Online Appendix

Battle Diffusion Matters: Examining the Impact of Microdynamics of Fighting on Conflict Termination

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Gaku Ito*
Hiroshima University
gkit@hiroshima-u.ac.jp

Kaisa Hinkkainen Elliott†
University of York
kaisa.hinkkainenelliott@york.ac.uk

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Contents

*Assistant Professor, Graduate School for International Development and Cooperation, Hiroshima University. 1–5–1 Kagamiyama, Higashihiroshima, Hiroshima 739–8529, Japan.

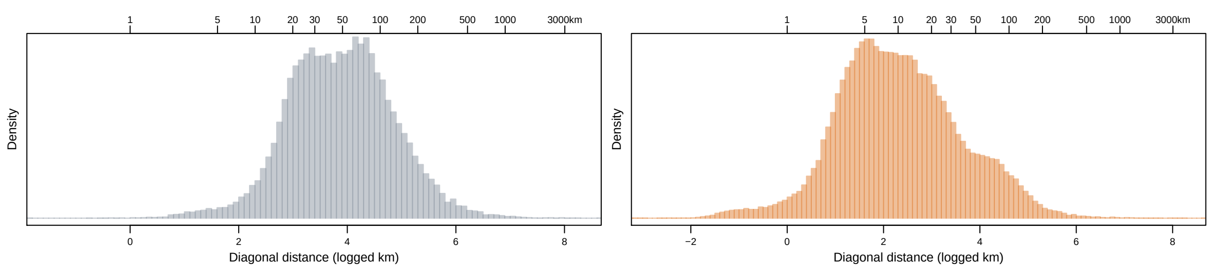
†Lecturer, Department of Politics, Derwent College, University of York. Heslington, York, YO10 5DD, United Kingdom

Overview

This Online Appendix provides supplementary figures to the baseline analysis and reports a series of additional estimation results to assess the robustness of the empirical findings reported in the main text. Appendix A provides supplementary figures briefly referred in the main text to describe the coding procedure. Appendix B reports the estimation results for *Naive Diffusion* across different spatial grid settings, and Sections C to G each address the major sensitivity concerns of the main empirical results, including the regressions distinguishing the instances of conflict termination with different outcomes. Reassuringly, none of these sensitivity tests yield results that deviate markedly from the main results reported in the main text. These results provide confidence that the specific parameter settings and assumptions are not driving our main empirical findings.

Note that we primarily relied on sf and sp packages in R (Bivand et al., 2013; Pebesma & Bivand, 2005) and a series of original R implementations in the geoprocessing operations. The accompanying files provide the data sets and R scripts required to replicate the main analysis and the additional estimations reported below.

A Supplements to the Main Analysis

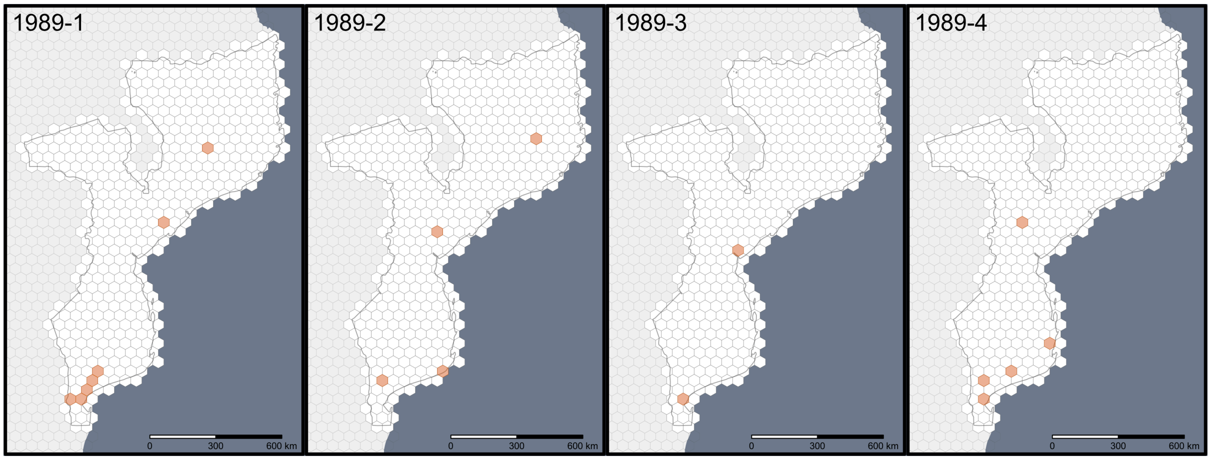


(a) Second-level administrative divisions (b) Third-level administrative divisions

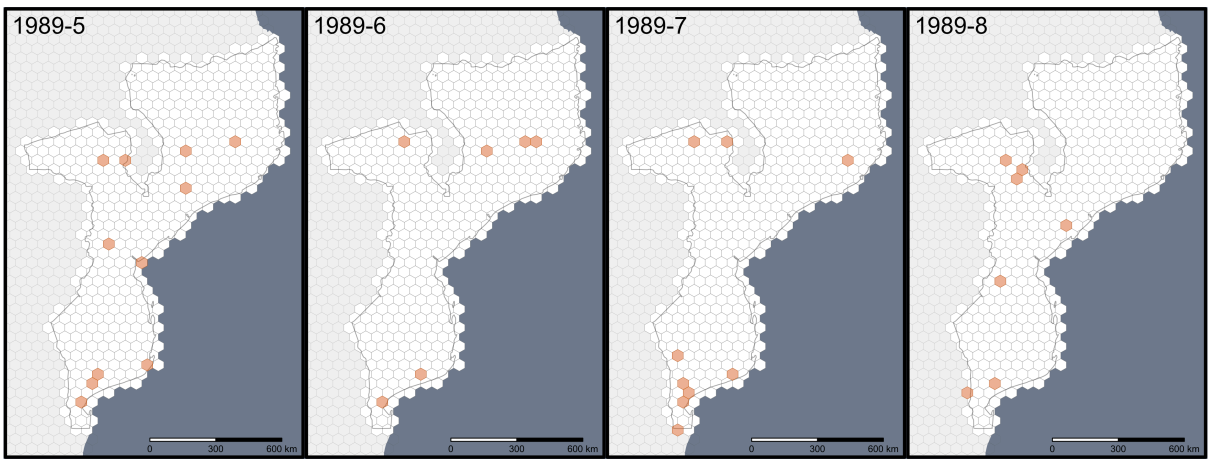
Figure A.1: Distribution of diagonal distance of administrative divisions
Note: Data derived from GADM database of Global Administrative Areas (http://www.gadm.org/).

B Effect of Naive Diffusion

Our empirical analysis suggests that *Naive Diffusion*, or the changes in the scope of conflict zones, are unlikely alter the prospects of conflict termination. Yet, as the MAUP



(a) January (b) February (c) March (d) April



(e) May (f) June (g) July (h) August

Figure A.2: Evolution of conflict geography in the Mozambican civil war, Jan–Aug, 1989

Note: (a)–(h) distribution of grid cells with 1+ battle events in the Mozambican civil war, 1989 (cells in orange). Spatial grids with resolution $r = 50$ are employed for the visibility purpose.

suggests, it is possible that the null findings are specific to the baseline spatial grid setting with resolution $r = 30$ km and neighborhood order $k = 1$.

To address this issue, Figure B.1 replicates the estimates of *Naive Diffusion* on conflict termination and outcomes varying the spatial grid specifications. As the results indicate, the effect of *Naive Diffusion* on the chance of conflict termination remains statistically and substantially insignificant across different spatial grid settings, suggesting that the baseline null finding is not likely to be the product of the arbitrary selection of grid resolution and neighborhood order.

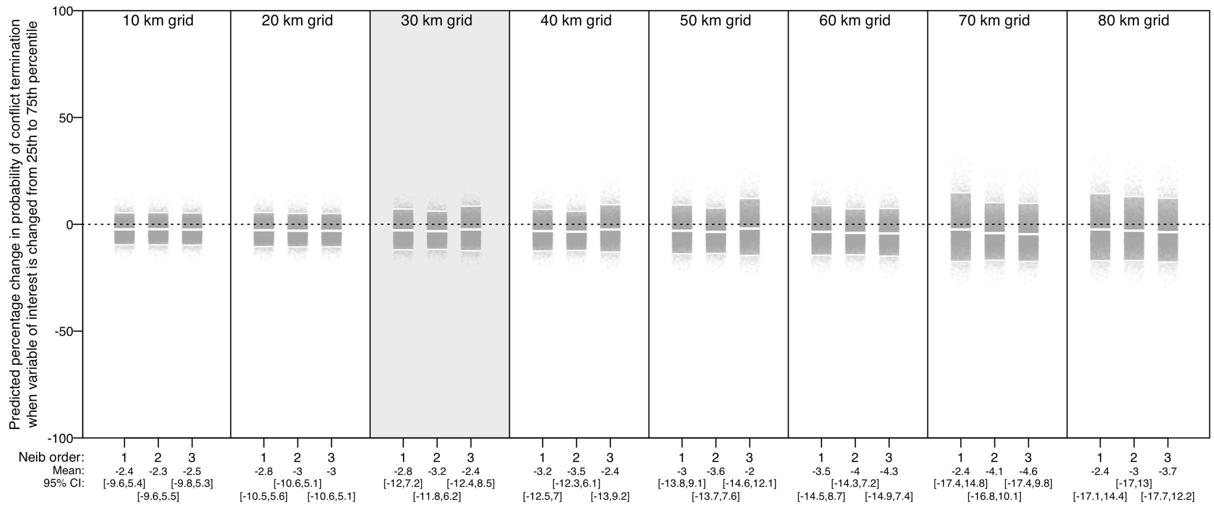


Figure B.1: Effect of *Naive Diffusion* as percentage change in probability of conflict termination across differently specified rectangular grids

Notes: See notes in Figure 4 in the main text.

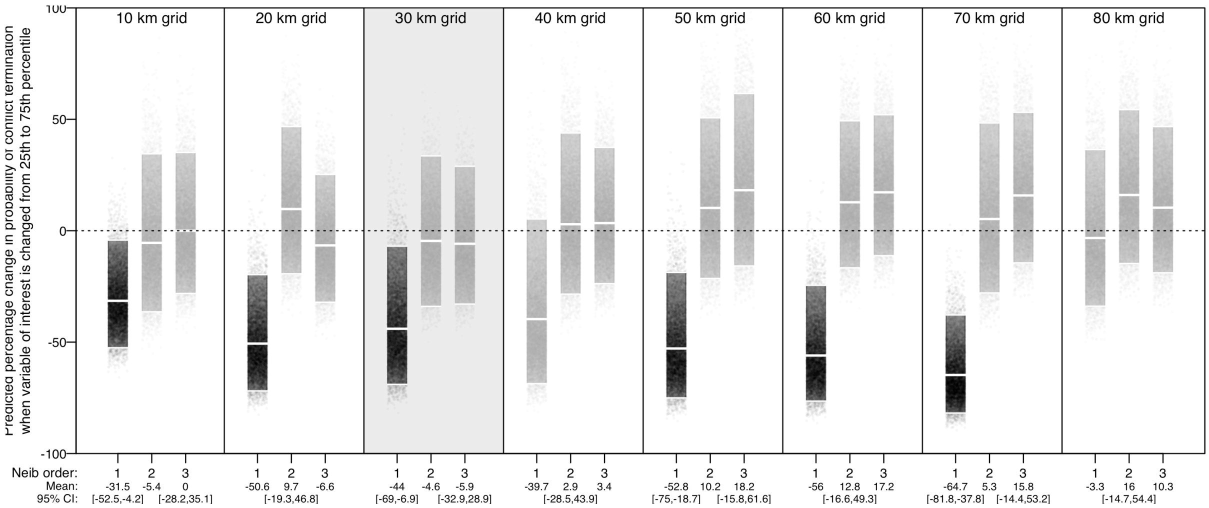
C Alternative Spatial Grid Specification

The results reported in the main text suggest that the estimations on the effect of diffusion terms can vary, either qualitatively or quantitatively, depending on the selection of gird resolution and neighborhood order. Because the selection of grid *shape* as well as grid resolution and neighborhood size could alter when detecting instances of proximate diffusion and distant diffusion, an explicit statistical examination is needed to ensure that the main findings reported in the main text are not results of arbitrary spatial grid definition.

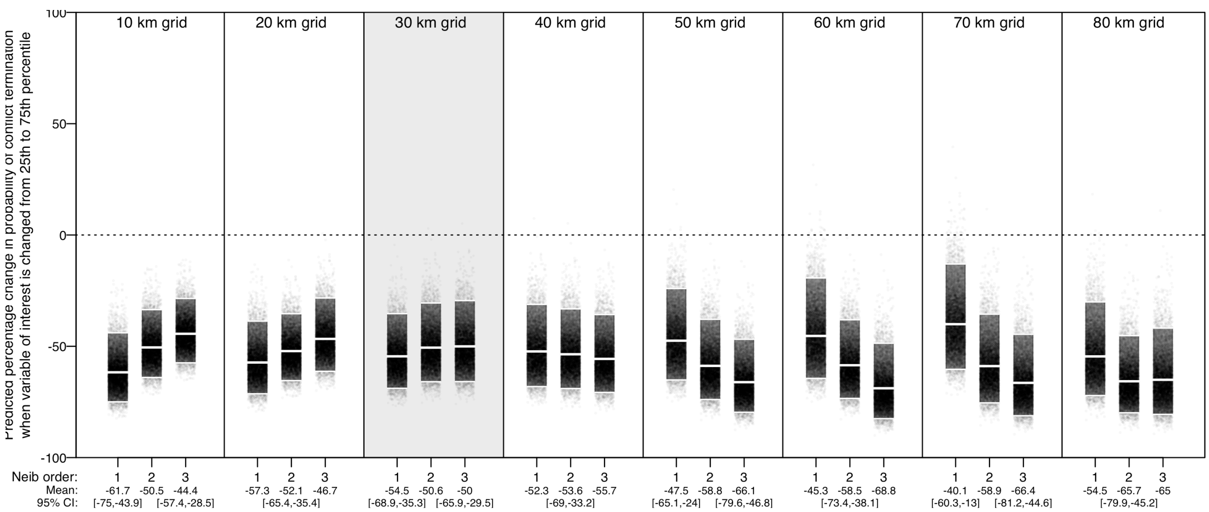
While the analysis in the main text employs a hexagonal grid to detect diffusion patterns, the following robustness check measures battle diffusion using rectangular grids and replicate the main regression models to explore the effect of the selection of spatial units on estimation results. Figure C.1 replicates the estimation reported in Table 3 and Figure 4 in the main text using differently specified rectangular grids.[1]

Reassuringly, the estimation results in Figures C.1(a) and C.1(b) do not deviate markedly from the main results: *Distant Diffusion* consistently has a substantial and negative impact on the probability of conflict termination across different grid settings, while the effect of *Proximate Diffusion* remains indeterminate or sensitive to the grid

[1] Neighborhood in a rectangular grid is defined as the Moore (Queen) neighborhood, where the neighborhood includes four orthogonal and four diagonal neighbors.



(a) First difference estimates for proximate diffusion



(b) First difference estimates for distant diffusion

Figure C.1: Effect of violence diffusion as percentage change in probability of conflict termination across differently specified rectangular grids

Notes: See notes in Figure 4 in the main text.

specifications. These additional results provide confidence that the specific parameter settings are not driving the main findings.

D Alternative Temporal-Window Specification

The baseline setting measures the diffusion terms as moving average over previous Δt months with $\Delta t = 6$. As the size of temporal window can affect the detection of the diffusion terms (and the estimates for all other covariates measured as moving-average), Figure D.1 replicates the main regression models with an alternative window size $\Delta t = 12$. These robustness checks do not alter the main findings qualitatively. Although the marginal effect estimates vary depending on the temporal window sizes, the results remain substantially unchanged across different temporal window settings.

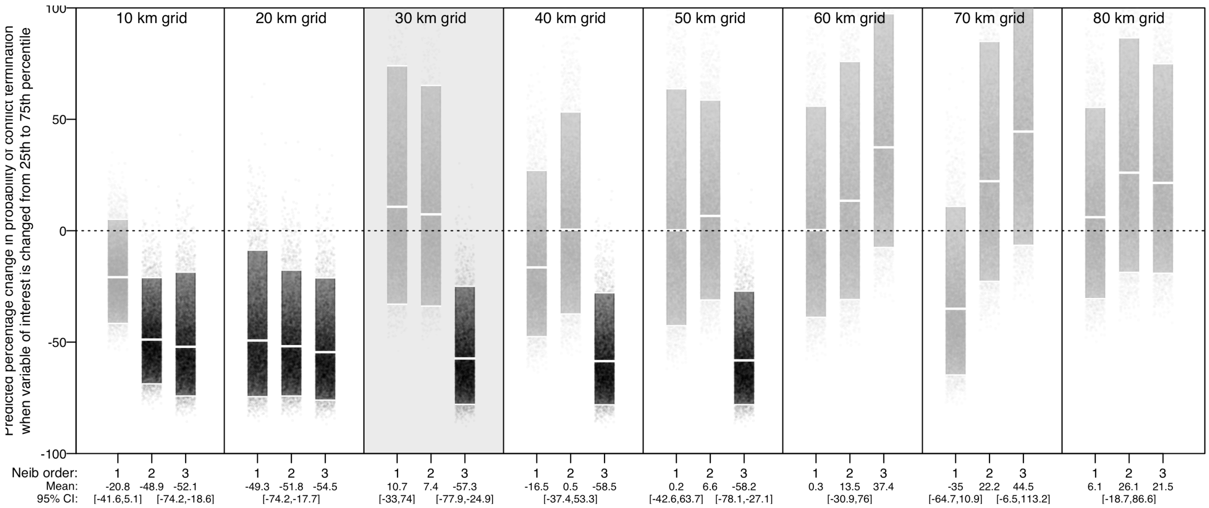
E Battle Diffusion and Conflict Outcomes

While our empirical analysis primarily focuses on the associations between different diffusion patterns of battle activities and conflict duration, the analysis presented in the following two sections also takes a closer look at *how*, as well as *when*, conflict ends. Specifically, we disaggregate the observations of conflict termination into two broad outcome categories of *Negotiated Settlement* ("ceasefire agreement" and "peace agreement") and *Military Outcome* ("victory for government side," "victory for rebel side," and "low activity" in the original coding of Kreutz, 2010). The analysis allows for exploring how diffusion dynamics shape the course of intra-conflict bargaining, which corresponds to our theoretical accounts. In our dataset, 59 cases of conflict termination are coded as *Negotiated Settlement* and 90 are coded as *Military Outcome*.

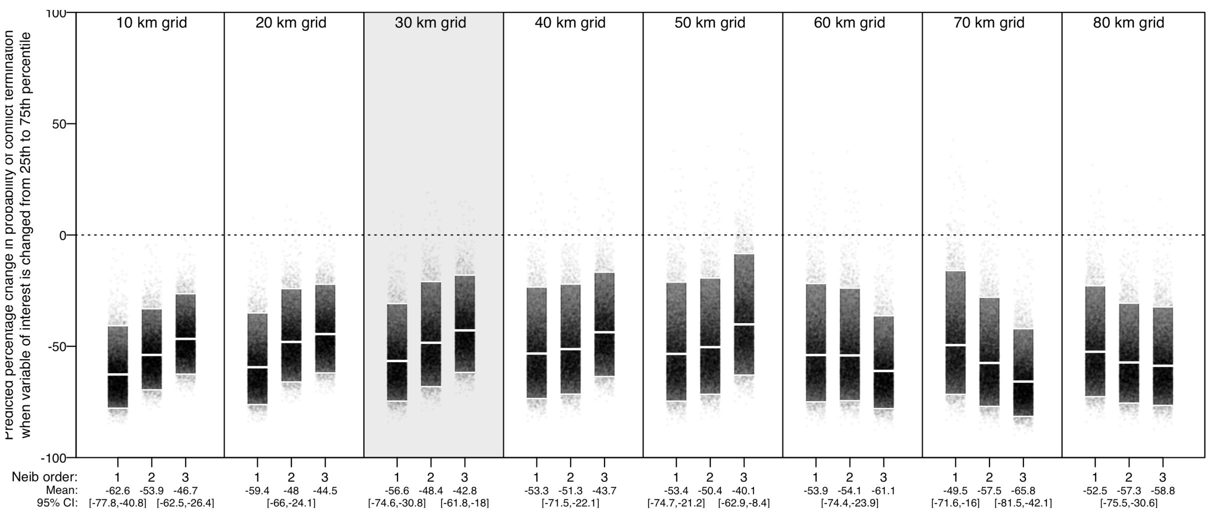
The following analysis utilizes the multinomial logit estimator to examine the determinants of conflict outcomes.[2] Table E.1 reports the outcome regression estimates, with the model specification following Model 3 in Table 3 in the main text. Figures E.1 and E.2 simulate and plot the first difference estimates for the impacts of *Distant Diffusion* and *Proximate Diffusion* on the likelihood of each conflict outcome compared to the baseline category of *Continuation*, respectively. Appendix F replicates the estimation with competing-risks regression models.

Two findings emerge and lend additional support for our argument. First, *Distant Diffusion* has a statistically and substantially significant impact on the chances of con-

[2]We replicated the following analysis using multinominal probit estimator and confirm that the alternative estimator yields similar results, suggesting that potential violation of the Independent and Irrelevant Alternatives (IIA) assumption is not likely to alter the main results.



(a) First difference estimates for proximate diffusion



(b) First difference estimates for distant diffusion

Figure D.1: Effect of violence diffusion as percentage change in probability of conflict termination with $\Delta t = 12$

Notes: See notes in Figure 4 in the main text.

flict termination with a negotiated settlement. In the baseline spatial grid setting with $r = 30$ km and $k = 1$, the coefficient estimate of -0.588 translates into a substantial interpretation that an interquartile increase in *Distant Diffusion* results in a 54.5% (95% CI: $-76.8, -19.0$) reduction in the probability of a civil conflict ending in a negotiated settlement. This estimated effect remains qualitatively unchanged across different spatial grid specifications (Figure E.1(a)). Similarly, increasing instances of *Distant Diffusion*

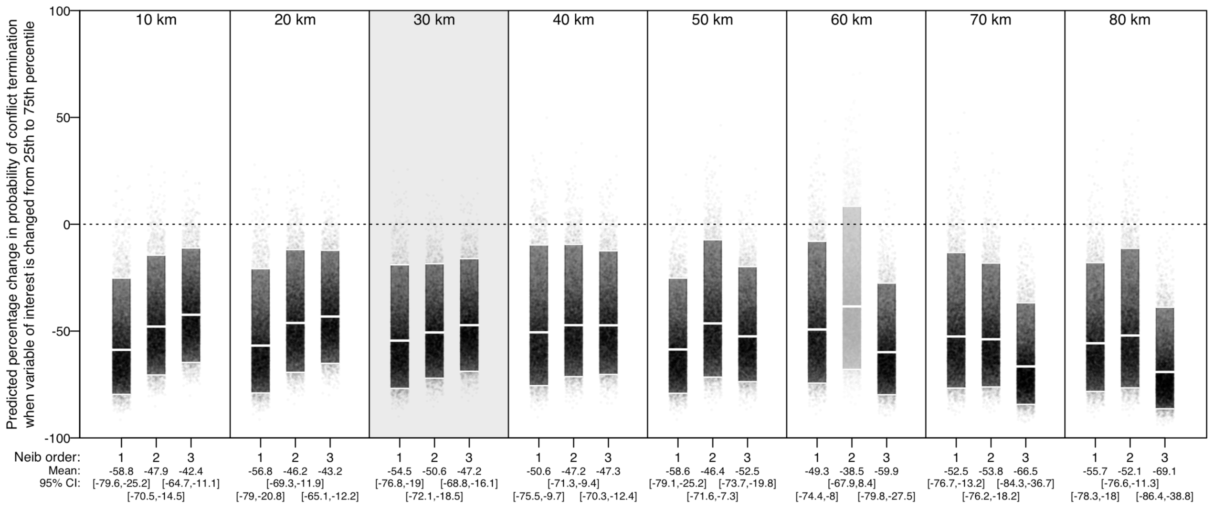
Table E.1: Multinominal logit model of conflict outcome

	Dependent variable: Conflict Outcome	
	Military Outcome	*Negotiated Settlement*
Violence diffusion		
Proximate Diffusion	0.200 (0.512)	−0.379 (0.673)
Distant Diffusion	−0.788** (0.162)	−0.588** (0.221)
Naive Diffusion	0.164 (0.167)	−0.172 (0.088)
Government attributes		
GDP	−0.338 (0.237)	−0.231 (0.452)
Democracy	−0.403 (0.351)	0.845 (0.493)
Country Size	−0.277 (0.285)	0.390 (0.356)
Rebel attributes		
Territorial Control	−0.253 (0.274)	0.004 (0.310)
Ethnic Claim	−0.127 (0.245)	0.092 (0.312)
Rebel Much Weaker	0.627* (0.255)	−1.334** (0.366)
Multi Party	0.232 (0.292)	−0.057 (0.305)
Conflict dynamics		
Conflict Intensity	−0.036 (0.123)	0.091 (0.133)
Cumulative Casualties	0.163* (0.076)	0.140 (0.079)
Collateral Damage	−0.118 (0.196)	−0.280 (0.294)
Govt OSV	−0.075 (0.136)	−0.169 (0.116)
Rebel OSV	−0.136 (0.184)	−0.272 (0.165)
Conflict geography		
Capital Distance	0.290 (0.317)	−0.634 (0.526)
Local Population	0.432 (0.247)	−1.058 (0.625)
Natural Resource Distance	0.248 (0.239)	−0.670** (0.205)
Ruggedness	−0.012 (0.236)	−0.011 (0.346)
Road Density	0.191 (0.182)	−0.138 (0.226)
Conflict duration polynomials	✓	✓
Observations	7,341	
Log Likelihood	−675.171	
AIC	1,398.342	
Multiclass in-sample AUC	0.734	

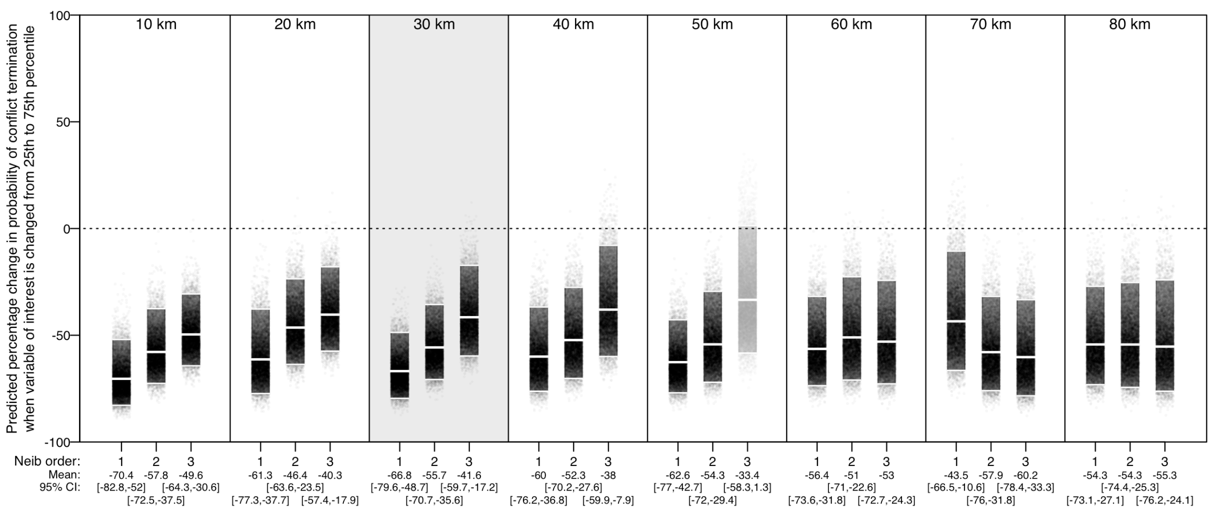
Note: $^{*}p < 0.05$; $^{**}p < 0.01$
Unit of analysis: Conflict dyad-month. Robust standard errors clustered on dyad in parentheses. Intercepts and conflict duration polynomials are omitted for brevity. The multiclass AUC score is computed using the method in Hand & Till (2001).

are also followed by a sizable reduction in the probability that a civil conflict terminates without seeing an negotiated settlement (−66.8%, 95% CI: −79.6, −48.7, with $r = 30$ km and $k = 1$); and the effect is robust to the selection of spatial grid resolution and neighborhood order (Figure E.1(b)). Second, turning to the estimates for *Proximate Diffusion*, the corresponding coefficient fails to retain a discernible effect at the conventional 5% level in almost all spatial grid settings. The results hold for both negotiated settlements and military outcomes (Figures E.2(a) and E.2(b)).

The estimates underscore the substantial impact of *Distant Diffusion* on conflict termination. Although our argument does not explicitly posit the underlying mechanism linking battle diffusion and conflict termination with an military outcomes, the sizable



(a) Effect of distant diffusion on probability of negotiated settlements

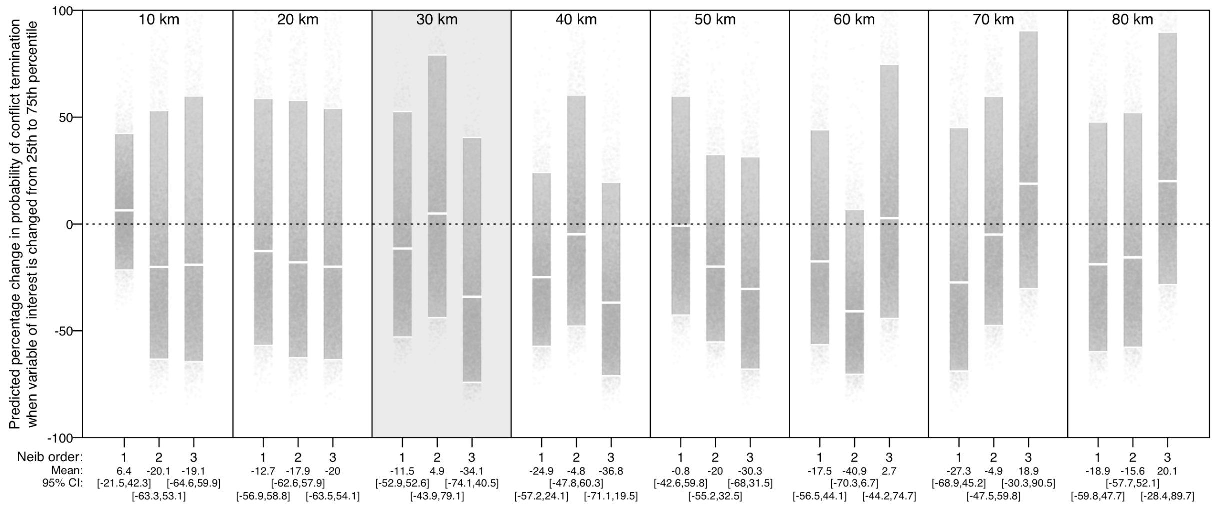


(b) Effect of distant diffusion on probability of military outcomes

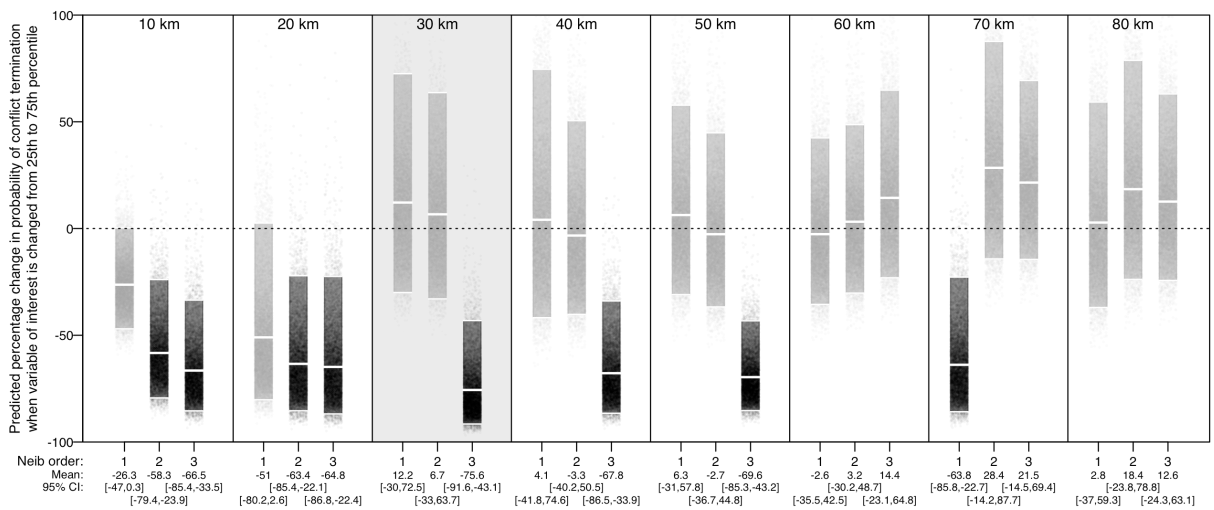
Figure E.1: Effect of distant diffusion as percentage change in probability of *Negotiated Settlements* and *Military Outcomes* across different spatial grid resolutions

Notes: See notes in Figure 4 in the main text. Simulations are based on regression estimate in Table E.1.

negative impact of distant diffusion on conflict termination holds when we focus on negotiated settlements of civil conflict. Combined with the main findings, these results confirm that it is not whether or not battle activities diffuse, but how they diffuse that substantially alters how civil conflict unfolds.



(a) Effect of proximate diffusion on probability of negotiated settlements



(b) Effect of proximate diffusion on probability of military outcome

Figure E.2: Effect of proximate diffusion as percentage change in probability of *Negotiated Settlements* and *Military Outcomes* across different spatial grid resolutions

Notes: See notes in Figure 4 in the main text. Simulations are based on regression estimate reported in Table E.1.

F Competing-Risks Regression

While the estimation in the previous section relies on the logit estimator, the following analysis employs the competing-risks Cox regression model as our dataset contains two possible conflict outcomes or competing risks, *Military Outcomes* and *Negotiated Settle-*

ments. mstate package in R is used to obtain the estimates (de Wreede et al., 2010, 2011; Putter et al., 2007). The competing-risks estimates are obtained using the model specification in Table E.1 in the main text.[3] The spatial grid is specified as in the baseline setting with grid resolution $r = 30$ km and neighborhood order $k = 1$.

Table F.1 reports the cause-specific hazard ratio estimates and corresponding 95% confidence intervals. The cause-specific hazard for cause j refers to the hazard of failing (conflict termination) from cause (outcome type) j in the presence of J competing risks (causes; Putter et al., 2007, 2397). Similar to standard Cox proportional hazard models in the absence of competing risks, cause-specific hazard ratios can be interpreted relative to 1. Cause-specific hazard ratios less than 1 indicate covariates associated with longer duration until conflict termination with a particular outcome, whilst those with cause-specific hazard ratios greater than 1 are associated with shorter duration.[4] As these estimations show, the main empirical results remain qualitatively unchanged: *Distant Diffusion* has a statistically and substantially negative impact on the chances of both *Military Outcomes* and *Negotiated Settlements*, while the cause-specific hazard ratio estimates for *Proximate Diffusion* and *Naive Diffusion* remain statistically indistinguishable from 1 at the conventional 5% level.[5]

Nonetheless, in the presence of competing risks, the (cause-specific) hazard ratio estimates alone only allow for limited interpretation of the substantial impacts of the corresponding covariates. This is primarily because the effect of a given covariate is modeled for more than one cause of failure (conflict outcomes) in competing-risks Cox regression models. Consequently, the substantial or marginal effect of a change in a given independent variable on cause j depends on its effect on the baseline hazards of all other causes as well as cause j (Beyersmann et al., 2012, 89–121; Putter et al., 2007, 2403–2409). In other words, while a change in a given independent variable can simultaneously affect the baseline cause-specific hazard of more than one cause, the cause-specific hazard ratio

[3]The multinomial logit model can be regarded as a discrete-time survival model in the presence of competing risks, with t^1, t^2, and t^3 mimicking the baseline hazard. See Barnett et al. (2009) and Beyersmann et al. (2012, 164–166) for a related discussion.

[4]The key assumption in the competing-risks Cox regression model is the proportional hazard assumption that the effect of a covariate on the baseline cause-specific hazard of cause j is constant over time. Schoenfeld residual-based tests detect no statistically significant violations of the assumption of proportional (cause-specific) hazards at the 5% level.

[5]We also estimated the competing risks model with frailty (random effect) to account for unobserved heterogeneity across rebel-government dyads using coxme package in R (Therneau, 2015). The results for the diffusion terms remained qualitatively unchanged.

Table F.1: Competing-risks estimates of conflict outcome

	Conflict outcome	
	Military Outcome Cause-specific hazard ratio (95% CI)	*Negotiated Settlement* Cause-specific hazard ratio (95% CI)
Violence diffusion		
Proximate Diffusion	1.250 (0.444, 3.518)	0.643 (0.174, 2.381)
Distant Diffusion	0.492** (0.354, 0.683)	0.597* (0.391, 0.912)
Naive Diffusion	1.173 (0.891, 1.545)	0.907 (0.786, 1.045)
Conflict dynamics		
Conflict Intensity	0.929 (0.712, 1.214)	1.044 (0.794, 1.372)
Cumulative Casualties	1.180* (1.021, 1.363)	1.195* (1.007, 1.419)
Collateral Damage	0.921 (0.612, 1.387)	0.782 (0.445, 1.374)
Govt OSV	0.951 (0.747, 1.211)	0.820 (0.661, 1.017)
Rebel OSV	0.873 (0.604, 1.261)	0.774 (0.568, 1.055)
Government attributes		
per capita GDP	0.662 (0.419, 1.046)	0.777 (0.317, 1.904)
Democracy	0.678 (0.345, 1.335)	2.193 (0.860, 5.592)
Country Size	0.770 (0.448, 1.323)	1.587 (0.781, 3.224)
Rebel attributes		
Territorial Control	0.766 (0.458, 1.280)	0.969 (0.530, 1.771)
Ethnic Claim	0.958 (0.619, 1.483)	1.175 (0.625, 2.208)
Rebel Much Weaker	1.777* (1.094, 2.887)	0.310** (0.156, 0.619)
Multi Party	1.198 (0.692, 2.071)	0.892 (0.468, 1.700)
Conflict geography		
Capital Distance	1.439 (0.779, 2.658)	0.497 (0.183, 1.350)
Local Population	1.553 (0.975, 2.474)	0.356 (0.116, 1.091)
Natural Resource Distance	1.262 (0.781, 2.042)	0.541** (0.361, 0.812)
Ruggedness	0.966 (0.628, 1.487)	0.932 (0.491, 1.770)
Road Density	1.213 (0.838, 1.756)	0.889 (0.576, 1.372)
Observations (months at risk)	7,341	
# Spells (conflict dyads)	199	
# Failures	90	59
Log Likelihood	−346.274	−206.345
Wald Test (df = 20)	67.130**	80.570**
LR Test (df = 20)	54.839**	53.420**
Score (Logrank) Test (df = 20)	53.184**	53.829**

Note: $^{*}p < 0.05$; $^{**}p < 0.01$
Unit of analysis: conflict dyad–month. 95% confidence intervals computed using robust standard errors clustered on dyad in square brackets.

estimate indicates its effect on the hazard of cause j without taking account for its effect on other causes.[6]

In order to facilitate better understanding of the effects of *Distant Diffusion*, the two panels in Figure F.1 plot the cumulative incidence functions (CIFs) of *Military Outcomes* and *Negotiated Settlements*, for median (dashed) and 99th percentile (solid) values of *Distant Diffusion* holding all other variables constant at their median (continuous) or mode (binary), respectively. Cumulative incidence functions in Figure F.1 represent the proba-

[6]Alternative approaches include regressing directly cumulative incidence functions rather than cause-specific hazards (Fine & Gray, 1999) and reduced rank proportional hazards models (Fiocco et al., 2006).

bility that conflict termination with *Military Outcomes* (left) and *Negotiated Settlements* (right) occur before time (conflict month) t for a given levels of covariates. Because cumulative incidence functions take account for the covariate effects for more than causes, these estimates allow for intuitive interpretation of substantial effect of *Distant Diffusion* on different conflict outcomes.

Figure F.2 plots the stacked transition probabilities to give another graphical representation of the competing-risks regression estimates, with median (left) and 99th percentile (right) values of *Distant Diffusion*. The left panel of Figure F.2 plots the dashed curves in the two panels of Figure F.1 in a single figure, whilst the right panel stacks the probabilities represented by solid curves in Figure F.1. As in Figure F.1, all other variables are held constant at their median or mode. In both panels, the horizontal axis indicates the number of months since the conflict onset, while the distance between two adjacent curves on the vertical axis indicates the estimated probability of being in the corresponding state (*Continuation*, *Military Outcome*, and *Negotiated Settlements*). As noted in the main text, the average duration of dyadic conflict episodes (spells) is 59.34 months (4.95 years), and the median duration is 30 months (2.5 years).

As Figures F.1 and F.2 show, escalating *Distant Diffusion* of battle activities is followed by substantial declines in the probabilities of failure (conflict termination) from *Military Outcomes* and *Negotiated Settlements* and a corresponding increase of probability of conflict continuation. These figures graphically demonstrate the substantial and negative impact of *Distant Diffusion* on conflict termination with different outcomes and provide further empirical support for our argument.

G Sample Selection and Outliers

The last sensitivity concern is that the sample selection, or the inclusion of outliers with a large number of diffusion observations in a single conflict may have a disproportionate effect on our estimates. To test whether these outliers drive our results, we report a series of subsample coefficient estimation results for the diffusion terms excluding one conflict episode at a time, or groupwise jackknifing of our sample by conflict dyads. As our dataset contains 199 unique dyadic conflict episodes, this dyad-wise jackknife procedure yields 199 distinct subsamples.

Figure G.1 uses a graph to summarize the results of 199 distinct estimations with

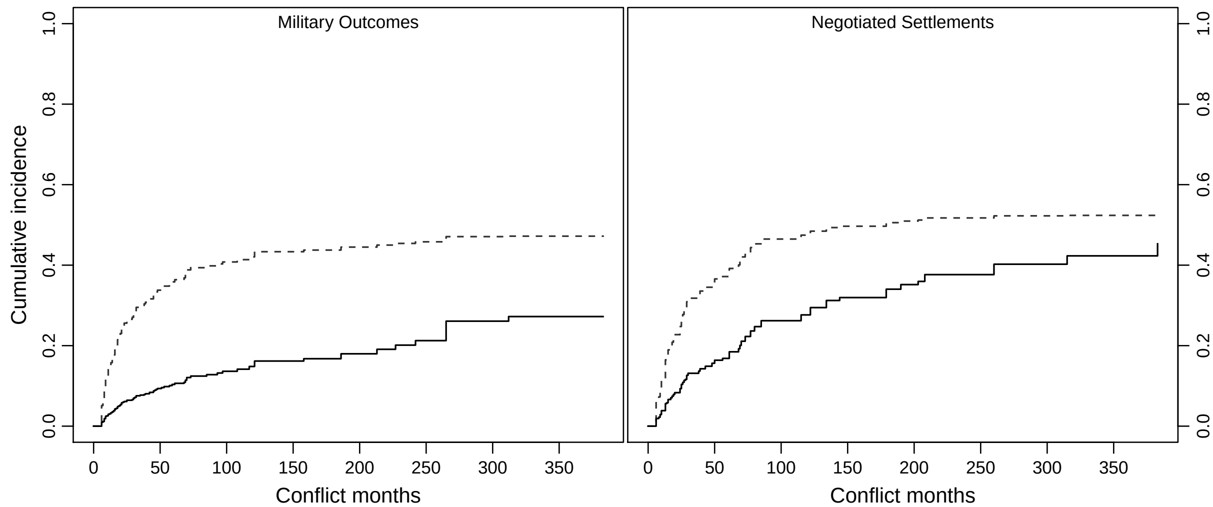


Figure F.1: Cumulative incidence functions for conflict outcomes across different values of *Distant Diffusion*

Notes: Cumulative incidence functions for *Military Outcomes* (left) and *Negotiated Settlements* (right). Solid curves indicate the cumulative incidence functions with *Distant Diffusion* at its 99th percentile value, whilst dashed curves indicate the estimates with *Distant Diffusion* at its median value while holding all other continuous variables constant at their median and binary variables at their mode.

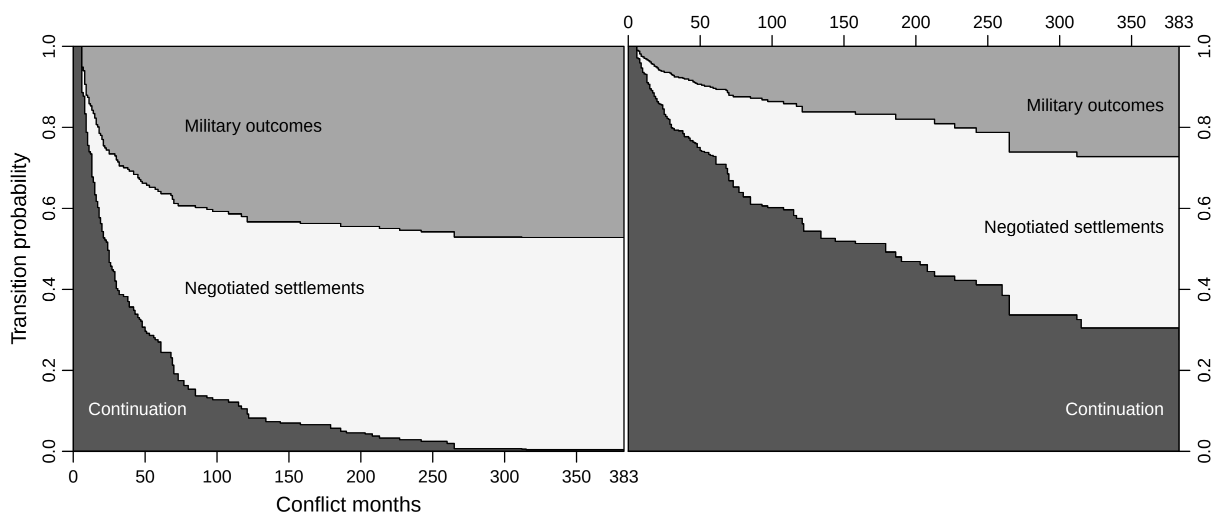
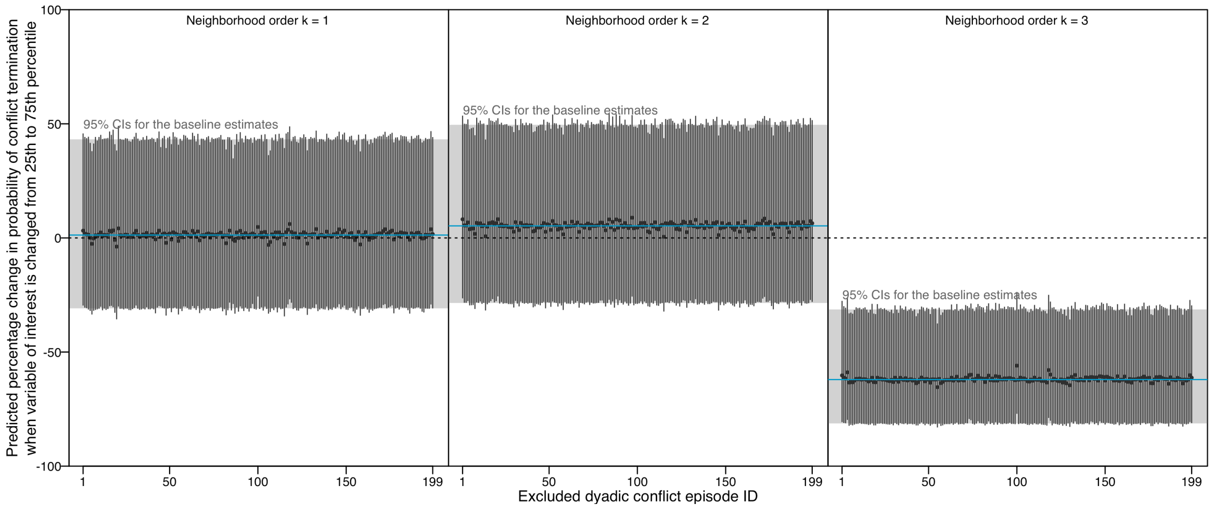
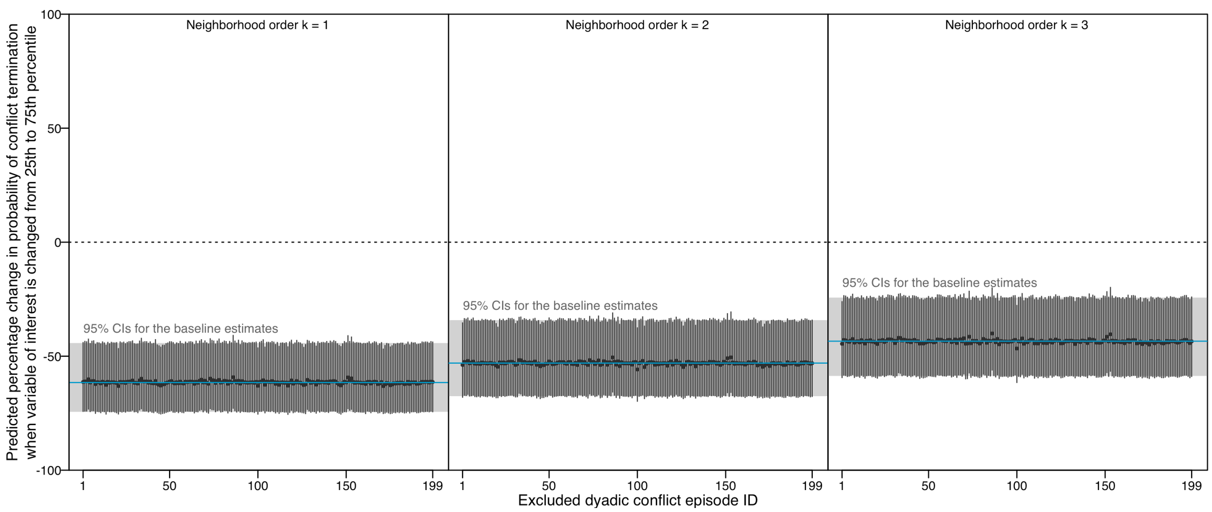


Figure F.2: Stacked transition probabilities of conflict outcomes across different values of *Distant Diffusion*

Notes: The distance between two adjacent curves indicates the estimated probability of being in the corresponding state (*Continuation*, *Negotiated Settlement*, and *Military Outcome*), with median (left) and 99th percentile (right) values of *Distant Diffusion*. All other continuous variables are held constant at their median and binary variables at their mode.



(a) Effect of proximate diffusion on probability of conflict termination



(b) Effect of distant diffusion on probability of conflict termination

Figure G.1: Effect of proximate diffusion as percentage change in probability of conflict termination across subsamples excluding a single dyadic conflict episode

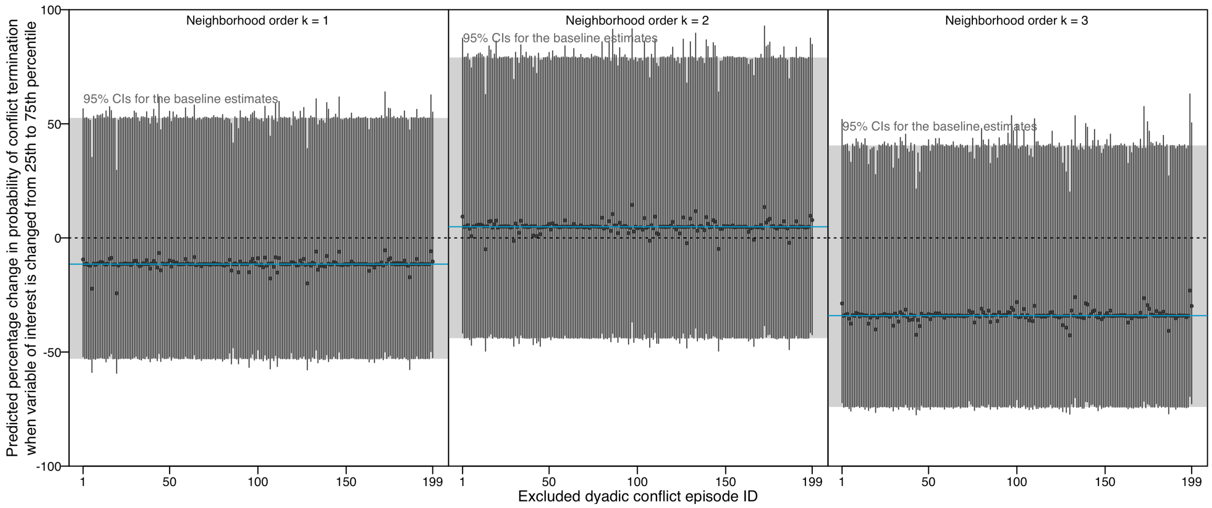
Notes: Each dot indicates a predicted change in probability of conflict termination drawn from a single simulation when *Proximate Diffusion* (*Distant Diffusion*) is changed from the 25th to 75th percentile (first difference estimate), holding all other variables constant at their median (continuous) or mode (binary). Vertical segments indicate the corresponding 95% confidence intervals of predicted values. Blue solid horizontal segment indicates the mean estimate for the full sample (baseline) regression, whereas gray shade represents the corresponding 95% confidence intervals. Black horizontal segment running through each panel indicates the zero-reference line. Uncertainty estimates are obtained by 10,000 simulations. Simulations are based on the model specification of Model 3 in Table 3 in the main text with grid resolution $r = 30$ km.

a different conflict episode excluded from the sample, with reference to the baseline full sample estimates. Specifically, it plots how a specific amount of increase in *Proximate Diffusion* and *Distant Diffusion* (25th to 75th percentile) changes the probability of conflict termination, holding all other continuous variables constant at their median and binary variables at their mode (first difference estimate). Each dot and vertical segment indicates the median estimates and corresponding 95% confidence intervals for a regression estimate excluding a single episode of dyadic conflict. Three panels represent the estimation results across different neighborhood orders. The grid specification is set as the baseline setting, or $r = 30$ km resolution hexagonal grid with neighborhood order k varying from 1 to 3. Uncertainty estimates for the predicted values are obtained via 10,000 simulations following the recommendation of King et al. (2000).[7] Blue solid horizontal segment in each panel indicates the mean estimate for the full sample (baseline) regression, whereas gray shade represents the corresponding 95% confidence intervals. Similarly, Figures G.2 and G.3 plot the simulated impacts of diffusion terms on *Military Outcomes* and *Negotiated Settlements* across different subsamples, respectively.[8]

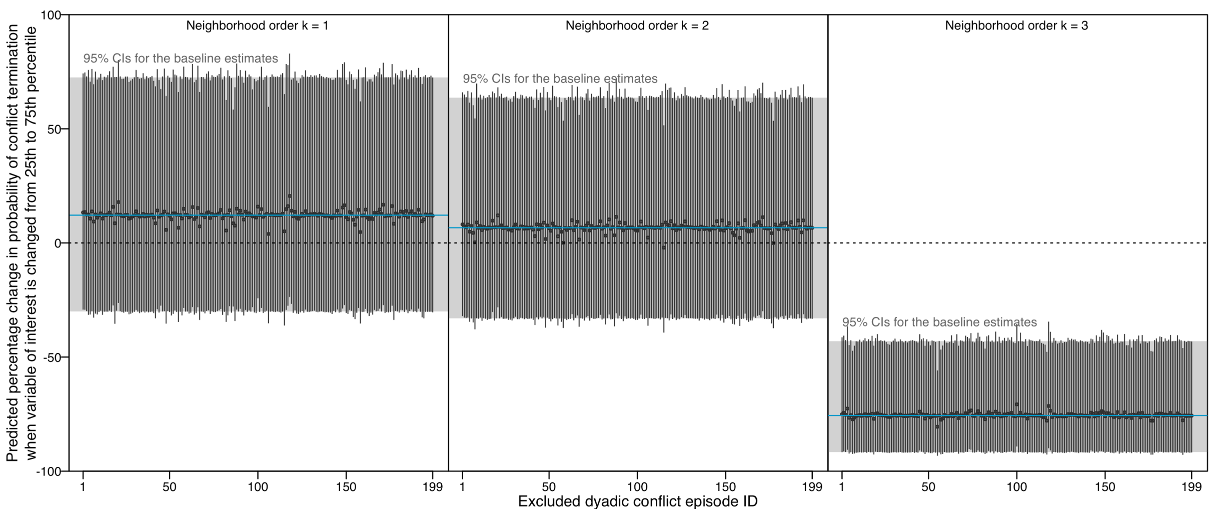
Rather than simply reporting the jackknife estimates, the graphical approach in Figures G.1 to G.3 allows us to easily detect the potential outliers on the estimation results. These three figures indicate heavy overlaps of the confidence intervals in the full sample and individual subsample estimations, suggesting that the main findings are not driven by outliers with an exceptional number of battle diffusion events.

[7] Simulations are based on the model specification of Model 3 in Table 3 in the main text.

[8] Simulations are based on the model specification in Table E.1.



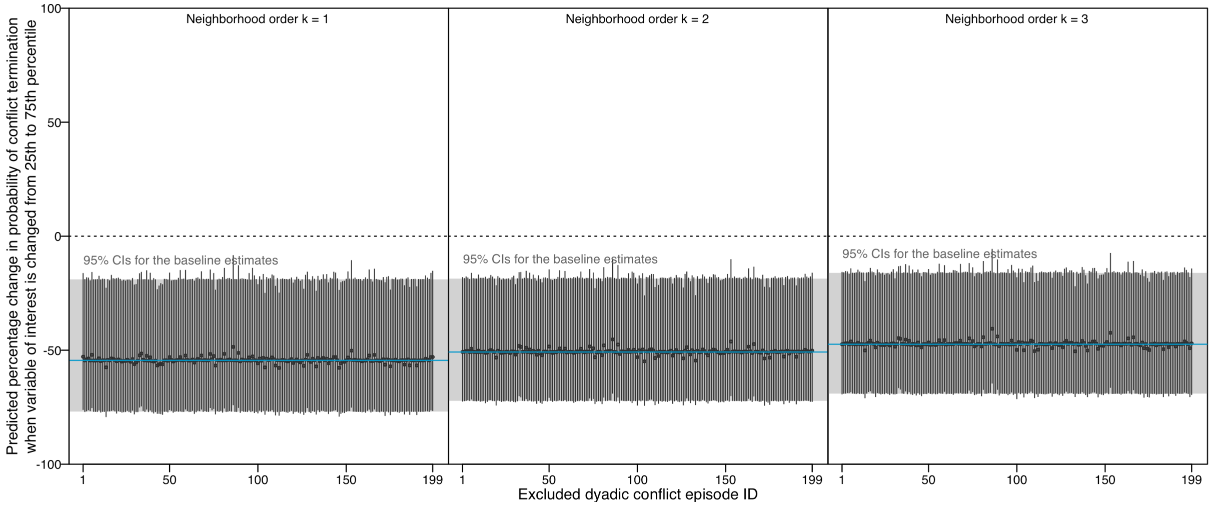
(a) Effect of proximate diffusion on probability of negotiated settlements



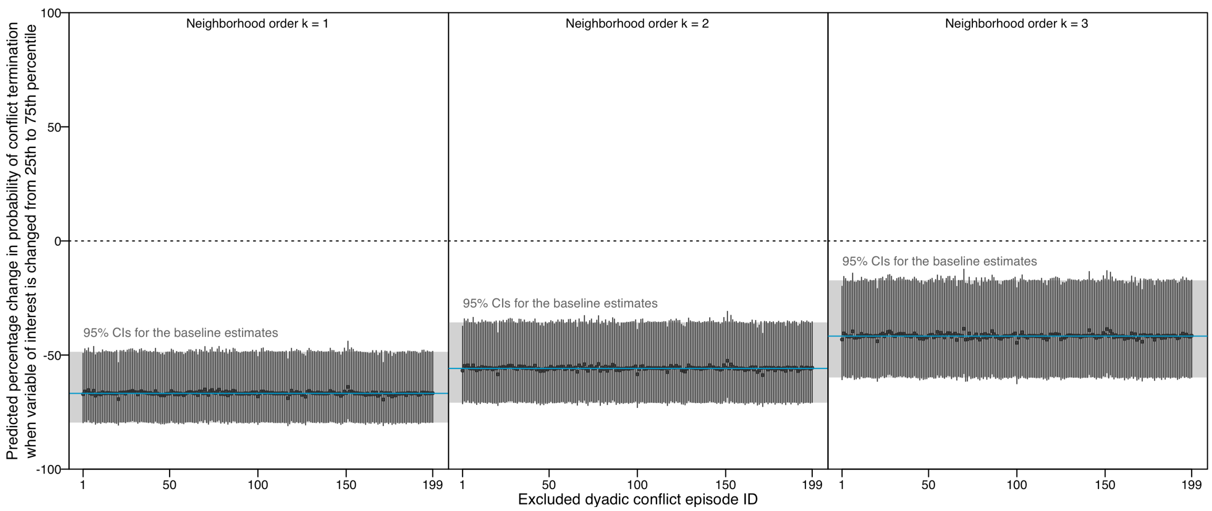
(b) Effect of proximate diffusion on probability of military outcomes

Figure G.2: Effect of proximate diffusion as percentage change in probability of military outcomes across subsamples excluding a single dyadic conflict episode

Notes: See notes in Figure 4. Simulations are based on the model specification in Table E.1 with grid resolution $r = 30$ km.



(a) Effect of distant diffusion on probability of negotiated settlements



(b) Effect of distant diffusion on probability of military outcomes

Figure G.3: Effect of proximate diffusion as percentage change in probability of negotiated settlements across subsamples excluding a single dyadic conflict episode

Notes: See notes in Figure G.1. Simulations are based on the model specification in Table E.1 with grid resolution $r = 30$ km.

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