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Spillover effect of violent conflicts on food insecurity in sub-Saharan Africa

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ABSTRACT

We examine violent conflict's spillover effects on food insecurity in Uganda, Ethiopia, and Malawi. Using a contiguity matrix weighted on the distance between housing units and data from the Living Standard Measurement Survey, we find a statistically significant spillover effect of violent conflict on food security in Ethiopia and Uganda. Statistically significant indirect effects of violent conflict on food security were negative within Malawi and positive within Ethiopia. Direct and spillover effects of violent conflicts and other covariates on food security are also analyzed.

1. Introduction

Violence, whether local or nationwide, is a critical factor included in many cross-disciplinary analyses aiming better to understand the determinants of economic progress and human flourishing. Outbreaks of violence are associated with reduced innovation (Cook, 2014), lower growth rates (de Groot et al., 2022; Young and Bologna, 2016), greater macroeconomic instability (Haroon and Jehan, 2020), and insecure property rights (North et al., 2013). Violence within lesser developed countries can be particularly detrimental to development by harming production and preventing exchanges that most benefit lower-income and vulnerable populations (George et al., 2020).

A critical but lesser-examined aspect of the impact of violence on economic development is its relationship to food security. By disrupting underlying institutional foundations that (ideally) provide the peaceful production and distribution of food, violence can serve to disrupt vital supply chains and hinder peaceful transactions needed to provide adequate food supply (George et al., 2020); Danneman and Ritter, 2014; Salehyan and Gleditsch, 2006). Further, food insecurity stemming from violence can provoke further violence to secure limited food supplies (Urrego-Mesa, 2021); Koren and Bagozzi, 2017). However, the impact of violence on food security and other factors remains a complex empirical question (Haroon and Jehan, 2020; Martin-Shields and Stojetz, 2019; Young and Bologna, 2016; de Groot, 2010).

Violence can also result in diseconomies, affecting neighboring countries even when they are comparatively more peaceful. For example, approximately 15.3 million Africans from South Sudan, Northeast Nigeria, and Somalia into Kenya, Ethiopia, Jordan, and Lebanon immigrated to neighboring African nations due to food insecurity stemming from periodic local violence (FAO, 2017). Concurrently, the WFP (2017) finds the highest rates of refugee migration are from countries with consistent violent conflicts and comparatively higher risks of food insecurity.

While a more robust understanding of the relationship between food insecurity and the spillover effects of violence is vital to reducing the risk of insufficient food supply and bolstering the prospects for peace, little research exists on this topic. Much previous literature examining the impact of violence on various factors analyzes internal conflict but does not include these affects at the household level (Danneman and Ritter, 2014; Salehyan and Gleditsch, 2006). This is similarly the case for the narrower literature examining the impact of violence on food security (George et al., 2020; Koren and Bagozzi, 2017).

Our analysis contributes to both literature by utilizing a spatial econometric empirical analysis to assess the impact of violent episodes on food insecurity at the household level. We specifically develop a matrix weighted on the distance between housing units to determine the spillover effect of violent conflict on food security by examining a household's food consumption score (FCS). This approach allows us to check for spatial dependence at the more granular household level-providing insight into how households respond to the spillover effects of violent activity. Given food security is fundamentally an individual or household-level concern, this unit of analysis seems appropriate for a

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spatial analysis (Cook and Weidmann, 2022).

We also focus our analysis on spillover effects within Uganda, Ethiopia, and Malawi. These Sub-Saharan African (SSA) countries are among the most violent and food insecure globally (FAO, 2017) but also socially similar providing for a fruitful analysis. Focusing on SSA nations also provides policy implications for aid and humanitarian efforts to help households facing food insecurity stemming from violence and other factors (DiRienzo and Das, 2017; Hendrix and Brinkman, 2013; De Groot, 2010).[1] Addressing whether the effects of violent conflicts on FCS in each household affect FCS measures in geographically neighboring areas, our analysis finds a statistically significant spillover effect of violent conflict on food security within Ethiopia and Uganda. We also find statistically significant indirect effects of violent conflict on food security were negative within Malawi and positive within Ethiopia.

This paper proceeds as follows. Section 2 reviews relevant literature on violence's role in developmental factors and food security. Section 3 develops our empirical approach and reviews our data. Section 4 provides our analysis. Section 5 concludes and provides suggestions for future research.

2. Literature review

Previous literature largely finds various forms of violence increase the risk of food insecurity. Koren and Bagozzi (2017) find political violence from governments and rebel factions within African countries strongly increases the risk of food insecurity for civilians, indicating a spillover effect. Adelaja and George (2019) find violence stemming from the Boko Haram conflict in Nigeria significantly curtailed the output production of sorghum, cassava, soya, and yam. In a similar study, George et al. (2020) find violence from the Boko Haram conflict reduced household consumption of preferred foods and limited the portion size of meals consumed.[2] Unlike many previous findings, Ledford et al. (2022) do not find a statistically significant relationship between food security and violence when examining African nations.[3] Curiously, Koren (2018) finds food abundance, rather than scarcity, could be a motive for violence.

Research examining regions outside Africa also finds violence tends to increase food insecurity. Dell'Angelo et al. (2021) document that violence across the globe within lesser-developed nations frequently involves agricultural lands, which negatively affects agribusiness, food supply, and food access. Adelaja et al. (2019) find terrorism is positively associated with greater food availability but negatively associated with greater food access. Examining the relationship between violence and food insecurity in US, Chilton, Rabinowich, and Woolf (2014) find women who experienced severe violence during childhood are at higher risk for food insecurity later in life. Examining the role of social capital- an informal means to deter violence and promote cooperation- Rayamajhee and Bohara (2019) find comparatively more social capital reduces the risk of food insecurity in Nepal.

How violence impacts third parties both domestically and transnationally remains less clear. Buhaug and Gleditsch (2008) and Gleditsch (2007) argue spatial violence clusters in physical space. However, Danneman and Ritter (2014) and Salehyan and Gleditsch (2006) find human rights violations in neighboring states can motivate violent rebellions in bordering nations.

Disagreements regarding how and to what extent the effects of violence extend to third parties could result from differing preexisting geographical, economic, and other factors. Adamson (2021) examines the spillover effects of fatalities from violence within Africa on neighboring countries and concludes geographically smaller nations tend to result in more spillover violence resulting in fatalities than comparatively larger nations. Buhaug and Gleditsch (2008) find less affluent neighborhoods within lower-income countries are considerably more likely to experience domestic conflict than less affluent neighborhoods in comparatively wealthier countries- further suggesting heterogeneous spillover effects. Carmignani and Kler (2016) find a positive correlation between violent domestic conflicts and violent conflicts in the neighborhood are positive- indicating violent conflicts cluster geographically. The authors also find a negative correlation between violent conflicts and GDP per capita, rough terrain, religious fragmentation, and polity measures.

While the previous literature provides fruitful conclusions regarding the complex relationship between violence, food insecurity, and potential spillover effects, it also contains noteworthy limitations. Primarily, few studies engage in household-level analysis to assess the impact of violence on food insecurity. Secondarily, even fewer analyses assess the spillover effects of violence on food security at a household level of analysis. Considering the relative commonality of food insecurity in different sections of the world in conjunction with the complex nature of diseconomies from violence, our analysis provides a much-needed contribution.

3. Model and data

Spatial autocorrelation can be divided into global and local spatial autocorrelation (LeSage and Pace, 2009). We account for both by utilizing Moran's (1950) and Geary's (1954) Index. Moran's Index for global spatial autocorrelation is represented in Eq. (1):

$$I = \frac{\sum_{i-1}^{n}\sum_{j-1}^{n} w_{ij}(Y_i - \overline{Y})(Y_j - \overline{Y})}{S^2\sum_{i-1}^{n}\sum_{j-1}^{n} w_{ij}} \tag{1}$$

Sample variance for the Moran Index is represented as $S^2 = \frac{\sum_{i-1}^{n}(Y_i - \overline{Y})^2}{n}$, with Y_i representing the observed value of FCS of household i. The weighted matrix is represented by $w_{ij.}$ The mean value of the observed variable Y_i is calculated $\overline{Y} = \frac{\sum_{i-1}^{n} Y_i}{n}$. The Index's values range from -1 to $+1$, indicating strong negative and positive spatial correlation respectively, with a value of 0 indicating a random pattern. Positive values refer to a high-high or low-low aggregation. Negative values indicate a high-low or low–high aggregation. In this analysis, positive or negative autocorrelations from Moran's Index indicate whether households with a higher concentration of FCS are adjacent to those with a higher concentration of FCS. On the other hand, households with lower FCS concentrations are adjacent to those households with a lower concentration of FCS.

3.1. Spatial regression methods

We begin with the standard OLS model as shown in Eq. (2):

$$Y = \alpha + X\beta + \varepsilon \tag{2}$$

Y is represents the FCS variable, X is a (1, K) row vector control variables, and β is a matching (K,1) column vector of unknown parameters. Error term ε is i.i.d with zero mean and variance σ^2 (Elhorst, 2010). However, if we observe spatial dependence in either X or Y, the OLS approach leaves the estimates biased and inconsistent, which is why we use spatial specification. To determine which model is most suitable given spatial dependence, we follow the Elhorst (2010) testing procedure. Elhorst (2010) starts with the general nested spatial model (GNS) in Eq. (3):

$$Y = \alpha + \rho WY + X\beta + WX\theta + u; \tag{3}$$

[1] Many humanitarian and policy efforts to address food insecurity issues in SSA emphasize household rather than national or regional insecurity.

[2] However, the authors did not find any relationship between the conflict and the total number of days a household went without eating.

[3] The authors suggest their findings are preliminary and mention future studies should include more controls to account for heterogeneous factors.

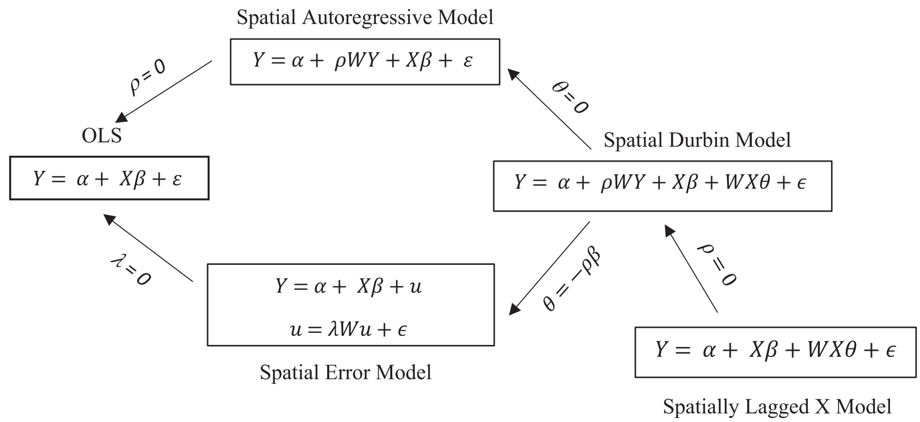

Fig. 1. Relationship between spatial models.

Table 1
Variables, Definitions, and Summary Statistics.

	Description	Ethiopia	Malawi	Uganda
FCS	Food consumption score	37.02 (16.18)	52.23 (18.00)	45.58 (18.48)
Violence	Binary variable indicating whether respondent household experience violent conflicts in last 12 months	0.01 (0.11)	0.08 (0.27)	0.012 (0.11)
Drought	Binary variable indicating whether respondent household experience drought in last 12 months	0.20 (0.40)	0.40 (0.49)	0.41 (0.49)
Flood	Binary variable indicating whether respondent household experience flood in last 12 months	0.02 (0.40)	0.17 (0.38)	0.039 (0.20)
Age	Age of head of household	46.66 (14.73)	44.31 (15.86)	47.57 (14.88)
Male	Binary variable indicating whether head of household is male	0.79 (0.40)	0.77 (0.42)	0.40 (0.49)
Income	Income of household (in USD)	108.36 (457.10)	166.23 (1427.84)	73.31 (338.83)
Pop. center	Distance of homestead to nearest population center with >20,000 population (in km)	37.88 (27.91)	29.25 (18.21)	24.40 (16.55)
Rain	Average total rainfall (mm)	1,158.46 (386.43)	1,060.95 (233.86)	1238.81 (177.35)
Temperature	Annual mean temperature (10*Celsius)	190.12 (32.21)	215.32 (18.56)	220.38 (17.67)
N	–	9,420	5,190	3,452

$$u = \lambda W\mu + \varepsilon$$

where Y is an $(N \times 1)$ vector of cross-sectional observations on the dependent variable. X is an $(N \times K)$ matrix of control variables weighted by the $(K \times 1)$ vector of coefficients. β; and ε are a $(K \times 1)$ vector. W is an $(N \times N)$ weight matrix that describes neighbor relations. Variables ρ and λ are scalar parameters. The θ parameter is a $(K \times 1)$ vector of parameters that define spatial effects across neighbors. When we observe no spatial dependence, ρ, θ, and λ all collapse to zero and we are left with the OLS model. Although GNS specification combines all forms of spatial dependence, this is not generally used in applied research as it is only weakly identifiable (Cook et al., 2015; Gibbons and Overman, 2012).

Table 2
Global Moran's I Values for FCS.

Country	Global Moran's I	
	I	p-value
Ethiopia	0.675	0.000
Malawi	0.283	0.000
Uganda	0.150	0.000

However, if spatial dependence is present, the parameter restrictions shown below can be utilized to test which spatial model is appropriate.

The spatial models considered for this study are the same as Elhorst (2010): spatial autoregressive/lag model (SAR), spatial error model (SEM), spatial lag-X model (SLX), and spatial Durbin model (SDM). The parameter restrictions on the general model (3) are presented below:

OLS: $\rho = \theta = \lambda = 0$.
SAR: $\theta = \lambda = 0$.
SEM: $\rho = \theta = 0$.
SLX: $\rho = \lambda = 0$.
SDM: $\lambda = 0$.

Among spatial models, we start with the spatial autoregressive model (SAR) is:

$$Y = \alpha + \rho WY + X\beta + \varepsilon \tag{4}$$

Variable ρ is the spatial autoregressive coefficient. W is the non-negative $(N \times N)$ row-standardized spatial weight matrix. This expression is directly related to the dependent variable of Y of the other cross-sectional units to the dependent variable Y of cross-sectional unit i (Hamzalouh et al., 2017). The error term is assumed to be an i.i.d. with zero mean and variance σ_ε^2 (Elhorst, 2014). We incorporate the spatially weighted dependent variable Y as an endogenous regressor. In our analysis, the SAR model can be used to assess whether the household FCS is directly influenced by the neighboring households' FCS for a specific period. The second specification is the spatial error model (SEM) shown in Equation (5).

$$Y = \alpha + X\beta + u; u = \lambda W\mu + \epsilon \tag{5}$$

where W is the non-negative weight matrix and λ is spatial autocorrelation coefficient. Here, we assume that the spatial correlation between units is caused by unobserved characteristics (u) represented by the parameter λ, but are independent of the covariates X and Y. The third specification is the spatially lagged X (SLX) model. This model does not incorporate spatial dependence on Y or the error term, but only on the X

Table 3
Model Specification Tests.

Dependent Variable	Lagrange Multiplier Tests		Robust LM Tests		Likelihood Ratio Test		RHO
	LM ERROR	LM LAG	RLM ERROR VS OLS	RLM LAG VS OLS	SDM vs SEM		$\rho = 0$
Ethiopia							
Violent Conflict	7343.4***	6975.2***	369.03***	0.824	−89.957***		0.609***
P value	0.000	0.000	0.000	0.364	0.000		
	Lagrange Multiplier Tests		Robust LM Tests		Likelihood Ratio Test		RHO
Dependent Variable	LM ERROR	LM LAG	RLM ERROR VS OLS	RLM LAG VS OLS	SDM vs SEM	SDM vs SAR	$\rho = 0$
Malawi							
Violent Conflict	248.41***	292.09***	25.002***	68.675***	−133.85***	−116.94***	0.248***
P value	0.000	0.000	0.000	0.000	0.000	0.000	
Uganda							
Violent Conflict	227.59***	211.2***	35.928***	19.535***	−76.06***	−95.701***	0.310***
P value	0.000	0.000	0.000	0.771	0.000	0.000	

Notes: *Denotes significance at the 10% level, ** significance at the 5% level, and *** significance at the 1% level.

as spatially lagged covariates. The SLX is presented below in Eq. (6):

$$Y = \alpha + X\beta + WX\theta + \epsilon \tag{6}$$

Here, θ refers to a $(K \times 1)$ vector of unknown estimated parameters. This model incorporates the direct effects (β) of X on Y and the indirect effects (θ) from the Xs of neighboring units. In our analysis, the covariates include violent conflict in neighboring households that might affect household FCS. The final specification we use is provided in Eq. (7):

$$inY = \alpha + \rho WY + X\beta + WX\theta + \epsilon \tag{7}$$

In this model, θ refers to a $(K \times 1)$ vector of unknown parameters that need to be estimated. This model combines the spatial spillover effects of the SLX and SAR, meaning we assume the presence of spatial dependence in both X and Y. In our context, this means that the covariates including the violent conflict in the neighboring household will affect FCS.

3.2. Model selection

Our weight matrix is constructed according to the “k-nearest neighbors” criterion where we include the 25 nearest neighbors. We calculate the distance between each household using household coordinates. All the houses beyond the 25 nearest neighbors are assigned a zero-weight value. The weighted matrix is row-normalized so the sum of each row adds up to 1.

Following Elhorst (2010), we use the Lagrange Multiplier test (LM) test, Likelihood Ratio (LR) test, and Wald test. We start with the Lagrange Multiplier (LM) test to decide whether to use OLS, SAR, or SEM model. SEM can be collapsed into the OLS if we assume $\lambda = 0$.[4] Similarly, the SAR can be collapsed into the OLS if we assume $\rho = 0$. If we reject either or both of the null hypotheses, we conclude that there is spatial dependence in the data. If we reject both the LM tests, we then estimate the SDM to conduct a likelihood ratio (LR) test to see if the SDM is more appropriate than the SEM or SAR.[5] If we reject both hypotheses, we conclude that the SDM is more appropriate than the SEM and SAR. However, if we fail to reject (H_0: $\theta + \rho\beta = 0$), we employ the SEM model if the robust form of the LM test also points to the SEM. Alternatively, if we fail to reject (H_0: $\theta = 0$), we employ the SAR model as long as the robust form of the LM test also points to the SAR. Lastly, if we choose the SDM, we still need to test if there is spatial dependence in only X or both X and Y. To do this, we test (H_0: $\rho = 0$) to see if ρ is significantly different from zero. If we reject the null hypothesis, we use the SLX model. Fig. 1 illustrates our selection process.

3.3. Data

We obtain household survey data from the Household Living Standards Measurement Survey - Integrated Surveys on Agriculture (LSMS-ISA) for Malawi, Uganda, and Ethiopia. For each of the three countries, we have data spanning multiple years. Malawi has data from 2019 to 20; Uganda has data from 2010 to 11; and Ethiopia has data from 2018 to 19. Our primary variable of interest is a household’s FCS, which we use to proxy food insecurity. Values for each household’s FCS are obtained following the World Food Program’s (WFP) method. This method involves asking a sampled household about their frequency of consumption for specific food items over the previous week. The study then aggregates the food items into eight basic food groups. Consumption frequencies per food item are aggregated and sorted into 8 food groups. Totals per truncated food group are multiplied with their corresponding weights and scored to obtain their FCS value. WFP (2008) classifies food security status by score. A household is considered food insecure if their FCS is below 21.5, borderline if between 21.5 and 35, and secure if above 35.

Our measure of conflict is obtained from LSMS’s “impacts of conflicts“ measure, which indicates whether a household experienced violent conflict in the past 12 months. Although this variable does not allow us to distinguish what form of violence each household experienced, how it is sampled allows us to better determine which households experienced violence. Because our analysis emphasizes spillover effects of violence on household food security, this measure allows us to most accurately assess this relationship. Other variables, their description, and summary statistics for each country examined are provided in Table 1.

4. Empirical analysis

Table 2 presents Moran’s values of FCS for Ethiopia, Malawi, and Uganda. The contiguity matrix is used as the weight matrix for estimation.

Moran’s index values range from 0.150 in Uganda and 0.675 in Ethiopia. The results show that all index values are statistically significant and greater than 0. These results suggest that there are positive

[4] The LM error test (where H_0: λ=0) is based on this principle.

[5] More specifically, we test whether the SDM can be collapsed into the SEM ($\theta + \rho\beta = 0$) or the SAR ($\theta = 0$).

Table 4
Marginal Effect Decomposition of SDM Models.

Variable	Ethiopia			Malawi			Uganda		
	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
Violence	−5.64***	13.01	7.37	−0.67	−15.94**	−16.67**	−4.91*	−8.23	−13.15
	(1.44)	(9.23)	(9.28)	(0.87)	(7.48)	(7.67)	(2.70)	(10.96)	(11.56)
N	9,420			5,190			3,452		

Notes: *Denotes significance at the 10% level, ** significance at the 5% level, and *** significance at the 1% level. k = 25 for each model.

Table 5
Summary of Robustness Checks.

Variables	Direct			Indirect		
	K = 50	K = 100	K = 200	K = 50	K = 100	K = 200
Ethiopia (k = 50, 100, 200)						
Violence	−3.977***	−6.811***	−5.484***	19.789***	38.747**	14.560
	(1.319)	(1.433)	(1.456)	(7.946)	(18.080)	(26.484)
Malawi (k = 50, 100, 200)						
Violence	−0.937	−0.981	−0689	−21.723***	−10.055	−15.899
	(0.900)	(0.909)	(0.903)	(7.904)	(8.261)	(13.978)
Uganda (k = 50, 100, 200)						
Violence	−4.598*	−4.151	−4.167	43.653	28.627	8.899
	(2.660)	(2.794)	(2.738)	(27.815)	(47.335)	(87.367)

Notes: *Denotes significance at the 10% level, ** significance at the 5% level, and *** significance at the 1% level.

autocorrelations from both indices indicating that households with higher FCS concentrations are adjacent to households with higher FCS concentrations. Similarly, households with lower FCS concentrations are adjacent to households with lower FCS concentrations. The spatial distribution of FCS is high-high and low-low aggregation suggesting food-insecure households are likely to be clustered together with Ethiopia having the strongest effect.

4.1. Primary results

Results from Tables 3 indicates spatial dependence, hence estimation of spatial models is preferred.[6] Both the LM error test and LM lag test for each country examined reject the hypothesis of no spatial dependence. Therefore, we utilized a Robust LM test to compare SEM and SAR models (as shown in columns three and four). Robust LM error results are statistically significant, implying that spatial models are preferred with SEM as the desired spatial model for Ethiopia and both SAR and SEM models for Malawi and Uganda.

Following Elhorst (2010), we estimate a SDM that integrates spatial dependence in both the dependent variable and independent variables. Column five in Table 3 reports p-values of LR test results and reject the hypothesis with a 1% significance level, indicating the SDM model is preferred over SEM and SAR.

Results from our SDM models analyzing the direct, indirect, and total effects of violence household spillover effect of violent conflicts along with other covariates in Ethiopia, Malawi, and Uganda are reported in Table 4.[7]

As demonstrated above, the effects of violence on a household's FCS value vary by effect and country. Direct effects of violence FCS were statistically significant and negative for Ethiopia and Uganda. Specifically, the direct effects of violence on households are associated with a decrease of approximately 5.64 points in FCS for Ethiopian households and a decrease in approximately 4.91 points in FCS for Ugandan households. These values constitute approximately 35% of one standard deviation for Ethiopian households and approximately 27% of one standard deviation for Ugandan households. Quantitatively, the WFP (2008) distinguishes food secure households from food-insecure households by 13.5 points. We did not find a statistically significant relationship between indirect and total violence on FCS for Ethiopia and Uganda households. These results indicate that the impact of the violent conflict falls within the household itself but dissipates before affecting neighboring households within Ethiopia and Uganda.

Our results also find a statistically significant negative relationship between indirect and total conflict for Malawian households. Specifically, our estimates find experiencing indirect violence is associated with approximately a 15.94-point decrease in FCS and approximately a 16.67-point decrease in FCS for total violence. These values constitute approximately 866% and 93% of a standard deviation. We did not find a statistically significant relationship between direct violence and FCS within Malawian households.

Heterogeneity in the significance and type of violence impacting FCS at the household level could be due to differing factors at the local or national level. For example, household income within Uganda is consistently statistically significantly positively related to household FCS. Household income was not a consistently statistically significant relationship within Malawi or Ethiopia. Similarly, having a male head of the household was consistently statistically significantly negative within Uganda. The relationship was less consistent within Ethiopian and Malawi. Differing household resources and structures could impact food security as well as how they are impacted through experiencing violence. Similar heterogeneity from demographic and climate-related controls can also explain varying access to food (and corresponding risk of food insecurity) as well as the potential for experiencing violence

[6] Estimates from our OLS estimations are provided in Table A1 in the online appendix.

[7] Complete results for our SDM model for Ethiopia, Malawi, and Uganda featuring each variable are provided in the online appendix.

or the spillover effects of violence.[8]

Overall, our primary results suggest measuring the direct and indirect impacts of violence are important for assessing the relative risk of food insecurity at the household level. Specifically, we can gain insights into the nature and meaning of spatial influences at a more granular level within three Sub-Saharan African nations at high risk for food insecurity. Our results specifically indicate that violent conflict can impact food security directly and indirectly- including neighboring households.

4.2. Robustness checks

To further verify our results, we engage in three robustness checks. First, to examine whether our results withstand different model specifications, we run SEM models for each country and SAR for Malawi and Uganda. Although we utilize SDM for our primary results, comparing findings from SEM models (which estimate average impacts) allows us to compare whether our estimated values are robust to similar models with separate specification assumptions. Further, because SDM can be collapsed into SAR, SAR results also examine the robustness of our findings. Overall, our SEM and SAR models generate comparable estimates, granting further robustness to our original findings.[9]

Second, we extend our original $k = 25$ assumption to include $k = 50$, $k = 100$, and $k = 200$ neighborhood spatial range to test our result's sensitivity to this specification. A summary of these robustness check findings is provided in Table 5.

Although some of our results from these robustness checks provide some differences magnitude and significance levels, all results were consistent in terms of signs. For example, the direct effects of violent conflicts were negative using the different k-nearest neighbors and positive indirect effects in Ethiopia and Uganda. Quantitatively, the largest direct effect in Ethiopia is on $k = 100$ with a one-unit increase in violent conflict is associated with -6.811 effect on FCS, followed by -5.484 at $k = 100$, and -3.977 at $k = 50$. Each relationship is statistically significant.[10]

Lastly, we performed a pooled analysis by combining observations across Ethiopia, Uganda, and Malawi to examine whether direct, indirect, and total effects of violence on household FCS extend across borders.[11] The results of direct, indirect, and total effects indicate no statistically significant impact on food security.[12] However, given the heterogeneity in significance and estimates of control variables in our primary analysis, interpreting findings from a pooled analysis is complex and difficult to interpret in terms of general food security. Therefore, we do not include these findings in our analysis.

5. Conclusion

We examine the impact of violence on food insecurity utilizing LSMS Word Bank data for the Sub-Saharan African countries Ethiopia, Malawi, and Uganda. Specifically, we utilize data calculating FCS values at a household level and survey data asking participants whether they experience violence. Our analysis leverages a spatial econometric model (SDM) to examine both direct, indirect, and total effects of violence on household FCS values. This data, empirical strategy, and level of analysis allow us to best examine food insecurity and the impact of violence at an informative level of analysis across heterogeneous social, environmental, and other considerations.

Our analysis finds a statistically significant negative spillover effect of violent conflict for household FCS in Ethiopia and Uganda. The indirect effects of violence on household FCS were statistically significant and negative for Malawi, but positive for Ethiopia. Total effects of violence were also statistically significant and negative for Malawi. Our findings remained largely consistent after engaging in several robustness checks where we varied the empirical model and spatial specifications. We attribute much of the differences in our primary findings are likely due to differences in household characteristics, weather and other environmental considerations, and broader economic conditions.

We draw three primary implications from our findings. First, we demonstrate the value of measuring both direct and indirect spillover effects at a household level. By doing so, we can gain a fuller understanding of how violent conflict impacts household and neighboring household food security. Secondly, our findings were generally consistent across three Sub-Saharan African nations, providing broad implications for mitigating the risk of food insecurity for regions comparatively more likely to endure it. Thirdly, our findings provide implications that policymakers must consider that conflict can impact food security even when only indirectly related.

While our analysis provides an important contribution to the literature examining the impact of violence on food security and implications aimed to reduce the risk of food insecurity, it also has several limitations. Most notably, our measure indicating a household experienced violence relies on self-reporting and does not provide details on what kind of violence a household experienced. The type and scale of violence- from domestic to international- will likely impact food security differently (including spillover effects). We also limited our analysis to three countries because the variables needed to construct FCS and some of the other independent variables were not available in other countries. To examine comparatively more food insecure households, including more countries would provide additional findings on how the spillover effects of violence impact food security.

Limitations to our analysis provided fruitful avenues for future research. Focusing on specific occurrences of violence would bolster our understanding of how violence can generate spillover effects on food supply. Similarly, extending our analysis to include other countries or utilizing other empirical approaches would provide further insight. Additional research exploring policy mitigating measures to prevent or reduce the spread of violence, especially at the household level, would also help reduce the risk of food insecurity within vulnerable populations. Areas of analysis including household resilience capacity, women empowerment, and microfinancing targeting could have profound implications in addressing food insecurity in Sub-Sahara Africa and other regions.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

See Tables A1–A13.

[8] Because our set of control variables are only indirectly related to our analysis, we do not include them in our manuscript. Complete results including control variables are provided in our online appendix.

[9] Complete findings for SEM and SAR robustness checks are provided in our online appendix.

[10] We provide complete findings for this robustness check as well as results for SEM and SAR model specifications while varying our spatial specifications in our online appendix.

[11] We are indebted to an anonymous reviewer for suggesting this.

[12] Estimates from our OLS estimations are provided in Table A12 in the online appendix.

Table A1
OLS Regression Results - Ethiopia, Malawi, and Uganda.

Coefficient	Ethiopia		Malawi		Uganda	
	Estimate	Std. error	Estimate	Std error	Estimate	Std error
Intercept	34.796***	1.524	58.222***	3.223	74.174***	4.489
Violence	−3.715*	1.475	−0.311	0.948	−4.383	2.801
Drought	−2.877***	0.436	−2.092***	0.521	−1.513*	0.668
Flood	1.862	1.093	−6.014***	0.690	2.037	1.604
Age	−0.058***	0.001	−0.050**	0.016	−0.012	0.021
Male	2.731***	0.409	3.661***	0.587	−3.254***	0.668
Income	0.002***	0.000	0.000**	0.000	0.004***	0.001
Population Center	0.007	0.006	−0.122***	0.013	−0.043*	0.020
Rain	−0.005***	0.000	0.003**	0.001	−0.009***	0.002
Temperature	0.040***	0.006	−0.023	0.014	−0.061***	0.018
R squared	0.0384		0.051		0.026	

Notes: *Denotes significance at the 10% level, ** significance at the 5% level, and *** significance at the 1% level.

Table A2
SEM Regression Results for Ethiopia, Malawi, and Uganda (k = 25).

Independent variables	Ethiopia		Malawi		Uganda	
	Coefficient	Std. error	Coefficients	Std error	coefficients	Std error
Intercept	38.979***	3.471	59.723***	4.075	74.294***	6.069
Violence	−6.307***	1.450	−0.661	0.929	−3.763	2.726
Drought	−4.590***	0.455	−1.139**	0.518	−2.130***	0.632
Flood	4.523***	0.993	−5.830***	0.682	1.020	1.555
Age	−0.049***	0.010	−0.053***	0.015	−0.025	0.021
Male	2.779***	0.370	3.564***	0.582	−4.555***	0.576
Income	0.001***	0.000	0.000***	0.000	0.003***	0.001
Population Center	−0.003	0.017	−0.083***	0.017	−0.038	0.027
Rain	−0.010***	0.001	0.002	0.001	−0.010***	0.003
Temperature	0.032	0.014	−0.031	0.018	0.057**	0.025
lambda	0.676		0.260		0.307	
Wald stat	2968.6		124***		159.51***	

Notes: *Denotes significance at the 10% level, ** significance at the 5% level, and *** significance at the 1% level.

Table A3
SAR Regression Results for Malawi and Uganda (k = 25).

Independent variables	Malawi		Uganda	
	Coefficients	Std error	Coefficients	Std error
Intercept	42.596***	3.514	53.995***	4.669
Violence	−0.066	0.928	−3.819	2.717
Drought	−1.524***	0.510	−1.945***	0.648
Flood	−5.573***	0.675	1.573	1.556
Age	−0.051***	0.015	0.019	0.020
Male	3.465***	0.575	−4.515***	0.649
Income	0.000***	0.000	0.003***	0.001
Population Center	−0.087***	0.014	−0.027	0.019
Rain	0.002**	0.001	−0.007***	0.002
Temperature	0.014	0.013	−0.039**	0.018
Rho	0.256		0.283	
Wald stat	126.99***		131.57	

Notes: *Denotes significance at the 10% level, ** significance at the 5% level, and *** significance at the 1% level.

Table A4
SDM Regression Results -Ethiopia (k = 25).

Independent variables	Coefficient	Std. error	Coefficients of W*Independent Variable	Std error
Intercept	11.089***	2.192		
Violence	−5.932***	1.487	8.413**	3.405
Drought	−4.824***	0.462	5.704***	7.772
Flood	4.349***	0.993	−10.489***	2.454
Age	−0.049***	0.010	0.032	0.028
Male	2.740***	0.369	−2.864***	1.088
Income	0.001***	3.269	0.003***	0.001
Population Center	0.058	1.171	0.059	0.117
Rain	0.017**	0.007	0.015*	0.008
Temperature	−0.09**	0.044	0.164**	0.04

Notes: *Denotes significance at the 10% level, ** significance at the 5% level, and *** significance at the 1% level.

Table A5
SDM regression results -Malawi (k = 25).

Independent variables	Coefficient	Std. error	Coefficients of W*Independent Variable	Std error
Intercept	40.931	4.284		
Violence	−1.159	0.923	5.257	2.390
Drought	−1.068	0.514	−5.133	0.974
Flood	−5.258	0.676	1.352	1.315
Age	−0.050	0.015	0.021	0.030
Male	3.491	0.575	−0.990	1.282
Income	0.000	0.000	0.000	0.000
Population Center	0.085	0.024	−0.213	0.026
Rain	−0.008	0.011	0.012	0.011
Temperature	0.183	0.092	−0.187	0.093

Table A6
SDM regression results -Uganda.

Independent variables	Coefficient	Std. error	Coefficients of W*Independent Variable	Std error
Intercept	39.432***	5.485		
Violence	−3.773	2.697	−0.452	5.547
Drought	−0.825	0.651	3.112	1.112
Flood	1.126	1.544	5.119	3.078
Age	−0.022	0.021	0.122	0.049
Male	−0.317	0.800	8.082	1.222
Income	0.003	0.001	0.005	0.002
Population Center	−0.120	0.146	0.099	0.148
Rain	0.004	0.014	−0.008	0.014
Temperature	0.062	0.136	−0.118	0.137

Table A7
SDM Marginal Effect Decomposition for Ethiopia (k = 50,100,200).

Variables	Direct			Indirect		
	K = 50	K = 100	K = 200	K = 50	K = 100	K = 200
Violence	−3.977***	−6.811***	−5.484***	19.789***	38.747**	14.560
	(1.319)	(1.433)	(1.456)	(7.946)	(18.080)	(26.484)
Drought	−3.121***	−3.190***	−3.283***	3.777***	3.482	−11.038**
	(0.455)	(0.416)	(0.437)	(1.741)	(20.234)	(5.132)
Flood	2.722***	2.643**	3.698***	−21.114***	−46.589***	20.268
	(1.008)	(1.109)	(1067)	(5.956)	(11.917)	(26.270)
Age	−0.053***	−0.054***	−0.055***	0.049*	0.493***	0.109
	(0.010)	(0.011)	(0.011)	(0.072)	(0.119)	(0.238)
Male	2.819***	2.792***	2.662***	−0.379	6.137	−14.302
	(0.377)	(0.376)	(0.380)	(2.692)	(4.262)	(10.370)
Income	0.001***	0.002***	0.001***	0.013***	0.016***	0.036***
	(0.000)	(0.000)	(0.000)	(0.003)	(0.004)	(0.007)
Population Center	0.006	0.023**	0.022***	0.001	−0.038**	−0.095**
	(0.003)	(0.009)	(0.007)	(0.018)	(0.023)	(0.038)
Rain	−0.011**	−0.006***	−0.002*	0.009	0.005**	−0.004
	(0.003)	(0.001)	(0.001)	(0.003)	(0.002)	(0.003)
Temperature	−0.010	0.005	0.025***	0.050***	0.069***	0.098***
	(0.019)	(0.010)	(0.008)	(0.022)	(0.019)	(0.035)
N	9,420					

Table A8
SDM Marginal Effect Decomposition for Malawi (k = 50,100,200).

Variables	Direct			Indirect		
	K = 50	K = 100	K = 200	K = 50	K = 100	K = 200
Violence	−0.937	−0.981	−0689	−21.723***	−10.055	−15.899
	(0.900)	(0.909)	(0.903)	(7.904)	(8.261)	(13.978)
Drought	−1.245**	−1.225**	−1.515***	0.810	−11.676***	−10.136**
	(0.525)	(0.521)	(0.542)	(2.840)	(2.777)	(4.425)
Flood	−5.107***	−5.069***	−5.145***	−11.712***	−5.430	−13.832***
	(0.686)	(0.697)	(0.720)	(3.835)	(3.447)	(4.458)
Age	−0.046***	−0.050***	−0.050***	−0.387***	0.090	−0.073
	(0.016)	(0.014)	(0.015)	(0.133)	(0.120)	(0.184)
Male	3.383***	3.355***	3.454***	13.278***	15.212***	−0.563
	(0.559)	(0.614)	(0.542)	(4.437)	(3.871)	(6.834)
Income	0.000***	0.000***	0.000***	0.000	0.000	0.005
	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.004)
Population Center	0.133***	−0.012	−0.065***	−0.326***	−0.201***	−0.220***
	(0.022)	(0.018)	(0.016)	(0.037)	(0.032)	(0.039)
Rain	−0.000	−0.005**	0.003	0.008	0.019***	0.010***
	(0.005)	(0.003)	(0.002)	(0.006)	(0.003)	(0.003)
Temperature	0.091**	0.002	0.035**	−0.096*	0.070**	0.025
	(0.046)	(0.021)	(0.018)	(0.056)	(0.033)	(0.038)
N	5,190					

Table A9
SDM Marginal Effect Decomposition for Uganda (k = 50,100,200).

Variables	Direct			Indirect		
	K = 50	K = 100	K = 200	K = 50	K = 100	K = 200
Violence	−4.598*	−4.151	−4.167	43.653	28.627	8.899
	(2.660)	(2.794)	(2.738)	(27.815)	(47.335)	(87.367)
Drought	−2.020***	−1.917***	−2.051***	5.843	−10.642*	−8.911
	(0.671)	(0.660)	(0.667)	(4.293)	(6.618)	(13.999)
Flood	1.581	1.951	1.849	29.892**	25.920	81.535*
	(1.581)	(1.673)	(1.526)	(14.489)	(21.470)	(48.649)
Age	−0.018	−0.015	−0.022	−0.212	0.583**	0.570
	(0.020)	(0.023)	(0.020)	(0.170)	(0.288)	(0.543)
Male	−3.395***	−3.170***	−3.441***	0.943	28.762*	−69.59*
	(0.677)	(0.682)	(0.647)	(7.006)	(16.787)	(42.508)
Income	0.003***	0.003***	0.003***	0.031***	0.041**	0.128***
	(0.001)	(0.001)	(0.001)	(0.010)	(0.017)	(0.044)
Population Center	−0.067**	−0.019	−0.009***	0.056	−0.040	−0.046
	(0.029)	(0.022)	(0.021)	(0.062)	(0.097)	(0.168)
Rain	−0.007*	0.002	−0.001	0.003	−0.027***	−0.026
	(0.004)	(0.003)	(0.003)	(0.007)	(0.010)	(0.021)
Temperature	−0.067	0.022	−0.009	−0.016	0.120	0.147
	(0.045)	(0.040)	(0.031)	(0.065)	(0.092)	(0.184)
N	3,452					

Table A10
Marginal effect decomposition of SDM for Ethiopia (k = 25).

Variables	Direct	Indirect	Total
Violence	−5.638***	13.012 (9.228)	7.374 (9.281)
Drought	(1.442)	7.274*** (1.957)	2.614 (1.952)
Flood	−4.660***	−22.100***	−18.250**
Age	(0.449)	(6.651)	(6.836)
Male	3.850*** (1.004)	0.002 (0.080)	−0.046 (0.081)
Income	−0.049***	−3.040 (3.015)	−0.370 (3.089)
Population	(0.010)	0.011*** (0.003)	0.012*** (0.003)
Center	2.671*** (0.375)	0.060 (0.117)	0.003 (0.017)
Rain	0.001*** (0.000)	0.010 (0.008)	−0.007***
Temperature	−0.057 (0.115)	0.135*** (0.044)	(0.001)
	−0.017**		0.047*** (0.015)
	(0.008)		
	−0.088**		
	(0.043)		
N	9,420		

Notes: *Denotes significance at the 10% level, ** significance at the 5% level, and *** significance at the 1% level.

Table A11
Marginal effect decomposition of SDM for Malawi (k = 25).

Variables	Direct	Indirect	Total
Violence	−0.670 (0.874)	−15.941**	−16.671**
Drought	−1.281**	(7.481)	(7.674)
Flood	(0.514)	−4.661* (2.340)	−5.943** (2.380)
Age	−5.143***	−6.838* (3.597)	−11.981***
Male	(0.687)	−0.288**	(3.691)
Income	−0.039***	(0.124)	−0.327** (0.127)
Population	(0.014)	6.546 (4.431)	9.871** (4.543)
Center	3.326*** (0.575)	0.000 (0.001)	0.001 (0.002)
Rain	0.000*** (0.000)	−0.342***	−0.161***
Temperature	0.181*** (0.025)	(0.038)	(0.031)
	−0.002 (0.006)	0.010 (0.007)	0.008*** (0.002)
	0.092 (0.061)	−0.056 (0.067)	−0.036 (0.033)
N	5,190		

Notes: *Denotes significance at the 10% level, ** significance at the 5% level, and *** significance at the 1% level.

Table A12
. Marginal effect decomposition of SDM for Uganda (K = 25).

VARIABLES	DIRECT	INDIRECT	TOTAL
Violence	−4.912* (2.696)	−8.237	−13.149
Drought	−1.932** (0.730)	(10.955)	(11.558)
Flood	1.671 (1.566)	3.705 (2.693)	1.773 (2.819)
Age	−0.017 (0.020)	13.222* (7.933)	14.892* (8.276)
Male	−3.412***	0.022 (0.099)	0.005 (0.104)
Income	(0.699)	−2.167 (2.845)	−5.579* (3.028)
Population	0.004*** (0.001)	0.009* (0.006)	0.013** (0.006)
Center	−0.127***	0.079 (0.049)	−0.048 (0.038)
Rain	(0.036)	0.009 (0.005)	−0.007** (0.003)
Temperature	−0.016* (0.005)	0.074 (0.051)	−0.085** (0.032)
	0.074 (0.045)		
N	3,452		

Notes: *Denotes significance at the 10% level, ** significance at the 5% level, and *** significance at the 1% level.

Table A13
Marginal effect decomposition of SDM pooled model (k = 25).

Variables	Direct	Indirect	Total
Violence	−2.307 (2.212)	2.088 (3.973)	−0.219 (5.359)
Drought	−3.203*** (0.826)	23.742 (15.237)	20.539 (15.542)
Flood	−2.566* (1.343)	−1.575 (3.947)	−4.141 (4.497)

Notes: *Denotes significance at the 10% level, ** significance at the 5% level, and *** significance at the 1% level.

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