Online Appendix for "Tug of War: The Heterogeneous Effects of Outbidding between Terrorist Groups"

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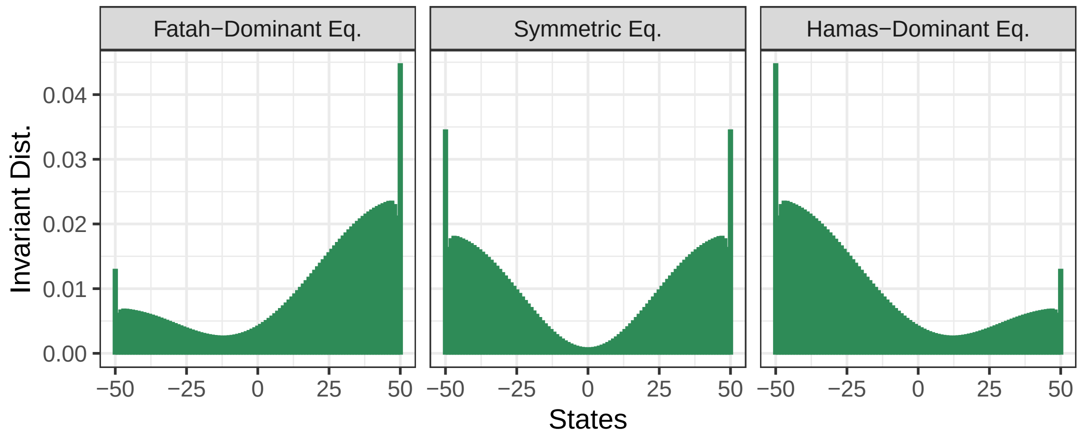
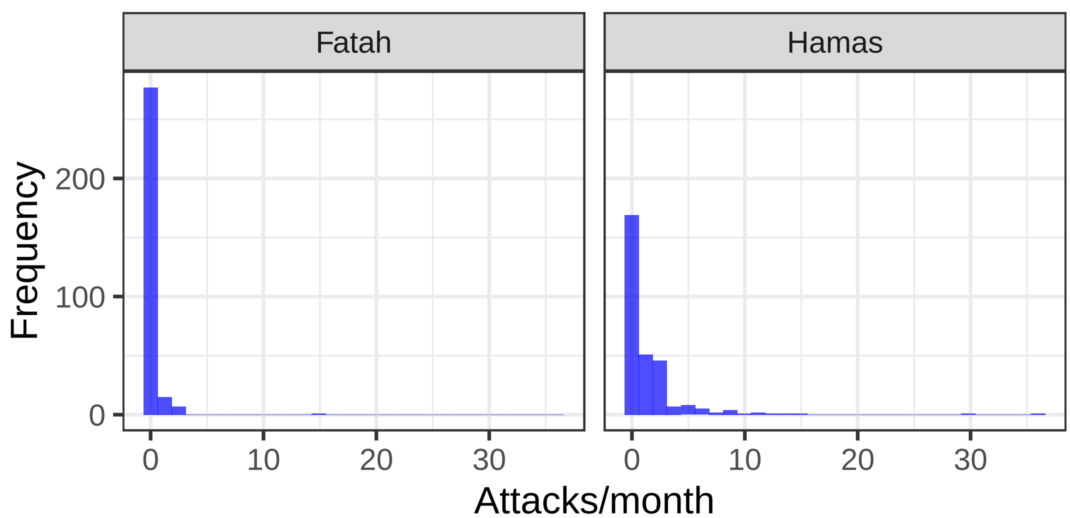
A Additional figures

Figure A.1: Equilibrium invariant distributions in the numerical example.



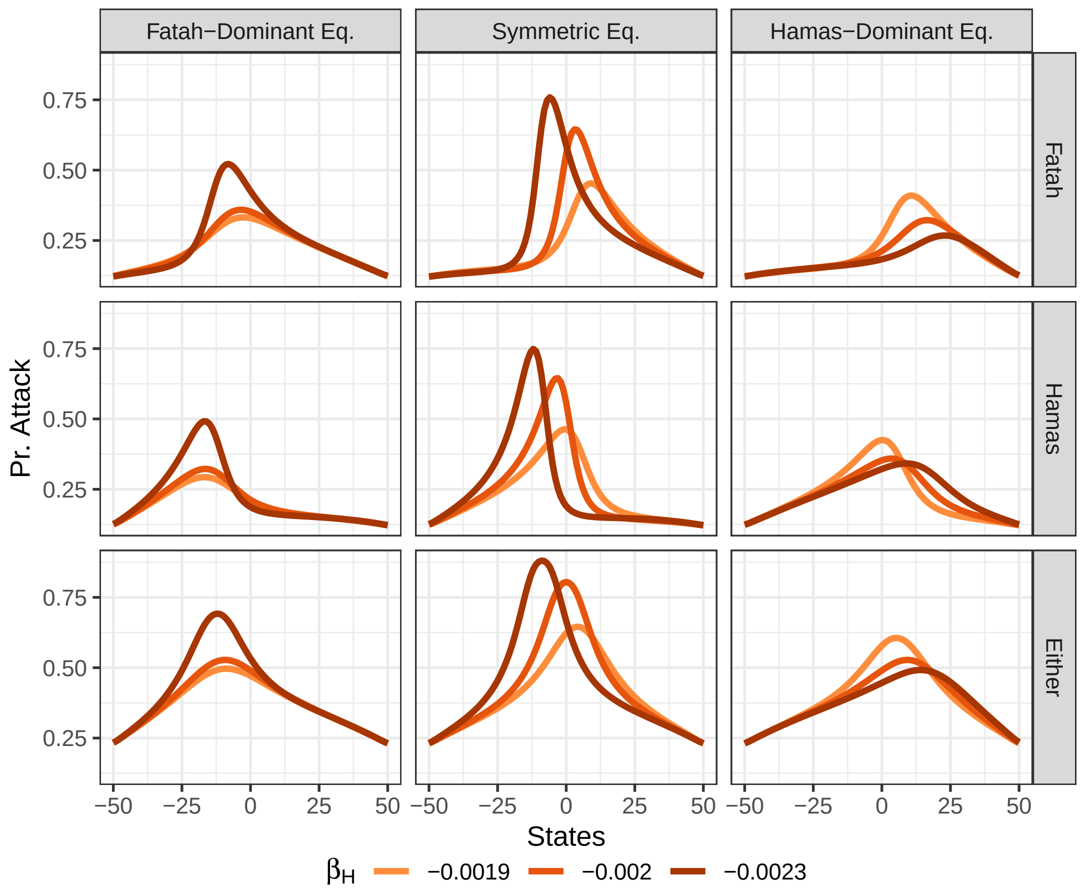
Note: The invariant distribution indicates how likely it is for the equilibrium path to visit each of the relative popularity levels in the long run. The equilibrium path in an asymmetric equilibria is more likely to visit popularity levels that are favorable to the dominant (more violent) actor. In the symmetric equilibrium, the invariant distribution is symmetric around zero. Spikes occur at the extreme values of the state space which reflects the fact that the interaction can bunch at high and low values due to relative popularity levels being bounded.

Figure A.2: Empirical distribution of the number attacks in each month.



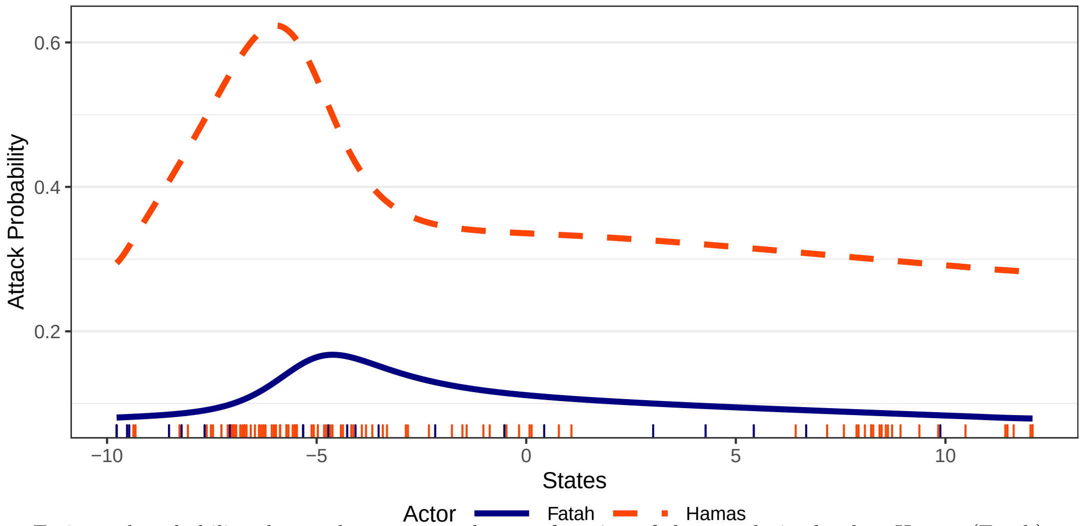
Note: For each month, we count the number of attacks attributed to Fatah (left) and Hamas (right) in the GTD and plot the distribution. For Hamas, the mean is 1.5, median is 0, and range is 0–36. For Fatah, the mean is 0.2, median is 0, and range is 0–15.

Figure A.3: Comparative statics in the numerical example.



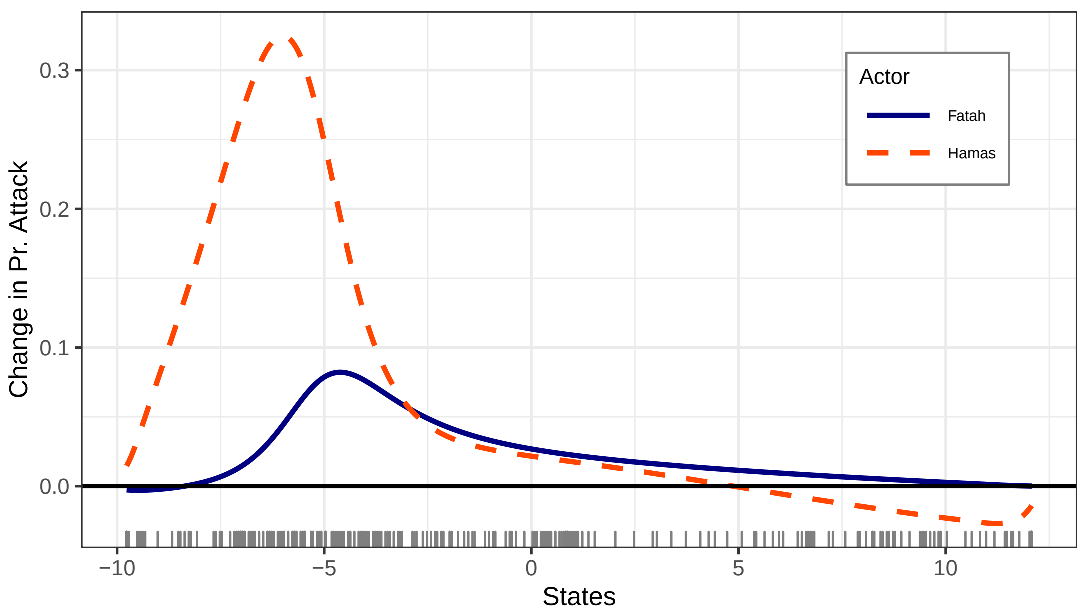
Note: We increase and decrease Hamas's value of popularity, β_H, from the baseline numerical example where $\beta_H = -0.002$. The horizontal axis is the relative popularity levels (smaller values are more favorable to Hamas) and the vertical axis is the probability of an attack. Columns correspond to the equilibrium and rows denote which group's probability of attacking is graphed. Darker red denotes stronger incentives to compete, β_H is more negative.

Figure A.4: Estimated equilibrium attack probabilities as a function of the state



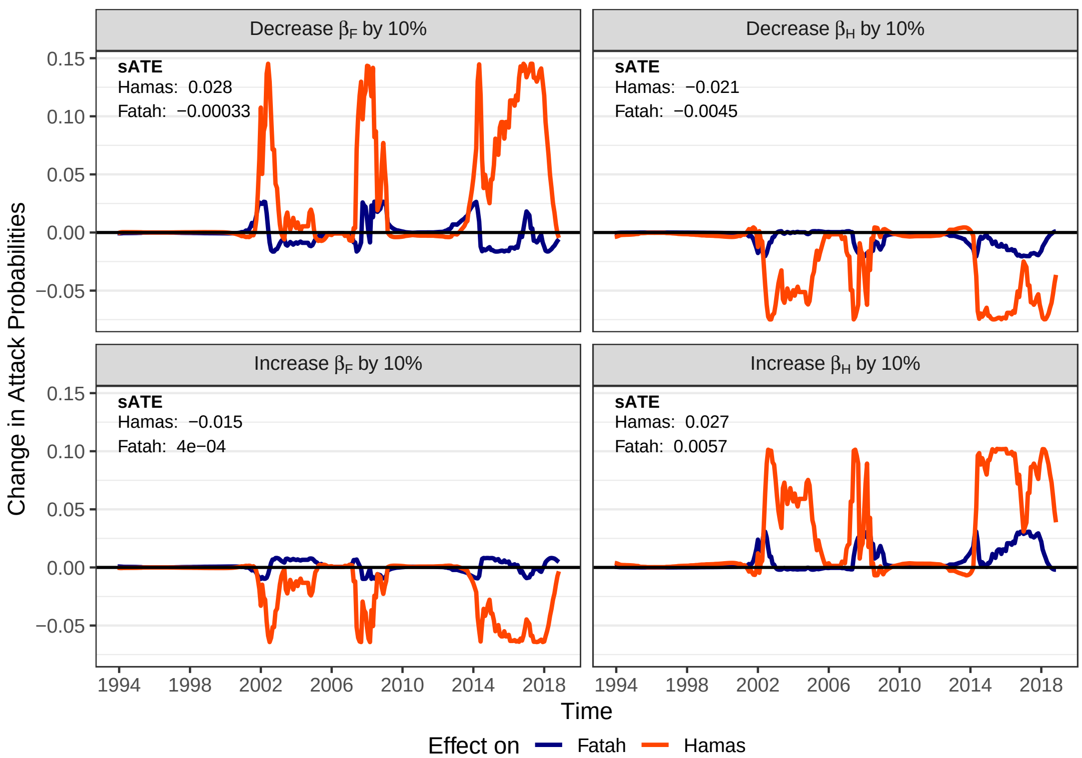
Note: Estimated probability that each group attacks as a function of the popularity level s. Hamas (Fatah) prefers smaller (larger) states. The horizontal axis includes a rug plot of observed attacks.

Figure A.5: Effects of competition on violence for all states s



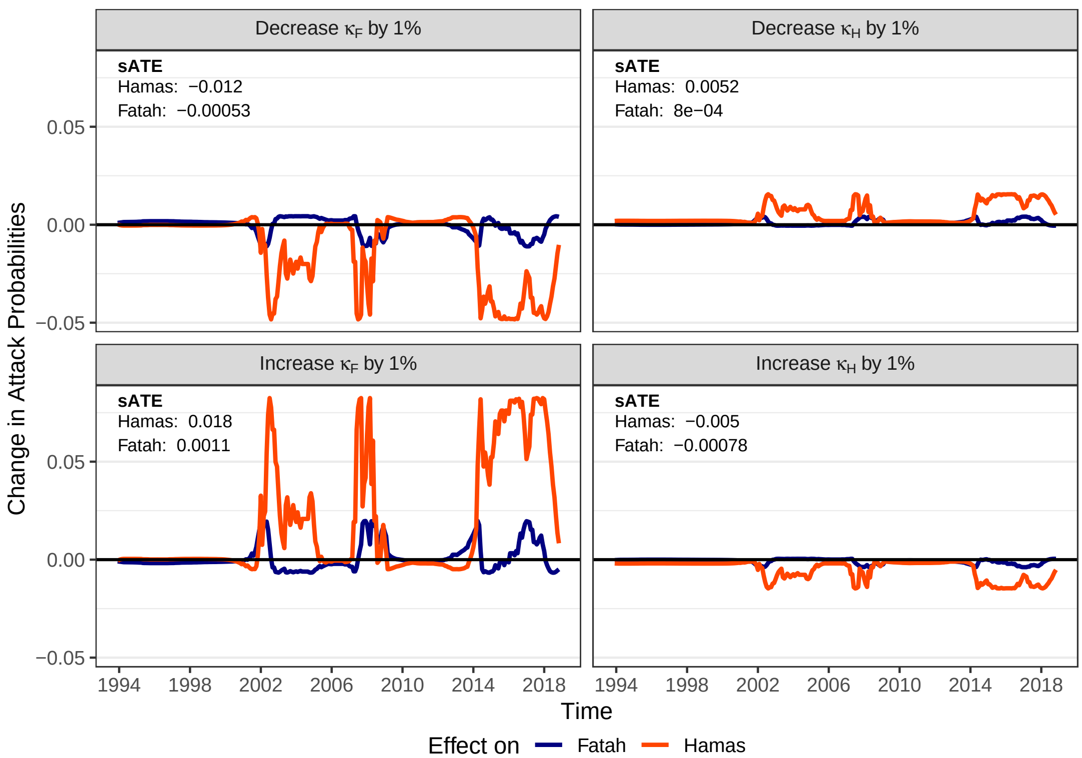
Note: We compare group i's equilibrium probability of terrorism in state s to the probability that would arise if i expects its rival to never use violence, by subtracting the latter from the former. Whereas Figure 6 graphs the difference over time conditional on the observed relative popularity s^t, Figure A.5 shows the difference as a function of all relative popularity levels s on the horizontal axis. Positive values indicate that competition increases violence by group i in state s; negative values indicate that competition decreases violence by group i in state s. Rug plot denotes observed states s^t.

Figure A.6: Relationship between terrorism and value of support in observed states.



Note: In each panel, we increase and decrease β_i for $i = H, F$ from its estimated value by 10%; all other parameters are held constant at their estimated values. Incentives to compete are greater when the value of support, β_i, is larger in magnitude. The horizontal axis denotes the period/month t. The vertical axis is the difference between equilibrium attack probabilities (Figure 5) and counterfactual attack probabilities given the change in β_i and observed state s^t. Positive (negative) values indicate that violence by group i increases (decreases) in the counterfactual.

Figure A.7: Relationship between terrorism and cost of attacking in observed states.



Note: In each panel, we increase and decrease κ_i for $i = H, F$ from its estimated value by 1%; all other parameters are held constant at their estimated values. Incentives to compete are greater when attack costs, κ_i, are closer to zero. The horizontal axis denotes the period/month t. The vertical axis is the difference between equilibrium attack probabilities (Figure 5) and counterfactual attack probabilities given the change in κ_i and observed state s^t. Positive (negative) values indicate that violence by group i increases (decreases) in the counterfactual.

B More details on the survey data and dynamic factor model

Table B.1 lists example wording of each survey question we used and the frequency at which it was asked. Table B.2 shows the raw correlations among the survey questions. Within each group trust and support are highly correlated (0.69 and 0.77 for Hamas and Fatah, respectively). Likewise, support for one group is negatively correlated with support for the other. The remaining correlations are almost all in the expected directions, suggesting that the population does in fact trade off among supporting these two leading actors. The only exceptions is the negative correlation between voting for and supporting Fatah and the positive correlation between supporting Fatah and voting for Hamas. However, trust in Fatah correlates highly with both supporting and voting for Fatah, while voting for Hamas correlates highly with support and trust in Hamas.

Table B.1: Survey questions and frequency

Source	Question	Frequency
JMCC	"Which political or religious faction do you trust the most?"	2-6 times/year
PCPSR	"Which of the following political parties do you support?"	2-9 times/year
JMCC	"If Legislative Council elections were held today, which party would you vote for?"	0-5 times/year starting in 2006

Table B.2: Correlations among survey responses

	Trust in Hamas	Trust in Fatah	Support for Hamas	Support for Fatah	Vote for Hamas	Vote for Fatah
Trust in Hamas	1.00	−0.19	0.77	−0.44	0.98	−0.72
Trust in Fatah	−0.19	1.00	−0.26	0.69	−0.54	0.92
Support for Hamas	0.77	−0.26	1.00	−0.57	0.89	−0.83
Support for Fatah	−0.44	0.69	−0.57	1.00	0.56	−0.32
Vote for Hamas	0.98	−0.54	0.89	0.56	1.00	−0.73
Vote for Fatah	−0.72	0.92	−0.83	−0.32	−0.73	1.00

To produce the latent state variable, we first let y^t be the column vector denoting the 6 survey values at time t such that

$$y^t = \begin{bmatrix} \text{\% of Population that trusts Fatah} \\ \text{\% of Population that trusts Hamas} \\ \text{\% of Population that supports Fatah} \\ \text{\% of Population that supports Hamas} \\ \text{\% of Population that plans to vote for Fatah} \\ \text{\% of Population that plans to vote for Hamas} \end{bmatrix}^t . \tag{B.1}$$

Let z^t denote the vector of z-transformed surveys, where for survey $j = 1, \ldots, 6$, $z_j^t = \frac{y_j^t - \bar{y}_j}{\sqrt{\mathrm{Var}(y_j)}}$. We construct a continuous state variable $\tilde{s}^t$ as a function of past terrorist attacks and past population support using the dynamic factor model given by

$$z^t = \tilde{s}^t \omega + \xi^t, \tag{B.2}$$

and

$$\tilde{s}^t = \rho \tilde{s}^{t-1} + \alpha_0 + a_H^{t-1} \cdot \alpha_H + a_F^{t-1} \cdot \alpha_F + \eta^t. \tag{B.3}$$

Here, a_F^{t-1} and a_H^{t-1} record attacks by Fatah and Hamas, respectively while the α_F and α_H weights the impact of those attacks. Including the attacks in the measurement of s^t reflects the strategic interdependence between the states and actions. Note that simply including attacks in the measurement model does not presuppose their relationship in the first-stage regressions below. The α_i can take on any value, including zero. Likewise, α_0 is a constant term, ω is a length-6 column vector of factor weights, and ρ is an AR(1) term on the state variable. Finally, $\eta^t \sim N(0, 1)$ and $\xi^t \sim N(0, \mathbf{1})$ are random perturbations, where $\mathbf{1}$ is the identity matrix.

The parameter vector $\Theta = (\omega, \rho, \alpha)$ can be estimated using maximum likelihood using the `MARSS` package for R (Holmes, Ward and Scheuerell 2018). Starting with an initial guess of the parameters $\hat{\Theta}_1$, the estimator relies on the following EM for iteration k:

1. **Expectation step:** Generate expected values of $\tilde{s}^t$ using a Kalman filter and current givens $\hat{\Theta}_k$, z_t, and a^{t-1}. During this step missing values in z^t are also imputed by a Kalman filter.

2. **Maximization step:** Using the generated values of $\tilde{s}^t$ and imputed z^t, maximize the multivariate normal log-likelihood. This step outputs $\hat{\Theta}_{k+1}$

3. Repeat the EM steps until no improvement in the log-likelihood is gained.

The estimates of (ω, α) are reported in Table B.3, while the estimates of $\tilde{s}^t$ are presented in Figure 4 (main text). Notice that the variables all load onto the dynamic factor in the expected direction: pro-Hamas responses have negative weights and pro-Fatah responses have positive weights.

Table B.3: ML estimates for the factor model

Equation	Variable	Estimate
Factor Weights (ω)	Trusts Hamas	-0.09
	Trust Fatah	0.06
	Supports Hamas	-0.11
	Supports Fatah	0.10
	Votes Hamas	-0.07
	Votes Fatah	0.07
AR(1) term (ρ)	Lagged DV	0.99
Additional inputs (α)	Constant	-0.01
	Hamas attack	-0.28
	Fatah attack	1.05

We also consider the robustness of this measurement model by comparing the estimated $\tilde{s}^t$ from the following six models.

1. Main specification (described above)

2. Fix $\rho = 1$. Modify Eq. B.3 s.t.

$$\tilde{s}^t = \tilde{s}^{t-1} + \alpha_0 + a_H^{t-1} \cdot \alpha_H + a_F^{t-1} \cdot \alpha_F + \eta^t.$$

3. Estimated and homoskedastic variance in ξ^t. Modify Eq. B.2 s.t. $\xi^t \sim N(0, \sigma_\xi^2 \mathbf{1})$.

4. Estimated and heteroskedastic variance in ξ^t. Modify Eq. B.2 s.t. $\xi^t \sim N(0, \sigma_{\xi,j}^2 \mathbf{1})$, where $j = 1, \ldots, 6$ indexes surveys

5. A model with $\alpha = 0$. Modify Eq. B.3 s.t.

$$\tilde{s}^t = \tilde{s}^{t-1} + \eta^t.$$

6. Remove the "plans to vote for" surveys (which start later than the other four). Modify y^t and z^t to only contain the first four survey responses.

Note that each of the robustness checks considers one change to the main specification (i.e., these are not cumulative changes to the factor analysis). Fitting these models gives us six specifications, each of which produces its own estimate of $\tilde{s}^t$. In Table B.4 we present the correlation matrix of these different approaches. Overall, we see that these methods all produce remarkably similar estimates. The biggest difference from the main model comes from heteroskedastic version, where a separate variance term is estimated for each of the six surveys. However, the correlation here is still roughly 0.9. As such, we conclude that these deviations from the main specification result in little change to $\tilde{s}^t$.

Table B.4: Correlations across measurement specifications

	Model 2	Model 1	Model 3	Model 4	Model 5	Model 6
Model 1	1.00	1.00	1.00	0.88	1.00	0.99
Model 2	1.00	1.00	0.99	0.87	0.99	0.99
Model 3	1.00	0.99	1.00	0.88	1.00	0.98
Model 4	0.88	0.87	0.88	1.00	0.89	0.91
Model 5	1.00	0.99	1.00	0.89	1.00	0.99
Model 6	0.99	0.99	0.98	0.91	0.99	1.00

C First stage robustness

In this appendix, we consider the robustness of the first-stage model and the estimates of γ. Specifically, we want to be sure that the relationship between attacks and relative popularity is not being driven or confounded by other factors that may affect each group's decision to attack and their relative popularity. In particular, we will consider economic factors, the conflict environment, and the public's underlying support for violence against Israel.

To measure the latent variables that describe attitudes toward violence and the economic situation we will again aggregate survey data using dynamic factor models. Both models use the same basic specification described in Equations B.2 and B.3, but with different surveys forming z^t and as such a different latent variable output (i.e., $\tilde{v}^t$ and $\tilde{u}^t$ for attitudes for violence and unemployment, respectively rather than $\tilde{s}^t$). For attitudes towards violence we use survey questions that record 26 different responses to various aspects of the conflict/peace process. From the surveys run by Jerusalem Media and Communication Centre (JMCC) (N.d) we include:

- 4 responses about attitudes to a two-state solution
- 2 responses about attitudes towards peace negotiations
- 2 responses about attitudes towards military operations against Israeli targets
- 2 responses about attitudes towards suicide bombings against Israeli civilians
- 4 responses about optimism/pessimism regarding a peaceful settlement with Israel

- 3 responses about attitudes towards the Oslo peace process
- 2 responses about attitudes towards the 2nd *Intifada*
- 3 responses about whether the current peace process is alive, dead, or unclear.

Additionally, we add some 4 responses from surveys by Palestinian Center for Policy and Survey Research (PCPSR) (N.d) that record support for armed attacks against

- Israel generally
- Israeli civilians
- Israeli soldiers
- Israeli settlers in the West Bank.

Many of these variable are correlated. We avoid perfect correlations between combinations of factors by the virtue of "don't know," "no answer," and similar non-answers. The high correlations across answers and across questions provides us with strong evidence that these responses can be reduced into a latent measure. The factor weights are reported in Table C.1. All of the surveys load in the expected way where surveys that should correlate with approval towards violent tactics load positively and surveys that correlate with approval of peaceful tactics and negotiated settlement load negatively. Additionally, we see that the latent support for violence reaches a minimum during Oslo and a maximum during the second *Intifada*. Overall, this give us strong assurance that the latent variable captures the Palestinian public's underlying attitudes toward violence against Israel at any given month.

For the unemployment latent variable we combine four survey responses

1. % of respondents telling pollster they are unemployed to Jerusalem Media and Communication Centre (JMCC) (N.d) pollsters
2. % of respondents telling pollster they are unemployed to Palestinian Center for Policy and Survey Research (PCPSR) (N.d) pollsters
3. Estimated true unemployment by Palestinian Center for Policy and Survey Research (PCPSR) (N.d)
4. Unemployment rate reported in Labor Force Surveys published by the Palestinian Central Bureau of Statistics (PCBS) (N.d)

These results are reported in Table C.2. Here we see that all the unemployment rates load onto the latent dimension in the same direction, but with different weightings.

Table C.1: ML estimates for latent support for violence

Variable	Est.
% Supporting two-state solution	-0.14
% Supporting a one shared state solution	0.02
% Supporting a one Islamic state solution	0.14
% Saying there is no solution	0.13
% Supporting a peace process	-0.16
% Opposing a peace process	0.16
% Supporting military action against Israel	0.16
% Opposing military action against Israel	-0.16
% Supporting suicide bombings	0.16
% Opposing suicide bombings	-0.16
% Very optimistic about peace	-0.15
% Optimistic about peace	-0.15
% Pessimistic about peace	0.12
% Very pessimistic about peace	0.16
% Strongly support Oslo	-0.11
% Support Oslo	-0.10
% Oppose Oslo	0.13
% Support the *Intifada*	0.09
% Oppose the *Intifada*	-0.08
% Who think peace is dead	0.09
% Who think the peace process is stalled	-0.02
% Who think peace is alive	-0.12
% Support armed attacks generally	0.16
% Support armed attacks against civilians	0.15
% Support armed attacks against soldiers	0.12
% Support armed attacks against settlers	0.11

With these measures in hand, we can check the robustness of the first stage relations. As seen in Table C.3 (which should be compared to Table 1 in the main text), the effect of attacks on relative popularity are similar across all specifications, and the new control variables are all related to popularity in expected directions. As the economy gets worse (changes in latent unemployment increase), the balance of support tends to shift toward Hamas, although this not significant in every model. Further as changes in the latent support for violence among the population increase, support moves towards Hamas. Finally, during the Second Intifada support was stronger for Hamas relative to other stages in the conflict.

Looking at the final model, we see that switch from a binary measure of terrorism to a count of the number of terrorist attacks in month t does not change the main result. This consistency across measurement is reassuring as we do not want the first stage to

Table C.2: ML estimates for latent unemployment conditions

Variable	Est.
Self reported unemployment rate (JMCC)	0.15
Self reported unemployment rate (PCPSR)	0.16
Estimated unemployment rate (PCPSR)	0.06
Estimated unemployment rate (PCBS)	0.17

Table C.3: Robustness checks for the first-stage model: Specification changes

	Dependent variable:					
	Δ State					
	(1)	(2)	(3)	(4)	(5)	(6)
Hamas Attacks	−0.21	−0.20	−0.23	−0.22	−0.20	−0.33
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.06)
Fatah Attacks	1.00	1.06	1.04	1.04	1.05	1.13
	(0.08)	(0.04)	(0.04)	(0.04)	(0.03)	(0.10)
Δ Lag state	0.34	0.30	0.24	0.20	0.18	0.14
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)
Second *Intifada*				−0.12	−0.13	−0.11
				(0.04)	(0.04)	(0.04)
Δ unemployment		−0.25	−0.13	−0.09	−0.06	−0.06
		(0.09)	(0.08)	(0.05)	(0.06)	(0.06)
Δ support for violence			−0.26	−0.30	−0.34	−0.25
			(0.06)	(0.06)	(0.06)	(0.07)
Time since last election					−0.003	−0.005
					(0.001)	(0.002)
Palestinian fatalities						−0.0001
						(0.0001)
Constant	−0.01	−0.01	0.01	0.02	0.08	0.12
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.04)
Interactions	No	Yes	Yes	Yes	Yes	Yes
T	298	298	298	298	298	212
adj. R^2	0.720	0.748	0.788	0.800	0.812	0.822
$\hat{\sigma}$	0.183	0.174	0.160	0.155	0.150	0.146

Note: Newey-West standard errors in parenthesis.

be dependent on the level of aggregation used.[1] Additionally, we see that the decision to include the interaction between the lagged state and the actions does not affect the

[1] The only circumstance where we fail to reject the null of equally effective groups is in Model 7, but only when $\tilde{s}^t < -11$. So if Hamas is *extremely* popular, the two groups might be equally effective at moving the states space according to one of the seven models.

Table C.4: Robustness checks for the first-stage model: Measurement changes

	Dependent variable:			
	Δ State			
	(1)	(2)	(3)	(4)
Hamas attacks (count)	−0.03			
	(0.01)			
Fatah attacks (count)	0.41			
	(0.05)			
Hamas attacks (binary)		−0.20		
		(0.03)		
Fatah attacks (binary)		1.02		
		(0.04)		
Hamas fatalities/attack				−0.02
				(0.01)
Fatah fatalities/attack				0.67
				(0.07)
Second Intifada	−0.17	−0.13	−0.16	−0.20
	(0.04)	(0.04)	(0.04)	(0.05)
Δ Lag unemployment	−0.08	−0.06	−0.06	−0.06
	(0.06)	(0.06)	(0.06)	(0.06)
Δ Lag support for violence	−0.31	−0.34	−0.31	−0.31
	(0.07)	(0.06)	(0.06)	(0.08)
Time since last election	−0.004	−0.003	−0.004	−0.003
	(0.001)	(0.001)	(0.001)	(0.001)
Δ Lag state	0.11	0.18	0.15	0.17
	(0.06)	(0.04)	(0.06)	(0.07)
Fatah Fatalities		0.01	0.31	
		(0.01)	(0.05)	
Hamas Fatalities		0.0005	−0.01	
		(0.001)	(0.002)	
Constant	0.08	0.08	0.07	0.07
	(0.04)	(0.03)	(0.03)	(0.04)
Interactions	Yes	Yes	Yes	Yes
T	298	298	298	298
adj. R^2	0.508	0.813	0.394	0.431
$\hat{\sigma}$	0.243	0.150	0.270	0.261

Note: Newey-West standard errors in parenthesis.

main result either. Overall, these various robustness checks of the AR(1) model provide confidence in our using it in the first stage of the analysis.

D Standard errors

In this appendix, we describe the standard errors reported for the two-step CMLE estimates and consider how sensitive the structural estimates of β and κ are to the first-stage estimates γ. The standard result on two-step estimation involving a maximum likelihood estimator comes from Murphy and Topel (1985). Aguirregabiria and Mira (2007) use this result to describe the asympotic distribution of the two-step pseudo-likelihood estimator from Hotz and Miller (1993) and we follow the same logic here. Specifically, let $\theta_2 = (\beta, \kappa, v)$ be the set of parameters estimated in the second stage, then the two-step correction gives the variance of $\hat{\theta}_2$ as

$$\widehat{\text{var}}(\hat{\theta}_2) = \hat{\Sigma}_{\theta_2} + \hat{\Sigma}_{\theta_2}\left(\hat{\Omega}\hat{\Sigma}_{\gamma}\hat{\Omega}^{\mathrm{T}}\right)\hat{\Sigma}_{\theta_2},$$

as described in Aguirregabiria and Mira (2007, Proposition 1). Here $\hat{\Sigma}_{\theta_2}$ is the ordinary CMLE covariance matrix described by Silvey (1959) which is

$$\hat{\Sigma}_{\theta_2} = \begin{bmatrix} H_{\theta_2} L(\hat{v}|Y) + J_{\theta_2}\mathcal{V}(\hat{\theta}_2;\hat{\gamma})^{\mathrm{T}} J_{\theta_2}\mathcal{V}(\hat{\theta}_2;\hat{\gamma}) & -J_{\theta_2}\mathcal{V}(\hat{\theta}_2;\hat{\gamma})^{\mathrm{T}} \\ -J_{\theta_2}\mathcal{V}(\hat{\theta}_2;\hat{\gamma}) & \mathbf{0} \end{bmatrix}^{-1},$$

where H_x and J_x respectively denote the Hessian and the Jacobian of a function with respect to x.

The remaining two matrices are related to the first-stage estimates $\hat{\gamma}$. The matrix $\hat{\Omega}$ describes how the CMLE's Lagrangian changes with respect to γ and θ_2 and is given by

$$\hat{\Omega} = \begin{bmatrix} J_{\theta_2} L^*(\hat{v}|Y,\hat{\gamma})^{\mathrm{T}} J_{\gamma} L^*(\hat{v}|Y,\hat{\gamma}) + J_{\theta_2}\mathcal{V}(\hat{\theta}_2;\hat{\gamma})^{\mathrm{T}} J_{\gamma}\mathcal{V}(\hat{\theta}_2;\hat{\gamma}) \\ \mathbf{0} \end{bmatrix}.$$

Here, L^* is the vector-valued log-likelihood of the entire data:

$$L^*(v|Y,\gamma) = \left(\log P(a_H^t; s^t, v_H) + \log P(a_H^t; s^t, v_H) + \log f(s^t; a^{t-1}, s^{t-1}, \gamma)\right)_{t=1}^{T}.$$

Note that for a given estimate of γ, the transition probabilities are fixed and so using either $L(v|Y)$ or $\sum_{t=1}^{T} L^*(v|Y,\hat{\gamma})$ as the CMLE's objective function will return the same constrained maximum likelihood estimates of θ_2.[2] The final piece is the first-stage covariance matrix $\hat{\Sigma}_{\gamma}$, which we construct using a parametric bootstrap.

[2]For completeness in L^* we impose $f(s^1; a^0, s^0, \gamma) = 1$ or $\log(f(s^1; a^0, s^0, \gamma)) = 0$

E Robustness to different time spans

In this appendix, we consider four different alternative time frames for the main model. We consider these different time spans because they all represent plausible break points in the Fatah-Hamas relationship, such that the underlying competition between the groups may have changed. As such we want to be sure that our estimates of the groups' preferences are robust to the exclusion of some of these later observations. Specifically, we consider the following three cutpoints:

1. The formation of the Fatah-Hamas unity government in April 2014 (last month is Mar. 2014)
2. The signing of the first Fatah-Hamas unity agreement in 2011 (last month is Apr. 2011),
3. Hamas wins the 2006 legislative elections (last month is Dec. 2005).
4. The start of the Second Intifada in 2001 (last month is Aug. 2000).

The results of these short-T robustness checks are presented in Table E.1 along with a reproduction of the main model (1994-2018) for comparison. Overall we see very few changes across the four models. In general, the estimates are very stable across samples. The CMLE failed to converge in the last sample so we employ an alternative estimation method called the nested-pseudo-likelihood estimator (Aguirregabiria and Mira 2007; Crisman-Cox and Gibilisco 2020).

Table E.1: Robustness to different time periods

	Full Sample	2014 Agreement	2011 Agreement	2006 Elections	Second Intifada†
β_H	−0.007	−0.007	−0.007	−0.021	−0.007
	(0.004)	(0.005)	(0.004)	(0.013)	(0.004)
β_F	0.0005	0.0006	0.0005	0.0005	0.0005
	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0152)
κ_H	−0.95	−0.90	−0.69	−0.74	−0.89
	(0.23)	(0.23)	(0.22)	(0.26)	(0.10)
κ_F	−2.45	−2.47	−2.31	−2.34	−2.89
	(0.28)	(0.31)	(0.28)	(0.26)	(0.23)
T	300	243	208	144	80
LL	−278.09	−230.98	−206.84	−125.27	−71.82

Note: †CMLE did not converge, estimates from nested-pseudo-likelihood (NPL) estimator. Samples begin at Jan. 1994 and end in one month prior to the event listed.

Table F.1: Discount factors and model fit

δ	Log-Likelihood
0	-284.18
0.9	-280.98
0.925	-281.54
0.95	-282.43
0.975	-283.67
0.99	-280.35
0.999	-278.09
0.9999*	-288.14

Note: * Model failed to converge.

F Choice of discount factor

In this appendix we consider how our choice of discount factor affects our results. Specifically we fix δ to 0 and then a few different values in the interval $[0.9, 1)$ and then reestimate the second-stage model at each value. Table F.1 shows the log-likelihood of the second-stage model under different fixed values of the discount factor δ. The model with the best fit among these options is $\delta = 0.999$. As such we use this value in both the main model specification and the numerical examples.

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