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The impact of conflict on food security: evidence from household data in Ethiopia and Malawi

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Abstract

Background Violent conflicts threaten food security and household welfare in sub-Saharan Africa. While a more robust understanding of the causal relationship between food security and conflict is vital in mitigating food insecurity and bolstering peace prospects, only limited research exists on this topic, especially at the household level where estimations are more empirically challenging given data constraints and identification issues. Our analysis utilizes a newly developed and novel difference-in-differences model developed by de Chaisemartin and D'Haultfoeuille (2020) to determine the causal relationship between violent conflicts and food security in two sub-Saharan African countries—Malawi and Ethiopia using household-level data from the World Bank's Household Living Standards Measurement Survey.

Results Our results suggest that exposure to violent conflict on average decreases the food consumption score (FCS) by 6.84 units, which corresponds to a 16.13% reduction in FCS. With respect to individual countries, Malawi shows the largest effect-size, with the FCS decreasing by 10.54 units (equivalent to a 20.22% reduction in FCS). In Ethiopia, the causal estimate was slightly smaller at −4.32 (equivalent to a 11.67% reduction in FCS) although the baseline food security status was lower relative to Malawi. Disaggregated analyses show that the effect-size can be several orders of magnitude larger when conflict is experienced simultaneously with natural shocks. Robustness checks using different iterations of propensity score matching generate comparable causal estimates and reinforce the overall findings.

Conclusions The findings help improve our understanding of a broader issue by providing new direct and granular evidence regarding the relationship between conflict and food security using household data. The results hold implications for aid and humanitarian efforts to help households facing food insecurity stemming from violence and other factors.

Keywords Food security, Violent conflict, Causal inference, Difference-in-difference, Propensity score matching, Sub-Saharan Africa

Introduction

The world is witnessing an increasing number of people living under conditions of food insecurity and hunger. According to the Food and Agriculture Organization (FAO) Food Summit 1996, food security exists if and only if "all people at all times have consistent physical, social, and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life" [27]. However, recent

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statistics indicate that sub-Saharan Africa (SSA) is one of the most food insecure regions in the world. A report estimates that one in three people in the sub-Saharan region are malnourished [31]. More recently, the World Health Organization (WHO) reported that 7.2 million people in East Africa are at risk of hunger in 2021, while 26.5 million are experiencing severe food insecurity [77]. World Bank [77] also reported that the share of people experiencing moderate to severe food insecurity has increased from 51.5 to 59.5% in the region, with some countries exceeding 80% share of population under food insecurity.

Food security is intertwined in a complex relationship with another aspect that sub-Saharan Africa has disproportionately been affected by conflict [47]. The relation between conflict and food security underscores the intricate interplay between socio-economic factors and political dynamics. In conflict-affected areas, disruption of agricultural activities, displacement of communities, and destruction of infrastructure can trigger and perpetuate food insecurity. Food insecurity, on the other hand, often arises from poverty, resource scarcity, and environmental degradation. In regions grappling with food insecurity, these conditions can create a fertile ground for conflict to take root. Scarcity of essential resources like food can exacerbate social tensions, trigger competition among groups, and lead to social unrest (see [43]). Addressing food insecurity not only addresses a fundamental human right, but also contributes to conflict prevention and peace-building efforts, emphasizing the critical need for holistic strategies that address both root causes and the multifaceted consequences of food insecurity.

Traditional definitions of conflict refer to situations where individuals or subnational groups use threats and intimidation against another individual outside of a direct victim to trigger violence in order to achieve a political goal [25]. Conflicts continue to exist in various forms and indicators globally [26]. According to most experts, violence, whether local or national, plays a crucial role in cross-disciplinary analyses that seek to understand the drivers of economic progress. With a proliferation of violence comes a reduction in output [16], a reduction in growth [56] (de Groot et al. [22]; Young and Bologna [78]), and an increase in macroeconomic uncertainty [17, 36].

The theory of conflict is not as well studied as the theory of crime. Becker's [10] approach to crime economics is rooted in rational choice theory. This laid the foundation for economic analysis of criminal behavior and provided valuable insights into the relationship between crime and conflict, highlighting the importance of rational decision-making, deterrence, and socio-economic factors in understanding conflicts. The theory of conflict underscores the importance of considering the economic costs of conflict [18], the impact on resource allocation and trade (Findlay and Amin [30]) [18, 44, 61], the role of long-term implications [49], and the relationship between governance and conflict [32, 44]. Further, the interconnections between conflict, governance, and economic growth are complex and are still being explored by economists and other social scientists [32].

Integrating seminal works on the economics of crime into the study of the economics of conflict offers a compelling framework to understand the rational decision-making processes that underlie both criminal behavior and acts of conflict. Similar to criminal activities, conflicts often involve individuals or groups weighing the costs and benefits of engaging in hostile actions, where potential gains must be balanced against potential losses, including the risks of violence, resource depletion, and social instability. The emphasis on the role of incentives, risk assessment, and the rational pursuit of self-interest provides a foundation for analyzing how actors in conflicts, whether on a small scale or international level, evaluate their options and make strategic choices. By drawing parallels between the economic calculations driving criminal actions and those guiding conflict dynamics, researchers can uncover valuable insights into the motives, escalation, and resolution of conflicts, enhancing our comprehension of human behavior in contexts of adversity and competition.

In this paper, we examine the causal relationship between conflicts and food security in two sub-Saharan African countries—Malawi, and Ethiopia using household-level data from the World Bank's Household Living Standards Measurement Survey (LSMS) using a newly developed and novel staggered difference-in-differences approach. These sub-Saharan African (SSA) countries are among the most conflict-prone and food insecure globally [28], but also socially similar, providing for a fruitful analysis. A critical reason for focusing on food security as the outcome is that food security measures not only have an immediate implication on household health, but is known to have more long-term impacts including worse economic and health outcomes in adulthood if experienced early in life. Our analysis is guided by the understanding that while food security and conflict have been studied extensively, either in isolation or in association, there is a critical need to understand the direct causal relationship between the two, and in particular, how conflict impacts food security at the household level. Understanding the nuanced nature of conflicts is pivotal for developing contextually informed policies aimed at promoting peace, stability, and sustainable development in the communities that experience conflict.

Our results provide specific estimates of the impacts of conflict on household food security. In the two countries combined, the average treatment effect of conflict was a 6.84 unit reduction in food consumption score, a measure of the diversity and frequency of food consumption in the household. This negative impact corresponds to an average of 16.13% reduction in food consumption score, implying that households in the two countries that experience conflict have their food security score reduced, on average, by almost one-sixths. The estimate for Malawi is even larger, showing that conflict exposure decreases FCS by 10.54 units (equivalent to an average reduction of 20.22% in the FCS). For Ethiopia, the estimate is slightly smaller at −4.316 units (equivalent to an average of 11.67% reduction in FCS) and statistically significant. We then perform the same difference-in-differences analyses in disaggregate groups of the population and find that when households experience conflict and drought in the same year, the decline in food consumption score in the two countries is 12.38 units, equivalent to a 29.20% decline on average; and when conflict is experienced simultaneously with flood, the decline in food security is even larger at 15.01 units, equivalent to a 35.20% decline in food consumption score. We also perform several iterations of robustness checks and find our results are robust to alternative estimation methods.

Background and context

Overall, SSA countries have had a disproportionate share of their countries suffering from violent conflicts relative to other regions in the world. As of the end of 2014, violent conflict and human rights violations had displaced 59.5 million people globally, out of which 38.2 million people were internally displaced persons (IDPs) [67]. More recent studies have shown that in 2018, an estimated 41.3 million people were identified as being internally displaced because of violent conflicts, with 29.4 million being refugees while approximately 600 million young people live in conflict-affected areas [70].

Ethiopia and Malawi, two countries in the study, have encountered distinctive yet consequential trajectories concerning conflicts. In Ethiopia, a nation characterized by its diverse ethnic composition and historical complexities, internal tensions and ethno-political dynamics have periodically escalated into conflicts, manifesting in both localized disputes and broader confrontations. In 2018, Ethiopia had the highest number of new internal displacements associated with conflict worldwide—almost 2.9 million new displacements, four times the figure for 2017 [15]. A study by ACLED [1] found over 230 incidents of civilian targeting during the first 6 months of 2022 in Ethiopia, resulting in more than 1220 fatalities. The authors reported that more than 810 of these fatalities occurred in Oromia, 3200 in the Afar and Amhara regions of Ethiopia between July and December 2021. This is a similar conclusion to the study by Palik et al. [53] who reported that in 2022, over 100,000 people died due to battles in Ethiopia's Tigray region. The United Nations High Commissioner for Refugees [68] estimates that Ethiopia is home to over 924,000 refugees and asylum seekers, most of whom are from South Sudan, Somalia, and Eritrea. Further, 3.5 million people are internally displaced of which 1.2 million were displaced during the first half of 2021 alone.

On the other hand, Malawi has faced relatively fewer instances of overt conflict, although sporadic inter-communal tensions and political uncertainties have marked its history. Ethnically diverse as well, Malawi has managed to uphold relative stability compared to some of its regional counterparts. Yet, violent conflict statistics are lacking and primarily concentrates on specific facets such as intimate partner violence and data relating to internally displaced populations. A study by Maine et al. [42] found that 34.5% of trauma patients suffered from intimate partner violence (IPV). This is consistent with findings from the World Bank, which reported that the number of internally displaced persons in Malawi increased from 117,000 in 2019 to 297,000 in 2022, representing an increase of 154% [75], although this is a reduction from the record high of 343,000 in 2015.

Both Ethiopia and Malawi have faced significant challenges in ensuring food security. In Ethiopia, recurrent droughts and climate-related disruptions have been a major concern, affecting agricultural productivity and exacerbating food insecurity, especially in rural areas. The Ethiopian government has taken measures such as setting up the Agricultural Transformation Agency to improve the livelihoods of smallholder farmers [64] and implementing the Productive Safety Net Program, which provides cash or food transfers to vulnerable households in exchange for participation in public works projects, helping to alleviate immediate food needs [76]. In Malawi, despite progress in recent years, issues like unreliable rainfall patterns and limited access to modern farming practices continue to impact agricultural production and food availability. The government of Malawi has also introduced policies like the Farm Input Subsidy Program, which provides subsidized fertilizers and seeds to smallholder farmers to enhance their productivity [66]. Additionally, organizations like the Food and Agriculture Organization (FAO) have collaborated with the government on initiatives to promote sustainable farming techniques and build the resilience of local communities against food insecurity. Despite the local, national, and multi-lateral efforts, the food security situation in both countries is among the worst in the world. In Ethiopia in

2023, 22.25% of the population was estimated to be food insecure and the World Food Program (WFP) estimates that 14–15 million people in Ethiopia are experiencing severe food insecurity [74]. Similarly, in Malawi, an estimated 3.8 million people, or 20% of the population, are food insecure and in need of food assistance [74].

The relationship between conflict and food security is complex and poorly understood. Violence can disrupt vital supply chains and peaceful transactions, thereby impeding the institutional foundations that enable food to be produced and distributed peacefully [19, 34, 60]. In addition, loss of income from agricultural production may increase motivation and lower the opportunity cost of being involved in violent conflicts by reducing food access [45, 54]. Furthermore, agricultural declines can lead to social inequalities [9, 37, 54, 55]. However, the precise mechanisms by which violence affects food security are still being debated [12, 36, 43, 51] (Young and Bologna [78]; de Groot [21]).

Despite the importance of understanding the causal relationship between food insecurity and violent conflicts, there is a paucity of research on this specific topic [28]. However, there exists a large literature on internal conflict and some specific components of food security, especially on children. For example, literature has identified adverse short-term effects of conflict exposure on children's nutritional status (see [13, 46, 48], (although George et al. [34] argue that these studies are in fact measuring chronic malnutrition as opposed to acute malnutrition, which may be more relevant in conflict context). Conflict has also been shown to have long-term damaging impact on physical and cognitive development (see [3, 24],on agricultural production (see [2, 11, 50, 52]), and food expense (see [69]). Violence has also been studied in the context of its impact on aggregate-level food security both nationally [19, 60] and cross-nationally (see [33]). However, much of these are descriptive studies, and a thorough examination of the causal impact of violence on food security at the household level is surprisingly scant [34, 59] (Koren and Bagozzi [39]), and this can be primarily attributed to the lack of consistent, multi-year household data and the methodological challenge of quantifying causal relationships. This is similarly the case for the narrower literature examining the impact of violence on food security [34] (Koren and Bagozzi [39]). Given food security is fundamentally an individual or household-level concern, this gap in literature is of significant concern.

Our unit of analysis must therefore be the household-level if we want to analyze these effects at a more granular level. Proper understanding of how violent conflicts affect livelihoods and food security is crucial for accurate mitigation and prevention responses. The findings in this study can support policymaking and have implications for aid and humanitarian efforts to help households facing food insecurity stemming from violence and other factors. The study also makes a methodological contribution by using a novel difference-in-differences estimator that allows for consecutive and non-consecutive treatment years and this is the first known application to conflict data in sub-Saharan Africa, providing a much-needed contribution to the field.

Data

This study uses household survey data from the Household Living Standards Measurement Survey (LSMS) for two sub-Saharan African (SSA) countries, Malawi and Ethiopia.[1] For Malawi, we have data from 2010, 2013, 2016, and 2019; and for Ethiopia we have data from 2011, 2014, 2016, and 2019. The LSMS is a repeated cross-sectional survey, but has information on the unique household identifier represented by an 11- or 13-digit household ID. Some new households are added, and some removed, while some households are interviewed every survey year. This allows us to use the unique ID to keep only the households interviewed every survey year and jettison the non-repeated households to convert the data to a panel structure that is required to run the difference-in-differences model. We do this for both countries separately and run separate difference-in-differences models on each; we also merge the data for two countries and run the difference-in-differences model on the combined data.

The basis of our data for violent conflict is a section in the survey called "impacts of wars/conflicts" making it convenient to capture conflict exposure at the household level and measure the welfare impacts of conflicts on household outcomes. One of the most relevant questions in the questionnaire asks if the household experienced conflict in the past 12 months. This variable is a typical binary variable with "1" indicating the household experienced conflict in the past 12 months and "0" otherwise. While this variable does not allow us to distinguish between the types of conflict, the study focuses on conflicts in general and not any specific type. An advantage of this data is that the way it is sampled allows us to directly link each household to conflict exposure information, and then harmonize with demographic and neighborhood characteristics of that particular

[1] Our choice of these two countries is due to data limitations. In our regression, we use data on many demographic, socio-economic, locational and climatic variables. However, (i) most countries in SSA did not have survey data on all these variables; and (ii) even when data were available, they were for two years, which precluded a DiD model. Our analysis is thus restricted to these two countries.

household. We know of no other publicly available, large, comprehensive survey that allows us to link households to conflict exposure specific to that household. This survey is thus unique because it makes it possible to directly establish a causal relationship and has been used successfully in prior studies (see [51]). The survey also has information about other kinds of shocks that can potentially affect food security (for e.g., droughts, floods) and these are also used in the study as control variables.

To measure food security at the household level, we use the Food Consumption Score (FCS), a composite indicator that measures dietary diversity and frequency of food intake. The FCS is calculated by aggregating household-level data on the consumption of eight basic food groups over the past seven days and any food group score greater than seven is truncated. Food groups are assigned weights based on their nutritional value, and the weighted food group scores are summed to obtain the final FCS score [72]. A lower FCS score indicates increasing levels of food insecurity. Following the World Food Program (WFP), households are classified as having poor, borderline, or acceptable food security based on their FCS scores. Following WFP [72], the household food security status is classified as poor if the FCS is below 21.5, borderline if FCS is between 21.5 and 35, and acceptable if the FCS is above 35.

We prefer the Food Consumption Score (FCS) over other methods of measuring food security, such as the household dietary diversity score, because the FCS incorporates consumption frequency and a longer reference period. As Kennedy et al. [38] note, the FCS provides a more comprehensive picture of household food consumption, which is important for in-depth food security assessments, especially when it is measured at the household level where a more granular, rather than aggregate, insight is required. In addition, WFP [72] suggests the use of a weighting system to capture both dietary diversity and food frequency (the number of days per week a particular food is consumed). The FCS, is therefore calculated using a weighting system that takes into account the nutritional value of different food groups. This is important because it ensures that the FCS is a complete measure of food security considering the frequency and nutritional value of consumption, and not simply a measure of dietary diversity. The household dietary diversity score, on the other hand, assigns equal weights to all food groups, which can lead to an underestimation of food insecurity in households that consume a limited variety of foods but consume them frequently.

The LSMS also has information including the annual value of crops harvested, value of livestock and livestock products (meat, eggs, milk, etc.) for each household as well as the costs associated with obtaining the livestock, for example, cost of purchase of the livestock, cost of transportation, cost of fodder, etc. The income from agricultural operations is then calculated by subtracting the cost of production and acquisition from the revenue obtained from selling the crop or livestock. Other variables that may affect food security, including age and gender of household head, distance of household from nearest population center with market, climate, etc., are also included in the model as control variables. A full list, description, and summary statistics for all variables in each country are provided in Table 1.

Methods and procedures

The baseline specifications for estimating the association of conflict exposure with food security uses the OLS regression in Eq. (1). While not a causal estimation method, the baseline model allows us to establish initial associations between food security and conflict after controlling for other variables. This is because our empirical identification strategy relies on a comparison of food consumption score for similar households that differ by their conflict exposure status:

$$\mathrm{FS}_{it} = \beta_o + \beta_1[\mathrm{Conflict}]_{it} + \beta_2 \boldsymbol{X_{it}} + \beta_3 C_t + \delta_i + \gamma_t + \epsilon_{it}, \tag{1}$$

where FS_{it} denotes the levels of FCS for household i at a specific time (t), $\mathrm{Conflict}_{it}$ is a dummy variable indicating exposure to the violent conflict described above, $\boldsymbol{X_{it}}$ is the vector of household variable characteristics that might affect household food security (income from agriculture and livestock, gender and age of household head, etc.) and C_t denotes time-varying region-specific characteristics (temperature, rainfall, distance to the population center, etc.). The δ_i are time-invariant household-specific effects included to capture the potential sources of bias relating to unobserved household characteristics that are correlated with conflict exposure and measures of food security like dietary preference. Finally, γ_t are year fixed effects (FE) and ϵ_{it} is the error term. The β_1 is the coefficient of interest that captures the specific relationship between conflict and food security.

Difference-in-differences strategy

The key causal estimation strategy in this study is a modified difference-in-difference (DiD) estimator where the main outcome is a continuous variable food consumption score (FCS). The treatment variable, violent conflict, is a dummy variable (1) if in the previous 12 months, the household experienced conflict and (0) if the household did not. In such instances, the average treatment effect (ATE) is typically determined by:

$$\alpha\mathrm{DiD} = E[\mathrm{FS}_{i1} - \mathrm{FS}_{i0}|\mathrm{Conflict} = 1] - E[\mathrm{FS}_{i1} - \mathrm{FS}_{i0}|\mathrm{Conflict} = 0], \tag{2}$$

Table 1 Variables, definitions, and summary statistics for all households

	Description	Ethiopia	Malawi
Score	Food consumption score (FCS)	36.99 (16.19)	52.14 (18.01)
Conflict (TREATMENT)	Binary variable indicating whether respondent household experience conflicts in last 12 months	0.01 (0.11)	0.05 (0.27)
Drought	Binary variable indicating whether respondent household experience drought in last 12 months	0.20 (0.40)	0.40 (0.49)
Flood	Binary variable indicating whether respondent household experience flood in last 12 months	0.02 (0.15)	0.17 (0.38)
Age	Age of head of household	46.66 (14.73)	44.31 (15.86)
Male	Binary variable indicating whether head of household is male	0.80 (0.40)	0.77 (0.42)
Income	Income of household from agriculture and livestock (in 2019 USD)	108.21 (456.78)	123.83 (1507.54)
Population center	Distance of homestead to nearest population center with > 20,000 population (in km)	37.89 (27.92)	29.30 (18.19)
Rain	Average total rainfall (mm)	1158.26 (386.46)	1060.57 (233.61)
Temperature	Annual mean temperature (× 10 degree Celsius)	190.13 (32.21)	215.32 (18.55)
Observations	–	9436	5236

where αDiD estimates the impact of conflict exposure on food security, FS_{i1} denotes the level of FCS for household i in period time = 1 (post-conflict) and FS_{i0} denotes the level of FCS for household i in period time = 0 (pre-conflict).

In our study on the causal effects of violent conflict, we encounter a situation where the treatment (conflict) is not applied to all households at the same time. This is known as staggered treatment timing. This poses a challenge for the standard difference-in-differences (DiD) estimation technique, which is commonly used to derive causal estimates. DiD compares the outcomes of households that are exposed to the treatment (conflict) to the outcomes of households that are not exposed to the treatment, while controlling for other factors that may affect the outcome. However, in the case of staggered treatment timing, estimating such treatment effects is problematic for two reasons. First, unlike regular DiD, in staggered DiD, there are two differences between the treatment and control groups: one difference stems from differences across households within the same treatment cohort, while the other difference stems from differences within households across different cohorts (those in earlier cohorts are more exposed to the treatment than those in later cohorts, so even treatment groups are exposed to the treatment for different lengths of time). And second, treatment effect is often heterogenous over time and across groups. When research settings combine staggered timing of treatment effects and treatment effect heterogeneity, staggered DiD estimates are likely biased (Chaisemartin and D'Haultfoeuille 2020).

One approach to estimating causal effects with staggered treatment timing is to use linear regressions with period and gro up fixed effects. This approach weighs different cohorts and estimates the ATE with a weighted sum of the cohort ATEs. However, as Chaisemartin and D'Haultfoeuille (2020) show, this method may generate negative weights for each cohort group meaning that the estimated ATE may be negative even when all the cohort ATEs are positive. Chaisemartin and D'Haultfoeuille (2020) find a novel approach to overcome this problem. Their approach generates asymptotically normal and unbiased estimates even when treatment is staggered and the effect is heterogeneous and differs from other methods (see [7, 14, 35, 63]) in one critical aspect: the Chaisemartin and D'Haultfoeuille (2020) estimator can be used in applications where, for each pair of consecutive dates, there are groups whose treatment status does not change. So even if two cohorts experience conflict in the same year, it treats the group that experiences conflict in consecutive periods differently from the group that experiences conflict in only one period.

This is particularly relevant for us since the data we use has households that are treated in consecutive time periods and some that are treated in only one. For example, in Malawi, the treatment years are 2013 and 2016. There are 1309 repeated households in the sample, 103 of which are treated in 2013, 175 of which are treated in

2016, and 48 of which are treated in *both* years (so for these 48 households, treatment status does not change). Similarly, in Ethiopia, the treatment years are 2014 and 2016, with 19 treated households in 2014, 100 in 2016, and 3 households being treated in both years. In these instances, the de Chaisemartin and D'Haultfoeuille [23] approach is a more reliable method than the alternatives. One additional benefit is that this method allows us to test for common pretrends, which is an assumption for estimating treatment effects. This test differs from the standard event study pretrends test (see [8]), which has been shown to be invalid when treatment effects are heterogeneous (see [63]).

We describe the Chaisemartin and D'Haultfoeuille (2020) estimator in more detail below. We consider observations that can be divided into G treatment groups and T periods. For every $(g,t)\epsilon\{1,\ldots,G\}\times\{1,\ldots,T\}$, let $N_{g,t}$ denote the number of observations in group g at period t, and let $N=\sum_{g,t}N_{g,t}$ be the total number of observations. The data may be an individual-level panel or repeated cross-section dataset.

We are interested in measuring the effect of a treatment on some outcome. Throughout the paper we assume that treatment is binary. Then, for every $(i,g,t)\epsilon\{1,\ldots,N_{g,t}\}\times\{1,\ldots,G\}\times\{1,\ldots,T\}$, let $D_{i,g,t}$ and $(Y_{i,g,t}(0),Y_{i,g,t}(1))$, respectively, denote the treatment status and the potential outcomes without and with treatment of observation i in group g at period t.

The outcome of observation i in group g and period t is $Y_{i,g,t}=Y_{i,g,t}(D_{i,g,t})$. For all (g,t), let:

$$D_{g,t}=\frac{1}{N_{g,t}}\sum_{i=1}^{N_{g,t}}D_{i,g,t},\,Y_{g,t}(0)=\frac{1}{N_{g,t}}\sum_{i=1}^{N_{g,t}}Y_{i,g,t}(0) \quad (3)$$

$$Y_{g,t}(1)=\frac{1}{N_{g,t}}\sum_{i=1}^{N_{g,t}}Y_{i,g,t}(1),\,\text{and}\,Y_{g,t}=\frac{1}{N_{g,t}}\sum_{i=1}^{N_{g,t}}Y_{i,g,t}. \quad (4)$$

Here, $D_{g,t}$ denotes the average treatment in group g at period t, while $Y_{g,t}(0)$, $Y_{g,t}(1)$, and $Y_{g,t}$, respectively, denote the average potential outcomes without and with treatment and the average observed outcome in group g at period t.

We can now define our estimator. For all $t\in\{2,\ldots.,T\}$ and for all $(d,d\prime)\in\{0,1\}$, let:

$$N_{d,d\prime,t}=\sum_{g:D_{g,t}=d,D_{g,t-1}=d\prime}N_{g,t} \quad (5)$$

denote the number of observations with treatment $d\prime$ at period $t-1$ and d at period t. Let:

$$\begin{aligned}DID_{+,t}=&\sum_{g:D_{g,t}=d,D_{g,t-1}=0}\frac{N_{g,t}}{N_{1,0,t}}\left(Y_{g,t}-Y_{g,t-1}\right)\\&-\sum_{g:D_{g,t}=,D_{g,t-1}=0}\frac{N_{g,t}}{N_{0,0,t}}\left(Y_{g,t}-Y_{g,t-1}\right)\end{aligned} \quad (6)$$

$$\begin{aligned}DID_{-,t}=&\sum_{g:D_{g,t}=,D_{g,t-1}=1}\frac{N_{g,t}}{N_{1,1,t}}\left(Y_{g,t}-Y_{g,t-1}\right)\\&-\sum_{g:D_{g,t}=0,D_{g,t-1}=1}\frac{N_{g,t}}{N_{0,1,t}}\left(Y_{g,t}-Y_{g,t-1}\right),\end{aligned} \quad (7)$$

where ($\mathrm{DID}_{+,t}$) is the average treatment effect of *joiners* (households who experience violent conflict) and ($\mathrm{DID}_{-,t}$) is the average treatment effect of *leavers* (households who experienced violent conflict in a previous time period but are not affected in the current time period).

Note that $\mathrm{DID}_{+,t}$ is not defined when there is no group such that $D_{g,t}=1,D_{g,t-1}=0$, or no group such that $D_{g,t}=0,D_{g,t-1}=0$. In such instances, we let $\mathrm{DID}_{+,t}=0$. Similarly, let $\mathrm{DID}_{-,t}=0$ when there is no group such that $D_{g,t}=1,D_{g,t-1}=1$ or no group such that $D_{g,t}=0,D_{g,t-1}=1$. Therefore, our final estimator becomes:

$$\mathrm{DID}_M=\sum\nolimits_{t=2}^{T}\left(\frac{N_{1,0,t}}{N_S}\mathrm{DID}_{+,t}+\frac{N_{0,1,t}}{N_S}\mathrm{DID}_{-,t}\right), \quad (8)$$

where:

- $\mathrm{DID}_{+,t}$ compares the evolution of the mean food security between $t-1$ and t between the joiners and the untreated group.
- $\mathrm{DID}_{-,t}$ compares the evolution of the food security between $t-1$ and t between the treated groups and the leavers.
- DID_M is the average treatment effect (ATE) that we are interested in and relies on a pretreatment common trend assumption; to test this, we computed a placebo estimator to compare the household FCS status one period before the treatment.

In sum, the Chaisemartin and D'Haultfoeuille (2020) estimator is a weighted sum of ATEs of cohorts who are currently treated and cohorts who were treated in some previous year but are no longer treated.

Robustness checks

As robustness checks, we address the selectivity bias problems associated with being treated and employ matching techniques in assessing the impact of violent conflicts on food security. Matching is a statistical method that compares treated units to control units that are as similar as possible in terms of their observable characteristics before treatment. This is done in order to isolate the causal effect of treatment on the outcome of interest. The best matched samples are those that achieve the most balance between the treated and control groups. This balance should include the initial differences between treated and untreated households, as well as the difference between the two groups in the potential effect of being treated.

The propensity score $p(Z_i)$ is defined as the conditional probability of participating in violent conflict activities given pre-participation characteristics:

$$p(Z_i) = Pr[L_i = |Z_i] = E[L_i|Z_i]; p(Z_i) = F\left\{h(Z_i)\right\}, \tag{9}$$

where $L_i = (0, 1)$ denotes participating in violent conflict and Z_i is a vector of pretreatment characteristics. $F\{h(Z_i)\}$ denotes a logistic cumulative distribution. The study uses propensity scores to estimate treatment effects. Given the propensity scores, we use average treatment effect (ATE) to capture the treatment effect for the entire sample:

$$\mathrm{ATE} = E\left[E\left\{Y_i^1\middle|L_i = 1, p(Z_i)\right\} - E\{Y_i^0\middle|L_i = 0, P(Z_i)\right\}\right], \tag{10}$$

where Y_i^1 is and Y_i^0 are the two counterfactual outcomes of treated and non-treated households on violent conflicts.

As robustness check, we employ four iterations of the matching technique. The nearest neighbor matching with $k = 1$ matches each treated household to the control household with the closest propensity score. Nearest neighbor matching with $k = 2$ matches each treated household to the two control households with the closest propensity scores. Caliper matching matches each treated household to the control households whose propensity scores are within a specified caliper. Kernel matching matches each treated household to a weighted distribution of control households, with the weights being inversely proportional to the distance between the treated household's propensity score and the control households' propensity scores. We use caliper matching with replacement to check for overlap of the propensity score distributions between the control and treated groups. This method has the advantage of only using households in the area of common support matching, which helps to ensure that the matched samples are comparable. Additionally, matching with replacement allows us to use the same control household to match multiple treated households, which can be helpful when there are few control households available. Previous studies have found that matching with replacement can often decrease bias because similar controls can be used multiple times to several treated households. This approach is helpful especially when we have few control households to compare with the treated household units [20]. Kernel matching tends to use more untreated for each treated household thereby reducing the variance but possibly increasing the bias because of the variance-bias trade-off. The caliper matching has the added advantage in that it can also use all the comparison households within the caliper.

Finally, we use both graphical diagnostics and standardized mean difference (SMD) to assess the balance of households' covariates after matching. Graphical diagnostics involves comparing the distribution of the propensity scores in the original and matched groups. If the distributions are similar, then we can be confident that the matching has achieved balance. We adopt Stuart [62]'s threshold of 0.25 for declaring imbalance. This means that we consider a covariate to be imbalanced if the difference in the means between the treated and control groups is greater than 0.25. Some studies, such as Rubin [58], have recommended a threshold of SMD greater than 0.1 for imbalanced covariates.

Empirical results

Table 1 presents the descriptive statistics for the study countries. The food consumption score from households in Malawi is relatively higher than households in Ethiopia. Malawi also experiences more conflict and flooding than Ethiopia. The mean age of household heads is largely uniform, 46 years and 44 years in Ethiopia and Malawi, respectively. Approximately, 80% and 77% of sampled households are male headed in Ethiopia and Malawi, respectively. Data also show that households in Malawi on average generate more income from the sale of crops, livestock, and poultry than in Ethiopia. Annual average rainfall ranges between 1061 and 1156 mm, with the highest rainfall in Ethiopia and the lowest rainfall in Malawi. Annual mean temperature ranges between 19.01 and 21.53 °C.

Table 2 disaggregates the data by treated and untreated groups and compares characteristics of households in conflict and non-conflict in the two countries combined

Table 2 Household characteristics by treatment status

	Mean of treated group [1]	Mean of control group [2]	Difference [1] – [2]
Score	46.08 (18.71)	42.26 (18.33)	3.82***
Drought	0.61 (0.49)	0.26 (0.44)	0.35***
Flood	0.37 (0.48)	0.07 (0.25)	0.30***
Age	42.23 (15.11)	45.95 (15.17)	– 3.72***
Male	0.80 (0.40)	0.78 (0.41)	0.02
Income	87.64 (289.58)	130.28 (940.46)	– 42.64**
Population center	35.62 (24.43)	34.79 (25.25)	0.83
Rain	1066.54 (266.99)	1125.47 (345.39)	– 58.93***
Temperature	216.30 (22.40)	198.49 (30.66)	17.81***

*Significant at 10%, ** significant at 5%, and *** significant at 1%

and their differences and significance level. The mean characteristics are somewhat mixed: along some dimensions, such as food security, households experiencing conflict appear to do better on average; the FCS for treated and untreated households was 46.08 and 42.26, respectively. This suggests that sampled households were, on average, marginally food secure regardless of treatment, although interestingly, households experiencing conflict have a higher FCS. This may also seem counterintuitive, but these figures are simply the difference in average without controlling for other variables. Our results also show that 61% of the households who experienced conflict also experienced droughts during the prior 12 months. On the other hand, 26% of untreated households experiences droughts. On the other hand, 37% of the treated households experiences flooding while 7% of untreated households experiences flooding. The mean age of the household head of the treated and untreated households is approximately 42 and 46 years, respectively. The majority (80% and 78%) of the total sampled households are male-headed households in treated and untreated households, respectively. The average annual income from crops, livestock, and livestock products of the treated and untreated groups is $88 and $130, respectively. These differences, however statistically significant, should not be viewed as being a result of conflict.

Baseline estimation

We begin by providing preliminary evidence about the effect of conflict on average food security status, disaggregated by country, both pre- and post-treatment in Table 3.[2] The purpose of this exercise is to compare the proportion of households in each of the food security categories before and after the years of conflict and provide a first indication that conflict is associated with lower food security. For pretreatment, we calculate the proportion of households in each category in the pretreatment years (2010 for Malawi and 2011 for Ethiopia). For post-treatment, we calculate the proportion of households in each category in the post-treatment years (2013, 2016, and 2019 for Malawi, and 2014, 2016, and 2019 for Ethiopia).

The combined dataset shows that 80.30% of households have an acceptable level of food security, 14.30% has borderline, and 5.40% has poor food security before conflict. In post-conflict years, the proportion of households with acceptable levels of food security drops to 53.42%, those with borderline increases to 36.26%, while those with poor food security doubles to 10.32%. This common pattern is observed at the level of the individual countries.

In Malawi, 98.29% of households have an acceptable level of food security, 1.63% has borderline food security, and 0.078% has poor food security in pre-conflict years. In post-conflict years, the proportion of households with an acceptable level of food security reduces to almost 77% and the proportion of households with borderline food security increases to 21.39%. This indicates that a significant number of households became vulnerable to food insecurity after conflict. Similarly, in Ethiopia, 70.78%, 21.05%, and 8.23% of households have acceptable, borderline, and poor levels of food security, respectively. After conflict, the percentage of households with acceptable food security drops to 40.18%, and those with borderline levels increase to 44.63%. Overall, we see that while the conflict does not result in a significant increase in households with poor food security, we do observe a substantial drop in households with acceptable levels of food security. The bulk of these households appear to fall from acceptable level to borderline levels of food security.

The baseline OLS results show that violent conflict is associated with a decrease of FCS by 1.74 units or approximately a 4.00% decrease on average in the FCS in the combined data set. Other shocks utilized in the model include drought and flood. Both shocks have a negative and significant association with FCS. A single instance of a season of drought is associated with a decrease of FCS by 2.67 units (equivalent to a decrease of 6.30% on average in the FCS). Similarly, a single instance of flooding in a year is associated with a decrease in FCS by 3.90 units (a decrease of 9.20% on average in the FCS).

[2] We thank an anonymous reviewer for suggesting this.

Table 3 Food security category by treatment status

	Total		Malawi		Ethiopia	
	Pre-treatment	Post-treatment	Pre-treatment	Post-treatment	Pre-treatment	Post-treatment
Acceptable (%)	80.30	53.42	98.29	76.96	70.72	40.18
Borderline (%)	14.30	36.26	1.63	21.39	21.05	44.63
Poor (%)	5.40	10.32	0.078	1.65	8.23	15.19

Pre-treatment years for Malawi is 2010, and for Ethiopia is 2011

Table 8 in the "Appendix" shows a low positive correlation between violent conflicts and other natural disasters (floods and droughts), implying that the effect of violent conflict on food security is not confounded by the effect of flood or drought.

Difference-in-differences estimation

We now present the de Chaisemartin and D'Haultfoeuille [23] difference-in-differences model (DID_M) on the combined data and then on the individual countries. The composite and country-specific results are presented in Table 4. The composite DID_M estimate for the two countries combined is −6.84 units. This negative impact corresponds to an average of 16.13% reduction in FCS. This implies that households in the two countries that experience conflict have their food security score reduced by almost one-sixth, which is a substantial reduction given the already borderline levels of food security. The DID_M estimate for Malawi is even larger, showing that conflict exposure decreases FCS by 10.54 units (equivalent to an average reduction of 20.22% in the FCS). Finally, the DID_M estimate for Ethiopia is slightly smaller at −4.316 units (equivalent to an average of 11.67% reduction in FCS) and statistically significant. It is worth noting that the true impact of conflict is even larger as the average treatment effect (ATE) in the above estimation is averaged across all households, regardless of whether they experience conflict or not. As FCS measures both consumption frequency and dietary diversity, the decline in household FCS suggests households have lowered their consumption patterns either through reduced meal frequency or diminished meal quality and quantity. It is also not uncommon for some households to go without food for some days.

The DID_M also allows us to generate placebo estimator results. A significant placebo effect coefficient implies a violation of the parallel trend assumption, and vice versa. Here, the placebo effect is not significant for the individual countries, or the countries combined, thus satisfying the parallel trends assumption.

Table 4 DID_M ATE estimates of conflict on food security

	Total	Malawi	Ethiopia
ATE	−6.84* (2.63)	−10.54*** (4.95)	−4.32* (2.24)
Placebo effect	3.15 (9.53)	22.48 (22.10)	1.64 (4.24)

*Significant at 10%, ** significant at 5%, and *** significant at 1%

Table 5 DID_M ATE estimates by disaggregated households

	Female-headed households	Male-headed households
ATE	−5.10** 1.42	−5.56*** 1.50
	No drought	**Drought**
ATE	−2.55 6.06	−12.38*** 2.88
	No flood	**Flood**
ATE	−1.76*** 0.49	−15.01*** 2.88
	HH head age above median	**HH head age below median**
ATE	−3.30*** 0.42	−5.64 3.81

*Significant at 10%, ** significant at 5%, and *** significant at 1%

This result could be explained by the fact that we do not have a differential pre-trend one year prior to treatment meaning that the households that experienced violent conflicts between $t-1$ and t did not experience significantly different trends in food security from $t-2$ to $t-1$ than household units where there were no violent conflicts.

While overall we find large negative impacts of exposure to conflict, it is important to know whether these effects are experienced equally by different disaggregated groups. In the remainder of this section in Table 5, we examine the differential impacts of conflict on female and male-headed households, households suffering from drought, flood in the same year as the conflict, and household heads aged above or below the median age of 44 years. The first row estimates indicate that, magnitudinally, female-headed households were marginally less affected by conflict (−5.10 or 12.01% drop in average FCS) relative to male-headed households (−5.56 or 13.12% drop), although the differential impact may not practically significant. The magnitudes and statistical significance are comparable to the key results in Table 4 (−6.84 or 16.13%), suggesting that the impact of conflict on FCS may not be significantly different among male and female-headed households. This is interesting, because unlike the literature on gender economics that generally finds a negative bias against female-headed households insecure [29, 41, 65], we find here that both male and female-headed households are negatively affected, with male-headed households experiencing a marginally larger decline in food security.

Next, we examine the differential impact by instances of drought and flood. Interestingly, the causal impact of conflict is substantially higher than when there are instances of drought or flood in the same year as the conflict. For example, the ATE is −2.55 (6.01%) when there is no drought and −1.76 (4.15%) when there is no flood. The impact increases alarmingly to −12.38 (29.20%) and −15.01 (35.20%) when there is drought or flood, respectively. This represents an increase in several orders of magnitudes of the impact of conflict when it is experienced simultaneously with either drought or flood.

Finally, we check whether the effect of conflict differs by age of household head. For this, we disaggregate groups by whether the household head is above the median age (44 years) or below. We find here that households headed by people aged above the median age suffer a decline in FCS by 3.30 (equivalent to a 7.78% decline on average in FCS). For households headed by people aged below median age, the causal impact of −5.64, although this is not statistically significant.

Overall, the results reveal that violent conflict has a strong negative and significant effect on food security, with the effect ranging from −4.32 to −10.54, which are equivalent to a 11.67–20.22% drop in food consumption score. The results are even starker when they are compared in disaggregate groups: when households experience conflict and drought, the decline in food consumption score is 12.38, equivalent to a 29.20% decline on average; and when conflict is experienced simultaneously with flood, the decline in food security is even larger at 15.01, equivalent to a 35.20% drop. These impacts are large and meaningful, particularly when compared to the existing food status of households. Table 1 shows that the average food consumption score in Ethiopia is 36.99, in Malawi it is 52.14, and in the two countries combined, it is 42.40; the "average" household has therefore an "Acceptable" level of food security status.

In the two countries combined, households experiencing conflict will experience a decline in food consumption score of 6.84, which means their FCS score on average will drop from 42.40 to 35.56, implying that households will get dangerously close to the cutoff for borderline food security status of 35. Similarly, in Ethiopia, households experiencing conflict will suffer a drop from 36.99 to 32.67 in their FCS, implying the status of the average household will drop from an "Acceptable" level of food security to a "Borderline" level of food security. These impacts of conflict are more alarming when experienced with other forms of nature-induced shocks such as droughts and floods. In such cases, the average household is likely to fall even deeper into food insecurity. For instance, if an "average" household in the two countries experiences conflict simultaneously with drought, the food consumption score will drop from 42.40 to 30.02; if instead of drought it experiences flooding, the score will drop even further to 27.39. Both these will place the average household within the "Borderline" level of food security status.

Understanding the specific impacts of conflict on food security is essential for developing adequate policy responses to protect households from the negative impacts of conflict. In order to fully address this question, we use detailed household-level data on food security and conflict event data along with data on income, location, climate, and other household-specific information to accurately measure their relationship. Our results provide some suggestive indication of the specific impact of conflict on a specific measure of food security. This is an important finding, as it highlights the need to accurately measure the impact of conflict on food security in order to assess the relative vulnerability of households in the sub-Saharan Africa region. The heterogeneity in the magnitude and significance of the causal effect can be attributed to the type of violence impacting food security at the household level and also the different factors unique

Table 6 Matching ATE of conflict on food security: robustness checks

Matching algorithm	Combined	Ethiopia	Malawi
Nearest neighbor ($k=1$)	−3.46** (1.61)	−8.36** (2.42)	1.49 (1.26)
Nearest neighbor ($k=2$)	−3.64** (1.57)	−7.91** (1.91)	1.05 (1.43)
Caliper (0.25 × SD of PS)	−2.06** (0.40)	−7.15** (1.95)	0.12 (1.17)
Kernel (Epanechnikov)	−0.90 (1.12)	−3.46** (1.21)	0.20 (1.08)

For the combined results, households are first matched by country, and then the matched data from individual countries are merged. *Significant at 10%, **significant at 5%, and ***significant at 1%

to the countries being studied at the local, regional or national level. For example, our results indicate that the male-headed households may be affected differently than female-headed households, although the difference may be practically insignificant. Similarly, conflict events occurring simultaneously with either drought or flood can substantially exacerbate the effect of conflicts. Finally, the age of the household head may also be a factor in determining how households are impacted by conflict. These findings suggest that there is a need to take a more nuanced approach to understanding the impact of conflict on food security.

Robustness checks

In addition to the previous approach using the modified difference-in-differences strategy, to further verify the robustness to alternative estimation methods, we use propensity score matching (PSM) with nearest neighbor ($k=1$ and $k=2$), caliper, and kernel matching methods. PSM allows us to control characteristics that might affect conflict exposure and reduce selection bias. Identification is driven by creating comparable groups with similar distributions of covariates, and then comparing households of the same characteristics, so making it more likely that any observed differences in outcomes between the groups are due to the treatment rather than pre-existing differences in covariates.

The results are presented in Table 6. We use four different matching methods to estimate the average treatment effect (ATE), and all results generally indicate large negative impacts of conflict exposure on food security. The first row shows the results of nearest neighbor matching. The ATE is negative and significant for both the combined data and Ethiopia, but not for Malawi. The second row shows the results of 2-nearest neighbor matching. The ATE is again negative and significant for the combined data and Ethiopia, but not for Malawi. The third row presents the estimates from caliper matching, where we matched on the logit of the propensity score using calipers of width equal to 0.25 of the standard deviation of the logit of the propensity score. Again, both the combined data and Ethiopia shows negative and statistically significant estimates while Malawi does not. The fourth row shows the results of Epanechnikov's kernel matching. The ATE is again negative and significant for Ethiopia, but not for Malawi or the combined countries. Throughout all estimation methods, the magnitude of the impact is larger for Ethiopia, followed by the combined results, although we are not able to fully establish statistical significance of Malawi's results. This may be driven by a relatively poorer matching in Malawi, which may itself be a result of there being more treated households relative to control households, and also the presence of more consecutively treated households. Our design of the PSM requires matching to be performed year-by-year, so for a household treated in consecutive years, there must be sufficiently close enough households who are not treated in either year. Given the relatively large number of treated households in Malawi's sample, the procedure may not have produced the best matches.

We show various measures of matching diagnostics in the "Appendix". In Table 9 in Appendix 3, we show the mean and median standardized difference for all the covariates. The first two columns show the mean and median bias as summary indicators of the distribution of the absolute bias.[3] The figures suggest that the household groups (disaggregated by treatment status) are quite similar in terms of characteristics after matching. The PSM logit results and the histogram of the estimated propensity scores for the treated and comparison units are also reported in the appendices. The distribution of propensity scores on a region of common support achieved shows that all the bins (0–0.05, 0.05–0.1, …, 0.95–1.00 for all algorithms) are balanced. This means that there are no bins where the number of treated units greatly outnumber the comparison units or vice versa. In other words, there is a significant overlap of comparison units with a broad range of treated units, which enables a proper comparison and give us confidence in our robustness tests. To achieve a better balance, the right and left skewed observations are removed. This removes observations that are outliers and that may bias the results of the PSM.

[3] The standardized % bias is the percentage difference of the sample means in the treated and non-treated (full or matched) sub-samples as a percentage of the square root of the average of the sample variances in the treated and non-treated groups.

Discussion of conflict impacts and mechanisms

Understanding the specific mechanisms through which conflict impacts food security is critical for developing effective policy responses. A detailed analysis of these mechanisms is beyond the scope of the paper, but a brief discussion is warranted. As most households in our data rely on farming for livelihood, disruption of agricultural activities seems to be the right way to start. A first possible mechanism identified in literature is that conflict often leads to the displacement of communities, which can disrupt farming and other agricultural activities (see [11, 50, 52, 57]). Farmers may be forced to abandon their fields, leading to decreased food production and eventually impacts access to proper nutrition and adequate food supply becomes challenging. In such situations, livestock and agricultural produce might be stolen, warehouses, food storage facilities, and distribution networks can be damaged or destroyed during conflict, affecting the efficient distribution of food.

Another possible mechanism is through the destruction of infrastructure, machinery, and livestock, leading to the loss of livelihoods for people dependent on agriculture and related industries [40]. Conflict can disrupt markets, making it difficult for farmers to sell their produce and for consumers to access food. Employment opportunities may be disrupted, reducing people's ability to purchase food. With jobs and businesses affected, households may lack the financial means to secure adequate nutrition. The absence of detailed household-level survey information, however, limits our ability to examine these issues more thoroughly.

Despite the lack of such data, our results provide some indicative evidence about the mechanism. Displacement of communities, disruption of farming and agricultural activities may not have been the contributing a key mechanism in our data, since we limited the analysis to households who lived in the same location (identified by coordinates) over the period of the study. Moreover, a key control variable in the data is income from farming and livestock, so the impact of conflict is isolated from the impact of harvest loss, disruption of business and livelihoods related to agriculture. We do not, however, have data on provisions of food aid although prior research suggests that relief efforts are often not restricted by conflict [5]. If that were indeed to be true, then our estimates of the causal effect are in fact underestimated.

The results of our study, though not directly comparable, are similar to those observed in prior literature on aggregate study areas. First, we examine conflict's causal effect. According to our robust findings, conflict exposure decreases FCS on average by 16.13% for both countries combined, 20.22% in Malawi and 11.67% in Ethiopia. George et al. [34] report similar results despite using Household Dietary Diversity Score (HDDS) as a measure of food security. They find that in the aftermath of the violent conflict, households' food insecurity conditions may have increased mainly because of disruptions to production and economic activities. A similarity between our results can also be drawn with Akresh et al. [4] who find that boys and girls born during the conflict in regions experiencing conflict are negatively affected, with height-for-age z-scores being 1.05 standard deviations lower. Similarly, Minoiu and Shemyakina [46, 48] find that children from regions more affected by conflict suffered significant health setbacks compared with children from less affected regions, and Akbulut-Yuksel [3] find exposure to destruction had long-lasting detrimental effects on human capital formation, health, and labor market outcomes of Germans who were of school-age during World War II. Rockmore [57] finds that conflict results in a large decrease in the size and value of livestock herds. And finally, Verwimp and Munoz-Mora [69] compare food security and nutritional status of formerly displaced households with their non-displaced neighbors and find formerly displaced have 5% lower food expenses and 6% lower calorie intake. While these studies examined specific components of food security (which is more of a composite measure), the direction of the relationship is largely identical with ours, and any heterogeneity in specific estimates may be due to the specific attributes studied, regional or cross-national variation and methodological variation. The results of our study therefore not only establish the causal linkage between food security and conflict, but also demonstrate the necessity of household-level targeting and mitigation strategies.

We also examine FCS levels among households in Malawi and Ethiopia separately and together. For the two countries combined, the proportion of households with an acceptable level of FCS decreases from 80.30 to 53.42% from pre-conflict years to post-conflict years. In Ethiopia, the proportion of households in the "Acceptable" category decreases from 70.72 to 40.18% in the pre-conflict years to post-conflict years; in Malawi, the same proportion was from 98.29 to 76.96%. While specific prior empirical evidence does not exist, this is far lower than the proportion recommended by the World Food Program, which recommends that 90% of households should typically be in the "Acceptable" category (Ambaw et al. [6]). Broadly, our results are also supported by Weldegiargis et al. [71] who show that 84.6% of households were food insecure in Tigray, Ethiopia, based on the household food insecurity access scale (HFIAS). Other comparable studies show varying FCS levels. For example, 30% of the population is poor and borderline in rural Uganda and 34% in poor and borderline category in the mountainous region of Nepal [73]. The lack of comparable prior empirical evidence also reinforces our confidence in the novelty of our research and findings.

Conclusions

A growing body of previous empirical studies has focused on national and regional comparisons of conflicts and food security. These have predominantly summarized that the nature of the effect resulting from conflicts may be quite diverse across different types and intensities of conflict and across the national and local institutions [43]. However, there is still little direct evidence that explicitly captures household variation in conflicts by understanding the causal mechanism. The study addresses this literature gap by estimating the causal impacts of conflicts on food insecurity in sub-Saharan Africa at the household level. Analyzing data at a granular level allows us to determine the impacts of conflicts that are not large enough to have a regional impact but have very significant impacts at the local or household level.

We employ the World Bank's Household Living Standards Measurement Survey data from two sub-Saharan African countries—Malawi, and Ethiopia, which are among the most conflict-prone and food insecure globally. The results reveal that conflict exposure decreases the food consumption score by 6.84 units on the composite data. This corresponds to a 16.13% or one-sixths reduction in the measure of food security. In Malawi, the causal estimate is even larger, at −10.541, representing a 20.22% drop in food consumption score. The estimate in Ethiopia was slightly smaller at −4.32 (representing a reduction of 11.67%), although the baseline food security status was much poorer in Ethiopia than Malawi. The findings remain largely consistent and robust in alternative estimation methods using different iterations of propensity matching techniques. These generated comparable estimates and reinforced the key results.

We then perform the same analyses in groups disaggregated by the gender and age of household head, and natural shock exposure. We find, contrary to literature, that the magnitude of the causal estimate for female-headed households is marginally smaller than male-headed households, although the difference may not be practically significant. Consistent with prior literature though, we find households headed by relatively older individuals are more vulnerable to conflict than those headed by younger individuals. We also find that when households experience conflict and drought simultaneously in a year, the decline in food consumption score in the combined data is 12.38, equivalent to a 29.20% decline on average; and when conflict is experienced simultaneously with flood, the decline in food security is even larger as 15.01, equivalent to 35.20%. Both these figures are comparable to and are several orders of magnitude larger than the aggregate average causal estimate of −6.84 units.

Our ability to accurately harmonize conflict data with household-level characteristics and employ a novel econometric approach that specifically adjusts for the nuances in the data strengthens our confidence in the results. Broadly, the findings in the paper help improve our understanding of the relationship between conflict and food security. Several implications can be drawn from these findings. First, we demonstrate the value of measuring conflict effects at a household level. By doing so, we gain insights into the nature and meaning of conflict exposure at a more granular level. Given food security is fundamentally an individual or household-level concern, this unit of analysis seems appropriate. The results indicate that under varying circumstances, food security measures can decline in the range of 16–35%, which is concerning given the already vulnerable state of food security in these countries and an alarming trend in conflict.

Our results also provide stronger and more direct evidence to support the conjecture that violent conflict not only affects the aggregate or regional food security, but also specific households. This reinforced the critical need for policymakers to target interventions and policy responses at the household level. The results of the study also suggest households respond to conflict differently, so an approach that takes into consideration the varied nature of the effects of conflict is critical to target interventions. These results are therefore relevant to current debates regarding best mitigating strategies that take more granular, rather than national or subnational perspectives in building regional stability.

While our analysis contributes substantially to the literature regarding violence and food security, as well as implications aimed at reducing the risk of food insecurity, it also has a number of limitations. It is noteworthy that our measure of whether a household has experienced violence relies on self-reporting and does not provide specific details as to what type of violence a household has experienced. Depending on the type and scale of violence—from domestic to international—food security may be affected differently. We also limited our analysis to two countries due to the lack of uniformity, homogeneity, and absence of some of the variables necessary to construct the food consumption score and other independent variables used in the study. Including more countries in the study would provide additional insight into how violence affects food security and generalize the findings over the sub-Saharan region.

The limitations of our analysis provide useful avenues for future research. By focusing on specific occurrences of violence, we will be able to gain a deeper understanding of how violence can lead to food insecurity. Further insight would be gained by extending our analysis to other countries or utilizing other empirical approaches. A further investigation of policy mitigation measures to prevent or reduce the spread of violence, particularly at the household level, would also reduce the likelihood of food insecurity within vulnerable populations. Future research can focus on identifying the specific mechanisms through which conflict leads to food insecurity, and on developing targeted interventions to mitigate the negative effects of conflict on food security.

Appendices

Appendix 1

See Table 7.

Table 7 OLS regression results

	Combined	Ethiopia	Malawi
Intercept	35.22** (1.35)	34.80*** (1.52)	58.22*** (3.22)
Treat	− 1.74* (0.77)	− 3.71* (1.47)	− 0.31 (0.94)
Drought	− 2.67*** (0.33)	− 2.87*** (0.43)	− 2.09*** (0.52)
Flood	− 3.90*** (0.55)	1.86 (1.09)	− 6.01*** (0.68)
Age	− 0.06*** (0.01)	− 0.05*** (0.01)	− 0.05** (0.02)
Male	3.04*** (0.34)	2.73*** (0.40)	3.66*** (0.59)
Income	0.01*** (0.00)	0.01*** (0.00)	0.01** (0.00)
Population center	− 0.02** (0.01)	0.01 (0.01)	− 0.12*** (0.01)
Rain	− 0.01*** (0.00)	− 0.01*** (0.00)	0.01** (0.00)
Temperature	0.04*** (0.00)	0.04*** (0.01)	− 0.02 (0.01)
Malawi (FE)	14.92*** (0.34)	–	–
R-squared	0.18	0.14	0.15

*Significant at 10%, ** significant at 5%, and *** significant at 1%

Appendix 2

See Table 8.

Table 8 Correlation between natural disasters

	Treat	Flood	Drought
Treat	1.00	0.21	0.14
Flood	0.21	1.00	0.18
Drought	0.14	0.18	1.00

Appendix 3

See Table 9.

Table 9 Summary of matching characteristics

	Mean Bias	Median Bias
Nearest neighbor ($k=1$)	7.91	7.88
Nearest neighbor ($k=2$)	15.24	9.50
Caliper (0.25 × SD of PS)	22.19	29.11
Kernel (Epanechnikov)	7.72	11.10

Appendix 4

See Table 10.

Table 10 Descriptive statistics between the treated and control group (matched)

	Description	Mean of treated group	Mean of control group
Drought	Binary variable indicating whether respondent household experience drought in last 12 months	0.61 (0.49)	0.54 (0.50)
Flood	Binary variable indicating whether respondent household experience flood in last 12 months	0.36 (0.48)	0.40 (0.49)
Age	Age of head of household	42.20 (15.11)	41.74 (14.21)
Male	Binary variable indicating whether head of household is male	0.80 (0.40)	0.79 (0.41)
Income	Annual income of household (in USD)	87.81 (290.87)	101.35 (199.21)
Population center	Distance of homestead to nearest population center with > 20,000 population (in km)	35.76 (24.47)	33.74 (23.21)
Rain	Average total rainfall (mm)	1066.85 (267.14)	1054.69 (276.02)
Temperature	Annual mean temperature (10*C)	216.24 (22.47)	217.21 (23.69)

Appendix 5

See Table 11.

Table 11 Logistic regression results

	Ethiopia	Malawi
Intercept	0.00*** (0.00)	0.22** (0.16)
Drought	5.57*** (1.19)	2.17*** (0.25)
Flood	1.00 (0.60)	5.65*** (0.73)
Age	1.00 (0.01)	0.99*** (0.00)
Male	0.91 (0.21)	1.200 (0.17)
Income	0.10 (0.00)	1.00* (0.00)
Population center	1.00 (0.00)	1.01** (0.00)
Rainfall	1.00*** (0.00)	1.00** (0.00)
Temperature	1.02*** (0.00)	1.00 (0.00)
Log-likelihood	− 581.64	− 1257.93

*Significant at 10%, **significant at 5%, and ***significant at 1%

Appendix 6a
See Table 12.

Table 12 ATE estimates for Ethiopia ($k=1$)

	Sample	Treated	Controls	Diff	SE	*T*-stat
Score	Unmatched	35.73	37.06	−3.33	1.96	−2.23
	ATT	33.99	40.53	−6.54	1.39	−4.70
	ATU	44.17	35.99	−10.18	–	–
	ATE	–	–	−8.36	2.42	–
Log likelihood	–	−375.73				

Appendix 6b
See Table 13.

Table 13 ATE Estimates for Malawi ($k=1$)

	Sample	Treated	Controls	Diff	SE	*T*-stat
Score	Unmatched	49.63	52.44	−2.817	0.94	−3.00
	ATT	49.76	50.47	−0.71	1.01	−0.70
	ATU	46.07	49.76	3.69	–	–
	ATE	0.45	–	1.49	1.26	–
Log-likelihood	–	−1043.45				

Appendix 7
See Table 14.

Table 14 Balance of covariates (*k*-nearest neighbor, $k=2$)

	Treated mean	Control means	% bias	T-score	$p>\|t\|$
Drought	0.73	0.76	−8.3	−1–16	0.25
Flood	0.42	0.61	−40.9	−5.71	0.00
Age	41.45	41.15	2.20	0.35	0.73
Male	0.72	0.62	22.0	3.08	0.00
Income	65.29	58.02	2.7	0.72	0.47
Popcenter	36.83	34.11	8.9	1.76	0.08
Rain	1058.2	1093.7	−12.2	−1.81	0.07
Temp	221.23	212.25	39.6	6.06	0.00

Appendix 8
See Table 15.

Table 15 PSM logit results ($k=1$)

	Coef	Std. Err	Marginal effect
Drought	−1.33***	0.21	0.03
Flood	−2.35***	0.19	−0.52
Age	0.01**	0.01	0.00
Male	0.61***	0.18	0.15
Income	0.00**	0.00	0.00
Popcenter	0.02***	0.00	−0.01
Rain	0.00	0.00	0.00
Temp	−0.03	0.00	−0.01
Intercept	9.10	1.02	–

Appendix 9

See Fig. 1.

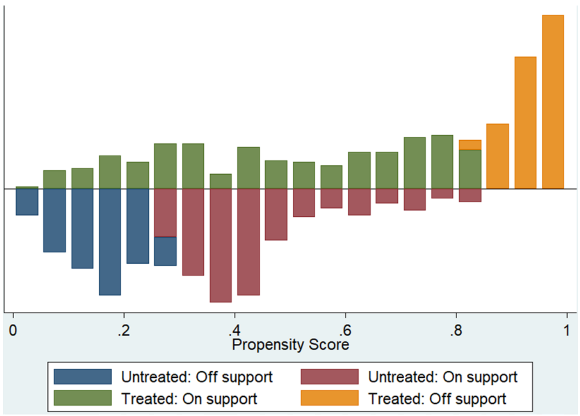

Fig. 1 Distribution of propensity scores on region of common support ($k=1$)

Appendix 10

See Fig. 2.

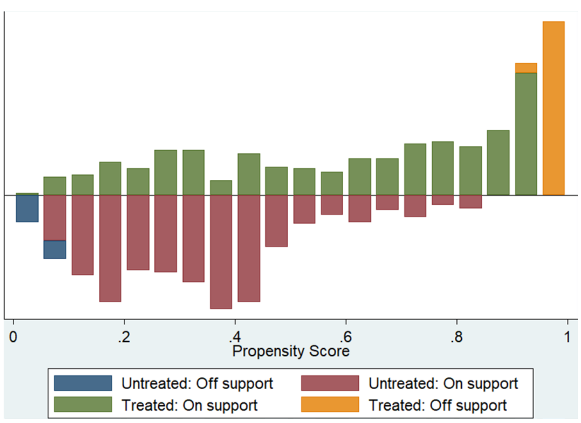

Fig. 2 Distribution of propensity scores on region of common support ($k=2$)

Appendix 11

See Fig. 3.

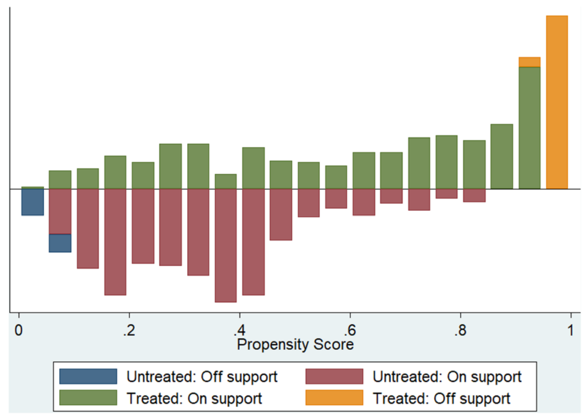

Fig. 3 Distribution of propensity scores on region of common support (Caliper matching)

Appendix 12

See Fig. 4.

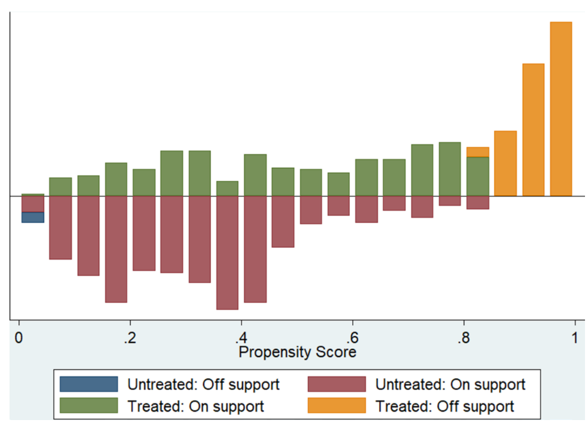

Fig. 4 Distribution of propensity scores on region of common support (Kernel matching)

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Author contributions
JM participated in conceptualization, methodology, writing—original draft, data curation, and formal analysis; DH was involved in conceptualization, supervision, project administration; SF did methodology, software, formal analysis, investigation, data curation, writing—original draft, writing—review and editing. All authors read and approved the final manuscript.

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Declarations

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Competing interests
The authors declare that they have no competing interests.

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