Online Appendix for
Escalation with Relocation: Unpacking the Local Geography of Aid and Battle Intensity in Civil Conflicts

June 24, 2020

This Online Appendix reports additional statistics and estimation results to address several concerns remaining in the empirical analysis in the main text. Section A provides supplemental balance statistics. Section B describes the details of the sensitivity analysis reported in Section 4 of the main text. Section C examines the impacts of humanitarian, instead of conventional or non-humanitarian, aid provision on subsequent battle intensity.

A Detailed Balance Statistics

Tables A.1 and A.2 report the detailed balance measures and descriptive statistics with the baseline spatio-temporal window setting of $r = 50$ and $w = 2$, with *Aid* and *Neighbor Aid* as the treatment indicator, respectively. Figures 2 and 3 in the main text visualize the reported statistics focusing on the (percentage-scale) absolute standardized mean difference (ASMD) and variance ratio. An AMSD is computed as ASMD $= \frac{|\bar{x}_T - \bar{x}_C|}{\sqrt{(s_T^2(x)+s_C^2(x))/2}}$ for continuous variables, and ASMD $= \frac{|\bar{x}_T - \bar{x}_C|}{\sqrt{(\bar{x}_T(1-\bar{x}_T)+\bar{x}_C(1-\bar{x}_C))/2}}$ for dichotomous variables, where $\bar{x}_T$ ($\bar{x}_C$) is the sample mean in the treatment (control) group, and $s_T^2(x)$ and $s_C^2(x)$ sample variance. Similarly, variance ratios are obtained as Variance Ratio $= \max\left(\frac{s_T^2(x)}{s_C^2(x)}, \frac{s_C^2(x)}{s_T^2(x)}\right)$. Figures A.1 and A.2 use graphs to summarize the balance statistics across different grid resolution and temporal window settings.

Table A.1: Covariate Balance with the Baseline Window Setting, *Aid* ($r = 50$ and $w = 2$)

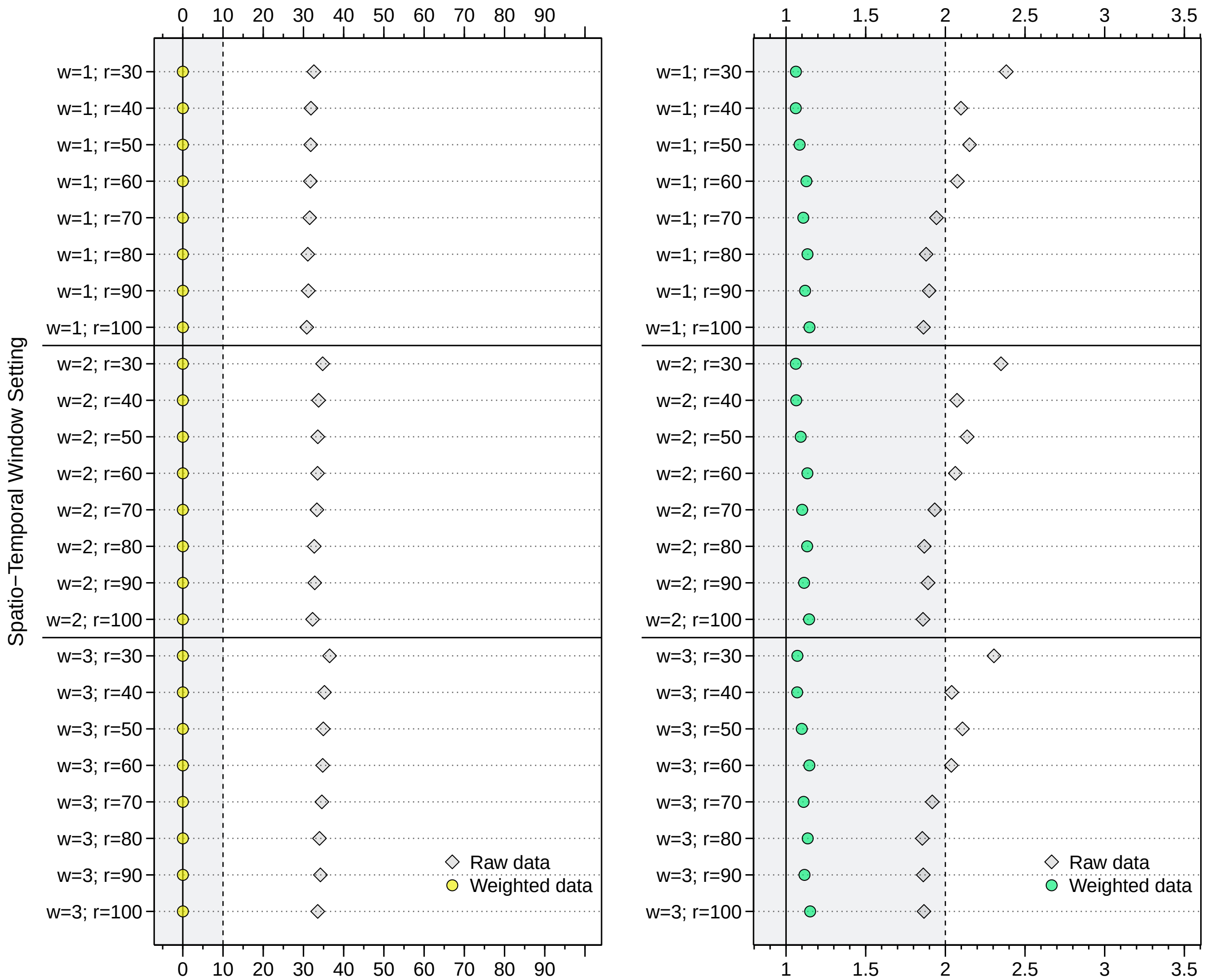
	Treatment ($N_T = 1,136$)		*Control, Raw Data* ($N_C = 23,415$)				*Control, Reweighted Data*			
	Mean	Variance	Mean	Variance	100 × ASMD	VR	Mean	Variance	100 × ASMD	VR
Aid and prior conflict										
Neighbor Aid	0.607		0.212		87.540		0.606		0.010	
Battlepre	0.313		0.101		54.330		0.313		0.010	
OSVpre	0.293		0.072		59.720		0.293		0.010	
Socioeconomic										
Population	4.221	1.899	2.442	1.679	133.010	1.131	4.221	1.735	0.010	1.094
Cropland	5.225	4.701	3.347	7.574	75.790	1.611	5.224	5.035	0.010	1.071
Nightlight	0.254	0.289	0.039	0.032	53.560	9.093	0.254	0.355	0	1.228
Geographic										
Rainfall Anomaly	0.027	1.014	0.067	0.947	4.020	1.070	0.027	1.038	0	1.024
Capital Distance	5.594	1.577	6.203	0.529	59.370	2.982	5.594	1.036	0	1.522
Border Distance	4.322	1.579	4.622	1.356	24.740	1.165	4.322	1.598	0	1.012
Road Length	4.931	0.454	4.549	0.744	49.460	1.638	4.931	0.518	0.010	1.139
Elevation	6.599	0.876	6.355	0.520	29.260	1.684	6.599	0.913	0	1.043
Ruggedness	3.820	1.391	3.257	1.300	48.500	1.070	3.820	1.312	0.010	1.060
Geocoordinates (divided by 100)										
Longitude	0.271	0.016	0.269	0.014	1.360	1.164	0.271	0.016	0	1.001
Latitude	0.037	0.005	0.066	0.009	34.990	1.724	0.037	0.005	0.010	1.000
Longitude squared	0.089	0.003	0.086	0.003	5.590	1.025	0.089	0.003	0	1.014
Latitude squared	0.006	0.00005	0.013	0.0001	67.770	3.067	0.006	0.00005	0.020	1.067
Longitude x Latitude	0.012	0.0005	0.019	0.001	32.690	1.493	0.012	0.0004	0.010	1.016
Year Dummies										
Year 1999	0.077		0.121		14.830		0.077		0	
Year 2000	0.117		0.121		1.080		0.117		0	
Year 2001	0.149		0.136		3.540		0.149		0	
Year 2002	0.098		0.111		4.480		0.098		0	
Year 2003	0.082		0.083		0.560		0.082		0	
Year 2004	0.078		0.079		0.310		0.078		0	
Year 2005	0.071		0.070		0.590		0.071		0	
Year 2006	0.151		0.110		12.290		0.151		0	
Year 2007	0.162		0.098		19.220		0.162		0	
Year 2008	0.015		0.071		27.830		0.015		0.040	

Notes: AMSD = absolute standardized mean difference. VR = variance ratio.

Table A.2: Covariate Balance with the Baseline Window Setting, *Neighbor Aid* ($r = 50$ and $w = 2$)

	Treatment ($N_T = 5,657$)		*Control, Raw Data* ($N_C = 18,894$)				*Control, Reweighted Data*			
	Mean	Variance	Mean	Variance	100 × ASMD	VR	Mean	Variance	100 × ASMD	VR
Aid and prior conflict										
Aid	0.122		0.024		38.480		0.122		0	
Battle^{pre}	0.171		0.093		23.470		0.171		0	
OSV^{pre}	0.142		0.064		25.700		0.142		0	
Socioeconomic										
Population	3.427	1.773	2.254	1.528	91.290	1.160	3.427	1.884	0	1.063
Cropland	4.675	5.887	3.062	7.509	62.320	1.276	4.675	5.879	0	1.001
Nightlight	0.093	0.090	0.036	0.032	23.240	2.823	0.093	0.099	0	1.105
Geographic										
Rainfall Anomaly	0.022	1.002	0.078	0.934	5.700	1.073	0.022	0.952	0	1.053
Capital Distance	5.825	0.961	6.280	0.436	54.490	2.205	5.825	0.904	0	1.063
Border Distance	4.474	1.326	4.648	1.377	15.020	1.039	4.474	1.479	0	1.116
Road Length	4.703	0.658	4.525	0.754	21.140	1.146	4.703	0.699	0	1.063
Elevation	6.522	0.768	6.319	0.461	25.950	1.665	6.522	0.659	0	1.166
Ruggedness	3.664	1.492	3.170	1.209	42.560	1.234	3.664	1.310	0	1.139
Geocoordinates (divided by 100)										
Longitude	0.271	0.017	0.269	0.013	1.660	1.270	0.271	0.017	0	1.000
Latitude	0.043	0.005	0.071	0.009	32.680	1.704	0.043	0.005	0	1.000
Longitude squared	0.090	0.003	0.085	0.003	8.090	1.066	0.090	0.004	0	1.054
Latitude squared	0.007	0.0001	0.014	0.0002	68.630	2.916	0.007	0.00005	0	1.103
Longitude x Latitude	0.013	0.0005	0.021	0.001	30.550	1.466	0.013	0.0005	0	1.075
Year Dummies										
Year 1999	0.085		0.129		14.260		0.085		0	
Year 2000	0.117		0.121		1.430		0.117		0	
Year 2001	0.144		0.135		2.790		0.144		0	
Year 2002	0.101		0.114		4.140		0.101		0	
Year 2003	0.083		0.083		0.050		0.083		0	
Year 2004	0.078		0.079		0.400		0.078		0	
Year 2005	0.074		0.069		2.040		0.074		0	
Year 2006	0.153		0.100		16.060		0.153		0	
Year 2007	0.149		0.086		19.670		0.149		0	
Year 2008	0.015		0.084		32.120		0.015		0.030	

Notes: AMSD = absolute standardized mean difference. VR = variance ratio.



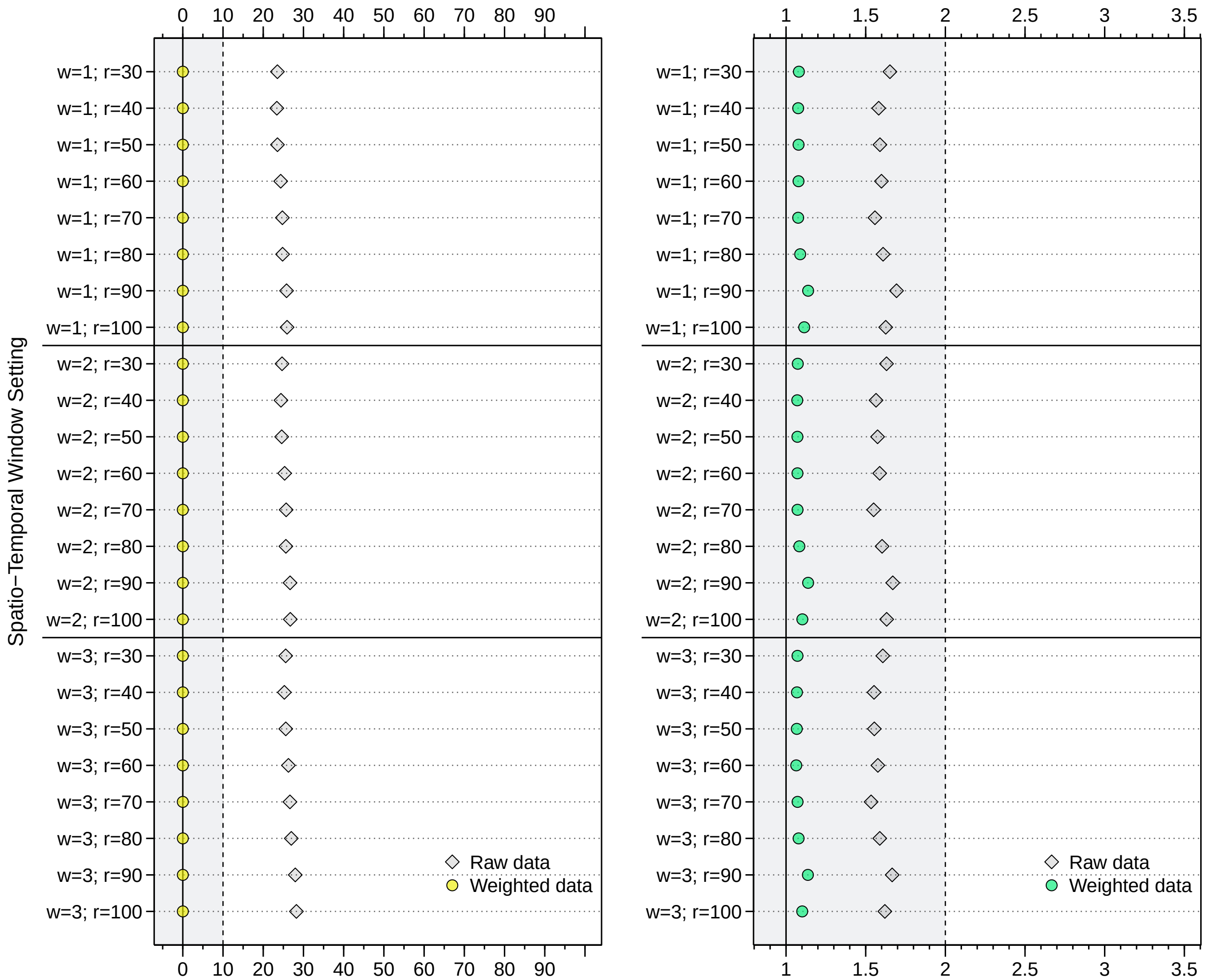
(a) Mean 100 × ASMD (b) Mean variance ratio

Figure A.1: Average covariate balance across spatio-temporal window settings, *Aid*

Notes: w (r) denotes temporal (spatial) window setting in years (kilometers). Horizontal solid segments separate different temporal window sizes. Mean $100 \times \text{ASMD} = \frac{1}{K}\sum_{k=1}^{K} 100 \times \text{ASMD}_k$, where k indexes covariates. Mean variance ratio is computed analogously.

B Sensitivity Analysis

As briefly discussed in the main text, an important concern remaining in the current analysis is unobserved confounding, such that the estimates are driven by omitted or unobserved confounders. Indeed, the current analysis relies on observational data and the ultimately untestable assumption of selection-on-observables. The reweighting preprocessing procedure in the main analysis addresses the covariate imbalance across *observed* confounders that are associated both treatment assignment (aid provision) and outcome (battle intensity).



(a) Mean 100 × ASMD (b) Mean variance ratio

Figure A.2: Average covariate balance across spatio-temporal window settings, *Neighbor Aid*
Notes: See notes in Figure A.1.

The preprocessing approach, however, does not necessarily mitigate the concern for omitted variable bias invited by unobserved confounders.

B.1 E-Value Approach

Although we cannot directly test the validity of the assumption, sensitivity analysis techniques help shed light on this concern. The current analysis utilizes the "E-value" approach developed in the biostatistics literature (Ding & VanderWeele, 2016; VanderWeele & Ding, 2017), a conservative bounding factor for sensitivity analysis with no assumptions about the prevalence of unobserved confounders. Building upon the classical Cornfield conditions (Cornfield et al., 1959) and the bounding factor developed by Ding & VanderWeele (2016), VanderWeele & Ding (2017) propose the E-value as a single-number, summary indicator of the minimum strength of unobserved confounding to wipe away a treatment effect adjusting for observed confounders. VanderWeele & Ding (2017) formally define the E-value as $E = RR_{\tau}^{+} + \sqrt{RR_{\tau}^{+}(RR_{\tau}^{+} - 1)}$, where $RR_{\tau}^{+} = \max(RR_{\tau}, 1/RR_{\tau})$, with RR_{τ} denoting a treatment effect in the risk-ratio scale adjusting for observed covariates. For a given RR_{τ} and hypothetical unobserved confounding "Treatment$(T) \leftarrow U \rightarrow$ Outcome (O)," or a pair of RR_{UT} $(U \rightarrow T)$ and RR_{UO} $(U \rightarrow O)$ associations, the E-value quantifies how strong the unobserved confounding (RR_{UT}, RR_{UO}) would have to be to explain away or eliminate the corresponding treatment effect RR_{τ}, under the simplification assumption of $RR_{UT} = RR_{UO}$. The E-value takes a value larger than 1, with a small (close to 1) indicating that weak confounding is sufficient to negate the treatment effect while a large value indicates that strong unobserved confounding is needed.

The E-values for *Aid* and *Neighbor Aid* based on the baseline estimates reported in Tables 1 and 2 in the main text ($r = 50$ and $w = 2$) indicate that a comparatively large amount of unmeasured confounding is needed to explain away the reported treatment effects of aid provision ob battle intensity. The estimate for *Aid* (Model 3 in Table 1) translates into $E^{\text{Aid}} = 2.11 + \sqrt{2.11(2.11 - 1)} = 3.64$ (with $RR_{\hat{\tau}}^{\text{Aid}} = e^{0.746} = 2.11$) for the point estimate, and 1.983 to reduce the treatment effect by half. In words, the E-value suggests that only confounding variables associated with both *Aid* (RR_{UT}) and *Battle* (RR_{UO}) by a risk ratio of 3.64-fold (or stronger) each can wipe out the treatment effect. Similarly, the coefficient estimate for *Neighbor Aid* of -0.509 produces $E^{\text{Neighbor}} = 2.714$ to fully explain away and 1.901 to halve the treatment effect (Model 5 in Table 2). Again, the results suggest that relatively strong unobserved confounding associations are required to move the point estimate to zero (2.714-fold) or halve the reported treatment effect (1.901-fold).

B.2 Observed and Unobserved Confounders

As explained above, these E-value estimates describe the minimum strength of unobserved confounding to negate the treatment effect under the assumption of $RR_{UT} = RR_{UO}$. Yet the sensitivity analysis would be move informative if it is combined with two additional layers of information: first, other possible combinations of unobserved confounding capable of negating the reported treatment effects, and second, the analogous effects of the observed covariates on the treatment assignment and outcome.

Figure 4 in the main text summarizes these two layers of information. First, as different combinations of (RR_{UT}, RR_{UO}) can induce the same strength of confounding summarized by the E-value, the solid curves in Figure 4 give the graphical displays of possible joint values of (RR_{UT}, RR_{UO}) strong enough to attenuate away the aid effectiveness. The general condition follows that to fully explain away RR_τ the joint values of RR_{UT} and RR_{UO} must be sufficiently large to satisfy the condition that $\frac{RR_{UT}RR_{UO}}{RR_{UT}+RR_{UO}-1} \geq RR_\tau^+$ (Ding & VanderWeele, 2016, 370–372). With $RR_{UT} \neq RR_{UO}$ and one parameter is smaller than the E-value, the other needs to be larger to suffice the general condition of $\frac{RR_{UT}RR_{UO}}{RR_{UT}+RR_{UO}-1} \geq RR_\tau^+$. In other words, if the association between unobserved confounder and treatment (outcome) is weaker than the strength specified by the E-value, the association between unobserved confounder and outcome (treatment) would have to be stronger to generate the same strength of confounding. The solid curves and gray-shaded regions in Figure 4(a) and (b) represent the pairs of (RR_{UT}, RR_{UO}) associations that suffice the general condition for the two treatment indicators, with the E-value under the assumption of $RR_{UT} = RR_{UO}$ as a special case.

Second, to judge whether these combinations are reasonable, Figure 4 also plots the corresponding effects of the observed covariates included in the main model (Model 2 in Table 1) on treatment assignment (horizontal axis) and outcome (vertical axis). The E-value informs us how large unobserved confounding would have to be to wipe out the treatment effect, but it alone tells us little about how realistic such confounding is present in given data. The effects of the observed covariates provides meaningful baseline for such investigation. The coefficient estimates are obtained by regressing the treatment (*Aid* and *Neighbor Aid*) and subsequent battle activities on the observed covariates while adjusting for a quadratic polynomial of geocoordinates and year fixed effects, with a Poisson (for the battle regression, RR_{UO}) and a logit link (for the treatment assignment regression, RR_{UT}), respectively. The effects of the observed covariates on treatment assignment in the risk ratio scale (RR_{UT}) are approximated by the odds ratio estimates obtained from a logit regression.[1]

Specifically, the estimates of the impacts of individual covariates on treatment assignment and outcome are derived from the following models:

$$g_D(\mathbb{E}[D_{ijt}]) = \boldsymbol{X}_{ij}^\top \boldsymbol{\alpha} + \boldsymbol{Z}_{ijt}^\top \boldsymbol{\beta} + f_1(\boldsymbol{s}_{ij}) + \gamma_t, \tag{1}$$

$$g_Y(\mathbb{E}[Y_{ijt}]) = \boldsymbol{X}_{ij}^\top \boldsymbol{\phi} + \boldsymbol{Z}_{ijt}^\top \boldsymbol{\eta} + f_2(\boldsymbol{s}_{ij}) + \zeta_t, \tag{2}$$

where D_{ijt} indicates treatment (*Aid* or *Neighbor Aid*) and Y_{ijt} reflects $Battle_{ijt}^{\text{post},w}$, $g_D(\cdot)$ and

[1] VanderWeele & Ding (2017, 4) suggest to replace RR_τ with an odds-ratio scale treatment effect OR_τ when computing the E-values with an outcome with a relatively small prevalence ($< 15\%$).

$g_Y(\cdot)$ are logit and Poisson link functions, respectively. $\boldsymbol{X}_{ij}^{\top}$ and $\boldsymbol{Z}_{ijt}^{\top}$ represent time-invariant (including intercepts) and time-varying covariates, and $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, $\boldsymbol{\phi}$, and $\boldsymbol{\eta}$ are the corresponding coefficient vectors. $f_k(\boldsymbol{s}_{ij}) = f_k(\text{Longitude}_{ij}, \text{Latitude}_{ij})$ with $k = \{1, 2\}$ and γ_t and ζ_t are a quadratic polynomial of the geographic coordinates of grid cells and year fixed effects.

The regression models are estimated for each of the raw and reweighted data, with and without country fixed effects as an additional right-hand side variable. The blue symbols ("$\times$"s and "$+$"s) and red symbols ("$\diamond$"s and "$\triangle$"s) in Figure 4 in the main text indicate the impacts of the observed covariates, estimated by the regressions using the reweighted and raw data with ("$+$"s and "$\triangle$"s) and without country fixed effects ("$\times$"s and "$\diamond$"s) as in Models 2 and 3 in Table 1.

Because the current analysis focuses on the *magnitude*, rather than the *direction*, of confounding, the effects of the observed covariates plotted in Figure 4 are obtained by transforming the corresponding coefficients as $RR^{+}_{\alpha(k)} = \max(\exp(\alpha_k), 1/\exp(\alpha_k))$. Note that this approach allows for examining the severity of omitted variable bias that the omission of each observed confounder can induce *regardless* of its direction. Because omitted variable bias can operate in upward and downward directions, omitting a confounder can result in underestimation as well as overestimation of the treatment effect. If a given observed covariate is capable of inducing sizable confounding bias that suffices $\frac{RR_{UT}RR_{UO}}{RR_{UT}+RR_{UO}-1} \geq RR^{+}_{\tau}$, the corresponding symbol would fall in the gray-shaded regions in Figure 4. For weaker confounders, in contrast, we would see the corresponding symbols located around the lower-left corners.

As briefly noted in the main text, the sensitivity analysis reveals that unobserved confounding needs to be at least far stronger than the effects of observed confounders to negate the reported treatment effects. As summarized in Figure 4, none of the observed covariates induces the confounding that suffices the minimum strength indicated by the E-values reported above. Indeed, most observed covariates are located around the lower-left corner for both treatment indicators, suggesting that the omission of these covariates would only induce limited omitted variable bias. While several covariates yield comparatively strong associations with subsequent battle intensity (location on the vertical axis), they fail to retain the effect on the treatment assignment (location on the horizontal axis) strong enough to fall within the gray-shaded regions. The results hold for both of the treatment indicators, *Aid* (Panel (a) in Figure 4) and *Neighbor Aid* (Panel (b)). Combined, these results suggest that unobserved confounding needs to be extremely strong, or at least stronger than the effects of the observed covariates, to attenuate away the reported effects of aid provision, providing further support to the theoretical claim of escalation-relocation dynamics.

C Humanitarian Aid and Civil War Battles

The main analysis restricts its scope to the effect of relatively large-scaled, conventional aid projects on subsequent battle intensity. Yet the analysis alone does not provide insights on if the main finding of the escalation-relocation dynamics travels to smaller-sized projects such as humanitarian aid. In order to account for this issue explicitly, the following section replicates the main analysis with alternative treatment indicators constructed using humanitarian, rather than conventional, aid projects. Here, *Humanitarian Aid* and *Neighbor Humanitarian Aid*, instead of *Aid* and *Neighbor Aid* in the baseline analysis, are used as the treatment indicators. The same reweighting preprocessing and model specifications are employed to derive the estimates.

Recall that the theoretical discussion does not lead us to see the escalation-relocation dynamics for the effects of comparatively small-sized humanitarian aid provision. If the empirical records of aid-conflict association are consistent with out theoretical predictions, we would not observe a similar escalation-relocation dynamics for humanitarian aid projects. The following analysis thus serves as an initial falsification test or a part of "pattern specificity" examination (Rosenbaum, 2005) for our theoretical argument.

Tables C.1 and C.2 report the results of Poisson regressions with balancing weights, varying grid resolution r and temporal window size w. As noted in Section 3 of the main text, the results should be interpreted with caution due to the small number of humanitarian aid projects. Indeed, the entropy balancing preprocessing generated noticeably large weights for some observations in Table C.1, leading the resultant treatment effect estimates to be potentially sensitive to the outlying weights.

Despite the limitation, an important result in the additional estimations is the *lack* of relocation effect for humanitarian aid provision. Rather, in contrast to the main findings, the analysis yielded an escalation effect *without* the relocation dynamics. On the one hand, Table C.1 reveals that humanitarian aid provision is followed by increased intensity of battle events in the targeted localities. On the other hand, as reported in Table C.2, the same aid inflows into adjacent regions fail to systematic influence battle activities in subsequent time periods. Although we see a weak and statistically insignificant negative association between aid and battle intensity with the baseline spatial window setting of $r = 50$ km, the negative association pattern turns out to be indeterminate and sensitive to the choice of grid resolutions at best.

These results provide further support for Hypotheses 1 and 2 in the main text. Also note that the escalation pattern without a relocation dynamic is consistent with the violence-

Table C.1: *Humanitarian Aid* and Battle Intensity at Multiple Spatial and Temporal Scales

	Dependent variable: Battle$^{\text{post}}$							
Panel A								
Temporal window, $w = 1$								
Grid Resolution, r	30 km	40 km	50 km	60 km	70 km	80 km	90 km	100 km
Humanitarian Aid	0.748***	0.557**	0.773**	0.934***	0.996***	0.986***	0.914***	1.062***
	(0.218)	(0.266)	(0.332)	(0.294)	(0.322)	(0.306)	(0.210)	(0.211)
Percentage Change	111.27%	74.48%	116.67%	154.4%	170.63%	168.04%	149.55%	189.27%
Percentage Change 95% CI	[37.89, 223.69]	[3.51, 194.12]	[13.12, 314.99]	[43.03, 352.47]	[44.02, 408.55]	[47.18, 388.16]	[65.32, 276.68]	[91.19, 337.65]
N treated	228	225	224	222	219	211	211	211
Observations	65,125	40,201	27,351	19,844	14,995	11,760	9,574	7,846
Akaike information criterion	2,501.447	3,319.006	3,765.011	4,342.128	4,210.904	5,590.788	5,659.994	5,470.465
Panel B								
Temporal window, $w = 2$								
Grid Resolution, r	30 km	40 km	50 km	60 km	70 km	80 km	90 km	100 km
Humanitarian Aid	0.667***	0.348	0.795***	0.938***	1.042***	0.944***	0.750***	0.953***
	(0.213)	(0.253)	(0.300)	(0.218)	(0.259)	(0.278)	(0.219)	(0.234)
Percentage Change	94.8%	41.63%	121.53%	155.48%	183.4%	157.09%	111.7%	159.39%
Percentage Change 95% CI	[28.44, 195.44]	[−13.76, 132.62]	[23.04, 298.86]	[66.52, 291.98]	[70.44, 371.24]	[49.22, 342.95]	[37.85, 225.11]	[63.94, 310.42]
N treated	206	205	203	201	200	191	193	193
Observations	58,492	36,100	24,551	17,814	13,461	10,556	8,594	7,043
Akaike information criterion	3,541.753	4,328.651	5,276.624	5,886.127	5,592.496	5,984.163	6,117.478	6,714.791
Panel C								
Temporal window, $w = 3$								
Grid Resolution, r	30 km	40 km	50 km	60 km	70 km	80 km	90 km	100 km
Humanitarian Aid	0.908***	0.541***	1.015***	1.106***	1.208***	1.011***	0.771***	1.024***
	(0.194)	(0.196)	(0.220)	(0.180)	(0.251)	(0.273)	(0.228)	(0.204)
Percentage Change	147.86%	71.72%	176.06%	202.16%	234.77%	174.94%	116.22%	178.36%
Percentage Change 95% CI	[69.62, 262.18]	[16.86, 152.34]	[79.52, 324.51]	[112.45, 329.75]	[104.86, 447.06]	[60.97, 369.6]	[38.4, 237.8]	[86.51, 315.46]
N treated	193	192	190	187	188	179	179	180
Observations	51,602	31,836	21,638	15,696	11,863	9,291	7,565	6,198
Akaike information criterion	4,165.051	4,881.151	6,293.265	7,042.031	6,907.871	7,218.264	7,037.083	7,907.840
Model Specification								
Covariates	✓	✓	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Spatial spline	✓	✓	✓	✓	✓	✓	✓	✓

Note: *p <0.1; **p <0.05; ***p <0.01.
Robust standard errors with multiway clustering on grid cells and years in parentheses.
Model specification follows Model (3) in Table 1. The estimate with $r = 50$ in Panel B ($w = 2$)

Table C.2: *Neighbor Humanitarian Aid* and Battle Intensity at Multiple Spatial and Temporal Scales

	Dependent variable: Battle$^{\text{post}}$							
Panel A								
Temporal window, $w = 1$								
Grid Resolution, r	30 km	40 km	50 km	60 km	70 km	80 km	90 km	100 km
Neighbor Humanitarian Aid	−0.206	−0.103	−0.204	0.118	0.245	−0.105	0.108	−0.369
	(0.246)	(0.274)	(0.240)	(0.290)	(0.323)	(0.329)	(0.322)	(0.363)
Percentage Change	−18.64%	−9.82%	−18.49%	12.55%	27.77%	−9.92%	11.38%	−30.85%
Percentage Change 95% CI	[−49.75, 31.73]	[−47.27, 54.22]	[−49.04, 30.38]	[−36.27, 98.77]	[−32.11, 140.45]	[−52.74, 71.67]	[−40.73, 109.31]	[−66.02, 40.75]
N treated	1481	1528	1445	1473	1409	1353	1299	1240
Observations	65,125	40,201	27,351	19,844	14,995	11,760	9,574	7,846
Akaike information criterion	5,812.790	7,932.762	9,029.413	12,106.440	12,485.150	14,383.820	14,281.300	14,943.480
Panel B								
Temporal window, $w = 2$								
Grid Resolution, r	30 km	40 km	50 km	60 km	70 km	80 km	90 km	100 km
Neighbor Humanitarian Aid	−0.017	0.044	−0.171	0.256	0.421	0.279	0.345	0.017
	(0.236)	(0.315)	(0.238)	(0.327)	(0.336)	(0.339)	(0.264)	(0.333)
Percentage Change	−1.66%	4.51%	−15.68%	29.18%	52.38%	32.13%	41.19%	1.75%
Percentage Change 95% CI	[−38.13, 56.32]	[−43.65, 93.84]	[−47.1, 34.41]	[−31.98, 145.31]	[−21.16, 194.49]	[−31.98, 156.66]	[−15.85, 136.88]	[−47.05, 95.51]
N treated	1368	1410	1339	1359	1302	1248	1201	1150
Observations	58,492	36,100	24,551	17,814	13,461	10,556	8,594	7,043
Akaike information criterion	7,986.782	11,161.620	13,795.960	18,191.260	19,163.770	20,837.520	20,201.230	22,469.190
Panel C								
Temporal window, $w = 3$								
Grid Resolution, r	30 km	40 km	50 km	60 km	70 km	80 km	90 km	100 km
Neighbor Humanitarian Aid	0.022	0.224	−0.033	0.412	0.364	0.397	0.350*	0.217
	(0.176)	(0.205)	(0.165)	(0.289)	(0.300)	(0.299)	(0.198)	(0.288)
Percentage Change	2.18%	25.07%	−3.22%	51.02%	43.92%	48.67%	41.87%	24.23%
Percentage Change 95% CI	[−27.58, 44.16]	[−16.39, 87.08]	[−29.99, 33.77]	[−14.34, 166.26]	[−20.11, 159.26]	[−17.2, 166.94]	[−3.78, 109.18]	[−29.31, 118.32]
N treated	1283	1318	1254	1264	1219	1166	1108	1069
Observations	51,602	31,836	21,638	15,696	11,863	9,291	7,565	6,198
Akaike information criterion	9,149.305	12,943.820	16,409.880	21,535.920	23,231.400	25,170.140	23,764.630	27,157.330
Model Specification								
Covariates	✓	✓	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Spatial spline	✓	✓	✓	✓	✓	✓	✓	✓

Note: *p <0.1; **p <0.05; ***p <0.01.
Robust standard errors with multiway clustering on grid cells and years in parentheses.
Model specification follows Model (3) in Table 2. The estimate with $r = 50$ in Panel B ($w = 2$)

increasing effect via the predation mechanism highlighted in the evaluation of the impact of humanitarian aid in Wood & Molfino (2016) and Wood & Sullivan (2015). Combined with the findings in the main text, the additional estimation results suggest that different types of aid projects have differing impacts on conflict dynamics through distinct mechanisms.

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