknifing Media Outlet, Pooled Results (using Rubin's rule).

	Budget	**Economy**	**Environment**	**Immigration**	**Welfare**
Sum	-1.59	-10.68**	-1.41	0.43	-1.50
	(0.86)	(3.48)	(1.31)	(0.44)	(0.86)
Individual heterogeneity	-2.02**	-0.69	-0.61	-0.40	-0.69**
	(0.66)	(0.87)	(1.27)	(0.50)	(0.26)
Objective attacks	0.05***	0.19	0.11	-0.04	0.01
	(0.01)	(0.23)	(0.07)	(0.26)	(0.02)
Issue owner (Target)	0.62*	-0.13	1.10*	0.94*	3.05*
	(0.29)	(0.17)	(0.55)	(0.47)	(1.26)
Issue owner (Attacker)	4.74***	0.36	0.33	0.96**	0.82
	(1.24)	(0.32)	(0.21)	(0.33)	(1.07)
Incumbent (Target)	1.35*	2.89*	1.48**	1.15***	0.85
	(0.67)	(1.35)	(0.50)	(0.25)	(0.46)
Party size	10.95***	6.99*	30.08**	9.42**	6.42***
	(3.01)	(2.85)	(9.39)	(3.09)	(1.50)
Ideological distance	0.02	0.05	-0.03	0.53*	0.09
	(0.05)	(0.10)	(0.14)	(0.25)	(0.11)
AIC	-958.16	-2325.12	-57.83	-200.65	-373.77
BIC	-946.95	-2313.91	-46.62	-189.44	-362.56
Log Likelihood	487.08	1170.56	36.92	108.33	194.88

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Significance of each parameters are calculated using pooled SEs.

[1] Since the number of attack relations reported in the media outlets is highly imbalanced, relying on delete-d jackknifing (and estimating delete d-jackknifing bias) is misleading in this case due to the imbalance of deleted data in each batch.

8. Results Dropping Left-Right Ideological Distance Term in the Model.

With respect to the issue ownership indicator, one may be concerned about the possibility that the issue ownership indicator is confounded with the general left-right dimension of each party (which we also control for in the model), such that two highly similar measures are simultaneously included in a single model specification. To address this possibility, we present an additional robustness check dropping the ideological distance on the left-right dimension in the model reported in Table S6.

With regard to parties' ideological distance on the left-right dimension, there is little effect of this factor one way or another, so dropping the variable makes no difference for the substantive results.

Table S6. Generalized ERGMs of campaign attacks (excluding ideological distance)

	Budget	**Economy**	**Environment**	**Immigration**	**Welfare**
Sum	-1.46^{*}	0.64^{*}	-4.88^{***}	-1.04	-0.79
	(0.67)	(0.32)	(1.37)	(0.66)	(0.57)
Individual heterogeneity	-0.66	-0.70^{***}	-0.88	-2.14^{***}	-0.54
	(0.54)	(0.19)	(1.03)	(0.60)	(0.39)
Objective attacks	0.11^{**}	0.05^{***}	0.34	0.22	0.01
	(0.04)	(0.01)	(0.18)	(0.17)	(0.02)
Issue owner (Target)	0.93	0.32	3.19^{***}	1.01^{***}	0.35
	(0.62)	(0.17)	(0.68)	(0.25)	(0.26)
Issue owner (Attacker)	0.99^{**}	-0.11	2.17^{**}	1.02^{*}	0.65^{**}
	(0.37)	(0.15)	(0.83)	(0.47)	(0.24)
Incumbent (Target)	1.29^{*}	1.13^{***}	0.77	0.69	1.31^{***}
	(0.59)	(0.23)	(0.74)	(0.38)	(0.35)
Party size	6.94^{***}	6.43^{***}	16.66^{***}	10.67^{***}	9.05^{***}
	(2.01)	(1.26)	(4.74)	(2.21)	(2.07)
AIC	-1140.59	-2769.59	-62.52	-249.29	-456.58
BIC	-1130.78	-2759.79	-52.71	-239.48	-446.77
Log Likelihood	577.29	1391.80	38.26	131.65	235.29

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Note: AIC for null model is defined as zero in valued ERGM

9. Visualization of Attack Networks

Below, we present a visualization of the attack networks in each topic area and of the network with all of the attacks combined. In the figures below, the size of the nodes is proportional to the party size, and the size of the arrows is proportional to the volume of attacks. The colors represent the official party colors.

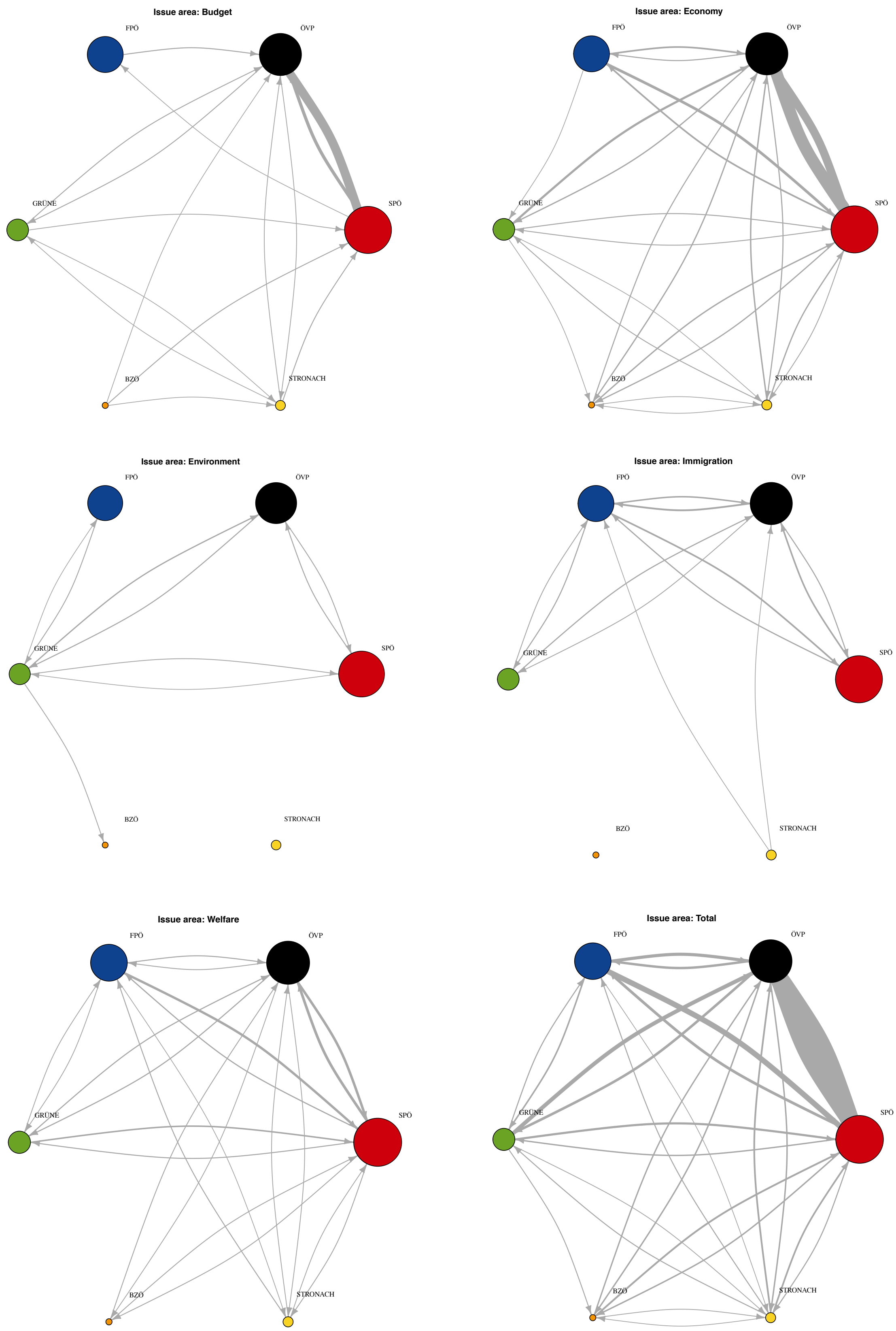


Figure S11. Visualization of the Attack Networks