Long-term Change in Conflict Attitudes: A Dynamic Perspective

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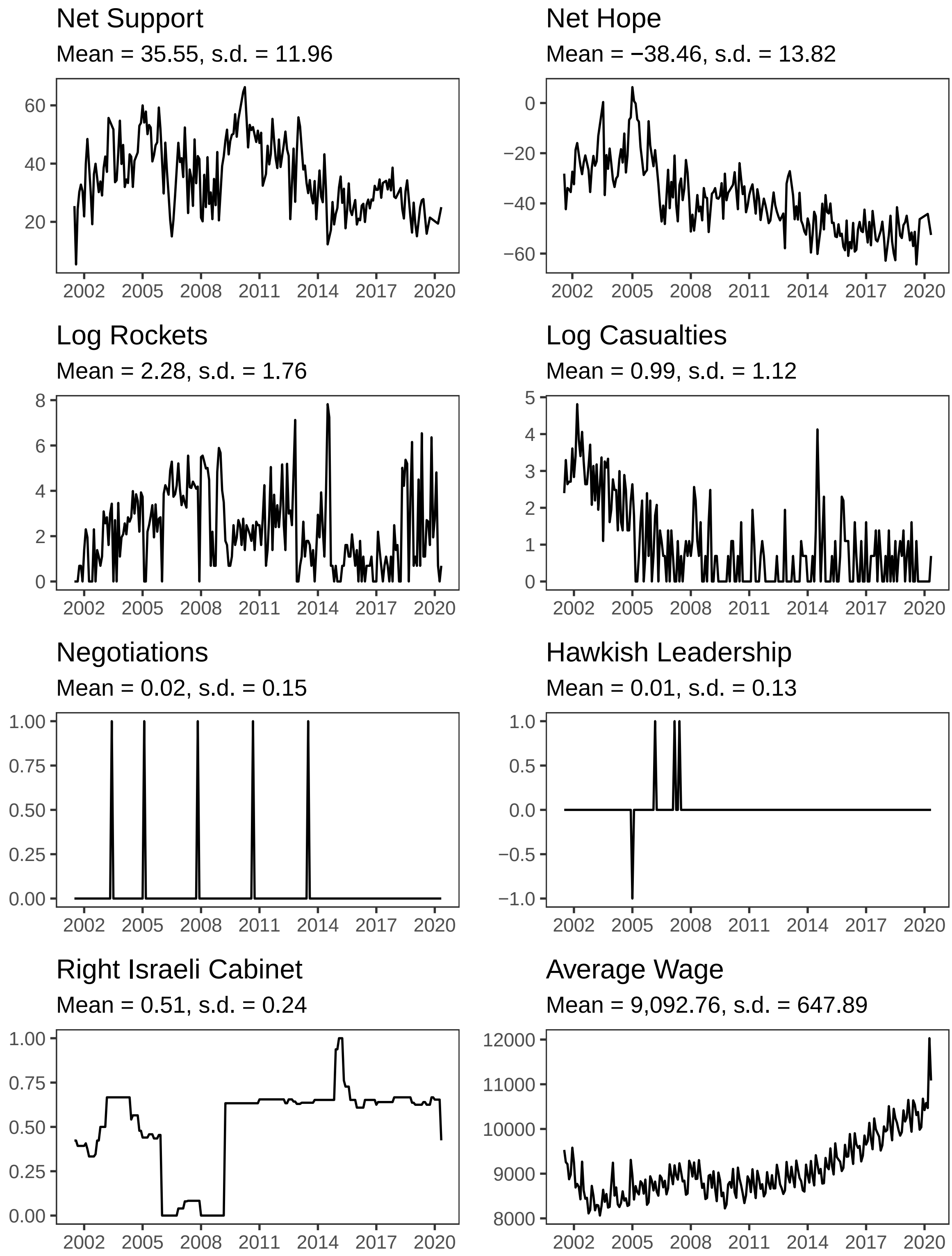
Supplementary Material

Contents

1 Descriptive Statistics

Figure A1: *Descriptive Plots, Mean, and Standard Deviation of the Dependent and Independent Variables*



2 Missing Observations and Interpolation

As we note in the paper, our two dependent variables have twenty-five missing observations (11% of the sample). These include sixteen months without surveys at all and nine more surveys that skipped the two relevant questions used as our dependent variables. In this section, we show that the missing observations are spaced far apart, mostly in single gaps, and are uncorrelated with the conflict's violent and non-violent events as measured by our independent variables. We also demonstrate that our findings are robust to several alternative interpolation methods and to the omission of the largest cumulative gap.

2.1 Missing Observations

We begin with the temporal distribution of the missing observations. The left-side panel in Figure A2 uses blue horizontal lines to mark months with missing observations throughout the two time series. The plot shows that the missing observations are spaced relatively evenly and far apart over time. Moreover, most missing observations appear in single gaps rather than in clusters. This point is further underscored by the bar graph on the right-side panel, which counts the occurrences of different gap clusters throughout the series. Seventeen missing observations (68%) appear as single gaps (1 NA), while the remaining eight cluster in two pairs (2 NA) and one larger gap of four missing observations (4 NA) toward the series' end.

Figure A2: *Missing Observations: Distribution and Gap Size Occurrence*

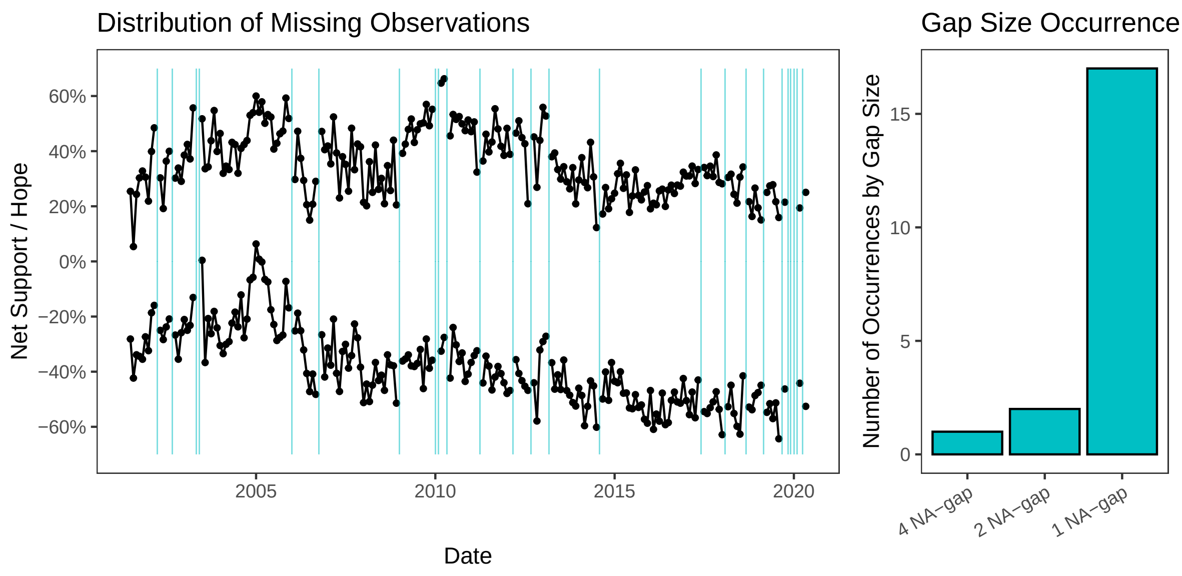
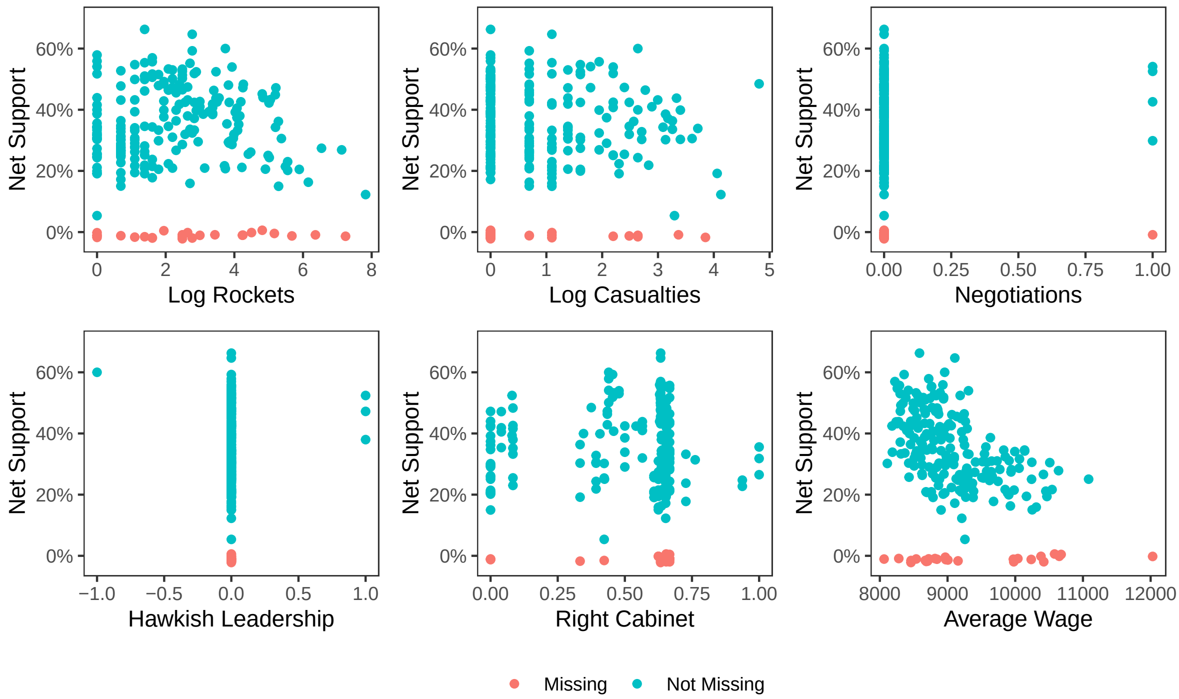


Figure A2 also indicates that the missing variables do not concentrate near particular trends in the series. Instead, their occurrences are quite heterogeneous, appearing in peaks and lows, upward and downward slopes, and volatile and stagnant periods alike. This heterogeneity rejects the concern that these observations are Missing Not at Random (MNAR), i.e., that their missingness is correlated with the series' own values and may thus bias our findings.

Next, we consider whether the missing observations are Missing Completely at Random (MCAR), i.e., their occurrences are uncorrelated with other variables in our models. Substantively, indications of MCAR would verify that the missingness is uncorrelated with conflict-related violent and non-violent events that could have created unobserved sharp breaks and bias our results.

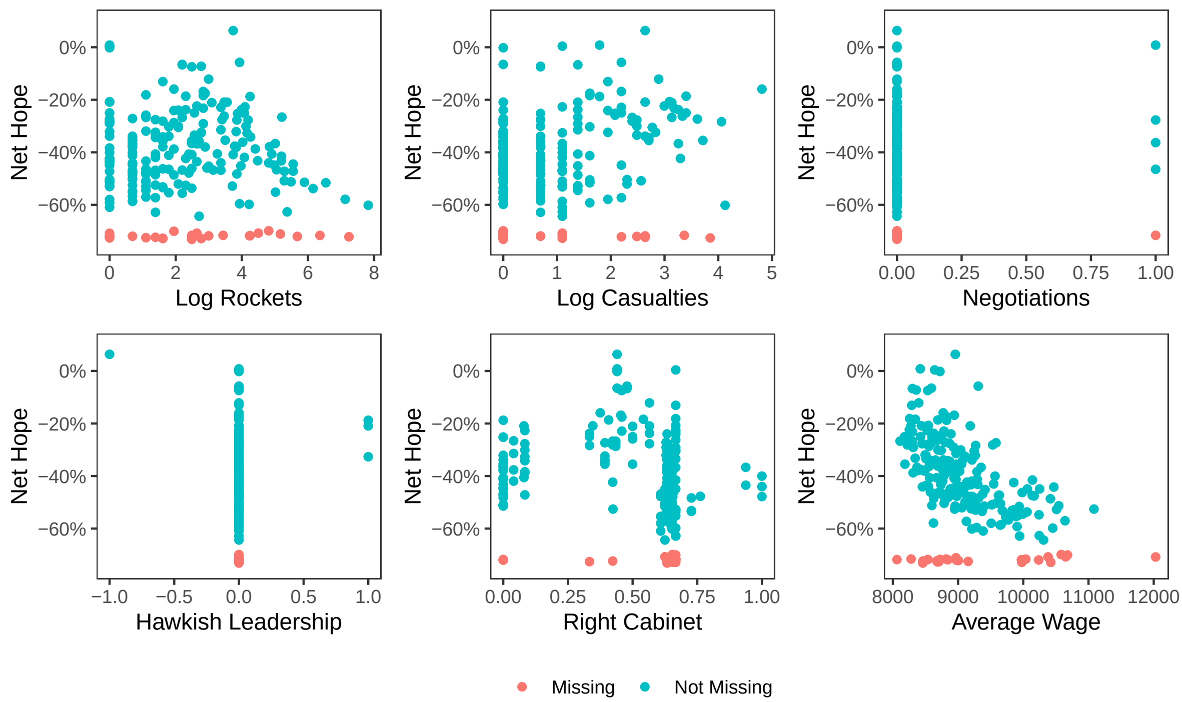
To do so, we first plot the bivariate relationships between each of our two dependent variables and the other covariates in our GECM models. The scatter plots shown in Figure A3 and Figure A4 graph these relationships while marking all missing observations in red. In all cases, the missing observations do not seem to cluster around particular values of the dependent variables.

Figure A3: *Bivariate Relationships Between the Missing Observations in Aggregate Net Support and Each Covariate*



To validate this point further, we coded a dummy variable indicating missing observations and estimated several logistic regressions with the key covariates related to the conflict: Log Rockets, Log Casualties, Negotiations, and Hawkish Leadership Selection by the Palestinians. The results, summarized in Table A1, do not find sta-

Figure A4: *Bivariate Relationships Between the Missing Observations in Aggregate Net Hope and Each Covariate*



tistically significant relationships with the conflict's events as measured by our key explanatory variables. Hence, we conclude that the missing observations are most likely MCAR, ruling out possible bias as a result.

Table A1: *Logit Regressions: Missing Observations and Conflict-Related Events*

	(1)	(2)	(3)	(4)	(5)
Log Rockets	0.181				0.193
	(0.117)				(0.119)
Log Casualties		-0.072			-0.118
		(0.200)			(0.209)
Negotiations			0.772		0.790
			(1.140)		(1.148)
Hawkish Leadership				-0.618	-0.772
				(1.776)	(1.688)
Constant	-2.589***	-2.066***	-2.158***	-2.132***	-2.525***
	(0.386)	(0.283)	(0.220)	(0.216)	(0.418)
N	227	227	227	227	227
Pseudo-R^2	0.015	0.001	0.003	0.001	0.021
AIC	154.860	157.084	156.825	157.092	159.969
BIC	161.710	163.934	163.675	163.942	177.094

Standard errors in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

2.2 Alternative Interpolation Methods

Based on these missingness characteristics, as well the strong serial autocorrelation in both series, we feel safe to impute the missing observations with a simple linear interpolation. Furthermore, since the missing values are only in the dependent variables, multiple imputation is an inappropriate alternative.[1] Nevertheless, as a robustness test, we examined whether our GECM findings substantively change with four other interpolation methods:[2]

- A Linear Weighted Moving Average (LWMA), which includes two periods before and two periods after the missing observation. The relative weight of these periods decreases arithmetically;
- An Exponential Weighted Moving Average (EWMA), which includes two periods before and two periods after the missing observation. The relative weight of these periods decreases exponentially;
- Kalman smoothing using a structural model fitted by maximum likelihood;
- Kalman smoothing using the state space representation of an ARIMA model.

The results, presented in Table A2 and Table A3, do not find meaningful differences compared to our linear interpolation, presented for reference in the first column.

2.3 Omission of a Four-Gap Cluster

Finally, as an additional robustness test, we reran our models while omitting the largest cluster of four consecutive missing observations. Since the cluster appears toward the end of the time series, we omit all observations after October 2019, when the gap begins. The results, summarized in Table A4, do not find meaningful differences compared to the full sample.

[1] von Hippel, Paul T. 2007. "Regression with Missing Ys: An Improved Strategy for Analyzing Multiply Imputed Data." *Sociological Methodology* 37(1): 83–117; Little, Roderick J.A. 1992. "Regression With Missing X's: A Review." *Journal of the American Statistical Association* 87(420): 1227–37;

[2] The alternative interpolations were calculated using the **imputeTS** package in R. See: Moritz Steffen and Thomas Bartz-Beielstein. 2017. "imputeTS: Time Series Missing Value Imputation in R." *The R Journal* 9(1), 207–218.

Table A2: GECM With Different Interpolation Methods, DV: Net Support

	Linear	LWMA	EWMA	Kalman Structural	Kalman ARIMA
	(1)	(2)	(3)	(4)	(5)
ΔLog Rockets	-0.890**	-0.754*	-0.788*	-0.733*	-0.767*
	(0.316)	(0.320)	(0.318)	(0.320)	(0.320)
Log Rockets$_{t-1}$	-0.221	-0.114	-0.141	-0.097	-0.118
	(0.333)	(0.335)	(0.333)	(0.335)	(0.335)
ΔLog Casualties	-1.716**	-1.720**	-1.712**	-1.731**	-1.757**
	(0.621)	(0.630)	(0.625)	(0.630)	(0.628)
Log Casualties$_{t-1}$	-2.184**	-1.951**	-2.000**	-1.955**	-1.985**
	(0.713)	(0.728)	(0.721)	(0.728)	(0.726)
Δ^2Negotiations	-0.297	-1.444	-1.326	-1.435	-1.636
	(3.341)	(3.372)	(3.349)	(3.372)	(3.367)
Negotiations$_{t-1}$	-3.504	-4.298	-4.408	-4.173	-4.658
	(7.658)	(7.713)	(7.663)	(7.713)	(7.702)
Negotiations$_{t-2}$	-7.637†	-5.888	-6.189	-5.838	-5.649
	(4.588)	(4.643)	(4.608)	(4.643)	(4.637)
Δ^2Hawkish Leadership	4.169	3.356	3.511	3.374	3.402
	(3.673)	(3.716)	(3.691)	(3.715)	(3.711)
Hawkish Leadership$_{t-1}$	4.589	3.685	3.830	3.663	3.645
	(8.314)	(8.415)	(8.353)	(8.415)	(8.401)
Hawkish Leadership$_{t-2}$	-17.346***	-16.681**	-16.799**	-16.716**	-16.664**
	(5.097)	(5.147)	(5.112)	(5.146)	(5.139)
ΔRight Cabinet	0.077	0.069	0.067	0.075	0.069
	(0.075)	(0.076)	(0.076)	(0.076)	(0.076)
Average Wage$_{t-1}$	-0.002	-0.002	-0.002	-0.002	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ΔAverage Wage	-0.003†	-0.003†	-0.003†	-0.003†	-0.003†
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)
Trend	-0.043**	-0.039*	-0.039*	-0.039*	-0.039*
	(0.016)	(0.017)	(0.016)	(0.017)	(0.016)
Constant	59.668***	56.609***	57.022***	56.879***	56.602***
	(11.392)	(11.712)	(11.585)	(11.723)	(11.632)
Lagged DV	Yes	Yes	Yes	Yes	Yes
First-diff. Lagged DV	Yes	Yes	Yes	Yes	Yes
N	225	225	225	225	225
R^2	0.376	0.394	0.390	0.394	0.392
AIC	1530.640	1535.281	1532.151	1535.201	1534.608
BIC	1588.714	1593.355	1590.225	1593.275	1592.682

Lagged dependent variables and their first differences included but not shown for ease of presentation.
Standard errors in parentheses, † $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A3: *GECM With Different Interpolation Methods, DV: Net Hope*

	Linear	LWMA	EWMA	Kalman Structural	Kalman ARIMA
	(1)	(2)	(3)	(4)	(5)
ΔLog Rockets	-0.654*	-0.631*	-0.633*	-0.653*	-0.666*
	(0.302)	(0.300)	(0.299)	(0.300)	(0.299)
Log Rockets$_{t-1}$	-0.185	-0.152	-0.153	-0.164	-0.188
	(0.318)	(0.315)	(0.315)	(0.315)	(0.315)
ΔLog Casualties	-1.536*	-1.525**	-1.531**	-1.540**	-1.560**
	(0.592)	(0.587)	(0.585)	(0.586)	(0.586)
Log Casualties$_{t-1}$	-0.935	-0.852	-0.858	-0.879	-0.935
	(0.643)	(0.640)	(0.638)	(0.639)	(0.638)
Δ^2Negotiations	-0.344	-1.743	-1.460	-1.704	-1.145
	(3.264)	(3.212)	(3.208)	(3.207)	(3.208)
Negotiations$_{t-1}$	-0.819	-1.793	-1.676	-1.617	-0.846
	(7.555)	(7.404)	(7.400)	(7.393)	(7.405)
Negotiations$_{t-2}$	-10.450*	-8.101†	-8.660*	-8.048†	-8.862*
	(4.385)	(4.330)	(4.321)	(4.324)	(4.323)
Δ^2Hawkish Leadership	1.625	1.463	1.471	1.466	1.487
	(3.466)	(3.441)	(3.432)	(3.438)	(3.434)
Hawkish Leadership$_{t-1}$	-1.288	-1.503	-1.451	-1.528	-1.533
	(7.900)	(7.849)	(7.824)	(7.842)	(7.834)
Hawkish Leadership$_{t-2}$	-10.286*	-10.061*	-10.089*	-10.041*	-10.019*
	(4.843)	(4.801)	(4.789)	(4.796)	(4.793)
ΔRightCabinet	0.060	0.063	0.057	0.066	0.067
	(0.072)	(0.071)	(0.071)	(0.071)	(0.071)
AverageWage$_{t-1}$	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ΔAverageWage	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Trend	-0.073***	-0.073***	-0.071***	-0.074***	-0.076***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Constant	26.473**	25.716**	25.499**	26.398**	26.896**
	(8.526)	(8.607)	(8.540)	(8.638)	(8.600)
Lagged DV	Yes	Yes	Yes	Yes	Yes
First-diff. Lagged DV	Yes	Yes	Yes	Yes	Yes
N	225	225	225	225	225
R^2	0.362	0.401	0.393	0.403	0.391
AIC	1508.464	1504.775	1503.634	1504.207	1503.820
BIC	1566.538	1562.848	1561.708	1562.281	1561.894

Lagged dependent variables and their first differences included but not shown for ease of presentation. Standard errors in parentheses, † $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A4: GECM: Full Sample Compared to Truncated Sample Up to October 2019

	ΔNet Support		ΔNet Hope	
	(1) Full	(2) Up to 10/2019	(3) Full	(4) Up to 10/2019
Net Support$_{t-1}$	-0.351***	-0.352***		
	(0.056)	(0.057)		
ΔNet Support$_{t-1}$	-0.143*	-0.145*		
	(0.061)	(0.062)		
Net Hope$_{t-1}$			-0.323***	-0.344***
			(0.063)	(0.066)
ΔNet Hope$_{t-1}$			-0.148*	-0.149*
			(0.065)	(0.066)
ΔLog Rockets	-0.890**	-0.939**	-0.654*	-0.765*
	(0.316)	(0.334)	(0.302)	(0.319)
Log Rockets$_{t-1}$	-0.221	-0.181	-0.185	-0.299
	(0.333)	(0.343)	(0.318)	(0.330)
ΔLog Casualties	-1.716**	-1.671**	-1.536*	-1.448*
	(0.621)	(0.631)	(0.592)	(0.601)
Log Casualties$_{t-1}$	-2.184**	-2.093**	-0.935	-0.915
	(0.713)	(0.728)	(0.643)	(0.655)
Δ^2Negotiations	-0.297	-0.440	-0.344	-0.030
	(3.341)	(3.379)	(3.264)	(3.301)
Negotiations$_{t-1}$	-3.504	-3.911	-0.819	-0.087
	(7.658)	(7.745)	(7.555)	(7.648)
Negotiations$_{t-2}$	-7.637†	-7.296	-10.450*	-10.549*
	(4.588)	(4.642)	(4.385)	(4.432)
Δ^2Hawkish Leadership	4.169	4.140	1.625	1.619
	(3.673)	(3.723)	(3.466)	(3.504)
Hawkish Leadership$_{t-1}$	4.589	4.689	-1.288	-1.049
	(8.314)	(8.426)	(7.900)	(7.983)
Hawkish Leadership$_{t-2}$	-17.346***	-17.344***	-10.286*	-10.149*
	(5.097)	(5.160)	(4.843)	(4.897)
ΔRight Cabinet	0.077	0.093	0.060	0.049
	(0.075)	(0.078)	(0.072)	(0.074)
Average Wage$_{t-1}$	-0.002	-0.003†	0.001	0.000
	(0.001)	(0.002)	(0.001)	(0.001)
ΔAverage Wage	-0.003†	-0.003*	-0.001	-0.001
	(0.001)	(0.002)	(0.001)	(0.002)
Trend	-0.043**	-0.038*	-0.073***	-0.076***
	(0.016)	(0.017)	(0.019)	(0.019)
Constant	59.668***	63.075***	26.473**	31.832**
	(11.392)	(12.135)	(8.526)	(9.869)
N	225	218	225	218
R^2	0.376	0.383	0.362	0.370
AIC	1530.640	1488.113	1508.464	1466.090
BIC	1588.714	1545.650	1566.538	1523.626

Standard errors in parentheses, † $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

3 Independence of Violent and Non-Violent Events

One possible concern may be that non-violent events initiate greater violence. In such a case, these factors would have a combined chain effect and would be inappropriate to model independently.

To verify that this is not the case, we regress both violence measures (logged rockets and logged casualties) on negotiation summits and hawkish leadership changes. To adjust for autocorrelation, we ran these models while gradually increasing the number of dependent-variable lags until we reached dynamic completeness based on Breusch-Godfrey LM tests. The eventual models include 6 DV lags in the case of logged rockets and 5 DV lags in the case of logged casualties. We also controlled for an independent time trend in both.

The results of these models are presented in Table A5. The estimations validate the assumption that the two event types are independent of one another and can therefore be included together without obscuring a complex mutual influence on pubic attitudes.

Table A5: *Violence Levels Regressed on Non-Violent Events*

	ΔLog Rockets			ΔLog Casualties		
	(1)	(2)	(3)	(4)	(5)	(6)
Negotiations$_t$	-0.327		-0.322	-0.059		-0.068
	(0.714)		(0.716)	(0.350)		(0.349)
Hawkish Leadership$_t$		0.332	0.326		-0.489	-0.463
		(0.793)	(0.795)		(0.386)	(0.385)
DV Lags	Yes	Yes	Yes	Yes	Yes	Yes
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
N	222	222	222	228	241	228
R^2	0.329	0.328	0.329	0.379	0.358	0.383
AIC	839.391	839.426	841.215	531.603	563.233	532.101
BIC	870.015	870.051	875.242	559.038	591.112	562.965

Standard errors in parentheses, † $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. There are six lagged dependent variables for logged rockets and five for casualties.

4 Unit Root Tests

Table A6 details a series of unit root tests for all our dependent and independent variables. Since all unit root tests have inherent flaws, we ran several tests and considered the overall pattern that arises across them. These tests include:

- Augmented Dickey-Fuller Tests with and without a trend term. The null hypothesis is that the series contains a unit root;
- Pillips-Perron Tests with and without a trend term. The null hypothesis is that the series contains a unit root;
- Lo-Mackinlay Variance Ratio Tests with two values of q corresponding with Schwert's short and long lag iteration formulas (4 and 14, respectively, for all our variables). The null hypothesis is that the series is a random walk;
- ADF-GLS Tests using different lag selection methods with and without a trend term. The number of lags used for each variable is noted in parentheses. The null hypothesis is that the series contains a unit root.

As the results show, the majority of these tests estimate that almost all variables are stationary, some with indications of a trend component, except for the share of right-wing ministers in the Israeli cabinet. The latter, accordingly, is only included as a first difference in our GECM models.

Table A6: *Unit Root Tests by Variable*

	Net Support	Net Hope	Log Rockets	Log Casualties
Augmented Dickey-Fuller Test				
Unit Root	-4.592***	-3.202**	-6.842***	-5.011***
Unit Root With Trend	-5.625***	-6.003***	-6.947***	-6.519***
Phillips-Perron Test				
Unit Root	-5.433***	-4.091***	-9.251***	-6.824***
Unit Root With Trend	-6.328***	-7.404***	-9.339***	-9.027***
Lo-MacKinlay Variance Ratio Test				
Variance ratio, k=4	0.451***	0.433***	0.345***	0.283***
Variance ratio, k=14	0.225***	0.195***	0.127***	0.109***
ADF-GLS Test (Lag in Parentheses)				
Schwert's Criterion	-1.586 (14)	-0.658 (14)	-0.717 (14)	-0.134 (14)
Schwert's Criterion, With Trend	-1.725 (14)	-2.332 (14)	-1.255 (14)	-1.774 (14)
Ng-Perron Sequential Method	-1.714* (7)	-0.717 (10)	-0.717 (14)	-0.272 (13)
Ng-Perron Sequential Method, With Trend	-1.861 (7)	-3.957*** (3)	-1.255 (14)	-1.965 (13)
AIC Score	-2.384** (3)	-1.547 (4)	-2.569** (3)	-1.072 (5)
AIC Score, With Trend	-2.640* (3)	-3.627*** (4)	-3.487*** (3)	-2.942** (5)
BIC Score	-2.794*** (2)	-1.547 (4)	-3.989*** (1)	-1.072 (5)
BIC Score, With Trend	-3.106** (2)	-3.627*** (4)	-5.285*** (1)	-2.942** (5)

	Negotiations	Hawkish Leadership	Right Cabinet	Average Wage
Augmented Dickey-Fuller Test				
Unit Root	-10.905***	-10.654***	-1.983	-2.127
Unit Root With Trend	-10.993***	-10.652***	-2.086	-4.959***
Phillips-Perron Test				
Unit Root	-15.309***	-15.067***	-1.978	-3.267**
Unit Root With Trend	-15.374***	-15.054***	-2.082	-6.617***
Lo-MacKinlay Variance Ratio Test				
Variance ratio, k=4	0.261***	0.26***	1.167	0.358***
Variance ratio, k=14	0.085***	0.102***	1.019	0.154***
ADF-GLS Test (Lag in Parentheses)				
Schwert's Criterion	-3.852*** (14)	-3.168***	-1.841* (14)	-0.070 (14)
Schwert's Criterion, With Trend	-4.152*** (14)	-3.195**	-2.091 (14)	-0.192 (14)
Ng-Perron Sequential Method	-15.108*** (0)	-3.168***	-1.871* (0)	0.081 (13)
Ng-Perron Sequential Method, With Trend	-15.225*** (0)	-3.195** (14)	-2.070 (0)	-0.056 (13)
AIC Score	-15.108*** (0)	-2.763***	-1.894* (1)	-0.070 (14)
AIC Score, With Trend	-15.225*** (0)	-2.791**	-2.097 (1)	-0.192 (14)
BIC Score	-15.108*** (0)	-15.021***	-1.894* (1)	-0.070 (14)
BIC Score, With Trend	-15.225*** (0)	-15.044***	-2.097 (1)	-0.192 (14)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The null hypotheses are the existence of a unit root/random walk.

5 Lag Selection

To select the proper number of lags in our GECMs, we used a general-to-specific approach: we iterated our models with different combinations of sequential lag lengths for each independent variable, starting with a high number of lags and reducing them gradually to optimize model fit based on Bayesian Information Criterion (BIC) and coefficient t-test scores. In this section, we present these steps in greater detail.

For ease of interpretation, we ran this process using an Autoregressive Distributed Lag (ADL) specification instead of a GECM. The ADL is mathematically equivalent to the latter and produces identical BIC scores, but, for our purposes, displays the lag chain more straightforwardly.[3] In technical terms, we estimated the following ADL model, where *n* notes the number of lags used in each iteration:

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \sum_{i=0}^{n} \boldsymbol{\beta_i'} \boldsymbol{X_{t-i}} + trend + \epsilon_t \quad (1)$$

As noted, equation 1 is mathematically equivalent to our standard GECM specification:

$$\Delta y_t = \alpha_0 + \alpha_1 y_{t-1} + \alpha_2 \Delta y_{t-1} + \boldsymbol{\beta_0'} \boldsymbol{\Delta^n X_t} + \sum_{i=1}^{n} \boldsymbol{\beta_1'} \boldsymbol{X_{t-i}} + trend + \epsilon_t \quad (2)$$

First, to establish a baseline reference, we iterated our model (in ADL form) with a common lag length for all independent variables. We started with five lags and then gradually reduced them with each round. Figure A5 graphs each model's BIC score as a function of the number of lags included for all covariates. In both series, when all independent variables are set at the same lag length, a single lag produces the best model fit (i.e., the lowest BIC score). Hence, our baseline model has one lag.

Second, building on this baseline specification, we iterated each model forward by gradually extending the lag length of each variable at a time while holding the rest at one lag. In each iteration, we examined two scores: the model's BIC score and whether the largest lag's t-score reaches statistical significance at the 95% level.

Figure A6 plots the BIC scores by lag for each covariate in the two series. Model iterations with a significant t-test for the largest lag are marked in blue. The results show that extending Log Rockets, Log Casualties, and Average Wage beyond a single lag neither improves model fit nor produces statistically significant coefficients for later lags. By contrast, extending Negotiations and Hawkish Leadership Selection beyond a single lag shows better results. Hawkish Leadership Selection produces both

[3] See: De Boef, Suzanna, and Luke Keele. 2008. "Taking Time Seriously." *American Journal of Political Science* 52(1): 184–200.

Figure A5: *BIC Scores by Number of Lags: All Independent Variables*

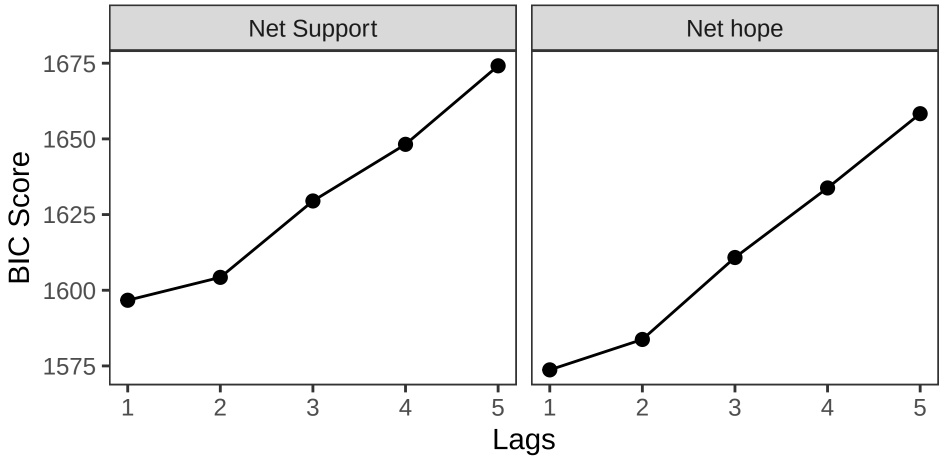
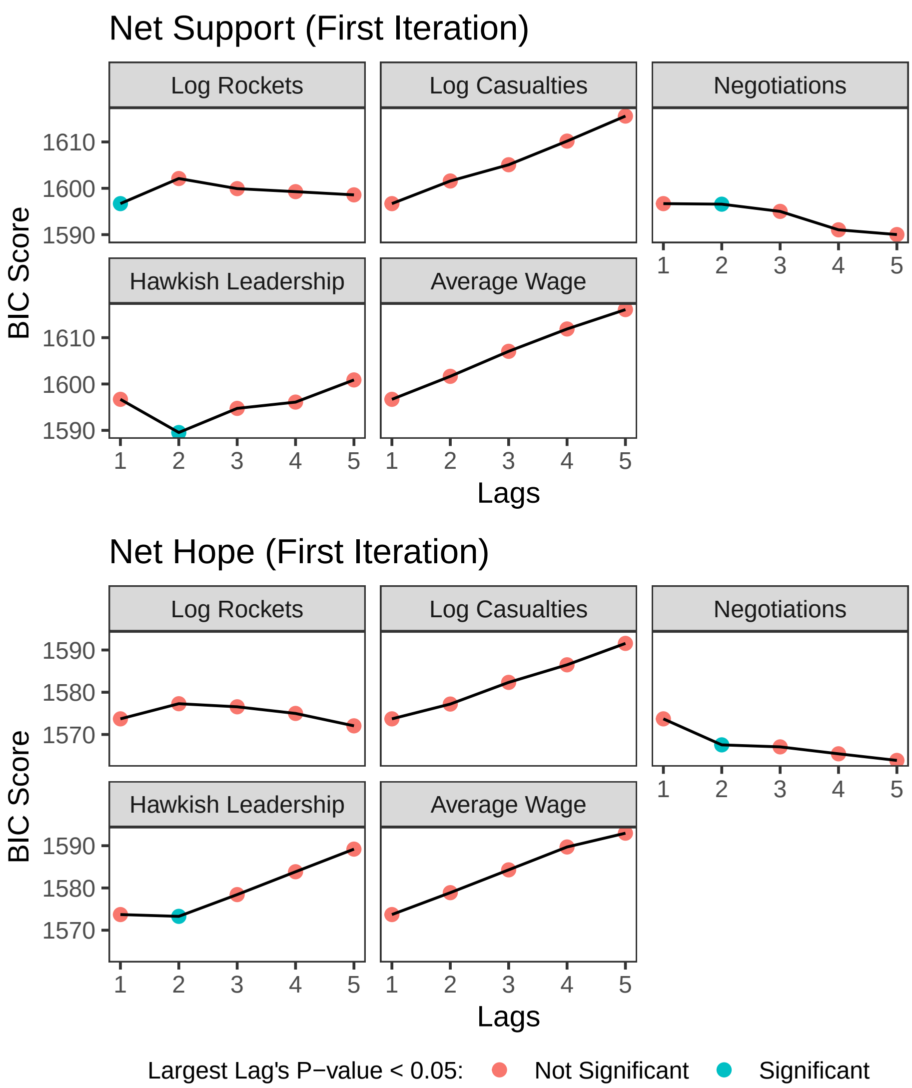


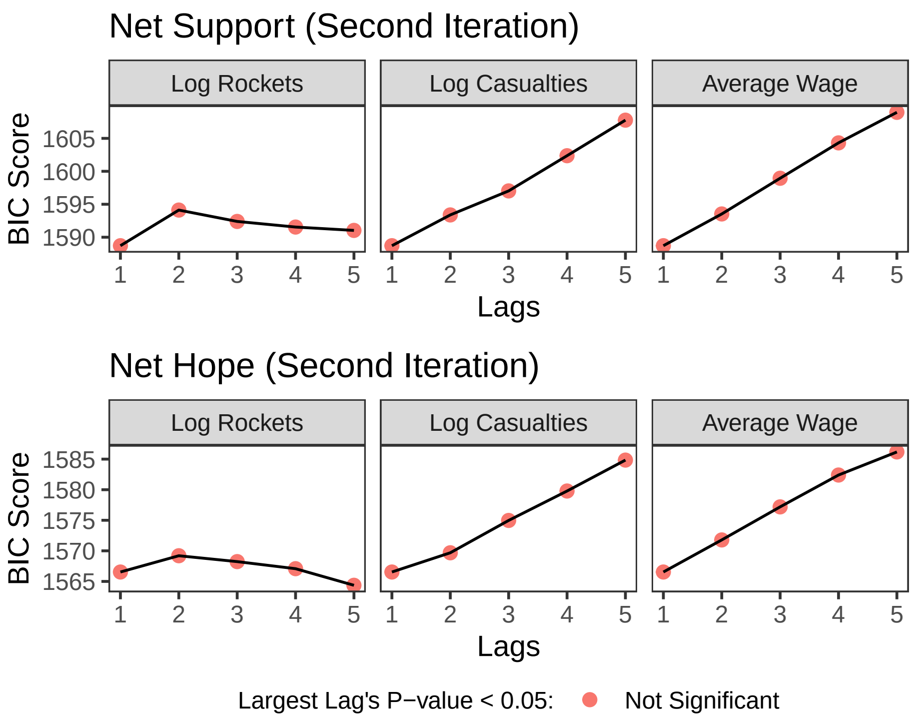
Figure A6: *BIC Scores by Number of Lags: Each Variable In turn (First Iteration)*



an optimal BIC score and a statistically significant coefficient with a second lag. The result for Negotiations is more complicated: it produces an increasingly lower BIC score as its number of lags consistently grows. However, only the second lag is statistically significant, and it remains so even as the cumulative lag length increases. Moreover, additional iterations, not plotted here, find that the downward trend in BIC scores continues even as the cumulative lag length reaches over a hundred lags, a theoretically implausible result. Hence, a second lag seems to be the best choice for Negotiations as well.

Finally, following the first round of iterations, we updated our baseline model to include two lags for Negotiations and Hawkish Leadership Selection and ran a second iterative round for the other three variables. As Figure A7 illustrates, we do not find sufficient support for additional lags in any of these covariates. In conclusion, based on this iterative procedure, we construct our models with two lags for Negotiations and Hawkish Leadership Selection and one lag for Log Rockets, Log Casualties, and Average Wage.

Figure A7: *BIC Scores by Number of Lags: Each Variable In turn (Second Iteration, Negotiations and Hawkish Leadership Set at Two Lags)*



6 Autocorrelation Tests

Table A7 details the results from Ljung-Box Q tests and Breusch-Godfrey LM tests for serial autocorrelation in both our GECM models. In both tests, the null hypothesis supposes that there is no autocorrelation.

We first ran these tests on our GECM models in their standard form, which includes only a single coefficient for the lagged dependent variable (Y_{t-1}). The results in the top part of Table A7 indicate that there remains serial autocorrelation in both dependent variables under this specification. As the bottom part of the table shows, adding the first difference of the lagged dependent variable (ΔY_{t-1}) to our models eliminates the problem and establishes dynamic completeness. Therefore, we include this added term in our final specification.

Table A7: *GECM Autocorrelation Tests With and Without ΔY_{t-1}*

	Net Support		Net Hope	
	Test Score	P-value	Test Score	P-value
Standard GECM (Y_{t-1} only)				
Ljung-Box Q test	57.623*	0.035	66.268**	0.006
Breusch-Godfrey LM test	5.676*	0.017	7.903**	0.005
Additional Control for ΔY_{t-1}				
Ljung-Box Q test	42.649	0.358	55.502	0.052
Breusch-Godfrey LM test	1.113	0.292	2.521	0.112

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

In addition to the previous test, we also reject the possibility of seasonal autocorrelation in our models. A series of Ljung-Box Q tests, detailed in Table A8, verify that there are no signs of seasonality with 6, 12, or 24 lags.

Table A8: *Ljung-Box Q Tests For Seasonality at Higher Lags*

	Net Support		Net Hope	
Lag	Test Score	P-value	Test Score	P-value
6	7.618	0.268	6.102	0.412
12	12.029	0.443	12.181	0.431
24	28.280	0.248	23.337	0.500

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

7 Structural Breakpoint Characteristics

7.1 Interrupted Time-Series Analysis

The first two columns in Table 2 in the paper summarize the direction of change in attitudinal levels and trends in the two series after each structural breakpoint. As we discuss in this section, these changes are validated econometrically by interrupted time-series models, which estimate (1) the series's trend before the breakpoint, (2) the change in its absolute levels when the breakpoint takes place, and (3) the change in the trend after the breakpoint occurred. In technical terms, interrupted time-series models are structured as follows:

$$y_t = \alpha_0 + \beta_1 Trend + \beta_2 X_t + \beta_3 Trend \times X_t + \epsilon_t \tag{3}$$

where $\beta 1$ estimates the series's trend before structural breakpoint X_t, β_2 estimates the change in the series's absolute levels right after the breakpoint, and β_3 estimates the change in the trend after the breakpoint.

Table A9: *Interrupted Time-Series with Breakpoints: Net Support*

	(1)	(2)
Trend	0.479***	0.255***
	(0.067)	(0.074)
Jan2006	-19.258***	-12.471***
	(3.191)	(3.158)
Trend × Jan2006	-0.541***	-0.258*
	(0.127)	(0.130)
Apr2009	23.332***	14.626***
	(2.959)	(3.321)
Trend × Apr2009	-0.344**	-0.264*
	(0.113)	(0.105)
Oct2016	14.253***	9.560***
	(2.784)	(2.740)
Trend × Oct2016	0.074	0.047
	(0.096)	(0.088)
Lagged DV	No	Yes
First-diff. Lagged DV	No	Yes
N	227	225
R^2	0.605	0.352
AIC	1574.687	1525.171
BIC	1602.087	1559.332

Standard errors in parentheses
$^{\dagger}\ p < 0.1$, $^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$

The estimations are presented in Table A9 (net support) and Table A10 (net hope)

Table A10: *Interrupted Time-Series with Breakpoints: Net Hope*

	(1)	(2)
Trend	0.269***	0.120†
	(0.060)	(0.061)
Apr2006	-23.174***	-13.006***
	(2.532)	(2.831)
Trend × Apr2006	-0.313***	-0.137*
	(0.067)	(0.069)
Sep2013	-9.879***	-6.171**
	(2.279)	(2.162)
Trend × Sep2013	0.025	0.013
	(0.047)	(0.043)
Lagged DV	No	Yes
First-diff. Lagged DV	No	Yes
N	227	225
R^2	0.718	0.316
AIC	1560.428	1506.063
BIC	1580.978	1533.391

Standard errors in parentheses

† $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

using their respective breakpoints. For each series, we estimated interrupted time-series models with the breakpoints alone (model 1) and while adding the lagged dependent variable (y_{t-1}) and its first-differences (Δy_{t-1}) to account for serial autocorrelation (model 2).

The results verify Table 2's summary in the paper. All structural breakpoints exhibit a statistically significant change in levels, corroborating their influence even when accounting for autocorrelation. Additionally, as we note in the paper, there are significant trend changes after the 2006 and 2009 breakpoints but not in 2013 and 2016, which also exhibit smaller level changes than the former.

7.2 Violence Levels

Table 2 in the paper also indicates whether the identified breakpoints had relatively low, average, or high violence levels compared to the rest of the sample. We find that none of the points occurred at notably violent moments, reflecting rocket and casualty levels that are either below or near the sample averages.

To see this pattern in greater detail, Table A11 and Table A12 list the number of rockets (Table A11) and casualties (Table A12) at each structural breakpoint (t) and one month earlier ($t-1$) and compare them with the average and standard deviation of the full sample period, the relevant decade, and the relevant year.

As the numbers demonstrate, all months display lower or average levels of rockets and casualties. Additionally, none of these months featured large-scale military operations. Hence, it is hard to link any of these change points to greater violence.

Table A11: *Rockets: Actual Levels Compared with Sample, Decade, and Annual Averages*

	Rockets		Full Sample		Decade		Year	
	t	*t-1*	Mean	s.d.	Mean	s.d.	Mean	s.d.
Net Support								
A. Jan. 2006	0	16	59.3	(219.4)	39.3	(66.7)	78.8	(60)
B. Apr. 2009	1	32	59.3	(219.4)	39.3	(66.7)	35.5	(82)
C. Oct. 2016	2	0	59.3	(219.4)	39.3	(301.7)	1.25	(1.5)
Net Hope								
D. Apr. 2006	58	69	59.3	(219.4)	39.3	(66.7)	78.8	(60)
E. Sep. 2013	2	4	59.3	(219.4)	39.3	(301.7)	3.3	(3.5)

Table A12: *Casualties: Actual Levels Compared with Sample, Decade, and Annual Averages*

	Casualties		Full Sample		Decade		Year	
	t	*t-1*	Mean	s.d.	Mean	s.d.	Mean	s.d.
Net Support								
A. Jan. 2006	0	8	5.1	(12)	8.7	(14.9)	1.9	(2.2)
B. Apr. 2009	5	0	5.1	(12)	8.7	(14.9)	1.2	(3.1)
C. Oct. 2016	2	1	5.1	(12)	1.6	(5.9)	0.9	(1.3)
Net Hope								
D. Apr. 2006	7	5	5.1	(12)	8.7	(14.9)	1.9	(2.2)
E. Sep. 2013	1	0	5.1	(12)	1.6	(5.9)	0.5	(0.7)