Supporting Information: Elite Interactions and Voters' Perceptions of Parties' Policy Positions

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A Event Data: Details and Descriptive Statistics

A.1 Discussion of Accuracy of the Machine Coding and Data Limitations

We use the ICEWS event data as the basis for our inter-party relationship scores. In this section, we discuss the accuracy of the machine coding as well as limitations of the data.

First, one concern about the data may be that the event collection skews towards violence and war, given that the goal of the ICEWS project is to assist the policy community in predicting political crises around the globe. In this respect, it is true that ICEWS tries to forecast rebellions or ethno-religious violence. However, it also focuses on domestic political crises, which are often non-violent in nature (see O'Brien, 2013). The project therefore aimed to assemble an event collection that reflects the activities of countries' main socio-political actors as accurately as possible, violent or not. It relies on a large number of national and international news sources, which should provide an extensive collection of events. The events are filtered to exclude reports on e.g. sports or entertainment, but all violent and non-violent socio-political events are retained.

A second concern is the accuracy of the machine coding. For one, the CAMEO coding scheme used to classify the events was originally developed to support efforts forecasting crises events. Does this skew the event collection towards violence? Of course, some of the verb categories of the CAMEO scheme (e.g. "use unconventional mass violence") will not apply outside a conflict setting. But the scheme is used to machine code events that are able to successfully forecast domestic political crises, which are often non-violent. As such, CAMEO can accurately classify news stories reporting conflict and cooperation between domestic political actors.

More broadly, how accurate is the machine coding of the news reports? A number of contributions have investigated this question. The developers of the BBN ACCENT algorithm report that in a validation study, the machine coding was judged to be correct in between 68 percent and 75 percent of cases, using a sample of 500 event codings for each of three top-level CAMEO event codes (Boschee, Natarjan and Weischedel, 2013). Accuracy rates in an evaluation using all 20 top-level CAMEO event codes vary between 58 percent and 88 percent (Boschee et al., 2015).

This compares well with the available alternative, which is human coding, a methodology known to be error-prone (Mikhaylov, Laver and Benoit, 2012). For example, King and Lowe (2003) evaluate event type coding done by trained undergraduates and find them to be correct in only 25 to 50 percent of cases. This is about as accurate as their machine coding, which was done by a comparatively simple algorithm. Given advances in this area since then, the machine coding of the news reports by BBN ACCENT is likely at least as accurate as human coding would be, and most likely better.

Note that in the ICEWS data, events are classified according to the roughly 350 CAMEO categories. However, they are dichotomized before they enter the latent factor network models. This should reduce incidences of coding errors significantly. For example, if an even reporting a verbal attack were to be misclassified into, say, "use unconventional mass violence" rather than the more appropriate "criticize or denounce", it would still be correctly classified as a conflictual interaction. Finally, we note that any miscodings make the cooperation scores more noisy, which should make it harder for us to find any connection between them and voters' or experts' policy perceptions.

Of course, the event data do have some limitations. Media reports tend to focus on high-level political and societal actors. Ministers, party leaders, or party spokespersons are well represented in our data, as are nationwide protest movements. What is less reported on are activities of e.g. backbencher MPs or societal actors at the local level. And of course, the data only covers public events. However, this is not a problem for our specific purpose in this article. We are interested in measuring the degree of inter-party relationships conveyed to voters and political experts through media reports. If backbencher MPs are not well represented in our data, they are also not present in the media reports that citizens read on a day-to-day basis.

Finally, there are differences in the extent to which the ICEWS data cover different countries. As shown below, for some countries we have thousands of events on which we can base our cooperation scores, whereas it is much less in particular for smaller nations. In addition, the way actors communicate with each other publicly may differ between countries depending on their laws, culture, institutions, or other differences. We account for this by including country-period fixed effects in all our regression models. By only exploiting variation between parties within country-periods, we can be sure that our findings are not driven by unobserved differences between the country-periods we analyze.

A.2 Sources

Table A1: Top 10 news report sources

Source	Proportion of all Events
Agence France-Presse	0.169
Reuters News	0.138
Associated Press Newswires	0.108
Athens News Agency	0.056
Irish Times	0.046
Dow Jones International News	0.045
Xinhua News Agency	0.034
BBC Monitoring European	0.033
El Pais - English Edition	0.031
Guardian Unlimited	0.024

List of all Sources: In total, reports from 205 sources were used. Note that a number of the sources originate from countries outside of Europe (e.g. Xinhua News Agency). However, reports from these sources still cover exclusively domestic events from one of the 13 Western European countries I consider in this article. ICEWS uses sources from around the world and employs an algorithm that identifies and deletes duplicate events. Thus, events reported by Xinhua News Agency likely are also reported by a European outlet such as Agence France-Presse or the BBC, but the de-duplification algorithm at times may only retain the report of a non-European source.

AAP Bulletins, Ad Dustour, Agence Europe, Agence France-Presse, Agencia Diarios y Noticias, Agencia EFE - Serviao em portugues, AGERPRES, AKIpress, Al-Bawaba News, Al Arabiya, Al Dia, Al Gomhuriah, Al Ittihad, Al Jazeera English, Al Shabiba, Algerie-Focus, All Africa, Anadolu News Agency, ANSA - Spanish Service (BASP), AP Spanish Worldstream, APANEWS, ARKA - News (Armenia), As Safir, Asharq Alawsat, Asia Pulse, Associated Press Newswires, Athens News Agency, Australian Associated Press, Australian Broadcasting Corporation (ABC) News, Baladna, Baltic Business Weekly, Baltic

Daily, Bangkok Post, BBC Monitoring, BBC Monitoring Africa, BBC Monitoring Americas, BBC Monitoring Asia Pacific, BBC Monitoring Caucasus, BBC Monitoring Central Asia, BBC Monitoring European, BBC Monitoring Former Soviet Union, BBC Monitoring Media, BBC Monitoring Middle East, BBC Monitoring Newsfile, BBC Monitoring South Asia, BBC Monitoring Ukraine & Baltics, Black Sea Press, BNS Baltic Business News, Bulgarian News Agency, Calgary Herald, Canada NewsWire, Cape Argus, Cape Times, Central News Agency English News, Channel NewsAsia, China Daily, CNN: Breaking News, Corporate Argentina, CTK Daily News, Daily Dispatch, Daily News, Daily Star, Daily Telegraph, Deutsche Welle, DJ em Portugues, Dow Jones Business News, Dow Jones Emerging Markets Report, Dow Jones en Espanol, Dow Jones International News, Dow Jones News Service, EFE News Service, El Clarin, El Comercio, El Cronista, El Economista, El Mercurio, El Nacional, El Norte, El Nuevo Dia, El Pais, El Pais - English Edition, El Universal, El Watan, eMarrakech, Esmerk Danish News, Esmerk Finnish News, EurActiv.fr, Euronews, Europolitique, FARS News Agency, Folha de Sao Paulo, Gazeta do Povo, Guardian Unlimited, HINA, Hindustan Times, Horizons, Il Sole 24 Ore, India Today, Indo-Asian News Service, Inter Press Service, Interfax News Service, Irish Times, ISI Emerging Markets Africawire, Israel Faxx, IT Market Statistics, ITAR Tass, Jeune Afrique.com, Jiji Press English News Service, Kyodo News, L' Orient-Le Jour, L'Essor, L'Expression, La Nacion, La Republica, Latin America News Digest, Latvian News Agency, Le Figaro, Le Monde, Le Progres Egyptien, Le Quotidien, Le Temps, Libya News Agency (LANA), Lithuanian News Agency - ELTA, London Evening Standard, Mainichi Daily News, Mist News, Mural, National Iraqi News Agency, New Straits Times, New Zealand Herald, New Zealand Press Association, O Estado de Sao Paulo, O Globo, Oman News Agency, Organisation de la Presse Africaine, Organisation of Asia-Pacific News Agencies, PACNEWS, the Pacific News Agency Service, Philippine Daily Inquirer, PNA (Philippines News Agency), Polish News Bulletin, Prime-News (Georgia), Reforma, Resource News International, Reuters - Noticias Latinoamericanas, Reuters EU Highlights, Reuters News, RIA Novosti, Rompres, Sueddeutsche Zeitung, SAINT (South

Atlantic Islands News Team), SAPA (South African Press Association), SBS World News Headline Stories, SeeNews, Servicio Universal de Noticias, SITA Slovenska Tlacova Agentura, South China Morning Post, Spiegel Online International, Straits Times, Syrian Arab News Agency, Taipei Times, TASR - Tlacova Agentura Slovenskej Republiky, Thai News Service, The Asian Wall Street Journal, The Australian, The Christian Science Monitor, The Courier-Mail, The Economist, The Hindu, The Jakarta Post, The Japan Times, The Jerusalem Post, The Korea Herald, The Mercury, The Moscow Times, The Nation (Thailand), The New York Times, The San Diego Union-Tribune, The Scotsman, The Sydney Morning Herald, The Times of India, The Toronto Star, The Tripoli Post, The Wall Street Journal, The Wall Street Journal Asia, The Wall Street Journal Europe, The Washington Post, Trend News Agency (Azerbaijan), Turan Information Agency (Azerbaijan), Turkish Daily News, Ukrainian National News Agency, United News of Bangladesh Limited, Unknown, UPI Energy Resources, USA Today, UzReport.com, Vietnam News Agency Bulletin, What The Papers Say, WPS: What the Papers Say, Xinhua News Agency, Yemen News Agency (SABA), Yonhap English News

A.3 Number of Events and Actors for each Survey

Table A2: Number of events and unique number of actors for each country-survey, based on events in the 12 months preceding the survey. Part 1 of 2

Country	Year	Month	Number of Events	Number of Actors
Austria	2004	06	178	25
Austria	2008	06	450	50
Austria	2009	06	376	54
Austria	2013	10	188	34
Austria	2014	06	92	30
Belgium	2009	06	185	47
Belgium	2014	06	138	44
Denmark	2004	06	72	35
Denmark	2005	02	102	44
Denmark	2007	01	486	69
Denmark	2009	06	101	44
Denmark	2014	06	32	27
Finland	2003	03	35	19
Finland	2004	06	28	19
Finland	2007	03	61	22
Finland	2009	06	46	28
Finland	2011	04	58	28
Finland	2014	06	38	16
France	2002	05	1218	122
France	2004	06	1415	133
France	2007	06	2037	143
Germany	2002	10	936	88
Germany	2004	06	992	103
Germany	2005	09	1243	110
Germany	2009	06	1063	96
Germany	2009	10	879	95
Germany	2013	09	621	83
Germany	2014	06	442	78
Greece	2004	06	551	70
Greece	2009	06	1504	79
Greece	2009	12	576	70
Greece	2012	01	2955	128
Greece	2014	06	770	80

Table A3: Number of events and unique number of actors for each country-survey, based on events in the 12 months preceding the survey. Part 2 of 2

Country	Year	Month	Number of Events	Number of Actors
Ireland	2002	06	303	81
Ireland	2004	06	339	73
Ireland	2007	07	525	88
Ireland	2009	06	460	84
Ireland	2011	03	591	73
Ireland	2014	06	225	56
Italy	2004	06	584	89
Italy	2006	05	1124	124
Netherlands	2002	05	57	30
Netherlands	2003	01	291	70
Netherlands	2004	06	110	38
Netherlands	2006	12	251	63
Netherlands	2009	06	170	50
Netherlands	2010	06	131	46
Netherlands	2012	09	112	46
Portugal	2002	03	152	34
Portugal	2004	06	100	36
Portugal	2005	03	308	49
Portugal	2009	06	48	21
Portugal	2009	09	56	22
Portugal	2014	06	32	17
Spain	2004	03	1424	88
Spain	2004	06	3816	125
Spain	2008	04	2722	117
Spain	2009	06	1690	106
Spain	2011	11	820	76
Spain	2014	06	1024	73
United Kingdom	2004	06	2030	169
United Kingdom	2005	08	4690	199
United Kingdom	2009	06	3314	204
United Kingdom	2014	06	2039	182

A.4 List of Political Parties

- **Austria**: FPO, OVP, Grune, BZO, SPO
- **Belgium**: CD&V, MR, PS, VLD
- **Denmark**: DKF, Social Democrats, DPP, Liberal Alliance, SF, Radikale Venstre, Venstre
- **Finland**: Centre, NCP, Green League, SDP, PS, Left Alliance, SFP
- **France**: EELV, FN, PCF, PS, MoDem, UMP
- **Germany**: CDU/CSU, FDP, Grune, PDS/Linke, SPD
- **Greece**: KKE, ND, PASOK, Syriza, ANEL, XA
- **Ireland**: Fine Gael, Fianna Fail, Labour, Sinn Fein
- **Italy**: AN, DL, DS, FI, PRC, LN, UdC
- **Netherlands**: CDA, LPF, D66, PvdA, GL, PVV, VVD
- **Portugal**: CDU, PS, PSD
- **Spain**: PP, PSOE
- **United Kingdom**: Conservative, Labour, LibDem

B Technical Details on Latent Factor Network Models

The paper gives an intuitive description of the latent factor network model. Here, we provide a more technical overview based on Weschle (2018) and the accompanying online appendix.

Suppose there are n actors, for whom we observe dyadic interactions over a period of time. In our case, this would be all actors from a certain country for whom at least one domestic interaction is reported in the ICEWS data in the 12 months before the survey in which respondents were asked about their perceptions of parties' policy positions. Note that the set of actors includes political parties as well as other socio-political actors. The number of cooperative interactions between two actors i and j is denoted by m_{ij}^{+}, and the number of conflictual interactions by m_{ij}^{-}. The set of all interactions is represented in an $n \times n$ sociomatrix $\mathbf{Y}$. An entry y_{ij} summarizes the direct dyadic interactions between i and j as follows: $y_{ij} = \ln\left(\frac{m_{ij}^{+}+1}{m_{ij}^{-}+1}\right)$. Interactions are treated as symmetric, so $y_{ij} = y_{ji}$.

The idea behind the latent factor model is that each actor can be represented through an unobserved, K-dimensional vector of characteristics $\boldsymbol{u}_i$. This is done by modeling the cells y_{ij} of $\mathbf{Y}$ as follows:

$$\begin{aligned} y_{ij} &= \alpha + a_i + a_j + \epsilon_{ij} + \boldsymbol{u}_i' \boldsymbol{\Lambda} \boldsymbol{u}_j \\ a_1, \ldots, a_n &\sim \text{i.i.d. } \mathcal{N}(0, \sigma_a^2) \\ \{\epsilon_{ij}\} &\sim \text{i.i.d. } \mathcal{N}(0, \sigma_e^2) \end{aligned} \tag{1}$$

α is the intercept, and a_i and a_j are random effects that capture overall differences in the tone of interactions by actors i and j. ϵ_{ij} is another random effects term that captures the correlation of actions between a dyadic pair of actors. Finally, the remaining variance in y_{ij} is absorbed by $\boldsymbol{u}_i' \boldsymbol{\Lambda} \boldsymbol{u}_j$, the multiplicative effects term that captures latent nodal characteristics.

The terms in $\boldsymbol{u}_i' \boldsymbol{\Lambda} \boldsymbol{u}_j$ are estimated using an eigenvalue decomposition. Denote the $n \times n$ matrix that captures the remaining variance of $\mathbf{Y}$ not explained by the other terms in Equation (1) by $\mathbf{M}$. The eigenvalue decomposition theorem states that any square matrix, such as $\mathbf{M}$, can be written as $\mathbf{M} = \mathbf{U}\boldsymbol{\Lambda}\mathbf{U}'$, where $\mathbf{U}$ is a matrix of eigenvectors and $\boldsymbol{\Lambda}$ a diagonal matrix with the corresponding eigenvalues on the diagonal. The term $\mathbf{U}\boldsymbol{\Lambda}\mathbf{U}'$ thus captures the remaining variance in $\mathbf{Y}$ not accounted for by the other parameters. Note that an element m_{ij} of $\mathbf{M} = \mathbf{U}\boldsymbol{\Lambda}\mathbf{U}'$ is $\boldsymbol{u}_i'\boldsymbol{\Lambda}\boldsymbol{u}_j$. The multiplicative effects term $\boldsymbol{u}_i'\boldsymbol{\Lambda}\boldsymbol{u}_j$ then represents the nature of the relationship between i and j. This is what we call the relationship score. For further details on the approach, see Hoff (2005), Hoff (2015), Minhas, Hoff and Ward (2019), and Weschle (2018).

C Additional Analyses and Robustness Checks

C.1 Results Dropping Austria, Denmark, Finland, Netherlands

The ICEWS data are based on a mixture of national news sources as well as international wire services. As can be seen in Section A.2 above, there are few national media sources from Austria, Denmark, Finland, and the Netherlands. To make sure that the potentially lower data quality and coverage is not driving the results, Table A4 shows the results from estimating the models in Table 2 of the article dropping observations from these countries. The point estimates are very similar, so the results are robust to accounting for potential data coverage problems.

Table A4: Robustness Check: Dropping AUT, DEN, FIN, NED. Results of regressions from Table 2 dropping countries with few national media sources in the data.

	Mean Perceived Positions		Sophia	
	Election	Non-Election	Election	Non-Election
Relationship Score	-0.650***	-0.091	-0.617***	-0.118
	(0.233)	(0.357)	(0.189)	(0.286)
Manifesto Difference	0.628***	0.834*	0.434**	0.538
	(0.237)	(0.484)	(0.198)	(0.386)
Coalition Partners	-0.481	-1.211*	-0.274	-1.055**
	(0.415)	(0.662)	(0.256)	(0.525)
Opposition Partners	-0.048	0.386	0.036	0.138
	(0.328)	(0.492)	(0.265)	(0.374)
N	164	84	164	84
R^2	0.38	0.32	0.51	0.37
Adjusted R^2	0.25	0.11	0.41	0.19

*p<0.1; **p<0.05; ***p<0.01

C.2 Results Using Direct Interactions Only

The cooperation scores are based on direct interactions among actors as well as their interactions through third parties. For example, if parties A and B both have a cooperative relationship with a union, a voter can reasonably conclude that A and B also have a good relationship with each other, even if they themselves do not interact. Similarly, if A is cooperative with the union and B is conflictual, then A and B are also likely to have a strained relationship. Indeed, there is a large literature on networks that highlights the importance of such third-order dependencies for social relationships. However, it is possible that voters might not take such higher-order information into account. We therefore construct an alternative relationship score between parties i and j that is based on direct interactions only:

$$y_{ij} = \ln\left(\frac{m_{ij}^{+} + 1}{m_{ij}^{-} + 1}\right) \tag{2}$$

Table A5 shows the results from estimating the models in Table 2 of the article with this alternative dependent variable. Note that due to the different scale of the variable, the size of the coefficients is not directly comparable to those in Table 2. However, it is clear that the substantive results are robust to this alternative dependent variable.

Table A5: Robustness Check: Direct Interactions Only. Results of regressions from Table 2 using a dependent variable based on direct interactions between parties only.

	Mean Perceived Positions		Sophia	
	Election	Non-Election	Election	Non-Election
Relationship Score (Direct)	-0.452***	-0.187	-0.362***	-0.126
	(0.161)	(0.197)	(0.129)	(0.150)
Manifesto Difference	0.644***	0.674*	0.452**	0.465
	(0.217)	(0.367)	(0.182)	(0.289)
Coalition Partners	-0.564**	-1.113***	-0.450**	-0.891***
	(0.235)	(0.358)	(0.178)	(0.285)
Opposition Partners	0.033	0.286	0.090	0.149
	(0.281)	(0.479)	(0.229)	(0.357)
N	225	127	225	127
R2	0.39	0.35	0.50	0.39
Adjusted R2	0.26	0.14	0.40	0.19

*p<0.1; **p<0.05; ***p<0.01

C.3 Results Using Only Events 9 or 6 Months Prior to Survey

In the manuscript, we base our cooperation score estimates on events in the 12 months preceding the survey, in line with evidence from the economic voting literature that voters pay attention to conditions in the year or so before elections. As a robustness check, Tables A6 and A7 show the results when using only events from the 9 and 6 months before the survey, respectively. The relationship scores continue to have a clear negative effect. Because the relationship scores are based on fewer interactions they are less precisely estimated, and we lose some observations due to a lack of reported events, so that the point estimates are slightly smaller in magnitude. However, the substantive results remain the same.

Table A6: Robustness Check: Using Only Events 9 Months Prior to Election. Results of regressions from Table 2 using a dependent variable based on the interactions in the 9 months before the election.

	Mean Perceived Positions		Sophia	
	Election	Non-Election	Election	Non-Election
Relationship Score	-0.481**	-0.011	-0.425**	-0.115
	(0.217)	(0.300)	(0.194)	(0.253)
Manifesto Difference	0.656***	0.760**	0.459**	0.528**
	(0.222)	(0.320)	(0.183)	(0.251)
Coalition Partners	-0.657***	-1.306***	-0.504***	-0.963***
	(0.244)	(0.360)	(0.167)	(0.276)
Opposition Partners	0.118	0.176	0.158	0.080
	(0.288)	(0.408)	(0.233)	(0.304)
N	229	145	229	145
R2	0.37	0.33	0.48	0.37
Adjusted R2	0.24	0.15	0.38	0.20

*p<0.1; **p<0.05; ***p<0.01

Table A7: Robustness Check: Using Only Events 6 Months Prior to Election. Results of regressions from Table 2 using a dependent variable based on the interactions in the 6 months before the election.

	Mean Perceived Positions		Sophia	
	Election	Non-Election	Election	Non-Election
Relationship Score	-0.418*	0.080	-0.316*	-0.019
	(0.219)	(0.301)	(0.188)	(0.255)
Manifesto Difference	0.661***	0.696*	0.466**	0.482*
	(0.222)	(0.364)	(0.185)	(0.288)
Coalition Partners	-0.683***	-1.261***	-0.551***	-0.961***
	(0.246)	(0.347)	(0.174)	(0.278)
Opposition Partners	0.054	0.226	0.106	0.116
	(0.286)	(0.470)	(0.234)	(0.350)
N	225	127	225	127
R2	0.37	0.35	0.48	0.39
Adjusted R2	0.24	0.14	0.38	0.19

*p<0.1; **p<0.05; ***p<0.01

C.4 Alternative Fixed Effects Structure

Because the latent space estimations upon which the relationship scores are based, Weschle (2018) recommends addressing potential comparability issues through fixed effects. In the manuscript, we present results from models with country-survey fixed effects. Here, we explore alternative fixed effects specifications. Table A8 shows results when using country fixed effects, and Table A9 includes in (separate) country and year fixed effects. The substantive results are similar to those in Table 2 of the manuscript.

Table A8: Robustness Check: Country Fixed Effects Only. Results of regressions from Table 2 using only country fixed effects..

	Mean Perceived Positions		Sophia	
	Election	Non-Election	Election	Non-Election
Relationship Score	-0.434**	-0.057	-0.397**	-0.014
	(0.203)	(0.267)	(0.169)	(0.222)
Manifesto Difference	0.406**	0.751***	0.262	0.454**
	(0.205)	(0.280)	(0.168)	(0.218)
Coalition Partners	-0.578**	-1.177***	-0.456***	-1.025***
	(0.244)	(0.331)	(0.172)	(0.224)
Opposition Partners	0.115	0.190	0.166	0.117
	(0.275)	(0.352)	(0.222)	(0.263)
N	237	149	237	149
R2	0.28	0.27	0.39	0.31
Adjusted R2	0.23	0.18	0.35	0.23

*p<0.1; **p<0.05; ***p<0.01

Table A9: Robustness Check: Separate Country and Year Fixed Effects Only. Results of regressions from Table 2 using only (separate) country and year fixed effects.

	Mean Perceived Positions		Sophia	
	Election	Non-Election	Election	Non-Election
Relationship Score	-0.483**	-0.044	-0.442**	-0.017
	(0.209)	(0.265)	(0.175)	(0.222)
Manifesto Difference	0.561***	0.720**	0.391**	0.471**
	(0.199)	(0.286)	(0.165)	(0.224)
Coalition Partners	-0.496*	-1.220***	-0.370**	-1.005***
	(0.263)	(0.310)	(0.187)	(0.229)
Opposition Partners	0.095	0.218	0.147	0.092
	(0.275)	(0.369)	(0.220)	(0.272)
N	237	149	237	149
R2	0.33	0.29	0.44	0.32
Adjusted R2	0.24	0.18	0.37	0.22

*p<0.1; **p<0.05; ***p<0.01

References

Boschee, Elizabeth, Jennifer Lautenschlager, Sean O'Brien, Steve Shellman, James Starz and Michael D. Ward. 2015. "ICEWS Coded Event Data." `http://dx.doi.org/10.7910/DVN/28075`.

Boschee, Elizabeth, Premkumar Natarjan and Ralph Weischedel. 2013. Automatic Extraction of Events from Open Source Text for Predictive Forecasting. In *Handbook of Computational Approaches to Counterterrorism*, ed. V.S. Subrahmanian. New York: Springer.

Hoff, Peter D. 2005. "Bilinear Mixed Effects Models for Dyadic Data." *Journal of the American Statistical Association* 100(469):286–295.

Hoff, Peter D. 2015. "Dyadic Data Analysis with amen." `http://arxiv.org/abs/1506.08237`.

King, Gary and Will Lowe. 2003. "An Automated Information Extraction Tool for International Conflict Data with Performance as Good as Human Coders: A Rare Events Evaluation Design." *International Organization* 57:617–642.

Mikhaylov, Slava, Michael Laver and Kenneth R Benoit. 2012. "Coder Reliability and Misclassification in the Human Coding of Party Manifestos." *Political Analysis* 20(1):78–91.

Minhas, Shahryar, Peter D. Hoff and Michael D. Ward. 2019. "Inferential Approaches for Network Analyses: AMEN for Latent Factor Models." *Political Analysis* 27(2):208–222.

O'Brien, Sean P. 2013. A Multi-Method Approach for Near Real Time Conflict and Crisis Early Warning. In *Handbook of Computational Approaches to Counterterrorism*, ed. V.S. Subrahmanian. New York: Springer.

Weschle, Simon. 2018. "Quantifying Political Relationships." *American Political Science Review* 112(4):1090–1095.