

Supplement to:

Kurzman, Charles and Aseem Hasnain. 2014. "When Forecasts Fail: Unpredictability in Israeli-Palestinian Interaction." *Sociological Science* 1: 239-259.

Appendix A: Supplementary Materials

Table A1. Recent Quantitative Studies of Israeli–Palestinian Interaction

Study	Time Period	Time Unit	Breaks	Variables	Method	Number of R^2 Statistics	Median R^2 Statistic	Conclusion
Beasley (2008)	2000–2006	Year	0	Killings; Palestinian prisoners, refugees, unemployment; Israeli settlers	Event history	0	–	Palestinians retaliate against killing of civilians
Braithwaite et al. (2010)	1970–2007	Month	4	Killings, Israeli electoral cycle, timing of peace process	Negative binomial	0	–	Palestinians respond to spoiler opportunities
Brandt and Freeman (2006)	1979–1988	Week	0	Israeli, Palestinian, and U.S. interactions (from Penn State data set)	Bayesian vector auto-regression	0	–	Israeli reciprocity short-lived, Palestinian reciprocity delayed
Brandt et al. (2008)	1996–2005	Month	0	Israeli, Palestinian, and U.S. interactions (from Penn State data set)	Bayesian structural vector auto-regression	0	–	Forecast increasing conflict in 2005
Brandt et al. (2011)	1996–2009	Month	0	Israeli, Palestinian interactions (from Penn State data set)	Markov-switching Bayesian vector auto-regression	0	–	Forecast increasing conflict in 2010
Brym and Andersen (2011)	1987–2007	Month	3	Killings	Negative binomial	7	0.62	Israelis retaliate differently in different periods
Brym and Araj (2006)	2000–2005	Month	1	Killings, Palestinian prisoners	Bivariate correlation	4	0.25	Both sides retaliate
Dugan and Chenoweth (2012)	1987–2004	Month	2	Israeli repression and conciliation, Palestinian terrorism	Negative binomial, general additive	0	–	Palestinians respond to conciliation, not repression, in some periods
Golan and Rosenblatt (2011)	2001–2008	Day	5	Killings, Palestinian rocket attacks	Vector auto-regression	18	0.03	Both sides retaliate in some periods, not in others
Hafez and Hatfield (2007)	2000–2004	Week	0	Killings, attempted killings, injuries	Ordinary least squares	29	0.02	Palestinians do not retaliate

Haushofer et al. (2010)	2001–2008	Day	0	Killings, Palestinian rocket attacks	Vector auto-regression	32	0.12	Both sides retaliate
Haushofer et al. (2011)	2001–2008	Day	0	Killings, Palestinian rocket attacks	Vector auto-regression	0	–	Both sides retaliate
Jaeger and Paserman (2006)	2000–2004	Day	0	Killings	Vector auto-regression	0	–	Israel retaliates more to some Palestinian groups than to others
Jaeger and Paserman (2008)	2000–2005	Day	6	Killings, length of separation barrier	Vector auto-regression	10	0.05	Israelis retaliate, Palestinians don't
Jaeger and Paserman (2009)	2000–2005	Day	6	Killings, attempted killings, length of separation barrier	Vector auto-regression	11	0.12	Israelis retaliate, Palestinian response is curvilinear
Kaplan et al. (2005)	2001–2003	Day	0	Killings, attempted killings, arrests	Maximum likelihood	0	–	Palestinians retaliate against targeted killings
Maoz (2007)	1949–2003	Year/month	0	Military operations, killings, Israeli election cycle, politically active Israeli chief of staff	Poisson	4	0.35	Both sides retaliate
Zeitsoff (2011)	2008–2009	Hour	2	Conflict (20-point scale)	Vector auto-regression	0	–	Israelis retaliate, Palestinian response is inconsistent

Table A2. Descriptive Statistics

	Israeli Actions toward Palestinians	Palestinian Actions toward Israelis
Days in data set	11,219	11,219
Days with news reports	5,254	4,001
Total number of news reports	9,655	6,438
Days with violent conflict	2,251	1,156
Mean daily event score	-0.89	-0.42
Minimum daily event score	-21	-19
Maximum daily event score	7	7
Number of reports on Saturdays	882	666
Mean number of reports on other days	1,439	950

Table A3. Israeli–Palestinian Interactions in Textbook Headings

Event	Caplan (2010)	Dowty (2012)	Gelvin (2007)	Harms and Ferry (2008)	Milton-Edwards (2009)	Smith (2010)	Tessler (2009)	Total
Begin presidency, early 1980s						•	•	2
Israeli-Lebanese war, 1982	•	•		•		•	•	5
Peace plans of the 1980s	•			•			•	3
Husayn/Arafat accord, 1985						•	•	2
First intifada, 1987	•	•	•	•	•	•	•	7
Emergence of Hamas, late 1980s			•			•		2
Israeli response to intifada, 1988					•		•	2
Madrid Conference, 1991	•			•	•	•	•	5
Gulf War, 1991	•			•		•	•	4
First Oslo Accord, 1993	•	•	•	•	•	•	•	7
Failure of Oslo Accords, mid-1990s		•	•				•	3
Oslo II, 1995				•		•		2
Netanyahu election, 1996						•	•	2
Hebron agreement, 1997				•		•		2
Wye River accord, 1998				•		•		2
Camp David II, 2000	•			•	•	•	•	5
Second intifada, 2000	•	•		•	•	•	•	6
Clinton peace plan, 2000				•		•		2
Taba summit, 2001				•		•		2
Bush road map, 2002				•		•		2
Separation barrier/wall, 2003			•	•		•		3
Track II diplomacy, 2003				•		•		2
Death of Arafat, 2004		•		•			•	3
Withdrawal from Gaza, 2005		•		•	•	•		4
Hamas election, 2006		•		•		•		3
Israeli-Hamas war, 2006			•	•		•		3
Israeli-Hizbullah war, 2006			•	•		•		3
Annapolis conference, 2007					•	•		2

Figure A4. Israeli–Palestinian Interactions: Squared Prediction Error Using Split Samples, 1979–2009. Prediction errors rise and fall in this split sample, based on separate models for each period, almost identically as in Figure 3, which was based on a single model for the entire 30-year period.

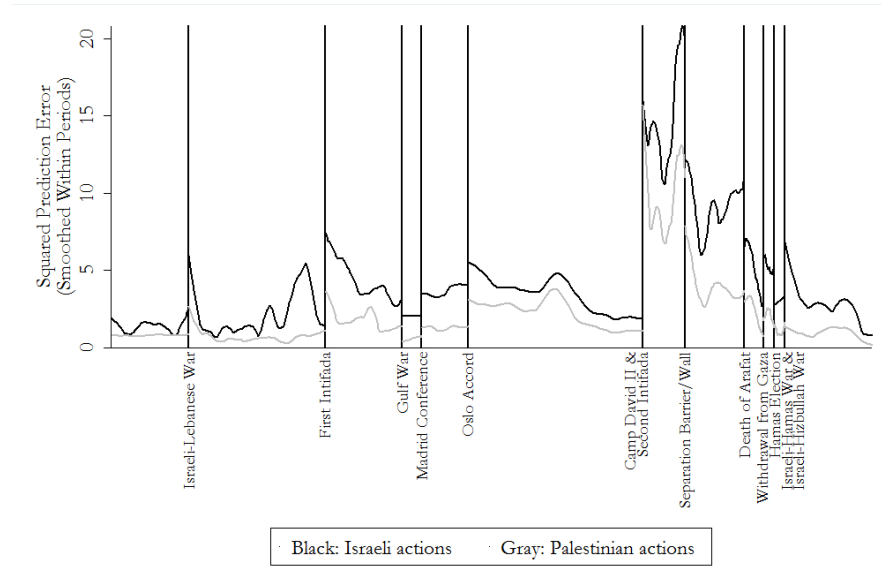


Table A5. Structural Breaks in Israeli–Palestinian Interactions

Breaks	Model 1. Joint Model of Israeli– Palestinian Interactions		Model 2. Israeli Actions toward Palestinians		Model 3. Palestinian Actions toward Israelis	
	RSS	BIC	RSS	BIC	RSS	BIC
0	92,003	55,587	50,525	48,794	24,948	40,883
1	90,285	55,553	49,747	48,722	24,614	40,835
2	88,964	55,565	49,106	48,679	24,167	40,732
3	87,854	55,601	48,690	48,687	23,955	40,736
4	86,807	55,644	48,342	48,709	23,775	40,753
5	85,886	55,702	48,037	48,740	23,610	40,778
6	84,984	55,760	47,781	48,783	23,448	40,804
7	84,286	55,845	47,543	48,830	23,290	40,830
8	83,638	55,936	47,300	48,875	23,174	40,877
9	83,023	56,030	47,062	48,921	23,081	40,934
10	82,461	56,131	46,851	48,973	22,973	40,984
11	81,959	56,240	46,655	49,029	22,879	41,041
12	81,458	56,348	46,474	49,088	22,797	41,103
13	81,054	56,470	46,310	49,150	22,724	41,170
14	80,609	56,585	46,134	49,211	22,659	41,240
15	80,160	56,700	45,960	49,271	22,597	41,312
16	79,757	56,820	45,781	49,330	22,542	41,387
17	79,379	56,944	45,617	49,392	22,494	41,466
18	78,999	57,068	45,477	49,460	22,447	41,545
19	78,621	57,191	45,318	49,523	22,393	41,620
20	78,265	57,318	45,177	49,591	22,345	41,699

Note. Calculated in *R* with the “strucchange” package (Zeileis et al. 2012a, 2012b), testing for up to 20 breaks. Shaded cells indicate the minimum values for the Residual Sum of Squares (RSS) and Bayesian Information Criterion (BIC) in each model.

Figure A6. Israeli–Palestinian Interactions: Squared Prediction Error Using Dummy Variable for Structural Break, 1979–2009. Prediction errors rise and fall in this analysis, incorporating a dummy variable for the period after the structural break of September 7, 2000, almost identically as in Figure 3, which did not include a dummy for “effect shock.”

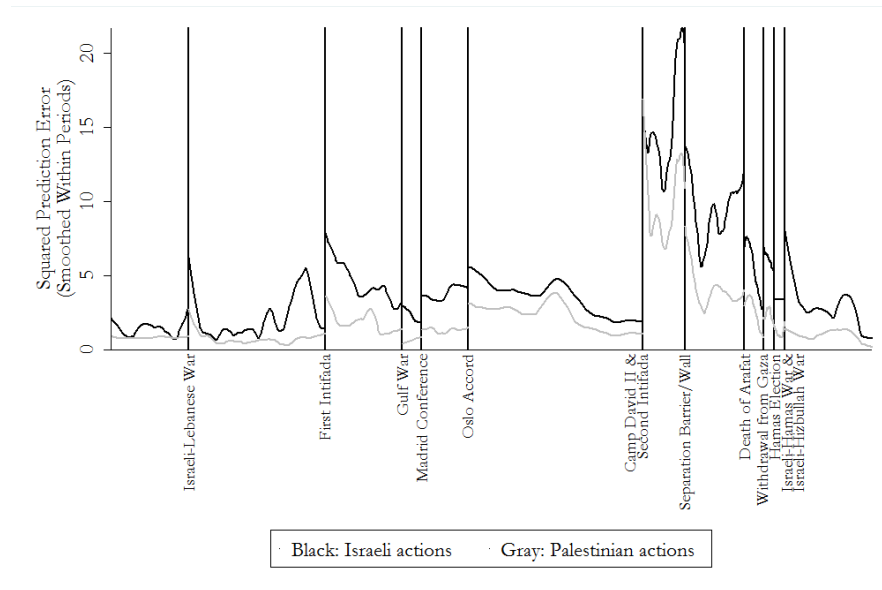


Figure A7. Impulse Response Functions for Israeli–Palestinian Interactions before the Second Intifada, 1979–2000. Prior to the outbreak of the Second Intifada on September 28, 2000, Israeli and Palestinian response functions reflect a limited pattern of tit-for-tat interaction (contrast with Figure 2). Based on the SBIC statistic, this model uses a lag of 5 days.

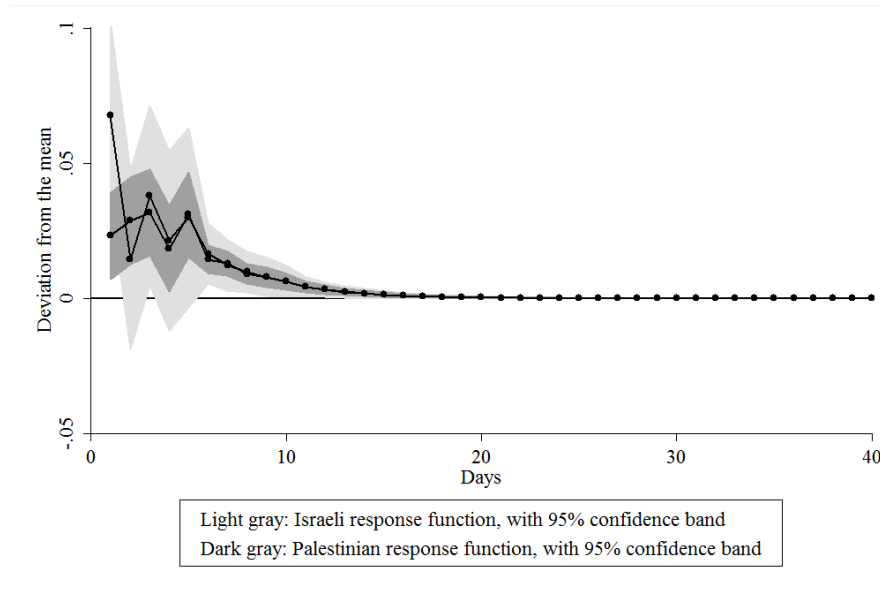
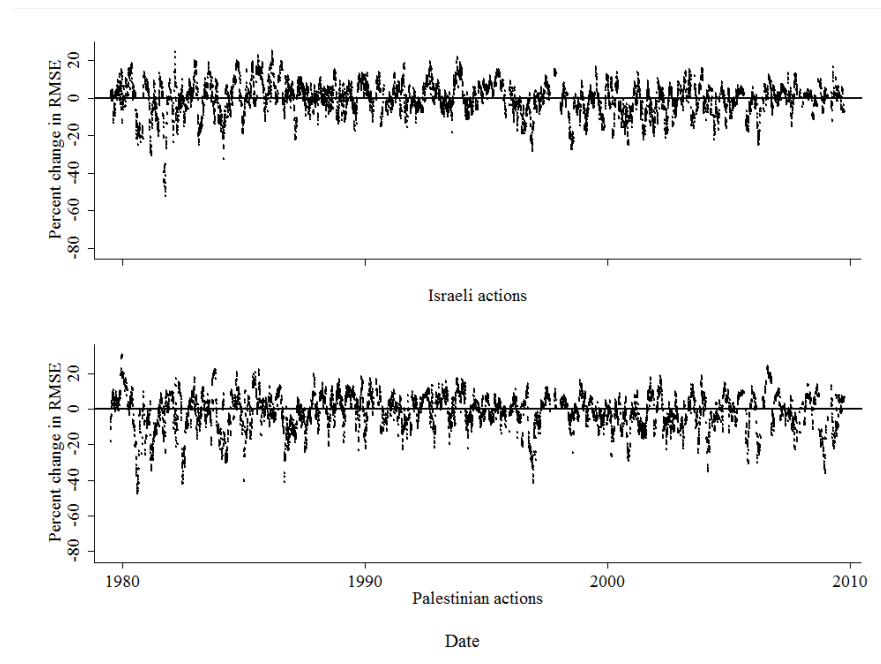


Figure A8. Effect of Including Lebanese Actors on Prediction Errors (Rolling 90-Day Windows). Including Lebanese actors in the vector autoregression model reduces prediction errors for Israeli and Palestinian actions toward one another at some points over the past 30 years and increases prediction errors at other points.



Appendix B: Bayesian Vector Autoregression Models

Several recent studies have applied Bayesian vector autoregression (BVAR) methods to the study of Israeli–Palestinian interaction (Brandt and Freeman 2006; Brandt, Colaresi, and Freeman 2008; Brandt, Freeman, and Schrodtt 2011), using software written in R specifically for this purpose (Brandt 2012, 2013). Advantages of this approach include its ability to generate a range of forecasts rather than a single point forecast and its adaptability to hyperparameters that reflect expert judgment about conflict processes. A disadvantage of this approach is that there is no clear guidance on how to turn expert judgments into hyperparameters—as shown in Table B1, hyperparameters are not entirely consistent among overlapping teams of scholars. Appendix B does not attempt to generate its own hyperparameters and instead follows a majority vote of prior studies.

Table B1. Hyperparameters for Bayesian Vector Autoregression Models of Israeli–Palestinian Interaction

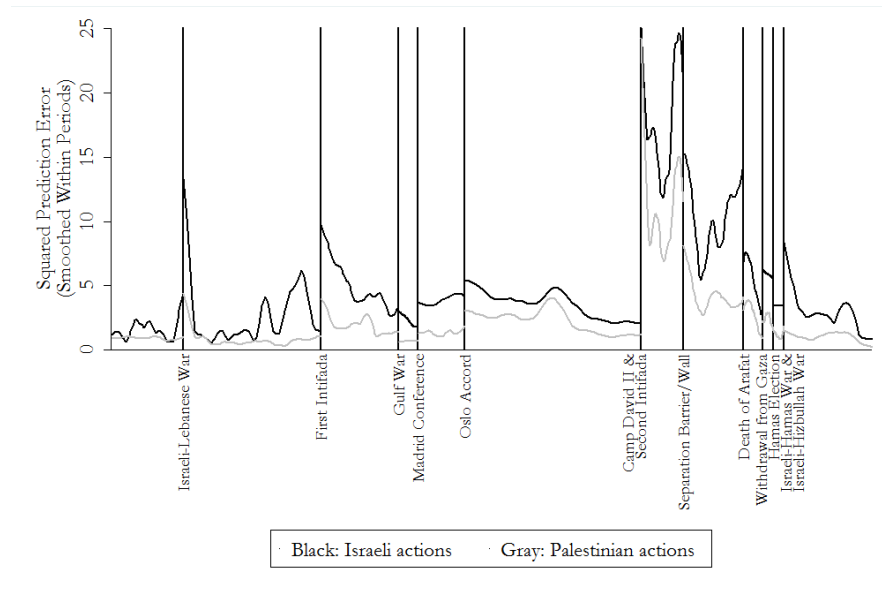
Hyperparameter	Description from Brandt (2013:77–78)	Brandt & Freeman (2006:27)	Brandt, Colaresi, & Freeman (2008:371)	Brandt, Freeman, & Schrodt (2011:55)	Brandt (2013:77)	Brandt (2013:80)	Brandt (2013:82)	This Article
Lambda0	“Overall tightness of the prior (discounting of prior scale).” Range 0–1.	0.6	0.8	0.6	0.8	0.6	0.6	0.6
Lambda1	“Standard deviation or tightness of the prior around the AR(1) parameters.” Range 0–1.	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Lambda2	[No longer specified in current version of MSBVAR.]	*	1	*	*	*	*	--
Lambda3	“Lag decay (> 0, with l=harmonic)”	2	1	2	1	2	2	2
Lambda4	“Standard deviation or tightness around the intercept > 0.”	0.5	0.1	0.5	0.1	0.25	0.5	0.5
Lambda5	“Standard deviation or tightness around the exogenous variable coefficients > 0.” [Possibly ≥ 0?]	*	0.05	*	0.05	0	0	0
Mu5	“Sum of coefficients prior weight ≥ 0. Larger values imply difference stationarity.”	0	0	0	0	0	*	0
Mu6	“Dummy initial observations or drift prior ≥ 0. Larger values allow for common trends.”	0	5	0	5	0	0	0
QM	“Frequency of the data for lag decay equivalence. Default is 4, and a value of 12 will match the lag decay of monthly to quarterly data. Other values have the same effect as ‘4.’”	*	*	*	12	4	4	4
Prior	“One of three values: 0 = Normal-Wishart prior, 1 = Normal-flat prior, 2 = flat-flat prior (i.e., akin to MLE)”	0†	0†	0†	*	0	0	0

* Not indicated in published version. † Value inferred from text of published paper.

We adopt the reduced form Sims–Zha Bayesian VAR model estimation (szbvar), which Brandt (2013:79) describes as the “work horse” of the MSBVAR package, using the hyperparameters listed in the right-hand column of Table B1. We begin with the initial 90 days of the time series to forecast the ninety-first day, then lengthen the observations to 91 days to forecast the ninety-second day, and so on, using the unconditional forecast density estimator (uc.forecast) in MSBVAR (Brandt 2013:80–83) with 1,000 burn-in draws and 3,000 cycles of the Gibbs sampler, generating 3,000 one-step forecasts for each directed dyad (Israeli actions toward Palestinians and Palestinian actions toward Israelis) for each day in the data set, beginning with the ninety-first day.

To begin to evaluate this approach, we compare the median forecasts for each day with the actual values of Israeli and Palestinian actions. The root mean squared error (RMSE) of these median forecasts is 2.17 for Israeli actions and 1.51 for Palestinian actions, very similar to results from in-sample and out-of-sample forecasts with non-Bayesian vector autoregression models (2 to 3 percent worse than in-sample forecasts and within 1 percent of out-of-sample forecasts; see Table 3). By this metric, Bayesian models do not generate more accurate forecasts than non-Bayesian models. Moreover, as with non-Bayesian models, median Bayesian forecasts jump during several historic moments in Israeli–Palestinian interaction, especially the First and Second Intifadas. The rise and fall of squared prediction errors of Bayesian mean forecasts, plotted in Figure B2, looks generally similar to the rise and fall of squared prediction errors of non-Bayesian forecasts (Figure 3).

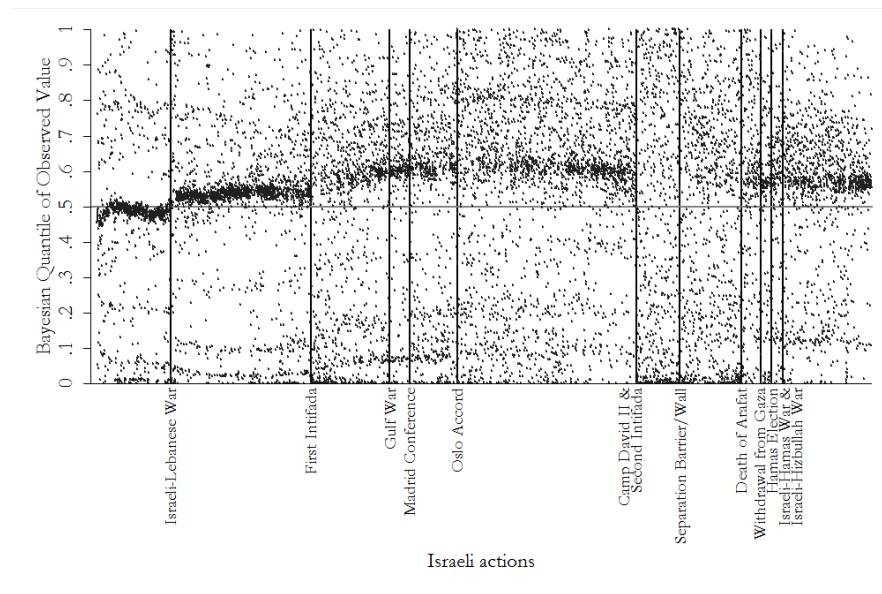
Figure B2. Israeli–Palestinian Interactions: Squared Prediction Error of Median Bayesian Forecasts, 1979–2009. The prediction error of median Bayesian forecasts leaps at many historic episodes in Israeli–Palestinian interaction, just as with non-Bayesian models reported in the body in the article. Events within three months of each other are displayed in this chart as a single line: Camp David II and the Second Intifada in 2000; Israeli–Hamás War and Israeli–Hizbullah War in 2006.

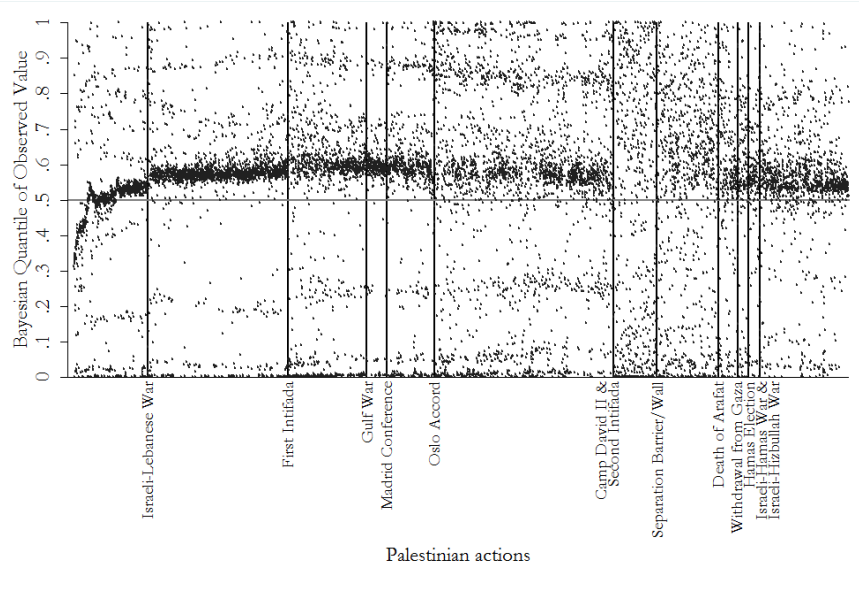


However, point forecasts such as the median Bayesian forecast may not be the best metric to evaluate Bayesian models (Brandt, Freeman, and Schrodt 2011). Instead, Bayesian scholars propose that we examine the entire forecast probability distribution. In this spirit, we examine the quantile of the observed value of Israeli and Palestinian actions within the 3,000 Bayesian forecasts for each day. A quantile of 0.5 indicates that the observed value coincides with the median Bayesian forecast. A quantile of 0.9 indicates that the observed value is greater than 90 percent of the Bayesian forecasts; a quantile of 0.1 indicates that the observed value is lower than 90 percent of the Bayesian forecasts.

Figures B3a and B3b plot the quantiles for the observed values for Israeli and Palestinian actions for each day. The dense horizontal band of observed values around the 0.6 quantile suggests that Israeli–Palestinian interactions are often more positive than most of the Bayesian forecasts but are frequently close to the median forecast. However, this pattern is inconsistent—at several historic moments, the horizontal stripe becomes noticeably less dense as the observed values spread out across the forecast distribution. The cluster of observed values at or near 0 during the First and Second Intifadas suggests that Israeli–Palestinian interactions were sometimes more negative than almost all of the 3,000 Bayesian forecasts. As with the point forecasts, Bayesian quantile forecasts appear to be less accurate during momentous historic episodes.

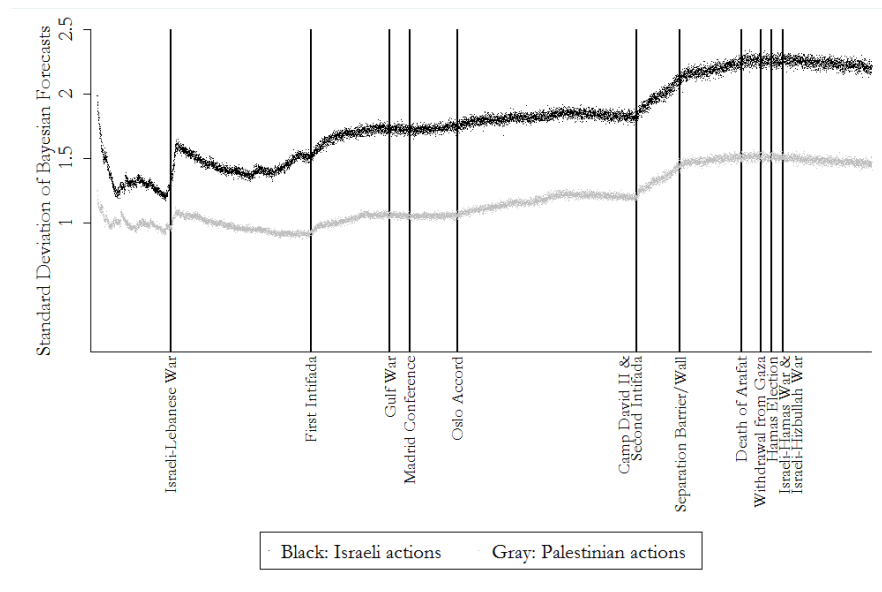
Figure B3. Bayesian Forecast Quantile of Observed Values, 1979–2009. Israeli and Palestinian actions cluster near the median out-of-sample Bayesian forecasts but are often observed above the ninetieth quartile of forecasts or below the tenth quartile.





In addition to forecast quantiles, Bayesian models also allow the analysis of forecast uncertainty. A greater range of Bayesian forecasts for a given day might signal a widening set of possible outcomes and hedge against overconfidence in the forecast. As a measure of forecast uncertainty, Figure B4 presents the standard deviation of the 3,000 Bayesian forecasts for each day for each directed dyad, after a burn-in of 1,000 draws. The standard deviation jumps with the onset of the Israeli–Lebanese War of 1982 and trends upward during the First and Second Intifadas, consistent with the greater volatility of Israeli–Palestinian interactions during those periods. However, these shifts in the standard deviation seem gradual and modest, as compared with the leaps in volatility visible in the squared prediction error (Figure B2) and the forecast quantiles (Figure B3). With the exception of the Israeli–Lebanese War of 1982, there seems to be little indication in these gentle slopes of abrupt shifts in forecast uncertainty, even when the point and quantile forecasts perform abruptly worse. It is also troubling, from a forecasting point of view, that the standard deviation rarely goes back down, even during periods of relative calm. Except in the early 1980s, the standard deviation of the Bayesian forecasts only ratchets upward, as though the incorporation of more years of data degrades the precision of the forecast distribution rather than improving it.

Figure B4. Standard Deviation of Bayesian Forecasts of Israeli and Palestinian Actions, 1979–2009. Forecast uncertainty, measured through the standard deviation of Bayesian forecasts, rises gradually during the First and Second Intifadas, giving little indication of the dramatic increase in forecast error during these periods.



Bayesian vector autoregression also allows for the detection of structural breaks between two or more “regimes” or “states.” The number of regimes must be specified in advance; we follow Brandt et al. (2011) in specifying two regimes. We also follow Brandt et al.’s priors and in-sample estimation method using the `msbvar` and `gibbs.msbvar` functions in the `MSBVAR` package in R with 1,000 burn-in draws and 2,000 Gibbs cycles (Brandt 2013:17–18). The dummy variable for Saturdays is excluded, because no exogenous variables are permitted in the current version of the `msbvar` function.

The gray dots in Figure B5 represent regime 1 probabilities for each lagged dependent variable and for each intercept for each day in the sample, ranging from 0 to 1. In two-regime models, regime 2 probabilities equal one minus the regime 1 probability. Moments when the regime 1 probability drops from above 0.5 to below 0.5 point to Markov-switching breaks in the “regime” of interaction from regime 1 to regime 2; moments when regime 1 probability rises from below 0.5 to above 0.5 point to switches from regime 2 to regime 1. Brandt et al. (2011:55–56), aggregating event data month by month, find a pattern of regime switching that corresponds roughly with major periods in Israeli–Palestinian interaction, with one regime associated with periods of high conflict and volatility and the other regime associated with lower conflict and less volatility. Our models, which aggregate event data day by day, display a less consistent pattern. Regime switching occurs several thousand times over the course of the 30 years of observations—on average, once every three days, with no lengthy periods within a single regime—for each lag and intercept.

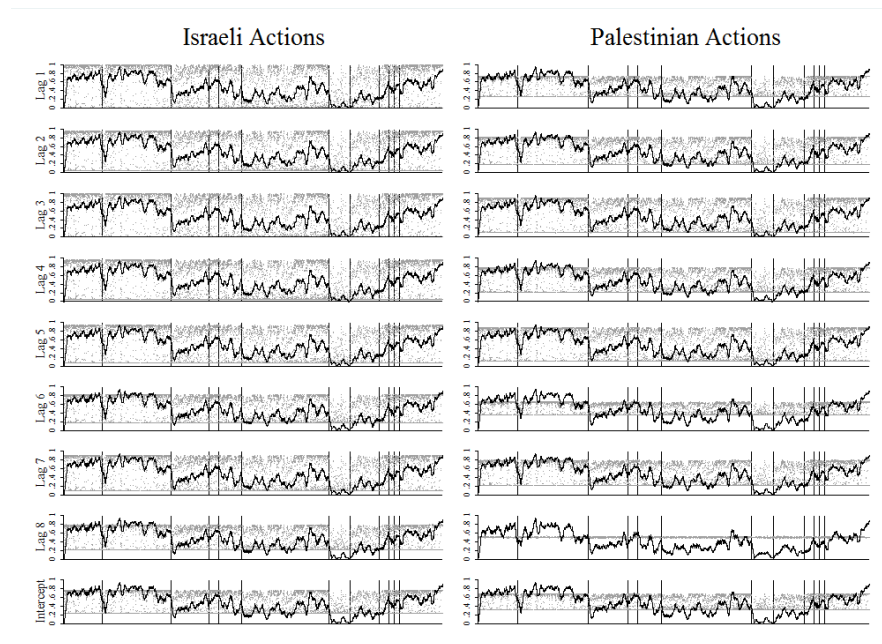
Despite this profusion of breaks, it appears that the probability of regime 1 is low during periods of heightened conflict, especially the Second Intifada. The dark horizontal lines in Figure B5 represent the percentage of days with a regime 1 probability greater than 0.5, calculated for a

moving-window period of 90 days, advancing one day at a time. During the Second Intifada, this percentage drops nearly to zero; it also drops sharply with the outbreak of the Israeli–Lebanese War of 1982 and the First Intifada. However, the percentage also remains low during the Oslo peace process, complicating any attempt to associate regime 1 with conflict and regime 2 with peace.

These Markov-switching Bayesian forecasts give little advance warning of upcoming historic breaks. Even with this in-sample analysis, which takes later events into account in the calculations, there is no consistent downturn in regime 1 probabilities prior to major historic moments. Instead, the most dramatic drops in regime 1 probabilities occur just after historic episodes, rather than forecast them in advance.

To sum up, Bayesian models forecast Israeli–Palestinian interactions no better than non-Bayesian vector autoregression models. Both sets of models meet the usual forecasting standards but generate wildly uneven prediction errors over time, faring worst at moments of historic change.

Figure B5. Regime Probability of Markov-Switching Bayesian Forecasts of Israeli and Palestinian Actions, 1979–2009. Regime switching occurs frequently in Israeli–Palestinian interactions, according to in-sample Markov-switching Bayesian forecasts. Regime 1 probability displayed as gray dots; regime 2 probability, not shown, equals one minus the regime 1 probability. The dark horizontal lines represent the percentage of regime 1 probabilities that are greater than 0.5 in 90-day moving windows. Vertical lines indicate major historical episodes, as in previous graphs.



Appendix C: Chow Tests for Structural Breaks

This article presents results from Bai and Perron's (2003) inductive method for the identification of "effect shocks" and "input shocks," examining the entire time series for structural breaks. An alternative approach is to look for breaks in shorter segments of the time series by applying a series of Chow tests on nonoverlapping periods around the moments identified as important by historians. This approach interacts all of the lagged dependent variables with a dummy variable equaling zero during the period prior to one historic event in Israeli–Palestinian relations, and 1 in the period afterward. (These periods cannot overlap, because Chow tests may not be applied multiple times to the same time series data.)

Table C1 presents the results of Chow tests for vector autoregression models with both Israeli and Palestinian actions, exploring what we call "effect shock." The two weeks between the outbreak of the Israeli– Hamas and Israeli– Hizbullah wars of 2006 are too brief to allow the calculation of the Chow test, so we use the same time period for both events in the second data column of Table C1: from the Hamas election on January 25, 2006, to the end of the time series data on December 31, 2009. Eight lags were selected for consistency with the full time series models; all eight lags exhibit significant autocorrelation, according to the Box–Pierce Q statistic, but partial autocorrelation is absent after the second lag. We get precisely analogous results if we apply the Chow tests to equations with two lags instead of eight lags.

Table C1. Effect Shock: Chow Tests for Structural Breaks in Israeli–Palestinian Interaction Around Major Historical Events

Event	Date	Time Periods			
		From Prior to Following Event	Constant Windows before and after Event		
			365 Days	180 Days	90 Days
Israeli–Lebanese war	June 6, 1982	48.4	50.4*	51.7*	46.2
Peace plans of the 1980s	No precise date	–	–	–	–
First Intifada	December 9, 1987	77.0†	56.8†	40.4	31.9
Gulf War	January 17, 1991	41.1	32.2	41.3	38.6
Madrid conference	October 30, 1991	39.1	32.7	39.5	42.5
First Oslo Accord	September 13, 1993	67.5†	39.0	31.9	29.8
Failure of Oslo Accords	No precise date	–	–	–	–
Camp David II	July 11, 2000	18.2	37.6	34.7	58.2†
Second Intifada	September 28, 2000	16.6	51.1*	39.4	33.5
Separation barrier/wall	June 16, 2002	68.2†	52.7*	52.9*	48.2
Death of Arafat	November 11, 2004	52.1*	60.2†	82.2†	71.0†
Withdrawal from Gaza	August 15, 2005	33.1	40.5	32.0	37.1
Hamas election	January 25, 2006	26.4	40.9	49.4*	28.3
Israeli–Hamas war	June 28, 2006	39.8	66.5†	40.9	35.4
Israeli–Hizbullah war	July 12, 2006	58.9†	46.6	40.2	62.1†

Note. Chi-square value shown. Asterisks indicate a statistically significant structural break in the coefficients of the independent variables, which we label “effect shock.”

* $p < 0.05$. † $p < 0.01$.

These results suggest that the identification of effect shock is sensitive to shifts in the time period under observation. When the time series considered in each Chow test is restricted to the periods between each historic event, we find that 5 of these 13 moments involve statistically significant structural breaks. If we adopt constant windows of 365 days around each historic moment, we find the same number of structural breaks (6 of 13), though not all of the breaks coincide with the previous test. As we restrict the window to 180-day and 90-day periods around each historic moment, the number of statistically significant effect shocks decreases (4 and 3 of 13, respectively). Only one effect shock is statistically significant regardless of the time period surrounding it: not the Second Intifada, which was identified as the most important structural break in the full time series analysis, and not the events that are most consistently identified as important by historians, but rather the death of Yassir Arafat, the longtime leader of the Palestinian Liberation Organization, in 2004.

It is interesting that the shorter the time period under consideration, the fewer historic events involve statistically significant effect shock. This runs counter to the expectation, which is implicit in much of time series analysis, that parameters may fluctuate over the short term and still be considered stable over the long run. By way of an analogy offered by a time series specialist in response to a draft of this article, we expect the surface of the earth to be rugged in places, while we accept that it is a spheroid on the whole. In this analysis, by contrast, the larger scale seems to exhibit significant effect shocks that are not visible with more finely focused granularity, possibly indicating slower-moving shocks such as smooth transition autoregressive processes that stretch over longer time periods.

We performed analogous tests for input shock on separate univariate time series of Israeli actions and Palestinian actions, with eight lagged values of the variable interacting with a

dummy variable that equals zero prior to each historic event identified by historians, and one afterward. The results are presented for various-sized windows in Tables C2 and C3. As with effect shock, we see fewer instances of input shock at the narrowest time periods around each historic event, especially for Palestinian actions, none of which exhibit structural breaks during 180-day and 90-day windows around each historic event.

Table C2. Input Shock: Chow Tests for Structural Breaks in Israeli Actions toward Palestinians Around Major Historical Events

Event	Date	Time Periods			
		From Prior to Next Event	Constant Windows before and after Event		
			365 Days	180 Days	90 Days
Israeli–Lebanese war	June 6, 1982	13.7	18.9*	23.6†	19.2*
Peace plans of the 1980s	No precise date	–	–	–	–
First Intifada	December 9, 1987	37.4†	27.7†	25.4†	19.5*
Gulf War	January 17, 1991	24.3†	10.4	19.7*	13.6
Madrid conference	October 30, 1991	16.6	12.6	12.6	5.02
First Oslo Accord	September 13, 1993	15.5	12.7	5.17	4.76
Failure of Oslo Accords	No precise date	–	–	–	–
Camp David II	July 11, 2000	4.22	25.6†	13.8	21.0†
Second Intifada	September 28, 2000	14.6	42.6†	25.4†	20.4*
Separation barrier/wall	June 16, 2002	19.3*	15.4	11.8	2.36
Death of Arafat	November 11, 2004	24.8†	24.0†	20.8*	14.2
Withdrawal from Gaza	August 15, 2005	6.15	8.32	7.94	10.9
Hamas election	January 25, 2006	8.23	12.7	12.3	8.10
Israeli– Hamas war	June 28, 2006	20.8*	17.2*	16.5	11.1
Israeli–Hizbullah war	July 12, 2006	26.0†	21.6*	19.9*	16.0

Note. *F* value shown. Asterisks indicate a statistically-significant structural break in the univariate independent variables, which we label “input shock.”

* $p < 0.05$. † $p < 0.01$.

Table C3. Input Shock: Chow Tests for Structural Breaks in Palestinian Actions toward Israelis Around Major Historical Events

Event	Date	Time Periods			
		From Prior to Next Event	Constant Windows before and after Event		
			365 Days	180 Days	90 Days
Israeli–Lebanese war	June 6, 1982	20.3*	11.0	15.2	15.9
Peace plans of the 1980s	No precise date	–	–	–	–
First Intifada	December 9, 1987	30.3†	12.8	8.68	9.01
Gulf War	January 17, 1991	7.04	7.75	4.75	3.61
Madrid conference	October 30, 1991	8.74	6.09	9.39	16.8
First Oslo Accord	September 13, 1993	6.78	10.4	7.68	8.72
Failure of Oslo Accords	No precise date	–	–	–	–
Camp David II	July 11, 2000	8.93	22.9†	8.80	10.9
Second Intifada	September 28, 2000	11.2	37.6†	15.8	16.8
Separation barrier/wall	June 16, 2002	38.7†	18.7*	12.7	8.48
Death of Arafat	November 11, 2004	11.7	17.9*	12.6	6.38
Withdrawal from Gaza	August 15, 2005	6.12	9.25	6.33	9.01
Hamas election	January 25, 2006	4.15	5.47	8.49	2.71
Israeli– Hamas war	June 28, 2006	8.73	13.5	7.91	9.72
Israeli–Hizbullah war	July 12, 2006	6.74	11.2	3.10	3.97

Note. *F* value shown. Asterisks indicate a statistically-significant structural break in the univariate independent variables, which we label “input shock.”

* $p < 0.05$. † $p < 0.01$.

These findings barely coincide with the input shocks identified through the “strucchange” analysis of the full time series. According to these Chow tests, short-term input shock in Israeli actions is most consistently visible in 1982, at the outbreak of the Israeli–Lebanese War; in late 1987, at the outbreak of the First Intifada; and in late summer 2000, at the outbreak of the Second Intifada; but less consistently visible at the second moment identified as a structural break in the full time series (October 2004). By contrast with the long-term analysis, which identified two breaks in Palestinian actions, there appears to be no consistent evidence for short-term input shocks in Palestinian actions during these major historical episodes. We know of no way to adjudicate between the findings of these Chow tests and the findings generated by Bai and Perron’s methods.