(Not-for-Publication) Online Appendix

How Natural Disasters Spread Conflict

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A Additional Data Description

A.1 Figures

Figure A.1: EM-DAT data extract

DisNo	Year	Disaster...	DisasterSubgroup	DisasterType	GeoLocations
2017-0306-GHA	2017	Natural	Hydrological	Flood	Birim Municipal, Ga South, Twifo Ati-Morkwa, Wassa Amenfi West (Adm2).
2019-0049-BDI	2019	Natural	Hydrological	Flood	Buterere, Kanyosha, Kinama, Musaga, Nyakabiga (Adm2).
2018-0008-MDG	2018	Natural	Meteorological	Storm	Analamanga (Adm1). Brickaville, Mahanoro, Mananjary, Nosy-Varika, Toamasina I, Toamasina II, Vatomandry (Adm2).
2017-0178-ZAF	2017	Natural	Meteorological	Storm	Cape Winelands District Municipality, City of Cape Town Metropolitan Municipality, Eden District Municipality (Adm2).
2019-0048-ZMB	2019	Natural	Hydrological	Flood	Chama, Chinsali, Isoka, Mpika, Nakonde (Adm2).

Source: EM-DAT

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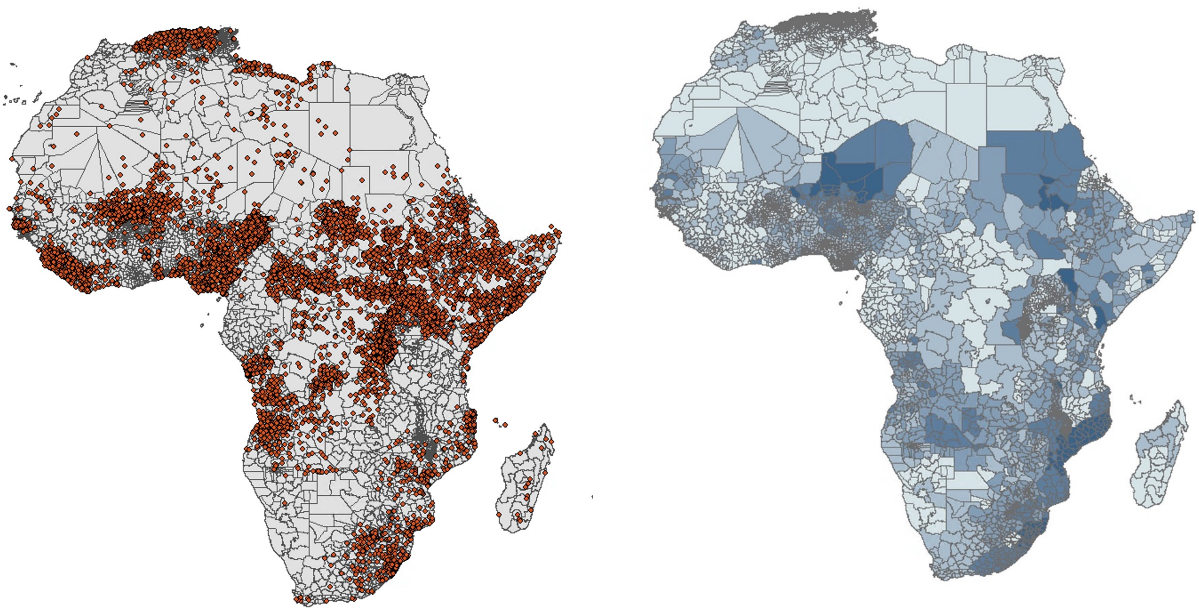
Figure A.2: Spatial distribution of conflicts and natural disasters in Africa

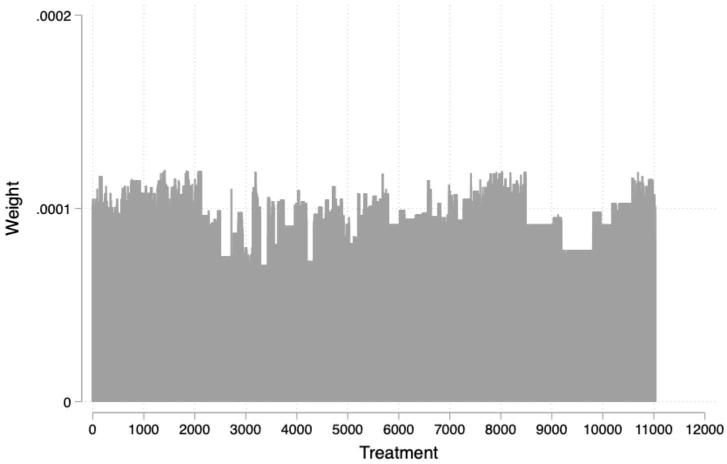


(a) Conflicts

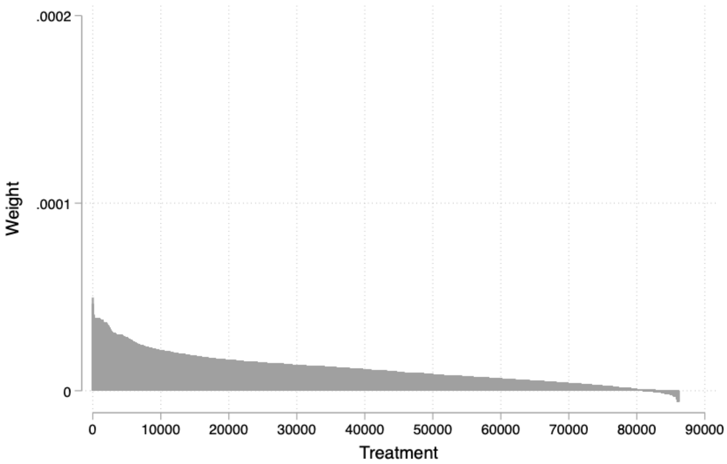
(b) Natural Disasters

Notes: Panel (a) shows the point locations of battle events in Africa, as per the UCDP data set. Panel (b) shows the district level dispersion of natural disasters in Africa, as per the EM-DAT data set. Darker colors indicate districts more prone to natural disasters over the sample period.

Figure A.3: Diagnostic tests - Weights attached to each treatment as per De Chaisemartin and D'Haultfœuille (2020)



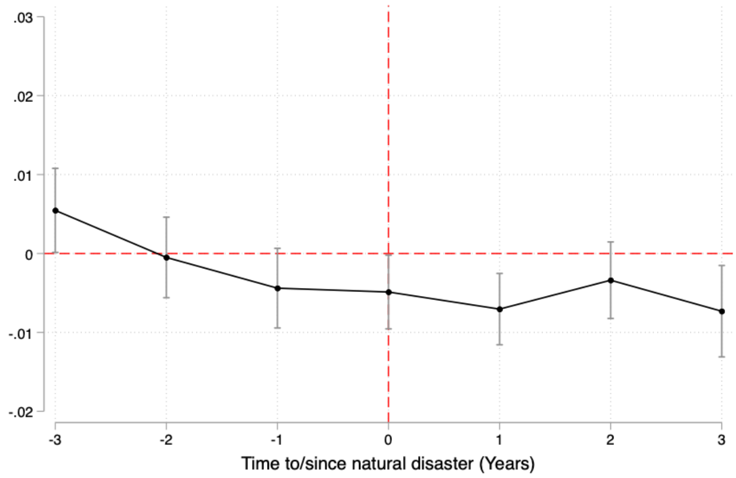
Panel A: Treatment DIS_{it}



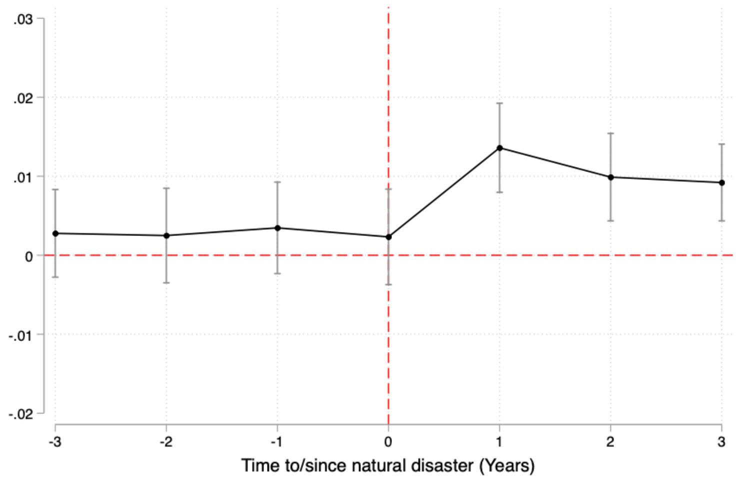
Panel B: Treatment $NDIS_{it}$ (based on inverse geographic distance)

Note: Figure shows the distribution of the weights attached to each ATE used in this study. This procedure was conducted using Stata's `twowayfeweights` estimator developed in line with De Chaisemartin and D'Haultfœuille (2020).

Figure A.4: Temporal dynamics



Panel A: Independent Variable DIS_{it}



Panel B: Independent Variable $NDIS_{it}$ (based on inverse geographic distance)

Note: Figure shows the direct and spillover effect of natural disasters in district i on conflict, for the 3 years before and after the natural disaster. The unit of observation is a district-year. Vertical lines depict the 95% level confidence intervals, based on Conley (1999) clustered standard errors, accounting for spatial correlation up to 500km and temporal correlation up to 3 periods.

A.2 Tables

Table A.1: Disasters by type

Disaster Type	*Frequency*
Flood	886
Drought	174
Storm	141
Landslide	52
Earthquake	27
Wildfire	25
Extreme Temp	13
Volcano	5
Wave/Surge	3
Total	1,326

Table A.2: Descriptive statistics for key variables

	Observations	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Conflict	190,208	0.0367	0.1880	0	1
DIS	190,208	0.0580	0.2337	0	1
Conflict if DIS >0	11,025	0.0309	0.1731	0	1
Conflict if DIS=0	179,183	0.0370	0.1888	0	1
Spillover effects					
NDIS	190,208	0.4526	0.4978	0	1
Conflict if NDIS >0	86,094	0.0376	0.1902	0	1
Conflict if NDIS=0	104,114	0.0359	0.1861	0	1

$Conflict$ and DIS are binary variables indicating the presence (=1) or absence (=0) of a battle resulting in at least one death, and a natural disaster event, respectively, in district i in in the given time unit. $NDIS$ is a binary variable indicating the presence (=1) or absence (=0) of a natural disaster event, in at least one of the neighbouring districts, where neighbourhood is defined as per the altitude-adjusted inverse geodesic network.

Table A.3: Correlation between natural disaster indicators and district level characteristics - Direct effect)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Dis	$LargeDis$	$SmallDis$	$ClimDis$	$GeoDis$	$Flood$	$Storm$	$Quake$	$Slide$	$Wildfire$	$Drought$
$Area$	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$PopDensity$	0.0000**	0.0000***	0.0000	0.0000**	-0.0000	0.0000**	-0.0000	0.0000	-0.0000	-0.0000	-0.0000**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$Temperature$	0.0578***	0.0442***	0.0419***	0.0581***	0.0016	0.0594***	-0.0144	0.0006	0.0013	-0.0112	0.0123
	(0.0104)	(0.0123)	(0.0100)	(0.0104)	(0.0013)	(0.0102)	(0.0102)	(0.0010)	(0.0011)	(0.0084)	(0.0115)
$Precipitation$	0.0016	0.0014	0.0007	0.0015	0.0003**	0.0013	0.0011*	0.0002*	0.0001*	0.0007	0.0001
	(0.0010)	(0.0010)	(0.0009)	(0.0010)	(0.0001)	(0.0010)	(0.0006)	(0.0001)	(0.0001)	(0.0005)	(0.0008)
$Elevation$	0.0003***	0.0002***	0.0003***	0.0003***	0.0001**	0.0003***	-0.0000	0.0000*	0.0000*	0.0000	0.0002***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
$Ruggedness$	-0.0003	-0.0006	0.0004	-0.0003	-0.0000	-0.0004	0.0002	0.0000	-0.0000	0.0004	0.0004
	(0.0005)	(0.0007)	(0.0005)	(0.0005)	(0.0001)	(0.0006)	(0.0002)	(0.0001)	(0.0000)	(0.0003)	(0.0004)
NTL	0.0024	0.0023	0.0038*	0.0024	0.0001	0.0029	0.0017	-0.0000	0.0002	0.0027	-0.0007
	(0.0020)	(0.0021)	(0.0020)	(0.0020)	(0.0004)	(0.0019)	(0.0022)	(0.0003)	(0.0002)	(0.0023)	(0.0021)
$MineCount$	0.0164	0.0274	0.0274**	0.0159	0.0078*	0.0158	0.0978**	0.0065**	0.0016	0.0621***	0.0304
	(0.0215)	(0.0255)	(0.0133)	(0.0212)	(0.0043)	(0.0210)	(0.0407)	(0.0029)	(0.0039)	(0.0137)	(0.0266)
$CroplandShare$	0.1683*	0.1357	0.1608**	0.1600*	0.0154	0.1777*	-0.0306	0.0150	0.0004	-0.0586*	-0.0485
	(0.0872)	(0.1076)	(0.0775)	(0.0903)	(0.0167)	(0.0904)	(0.0653)	(0.0159)	(0.0086)	(0.0301)	(0.1201)
$PrimaryRoadKM$	0.0010***	0.0010**	0.0002	0.0010***	0.0001**	0.0010***	0.0004	0.0000	0.0001	0.0004**	0.0003
	(0.0003)	(0.0004)	(0.0004)	(0.0003)	(0.0001)	(0.0003)	(0.0003)	(0.0001)	(0.0001)	(0.0002)	(0.0006)
$SecondaryRoadKM$	0.0006***	0.0007***	0.0008***	0.0006***	-0.0001***	0.0006***	0.0006**	-0.0001**	-0.0000	0.0005***	0.0008**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0003)	(0.0000)	(0.0000)	(0.0001)	(0.0003)
$Distancetocapital$	0.0000**	0.0000**	0.0000**	0.0000**	0.0000	0.0000**	0.0000**	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$Port$	-0.0402	-0.0406	-0.0111	-0.0383	0.0126	-0.0547	-0.0057	-0.0057	0.0122	-0.0278	0.0205
	(0.0406)	(0.0430)	(0.0399)	(0.0406)	(0.0125)	(0.0428)	(0.0287)	(0.0058)	(0.0107)	(0.0277)	(0.0348)
$PowerPlant$	0.0143	0.0130	0.0236*	0.0133	0.0110	0.0133	0.0069	0.0059	0.0034	0.0075	0.0010
	(0.0100)	(0.0114)	(0.0124)	(0.0101)	(0.0066)	(0.0100)	(0.0079)	(0.0052)	(0.0030)	(0.0085)	(0.0051)
$Pre-ColonialInst.$	-0.1064***	-0.1140**	-0.1101**	-0.1025**	-0.0108	-0.0986**	-0.0786*	-0.0070	-0.0037	-0.0168	-0.0399
	(0.0394)	(0.0431)	(0.0455)	(0.0392)	(0.0107)	(0.0387)	(0.0403)	(0.0085)	(0.0050)	(0.0114)	(0.0405)
Observations	5,682	5,682	5,682	5,682	5,682	5,682	5,682	5,682	5,682	5,682	5,682
R-squared	0.3878	0.3044	0.2024	0.3831	0.0516	0.3885	0.2176	0.0259	0.0295	0.2055	0.1681

Outcome variables are binary variables indicating the presence (=1) or absence (=0) of a natural disaster event in the given district over the sample period. Standard errors are clustered at the country level. *** p<0.01, ** p<0.05, * p<0.1

Table A.4: Correlation between natural disaster indicators and district level characteristics - Spillover effect)

	(1) $N(Dis)$	(2) $N(LargeDis)$	(3) $N(SmallDis)$	(4) $N(ClimDis)$	(5) $N(GeoDis)$	(6) $N(Flood)$	(7) $N(Storm)$	(8) $N(Quake)$	(9) $N(Slide)$	(10) $N(Wildfire)$	(11) $N(Drought)$
$Area$	-0.0000*	-0.0000**	-0.0000	-0.0000*	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$PopDensity$	0.0000	0.0000	0.0000	0.0000	0.0000***	-0.0000	0.0000	-0.0000	0.0000***	0.0000**	-0.0000*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$Temperature$	0.0048	0.0048	0.0742***	0.0048	0.0064	0.0313***	0.0312*	0.0067	0.0073	-0.0480***	0.0829***
	(0.0041)	(0.0041)	(0.0084)	(0.0041)	(0.0139)	(0.0072)	(0.0175)	(0.0109)	(0.0131)	(0.0104)	(0.0101)
$Precipitation$	0.0010*	0.0010**	0.0034***	0.0010*	0.0061***	0.0023*	0.0036**	0.0015**	0.0059***	0.0019**	-0.0010
	(0.0005)	(0.0005)	(0.0009)	(0.0005)	(0.0008)	(0.0012)	(0.0016)	(0.0007)	(0.0008)	(0.0007)	(0.0017)
$Elevation$	0.0001***	0.0001***	0.0004***	0.0001***	0.0003***	0.0002***	0.0003***	0.0005***	0.0003***	-0.0002***	0.0006***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$Ruggedness$	-0.0005*	-0.0005*	-0.0004	-0.0005*	-0.0011***	-0.0011**	-0.0007	-0.0008*	-0.0010***	0.0004	0.0002
	(0.0003)	(0.0003)	(0.0005)	(0.0003)	(0.0003)	(0.0005)	(0.0006)	(0.0005)	(0.0004)	(0.0006)	(0.0006)
NTL	-0.0001	-0.0001	0.0011	-0.0001	0.0003	0.0027	-0.0014	0.0019	0.0006	0.0024	0.0022
	(0.0013)	(0.0013)	(0.0022)	(0.0013)	(0.0017)	(0.0022)	(0.0031)	(0.0021)	(0.0018)	(0.0019)	(0.0027)
$MineCount$	0.0118	0.0070	0.0447	0.0118	0.0355	0.0219	0.0513	0.0795**	0.0090	0.0419	0.0418
	(0.0097)	(0.0073)	(0.0400)	(0.0097)	(0.0248)	(0.0229)	(0.0515)	(0.0379)	(0.0193)	(0.0363)	(0.0388)
$CroplandShare$	0.0741	0.0740	0.0343	0.0741	0.1134	0.1227	0.1982**	0.2004*	0.1197	-0.0836	0.1356
	(0.0552)	(0.0553)	(0.0757)	(0.0552)	(0.1170)	(0.1006)	(0.0979)	(0.1093)	(0.1134)	(0.1067)	(0.1029)
$PrimaryRoadKM$	0.0001**	0.0001**	0.0006*	0.0001**	0.0009	0.0003*	0.0008	0.0004	0.0008*	0.0010	0.0008**
	(0.0001)	(0.0001)	(0.0003)	(0.0001)	(0.0006)	(0.0002)	(0.0007)	(0.0006)	(0.0004)	(0.0006)	(0.0003)
$SecondaryRoadKM$	0.0001**	0.0001**	0.0005***	0.0001**	0.0003	0.0002**	0.0002	-0.0000	0.0004***	0.0004	0.0003*
	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0002)	(0.0001)	(0.0003)	(0.0003)	(0.0001)	(0.0003)	(0.0002)
$Distancetocapital$	0.0000	0.0000	0.0000	0.0000	-0.0000	0.0000	0.0000	0.0000	0.0000	-0.0000**	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$Port$	-0.0298	-0.0281	-0.0332	-0.0298	-0.0615	-0.0010	-0.0076	-0.0069	-0.0473	-0.1286***	0.0467
	(0.0202)	(0.0200)	(0.0602)	(0.0202)	(0.0560)	(0.0285)	(0.0311)	(0.0244)	(0.0553)	(0.0400)	(0.0418)
$PowerPlant$	-0.0243*	-0.0247*	0.0036	-0.0243*	0.0240**	-0.0042	-0.0022	0.0071	0.0182	-0.0284**	-0.0046
	(0.0141)	(0.0140)	(0.0078)	(0.0141)	(0.0117)	(0.0168)	(0.0084)	(0.0063)	(0.0113)	(0.0137)	(0.0078)
$Pre-ColonialInst.$	-0.0140	-0.0149	-0.0325	-0.0140	0.0422	-0.0992	-0.1150**	0.0030	0.0865	-0.0632	-0.1129**
	(0.0148)	(0.0146)	(0.0292)	(0.0148)	(0.0553)	(0.0702)	(0.0490)	(0.0343)	(0.0519)	(0.0781)	(0.0552)
Observations	5,682	5,682	5,682	5,682	5,682	5,682	5,682	5,682	5,682	5,682	5,682
R-squared	0.1187	0.1206	0.7658	0.1187	0.4685	0.3790	0.3320	0.3699	0.4547	0.1763	0.4924

Outcome variables are binary variables indicating the presence (=1) or absence (=0) of a natural disaster event in the given district over the sample period.
Standard errors are clustered at the country level. *** p<0.01, ** p<0.05, * p<0.1

Table A.5: Temporal and spatial autocorrelation of natural disasters

	(1) $DIS_{i,t}$	(2) $NDIS_{i,t}$	(3) $DIS_{i,t}$
$DIS_{i,t-1}$	0.0021		0.0087
	(0.0133)		(0.0132)
$DIS_{i,t-2}$	-0.0203		
	(0.0150)		
$DIS_{i,t-3}$	-0.0085		
	(0.0133)		
$NDIS_{i,t}$			0.0176***
			(0.0040)
$NDIS_{i,t-1}$		0.0103	0.0048
		(0.0199)	(0.0066)
$NDIS_{i,t-2}$		-0.0011	
		(0.0213)	
$NDIS_{i,t-3}$		-0.0171	
		(0.0155)	
Observations	172,376	172,376	184,264
District FE	YES	YES	YES
Country× Year FE	YES	YES	YES

DIS is a binary variable indicating the presence (=1) or absence (=0) of a natural disaster event in the given district in the given time period. $NDIS$ is a binary variable indicating the presence (=1) or absence (=0) of a natural disaster event, in any one of the district's neighbours, within the given time period. Neighbourhood is based on the altitude-adjusted inverse distance matrix, truncated at 500km. Disasters exclude droughts. Conley (1999) clustered standard errors, accounting for spatial correlation up to 500km and temporal correlation up to 1 period are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

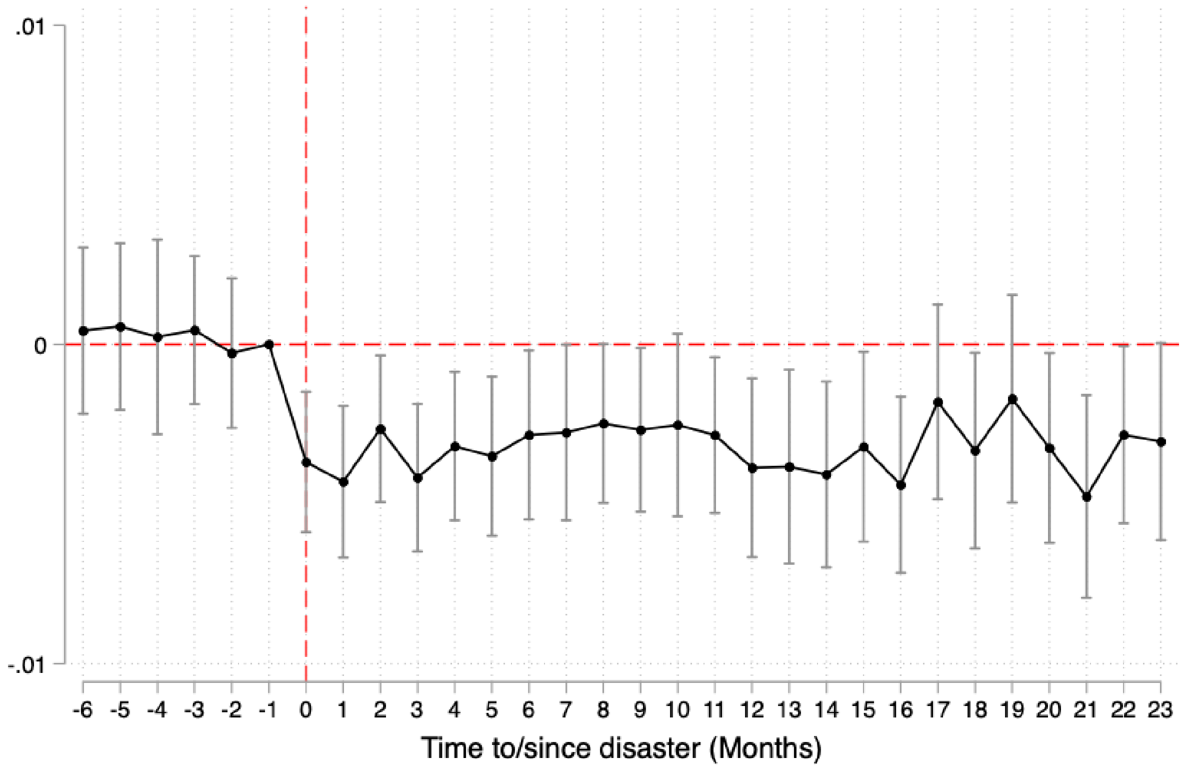
A.3 Direct effect of natural disasters on conflict at the district×month level

The EM-DAT data contains information about the date of the natural disaster event and we use this information to build a dataset at the district×month level. Figure A.5 presents the results of an event study analysis to estimate the direct effect of natural disasters on conflict using monthly data. We observe that the direct effect materialises in the contemporary month itself, and persists for up to two years.

At the district×year level estimates in Table 1, the direct effect is not statistically significant in the contemporary year, and only becomes statistically significant in $t + 1$. To examine this discrepancy, we conduct a test in Table A.6, where we re-estimate the direct effect of natural disasters on conflict at the district×year level, and add the different sets of fixed effects stepwise. In Column (1) we include district fixed effects only, and the effect is negative and statistically significant, indicating that the effect materialises contemporaneously. However, when we add country×year fixed effects in Column (2), the statistical significance disappears. In Column (2) we include both sets of fixed effects along with previous period's natural disaster indicator. Here, the negative effect is statistically significant at the 10% level.

These results suggest that the pattern of negative effect of natural disasters on conflict does exist in the contemporary time period, but the inclusion of a relatively conservative set of country×year fixed effects results in a p-value below the standard threshold of statistical significance.

Figure A.5: Event study of the effect of natural disasters on conflict - at the district×month level



Notes: Figure shows event study estimates of the effect of natural disasters on conflict, at the district×month level. Estimates include district and year×month fixed effects. Dots show the estimated coefficients while vertical lines show the 90% confidence intervals based on standard errors clustered at the country×year level.

Table A.6: Direct effects of natural disasters on conflict at the year level - Stepwise addition of controls

	(1) $Conflict_{i,t}$	(2) $Conflict_{i,t}$	(3) $Conflict_{i,t}$
$DIS_{i,t}$	-0.0129***	-0.0023	-0.0026
	(0.0046)	(0.0035)	(0.0035)
$DIS_{i,t-1}$			-0.0053*
			(0.0030)
Observations	190,208	190,208	184,264
District FE	YES	YES	YES
Country× Year FE	NO	YES	YES

$Conflict$ and DIS are binary variables indicating the presence (=1) or absence (=0) of a battle resulting in at least one death, and natural disaster event, respectively, in the given district in the given time period. Disasters exclude droughts. () present country×year clustered standard errors. *** p<0.01, ** p<0.05, * p<0.1

B Robustness checks

Table B.1: Dynamic difference-in-differences estimates as per de Chaisemartin and D'Haultfœuille (2024)

	$Conflict_{i,t}$			
	Panel 1: Direct		Panel 2: Spillover	
	Coeff.	*SE*	*Coeff.*	*SE*
$DIS_{i,t}$	-0.0067**	(0.0033)		
$DIS_{i,t-1}$	-0.0070*	(0.0041)		
$Avg\ Direct\ Effect$	-0.0122**	(0.0061)		
$NDIS_{i,t}$			0.0082**	(0.0041)
$NDIS_{i,t-1}$			0.0089*	(0.0054)
$Avg\ Spillover\ Effect$			0.0120*	(0.0062)

This table presents dynamic difference-in-differences estimates as per de Chaisemartin and D'Haultfœuille (2024), estimated separately for direct and spillover treatments. Total number of observations considered is 184,264. $Conflict_{i,t}$ is a binary variable indicating the presence (=1) or absence (=0) of a battle resulting in at least one death in district i in year y. $DIS_{i,t}$ and $DIS_{i,t-1}$ are binary variables indicating the presence (=1) or absence (=0) of a natural disaster event in district i in years y and $t-1$, respectively. $NDIS_{i,t}$ is a binary variable indicating the presence (=1) or absence (=0) of a natural disaster event, in any one of district i's neighbours in year y. Neighbourhood is based on the altitude-adjusted inverse geodesic distance network truncated at 500km. For the direct effect estimation, $NDIS_{i,t}$ and $Conflict_{i,t-1}$ are included as controls. For the spillover effect estimation $DIS_{i,t}$ and $Conflict_{i,t-1}$ are included as controls. Estimates include district and year fixed effects. Disasters exclude droughts. The effects were calculated using the $did_multiplegt_dyn$ command in Stata 18. *** p<0.01, ** p<0.05, * p<0.1

Table B.2: Alternative spatial models

	(1) $Conflict_{i,t}$ GNS	(2) $Conflict_{i,t}$ SLX
$DIS_{i,t}$	-0.0019	-0.0028
	{0.0027}	{0.0030}
	(0.0031)	(0.0035)
$DIS_{i,t-1}$	-0.0049**	-0.0056**
	{0.0025}	{0.0028}
	(0.0025)	(0.0029)
$NDIS_{i,t}$	0.0044	0.0055*
	{0.0028}	{0.0033}
	(0.0029)	(0.0035)
$NDIS_{i,t-1}$	0.0097***	0.0104***
	{0.0028}	{0.0033}
	(0.0032)	(0.0037)
$Conflict_{i,t-1}$	0.2315***	
	{0.0105}	
	(0.0126)	
Observations	184,264	184,264
Distance Cut-off	500km	500km
District FE	YES	YES
Country× Year	YES	YES
$NConflict_{i,t}$	YES	NA
$NConflict_{i,t-1}$	YES	NA

$Conflict_{i,t}$ is a binary variable indicating the presence (=1) or absence (=0) of a battle resulting in at least one death in district i in year t. $DIS_{i,t}$ and $DIS_{i,t-1}$ are binary variables indicating the presence (=1) or absence (=0) of a natural disaster event in district i in years y and $t-1$, respectively. $NDIS_{i,t}$ ($NConflict_{i,t}$) are binary variable indicating the presence (=1) or absence (=0) of a natural disaster event (battle), in any one of district i's neighbours in year t. Neighbourhood is based on the altitude-adjusted inverse geodesic distance network, truncated at 500km. Disasters exclude droughts. {} present Conley (1999) clustered standard errors, accounting for spatial correlation up to 500km and temporal correlation up to 1 period, while ( ) present standard errors clustered at the country×year level. *** p<0.01, ** p<0.05, * p<0.1

Table B.3: Effect of natural disasters including droughts

	(1) $Conflict_{i,t}$	(2) $Conflict_{i,t}$
$DIS_{i,t}$	-0.0018	-0.0018
	(0.0029)	(0.0029)
$DIS_{i,t-1}$	-0.0018	-0.0019
	(0.0029)	(0.0028)
$NDIS_{i,t}$		0.0081***
		(0.0031)
$NDIS_{i,t-1}$		0.0112***
		(0.0032)
Observations	184,264	184,264
Distance Cutoff	NA	500km
District FE	YES	YES
Country× Year FE	YES	YES
$NConflict_{i,t}$	NA	YES
$NConflict_{i,t-1}$	NA	YES

$Conflict$ and DIS are binary variables indicating the presence (=1) or absence (=0) of a conflict resulting in at least one death, and natural disaster event, respectively, in the given district in the given time period. $NDIS$ ($NConflict$) is a binary variable indicating the presence (=1) or absence (=0) of a natural disaster event (conflict), in any one of the district's neighbours, within the given time period. Neighbourhood is based on the altitude-adjusted inverse distance matrix, truncated at 500km. Conley (1999) clustered standard errors, accounting for spatial correlation up to 500km and temporal correlation up to 1 period, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B.4: Restricting the sample from 2000-2020

	(1) $Conflict_{i,t}$	(2) $Conflict_{i,t}$
$DIS_{i,t}$	-0.0012	-0.0010
	(0.0037)	(0.0037)
$DIS_{i,t-1}$	-0.0051	-0.0053
	(0.0032)	(0.0032)
$NDIS_{i,t}$		0.0020
		(0.0038)
$NDIS_{i,t-1}$		0.0100***
		(0.0038)
Observations	118,880	118,880
Distance Cutoff	NA	500km
District FE	YES	YES
Country× Year FE	YES	YES
$NConflict_{i,t}$	NA	YES
$NConflict_{i,t-1}$	NA	YES

$Conflict$ and DIS are binary variables indicating the presence (=1) or absence (=0) of a conflict resulting in at least one death, and natural disaster event, respectively, in the given district in the given time period. $NDIS$ ($NConflict$) is a binary variable indicating the presence (=1) or absence (=0) of a natural disaster event (conflict), in any one of the district's neighbours, within the given time period. Neighbourhood is based on the altitude-adjusted inverse distance matrix, truncated at 500km. Disasters exclude droughts. Sample is restricted to years 2000-2020. Conley (1999) clustered standard errors, accounting for spatial correlation up to 500km and temporal correlation up to 1 period, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B.5: Estimates by disaster category

	(1) $Conflict_{i,t}$	(2) $Conflict_{i,t}$	(3) $Conflict_{i,t}$	(4) $Conflict_{i,t}$
Disaster Category	*Large*	*Small*	*Climatic*	*Geologic*
$DIS_{i,t}$	-0.0014	-0.0021	-0.0023	-0.0123
	(0.0035)	(0.0043)	(0.0030)	(0.0233)
$DIS_{i,t-1}$	-0.0032	-0.0061	-0.0059**	0.0049
	(0.0034)	(0.0039)	(0.0028)	(0.0200)
$NDIS_{i,t}$	0.0044	0.0064**	0.0062*	0.0147
	(0.0042)	(0.0027)	(0.0033)	(0.0144)
$NDIS_{i,t-1}$	0.0172***	0.0013	0.0125***	0.0017
	(0.0040)	(0.0028)	(0.0033)	(0.0114)
Observations	155,494	139,480	182,576	97,752
Distance Cut-off	500km	500km	500km	500km
District FE	YES	YES	YES	YES
Country× Year FE	YES	YES	YES	YES
$NConflict_{i,t}$	YES	YES	YES	YES
$NConflict_{i,t-1}$	YES	YES	YES	YES

$Conflict_{i,t}$ is a binary variable indicating the presence (=1) or absence (=0) of a conflict resulting in at least one death in district i in year t. $DIS_{i,t}$ and $DIS_{i,t-1}$ are binary variables indicating the presence (=1) or absence (=0) of a natural disaster event in district i in years y and $t-1$, respectively. $NDIS_{i,t}$ ($NConflict_{i,t}$) are binary variable indicating the presence (=1) or absence (=0) of a natural disaster event (conflict), in any one of district i's neighbours in year t. *Large* disasters are those that either (i) kills at least 1000 people, or (ii) affects at least 100,000 people in total, or (iii) causes damages of at least one billion (real) dollars, while remaining disasters are classified as *Small*. *Geologic* disasters include landslides, and earthquakes. *Climatic* disasters include floods, cyclones, hurricanes and storms. Neighbourhood is based on the altitude-adjusted inverse geodesic distance network, truncated at 500km. Disasters exclude droughts. Conley (1999) clustered standard errors, accounting for spatial correlation up to 500km and temporal correlation up to 1 period, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B.6: Estimates by disaster type

	(1) $Conflict_{i,t}$	(2) $Conflict_{i,t}$	(3) $Conflict_{i,t}$	(4) $Conflict_{i,t}$	(5) $Conflict_{i,t}$	(6) $Conflict_{i,t}$
$DisasterType$	$Flood$	$Landslide$	$Earthquake$	$Drought$	$Storm$	$Wildfire$
$DIS_{i,t}$	-0.0038	0.0130	-0.0231	0.0049	0.0165	-0.0055
	(0.0031)	(0.0344)	(0.0210)	(0.0075)	(0.0108)	(0.0160)
$DIS_{i,t-1}$	-0.0071**	-0.0137	-0.0061	0.0227**	0.0066	0.0008
	(0.0029)	(0.0252)	(0.0255)	(0.0102)	(0.0095)	(0.0183)
$NDIS_{i,t}$	0.0085**	-0.0015	0.0290**	0.0116*	-0.0046	0.0130*
	(0.0036)	(0.0235)	(0.0136)	(0.0070)	(0.0052)	(0.0073)
$NDIS_{i,t-1}$	0.0150***	-0.0042	0.0107	0.0234***	0.0027	0.0200**
	(0.0036)	(0.0158)	(0.0111)	(0.0081)	(0.0050)	(0.0082)
Observations	173,266	90,997	87,744	107,325	106,166	87,390
Distance Cut-off	500km	500km	500km	500km	500km	500km
District FE	YES	YES	YES	YES	YES	YES
Country× Year FE	YES	YES	YES	YES	YES	YES
$NConflict_{i,t}$	YES	YES	YES	YES	YES	YES
$NConflict_{i,t-1}$	YES	YES	YES	YES	YES	YES

$Conflict_{i,t}$ is a binary variable indicating the presence (=1) or absence (=0) of a conflict resulting in at least one death in district i in year t. $DIS_{i,t}$ and $DIS_{i,t-1}$ are binary variables indicating the presence (=1) or absence (=0) of a natural disaster event in district i in years y and $t-1$, respectively. $NDIS_{i,t}$ ($NConflict_{i,t}$) are binary variable indicating the presence (=1) or absence (=0) of a natural disaster event (conflict), in any one of district i's neighbours in year t. Neighbourhood is based on the altitude-adjusted inverse geodesic distance network, truncated at 500km. Disasters exclude droughts. Conley (1999) clustered standard errors, accounting for spatial correlation up to 500km and temporal correlation up to 1 period, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B.7: Direct and spillover effects of SPEI

	(1) $Conflict_{i,t}$	(2) $Conflict_{i,t}$
$SPEI_{i,t}$	0.0121***	0.0029
	(0.0041)	(0.0044)
$SPEI_{i,t-1}$	0.0042	-0.0045
	(0.0039)	(0.0042)
$NSPEI_{i,t}$		0.0236***
		(0.0082)
$NSPEI_{i,t-1}$		0.0219***
		(0.0081)
Observations	172,376	172,376
Distance Cut-off	NA	500km
District FE	YES	YES
Country× Year FE	YES	YES
$NConflict_{i,t}$	NA	YES
$NConflict_{i,t-1}$	NA	YES

$Conflict$ is a binary variable indicating the presence (=1) or absence (=0) of a conflict resulting in at least one death in the given district in the given time period. $SPEI$ is the Standardised Precipitation-Evapotranspiration Index for the district, while $NSPEI$ is the spatial lag of the SPEI index for district's neighbours for the given year. $NConflict$ is a binary variable indicating the presence (=1) or absence (=0) of a conflict in any one of the district's neighbours. Neighbourhood is based on the altitude-adjusted inverse distance matrix, truncated at 500km. Conley (1999) clustered standard errors, accounting for spatial correlation up to 500km and temporal correlation up to 1 period, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B.8: Estimates by conflict type

	(1) $Conflict_{i,t}$	(2) $Conflict_{i,t}$	(3) $Conflict_{i,t}$
Conflict Type	*State*	*Non − State*	*Onesided*
$DIS_{i,t}$	-0.0002	-0.0002	-0.0007
	(0.0022)	(0.0019)	(0.0019)
$DIS_{i,t-1}$	-0.0034*	-0.0005	-0.0036*
	(0.0020)	(0.0019)	(0.0019)
$NDIS_{i,t}$	0.0031	0.0024	-0.0002
	(0.0028)	(0.0016)	(0.0021)
$NDIS_{i,t-1}$	0.0049*	0.0041**	0.0032
	(0.0027)	(0.0016)	(0.0022)
Observations	184,264	184,264	184,264
Distance Cut-off	500km	500km	500km
District FE	YES	YES	YES
Country× Year FE	YES	YES	YES
$NConflict_{i,t}$	YES	YES	YES
$NConflict_{i,t-1}$	YES	YES	YES

$Conflict_{i,t}$ is a binary variable indicating the presence (=1) or absence (=0) of a conflict resulting in at least one death in district i in year t. $DIS_{i,t}$ and $DIS_{i,t-1}$ are binary variables indicating the presence (=1) or absence (=0) of a natural disaster event in district i in years y and $t-1$, respectively. $NDIS_{i,t}$ ($NConflict_{i,t}$) are binary variable indicating the presence (=1) or absence (=0) of a natural disaster event (conflict), in any one of district i's neighbours in year t. Neighbourhood is based on the altitude-adjusted inverse geodesic distance network, truncated at 500km. Disasters exclude droughts. Conley (1999) clustered standard errors, accounting for spatial correlation up to 500km and temporal correlation up to 1 period, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B.9: ACLED vs UCDP comparison

	(1) ACLED $Violence_{i,t}$	(2) UCDP $Violence_{i,t}$	(3) Pooled $Violence_{i,t}$
$DIS_{i,t}$	-0.0014	-0.0019	-0.0008
	(0.0042)	(0.0033)	(0.0046)
$DIS_{i,t-1}$	-0.0013	-0.0058*	-0.0026
	(0.0042)	(0.0031)	(0.0045)
$NDIS_{i,t}$	0.0108**	0.0045	0.0118**
	(0.0042)	(0.0037)	(0.0046)
$NDIS_{i,t-1}$	0.0102**	0.0113***	0.0149***
	(0.0042)	(0.0036)	(0.0045)
Observations	136,712	136,712	136,712
Distance Cutoff	500km	500km	500km
District FE	YES	YES	YES
Country× Year FE	YES	YES	YES
$N(Outcome)_{i,t}$	YES	YES	YES
$N(Outcome)_{i,t-1}$	YES	YES	YES

DIS is a binary variable indicating the presence (=1) or absence (=0) of a natural disaster event in the given district in the given time period. The outcome variable in Column (1) is a binary variable indicating the presence (=1) or absence (=0) of a violent event as per the ACLED database. The outcome variable in Column (2) is a binary variable indicating the presence (=1) or absence (=0) of a violent event as per the UCDP database, for the same sample as in Column (1). The outcome variable in Column (3) is a binary variable indicating the presence (=1) or absence (=0) of a violent event as per either the ACLED or the UCDP database. $NDIS$ and $N(Outcome)$ are binary variables indicating the presence (=1) or absence (=0) of a natural disaster event or the outcome variable of interest, respectively, in any one of the district's neighbours. Neighbourhood is based on the altitude-adjusted inverse distance matrix, truncated at 500km. Conley (1999) clustered standard errors, accounting for spatial correlation up to 500km and temporal correlation up to 1 period, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B.10: Analysis for districts with area $\leq 55\text{km}^2$ and using Dartmouth Flood Observatory (DFO) data at the Grid cell level

	Districts $\leq 55\text{km}^2$ area		DFO data & Grid cells	
	(1)	(2)	(3)	(4)
	$Conflict_{i,t}$	$Conflict_{i,t}$	$Conflict_{i,t}$	$Conflict_{i,t}$
$DIS_{i,t}$	0.0004	0.0005		
	(0.0034)	(0.0034)		
$DIS_{i,t-1}$	-0.0052*	-0.0051*		
	(0.0031)	(0.0031)		
$NDIS_{i,t}$	0.0038	0.0039		
	(0.0041)	(0.0041)		
$NDIS_{i,t-1}$	0.0101**	0.0102**		
	(0.0040)	(0.0040)		
$Flood_{i,t}$			-0.0075	-0.0075
			(0.0074)	(0.0074)
$Flood_{i,t-1}$			-0.0106	-0.0107
			(0.0079)	(0.0079)
$NFlood_{i,t}$			0.0035**	0.0033**
			(0.0014)	(0.0014)
$NFlood_{i,t-1}$			0.0039***	0.0038***
			(0.0014)	(0.0014)
Observations	156,922	156,922	320,385	320,385
Distance Cut-off	500km	500km	500km	500km
District/Grid cell FE	YES	YES	YES	YES
Country× Year FE	YES	YES	YES	YES
$NConflict_{i,t}$	NO	YES	NO	YES
$NConflict_{i,t-1}$	NO	YES	NO	YES

Columns (1) and (2) replicate the baseline analysis for districts with area $\leq 55\text{km}^2$. Columns (3) and (4) replicate the baseline analysis, at the grid cell level, using data on floods from the DFO. $Conflict$, DIS and $Flood$ are binary variables indicating the presence (=1) or absence (=0) of a battle resulting in at least one death, natural disaster event or flood, respectively, in the given district in the given time period. $NDIS$, $NConflict$ and $NFlood$ are binary variables indicating the presence (=1) or absence (=0) of a natural disaster event, battle or flood, in any one of the district's neighbours. Disasters exclude droughts.() present Conley (1999) clustered standard errors, accounting for spatial correlation up to 500km and temporal correlation up to 1 period. *** p<0.01, ** p<0.05, * p<0.1

Table B.11: Conflict onset and termination

	(1) $Onset_{i,t}$	(2) $Termination_{i,t}$
$DIS_{i,t}$	-0.0018	-0.0007
	(0.0015)	(0.0014)
$DIS_{i,t-1}$	-0.0025	-0.0003
	(0.0016)	(0.0015)
Observations	146,805	161,534
District FE	YES	YES
Country × Year FE	YES	YES

Onset is a binary indicator = 0 in periods with no conflict events; = 1 in the first time period a district experiences a conflict; and missing in subsequent time periods. *Termination* is a binary indicator = 0 in periods of conflict; = 1 in the first period with no conflict; and missing in subsequent time periods. *DIS* is a binary variable indicating the presence (=1) or absence (=0) of a natural disaster event in the given district in the given time period. Disasters exclude droughts. Conley (1999) clustered standard errors, accounting for spatial correlation up to 500km and temporal correlation up to 1 period, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B.12: Alternative distance cut-offs

	(1) $Conflict_{i,t}$	(2) $Conflict_{i,t}$	(3) $Conflict_{i,t}$	(4) $Conflict_{i,t}$	(5) $Conflict_{i,t}$
$DIS_{i,t}$	-0.0016	-0.0032	-0.0028	-0.0025	-0.0027
	(0.0026)	(0.0027)	(0.0028)	(0.0029)	(0.0030)
$DIS_{i,t-1}$	-0.0047*	-0.0057**	-0.0059**	-0.0058**	-0.0056**
	(0.0025)	(0.0026)	(0.0028)	(0.0028)	(0.0028)
$NDIS_{i,t}$	-0.0022	0.0045**	0.0053**	0.0045	0.0057*
	(0.0020)	(0.0022)	(0.0026)	(0.0029)	(0.0033)
$NDIS_{i,t-1}$	-0.0007	0.0027	0.0054**	0.0086***	0.0105***
	(0.0019)	(0.0022)	(0.0026)	(0.0029)	(0.0033)
Observations	184,264	184,264	184,264	184,264	184,264
Distance Cutoff	100km	200km	300km	400km	500km
District FE	YES	YES	YES	YES	YES
Country× Year FE	YES	YES	YES	YES	YES
$NConflict_{i,t}$	YES	YES	YES	YES	YES
$NConflict_{i,t-1}$	YES	YES	YES	YES	YES

$Conflict$ and DIS are binary variables indicating the presence (=1) or absence (=0) of a conflict resulting in at least one death, and natural disaster event, respectively, in the given district in the given time period. $NDIS$ ($NConflict$) is a binary variable indicating the presence (=1) or absence (=0) of a natural disaster event (conflict), in any one of the district's neighbours, within the given time period. Neighbourhood is based on the altitude-adjusted inverse distance matrix, truncated at the indicated distance cut-off. Disasters exclude droughts. Conley (1999) clustered standard errors, accounting for spatial correlation up to 500km and temporal correlation up to 1 period, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B.13: Alternative connectivity networks

Connectivity	(1) Contiguity	(2) Ethnicity	(3) Roads	(4) Inverse Distance (no altitude adjusment)
	$Conflict_{i,t}$	$Conflict_{i,t}$	$Conflict_{i,t}$	$Conflict_{i,t}$
$DIS_{i,t}$	-0.0007	-0.0024	-0.0032	-0.0027
	(0.0029)	(0.0030)	(0.0030)	(0.0030)
$DIS_{i,t-1}$	-0.0058**	-0.0058**	-0.0064**	-0.0056**
	(0.0028)	(0.0028)	(0.0028)	(0.0028)
$NDIS_{i,t}$	-0.0017	-0.0006	0.0053**	0.0057*
	(0.0024)	(0.0024)	(0.0021)	(0.0033)
$NDIS_{i,t-1}$	0.0025	0.0019	0.0040*	0.0105***
	(0.0025)	(0.0025)	(0.0021)	(0.0033)
Observations	184,264	184,264	184,264	184,264
Distance Cut-off	NA	NA	500km	500km
District FE	YES	YES	YES	YES
Country× Year FE	YES	YES	YES	YES
$NConflict_{i,t}$	YES	YES	YES	YES
$NConflict_{i,t-1}$	YES	YES	YES	YES

$Conflict$ and DIS are binary variables indicating the presence (=1) or absence (=0) of a battle resulting in at least one death, an d natural disaster event, respectively, in the given district in the given time period. $NDIS$ ($NConflict$) is a binary variable indicating the presence (=1) or absence (=0) of a natural disaster event (battle), in any one of the district's neighbours, defined as per contiguity (Column 1), ethnicity (Column 2), inverse road distance (Column 3) and inverse geodesic distance with no altitude adjustment (Column 4). The contiguity network identifies neighbours with whom district i shares a common border. The ethnicity network identifies whether the majority ethnic group (as per Murdock (1959)) in districts i and j are the same. The inverse road distance network is based on the Open Street Map data on major roads in Africa as of 2016, and is truncated at 500km. Disasters exclude droughts. present Conley (1999) clustered standard errors, accounting for spatial correlation up to 500km and temporal correlation up to 1 period, while () present country×year clustered standard errors. *** p<0.01, ** p<0.05, * p<0.1

Table B.14: Incorporating country connectivity networks

	(1)	(2)	(3)	(4)	(5)
			$State$	$Non-State$	$Onesided$
	$Conflict_{i,t}$	$Conflict_{i,t}$	$Conflict_{i,t}$	$Conflict_{i,t}$	$Conflict_{i,t}$
$DIS_{i,t}$	-0.0019	-0.0016	-0.0001	0.0005	-0.0004
	(0.0030)	(0.0030)	(0.0022)	(0.0020)	(0.0019)
$DIS_{i,t-1}$	-0.0059**	-0.0059**	-0.0036*	-0.0008	-0.0043**
	(0.0028)	(0.0028)	(0.0020)	(0.0019)	(0.0019)
$NDIS_{i,t}$	-0.0004	-0.0002	-0.0003	-0.0022	0.0011
(within country)	(0.0035)	(0.0035)	(0.0028)	(0.0017)	(0.0021)
$NDIS_{i,t-1}$	0.0038	0.0042	0.0013	0.0026*	0.0006
(within country)	(0.0032)	(0.0032)	(0.0026)	(0.0016)	(0.0022)
$NDIS_{i,t}$		0.0039	0.0012	0.0024*	-0.0003
(Outside country)		(0.0028)	(0.0022)	(0.0015)	(0.0018)
$NDIS_{i,t-1}$		0.0055*	0.0016	0.0021	0.0024
(Outside country)		(0.0028)	(0.0022)	(0.0015)	(0.0019)
Observations	184,264	184,264	184,264	184,264	184,264
Distance Cut-off	500km	500km	500km	500km	500km
District FE	YES	YES	YES	YES	YES
Country× Year FE	YES	YES	YES	YES	YES
$NConflict_{i,t}$	YES	YES	YES	YES	YES
$NConflict_{i,t-1}$	YES	YES	YES	YES	YES

$Conflict$ and DIS are binary variables indicating the presence (=1) or absence (=0) of a battle resulting in at least one death, an d natural disaster event, respectively, in the given district in the given time period. $NDIS$ (*within country*) is a binary variable indicating the presence (=1) or absence (=0) of a natural disaster event, in any one of the district's neighbours, within 500km, and within country borders. $NDIS$ *outside country*) is a binary variable indicating the presence (=1) or absence (=0) of a natural disaster event, in any one of the district's neighbours,within 500km but outside country borders. Disasters exclude droughts. () present Conley (1999) clustered standard errors, accounting for spatial correlation up to 500km and temporal correlation up to 1 period. *** p<0.01, ** p<0.05, * p<0.1

Table B.15: Natural disasters and economic activity

	(1) $Light_{i,t}$	(2) $Conflict_{i,t}$
$DIS_{i,t}$	-0.0215	-0.0024
	(0.0258)	(0.0027)
$DIS_{i,t-1}$	0.0066	-0.0057**
	(0.0198)	(0.0025)
$NDIS_{i,t}$	0.0260	0.0043
	(0.0244)	(0.0028)
$NDIS_{i,t-1}$	-0.0083	0.0097***
	(0.0256)	(0.0029)
Observations	166,432	166,432
Distance Cutoff	500km	500km
District FE	YES	YES
Country× Year FE	YES	YES
Controls	YES	YES

Disaster is a binary variable indicating the presence (=1) or absence (=0) of a natural disaster event in the given district in the given time period. $NDIS$ is a binary variable indicating the presence (=1) or absence (=0) of a natural disaster event, in any one of the district's neighbours, within the given time period. Neighbourhood is based on the altitude-adjusted inverse distance matrix, truncated at 500km. *Light* represents the average value of night-time lights in the given district for the given time period. Controls for Column (1) are $NLight_{i,t}$, $NLight_{i,t-1}$ and $Light_{i,t-1}$. Controls for Column (2) are $Light_{i,t}$, $Conflict_{i,t-1}$, $NLight_{i,t}$, $NLight_{i,t-1}$, $NConflict_{i,t}$ and $NConflict_{i,t-1}$. Conley (1999) clustered standard errors, accounting for spatial correlation of up to 500km and temporal correlation up to 1 period, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B.16: Heterogeneity by nighttime light, mining and agriculture

	(1) Z=Light $Conflict_{i,t}$	(2) Z=Light $Conflict_{i,t}$	(3) Z=Agri $Conflict_{i,t}$	(4) Z=Agri $Conflict_{i,t}$	(5) Z=Mine $Conflict_{i,t}$	(6) Z=Mine $Conflict_{i,t}$
$DIS_{i,t} \times No\ Z_i$	0.0067	0.0070	0.0003	-0.0008	-0.0032	-0.0025
	(0.0045)	(0.0047)	(0.0044)	(0.0044)	(0.0076)	(0.0073)
$DIS_{i,t} \times Low\ Z_i$	-0.0049	-0.0055	-0.0042	-0.0051	0.0006	-0.0003
	(0.0037)	(0.0037)	(0.0037)	(0.0037)	(0.0073)	(0.0071)
$DIS_{i,t} \times High\ Z_i$	-0.0053	-0.0051	-0.0027	-0.0021	0.0010	-0.0014
	(0.0062)	(0.0061)	(0.0043)	(0.0043)	(0.0071)	(0.0073)
$DIS_{i,t-1} \times No\ Z_i$	0.0071*	0.0088**	0.0027	0.0023	-0.0018	-0.0005
	(0.0042)	(0.0042)	(0.0042)	(0.0043)	(0.0076)	(0.0074)
$DIS_{i,t-1} \times Low\ Z_i$	-0.0080**	-0.0096***	-0.0087**	-0.0095***	-0.0033	-0.0049
	(0.0037)	(0.0037)	(0.0036)	(0.0036)	(0.0074)	(0.0071)
$DIS_{i,t-1} \times High\ Z_i$	-0.0081	-0.0067	-0.0074*	-0.0075*	-0.0113*	-0.0114*
	(0.0060)	(0.0059)	(0.0040)	(0.0039)	(0.0067)	(0.0068)
$NDIS_{i,t} \times No\ Z_i$		0.0016		0.0093***		0.0001
		(0.0033)		(0.0035)		(0.0062)
$NDIS_{i,t} \times Low\ Z_i$		0.0049		0.0070**		0.0054
		(0.0039)		(0.0035)		(0.0061)
$NDIS_{i,t} \times High\ Z_i$		0.0060		0.0020		0.0132**
		(0.0046)		(0.0046)		(0.0066)
$NDIS_{i,t-1} \times No\ Z_i$		-0.0045		0.0093***		-0.0039
		(0.0037)		(0.0036)		(0.0062)
$NDIS_{i,t-1} \times Low\ Z_i$		0.0137***		0.0115***		0.0143**
		(0.0039)		(0.0035)		(0.0061)
$NDIS_{i,t-1} \times High\ Z_i$		0.0071		0.0109**		0.0094
		(0.0046)		(0.0045)		(0.0072)
Observations	184,264	184,264	184,264	184,264	184,264	184,264
District FE	YES	YES	YES	YES	YES	YES
Country-Year FE	YES	YES	YES	YES	YES	YES
$NConflict_{i,t}$	YES	YES	YES	YES	YES	YES
$NConflict_{i,t-1}$	YES	YES	YES	YES	YES	YES

$Conflict$ and DIS are binary variables indicating the presence (=1) or absence (=0) of a conflict resulting in at least one death, and natural disaster event, respectively, in the given district in the given time period. $NDIS$ ($NConflict$) is a binary variable indicating the presence (=1) or absence (=0) of a natural disaster event (conflict), in any one of the district's neighbours. Disasters exclude droughts. The set of districts is divided as no, low or high levels of activity based on binary indicators that capture the intensity of Nighttime Light, Mining and Agricultural activity. () present Conley (1999) clustered standard errors, accounting for spatial correlation up to 500km and temporal correlation up to 1 period. *** p<0.01, ** p<0.05, * p<0.1

Table B.17: Estimates by OFDA receipt-status of natural disasters

	(1)
	$Conflict_{i,t}$
$DIS_{i,t}$	-0.0030
	(0.0033)
$DIS_{i,t} \times$ Aid	0.0037
	(0.0070)
$DIS_{i,t-1}$	-0.0078**
	(0.0031)
$DIS_{i,t-1} \times Aid$	0.0125*
	(0.0068)
$NDIS_{i,t}$	0.0063*
	(0.0034)
$NDIS_{i,t} \times Aid$	-0.0034
	(0.0041)
$NDIS_{i,t-1}$	0.0128***
	(0.0035)
$NDIS_{i,t-1} \times Aid$	-0.0136***
	(0.0041)
Observations	184,264
Distance Cut-off	500km
District FE	YES
Country× Year FE	YES
$NConflict_{i,t}$	YES
$NConflict_{i,t-1}$	YES

$Conflict$ and DIS are binary variables indicating the presence (=1) or absence (=0) of a conflict resulting in at least one death, and natural disaster event, respectively, in the given district in the given time period. $NDIS$ ($NConflict$) is a binary variable indicating the presence (=1) or absence (=0) of a natural disaster event (conflict), in any one of the district's neighbours. Disasters exclude droughts. *Aid* is a binary indicator that identifies whether or not the natural disaster, whether in district i or in the neighbouring districts, received foreign aid from the OFDA. () present Conley (1999) clustered standard errors, accounting for spatial correlation up to 500km and temporal correlation up to 1 period. *** p<0.01, ** p<0.05, * p<0.1

C A possible theoretical mechanism

In this section, we provide a possible mechanism of our empirical results, which show how a negative shock on a district negatively affects the battle on this district, but also affects the neighbouring districts.

C.1 The general model

Players, districts, and battles Consider a set of players (which can be local military forces or militia) and different possible battles between them. The network represents the nodes (players) and the links (battles) between them. We use $n = 1, 2, 3, \cdots, i, j, \cdots$, to denote players and $\alpha = a, b, c, \cdots$, to denote battles. The set of players is denoted by $\mathcal{N}$, with $N = |\mathcal{N}| \geq 2$, and the set of battles by $\mathcal{T}$, with $T = |\mathcal{T}| \geq 1$.

Network We use an $N \times T$ matrix $\mathbf{\Gamma} = (\gamma_i^\alpha)$ to represent the battle structure. Specifically, we let $\gamma_i^\alpha = 1$ if player i is part of battle α; otherwise $\gamma_i^\alpha = 0$. Each player can be part of *multiple battles* and different battles may involve different subsets of players. Let $\mathcal{N}^\alpha = \{i \in \mathcal{N} : \gamma_i^\alpha = 1\} \subseteq \mathcal{N}$ denote the set of participants (players) in battle α. Let $n^\alpha = |\mathcal{N}^\alpha| \geq 2$ denote its cardinality. Similarly, let $\mathcal{T}_i = \{\alpha \in \mathcal{T} : \gamma_i^\alpha = 1\} \subseteq \mathcal{T}$ denote the set of battles that player i takes part in. Let $t_i = |\mathcal{T}_i| \geq 1$ denote the cardinality. Clearly, $i \in \mathcal{N}^\alpha$ if and only if $\alpha \in \mathcal{T}_i$.

Consider the following figure, which represents a star network:

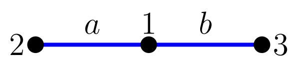


Figure C.1: A star network

The matrix $\mathbf{\Gamma}$ representing the network depicted in Figure C.1 is given by:

$$\mathbf{\Gamma} = \begin{bmatrix} 1 & 1 \\ 1 & 0 \\ 0 & 1 \end{bmatrix}$$

where rows correspond to players and columns to battles. We see that player 1 engages in a battle with players 2 and 3; whereas, player 2 engages in battle a with player 1 and player 3 engages in battle b with player 1. We have: $\mathcal{N} = \{1, 2, 3\}$, $\mathcal{T} = \{a, b\}$, $\mathcal{N}^a = \{1, 2\}$, $\mathcal{N}^b = \{1, 3\}$, $\mathcal{T}_1 = \{a, b\}$, $\mathcal{T}_2 = \{a\}$, $\mathcal{T}_3 = \{b\}$.

Districts From the network, we can aggregate the players and the battles to obtain a *district*. Thus, a district corresponds to a battle and we assume that, in each district, only one battle can take place. We can define a connectivity matrix $\mathbf{\Omega} = (\omega_{ab})$ such that $\omega_{ab} \in [0, 1]$ if a link exists between two districts a and b and $\omega_{ab} = 0$ otherwise. For example, in the star network of Figure C.1, there are two districts: district a, which encompasses players 1 and 2 and where battle a takes place, and district b, which is made of players 1 and 3, and where battle b takes place, so that $\omega_{ab} > 0$. This can be represented as follows:

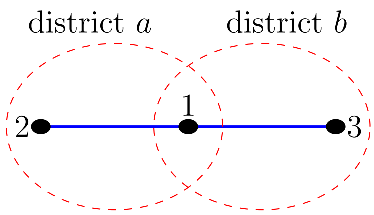


Figure C.2: A star network

Of course, any other district representation can be made from Figure C.1. In the empirical analysis, a district was defined by its *geographical* position and there will be a link between two districts if there is a major road between them and thus $\omega_{ab} > 0$.[5] For exam-

[5]In the empirical analysis, we also used the inverse distance between two districts to define a link between them.

ple, in Figure C.2, there are two districts a and b and they are geographically adjacent to each other (i.e., there is a major road between them). In that case, there are two layers of proximity, which involve different actors: (i) the *Conflict proximity* where, as in Figure C.1, a link is when two *players* have a battle with each other; this is captured by the matrix $\mathbf{\Gamma}$, (ii) the *geographical proximity* where, as in Figure C.2, there is a link between two *districts* when they are spatially adjacent to each other; this is captured by the matrix $\mathbf{\Omega}$.

Payoffs Taking the battle structure $\mathbf{\Gamma}$ as given, player i's strategy is to choose a nonnegative effort x_i^α for each battle $\alpha \in \mathcal{T}_i$ she is involved in. Thus, player i's strategy is a vector $\mathbf{x}_i = \{x_i^\alpha\}_{\alpha \in \mathcal{T}_i} \in \mathbf{R}_+^{t_i}$. Given player i's strategy $\mathbf{x}_i$, we denote $\mathbf{x} = (\mathbf{x}_1, \cdots, \mathbf{x}_n) \in \mathbf{R}_+^{\bar{n}}$ as the whole strategy profile, and $\mathbf{x}^\alpha = \{x_i^\alpha\}_{i \in \mathcal{N}^\alpha} \in \mathbf{R}_+^{n^\alpha}$ as the effort vector in battle α. Here $\bar{n} = \sum_{\alpha \in \mathcal{T}} n^\alpha = \sum_{i \in \mathcal{N}} t_i = \sum_{i \in \mathcal{N}, \alpha \in \mathcal{T}} \gamma_i^\alpha$ denote the dimension of strategy profile $\mathbf{x}$.

The payoff function of player $i \in \mathcal{N}$ is equal to:

$$\Pi_i(\mathbf{x}_i, \mathbf{x}_{-i}) = \sum_{\alpha \in \mathcal{T}_i} v^\alpha p_i^\alpha(\mathbf{x}^\alpha) - C_i(\mathbf{x}_i), \tag{C.1}$$

which is just the net expected value of winning the battle(s). Indeed, in (C.1), $p_i^\alpha(\mathbf{x}^\alpha)$ is the probability of winning battle α for player i. It is given by the following Tullock CSF:

$$p_i^\alpha(\mathbf{x}^\alpha) = \frac{x_i^\alpha}{\sum_{j \in \mathcal{N}^\alpha} x_j^\alpha}. \tag{C.2}$$

Moreover, each battle α generates a benefit $v^\alpha > 0$ for the player who wins the battle. This value might vary across battles. Finally, there is a total cost of $C_i(\mathbf{x}_i)$, which depends on all the efforts player i exerts in each battle she is involved in.

Note that, in the data (Section 2), we only observe the total battle at the district level and the geographical link between districts and analyze how a negative shock (disaster) on a district affects the total battle in the different districts that are spatially connected. We do not, however, observe the players involved in battles in each district. Consider Figure C.2. In our model, this translates by studying how a decrease in v^a (the value of battle a) affects $x_1^a + x_2^a$, the total battle in district a, and $x_1^b + x_3^b$, the total battle in the (spatially) adjacent district b.

Nash equilibrium Let us solve the Nash equilibrium of this game for any network and any player. We are interested in the pure strategy Nash equilibrium of this battle game. A strategy profile $\mathbf{x}^* = (\mathbf{x}_1^*, \cdots, \mathbf{x}_n^*)$ is an equilibrium of the battle game if for every player $i \in \mathcal{N}$,

$$\Pi_i(\mathbf{x}_i^*, \mathbf{x}_{-i}^*) \geq \Pi_i(\mathbf{x}_i, \mathbf{x}_{-i}^*), \quad \forall \mathbf{x}_i. \tag{C.3}$$

This model is very general because it incorporates any network structure, the best response functions are non-linear but, more importantly, each agent is involved in many battles. We can still show that the equilibrium exists and is unique for any network structure and give conditions for which the equilibrium efforts are strictly positive. It is, however, difficult to explicitly characterize the Nash equilibrium of this game and to derive comparative statics results. Because we want to provide a mechanism of our empirical results, we would like to derive some properties of this equilibrium for specific networks that we could test empirically. We will mainly consider the star network of Figure C.1 or Figure C.2 because it is tractable and still provides all the intuition we need for our empirical analysis.[6]

The key aspect of our model is that agents are involved in *many battles*. This will explain why, after a negative shock, such as a disaster, agents shift their effort to other battles and can, thus, explain the propagation of shocks in path-connected districts. We can derive abstract comparative statics results for general network structures but, to understand how a shock propagates to other districts, we need to focus on specific networks.

[6]In Section C.3, we provide similar results for a line network with more agents and more battles.

C.2 Star network

C.2.1 The model

Consider the star network depicted in Figure C.1 where $\alpha = a, b$ (two battles and three players). Given the network structure, the strategies of the players are: $\mathbf{x}_1 = (x_1^a, x_1^b)$, $\mathbf{x}_2 = (x_2^a)$ and $\mathbf{x}_3 = (x_3^b)$. To keep the model tractable, we assume that the cost function is quadratic so that each player's payoff can be written as:

$$
\begin{aligned}
\Pi_1(\mathbf{x}_1, \mathbf{x}_{-1}) =& v^a \frac{x_1^a}{x_1^a + x_2^a} + v^b \frac{x_1^b}{x_1^b + x_3^b} - \frac{s_1}{2}(x_1^a + x_1^b)^2, \\
\Pi_2(\mathbf{x}_2, \mathbf{x}_{-2}) =& v^a \frac{x_2^a}{x_1^a + x_2^a} - \frac{s_2}{2}(x_2^a)^2, \\
\Pi_3(\mathbf{x}_3, \mathbf{x}_{-3}) =& v^b \frac{x_3^b}{x_1^b + x_3^b} - \frac{s_3}{2}(x_3^b)^2.
\end{aligned} \tag{C.4}
$$

C.2.2 Equilibrium analysis

Even in this simple network structure, closed-form expressions of the Nash equilibrium efforts are not possible, but we can use the first-order conditions (FOCs) of players to characterize the Nash equilibrium. Let

$$F_1(x_1^a, x_1^b, x_2^a) := \frac{\partial \Pi_1}{\partial x_1^a} = \frac{v^a x_2^a}{(x_1^a + x_2^a)^2} - s_1(x_1^a + x_1^b), \tag{C.5}$$

$$F_2(x_1^a, x_1^b, x_3^b) := \frac{\partial \Pi_1}{\partial x_1^b} = \frac{v^b x_3^b}{(x_1^b + x_3^b)^2} - s_1(x_1^a + x_1^b), \tag{C.6}$$

$$F_3(x_1^a, x_2^a) := \frac{\partial \Pi_2}{\partial x_2^a} = \frac{v^a x_1^a}{(x_1^a + x_2^a)^2} - s_2 x_2^a, \tag{C.7}$$

$$F_4(x_1^b, x_3^b) = \frac{\partial \Pi_3}{\partial x_3^b} = \frac{v^b x_1^b}{(x_1^b + x_3^b)^2} - s_3 x_3^b. \tag{C.8}$$

We have the following results:[7]

Proposition 1. *Consider the star network depicted in Figure C.1 and the payoff functions given by* (C.4)*. Then, there exists a unique interior Nash equilibrium* $(x_1^{a*}, x_1^{b*}, x_2^{a*}, x_3^{a*})$ *that simultaneously solves:*

$$\begin{cases} F_1(x_1^{a*}, x_1^{b*}, x_2^{a*}) = 0 \\ F_2(x_1^{a*}, x_1^{b*}, x_3^{b*}) = 0 \\ F_3(x_1^{a*}, x_2^{a*}) = 0 \\ F_4(x_1^{b*}, x_3^{b*}) = 0 \end{cases} \tag{C.9}$$

Given the existence, uniqueness, and interiority of the Nash equilibrium, we are interested in the effect on the shock of the valuations v^a and v^b on the battle levels of each district. Note that the system (C.9) is highly non-linear and, therefore, there are no explicit expressions for the equilibrium. Instead, we apply the implicit function theorem to the system (C.9) in order to derive the comparative statics results. Before performing these exercises, the following lemma will help us interpret our results.

Lemma 1. *For* $v > 0, s > 0$*, define*

$$z(x, y) = \frac{vx}{x + y} - \frac{s}{2}x^2. \tag{C.10}$$

For each $y > 0$*, there exists a unique maximizer* $x^*(y) = \arg\max_{x>0} z(x, y)$*. Moreover,* $x^*(y)$ *is first increasing, then decreasing in* y *with sign* $\left(\frac{\partial x^*}{\partial y}\right) = sign(x^* - y)$*.*

We can see from equations (C.5)–(C.8) that Lemma 1 describes the best response function $x^*(\cdot)$. In particular, Lemma 1 shows that $x^*(\cdot)$ first increases with y up to the maximum, which occurs at $x^* = y$, and then decreases. There is therefore a *non-monotonic bell shaped*

[7] All the proofs of the theoretical model can be found in Appendix C.5.

relationship between the efforts of two players involved in the same battle. Figure C.3 depicts this relationship.

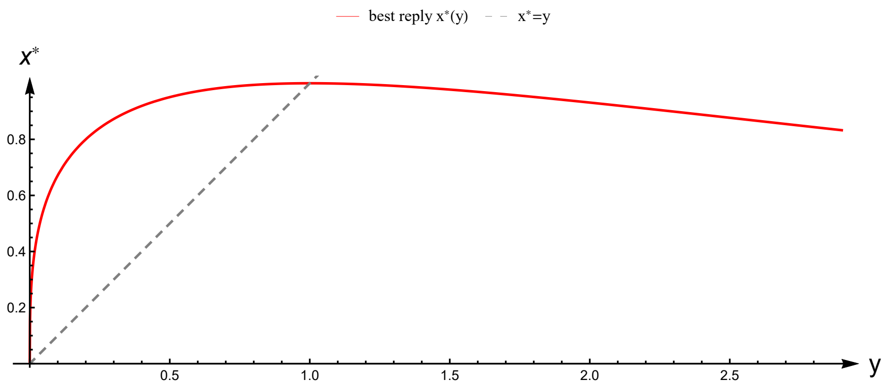


Figure C.3: Best response function $x^*(y)$

To see the implication of this Lemma, for example, consider the first-order condition of x_2^a, that is, $F_3(x_1^{a*}, x_2^{a*}) = 0$. Using Lemma 1, we know that the sign of $\frac{\partial x_2^{a*}}{\partial x_1^a}$ is the same as the sign of $(x_2^{a*} - x_1^{a*})$ and that the relationship is bell-shaped where the maximum occurs at $x_2^{a*} = x_1^{a*}$. Indeed, when $x_1^{a*} < x_2^{a*}$, which means that player 1 is "weak" because $p_2^a(x_1^a, x_2^a) = x_2^a/(x_1^a + x_2^a)$, the probability of winning battle a for player 2, is greater than 50%, then player 2's best response to an increase of x_1^{a*}, is to increase her effort x_2^a. By contrast, when $x_1^{a*} > x_2^{a*}$, we are on the decreasing part of the relationship because player 2 is now the "weak"player in battle a because she has a lower chance of winning the battle. Therefore, when player 1 increases her effort, player 2's best response is to decrease her effort. Indeed, player 2 knows that her marginal chance of winning the battle is lower and thus basically gives up by reducing her effort.

Observe that Lemma 1 provides the best response function of a player within an *isolated* battle and, hence, abstracts from the general equilibrium effects, that is, the link between battles through the cost function. In our model, a player may have multiple battles, For example, for player 1, who is involved in battles a and b, her cost function, $C_1(x_1^a, x_1^b) = \frac{s_1}{2}(x_1^a + x_1^b)^2$, is convex in her total effort $x_1^a + x_1^b$. This implies that increasing effort in one battle leads to higher marginal cost of effort in the other battle, that is, $\frac{\partial^2 C_1}{\partial x_1^a \partial x_1^b} = s_1 > 0$. This is not captured by Lemma 1, but we need to take this into account in the calculation of our comparative statics results.

C.2.3 Comparative statics: Negative shock on a district

As stated above, we do not observe the players involved in each battle in each district in the data. However, we observe the total battle in each district. Consider Figure C.2. In this section, we will study how a decrease in v^a, i.e., a negative shock on district a, affects $x_1^a + x_2^a$, the total battle in district a, and $x_1^b + x_3^b$, the total battle in the (spatially) adjacent district b.[8] To understand the mechanism behind the results, we will also study how a decrease in v^a affects the effort of each player involved in each battle.

Proposition 2. *Consider the star network depicted in Figures C.1 and C.2 and the payoff functions given by (C.4). When v^a, the value of battle a, decreases,*

1. *both players 1 and 2 decrease their efforts in battle a, that is, $\frac{\partial x_1^{a*}}{\partial v^a} > 0$ and $\frac{\partial x_2^{a*}}{\partial v^a} > 0$,*
2. *the total battle intensity in district a reduces, that is, $\frac{\partial (x_1^{a*} + x_2^{a*})}{\partial v^a} > 0$,*
3. *player 1 increases her effort in battle b, that is, $\frac{\partial x_1^{b*}}{\partial v^a} < 0$,*
4. *the total effort of players involved in battles a and b decreases, that is, $\frac{\partial (x_1^{a*} + x_1^{b*})}{\partial v^a} > 0$,*
5. *the effect on the effort of player 3 in battle b is ambiguous, that is, $\frac{\partial x_3^{b*}}{\partial v^a} \gtreqless 0$. Particularly, $sign \frac{\partial x_3^{b*}}{\partial v^a} = sign(x_1^{b*} - x_3^{b*})$.*
6. *the total battle intensity in district b increases, that is, $\frac{\partial (x_1^{b*} + x_3^{b*})}{\partial v^a} < 0$.*

[8] Without loss of generality, we focus on district a as the analysis for district b is similar because of the symmetry of the locations of these two districts.

The first result of this proposition is straightforward. When v^a, the value of battle a, decreases, both players involved in battle a spend less effort in that battle and, thus, x_1^a and x_2^a decrease. This leads to the fact that the total effort in battle a is reduced (result 2).

Moreover, because $C_1(x_1^a, x_2^a)$, player 1's cost, and v^b, the value of battle b, are fixed, player 1's incentive in battle b is higher because lower x_1^a decreases her marginal cost in battle b. Indeed, efforts x_1^a and x_1^b are *strategic substitutes* because

$$\frac{\partial^2 \Pi_1}{\partial x_1^a \partial x_1^b} = -\frac{\partial^2 C_1}{\partial x_1^a \partial x_1^b} = -s_1 < 0. \tag{C.11}$$

consequently, when v^a decreases, player 1 increases x_1^b, her effort in battle b (result 3). However, the aggregate effort of player 1 still goes down as the decrease in battle a dominates the increase in battle b (result 4).

The fifth result of this proposition is more complex and one needs to use Lemma 1 to understand this result. Indeed, when v^a decreases, player 1 decreases her effort in battle a and increases x_1^b, her effort in battle b. However, player 3's effort in battle b, depends on whether she is "weak"or "strong"in that battle. By the Chain rule,

$$\frac{\partial x_3^{b*}}{\partial v^a} = \frac{\partial x_3^{b*}}{\partial x_1^{b*}} \underbrace{\frac{\partial x_1^{b*}}{\partial v^a}}_{<0}$$

By Lemma 1, $sign\frac{\partial x_3^{b*}}{\partial x_1^{b*}} = sign(x_3^{b*} - x_1^{b*})$, therefore, $sign\frac{\partial x_3^{b*}}{\partial v^a} = sign(x_1^{b^*} - x_3^{b*})$. Intuitively, if player 3 is "weak", for example, because she has a very high marginal cost s_3, so that her effort x_3^{b*} is lower than $x_1^{b^*}$, then a decrease in v^a will increase player 1's effort in battle b x_1^{b*}. As a best response, player 3 lowers her effort x_3^{b*}. The opposite occurs if player 3 is "strong"in battle b.

The last result, where the intensity of the total battle in district b reduces, is because the direct effect of a decrease in v^a on battle a for player 1 is stronger than the indirect effect on battle b for player 3, even when the latter leads to more effort.

In summary, a negative shock to district a (i.e., a decrease in v^a) leads to a smaller battle in district a but a bigger battle in district b. Player 1's total effort decreases whereas player 3's effort can increase or decrease. The first result demonstrates that a negative local shock on district a has an effect on the adjacent district b through the general equilibrium effect. The mechanism behind this result is that the central player (or the player involved in many battles) must re-allocate efforts in both battles in order to maximize total payoff, whereas other players must respond optimally.

In Figure C.4, we illustrate our results by plotting the four efforts of the different players when v^a increases.[9] Consistent with Proposition 2, an increase in v^a leads to a big increase for the players in district a, that is both x_2^a, the effort of player 2 in battle a (blue curve) and x_1^a, the effort of player 1 in battle a (red curve) increase. We can also see that the effect of an increase of v^a is much smaller for the adjacent district b because x_1^b (dotted orange curve) slightly decreases, whereas x_3^b (solid black curve) is nearly unaffected. This is because, in this example, the effect of v^a does not spill over to player 3 involved in another battle.

[9]We use the following values for the parameters: $v^b = 1$, $s_1 = 0.35$, $s_2 = 0.35$, and $s_3 = 0.7$.

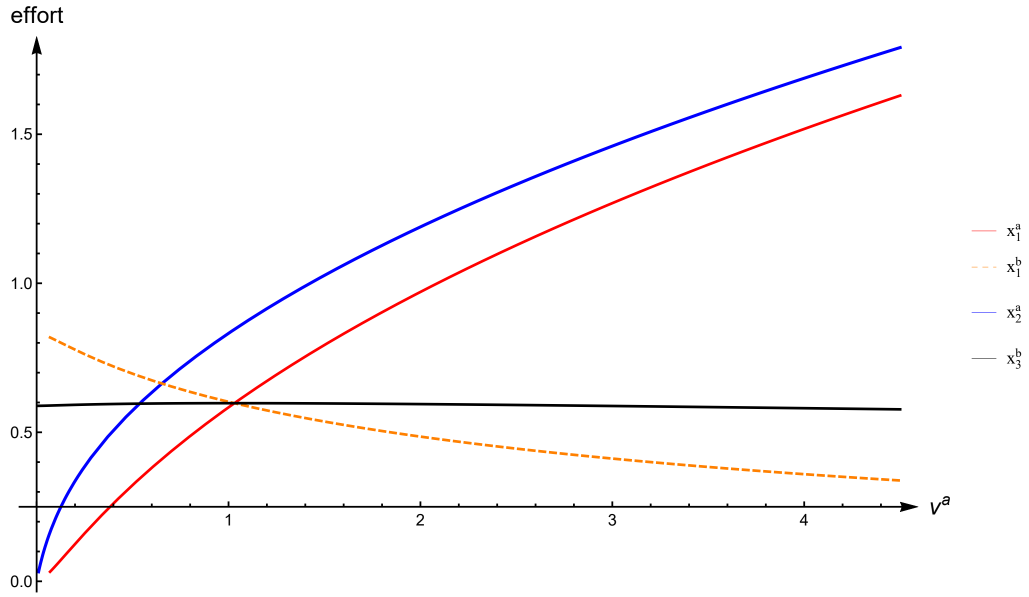


Figure C.4: The effect of an increase of v^a on the effort of each agent involved in battles in the network described in Figure C.1

More generally, our comparative statics results highlight the importance of three aspects of the model: (*i*) the cost linkage for a player/district participating in multiple battles, (*ii*) the relative position of a district within a given battle, and (*iii*) the non-monotonic best response function of each player.

C.3 More complex network structure: A line network

Consider the following figure, which represents a line network with four players and three battles:

Figure C.5: A line network with four players and three battles

Observe that this network is similar to the one depicted in Figure C.1; however, we added a link between players 2 and 4 and battle c.

The matrix $\mathbf{\Gamma}$ representing the network depicted in Figure C.5 is given by:

$$\mathbf{\Gamma} = \begin{bmatrix} 1 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

where rows correspond to players and columns to battles. We have: $\mathcal{N} = \{1,2,3,4\}$, $\mathcal{T} = \{a,b,c\}$, $\mathcal{N}^a = \{1,2\}$, $\mathcal{N}^b = \{1,3\}$, $\mathcal{N}^c = \{2,4\}$, $\mathcal{T}_1 = \{a,b\}$, $\mathcal{T}_2 = \{a,c\}$, $\mathcal{T}_3 = \{b\}$, and $\mathcal{T}_4 = \{c\}$.

Districts From the network, we can aggregate the players and the battles to obtain a district. In the line network of Figure C.5, there can be four districts, each corresponding to a battle: districts a, b, c, d. This network with districts can be represented as follows:

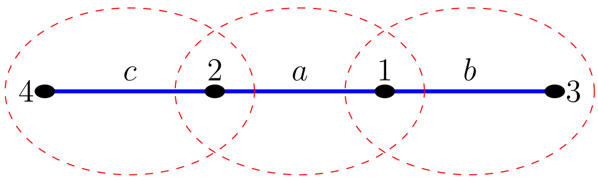


Figure C.6: A line network with three districts

As stated above, in the data, we only observe the total conflict at the district level and the geographical link between districts. In our model, let us study how a decrease in v^b, *a negative shock on district* b *(disaster)* affects the total conflict in the different districts a, b, c. In particular, we would like to show how a decreases in v^b (district located at the extreme right of the line network) affects the total conflict $x_2^c + x_4^c$ in district c (district located at the extreme left of the line network), even if districts b and c are *not* adjacent and involved different agents.

As above, to keep the model tractable, we assume that the cost function is quadratic; hence, each player's payoff can be written as:

$$
\begin{aligned}
\Pi_1(\mathbf{x}_1, \mathbf{x}_{-1}) =& v^a \frac{x_1^a}{x_1^a + x_2^a} + v^b \frac{x_1^b}{x_1^b + x_3^b} - \frac{s_1}{2}(x_1^a + x_1^b)^2, \\
\Pi_2(\mathbf{x}_2, \mathbf{x}_{-2}) =& v^a \frac{x_2^a}{x_1^a + x_2^a} + v^c \frac{x_2^c}{x_2^c + x_4^c} - \frac{s_2}{2}(x_2^a + x_2^c)^2, \\
\Pi_3(\mathbf{x}_3, \mathbf{x}_{-3}) =& v^b \frac{x_3^b}{x_1^b + x_3^b} - \frac{s_3}{2}(x_3^b)^2, \\
\Pi_4(\mathbf{x}_4, \mathbf{x}_{-4}) =& v^c \frac{x_4^c}{x_2^c + x_4^c} - \frac{s_4}{2}(x_4^c)^2.
\end{aligned}
\tag{C.12}
$$

We have the following result:[10]

Proposition 3. *Consider the line network depicted in Figures C.5 and C.6 and the payoff functions given by (C.12). When v^b, the value of battle b, decreases,*

1. *both players 1 and 3 decrease their efforts in battle b, that is, $\frac{\partial x_1^{b*}}{\partial v^b} > 0$ and $\frac{\partial x_3^{b*}}{\partial v^b} > 0$, and the total battle intensity in district b is reduced, that is, $\frac{\partial (x_1^{b*} + x_3^{b*})}{\partial v^b} > 0$;*

2. *player 1 increases her effort in battle a, that is, $\frac{\partial x_1^{a*}}{\partial v^b} < 0$, but her total effort decreases, that is, $\frac{\partial (x_1^{a*} + x_1^{b*})}{\partial v^a} > 0$;*

3. *the effect on the effort of player 2 in battle a and in battle c as well as on her total effort is ambiguous. Particularly, $sign \frac{\partial x_2^{a*}}{\partial v^b} = sign(x_1^{a^*} - x_2^{a*})$, $sign \frac{\partial x_2^{c*}}{\partial v^b} = sign(x_2^{a^*} - x_1^{a*})$, and $sign \frac{\partial (x_2^{a*} + x_2^{c*})}{\partial v^b} = sign(x_1^{a^*} - x_2^{a*})$;*

4. *the total battle intensity in district a increases, that is, $\frac{\partial (x_1^{a*} + x_2^{a*})}{\partial v^b} < 0$.*

5. *the effect on the effort of player 4 in battle c as well as the total effect on battle c is ambiguous. Particularly, $sign \frac{\partial x_4^{c*}}{\partial v^b} = sign(x_1^{a^*} - x_2^{a*})(x_2^{c^*} - x_4^{c*})$ and $sign \frac{\partial (x_2^{c*} + x_4^{c*})}{\partial v^b} = sign(x_2^{a^*} - x_1^{a*})$.*

[10] Even though it is more cumbersome, the proof of Proposition 3 is similar to that of Proposition 2 and is thus omitted.

The results of this proposition are similar to that of Proposition 2 since the effect of a negative shock on the district negatively affects the efforts of the agents involved in this district and, thus, the total conflict in this district (part 1), but it also propagates to other districts, depending on the origin of the shock (i.e., how far a district is located from the district that experiences the shock) and whether a player is "weak" or "strong" in the battle she is involved in. This is a general pattern that holds whenever the network does not have a cycle; for example, a tree network.

Interestingly, because the network depicted in Figure C.5 is longer than the one in Figure C.1, Proposition 3 shows that a negative shock (such as a natural disaster) in district b, located at the extreme right of the network, affects the effort of agent 4, located at the extreme left of the network, and thus the conflict in district c, which is not adjacent to district b. Indeed, some agents are involved in two battles. Thus, when deciding how much effort to devote to each battle/district, they evaluate their relative strength and their relative chances of winning a battle and decide to exert more effort in battles they have the highest chances of winning. However, when there is a negative shock in a given district, the value of winning a battle goes down and thus agents shift their effort to the other battle they are involved in. For example, when v^b decreases, agent 1 decreases her effort in battle b but increases it in battle a. This negative shock propagates to other agents and battles who are path-connected in the network but has a lower effect on them. This is why a decrease of v^b affects the effort of agent 4 but the agent 4's effort will increase or decrease depending her relative strength compared to agent 2, who is involved in the same battle as agent 4 (battle c), but also on the relative strength of agent 2 compared to agent 1 in battle a (part 5 of Proposition 3). This is the propagation of the shock on district b, which first *directly* affects the agents involved in district b, that is, agents 1 and 3, and then *indirectly* affects the other path-connected agents, that is, first, agent 2, who is in conflict with agent 1 in battle a and, then, agent 4, who is in conflict with agent 2 in battle c.

C.4 Discussion

C.4.1 Mechanism consistent with our model

Even though our model is based on a very specific network structure (the star and the line network), we believe that the intuition and the prediction of the model carry over qualitatively to more complex network structures. Thus, our model is able to provide a simple mechanism that explains (*i*) how a negative shock (a natural disaster in the data) on a given district negatively affects the total battle in this district and (*ii*) how this negative shock affects the total battle in the (spatially) adjacent districts. Our model shows that (*i*) when a natural disaster occurs in a district, the agents involved in a conflict in this district will decrease their effort because there are less resources to grab. Consequently, (*ii*) these agents will shift their effort to spatially adjacent districts, thereby increasing the conflict in these districts; the effect will fade away for districts located further away from the district directly affected by the disaster. Our model also predicts that the intensity of the conflict in spatially adjacent districts will depend on the relatively strength of the agents involved in the conflicts in these districts. Another prediction of our model is that more "valuable" districts (higher v^{α}), that is, districts with more economic activity, agricultural land, or mineral mines are more likely to be worth fighting over, to capture local rents from economic activity or mineral resources or for strategic reasons. If a disaster hits those districts, the damages are likely to be higher and therefore the benefits of fighting might be lower as well.

Our empirical results are in accordance with the predictions of the model. First, (*i*) we show in Table 1 and Figure A.4 that the occurrence of a natural disaster in a district reduces the battle probability in this district. Moreover, (*ii*) in Table 1, we show that the occurrence of a natural disaster in a given district leads to a positive and significant battle spillovers to districts that are linked by major road network and geographic proximity. Finally, in Figure 1(b), we show that the battle diffusion occurs if the neighboring district is an agricultural district.

C.4.2 Other possible mechanisms

First, when interpreting the negative effect of a natural disaster in a district on fighting in that district, two interpretations are possible: "incapacitation" or an "economic loss" channel. Incapacitation means that if there is a flood, then nobody can fight. Economic loss would mean that the shock decreases the value of production in that district. In our empirical analysis, we showed the floods are the most prominent type of natural disaster in our sample (see Table A.1). This means that we have an incapacitation effect (at least in the short run), because it makes it impossible for conflicts to operate.

Our model only offers one possible mechanism, that is, when there is a negative shock (e.g., floods) in a district, central players relocate their forces and thus spread the conflicts to path-connected districts. From our empirical analysis, it is hard to infer whether rebels relocate because fighting has become complicated or simply because their targets have moved. Other mechanisms may be at work. For example, it is possible that, following a negative shock, populations may migrate in response to these shocks. Indeed, a natural disaster that afflicts an area may produce a wave of refugees and movement of people who subsequently heighten frictions and escalate violence in another adjacent areas. Given that we have aggregate data, we cannot test whether this mechanism or the one proposed by our model is at work.

C.5 Proofs of the Theoretical Model

Proof of Proposition 1: The existence and uniqueness result of the Nash equilibrium result of this proposition follows directly from Theorems 1 and 2 in Xu et al. (2022). Indeed, the cost function is quadratic, and therefore convex and strongly monotone, and the Tullock contest success function (CSF), given by (C.2), satisfies the assumption on the CSF assumption in Xu et al. (2022). This shows the existence and uniqueness of the Nash equilibrium. Moreover, Xu et al. (2022) also show the unique equilibrium satisfies the property that every conflict contains at least two contestants with positive efforts. Since, in the star depicted in Figure C.1, each conflict only has two contestants, this unique equilibrium is interior. □

Proof of Lemma 1: It is easily verified that $\frac{\partial^2 z(x,y)}{\partial x^2} < 0$ so that z is strictly concave in x. Moreover,

$$\frac{\partial z}{\partial x}(0, y) = v/y > 0,$$

and

$$\lim_{x \to \infty} \frac{\partial z}{\partial x}(0, y) = -\infty,$$

so there exists a unique $x^*(y)$ such that $\frac{\partial z}{\partial x}(x^*(y), y) = 0$. Clearly such x^* is the maximizer by the concavity of z.

Moreover, by the implicit function theorem,

$$\frac{\partial x^*}{\partial y} = -\left(\frac{\partial^2 z}{\partial x^2}\right)^{-1} \frac{\partial^2 z}{\partial x \partial y}|_{x=x^*}.$$

Since

$$\frac{\partial^2 z}{\partial x^2} < 0, \frac{\partial^2 z}{\partial x \partial y} = \frac{v(x-y)}{(x+y)^3},$$

so

$$sign \frac{\partial x^*}{\partial y} = sign(x^* - y).$$

This completes the proof of the lemma. □

Proof of Proposition 2: By applying the implicit function theorem to system (C.9) for the parameter v^a, we obtain:

$$\begin{pmatrix} \frac{\partial x_1^a}{\partial v^a} \\ \\ \frac{\partial x_1^b}{\partial v^a} \\ \\ \frac{\partial x_2^a}{\partial v^a} \\ \\ \frac{\partial x_3^b}{\partial v^a} \\ \end{pmatrix} = -\mathbf{M}^{-1} \begin{pmatrix} \frac{\partial F_1}{\partial v^a} \\ \\ \frac{\partial F_2}{\partial v^a} \\ \\ \frac{\partial F_3}{\partial v^a} \\ \\ \frac{\partial F_4}{\partial v^a} \end{pmatrix} \tag{C.13}$$

where

$$\mathbf{M} := \begin{pmatrix} \frac{\partial F_1}{\partial x_1^a} & \frac{\partial F_1}{\partial x_1^b} & \frac{\partial F_1}{\partial x_2^a} & \frac{\partial F_1}{\partial x_3^b} \\ \\ \frac{\partial F_2}{\partial x_1^a} & \frac{\partial F_2}{\partial x_1^b} & \frac{\partial F_2}{\partial x_2^a} & \frac{\partial F_2}{\partial x_3^b} \\ \\ \frac{\partial F_3}{\partial x_1^a} & \frac{\partial F_3}{\partial x_1^b} & \frac{\partial F_3}{\partial x_2^a} & \frac{\partial F_3}{\partial x_3^b} \\ \\ \frac{\partial F_4}{\partial x_1^a} & \frac{\partial F_4}{\partial x_1^b} & \frac{\partial F_4}{\partial x_2^a} & \frac{\partial F_4}{\partial x_3^b} \end{pmatrix} \quad \textit{and} \quad \begin{pmatrix} \frac{\partial F_1}{\partial v^a} \\ \\ \frac{\partial F_2}{\partial v^a} \\ \\ \frac{\partial F_3}{\partial v^a} \\ \\ \frac{\partial F_4}{\partial v^a} \end{pmatrix} = \begin{pmatrix} \frac{x_2^a}{(x_1^a+x_2^a)^2} \\ \\ 0 \\ \\ \frac{x_1^a}{(x_1^a+x_2^a)^2} \\ \\ 0 \end{pmatrix} \tag{C.14}$$

with

$$\frac{\partial F_1}{\partial x_3^b} = \frac{\partial F_2}{\partial x_2^a} = \frac{\partial F_3}{\partial x_1^b} = \frac{\partial F_3}{\partial x_3^b} = \frac{\partial F_4}{\partial x_1^a} = \frac{\partial F_4}{\partial x_2^a} = 0 \tag{C.15}$$

$$\begin{aligned} \frac{\partial F_1}{\partial x_1^a} = -s_1 - \frac{2v^a x_2^a}{(x_1^a+x_2^a)^3}, \frac{\partial F_1}{\partial x_1^b} = -s_1, \frac{\partial F_1}{\partial x_2^a} = \frac{v^a}{(x_1^a+x_2^a)^2} - \frac{2v^a x_2^a}{(x_1^a+x_2^a)^3}, \\ \frac{\partial F_2}{\partial x_1^a} = -s_1, \frac{\partial F_2}{\partial x_1^b} = -s_1 - \frac{2v^b x_3^b}{(x_1^b+x_3^b)^3}, \frac{\partial F_2}{\partial x_3^b} = \frac{v^b}{(x_1^b+x_3^b)^2} - \frac{2v^b x_3^b}{(x_1^b+x_3^b)^3}, \\ \frac{\partial F_3}{\partial x_1^a} = \frac{v^a}{(x_1^a+x_2^a)^2} - \frac{2v^a x_1^a}{(x_1^a+x_2^a)^3}, \frac{\partial F_3}{\partial x_2^a} = -s_2 - \frac{2v^a x_1^a}{(x_1^a+x_2^a)^3}, \\ \frac{\partial F_4}{\partial x_1^b} = \frac{v^b}{(x_1^b+x_3^b)^2} - \frac{2v^b x_1^b}{(x_1^b+x_3^b)^3}, \frac{\partial F_4}{\partial x_3^b} = -s_3 - \frac{2v^b x_1^b}{(x_1^b+x_3^b)^3}. \end{aligned} \tag{C.16}$$

Note that $\mathbf{M}$ is just the Jacobian matrix of system (C.9) with respect to $(x_1^a, x_1^b, x_2^a, x_3^b)$.

We can easily verify that the sign of the determinant of $\mathbf{M}$ is given by:

$$det(\mathbf{M}) := J = \begin{vmatrix} \frac{\partial F_1}{\partial x_1^a} & \frac{\partial F_1}{\partial x_1^b} & \frac{\partial F_1}{\partial x_2^a} & \frac{\partial F_1}{\partial x_3^b} \\ \frac{\partial F_2}{\partial x_1^a} & \frac{\partial F_2}{\partial x_1^b} & \frac{\partial F_2}{\partial x_2^a} & \frac{\partial F_2}{\partial x_3^b} \\ \frac{\partial F_3}{\partial x_1^a} & \frac{\partial F_3}{\partial x_1^b} & \frac{\partial F_3}{\partial x_2^a} & \frac{\partial F_3}{\partial x_3^b} \\ \frac{\partial F_4}{\partial x_1^a} & \frac{\partial F_4}{\partial x_1^b} & \frac{\partial F_4}{\partial x_2^a} & \frac{\partial F_4}{\partial x_3^b} \end{vmatrix} > 0. \tag{C.17}$$

We apply the Cramer's rule to compute each component of the left-hand side (LHS) of (C.13). After some simplifications, we obtain:

$$\frac{\partial x_1^a}{\partial v^a} = \frac{(v^a x_1^a + s_2 x_2^a (x_1^a + x_2^a)^2)((v^b)^2 + s_1 s_3 (x_3^b + x_1^b)^4 + 2v^b (x_3^b + x_1^b)(s_3 x_3^b + s_1 x_1^b))}{J(x_1^a + x_2^a)^4 (x_3^b + x_1^b)^4} > 0 \tag{C.18}$$

$$\frac{\partial x_1^b}{\partial v^a} = -\frac{s_1 (v^a x_1^a + s_2 x_2^a (x_1^a + x_2^a)^2)(2v^b x_1^b + s_3 (x_3^b + x_1^b)^3)}{J(x_1^a + x_2^a)^4 (x_3^b + x_1^b)^3} < 0 \tag{C.19}$$

$$\frac{\partial x_1^a}{\partial v^a} + \frac{\partial x_1^b}{\partial v^a} = \frac{v^b (v^a x_1^a + s_2 x_2^a (x_1^a + x_2^a)^2)(v^b + 2 s_3 x_3^b (x_3^b + x_1^b))}{J(x_1^a + x_2^a)^4 (x_3^b + x_1^b)^4} > 0 \tag{C.20}$$

$$\begin{aligned} \frac{\partial x_2^a}{\partial v^a} = & \frac{s_1 \left[(v^b)^2 x_1^a (x_1^a + x_2^a)^2 + s_3 v^a x_2^a (x_3^b + x_1^b)^4 + 2v^b (x_3^b + x_1^b)(s_3 x_1^a x_3^b (x_1^a + x_2^a)^2 + v^a x_2^a x_1^b) \right]}{J(x_1^a + x_2^a)^4 (x_3^b + x_1^b)^4} \\ & + \frac{v^a v^b x_2^a (v^b + 2 s_3 x_3^b (x_3^b + x_1^b))}{J(x_1^a + x_2^a)^4 (x_3^b + x_1^b)^4} > 0 \end{aligned} \tag{C.21}$$

$$\frac{\partial x_3^b}{\partial v^a} = \frac{s_1 v^b (x_1^b - x_3^b)(v^a x_1^a + s_2 x_2^a (x_1^a + x_2^a)^2)}{J(x_1^a + x_2^a)^4 (x_3^b + x_1^b)^3} \tag{C.22}$$

$$\frac{\partial x_1^b}{\partial v^a} + \frac{\partial x_3^b}{\partial v^a} = -\frac{s_1 (v^a x_1^a + s_2 x_2^a (x_1^a + x_2^a)^2)(v^b + s_3 (x_3^b + x_1^b)^2)}{J(x_1^a + x_2^a)^4 (x_3^b + x_1^b)^2} < 0 \tag{C.23}$$

This completes the proof of the proposition. □