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ABSTRACT

Spatial Spillovers of Conflict in Somalia

Due to economic interconnectedness across regions, locally confined violent conflict may have welfare effects far beyond directly affected areas. This paper focuses on Somalia's al-Shabaab insurgency and investigates whether the food transportation network propagates the effects of violent conflict to distant locations. Combining granular geospatial information on agricultural areas, roads, and itineraries, we show that conflict along transportation routes significantly increases food prices at markets located hundreds of kilometers away. Standardized estimates amount to up to half the magnitude of the effect of rainfall. Negative effects of conflict on road traffic as measured by satellite images of light emissions point towards decreases in food transportation. Moreover, conflict decreases food security, nutrition, health, and education for households living in far-away market areas. This suggests that food prices act as a propagating mechanism that links – among others – human capital to far-away conflict. Back-of-the-envelope calculations suggest that spatial spillovers add an additional 30% to the welfare cost of local conflict.

JEL Classification: D74, I15, I25, Q18

Keywords: conflict, spillover effects, food security, health, education

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1 Introduction

A common conjecture in policy and research is that the effects of violent conflict are highly localized. As a result, policy responses to conflict, such as humanitarian aid, protection efforts, or asylum status eligibility, commonly focus on areas where violence occurs.¹ This approach matches an ample body of research that has documented links between local conflict, food security and human capital (see Verwimp et al., 2019; for a recent overview). Yet, it is possible for conflict to affect areas far from its location (which we refer to as *spatial spillover effects*). One instance where such spillovers are likely is when conflict disrupts food distribution networks. For example, the UN warns of the global ripple effects of the blockage of Ukrainian grain export routes due to the 2022 Ukraine war and estimates that it could push 47 million people mainly in sub-Saharan Africa into food insecurity.² Similarly, the Boko Haram insurgency in Nigeria led to widespread hunger³ and eroded human capital of children⁴ far beyond the areas where the fighting occurred. The presence of spatial spillovers has far-reaching implications. It implies not only that the effects of conflict may be stronger than the literature thus far suggests, but also that policy responses focusing on areas where violence occurs may be sub-optimal.⁵ However, the exact reach of conflict and which type of conflict is likely to lead to spatial spillovers have remained under-explored.

This paper investigates whether conflict in one location affects food prices, nutrition, health, and education in far-away areas. The setting for our analysis is Somalia, which

¹For example, the World Health Organisation (WHO) provides emergency medical supplies to areas affected by conflict – see http://www.emro.who.int/images/stories/somalia/documents/technical_programme_update_september_december_2018.pdf?ua=1 (accessed December 2021). The High Commissioner for Refugees report (United Nations High Commissioner for Refugees, 2010) ties protection status to residing in those areas of Somalia affected by conflict.

²<https://www.fao.org/3/cc0364en/cc0364en.pdf>, p.10, accessed August 2022.

³[https://www.thelancet.com/journals/lancet/article/PIIS0140-6736\(17\)30198-8/fulltext](https://www.thelancet.com/journals/lancet/article/PIIS0140-6736(17)30198-8/fulltext), accessed August 2022.

⁴<https://www.science.org/content/article/hunger-amplifies-infectious-diseases-million-s-fleeing-violence-boko-haram>, accessed August 2022.

⁵Regional spillovers of conflict can also invalidate common research designs that compare individuals close to and far from conflict. Apart from not capturing the regional spillover, such a research design would be likely to underestimate the effects of localized conflict if the comparison group is affected by conflict through spillovers.

experienced a stark increase in violence during the al-Shabaab insurgency from the mid-2000s onwards. Our research design uses granular geospatial information to identify incidences of conflict hitting food transportation networks and to estimate their effects on far-away areas. This spatially disaggregated approach rules out many common endogeneity concerns. The 'treatment' (i.e. conflict along the transportation route) occurs far away from regions where the outcomes are measured. Identification issues, such as omitted variable bias or reverse causality, by contrast, would typically induce spurious correlation between violence and outcomes *in the same local area*, with little reason why they should increase conflict at a considerable distance away and along very specific overland routes. Nevertheless, as we describe below, we probe our identification strategy in several ways.

In the first part of our analysis, we assess whether conflict along the food logistics network changes prices in markets located hundreds of kilometres away. This can be the case, for instance, because violence along transit routes can drive up transportation costs or cause shortages in market regions. We focus on the price of maize, a staple food widely eaten throughout Eastern Africa. In Somalia, maize is produced domestically in three growing regions and transported on roads to selling points. We follow recent work on transportation networks (Dell, 2015; Korovkin and Makarin, 2021) and identify incidences of conflict hitting the maize distribution system. To this end, we combine the exact geographical coordinates of growing regions, markets, and overland roads with detailed information on the precise routes used for transportation based on information from NGOs working on the ground. For each market in our sample, we draw a corridor five kilometres either side of the transportation route supplying that market with maize. Using the exact geographical coordinates of incidences of conflict from the Armed Conflict Location & Event Data Project (ACLED), we estimate the effect of violent events occurring each month within this corridor—and far away from markets—whilst also controlling for conflict in the proximity of markets. Thus, our approach complements the existing literature (see Blattman and Miguel, 2010; Martin-Shields and Stojetz, 2019; for overviews) focusing on conflict in proximity to respondents.

Based on monthly maize price data for ten markets from 2001 to 2018 in Somalia provided by the Food and Agricultural Organisation (FAO), we show that each incidence of conflict along transportation routes (and at some distance from markets) increases the price of maize by around 0.4 percent. Our estimates imply that for the most affected regions at the height of the al-Shabaab insurgency violent incidences occurring very close to transportation roads *alone and irrespective of any other conflict* increase maize prices by around 11 percent over sustained periods of time. During this time, the standardized effect size is around half as large as the one of rainfall, highlighted as one of the most important determinants of food prices in general (Food and Agricultural Organisation, 2011; Chavas et al., 2014) and of maize in particular (Berry et al., 2014). Moreover, we find that the effects of conflict along the transport route can still be detected in markets up to 900 kilometres away, corresponding to 17 hours driving time on Somali roads. All effects are robust to controlling for local conflict.

In terms of mechanisms, we find that conflict along transit roads dims light emitted on these roads several hundreds of kilometres away (excluding cities and towns). This decrease in road traffic is suggestive of a reduction in maize supplies transported from growing areas to markets. Moreover, using rich information contained in the Global Terrorism Database (GTD) on characteristics of each attack, we find that effects are not driven by incidences of conflict involving explosive weapons or attacks resulting in property damage. This suggests that an effect of conflict operating through infrastructure destruction is unlikely. By contrast, we find strong effects of kidnappings and assaults suggesting increased fear and uncertainty as a further relevant mechanism of impact. Moreover, when isolating violent incidences occurring only in growing regions we find no evidence suggesting that conflict in Somalia disrupts the agricultural production of maize. This is consistent with the fact that we are only considering conflict within a narrow geographical corridor around transportation routes, which makes effects through destruction of maize fields unlikely. Furthermore, when analyzing price patterns, we do not find any evidence suggesting that maize traders adjust to shocks by increasing local buffer stocks or by using alternative supply routes. This finding

tallies with policy reports documenting limited storage facilities (FAO, 2018) and a very rudimentary overland road network in Somalia (Government of Somalia, 2018).

The second part of our analysis provides evidence that conflict occurring hundreds of kilometres away from individuals affects their food security and that food prices are a likely propagation mechanism. We implement the same research design based on conflict along maize transportation routes using the 2016 and 2017 waves of the Somali High Frequency Survey (SHFS), which contain rich information on food consumption, food security, health and education. We find not only that conflict en route increases self-reported purchase prices but also that households report having to adjust eating patterns due to food price shocks, thus suggesting that food prices are indeed a mechanism through which far-away conflict can affect food security. The results further show that households attempt to mitigate the increase in maize prices by changing their consumption patterns. Conflict along transportation roads leads households to substitute more expensive maize with sorghum, increase spending out of savings and reduce non-food expenditures, including on health and education. Despite such strategies, we nevertheless find that conflict along transportation routes reduces households' food security, decreases nourishments available and forces households to change eating habits.

The final part of the paper investigates child outcomes. Food prices can affect children's health and education in a number of ways. Aside from generating income effects that reduce education and health expenditures, or create incentives for child labor instead of schooling, high prices can lead to food insecurity. In fact, both policy⁶ and research have singled out food insecurity as a major obstacle to children's health and education (Scrimshaw, 2003; Behrman et al., 2004; Glewwe and Miguel, 2007; Black et al., 2008; Calder, 2013). Motivated by this body of work and by our findings that far-away conflict decreases food security, we estimate its effects on health and education of children. Our results show that conflict along maize transportation routes (and far from respondents) increases the incidences of infectious

⁶<https://www.wfp.org/school-meals>, accessed August 2022.

diseases, such as gastroenteritis, malaria and typhoid, in line with well-known links between malnutrition and infectious diseases (see Scrimshaw, 2003; Black et al., 2008; Calder, 2013; for instance). These effects are stable when controlling for local conflict. As a placebo, we also analyse illnesses unrelated to nutrition and find no effects. Schooling information, further, shows that far-away conflict along routes decreases school enrolment. The estimate size corresponds to 18-35 percent of the effect of local conflict found by previous studies in comparable settings (e.g. Bertoni et al., 2018). All the above results are robust to excluding migrants thus suggesting that selective migration is not biasing the results.

We probe our identification strategy in a number of ways. First, we address the possibility of combatants targeting particular areas based on time-varying, unobserved factors. Following approaches by Jones and Olken (2009) and Brodeur (2018), we exploit the inherent randomness in success rates of attacks and estimate the effect of successful attacks conditional on all attempted attacks. The results remain robust. Second, we provide evidence against the concern that our results are contaminated by omitted variables at a supra-regional level or by generalized waves of violence. For instance, since Somali territory is controlled by different fractions, it could be that supra-regional institutions introduce spurious correlation between market prices and conflict including—crucially—conflict further away from markets. Using the exact geo-coordinates of attacks, we show that our effect is precisely driven by attacks happening along the transportation network. By contrast, other attacks that occur between growing regions and markets, but not along transport roads, have no effect. Third, we tackle the possibility of endogenous road construction by replicating our results using conflict occurring on roads in growing areas and omitting the remaining road network. Fourth, we show that prices at a given market are only affected by attacks along its own transportation route, but not by attacks on the transportation routes to other markets, ruling out concerns of indirect effects on other markets. We also carry out a number of further checks, such as, for instance, estimating the effect of terrorist attacks drawn from the GTD, dropping any attacks explicitly targeting the transportation network, and using the price of

(not locally grown) rice and conflict during lean seasons as placebos.

This study is the first to document that food prices play an important role in enabling conflict to affect important human capital outcomes (nutrition, health and education) of individuals hundreds of kilometres away. Our findings have wide-ranging policy implications. Spatial spillovers of conflict induce important additional welfare costs, implying that the adverse effects of conflict on human capital are larger than commonly assumed. Back of the envelope calculations suggest that spatial spillovers add around 30% to the welfare cost of local conflict, further strengthening the case for humanitarian interventions in response to violent conflict, possibly through nutritional subsidies. Our findings also have important implications for the regional targetting of policies such as humanitarian aid, protection efforts, or asylum status eligibility, which would potentially need to be broadened. In Somalia, for instance, the World Health Organisation (WHO) provides emergency medical supplies to areas affected by conflict.⁷ Our findings that individuals far away from conflict are impacted make the case to extend such aid to other areas of the country. Our findings are particularly relevant to Somalia and Eastern Africa, which is characterized by violent conflict (see also McGuirk and Nunn, Working Paper).

By highlighting that food prices can be a mechanism through which conflict affects not only individuals in directly affected areas but also those living far away, we contribute to several strands of the literature. We contribute to a large number of studies that have documented a negative effect of conflict and violence on education (León, 2012; Justino et al., 2013; Brown and Velásquez, 2017; Bertoni et al., 2018; Fransen et al., 2018; Brück et al., 2019; Foureaux Koppensteiner and Menezes, forthcoming), health (Bundervoet et al., 2009; Akresh et al., 2011; Minoiu and Shemyakina, 2014; Arcand et al., 2015; Valente, 2015; Dagnelie et al., 2018; Phadera, 2021) and nutrition (D’Souza and Jolliffe, 2013; Dabalén and Paul, 2014; Serneels and Verpoorten, 2015). Whilst many of these studies mention direct effects such as infrastructure destruction, forced displacement or fatalities (see Brück and

⁷For example: http://www.emro.who.int/images/stories/somalia/documents/technical_programme_update_september_december_2018.pdf?ua=1, accessed December 2021.

Schindler, 2009; Justino and Verwimp, 2013; Williams, 2013; for instance), other, indirect mechanisms have received considerably less attention.

Our study also speaks to a small but growing literature on spatial spillovers of conflicts. Differently from our focus on food prices, the channels of propagation in these papers are the erosion of social capital (Hjort, 2014; Korovkin and Makarin, forthcoming), international trade flows (Qureshi, 2013), input-output relationships in production networks (Korovkin and Makarin, 2021; Couttenier et al., 2022), the diversion of police presence following violent attacks (Di Tella and Schargrodsy, 2004; Draca et al., 2011), and U.S. legislation in a border state (Dube et al., 2013).⁸

Finally, by providing novel evidence on the causal link from conflict to food prices, we add to an existing literature that has focused on the reverse causal flow, from the level or volatility of food prices to conflict (Berazneva and Lee, 2013; Smith, 2014; Bellemare, 2015; Bessler et al., 2016; Bush and Martiniello, 2017)—as pointed out in a recent overview article (Brück and d’Errico, 2019).

The next section provides background to our study. Section 3 describes the data and provides summary statistics. Section 4 lays out our empirical strategy. The results for food prices and human capital are discussed in sections 5 and 6. Section 8 concludes.

2 Background

2.1 Maize in Somalia

Maize is a staple food in Somalia. Usually prepared as a flour, it is inexpensive, high in energy and widely eaten throughout the country. For many Somalis maize along with other staple foods are the only affordable nourishments (WFP, 2019).

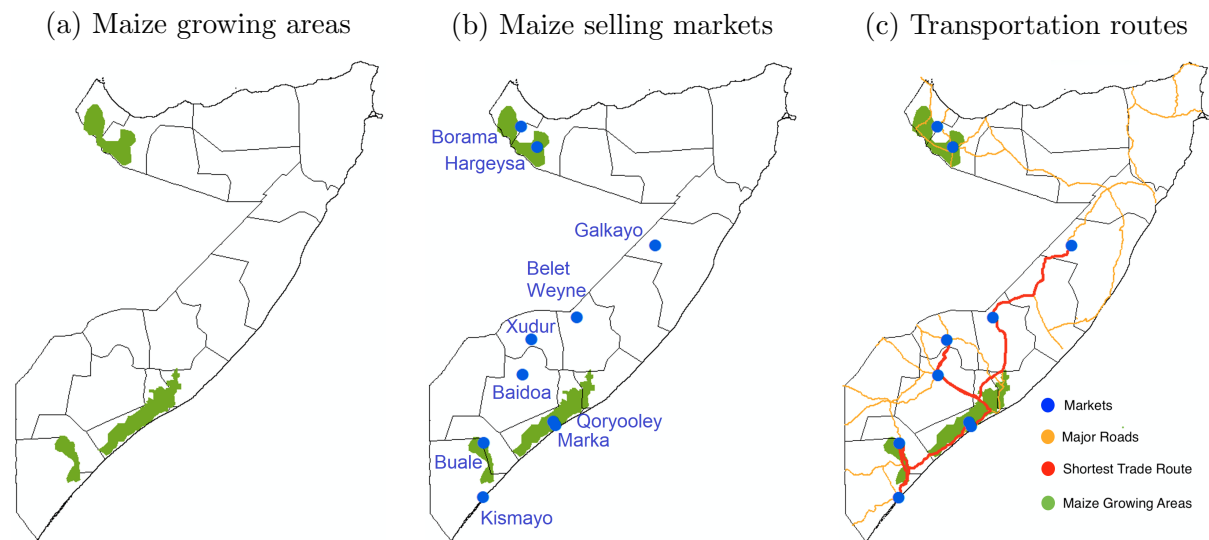
Maize is produced in three areas. These, along with Somalia’s 16 administrative areas—

⁸In related papers, Yanagizawa-Drott (2014) and Mueller et al. (2021) document different mechanisms through which violent conflict itself spreads across space.

so-called regions—are shown in figure 1a. Maize production is mainly rainfed and concentrated predominantly in the Lower Shebelle region, which accounts for 80 percent of production. In an average year, Somalia produces around 130,000 mega tonnes of maize, which suffices to meet domestic demand making the country largely self-sufficient regarding maize (FEWS, 2017; WFP, 2019). Appendix Figure A.2 shows a relatively low importance of international trade in maize for Somalia. Maize imports make up around 8 percent of domestic maize production evaluated at the average retail price. Moreover, imports and exports appear uncorrelated with conflict and follow droughts instead.

In sum, the bulk of maize consumed in Somalia is produced domestically. Moreover, imported cereal price fluctuations are not expected to affect much the prices of locally produced food (WFP, 2011).

Figure 1: Maize growing areas, markets and transportation routes



Notes: Maps report geographical location of maize growing areas (panel a), markets selling maize (panel b) and most frequently used transportation routes for maize in a typical year (panel c). **Data sources:** FAO, FEWS NET.

2.2 Food logistics network in Somalia

We identify transportation routes for maize by combining the exact geographical coordinates of maize growing areas (Figure 1a) and the ten markets for which we have monthly prices

from the FAO (Figure 1b) with information on transportation routes for maize provided by practitioners and NGOs working locally.

Maize in Somalia is mainly cultivated by small-scale farmers. After harvests, farmers store the maize locally, usually in underground storages (FAO, 2018). The maize is subsequently transported to markets via road, which is the main source of transport. There is no railway and water or air transportation are not generally feasible. Only major roads, of which there are only few, are paved, see Figure 1c. Smaller roads are not paved and not usable for parts of the year at least (Government of Somalia, 2018).

Information on maize transportation routes is provided by the Famine Early Warning Systems Network (FEWS NET). Funded by the United States Agency for International Development (USAID) and collaborating with the FAO, FEWS NET is a leading provider for the analysis of food insecurity throughout the world. In collaboration with local government ministries, market information systems, NGOs, and private sector partners, FAO and FEWS NET produce maps denoting the roads along which maize is transported from growing areas to markets in Somalia.⁹ These maps also contain information on food scarcity and are used by the FAO to monitor nutrition and to plan humanitarian interventions.

We overlay the trade route maps provided by FEWS NET with the Somali road network to identify the exact geographical locations of the roads via which maize is most frequently transported to each of the markets in a typical year (see Figure 1c in red). To identify incidences of conflict occurring along transportation routes, we draw a corridor of 5 kilometres either side of the transportation route to each of our ten markets. For robustness we also vary the width of the corridor. Our definition excludes the administrative area each market is located in and any violent incidences occurring in towns or cities along the route; see section 4 for a detailed description. Finally, we match these ten corridors to the geographical coordinates of violent incidences (either the ACLED or the GTD) and sum the number of incidences occurring within each corridor per month. Two examples of trade routes to

⁹Food transportation networks are available under <https://fews.net/east-africa/somalia>. Accessed July 2021.

individual markets are provided in parts (b) and (c) of Appendix Figure A.1, and part (d) of that figure provides an example of attacks falling within the 5 kilometre corridor.

3 Data and Descriptives

3.1 Data

Conflict: Our main source of conflict data is the Armed Conflict Location & Event Data Project (ACLED), which collects the dates, actors involved, fatalities and modalities along with the exact geographical coordinates on all reported violent events across Africa and other continents.¹⁰ We complement these data with information drawn from the Global Terrorism Database (GTD), an event database of terrorist attacks, which gathers information on, among other things, the geographic coordinate, number of casualties and group responsible.¹¹ To disentangle the mechanisms of impact and to improve identification, we use detailed information on success of attacks, weapons used, property damage, and targets.

Maize prices: Monthly maize retail price data for ten markets between 2001 and 2018 are drawn from the Food and Agricultural Organisation (FAO) food price monitoring and analysis tool, which contains information and analysis on domestic prices of basic food items for many low income countries. These data are used by the FAO in its early warning systems on high food prices for vulnerable countries.¹² For all ten markets, monthly maize prices are available for years before and after the al-Shabaab insurgency, 2001 to 2018. Between 2001 and 2018, around 9 percent of month-market observations have missing values for prices. This missing information is concentrated in the early years; for the last ten years (2009 to 2018), for instance, only 0.7 percent of prices are missing. We check the robustness of our estimates to using different time periods and the results remain robust.

Food security, education, health, and expenditures: The main data sources are

¹⁰The data are available at <https://acleddata.com>.

¹¹The data are available at <https://www.start.umd.edu/gtd/about/>.

¹²The data are available at <https://fpma.apps.fao.org/gIEWS/food-prices/tool/public/#/home>.

the two rounds of the Somali High Frequency Survey (SHFS), which was collected and funded by the World Bank in collaboration with Somali statistical authorities. The first wave was implemented between February and March 2016 and interviewed 4,117 households across 9 regions.¹³ The second round interviewed 6,092 households in 17 regions during December 2017.¹⁴ Both rounds contain information on economic conditions, food security, education, employment, and health, as well as detailed consumption expenditure data.

We complement these survey data with the percentage of children aged 6 to 59 months who are classified with low weight-for-height and/or oedema as collected by the Food Security and Nutrition Analysis Unit (FSNAU) in collaboration with the FAO. The FSNAU divides Somalia into livelihood zones and classifies these twice yearly (after the Deyr and Gu harvests) as *critical* if the proportion of malnourished children exceeds 0.15.¹⁵

3.2 Conflict in Somalia

Somalia is a violent country. Most of the fighting in Somalia consists of clashes between armed fractions fighting for territorial control. According to ACLED, between the years 2001 and 2018 the country experienced 27,169 incidences of conflict, see panel A of Table 1. The majority of conflict in Somalia consist of *battles* (13,343), defined as 'violent clashes between at least two armed groups' and *violence against civilians* (6,374) defined as 'violent attacks on unarmed civilians'. According to the GTD, Somalia experienced 4,498 terrorist attacks during the same time period, see panel C of Table 1. Figure 2a shows the geographical distribution of attacks. While there is a higher concentration in the more populated southern part of the country, no region has been spared.

The evolution of attacks over time (Figure 2b) reveals a sharp increase of violence in Somalia from the mid-2000s onwards. This drastic increase coincided with the rise of al-Shabaab, an Islamist terror organisation founded in the early 2000s with the aim of over-

¹³The data are available at <https://microdata.worldbank.org/index.php/catalog/2738>.

¹⁴The data are available at <https://microdata.worldbank.org/index.php/catalog/3181>.

¹⁵The data are available at <http://fsnau.org/nutrition/>.

Table 1: Summary statistics

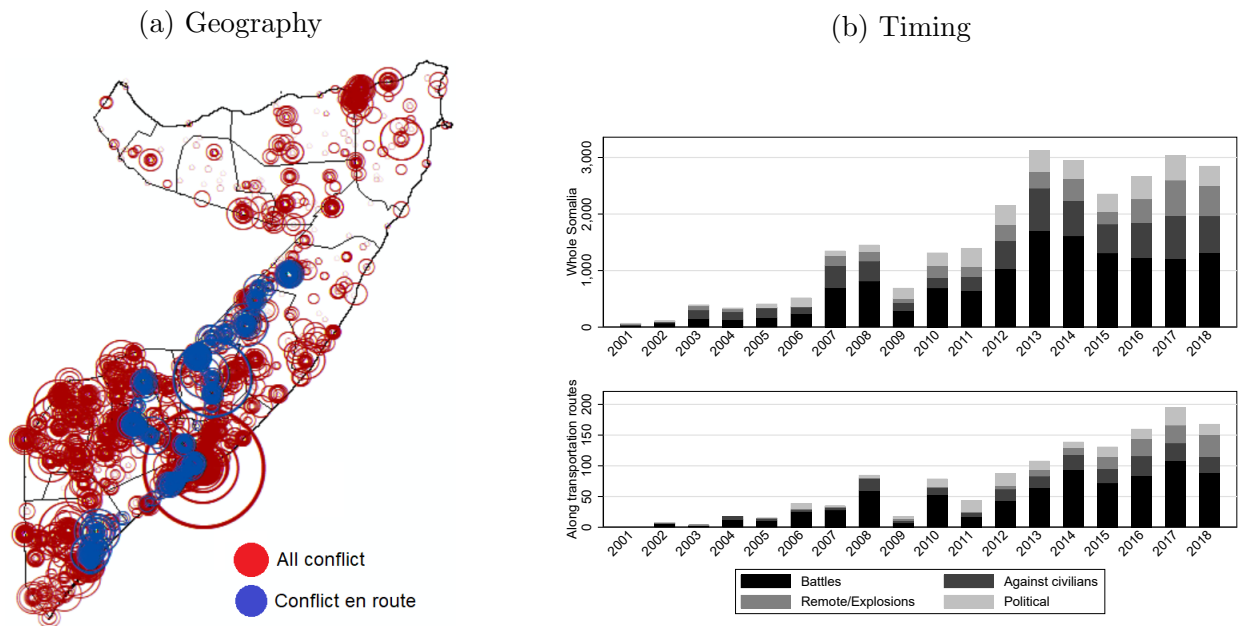
A: All violent incidences (ACLED)					
Type of incidence	All	Battles	Against Civilians	Explosions	Other
Nr of incidences	27,169	13,343	6,374	3,761	3,691
% of total		49.1%	23.5%	13.8%	13.6%
B: Conflict along transportaiton routes (ACLED)					
Type of incidence	All	Battles	Against Civilians	Explosions	Other
Nr of incidences	1,334	781	225	157	171
% of total		58.5%	16.9%	11.8%	12.8%
C: Terrorist attacks (GTD)					
Type of incidence	All	Aimed at Military	Aimed at transport	Aimed at other	Involving barricades
Nr of incidences	4,498	1,890	37	2,571	12
% of total		42.0%	0.8%	57.2%	0.3%
D: Terrorist attacks along transportation routes (GTD)					
Type of incidence	All	Aimed at Military	Aimed at transport	Aimed at other	Involving barricades
Nr of incidences	180	114	4	62	0
% of total		63.3%	2.2%	34.4%	0%
E: Household and child characteristics (SHFS)					
	Below poverty line	Not enough food	Literacy	School enrollment (age 6-14)	Access to improved sanitation
Mean	0.47	0.25	0.57	0.53	0.10
Observations	6,417	6,417	6,417	8,134	n.a.

Notes: Table reports summary statistics on conflict and characteristics of households in Somalia. Panel A: reports incidences of conflict in Somalia by type (based on ACLED); Panel B: reports incidences of conflict within 5 kilometres either side of transportation routes by type (based on ACLED); Panel C: reports terrorist attacks in Somalia by target (based on GTD); Panel D: reports terrorist attacks within 5 kilometres either side of transportation routes by target (based on GTD); Panel E: the first four columns report summary statistics from own calculations based on the SHFS survey data for 2016 and 2017. The literacy rate covers adults and children from the age of 6 onwards. The fifth column reports access to improved sanitation taken from Table B.3 of The World Bank (2017) based on SHFS data. The World Bank defines an improved sanitation facility as one that hygienically separates human excreta from human contact. **Data sources:** ACLED, GTD, SHFS, The World Bank (2017).

throwing governments in the Horn of Africa region and to install Islamic rule. A comparison of conflict in Somalia and along transportation routes only (blue circles in figure 2a) shows not only a similar temporal pattern but also similar classifications in terms of the types of violence (lower panel of figure 2b).

In the next section we explain our empirical strategy that exploits both the regional and temporal variation in attacks, together with the geo-coded information on market location and the food transportation network.

Figure 2: Conflict in Somalia - Geographical and temporal variation



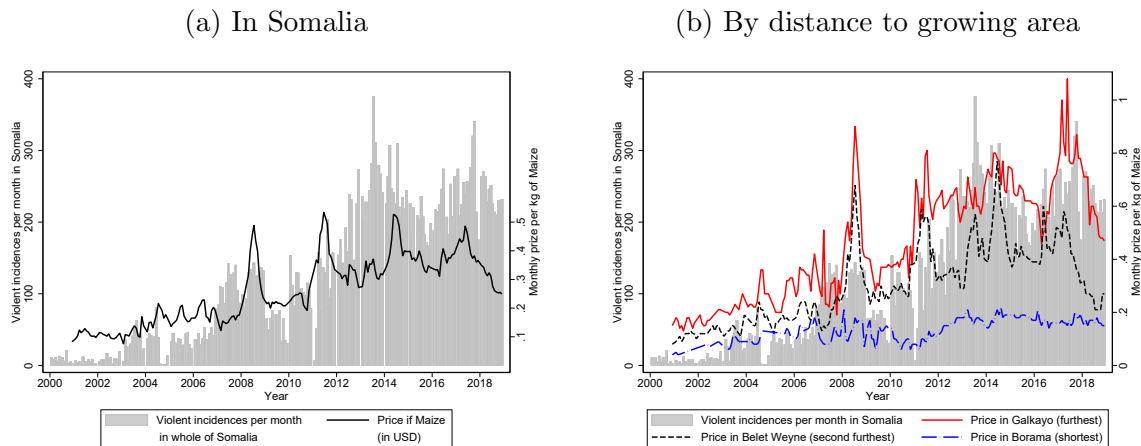
Notes: Figure reports geographical and temporal variation of incidences of conflict in Somalia between 2001 and 2018. **Panel a:** shows geographical location of incidences of conflict occurring anywhere (red) and along transportation routes (blue); radii are proportional to number of fatalities. **Panel b:** shows temporal variation in all incidences of conflict (top) and conflict along transportation routes (bottom) by classification. **Data source:** ACLED.

3.3 Effect of conflict along routes: descriptive evidence

In Figure 3, we exploit the sudden increase in violence during the al-Shabaab insurgency to provide descriptive evidence that conflict along the transportation route increases prices. Figure 3a shows that both the average price of maize across our ten markets and countrywide

conflict in Somalia increase over the sample period. Figure 3b shows the price in three selected markets, each located at a different distance to growing areas. Before the al-Shabaab insurgency in the early-2000s, prices are similar and show parallel trends. After the insurgency, price increases are strongest in Galkayo (transportation route of 900 kilometres, with many attacks en route), followed by Belet Weyne (transportation route of 400 kilometres, with fewer attacks en route) with no changes in Borama (located next to a growing area, therefore no attacks along the road). These descriptive results provide preliminary evidence of a positive association between market prices and attacks along the transportation routes serving the markets. Appendix Figure A.1a provides a map of the geographical location of the three markets.

Figure 3: Price of maize over time



Notes: Figure reports conflict and maize prices over time in Somalia. Lines denote monthly maize prices and bars monthly incidences of conflict. Panel a: shows average monthly maize price for all ten markets; Panel b: shows monthly maize price for three selected markets: Borama in blue (an example of a short transportation route), Belet Weyne in black (an example of a medium length transportation route), and Galkayo in red (an example of a long transportation route). **Data sources:** ACLED, FAO.

4 Empirical strategy

The empirical analysis proceeds in several steps. First, we estimate the effect of conflict along transit routes on maize prices as reported in markets located far away from where

the violence occurs. Second, we investigate the impact of conflict on food security at some distance and whether food prices are a possible propagation mechanism. These estimations follow several policy reports linking food prices and food security in Africa¹⁶ in general and in Somalia¹⁷ in particular. Adverse effects of food prices on food security have also been documented in various research reports (Sanogo, 2009; Compton et al., 2010; Security, 2011).

Finally, we explore whether conflict along transportation routes affects child health and education in far-away areas, which can occur through several channels. First, high food prices can lead to an income effect, which causes households to reduce health and education expenditures. Alternatively, the family could also supplement household income by taking children out of school to work. A number of papers have established a link between food prices and education. Grimm (2011) finds that negative income shocks due to high food prices reduce school enrolment in Burkina Faso. Singh and Vatta (2013) and Raihan (2009) document negative effects of high food prices on educational outcomes in Punjab and Bangladesh, respectively. Historically, Baten et al. (2014) find that high food prices in 18th and 19th century Britain reduced numeracy.

Second, food prices can adversely affect health and education via hunger or poor nutrition. Among public health researchers and nutritionists the adverse effects of malnutrition on disease and infection are well known (Scrimshaw, 2003; Black et al., 2008; Calder, 2013). A growing body of research by nutritionists and economists has also established that poorly nourished children in developing country contexts start school later, complete lower levels of schooling, have higher rates of absenteeism at school, and learn less while at school (for overviews see Behrman et al., 2004; Glewwe and Miguel, 2007).

Health itself can have a direct effect on schooling as it reduces children's capability of attending school and their readiness to learn. Additionally, health can also reduce schooling indirectly through behavioral responses of parents, who may choose to invest less into the

¹⁶<https://www.unicef.org/wca/press-releases/soaring-food-costs-low-rainfall-and-insecurity-leave-children-sahel-risk>, accessed August 2022.

¹⁷<https://www.fao.org/newsroom/detail/as-rains-fail-again-catastrophic-hunger-looms-over-somalia/en>, accessed August 2022.

education of poorly nourished children (Behrman et al., 2004). In fact, policy makers have recognized hunger and malnutrition as important impediments to good health and schooling (see World Food Programme and the FAO¹⁸ for a recent example).

4.1 Spatial spillover effects on food prices

We estimate spatial spillover effects of conflict on maize prices using the following regression of the log price of maize in USD ($\log(\text{price}_{itm})$) in market i , in year t and month m :

$$\begin{aligned} \log(\text{price}_{itm}) = & \alpha_1 \text{conflict}_{\text{route}_{itm}} + \alpha_2 \text{conflict}_{\text{local}_{itm}} + \alpha_3^T X_{itm} \\ & + \eta_i \times \tau_t + \eta_i \times \mu_m + \epsilon_{itm}. \end{aligned} \quad (1)$$

Our main focus lies on estimating the effect of $\text{conflict}_{\text{route}_{itm}}$, capturing violent incidences occurring along the maize transportation route at some distance from markets. This variable counts the number of violent incidences in year t and month m occurring five kilometres either side of the transportation route used to supply market i with maize, but excluding any violent incidences occurring in the same administrative area that market i is located in.¹⁹ We further exclude from $\text{conflict}_{\text{route}_{itm}}$ any violent incidences which occur in cities or towns located along the transportation route.²⁰ The main reason to exclude this is that typically there are multiple routes that allow crossing an urban area, making the definition of the transportation route ambiguous in these areas. The coefficient α_1 captures the spatial spillover effect of violence occurring hundreds of kilometres away along transport routes on prices at the markets served by these routes. In section 5.3 we also exploit the fact that markets are located at different distances from their growing areas to explore how far away the effects of conflict can still be detected.

¹⁸<https://www.wfp.org/news/fao-and-wfp-join-forces-boost-childrens-right-food-schools>, accessed August 2022.

¹⁹See section 2.2 and Figure 3c for detailed descriptions and the maps in figures A.1b and A.1c as two examples.

²⁰We take the city or town centre and exclude any violent incidences within a 15 kilometre radius.

In line with previous research, we also examine the role of violent incidences occurring in the vicinity of markets. For this, we define the variable $conflict_{local_{itm}}$, which counts the number of violent events in year t and month m occurring in the same administrative area as market i . As an alternative definition of $conflict_{local_{itm}}$, we also identify all violent incidences occurring within a 15 kilometre radius of market m .

In X_{itm} we include growing season specific rainfall as a control, which has been highlighted as an important determinant of food prices (e.g., FAO 2011).²¹ In extended versions of eq. (1), X_{itm} will be augmented to include variables such as lagged values of conflict, or conflict in additional geographical locations.

Finally, we control flexibly for unobserved regional characteristics, which are allowed to vary by year and calendar month using market-by-year ($\eta_i \times \tau_t$) and market-by-month ($\eta_i \times \mu_m$) fixed effects.

The inclusion of these two sets of fixed effects implies that estimation of (1) exploits variation in the regressors that consists of deviations from the yearly and calendar month averages for each particular market. Our flexible specification thus allows for various forms of unobserved heterogeneity and controls for a number of sources of potentially confounding variation. In a first instance, equation (1) differences out any unobserved factors particular to each of our ten markets in each year from 2001 to 2018. This, for example, would account for a drought in a particular year to affect each of our ten markets differently. Moreover, our specification also allows for any unobserved heterogeneity specific to each market and calendar month thus accommodating the possibility that prices may fluctuate differently throughout the calendar year in each market. In addition, if traders form expectations about which markets in which periods are particularly violent, then a possible interpretation of the two sets of fixed effects is that they control for each market's expected levels of violence per year and calendar month, and our identifying variation consisting of the remaining

²¹We use cropland-specific rainfall data from the United Nations' World Food Programme to calculate harvest specific rainfall for each market by averaging precipitation in the growing area supplying maize over the previous growing season (either Gu or Deyr).

'unexpctced' fluctuations.

Identification. For causal identification of the spatial spillover effect we do not only rely on the tight control strategy described above. Crucially, our research design exploits the structure of the food transportation network to causally identify conflict's effect on far-away areas. The incidences of conflict captured by $conflict_{route_{itm}}$ occur along maize transportation routes and exclude conflict in proximity to markets. As a result, the spillover effect α_1 is identified by incidences of conflict that occur far outside of the market region where the price is measured. This research design rules out a range of common endogeneity concerns. For example, a common problem in analysing the effect of conflict on food prices is reverse causality where high prices cause dissatisfaction amongst the population and lead to violence. Such types of conflict, however, would be expected to occur in proximity to markets, and reverse causality would thus be unlikely to explain violence that occurs along transportation routes hundreds of kilometres away, as captured by $conflict_{route_{itm}}$.²² Moreover, potential omitted variables such as corrupt or inefficient local institutions, would affect both prices and conflict *in the same area* and not hundreds of kilometres away and along very specific roads.²³

Nevertheless, we carry out a number of identification checks which include: i) addressing the possibility of omitted variables at the supra-regional level by including additional controls for conflict in a wider area away from transport routes, ii) tackling the possibility of endogenous target choices by exploiting the inherent randomness in whether an attack is successful, iii) addressing the possibility of endogenous road construction by estimating the effect of conflict along roads in growing areas only (whilst omitting the remaining road

²²Moreover, because our definition of violent attacks along the transportation route excludes violent attacks in towns and cities along the route, $conflict_{route_{itm}}$ would not pick up the confounding variation even if there was a mechanism that would spread violent protest due to dissatisfaction with high prices from the market regions to other towns further away along the transportation route.

²³This implies that conflict in the local market area $conflict_{local_{itm}}$ might be endogenous. In our application, the two conflict variables $conflict_{route_{itm}}$ and $conflict_{local_{itm}}$ are orthogonal conditional on the controls. Therefore, as we show in the results section, including or excluding local conflict does not change our estimates of the effect of conflict along the transportation route.

network), iv) replicating our ACLED results using GTD data, v) dropping attacks explicitly aimed at food, vi) using the price of rice, which is transported along other routes, as placebo, vii) considering the importance of possible detours taken by drivers, and viii) examining the relevance of maize traders accumulating buffer stocks. The details of these checks are discussed together with the results in section 5.2.

4.2 Spatial spillover effects on food security and human capital

The policy reports and pieces of research outlined at the beginning of section 4 highlight the effect of food prices on food security, which, in turn, affects the human capital of children. Motivated by these findings, we estimate spatial spillover effects of conflict on food security, child health and education using a variety of outcomes measured in the 2016 and 2017 rounds of the SHFS. The regression equation for outcome y_{jtr} for individual or household j in year t and region r is given by

$$\begin{aligned}
 y_{jtr} = & \beta_1 \mathit{conflict}_{route_{jtr}} + \beta_2 \mathit{conflict}_{local_{jtr}} + \beta_3^T Z_{jtr} \\
 & + \mu_r + \tau_t + \nu_{jtr}
 \end{aligned}
 \tag{2}$$

As outcomes we consider survey information on nutrition, health, and education measured at the household or the individual level. Equation (2) employs a similar research design as equation (1), based on conflict occurring along maize transportation routes. For each Somali region of residence r we determine from which maize growing area the markets in the region are supplied. As before, we combine the geo-coordinates of growing areas and roads with information on transportation routes provided by FEWS NET and define $\mathit{conflict}_{route_{jtr}}$ as all incidences of conflict occurring within a 5km corridor either side of the the transport route from the respective growing areas to the markets in region r . From this we exclude violent incidences in region r itself, which form our measure of conflict in the own local area, $\mathit{conflict}_{local_{jtr}}$. We typically define the conflict variables by counting violent incidences in the

month preceding the SHFS survey date for each of the rounds. However, for retrospective questions involving a longer recollection period (such as, for instance, expenditure items over the past year), we adjust the period over which we measure incidences of conflict accordingly. When doing so, we state the definition in the results tables.

As control variables Z we include household size, gender of the household head, the proportion of literate household members, indicators for the household having at least one economically active member, and whether the household is below the poverty line. For individual outcomes, Z also includes age fixed effects.

Due to the inclusion of region fixed effects μ_r and year fixed effects τ_t , the variation exploited by equation (2) to identify the spatial spillover effect β_1 is a difference-in-differences type of variation that nets out common year effects and time-constant unobserved differences between regions.²⁴ However, in contrast to standard difference-in-differences approaches used in previous studies, our 'treatment' consists of conflict occurring along roads located far away from households and children. Thus, similarly to equation (1), specification (2) exploits the transport network structure to isolate conflict occurring far away from respondents and also along a narrow corridor around transportation routes. Hence the same arguments for identification as discussed above apply.

5 Spatial spillover effects of conflict on food prices

This section presents the estimates for the effect of conflict along transportation routes on far-away maize prices. After presenting the baseline results, we address numerous identification checks. Thereafter, we explore the exact length of conflict's reach and provide suggestive evidence on the mechanisms of impact.

²⁴A small number of outcomes is only available in one of the survey rounds. In these cases we estimate equation (2) as a cross-sectional regression without region and year effects. We indicate these cases in the results tables.

5.1 Baseline results

Column (1) of Table 2 reports our main result: one incidence of conflict along the transportation route ($conflict_{route_{itm}}$ in equation 1) increases the price of maize by 0.37 percent. The high R-squared suggests that our model captures variation in maize prices well. Given that our sample consists of ten markets, we also estimate p-values using the Wild Cluster Bootstrap method, which shows that our estimates remain statistically significant throughout.²⁵

In column (2), we focus on the years 2016 to 2018, which are around the height of the al-Shabaab insurgency and also close to the time period covered by the SHFS survey that we will use in section 6. For this time period, each attack increases maize prices by 1.1 percent. At an average number of around 10 incidences of conflict per month for the most affected markets, our results imply that conflict occurring within a 5km corridor either side of roads along and independent of any other conflict raises maize prices by around 11 percent. Column (3) compares this effect to rainfall, highlighted as one of the most important determinants of agricultural prices (see Food and Agricultural Organisation, 2011; for instance). The estimates based on z-scores show that conflict is around half as important as rainfall for maize prices. In column (7) of table A.1 we also use a corridor of only 1km either side of transportation roads and find similar results.

Columns (4) and (5) investigate the importance of conflict occurring in proximity to markets ($conflict_{local_{itm}}$ in equation 1). We use two separate measurements for this variable: incidences of conflict occurring in the same region as market i (column 4) and 15 kilometres around market i (column 5). In both cases, the parameter estimates for violent incidences occurring adjacently to markets are small in size. The coefficient on conflict along transportation routes, by contrast, remains virtually unchanged. This pattern suggest that the two types of conflict are conditionally independent (which we also find when regressing one

²⁵We carry out hypothesis testing using Wild Bootstrap with 1000 replications. We bootstrap at the market level with 1,000 replications using the command *boottest* (Roodman et al., 2018).

on the other).

5.2 Identification checks

Here we probe our specification against the endogeneity concerns listed in section 4.1.

Supra-regional omitted variables. A possible identification concern relates to omitted variables at a supra-regional level, which could introduce a spurious correlation between market prices and conflict, including further away from markets. As an example, the Somali territory is under the control of three separate entities: the Somali government together with its AMISOM allies, al-Shabaab and Somaliand. Institutions specific to each faction could differ in terms of their efficiency, and inefficient institutions could cause both, high prices (because of less efficient markets) and more violence (because of lack of institutions or enforcement, or in protest to high prices). As such, those parts of the country characterised by less efficient institutions are likely to experience both higher prices and generally more incidences of conflict, including along transportation routes.

In fact, our baseline specification (1) in part already addresses the aforementioned concern. By controlling for local violence in market i 's administrative area and for market-specific year and month effects, our specification allows for changes in general levels of violence at the supra-regional level.

To further address this concern, however, we show results where we augment equation (1) with an additional covariate $conflict_{all_{itm}}$. This variable measures all incidences of conflict between market i and its supplying growing region *excluding* those incidences along the transportation route already included in $conflict_{route_{itm}}$. The covariate $conflict_{all_{itm}}$ acts as a further control for generalised conflict and helps us to establish whether the effect is driven by more general incidences of conflict, or specifically by those occurring along transportation routes.

Column (6) of Table 2 shows the results when we augment equation (1) by including

Table 2: Effect of conflict along transportation route on price of maize

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent variable: log price of									
	Maize	Maize	Maize	Maize	Maize	Maize	Rice	Maize	Maize	Maize
Conflict en route (excl. same region)	0.0037 (0.0010)	0.0108 (0.0040)		0.0035 (0.0011)	0.0038 (0.0016)	0.0032 (0.0012)	0.0012 (0.0011)	0.0035 (0.0011)		0.0034 (0.0010)
Conflict en route (z-score)			0.0569 (0.0209)							
Rainfall in growing region (z-score)			-0.0999 (0.0666)							
Conflict in same region as market				0.0012 (0.0010)		0.0011 (0.0010)	0.0017 (0.0012)	0.0012 (0.0010)		
Conflict 15km around market					0.0019 (0.0031)					
Conflict betw. growing area and market						0.0007 (0.0004)	0.0000 (0.0006)			
Conflict on 2nd shortest route								0.0008 (0.0042)		
Conflict en route out of lean season									0.0105 (0.0052)	
Conflict en route in lean season									0.0023 (0.0007)	
Conflict en route 1 month lag										0.0007 (0.0013)
Conflict en route 2 months lag										0.0009 (0.0021)
Observations	1,965	357	357	1,965	1,965	1,965	1,794	1,965	1,965	1,965
R ²	0.925	0.944	0.944	0.926	0.926	0.926	0.968	0.926	0.925	0.925
Wild Bootstrap p-value	[0.026]	[0.037]	[0.037]	[0.034]	[0.013]	[0.031]	[0.426]	[0.031]	[0.081]	[0.031]
Years	2001-18	2016-18	2016-18	2001-18	2001-18	2001-18	2001-18	2001-18	2011-18	2011-18

Notes: Table reports effect of incidences of conflict occurring along transportation routes on food prices. Estimations are based on equation (1). *Conflict en route (excl. same region)* denotes incidences of conflict occurring 5 kilometres either side of the transportation route supplying maize to each market and not located in the same administrative unit as the market; *Conflict in same region as market* denotes incidences of conflict occurring in the same sub-national administrative area each market is located in; *Conflict 15km around market* denotes incidences of conflict occurring within a 15 kilometre radius of each market; *Conflict betw. growing area and market* denotes incidences of conflict occurring in any administrative region located between each market and its growing area *excluding* any incidences within 5 kilometres of the transportation route to that market; *Conflict on 2nd shortest route* denotes incidences of conflict along second shortest transportation road from agricultural growing area to market, *Conflict en route out of lean season* denotes incidences of conflict along the transportation route outside of the lean season (January, February, March, April, August, September); *Conflict en route in lean season* denotes incidences of conflict along the transportation route during the lean season (May, June, July, October, November, December); *Conflict en route 1 month lag* and *Conflict en route 2 months lag* are conflict along transportation roads lagged by one and two months respectively, all regressions control for rainfall (in mm) during previous growing season; Standard errors are clustered at market and reported in parentheses; Wild cluster bootstrap p-values for *Conflict en route* (999 replications) are reported in brackets. **Data sources:** ACLED, FAO, GTD.

$conflict_{all_{itm}}$, capturing violence anywhere between market i and its supplying growing region, except those incidences along the transportation route included in $conflict_{route_{itm}}$. Together with the inclusion of local violence close to markets, this additional variable helps to control for generalised violence in the wider area or part of Somalia in which a given market and its transportation routes are located. The results show that the effect of violence along the transportation route remains robust and that there is no effect of violence between growing areas and markets that does not occur along the transportation route. Violence close to markets also continues to have no statistically significant effect. This implies that the effect of violence along transportation routes is unlikely to be driven by a spurious correlation induced by supra-regional differences in generalised violence across different parts of the country. Instead, it seems to be driven by something very specific to transportation routes.

Endogeneity of road network. Another identification concern would be if the Somali road network changes in response to conflict. It is possible, in theory, that some areas of the country are characterized by efficient institutions, which both alter the location of routes to avoid conflict and also keep prices low (via well-run markets, for example).

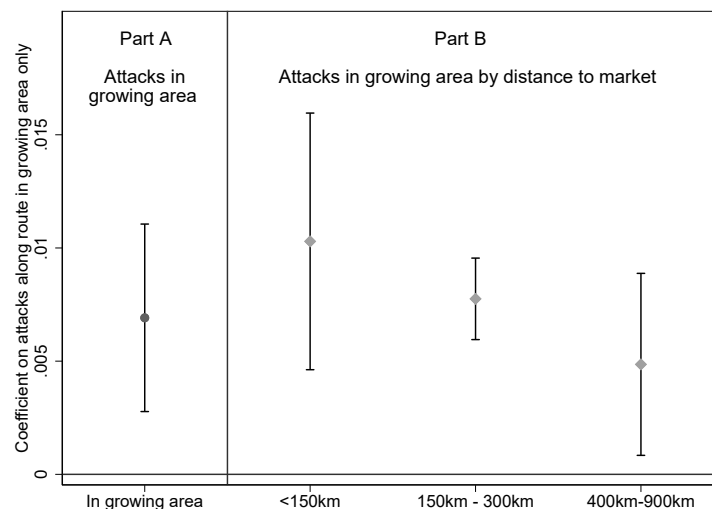
To address this concern, we estimate the price effects of conflict occurring along routes in growing areas only whilst ignoring the remaining road network. To this end, we define a variable $conflict_{growing_{itm}}$ which counts all incidences occurring within a 5km corridor around roads *located in growing areas only*. We then link this conflict variable with prices in those markets served by each respective growing area. This linkage does not rely on the exact shape of the road network between growing areas and markets.²⁶ Thus, any alterations to the road network would not affect the definition of $conflict_{growing_{itm}}$, neither will the exact shape of the road network. Moreover, because this variable only considers violence in a

²⁶The growing region in Lower Shebelle serves the following markets: Baidoa, Belet Weyne, Galkayo, Hudur, Qorioley, and Marka. The growing region in Middle Juba serves the following markets: Buale and Kismayo. The growing region in Woqooyi Galbeed serves the market of Hargeisa. The growing region in Awdal serves the market of Borama.

narrow corridor around roads, $conflict_{growing_{itm}}$ is unlikely to contain conflict destroying the supply of maize by destroying maize fields.

The resulting effect depicted in the left part of Figure 4 implies that each attack occurring on the road in growing regions increases the price of maize by 0.7 percent. This is slightly larger, although not statistically significantly different, from our baseline effect from ACLED data in Table 2 and rules out that our baseline effect is driven by an endogenous location of the road network.

Figure 4: Effect of conflict in growing area by distance to market



Notes: Figure reports effect of conflict occurring within a 5 kilometre corridor either side of transportation routes *in maize growing areas only*. Dots and diamonds denote point estimates and vertical lines 95% confidence; regressions also control for market-by-year and market-by-month fixed effects and rainfall in growing area. Left part: reports parameter estimate for conflict occurring on transportation route in the growing area supplying each market with maize only. Right part: groups markets into three bins (less than 150 kilometres, 150 to 300 kilometres and 400 to 900 kilometres). **Data sources:** ACLED, FAO.

Placebo treatment. To further rule out any spurious correlations between conflict and prices, we carry out a placebo check. Any spurious relation between conflict and prices would affect prices of a range of goods, not just of maize. The mechanism we wish to investigate, by contrast, implies that conflict along transportation routes for maize should very specifically affect the price of maize. For the placebo check we therefore use the price of rice as an outcome. Rice is transported along different routes and, consequently, its

price should not be directly affected by violence along the transportation route for maize.²⁷ Column (7) of table 2 shows very small yet precisely estimated coefficients of conflict along the transportation route for maize on the price of rice. By contrast, the coefficient estimate on *local* violence remains very similar to the analogous specifications for maize (see columns 4 and 7). Thus, not only is our main effect an effect specific to transportation routes, it is also a very specific effect of the transportation route *for maize* on the prize of maize, but not of rice.²⁸

Second shortest transportation routes. To investigate the importance of alternative transportation routes, we estimate the importance of second shortest transportation routes. We re-estimate equation (1) with the addition of all incidences of conflict occurring 5km either side of the *second shortest* transportation route from a growing area to the market it supplies. As column (8) of table 2 shows, attacks along shortest routes do not matter for maize prices. This suggests that our measure of the shortest route indeed identifies the correct maize transportation routes, and alternative routes seem to be of little relevance.

High and lean seasons. As a further check, we exploit the fact that the production of maize and thus the amount transported along roads varies along the crop calendar. Somalia has two lean and two high seasons, determined by its two rainy seasons, the Deyr and the Gu. During lean season, when farmers' stocks of maize are running low, less maize is transported along roads and the effect of attacks should be less pronounced. Distinguishing violent incidences during lean and high seasons in column (9) of table 2, we find that the effect of conflict occurring during high seasons is five times as large as the effect of violent

²⁷Rice is not grown in Somalia but imported by sea through four ports: Bernera and Bossaso in the north of the country and Mogadishu and Kismayo in the south from where it is transported to markets throughout the country. We obtained rice price data for 9 of our 10 markets.

²⁸Conflict along the transportation route for maize could of course affect the rice price indirectly via consumer demand, if rice is an important substitute for maize. We investigate spillover effects on the demand for other staples in section 6, where we find some evidence for substitution of maize with sorghum, but not rice.

incidences occurring during lean seasons.²⁹

Buffer stocks by traders. Supply disruptions of maize due to violence could incentivize traders in market areas to keep a buffer stock of maize to insure against disruptions. If traders store maize over a few months, their sales price at a given point of time is likely to be a weighted average of the purchase prices they paid over the past months. In such a case, lagged conflict is predicted to have an effect on current maize prices.³⁰ In column (10) of table 2 we re-estimate equation 1 including one and two months' lag of conflict along transportation routes. We find the lagged effects to be precisely estimated zero effects, meaning there is little evidence of storage being used as buffer by traders, in line with the reported practice that maize is predominantly stored with farmers (see section 2.2).

Alternative measure of attacks. Next we explore the question whether our results might be affected by ACLED not recording all violent incidences that may be relevant for the price of maize. Al-Shabaab employs a number of terrorist tactics, such as bombings, hijackings or abductions, which might not be recorded by ACLED. To address this concern, we use information drawn from the GTD and re-define the variable $conflict_{route_{itm}}$ as *terrorist attacks* occurring 5 kilometres either side of the shortest transportation route. As column (1) in Table 3 shows, each terrorist attack en route increases the price of maize by around 1.6 percent (whilst controlling for terrorist attacks within the same region as each market). In order to compare the effects across the ACLED and GTD databases, we convert the two measures for conflict to z-scores. As columns (2) and (3) show, the effect of a one standard deviation increase in conflict is remarkably similar across the ACLED and GTD, at 1.1 percent.

²⁹The lean seasons are May to July and October to December.

³⁰Buffer stocks might also allow traders to buy less when prices are high, and more when prices are low, which would lead to some price smoothing and would generally reduce the effects of violence on prices.

Endogenous targeting of transport routes. As a further identification check, we address the possibility that specific transport routes are being targeted by al-Shabaab according to unobserved factors that correlate with prices at exactly the markets served by these routes. We provide two pieces of evidence.

First, using detailed information on success rates of attacks from the GTD, we follow the approach by Jones and Olken (2009) and Brodeur (2018), which exploits the inherent randomness of success of violent incidences. Whilst targeting of a specific area might be selective, whether an attack is successful or not is more likely to be (conditionally) quasi-random. We restrict the sample to only month-market observations that experienced terrorist attacks, thus conditioning on markets in given points of time being targeted. Conditionally on being targeted, we then regress food prices on *successful* attacks. The results in column (4) of table 3 confirm that each successful terrorist attack (conditional on attempted attacks) increases the price of maize by 1.92 percent, which is very similar to the 1.56 percent of the baseline specification in column (1) of the same table.

Second, we use detailed information contained in the GTD on characteristics of violent incidences and drop all incidences of conflict coded as aimed at food consumption and distribution. Column (5) shows that the results remain stable. These results make us confident that our baseline effects are not driven or confounded by by endogenously targeted attacks.

Robustness. In the Appendix, we submit the spatial spillover effects on maize prices to additional robustness checks and find that the effects remain stable throughout. Columns (1) to (6) in Appendix Table A.1 show that our effects are stable to the exclusion of various subsamples. Column (1) drops markets located in Somaliland, since these locations may be subject to different institutions. Column (2) and (3) drop markets located close to the Kenyan and Ethiopian border respectively, since these areas may import maize from those countries. Columns (4), (5) and (6) restrict the analysis to the years 2009 to 2018, to 2012 to 2017 and to February 2016 to December 2017 (the dates of the two rounds of the SHFS),

respectively.

5.3 Length of reach

To explore conflict’s length of reach, we estimate the effect of conflict on transport roads in growing areas only ($conflict_{growing_{itm}}$) distinguishing markets located at different distances to growing areas. Doing so allows us to estimate at which distance from a violent incidence its effect can still be detected.

A common implicit assumption in the analysis of conflict is that entities far away from conflict remain unaffected (see Blattman and Miguel, 2010; Verwimp et al., 2019; for overviews). In our study context the assumption that distant markets are unaffected would only be plausible if more distant markets had better access to alternative maize supplies (e.g., from other growing areas). In absence of alternative sources of supply to distant markets, the effect of conflict would be propagated through space and remote markets would be affected by incidences of conflict occurring far away. If conflict causes scarcity of produce or transport capacity, markets closer to growing areas might be served first, which could in principle even lead to more distant markets experiencing higher scarcity and stronger price rises than less distant ones.

The right part of Figure 4 (page 26) shows the effect of conflict along roads in growing areas obtained from grouping markets into three bins: markets located less than 150km (an 2 hour drive in Somalia), 150km to 300km (a drive of between 2 and 4 hours), and between 400 and 900 kilometres from the growing area (corresponding to a 8 to 17 hour drive on Somali roads).³¹

For the nearest markets, the effect of violent incidences in growing regions is very strong, around 1 percent per attack. The strength of the effect decreases monotonously across the groups, reaching around 0.5 percent per attack for the markets furthest away from the growing areas, although the effect differences are not statistically significant. The main

³¹We used Google Maps to calculate driving times.

Table 3: Effect of conflict along route on maize price - Identification and mechanisms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Panel A: Identification					Panel B: Mechanisms				
Dependent variables	log price of maize					log night-lights on roads only	log price of maize			
Terrorist en route: (excl. same region)	0.0156 (0.0068)					-0.0198 (0.0044)			0.0158 (0.0068)	0.0174 (0.0089)
Conflict en route (z-score)		0.0110 (0.0048)	0.0113 (0.0037)							
Conflict en route:										
Successful				0.0192 (0.0090)						
No food target					0.0166 (0.0072)					
No explosives							0.0203 (0.0064)			
Using explosives							0.0059 (0.0082)			
Kidnappings								0.0329 (0.0114)		
In growing area									0.0027 (0.0057)	
On routes to all <i>other</i> markets										-0.0008 (0.0017)
Observations	1,965	1,965	1,965	745	1,965	242	1,965	1,965	1,965	1,965
R²	0.926	0.926	0.926	0.906	0.926	0.919	0.926	0.926	0.926	0.926
Data source	GTD	GTD	ACLED	GTD	GTD	GTD	GTD	GTD	GTD	GTD

Notes: Table reports effect of conflict along maize transportation routes on the price of maize. Estimations are based on equation (1). Dependent variable is the log of the price of maize apart from column 6 which is log of nightlight density on roads only and excluding any light emitted from cities or towns. All regressions apart from column 6 control for conflict or terrorist attacks carried out in same region as market and for season specific rainfall in growing region. *Terrorist en route* counts number of terrorist attacks occurring within a 5km radius either side of the most frequently used route between maize growing area and market per month and excluding attacks in same administrative area market is located in, *Conflict en route* counts number of terrorist attacks in column 2 (based on GTD) and incidences of conflict in column 3 (based on ACLED) occurring within a 5km radius either side of the most frequently used route between maize growing area and market per month, *Successful* denotes number of successful terrorist attacks en route, *No food target* denotes number of terrorist attacks en route not aimed at food distribution and production, *No explosives* and *Using explosives* denote terrorist attacks en route without and with use of explosive devices respectively, *Kidnappings* denotes terrorist attacks en route that are classified as kidnappings, hijackings, armed and unarmed assaults, *In growing area* denotes terrorist attacks in area where maize is cultivated that supplies each market (excluding roads and cities within that area), *On routes to all other markets* denotes terrorist attacks 5km either side of the main transportation routes to all *other* markets (excluding the market's own transportation route). **Data sources:** ACLED, FAO, FSNAU, GTD, NASA.

conclusion from this exercise is that there remains an important and statistically significant effect on maize prices even from violent attacks that occur up to 900 kilometres away from the market.

5.4 Mechanisms

We consider four mechanisms of impact: decreases in maize transport, the role of infrastructure destruction, the production of maize, and diversion of maize supply from one market to the next.

Effect of conflict on road traffic. One mechanism through which conflict along transportation routes can increase prices is by decreasing the frequency with which maize is transported along roads, thus decreasing its supply. Whilst there is no information on the volume of maize sales in Somalia, we document spatial spillover effects of conflict along transportation routes on far-away road traffic as detected by satellite images of light emissions. Our datasource is the Visible and Infrared Imaging Suite (VIIRS) Day Night Band (DNB) data.³² The increased precision of the the VIIRS has made it possible to measure road traffic using nightlight emissions (see Chang et al., 2020; for instance).

For this exercise, we calculate light emissions 5km either side of maize transportation roads, averaged to a monthly frequency. Crucially, we do not consider any emissions from cities or towns. As such, our measurement is likely to capture only road traffic and not economic activity as done in many other contexts (see Michalopoulos and Papaioannou, 2013; for instance). We focus on Somalia’s major road connecting Lower Shebelle with Mudug, which encompasses the three markets of Galkayo, Qorioley, and Marka (see appendix A.1b in turquoise), and where nightlight density on roads only is strong enough to detect. Our specification regresses nightlights emitted along this road close to each market area on attacks occurring hundreds of kilometres away along the same transportation route. The results in

³²Data are freely available at <https://eogdata.mines.edu/products/vn1/>. The data are available only from April 2012 to December 2018.

column (6) of Table 3 show that conflict along roads decreases nightlights along the same road hundreds of kilometres away by around 2 percent. This negative effect on road traffic suggests decreased maize supply in market areas as a possible pathway of impact.

Infrastructure destruction versus uncertainty. Violent incidences can reduce road traffic either via infrastructure destruction or by increasing fear and uncertainty. Several pieces of evidence suggest that the latter is at play in our context. First, when we re-estimate the effect of conflict along transit routes whilst also controlling for two months' lags (column 10 of Table 2), we find that the effect of conflict along transportation routes is driven by contemporaneous conflict only. Occurrences of conflict in the two months before, by contrast, have no effect on maize prices. The absence of lagged effects is an indication that the effect is driven by mechanisms that tend to reverse themselves within a month after the attack, which makes major infrastructure destruction which would take longer to rebuild an unlikely channel.

Second, we exploit the rich information in the GTD on type of attacks, their target, and their damage caused to identify attacks that could plausibly destroy infrastructure. We start by distinguishing terrorist attacks that use explosives (and are thus more likely to damage infrastructure) from attacks that do not. The parameter estimates in column (7) of Table 3 show that the effect of attacks that do not use explosives is markedly larger than the effect of attacks with the use of explosives. Moreover, in Appendix Table A.1 we use information in the GTD to distinguish terrorist attacks that do and do not damage property. Again, the effect of attacks not resulting in property damage is considerably larger. Next, we use the GTD data to identify terrorist attacks classified as kidnappings and hijackings as well as armed and unarmed assaults. These are unlikely to destroy infrastructure, but are instead likely to cause fear and uncertainty. As column (8) of Table 3 shows, we find a strong effect of these types of attacks.

Overall, these patterns of results suggest that conflict's effect on food prices does not

predominantly operate through infrastructure destruction. Instead, effects are more likely to be driven by indirect consequences of violent conflict, including fear and uncertainty, which may give rise to risk mitigation or compensation strategies that can disrupt supply and increase transport cost.

Production of maize. We next investigate whether conflict possibly affects the production of maize in Somalia. To this end, we estimate the effect of attacks occurring in the rural parts of growing areas, away from roads. The aim is to identify attacks with a potential of destroying maize supply, but not affecting the transport network as such. We define a variable $conflict_{agricult_{itm}}$, which counts the number of violent incidences per month and year that occur *only* in the maize growing area that supplies market i , excluding any conflict occurring within cities and roads located in growing regions. Augmenting equation (1) by $conflict_{agricult_{itm}}$ in column (9) of Table 3 shows two noteworthy findings. First, the coefficient on conflict en route remains almost unaffected compared the baseline specification in column (1). Second, we only find a very small positive coefficient on $conflict_{agricult_{itm}}$ suggesting that violence does not disrupt the cultivation of maize itself.

Re-routing of maize. We also investigate whether traders in Somalia react to conflict by re-routing maize to other markets. This could lead to spillovers across markets, where conflict along the transportation route to one market could affect prices at other markets. To test for this, we construct for every market in year t and month m all incidences of conflict occurring along the transportation routes to *all other markets*, excluding incidences on the market's own transportation route. Column (10) of Table 3 shows that the inclusion of conflict along the routes to all other markets does not change our main effect of conflict along the market's own transportation route. Moreover, the effect of conflict along the routes to other markets is small and not statistically significantly different from zero. This finding suggests that the Somali economy does not respond to conflict along the transportation network by re-routing supplies to other markets. Given that our nightlight results suggest that the frequency of

transport to markets affected by violence along the route decreases, absence of re-routing implies that maize is stored at cultivation sites for longer.

6 Spatial spillovers of conflict on food security and human capital

We now turn to survey data to verify whether we can replicate the price effects in household purchase data, and whether there are further ripple effects on food security and human capital of households in the affected market regions.

The summary statistics based on the SHFS in panel E of Table 1 highlight the very low socio-economic status of respondents. Almost half of respondents across the 2016 and 2017 surveys were classified to be below the standard international poverty line, earning less than \$1.90 a day evaluated at 2011 purchasing power parities. Moreover, the literacy rate among adults and school-aged children and children's school enrolment (at age 6-14) are low at 57 and 53 percent respectively. Finally, only 10 percent have access to improved sanitation.

Self-reported purchase prices. We start by replicating the spatial spillover effect on prices documented in Table 2 using purchase prices as reported by SHFS respondents. The SHFS inquires about food purchases of households within the 7 days before the interview, which allows us to calculate food prices per kg. Columns (1) and (2) of Table 4 report estimates of equation (2) with logs of prices of maize and of rice as the dependent variables. The results from the survey data in column (1) replicate our previous findings using FAO price data with a positive effect of 2 percent per attack en route for maize. The effect is larger yet still comparable to the one reported in column (2) of Table 2 using FAO data on similar years as the implementation of the SHFS. One explanation for the larger effect in column (1) is that self-reported prices include intermediary markup, which might also respond to conflict. As before, we cannot detect any effect on the price of rice in column

(2).³³

Consumption of food staples. Columns (3) to (6) of Table 4 report the effects of conflict along the transportation route for maize (and far away from respondents) on the consumption of maize and of three other food staples that can serve as potential substitutes for maize. The point estimates suggest a reduction in the consumption of maize, accompanied by an increase in the consumption of sorghum and rice, yet only the effect on sorghum is statistically significant. The relatively small sizes of the substitution effects in columns (3) to (6) of Table 4 might appear surprising at first, especially considering the low economic status of SHFS respondents. However, our results tally with previous work documenting the slow changing nature of nutritional preferences and behaviour. For instance, studies show habit formation for food preferences (Atkin, 2013) and how culture can constrain caloric intake (Atkin, 2016). As such, it remains an open question whether these consumption changes suffice to mitigate the effect of the price shock. We therefore go on to investigate further knock-on effects of conflict along transportation routes of maize and far away from respondents on food security, spending patterns, and on health and education outcomes.

Food security. In this section we exploit information on food security from two different sources: self-reported food security information from the SHFS household survey, and the official classification of food security that we digitized from the FSNAU. The results from the self-reports not only show that conflict along transportation routes (and at some distance from households) decreases food security, they also suggest food prices as a mechanism through which this effect operates. Moreover, the official FSNAU data show that conflict along transportation routes increases the likelihood of an area being classified as 'food insecure'.

The results are reported in Table 5. In this part of the analysis, we adjust our conflict

³³The small effect difference between FAO and survey data is unlikely to be due to differences in the time periods covered. In column (6) of Appendix Table A.1 we show that the results remain very similar when we re-estimate the price effect in the FAO data using exactly the months between both survey dates.

Table 4: Effect of conflict along transportation routes on food prices and consumption

	(1)	(2)	(3)	(4)	(5)	(6)
	Log price of		Dependent variables: Log quantity consumed per household of			
	Maize	Rice	Maize	Sorghum	Rice	Pasta
Conflict en route (excl. same region)	0.023 (0.010)	-0.001 (0.013)	-0.018 (0.017)	0.034 (0.012)	0.015 (0.020)	-0.001 (0.011)
Observations	3,170	5,176	8,137	8,113	10,057	6,531
R^2	0.33	0.36	0.12	0.10	0.05	0.15

Notes: Table reports effects of conflict along transportation routes on the log of self-reported food prices and on the log of quantity of food staples consumed per household over the past 7 days. All specifications are based on equation (2) and include region and year fixed effects and control for attacks in own area, household size, proportion literate in household, gender of household head, and household below poverty line. Violent incidences are averaged over the survey month. Sample sizes vary across columns because not all households were asked about all food items, and because columns (1) and (2) are conditional on having made a purchase of the food item. Robust standard errors clustered at the region level are in parentheses. **Data source:** SHFS.

measures in accordance with the time horizon each question or classification refers to.³⁴ Column (1) of Table 5 shows that conflict along transportation routes increases the probability that households experience high food prices and change their eating patterns as a result. The remaining columns further corroborate significant effects on food security and indicate that far-away conflict along the route increases the probability that a household is lacking enough food to eat by about 2.8 percentage points (column 2) and the probability that a household member had to eat elsewhere by 0.4 percentage points per incidence of conflict (column 3).

Column (4) provides evidence on spatial spillover effects on a food security classification system, which is widely employed by policy makers, such as the FAO, for instance. The Integrated Food Security Phase Classification (IPC, 2021) system divides Somalia into livelihood zones and evaluates each twice a year (after the Gu and Deyr harvests). We digitised data

³⁴As the column titles indicate, some of the outcomes refer to the past month, and others to the past year prior to the survey interview. We therefore define the explanatory variable of conflict en route accordingly as either the average incidences over the past month, or the average monthly incidences over the past year.

Table 5: Effect of conflict along transportation routes on food security

	(1)	(2)	(3)	(4)
	High food prices affecting eating pattern (past year)	Not enough food to eat in house (past 4 weeks)	HH member ate elsewhere (past 30 days)	= 1 if nutrition classified as critical
Attacks period	Past year	Past month	Past month	Past growing season
Conflict en route (excl. same region)	0.008 (0.003)	0.028 (0.006)	0.004 (0.001)	0.015 (0.002)
Observations	5354	6417	2541	190
R^2	0.017	0.141	0.031	0.695
Mean Dep. Variable:	0.01	0.25	0.08	0.49
Data Source:	SHFS	SHFS	SHFS	FSNAU

Notes: Table reports effect of conflict along maize transportation route on food security. Conflict en route is either averaged over the month preceding the survey month, the year preceding or the growing season prior to the survey month as indicated (see row 'attack period') in accordance with the time period to which the respective outcome refers. Columns (1) to (3): are based on SHFS, were asked only in 2016 and exploit cross-sectional variation only. Regressions are based on equation (2) and control for the number of incidences of conflict occurring within region of residence. Column (4): is based on FSNAU data we digitised for the years 2009 to 2018 and is based on equation (1) with market-by-season and market-by-year fixed effects. Robust standard errors clustered at region (columns 1 to 3) and market (column 4) level are in parentheses. **Data source:** SHFS, FSNAU.

between 2009 and 2018, matched the livelihood zones to the ten markets for which we have price information, and estimate a specification analogous to equation (1).³⁵ The dependent variable takes the value one if at least 15 percent of children aged 6 to 59 months exhibit low weight-for-height and/or oedema, which the IPC defines as 'critically food insecure'. Column (4) of Table 5 shows that each incidence of conflict along transportation routes increases the probability of critical levels of malnutrition by 1.5 percentage points on a mean of around 49 percent.

Household expenditures. Using detailed information on household expenditures, our results also show that households adjust to conflict along far away transit routes by changing their spending patterns, which may have consequences on children's health and education. As reported in column (1) of Table 6, an additional incidence of conflict along transportation routes increases the probability of spending out of a household's savings by 0.4 percentage points. It also reduces the number of non-food categories within which households have made an expenditure over a 12 month period by about a quarter of a category (column 2).³⁶ In columns (3) to (6) we focus on human capital investments in the form of expenditures on health and education. For general healthcare (column 3) and educational (column 5) expenses, point estimates are negative but not statistically significant. However, for the more specific items of spending on health and other insurance (column 4) and books and newspapers (column 6) there emerge sizeable and statistically significant effects. Overall, this suggests that the apparent substitution of maize by sorghum (see Table 4) is not sufficient to avoid adverse effects on food security and on non-food expenditure.

Health. Columns (1) to (7) of Table 7 report effects of conflict occurring on far-away transportation routes on health outcomes of children aged below 10 years. The most likely

³⁵Because the IPC evaluates livelihood zones only twice a year, each market contributes only two observations per year.

³⁶This index ranges from 0 to 8 and is constructed as the sum of eight dummies indicating any spending in eight important non-food categories (see table notes for details).

Table 6: Effect of conflict along transportation routes spending patterns

	(1)	(2)	(3)	(4)	(5)	(6)
	HH spent savings (past 30 days)	Index of non-food spending (past 12 months)	Any spending over the past 12 month on . . .			
			Health-care	Health and other insurance	Educational expenses	Books, newspapers
Attacks period	Past month	Past year	Past year	Past year	Past year	Past year
Conflict en route (excl. same region)	0.004 (0.002)	-0.259 (0.048)	-0.081 (0.093)	-0.117 (0.049)	-0.03 (0.043)	-0.048 (0.012)
Observations	2442	5759	6542	4372	6542	5751
R^2	0.019	0.111	0.111	0.192	0.184	0.013
Mean Dep. Variable:	0.07	6.72	0.31	0.64	0.27	0.72

Notes: Table reports effects of violent incidences along maize transportation route on food security and expenditure outcomes. Conflict en route is either averaged over the month preceding the survey month, or the year preceding the survey month as indicated (see row 'attack period) in accordance with the time period to which the respective outcome refers. The outcomes in column (1) was asked only in 2016 and exploit cross-sectional variation only. All other specifications are on the combined 2016 and 2017 sample and include region and year fixed effects. Further control variables in all specifications are attacks in own area, household size, proportion literate in household, gender of household head, and household below poverty line. The index in column (2) is the sum of eight dummies indicating any spending in the non-food categories public transport, soaps/toiletries/cosmetics, energy/utilities, donations, domestic help/repair/maintenance, music/entertainment, clothing, and homeware. All other outcomes are dummy variables. All regressions are based on equation (2) and control for the number of incidences of conflict occurring within region of residence. Robust standard errors clustered at the region level are in parentheses. **Data source:** SHFS.

reason why health outcomes could be affected by conflict along transportation routes is malnutrition as a result of the reduced food availability documented above. In column (1), we find no general effect on having suffered any illness over the past two months. We therefore break up illnesses into infectious illnesses and non-infectious ones, motivated by the well-known links between malnutrition and infectious diseases (Scrimshaw, 2003; Black et al., 2008; Calder, 2013). The results show that an increase in conflict en route and at some distance from respondents indeed increases infectious illnesses by about half a percentage point (column 2), an effect of five percent relative to the mean. On non-infectious illnesses, however, which are much less likely to be affected by malnutrition, we find no effect (column 3), as might be expected.³⁷ In columns (4) to (7) we show effects on the individual health conditions that make up the infectious illnesses. All effects are statistically significant. The largest effect is for gastro-enteritis, which counts among the leading causes of death among children in Sub-Saharan Africa (Jamison et al., 2006; Table 5.11).

While the absolute effect sizes on these health outcomes are relatively small, they are more sizable in relative terms. Across all the outcomes in columns (4) to (7) relative effects sizes range between 3 and 12 percent of the mean of the dependent variable.

Education. Column (8) shows that an additional violent incident along the maize transportation route reduces the probability of children’s primary and middle school enrolment (age 6-14) by 0.43 percentage points. Given that the conflict en route occurs some distance away, the mechanism of the effect on enrolment is unlikely to be one of safety concerns, but more likely to be related to the economic effects of price rises, which make schooling less affordable. To test whether this goes in hand with children being more likely to engage in child labour to supplement the household’s income, we also report results on whether children are in paid work (column 9). While the point estimate is positive, the effect is not statistically

³⁷One channel by which non-infectious illnesses could be affected, would be if the reduction in healthcare insurance and expenditure documented in Table 5 would reduce preventative health care. Yet, this is not very likely in our study context, because among very poor households in Somalia preventative health care is likely to be at very low levels anyway.

significant. Our spillover estimate on school enrolment of 0.43 percentage points amounts to 18-35 percent of the effect of local conflict on school enrolment estimated in comparable settings. In northern Nigeria, for instance, Bertoni et al. (2018) document that each conflict event reduces the probability of school enrolment by 2.4 percentage points. In Kenya, Alfano and Görlach (2022) find that an additional al-Shabaab terrorist attack decreases school enrolment by 1.2 percentage points.

Table 7: Effect of conflict along transportation routes on health and education

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	In the past 2 months child (age < 10) suffered from								
	Any illness	Infectuous illness	Non-infectuous illness	Gastro-enteritis	Malaria	Typhoid fever	Chest infection	Not enrolled in school (age 6-14)	Paid work past 7 days (age 10-18)
Conflict en route (excl. same region)	0.004 (0.002)	0.005 (0.001)	0.0007 (0.0004)	0.002 (0.001)	0.004 (0.001)	0.0002 (3.1E-05)	0.0001 (3.4E-05)	0.0043 (0.0018)	0.0028 (0.0028)
Observations	8180	8180	8180	8180	8180	8180	8180	8134	6380
R^2	0.04	0.06	0.00	0.05	0.03	0.004	0.003	0.43	0.14
Mean Dep. Variable:	0.18	0.11	0.02	0.08	0.04	0.002	0.003	0.47	0.08

Notes: Table reports effects of violent incidences along maize transportation route on children’s health and education outcomes. Health outcomes are for children aged 0-10, schooling outcomes for children 6-14 and work outcomes for children 10-18. Infectious illness is an indicator for having suffered from any of the four infectious illnesses reported in columns (4)-(7). Non-infectious illness is an indicator for having suffered from dental problem, fracture, wound, mental disorder, asthma, headache, fainting, eye problem, backache, or an unspecified long-term illness. The outcomes in columns (1)-(7) were asked only in 2016 and exploit cross-sectional variation only. All other specifications are on the combined 2016 and 2017 sample and include region and year fixed effects. All specifications control for child age dummies, household size, proportion literate in household, gender of household head, and household below poverty line. All regressions are based on equation (2) and control for the number of incidences of conflict occurring within region of residence. Robust standard errors clustered at the region level are in parentheses. **Data source:** SHFS.

Robustness. For some of the effects on food security, health and education, we measure conflict along the transportation route over the year prior to the survey date. For households that have migrated over the past year this would introduce measurement error in the conflict variables, because at their previous place of residence they would have been exposed to a

different level of conflict along the route. This might not be just random error, but could be systematically related to violence, if the effects of conflict cause households to migrate. To check to what extent this is likely to be a problem, we run robustness checks where we exclude households that have migrated in the past.³⁸ The results are in Table A.2 in the Appendix and show that our main conclusions carry through and are quite robust in terms of their magnitudes in the sample that excludes migrated households.

7 Welfare impact of spatial spillovers

After estimating the magnitude of spatial spillovers, this section approximates their welfare impact by carrying out a back-of-the-envelope calculation. Regressing a welfare index on local conflict and conflict en route and weighting each by their respective frequencies, we find that spatial spillovers add around 30% to the effects of conflict. Combining this with information from the Institute for Peace and Economics (IEP, 2022), we estimate that spatial spillovers of conflict could be worth USD 3-4 trillion worldwide in 2019, or 2-3 percent of global GDP. In the following we outline our calculations and the assumptions they are based on (along with additional details in appendix B).

We start by aggregating four commonly used welfare measures into a single standardised index (these are food security, non-food purchases, health, and education, see appendix B). Regressing this welfare index on local conflict and conflict en route (using equation 2) shows that an additional attack along the transportation route leads to a reduction of 23% of a standard deviation. A local attack, in turn, reduces the index by close to 4% of a standard deviation—see appendix Table B.1.

Whilst the large relative effect of conflict along routes may seem surprising, it is ex-

³⁸We define a household with a migration history as a household in which the household head lives in a different region of Somalia where they were born (information available in both the 2016 and 2017 waves), or if the number of years any of the household members has lived in the current district is smaller than their age (available in the 2016 wave), or if the household counts under the UNHCR Internally Displaced People definition (available in the 2017 wave) of having ever left their usual place of residence due to conflict, violence, human rights violations or disasters.

plained by the fact that these incidences occur within a narrow corridor around the main transportation routes of the most important food staple to the region. As such, any attack along these roads potentially affects all residents in the market region. The potential for disruption is exacerbated by Somalia’s rudimentary overland road network, which makes alternative routes difficult to find (see Government of Somalia, 2018; for more details). By contrast, local conflict can occur anywhere in the administrative region the respondent resides in. Since regions in Somalia cover large areas, violent occurrences may occur far away from respondents interviewed by the SHFS. Thus, whilst each local attack may have devastating effects in its immediate vicinity, the fact that these incidences can be dispersed across the region means that their average effect on the region is likely to be smaller.

In addition to the above, attacks along transit routes and local attacks occur at very different frequencies. Consequently, comparing estimates per incidence would not adequately reflect the respective importance of both types of conflict. Instead, we weight each occurrence of conflict by their respective frequency. As table 1 shows, this corresponds to one attack along the transportation route per 20 local attacks. The resulting welfare cost of spatial spillover effects through the transport network amounts to 30% of the welfare costs of local conflict.³⁹ This estimate is somewhat smaller than those reported in the only two papers we are aware of that also quantify spillovers of conflict. Analyzing production networks in India and Ukraine, respectively, Couttenier et al. (2022) and Korovkin and Makarin (2021) calculate spillover effects of around 70%. A possible reason for our estimates being smaller is that Couttenier et al. (2022) and Korovkin and Makarin (2021) consider spillovers on economic activity across wide sets of industries, while we focus specifically on the distribution of maize.⁴⁰

Using the often cited estimates on the annual cost of conflict by the IEP (2022), we can

³⁹This is computed as $-0.23/(-.039*20)=0.295$.

⁴⁰Another difference is that these studies estimate spillovers on firm performance (Couttenier et al., 2022) and inter-firm trade (Korovkin and Makarin, 2021), while we focus on household-level welfare measures. As we discuss in appendix B, the magnitudes of these types of calculations generally dependent on the context, such as the nature and spatial distribution of conflict, or the features of the network under study.

convert the relative importance of spillovers of conflict into an absolute number. The IEP estimates the total global cost of violence in 2019 at USD 14.4 trillion. We use this as an upper bound number for the total cost of local conflict, and in appendix B we also derive a more conservative total by excluding some elements that do not necessarily correspond to local effects of armed conflict. Combining this with our above estimates, we find that spatial spillovers of conflict amount to around USD 3-4 trillion in 2019, equivalent to 2-3 percent of global GDP, depending on the assumptions used. While this back-of-the-envelope calculation is based on a range of assumptions that we discuss in appendix B, it clearly suggests that omitting spatial spillovers can lead to a severe underestimate of the true welfare effects of violence.

8 Discussion and Conclusion

Our analysis has documented that conflict occurring in one part of Somalia can affect food prices, food security, health and education in areas located far away. Despite much of the fighting being concentrated in the Southwest of Somalia, our analysis shows that the effects of conflict are felt in areas at a distance of almost 1,000 kilometres. These findings potentially have far reaching consequences for both policy makers and researchers.

Humanitarian interventions or refugee policies most commonly focus on those locations where the conflict occurs. The World Food Programme (WFP, 2021), for instance, provides nutritional assistance to areas around Mogadishu, in the Southwest of Somalia where most of the fighting is concentrated. Similarly, when evaluating asylum eligibility, the United Nations High Commission for Refugees report (UNHCR, 2010) highlights the Southwest of Somalia in particular as the area where individuals are *at risk of serious harm*. By contrast, our results provide evidence that individuals can be affected by conflict even if it occurs far away. For instance, the city of Galkayo (located 700km from Mogadishu, corresponding to a 14 hour drive) is part of the northeastern region of Puntland and as such not covered by

either the WFP or UNHCR policies mentioned above. Our analysis, however, shows that conflict occurring in the Southwest increases food prices, decreases food security and erodes human capital in Galkayo thus suggesting that policies regarding conflict should broaden their scope.

The spatial spillover effects we document also have important consequences for research designs in which the treatment group consists of a region affected by conflict, and the control group consists of a neighboring or more distant region. In contexts where spatial spillovers are important, the control group might thus also be affected by conflict, most likely leading to attenuation in the estimates. Whilst the degree of spatial spillovers will vary across contexts, their possibility implies that traditional research designs might in some cases have provided lower bound estimates. In those cases where spatial spillovers are in fact present, the effect of local conflict is likely to be larger than thus far assumed, hence providing further reasons to invest in humanitarian interventions in conflict zones.

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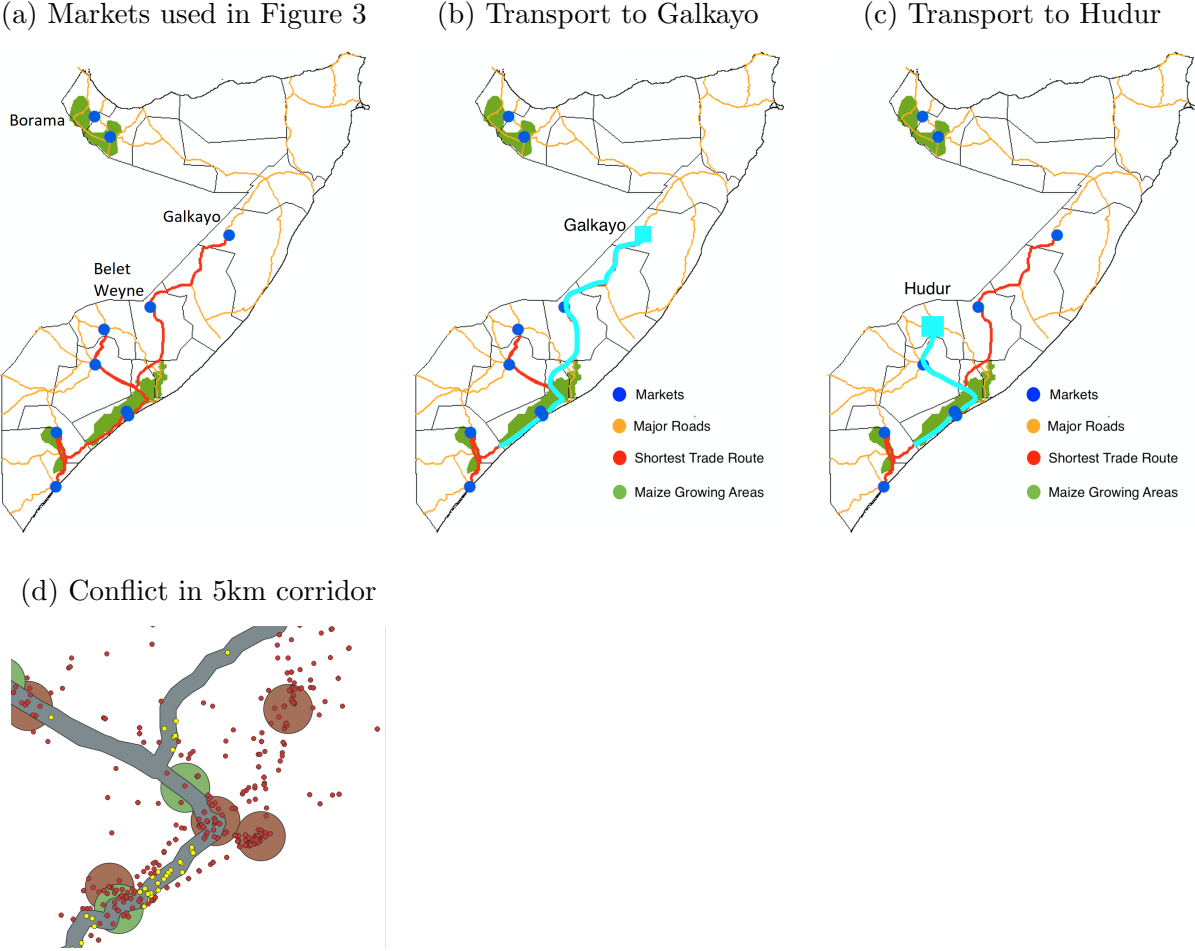
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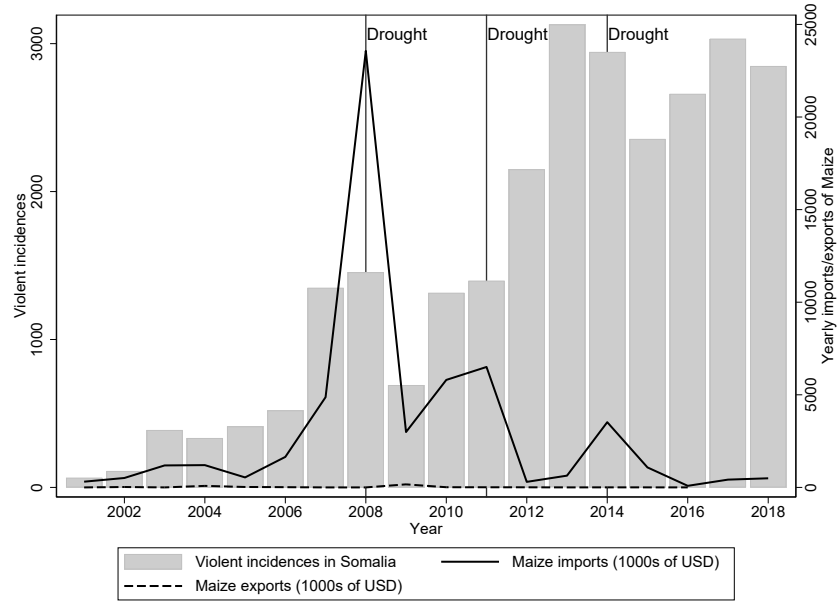
A Appendix figures and tables

Figure A.1: Additional maps



Notes: Map a: shows geographical location of three markets reported in Figure 3; Map b: shows transportation route used to supply market of Galkayo with maize; Map c: shows transportation route used to supply market of Hudur with maize; Map d: shows geographical location of roads (grey), towns (maroon) and cities (green), incidences of conflict falling within 5 kilometres of transportation routes are denoted as yellow dots and incidences falling outside of the corridor as red dots.

Figure A.2: Imports and exports of maize



Notes: Figure reports conflict in Somalia along with imports and exports of maize. Bars indicate yearly incidences of violence drawn from ACLED; solid line refers to yearly imports of maize in 1000s USD drawn from United Nations Conference on Trade and Development (UNCTAD); dashed line refers to yearly exports of maize in 1000s USD drawn from United Nations Conference on Trade and Development (UNCTAD); vertical lines denote incidences of droughts. The UNCTAD trade data are freely available at <https://unctadstat.unctad.org/EN/>

Table A.1: Robustness of the spatial spillover effects on maize prices

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent variables:							
	Log price of maize							
Conflict en route: (excl. same region)	0.0035 (0.0011)	0.0029 (0.0011)	0.0049 (0.0016)	0.0059 (0.0023)	0.0057 (0.0022)	0.0098 (0.0041)	0.0055 (0.0028)	
Terrorist attacks with damage								0.0036 (0.0058)
Terrorist attacks without damage								0.0386 (0.0183)
Observations	1,588	1,613	1,551	1,192	714	227	1,965	1,965
R^2	0.917	0.936	0.921	0.926	0.930	0.961	0.925	0.925
Sample	No Somali- land FAO 5km	Not next to Kenya FAO 5km	Not next to Ethiopia FAO 5km	2009-18 FAO 5km	2012-17 FAO 5km	Feb 2016 to Dec 2017 FAO 5km	All FAO 1km	All FAO 5km
Data source								
Corridor width								5km

Notes: Table reports effect of incidences of conflict along maize transportation route on the price of maize using different samples and specifications. *Conflict en route* counts number of violent incidences occurring within a 5km radius either side of the shortest route between maize growing area and market per month. *Terrorist attacks with damage* counts number of terrorist attacks within a 5km radius either side of the shortest route that lead to property damage. *Terrorist attacks without damage* counts number of terrorist attacks within a 5km radius either side of the shortest route that do not lead to property damage. Dependent variable is the log of the price of maize. Column (1) drops markets located in Somaliland (Borama and Hargeisa), column (2) drops markets located close to Kenya (Buale and Kismayo), column (3) drops markets located close to the Ethiopian border (Belet Weyne and Hudur), column (4) uses only years 2009 to 2018, column (5) only uses years 2012 to 2017, column (6) uses only observations between February 2016 and December 2017, column (7) uses whole sample but counts conflict only 1km either side of the road, column (8) estimates effect of terrorist attacks that do and that do not lead to property damage using whole sample. **Data sources:** ACLED, FAO.

Table A.2: Robustness against excluding migrant households

	(1)	(2)	(3)	(4)	(5)	(6)
	Log Consumption Maize	Consumption Sorghum	Not enough food to eat in house (past 4 weeks)	High food prices affecting eating pattern (past year)	HH member ate else- where (past 30 days)	
Conflict en route (excl. same region)	-0.019 (0.025)	0.040* (0.021)	0.029* (0.013)	0.003 (0.002)	0.005*** (0.001)	
Observations	5551	5516	4367	3636	1975	
R2	0.12	0.103	0.13	0.017	0.031	
	HH spent savings (past 30 days)	Index of non- food spending (past 12 months)	Any spending over the past 12 month on. . . .			
			Health- care	Health and other insurance	Educational expenses	Books, newspapers
Conflict en route (excl. same region)	0.006** (0.002)	-0.274*** (0.072)	-0.06 (0.102)	-0.147** (0.053)	-0.034 (0.063)	-0.059*** (0.017)
Observations	1886	3863	4454	3154	4454	3906
R2	0.019	0.119	0.115	0.143	0.182	0.013
	In the past 2 months child suffered from					
	Any illness	Infectuous illness	Non- infectuous illness	Not enrolled in school (aged 6-14)	Paid work past 7 days (aged 10-18)	
Conflict en route (excl. same region)	0.003 (0.002)	0.004*** (0.001)	0.0006 (0.000)	0.068*** (0.018)	-0.018 (0.051)	
Observations	7414	7414	7414	6159	4744	
R ²	0.047	0.069	0.004	0.433	0.123	

Notes: Table replicates the effects of violent incidences along maize transportation routes on key outcomes from Tables 4 - 7 excluding migrant households. All specifications are similar to the corresponding specifications in Tables 4 - 7. Robust standard errors clustered at the region level are in parentheses. **Data sources:** SHFS.

B Details on the welfare analysis

This appendix discusses the assumptions underlying our welfare analysis in section 7 and provides more details on our calculations.

Scope of the welfare analysis: The welfare analysis is partial in the sense that it aims to address the welfare costs to consumers who are at risk of suffering from higher food prices. Our data do not allow us to identify maize farmers, transporters or traders, who could in theory benefit from higher prices, although price increase due to conflict do not necessarily constitute pure windfall gains to them because conflict can also increase transport costs.

Construction of welfare index: We add up standardised scores of the outcomes ‘Not enough food to eat in house’, ‘Index of non-food spending’, ‘infectious illness,’ and ‘not enrolled in school’, and we standardise the resulting score on our regression sample. Given that infectious disease is only defined in one of the survey waves and thus contributes to the welfare index only in that year, we ran a robustness check where we omitted this outcome from the index. The results of the back-of-the-envelope calculation remained unchanged.

Weighting conflict along transportation routes and local conflict: Because all violent incidences count as local conflicts, but only some violent incidences occur along transportation routes, we divide the number of all violent incidences (Panel A of Table 1) by the number of violent incidences along transportation routes (Panel B of Table 1), yielding $27,169/1,334 = 20.37$, i.e., one incidence of violent conflict along the transportation route for 20 local incidences of conflict.

Interpretation of coefficients: One of the main assumptions underlying this calculation is that the coefficients in Table B.1 can be interpreted as causal. As argued in section 4, our strategy aims to causally identify the effect of violence along the route, but it is harder to argue that our effect of local violence is causal. Yet, if the effect of local violence was over-estimated, then spatial spillovers would be comparatively even more important than our calculation suggests. Additional reasons why our calculation may be an underestimate of the importance of spatial spillovers are that we look only at one specific channel of spillovers (through the transportation network for one specific food staple), and that our outcomes do not cover all possible welfare effects of conflict (such as additional long-run effects for example).

Context dependence: A further important caveat of this welfare calculation is that it is dependent on the context. For example, spatial spillovers due to conflict along transportation routes are likely to be stronger the more basic the transportation system is and the less alternative routes and modes of transport it offers. As such, our effects are more likely to have external validity for other African countries with a similar transport network as Somalia than for countries where such networks are more developed. Furthermore, it is important to note that the effect sizes of local conflict are likely to depend on how large or small a locality is defined. Our number of 30% additional welfare costs due to spillovers therefore needs to

be related to estimates of the welfare costs of local conflict that use a similar definition of localities as we do (administrative regions of Somalia).

Extrapolation: To get to an absolute figure for the welfare cost of spatial spillovers of conflict, we multiply our estimate of their relative importance of 30% with monetary estimates for the global annual cost of conflict. An important assumption in doing this is that our figure of 30% can be extrapolated beyond our study context. While there are reasons to believe that the importance of spatial spillovers could be smaller in other contexts (see 'context dependence'), this concern is partially mitigated by the fact that our welfare calculation requires us not to extrapolate to all other countries, but to countries affected by conflict, and that conflict is concentrated more heavily in poorer countries more similar to our study context. Secondly, there are also reasons to believe that we may have under-estimated the relative importance of spatial spillovers of conflict (see 'interpretation of coefficients'). We therefore believe it is reasonable to apply our 30% estimate as a best guess.

Details on accounting of economic costs of conflict: Our upper bound for the monetary cost of spatial spillovers of conflict simply multiplies the global annual cost of conflict of USD 14.4 trillion by the Institute for Peace and Economics (2022) with our estimate for the relative importance of spillovers of 30%, yielding a figure of USD 4.3 trillion. This assumes, however, that the global cost estimate of the IEP captures purely the local cost of conflict and does not already include spatial spillovers. The IEP calculates the costs of conflict from a total of 18 indicators (see appendix B of IEP, 2022). Some of these indicators might partly include spatial spillovers, in particular their items on containment of violence (military expenditure, internal security expenditure, private security, incarceration, small arms imports) and their item on national GDP losses per year of conflict. For a more conservative estimate of the effects of local violence we mark these items down by 30% and also exclude the cost of suicide (as self-harm does not constitute violent conflict). This yields an adjusted annual total of USD 10.1 trillion, and multiplying by 30% yields an estimated cost of spatial spillovers of USD 3 trillion. Given that IEP (2022) equates its USD 14.4 trillion estimate to 10.5 percent of global GDP, our range of USD 3-4 trillion corresponds to roughly 2-3 percent of global GDP.

Table B.1: Welfare index, attacks along the route, and local conflict

	Welfare index
Conflict en route	-0.227 (0.092)
Conflict in same region as market	-0.039 (0.011)
Observations	3598

Notes: Table includes results from a regression of a welfare index on conflict along the route and local conflict. The specification is based on equation (2) and includes region and year fixed effects and controls for household size, proportion literate in household, gender of household head, and household below poverty line. Violent incidences are averaged over the year preceding the survey interview. Robust standard errors clustered at the region level are in parentheses. **Data sources:** SHFS.