Spatial Spillovers of Conflict in Somalia

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Spatial Spillovers of Conflict in Somalia

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Abstract

Conflict along transportation routes during Somalia's al-Shabaab insurgency significantly increases maize prices at distant locations, decreasing food security, health, and education. Estimated conflict risk has strong price effects independently of realized conflict, highlighting the importance of safety concerns. A model of least-cost route choice in the presence of conflict reveals that more and shorter alternative routes to circumvent conflict can lower prices but their effectiveness diminishes as violence becomes more correlated across routes. Alternatively, securing key transportation routes would alleviate price increases. A market access approach suggests spatial spillovers of conflict also matter for prices of more general baskets of food and non-food items.

JEL Classifications: 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*). Conflict may hinder trade and increase trade costs, potentially resulting in higher prices even in remote destination markets. One prominent example is the global food insecurity triggered by the disruption of Ukrainian grain exports during the 2022 war, which the UN warned could push 47 million people—primarily in sub-Saharan Africa—into food insecurity.[2] The presence of spatial spillovers 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.[3]

This paper investigates whether conflict along transportation routes affects food prices, nutrition, health, and education in destination markets that can be located hundreds of kilometres away from where the violence occurs. Our analysis is set in Somalia around the onset of the al-Shabaab insurgency, a period marked by increasing violent conflict and persistent food insecurity. In this setting, frequent violent attacks along the food transportation network have a high potential to disrupt trade, giving rise to spatial spillovers. First, we estimate the effect of conflict along major food transportation routes on prices in geographically distant markets, focusing on maize, a key staple in the Somali diet. This reduced-form approach takes route choices for each destination market as fixed and serves to establish baseline results, shed light on mechanisms, and investigate further ripple effects on household outcomes. Second, we develop a trade-cost model in which conflict determines maize traders' route choices and, in turn, maize prices. This added structure allows us to simulate a range of policy-relevant counterfactual scenarios, shedding light on how improvements in security or infrastructure could mitigate the spillover effects of conflict on prices. Finally, we move beyond the market for maize and augment a general market access measure (e.g., Chiovelli et al., 2024, Jedwab and Storeygard, 2022) with attacks along transportation routes to examine whether spatial spillovers generalize to a broader set of food and non-food

[1]For example, 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]Regional spillovers of conflict can also bias common research designs as they can cause the effects of conflict to spill over to the control group.

commodities.

Our analysis is based on monthly maize price data from 2001 to 2018 for eleven trading hubs covering major parts of the Somali maize distribution network. We combine the exact geographical coordinates of growing areas (origins), destination areas (markets), and transit routes with detailed information on the precise routes used for transportation based on information from NGOs working on the ground, cross-validated with fastest routes as calculated by mapping software. For each destination market in our sample, we draw a corridor along the transportation route supplying that market with maize. Using the exact geographical coordinates of incidents of conflict from the Armed Conflict Location & Event Data Project (ACLED), we estimate the effect of violent events occurring each month within this corridor whilst also controlling for conflict in the proximity of markets.

We find that each incidence of conflict along transportation routes increases the price of maize in destination markets by around 0.4 percent. In standardized terms, the effect size of conflict along transportation routes amounts to between 15% and 44% of the effects of other important determinants of prices such as maize production, rainfall and drought measures. 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 14 hours driving time on Somali roads. Our evidence also shows that maize prices react strongly to sudden event-driven changes in conflict, such as battles or ceasefires.

Since conflict along transit routes occurs far away from where outcomes are measured, our research design rules out many common endogeneity concerns. Nevertheless, we carry out a range of identification checks, such as exploiting the inherent randomness in success rates of attacks, or using conflict during lean seasons and goods transported along other routes as placebos. We also show that only attacks along transport routes drive our results, while nearby off-road attacks have no effect.

Our mechanism analysis indicates that perceived conflict risk—independent of actual attacks—raises prices, suggesting that safety concerns are a key driver. By contrast, using rich information from the Global Terrorism Database (GTD) on characteristics of attacks, we find that effects are not driven by incidents of conflict resulting in property damage suggesting that an effect of conflict operating through infrastructure destruction is unlikely. Moreover, we find that our effects operate independently of violence occurring in growing areas and disrupting the agricultural production of maize.

Using the Somali High Frequency Survey (SHFS), we find that conflict along transport routes increases the likelihood that households adjust their eating patterns in response to food price shocks. This suggests that food prices are a key mechanism through which distant conflict affects food security. Moreover, conflict along maize transportation routes increases the incidents of infectious diseases such as gastroenteritis amongst children, and reduces school enrolment.

The second part of our analysis introduces a trade-cost model in which maize traders select routes optimally by trading off the level of violent attacks against travel time. Under the baseline scenario, we find that traders make virtually no use of alternative routes despite frequent attacks. This is because the next best alternative routes are, on average, about 40% longer and are affected by levels of violence highly correlated over time with those on the shortest routes. Our policy simulations suggest that alternative routes would provide a meaningful alternative only if they were either attack-free or comparable in length to the shortest routes. In this counterfactual, maize prices would fall by up to 5% across all market-months affected by violence, and by as much as 20% in the most affected market-months. Comparable price reductions could be achieved by securing key transport routes in the Lower Shebelle region, requiring the prevention of just one-fifth of the attacks.

The final part of our analysis examines how conflict reduces market access, a measure of how well markets are connected via the transport system. We find that increased attacks along Somalia's transportation routes over the past two decades have lowered market access by close to 70%, pushing up prices by 6–11% across a wider range of food and non-food goods. These findings suggest that the effects of violence along transportation routes generalize beyond maize, to a wider set of routes and a wider set of prices. In a final step of generalization, our results also show negative effects, specifically on non-food prices, from violence *in other cities*, that are likely to distribute or produce goods.

This study is the first to document that food prices play an important role in enabling conflict to affect important outcomes (food security, health and education) of individuals hundreds of kilometers away. Our findings have wide-ranging policy implications. The additional costs implied by spatial spillover effects imply that the adverse effects of conflict are greater than commonly assumed, further strengthening the case for humanitarian interventions. Spatial spillovers also imply that policies such as humanitarian aid and protection efforts may need to target less narrowly defined regions. In Somalia, for instance, the World Health Organisation (WHO) provides emergency medical supplies to areas affected by conflict.[4] Our findings that individuals far away from conflict are impacted make the case to extend such aid to other areas of the country.

By highlighting food prices as a mechanism through which conflict affects not only individuals in directly exposed areas but also those living far away, we contribute to a large number of studies that have documented a negative effect of conflict and violence on edu-

[4]For example: http://www.emro.who.int/images/stories/somalia/documents/technical_programme_update_septmeber_december_2018.pdf?ua=1, accessed December 2021.

cation (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, 2021), 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; Tapsoba, 2023), and nutrition (D'Souza and Jolliffe, 2013; Dabalen and Paul, 2014; Serneels and Verpoorten, 2015). This existing literature has typically focused on conflict in proximity to respondents (see Blattman and Miguel, 2010; Martin-Shields and Stojetz, 2019; for overviews). We focus on effects of conflict occurring at some distance and propose food prices as a novel and thus far neglected pathway of impact for this literature, which has predominantly focused on infrastructure destruction, forced displacement or fatalities (see Brück and Schindler, 2009; Justino and Verwimp, 2013; Williams, 2013; for instance).

By identifying an important role of the food transportation network in spreading the effects of violence, our paper also relates to a literature showing that reduced trade costs and better market access through improved transport links has positive impacts on economic development (Donaldson and Hornbeck, 2016; Donaldson, 2018; Chiovelli et al., 2024; Jedwab and Storeygard, 2022). We contribute to this literature by incorporating conflict along transit routes as an additional trade cost and showing that an expanded road network with more choice of alternative routes, as well as increased safety on key transportation routes, can reduce the price effects of such conflict.

Our work also relates to a literature on conflict and trade. Most closely related is the work by Besley et al. (2015) who estimate the effect of Somali piracy on international shipping costs. Other important empirical work has analysed effects of conflict on domestic trade (Korovkin and Makarin, 2023, 2022), international trade (e.g., Qureshi, 2013; Blomberg and Hess, 2006), and access of firms to foreign inputs (Amodio and Di Maio, 2018).[5]

Taken together, past research has shown that effects of conflicts can spill over to other geographic areas through, e.g., the erosion of social capital (Korovkin and Makarin, 2023), international trade flows (Qureshi, 2013; Blomberg and Hess, 2006), input-output relationships in production networks (Korovkin and Makarin, 2022; Couttenier et al., 2022), and the diversion of police presence following violent attacks (Di Tella and Schargrodsky, 2004; Draca et al., 2011). Such spillovers affect trade (Korovkin and Makarin, 2023; Qureshi, 2013; Blomberg and Hess, 2006), firm revenues (Korovkin and Makarin, 2022), aggregate output (Couttenier et al., 2022), and crime (Di Tella and Schargrodsky, 2004; Draca et al., 2011).[6]

[5]The relationship between conflict and trade has also been subject to theoretical analysis, pointing out that trade can promote peace (Martin et al., 2008) and that this balance can be persistently broken when conflict undermines future trust and trade, leading to persistent conflicts (Rohner et al., 2013).

[6]In further related papers, Yanagizawa-Drott (2014) document different mechanisms through which violent conflict itself spreads across space, König et al. (2017) provide a theory to help understand the

We add important new insights to this literature by proposing food distribution as a novel propagation mechanism of high policy relevance. Violent conflict around the world regularly affects transportation networks and the scarcity of consumer staples, so price reactions will be ubiquitous across many such contexts. The link we draw from conflict along food transit routes to first-order outcomes of individual well-being (food security, health, and education) suggests novel avenues for policy. Our findings imply that in addition to conflict-induced losses in agricultural production (see, e.g., Deininger et al. (2022) on war-induced crop losses in Ukraine), disruptions of food *distribution* also affect prices and hunger in important ways.

2 Background

The al-Shabaab insurgency. The al-Shabaab insurgency began in the mid-2000s following the collapse of the central Somali authority in the early 1990s. Al-Shabaab's aim is to impose Islamic rule across the Horn of Africa. The designated terrorist organization has engaged in sustained guerrilla warfare against the Somali government and against African Union forces operating predominantly in southern and central Somalia. See section 3.2 for descriptive statistics.

Maize production. 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—shown in figure 1a in green, with a strong concentration in the Lower Shebelle region that accounts for 80 percent of production. Traditionally, maize cultivation is rainfed in combination with labor intensive furrow irrigation, with minimal reliance on external fertilizers or mechanical tools (FAO, 2024). After harvests, farmers store the maize locally, usually in underground storages (FAO, 2018). Typically, maize is harvested twice a year in Somalia after the two main rainy seasons. The Gu rainy season runs from April to June and maize is harvested August. The Deyr rainy season runs from October to December and harvesting commences in January.[7] Lean seasons precede these harvest periods. During these times, food stocks from the previous harvest are frequently depleted, and households often experience food insecurity. In an average year, Somalia produces

patterns of armed activity when there are networks of allies and enemies, Dube et al. (2013) show how easing of U.S. gun control legislation in a border state spills over into violent crime in Mexico, Getmansky et al. (2019) analyze how smuggling activity re-locates across space after the construction of a border fence, Hjort (2014) shows how national-level ethnic tensions affect firm-level production at the micro level, and Amodio and Di Maio (2018) show that domestic conflict distorts the allocation of production inputs because it reduces firms' access to imported inputs.

[7] See https://www.fao.org/giews/countrybrief/country.jsp?code=SOM; accessed September 2024.

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. The low level of maize trade appears uncorrelated with conflict and follow droughts instead.

Small-scale farmers are responsible for approximately 70 percent of Somalia's maize production. Any surplus produced is sold to intermediaries and wholesalers, who aggregate the production of numerous small-scale farmers up together with that of medium- and large-scale commercial farmers. Wholesalers, in turn, distribute maize to retailers, who sell to consumers in local markets or shops. It is estimated that 60 percent of total production is consumed in rural areas, with 40 percent consumed by urban households (see FAO, 2024; for an overview).

Maize distribution. Somalia's road network is the primary mode of maize transportation. The country lacks rail infrastructure, and water or air transport is generally not viable. Only a few major roads are paved (see Figure 1a) while smaller roads are unpaved and often impassable during parts of the year (Government of Somalia, 2018). The road network, constructed in the 1990s, has seen little to no maintenance or upgrades since then, and road quality is widely regarded as poor.[8]

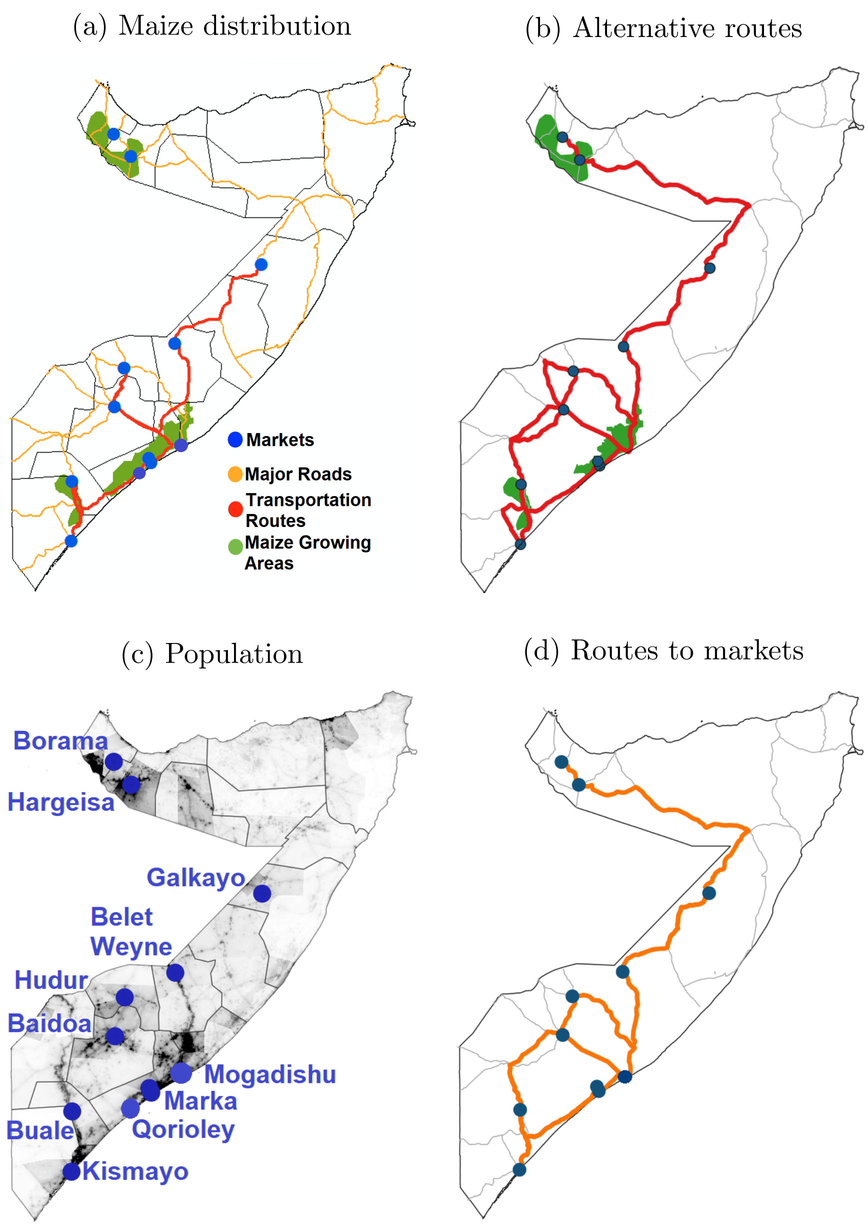
Information on maize transportation routes is provided by the Famine Early Warning Systems Network (FEWS NET), which collaborates with FAO and local government ministries. These organizations produce maps identifying the primary roads used to transport maize from growing areas to markets (see Appendix H). These maps form the basis for our identification of conflict events along transportation routes (see Figure1a).

We complement these trade maps with shortest transit routes as calculated by the mapping software Quantum GIS (QGIS). We take the Somali road network as provided by the FAO, depicted on Figure 1b (see Appendix H for the source), and specify road speeds as in Jedwab and Storeygard (2022).[9] The FAO road network closely resembles the major roads used by Jedwab and Storeygard (2022), see figure A.1g). In fact, in Appendix B we show that we would get very similar results using the major roads in their road network. As we also show, secondary roads, by contrast, do not seem to matter for food prices in our context.

[8]`https://lca.logcluster.org/23-somalia-road-network`; accessed September 2024. The stability of the Somali road network over the 2000s is also confirmed by the maps in Jedwab and Storeygard (2022)'s supplementary material.

[9]We define road speeds as follows: open road, normal traffic (60km/h), open rough road (40km/h), open traffic very slow (12km/h), open, very bad road (12km/h), and conditions unknown (12km/h).

Figure 1: Maize growing areas, markets, population density and transportation routes



Notes: Maps report geographical location of maize growing areas, selling points, and distribution network. Panel a shows location of maize growing areas together with most frequently used transportation routes for maize in a typical year according to FEWS NET trade maps. Panel b shows the network of alternative transport routes (in red) between growing areas and markets available for food transports according to the FAO. Panel c shows location of eleven major markets selling maize and Somali population density (darker shading indicates higher values). Panel d shows the network of shortest transport routes (in orange) between all markets computed from the FAO road network. **Data sources:** FAO, FEWS NET.

Importance of our markets. The eleven markets included in our analysis represent the core of Somalia's maize distribution network and provide a representative picture of national maize price dynamics. As shown in 1c), these markets are located in the most densely populated areas of the country, collectively accounting for 38% of the total population and 61% of the urban population (UNOCHA, 2005). These markets also serve as wholesale distribution centers for smaller, surrounding rural markets (FAO, 2018). The World Food Programme's Logistics Cluster identifies them as the country's major overland transportation hubs. Furthermore, these markets form the basis of the FAO's price monitoring system (FAO, 2022), which is widely used by international organizations such as the World Bank and the World Food Programme.[10]

3 Data and Descriptives

3.1 Data

We use several independent and renowned data sources. Appendix H reports the links to these. **Conflict:** Our main source of conflict data is the Armed Conflict Location & Event Data Project (ACLED), complemented with the Global Terrorism Database (GTD), and airstrike data from the Bureau of Investigative Journalism (TBIJ). The GTD contains very detailed information on the characteristics of attacks, which we exploit for causal identification and to uncover pathways of impact.

Maize prices: Monthly maize retail price data for Somalia's most important eleven markets between 2001 and 2018 are drawn from the Food and Agricultural Organisation (FAO) food price monitoring and analysis tool used in FAO's early warning systems on high food prices for vulnerable countries.

Food security, education, health, and expenditures: The main data sources are 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. The second round interviewed 6,092 households in 17 regions during December 2017. Both rounds contain information on economic conditions, food security, education, and health, as well as detailed consumption expenditure data.

Food and Non-food basket prices. From 2011 onwards, the Food Security and Nutrition Analysis Unit (FSNAU) provides monthly data on prices for food and non-food baskets.

[10] https://logcluster.org/document/somalia-operation-overview-november-2022., accessed January 2023.

These 'Minimum Expenditure Basket' (MEB) prices include the minimum quantities of essential food and non-food items necessary for basic survival. The food item basket is designed to meet a daily energy requirement of 2,100 kilocalories per person for a household of 6 to 7 members and includes prices for sorghum, vegetable oil, and sugar. Essential non-food items include water, kerosene, firewood, soap, and cereal grinding costs.

Table 1: Summary statistics

	A: All violent incidents (ACLED)				
Type of incidence	All	Battles	Civilians	Explosions	Other
Nr of incidents	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	Civilians	Explosions	Other
Nr of incidents	1,334	781	225	157	171
% of total		58.5%	16.9%	11.8%	12.8%
	C: Household and child characteristics (SHFS)				
	Below pov line	Too little food	Literacy	School enrollment	Improved sanitation
Mean	0.47	0.25	0.57	0.47	0.10
Observations	6,417	6,417	6,417	8,134	n.a.

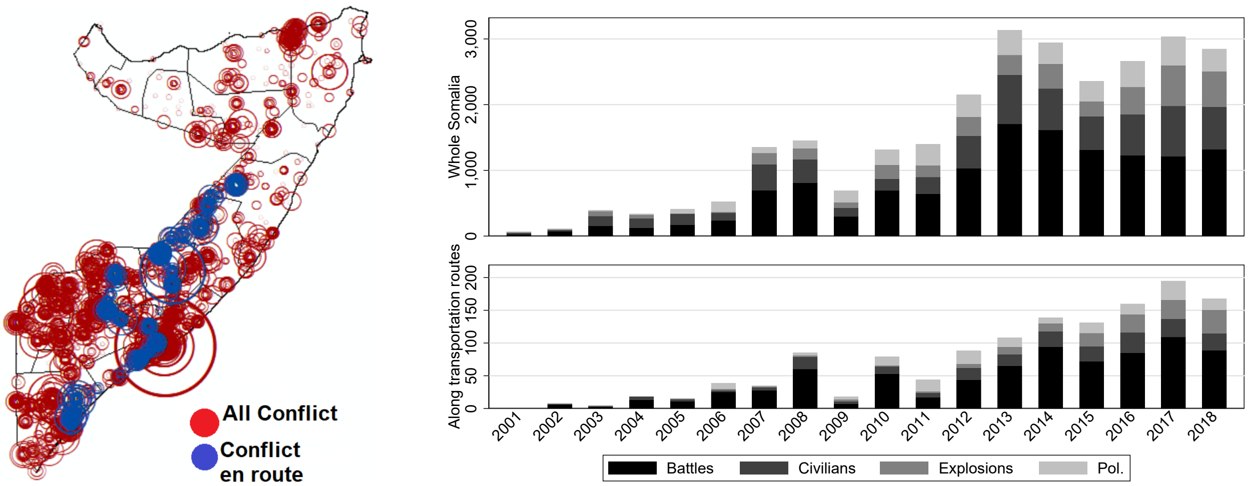
Notes: Table reports summary statistics on conflict and characteristics of households in Somalia. Panel A: reports incidents of conflict in Somalia by type (based on ACLED); Panel B: reports incidents of conflict within 5 kilometres either side of transportation routes (outside cities) by type (based on ACLED); Panel C: 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).

3.2 Conflict in Somalia

According to ACLED, between the years 2001 and 2018 the country experienced 27,169 incidents 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'. As panel B shows, attacks along transportation routes (outside cities and towns) make up about 5% of all

Figure 2: Conflict in Somalia - Geographical and temporal variation

(a) Geography (b) Timing



Notes: Figure reports geographical and temporal variation of incidents of conflict in Somalia between 2001 and 2018. Panel a: shows geographical location of incidents of conflict occurring anywhere (red) and along transportation routes (blue); radii are proportional to number of fatalities. Panel b: shows temporal variation in all incidents of conflict (top) and conflict along transportation routes (bottom) by classification. Panel c: shows the share of attacks along transportation routes affecting 1, 2, or more markets. **Data source:** ACLED.

attacks and exhibit a similar distribution across types of violence. According to the GTD, Somalia experienced 4,498 terrorist attacks during the same time period, see panel A of Appendix Table A.1. Figure 2a shows the wide geographical distribution of attacks.

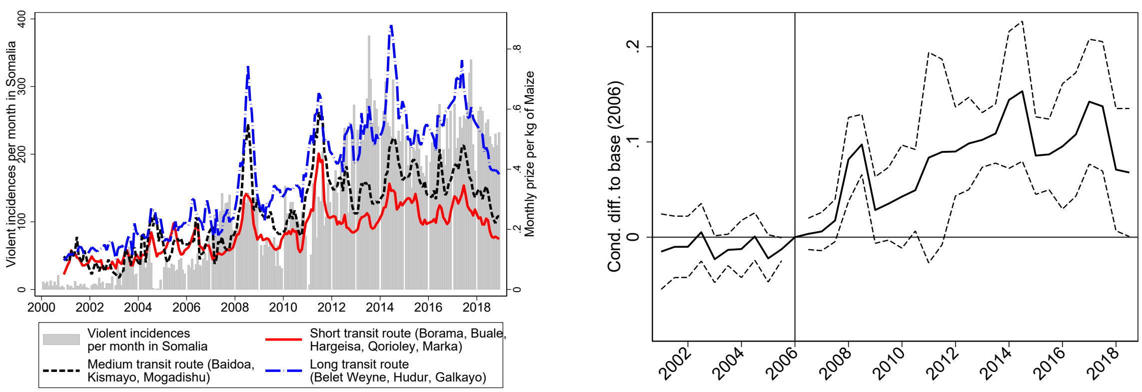
The evolution of attacks over time (Figure 2b) reveals a sharp increase of violence as a result of the al-Shabaab insurgency from the mid-2000s onwards. A comparison of conflict in Somalia and along transportation routes only (blue circles in figure 2a) shows not only a similar temporal pattern but also similar classifications in terms of the types of violence (lower panel of figure 2b). Since some markets are located along the same transportation route, a single attack can impact multiple markets. Approximately 30% of attacks along transportation routes affect one market and around 30% two markets. The roughly 40% of attacks that affect more than two markets at varying distances are a fact we exploit to estimate how far away the effect of attacks can be detected (section 4.4).

3.3 Conflict along routes and maize prices: 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 the price in three groups of markets: locations with a short (Borama, Buale,

Figure 3: Price of maize over time

(a) Averages by distance (b) Conditional event study



Notes: The figure reports conflict and maize prices over time in Somalia. Lines denote monthly maize prices and bars monthly incidents of conflict. Panel a: shows monthly maize price for three groups of markets: short transit routes (Borama, Buale, Hargeisa, Qorioley, and Marka in red), medium transit routes (Baidoa, Kismayo, and Mogadishu in black), and long transit routes (Belet Weyne, Hudur, and Galkayo in blue). Panel b: shows point estimates (solid lines) and 95% confidence intervals (dashed lines) for 6-month dummies interacted with the log of the aerial distance between each market and its supplying growing area (in km), using the first half of 2006 as the reference period. Regression controls for market, year, and month fixed effects. **Data sources:** ACLED, FAO.

Hargeisa, Qorioley, and Marka in red), medium (Baidoa, Kismayo, and Mogadishu in black) and long transportation route (Belet Weyne, Hudur, and Galkayo in blue) from their nearest growing area. Appendix figure A.3 reports the prices for all 11 markets separately. Before the al-Shabaab insurgency in the early-2000s, prices in all three groups are similar and show parallel trends. After the onset of the insurgency, exposure to attacks en route is likely to increase with the length of transportation routes. Accordingly, figure 3a shows that price increases are strongest for the markets with long transportation routes, less pronounced for markets with medium transit routes, and smallest for the markets located close to growing areas. Figure 3b illustrates the same patterns as a conditional event study in which we allow the coefficient on the interaction between log aerial distance between each market and its supplying growing area to vary in 6-monthly intervals, relative to the first half of 2006. Before the stark increase in violence roughly around 2006, the relation log distance on maize prices was stable. As violence increases, so does the association between log distance and maize prices.

4 Spatial Spillovers on maize prices, food security, and human capital

4.1 Empirical strategy

To identify spatial spillovers of conflict, we start by examining whether conflict along transportation routes has detectable impacts on prices in destination markets that can be located hundreds of kilometres away from where the violence occurs. A simple trade-cost framework motivates this relationship. In our context, maize is a homogeneous commodity and each destination market is supplied by a single location of origin.[11] This implies that the price of maize p_{itm} at a destination market i in year t and month m is a function of the origin price and the trade cost, leading to the following equation:

$$\ln p_{itm} \quad = \quad \ln \tau_{iotm} + \ln p_{otm}, \tag{1}$$

where p_{otm} is the price at the origin location and τ_{iotm} is an 'iceberg' trade cost between origin o and destination i.[12]

Conflict along the transportation route between origin and destination is likely to be an important determinant of trade cost. In our reduced-form approach we thus replace τ_{iotm} by the number of violent incidents along the route supplying market i with maize ($conflict_{route_{itm}}$), while controlling for other components of trade cost and determinants of the origin price, as explained below. This motivates the regression specification

$$\begin{aligned} \ln p_{itm} \quad &= \quad \alpha_1 conflict_{route_{itm}} + \alpha_2 conflict_{local_{itm}} + \alpha_3^T X_{itm} \\ &\quad +\eta_i \times \tau_t + \eta_i \times \mu_m + \epsilon_{itm}, \end{aligned} \tag{2}$$

where α_1 captures our spatial spillover effect of interest. To measure incidents of conflict occurring along transportation routes ($conflict_{route_{itm}}$), we draw a corridor of 5 kilometres either side of the transportation route to each of our eleven markets. In our baseline approach we use the maize transportation routes as identified by the FEWS NET trade maps (see section 2 and Figure 1a). We then match these eleven corridors to the geographical coor-

[11]The fact that each destination is supplied by a single location is supported by the FEWS NET trade maps, and by our result in Table 2 showing that attacks on routes to alternative growing areas are irrelevant.

[12]In non-logarithmic form, $p_{itm} = \tau_{iotm} p_{otm}$. The term 'iceberg' trade cost for $\tau_{iotm} \geq 1$ conveys the intuition that, similarly to an iceberg, part of the product 'melts' away during transport, i.e., τ units need to be produced for one unit to arrive, raising the unit cost by the factor τ. For a similar set-up, in which the difference between the price at origin and the price at destination identifies trade costs for a homogeneous good with fixed origin-destination pairs, see Donaldson (2018).

dinates of violent incidents (either from the ACLED or the GTD data) and sum the number of incidents occurring within each corridor per month, but excluding any violent incidents occurring within a radius of 15km around market i itself, or around cities or towns located along the transportation route. The reason to exclude urban areas along the route is that they can typically be crossed via multiple routes, making the definition of the transportation route ambiguous in these areas.[13]

In line with previous research, we also examine the role of violent incidents occurring in the vicinity of markets defined as $conflict_{local_{itm}}$, which counts the number of violent events in year t and month m occurring within a 15km radius of market i.

In X_{itm} we include growing-season specific rainfall as a control, an important determinant of food prices (e.g., FAO 2011), i.e., the price at origin in (1). This also helps to control for droughts, that have been shown to affect conflict (Harari and La Ferrara, 2018).[14] In extended versions of eq. (2), X_{itm} will be augmented to include variables such as lagged values of conflict, or conflict in additional geographical locations. Finally, we include market-by-year ($\eta_i \times \tau_t$) and market-by-month ($\eta_i \times \mu_m$) fixed effects.

This reduced-form approach assumes fixed and known transport routes between given origin–destination pairs. In this case, alternative route choices can be ignored, and market fixed effects capture the typical travel time between origin and destination—a key component of the trade cost τ_{iotm} in equation (1). In section 4.2 we extend this baseline approach by using fastest routes calculated via mapping software and allowing for alternative routes. In section 5 we introduce additional structure to model τ_{iotm} as a function of both travel time and violent conflict, allowing us to quantify the trade-off between these two components of trade cost.

Identification. To obtain an unbiased estimate of the spatial spillover effect α_1, we must rule out unobserved confounders that influence market prices and correlate with violent conflict along transportation routes. Our baseline approach tackles this in two ways. First, the inclusion of market-by-year and market-by-month fixed effects implies that equation (2) is identified from within-market deviations from yearly and calendar-month averages. This controls for time-varying, market-specific unobservables, such as the differential effects of a

[13]Two examples of trade routes to individual markets are provided in parts (a) and (b) of Appendix Figure A.1, and part (e) of that figure provides an example of attacks falling within the 5 kilometre corridor. Since $conflict_{route_{itm}}$ captures the total number of attacks irrespective of route length, we control for market fixed effects throughout to account for distance differences.

[14]We use cropland-specific rainfall data from the United Nations' World Food Programme and average precipitation in the growing area supplying maize over the previous growing season (either Gu or Deyr). In Appendix A, we use two alternative measures—the Standardised Precipitation-Evapotranspiration Index (SPEI) and maize production—with very similar results.

drought across markets in a given year. The specification also accounts for market-specific seasonal price patterns that may correlate with seasonal variation in violence. Moreover, if traders form expectations about the timing and location of violence, these fixed effects can be interpreted as capturing each market's expected levels of conflict by year and month. In this case, identification comes from the residual, unanticipated variation in conflict exposure.

Second, our research design leverages the structure of the food transportation network to causally identify the effect of conflict on distant markets. The conflict measure $conflict_{route_{itm}}$ captures violence occurring along maize transport routes, excluding incidents near destination markets. As a result, the estimated spillover effect α_1 is identified from conflict incidents that occur well outside the regions where prices are measured. This spatial separation helps rule out a broad range of standard endogeneity concerns.

For example, a common problem in analyzing 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 $conflict_{route_{itm}}$.[15] 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.[16] Nevertheless, in Appendix C we discuss potentially remaining endogeneity concerns and address them through a range of identification checks.

Spatial spillover effects on food security and human capital To explore the broader implications of conflict beyond food prices, we examine whether violence along transportation routes also affects household-level outcomes related to food security, health, and education. For this analysis, we use a similar research design to equation (2) with outcomes measured for household j in year t and region r, based on the SHFS household survey. As above, we determine which growing area supplies region r with maize and define $conflict_{route_{jtr}}$ as all incidents of conflict occurring within a 5km corridor either side of the transport route from the respective growing areas to the markets in region r. Since we do not know the exact location of respondents, we exclude any violent incidents occurring within the same

[15] Moreover, 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.

[16] This 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.

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent variable: log prize of maize						
Conflict en route	0.0038 (0.0014)	0.0037 (0.0014)	0.0029 (0.0013)	0.0028 (0.0014)	0.0031 (0.0011)	0.0038 (0.0014)	0.0097 (0.0033)
Conflict 15km around market		0.0011 (0.0008)	0.0011 (0.0008)	0.0011 (0.0008)	0.0012 (0.0008)	0.0011 (0.0008)	0.0010 (0.0008)
2nd and 3rd shortest routes				0.0011 (0.0018)			
All alternative routes					−0.0007 (0.0018)		
Shortest route to 2nd growing region						−0.0026 (0.0016)	
Conflict en route × lean season							−0.0071 (0.0032)
Observations	2,085	2,085	2,085	2,085	2,085	2,085	2,085
R^2	0.925	0.925	0.925	0.925	0.925	0.925	0.926
Wild Bootstrap p-value	[0.002]	[0.002]	[0.059]	[0.131]	[0.003]	[0.004]	[0.014]
Random. inf. p-value	[0.003]	[0.003]	[0.023]	[0.034]	[0.015]	[0.003]	[0.001]
Shortest route as defined by	FEWS NET	FEWS NET	Mapping software	Mapping software	Mapping software	FEWS NET	FEWS NET

Notes: Table reports effect of incidents of conflict occurring along transportation routes on maize prices. Estimations are based on equation (2). Dependent variable is log price of maize. *Conflict en route* counts incidents of conflict per month occurring 5 kilometres either side of the transportation route supplying maize to each market, excluding attacks within a 15km radius of market; *Conflict 15km around market* denotes incidents of conflict occurring within a 15km radius of each market; *2nd and 3rd shortest routes* counts incidents of conflict per month occurring 5 kilometres either side of the second and third fastest transportation routes excluding any attacks occurring on the shortest route and any attacks within a 15km radius of market; *All alternative routes* counts incidents of conflict per month occurring 5 kilometres either side of all alternative transportation routes (up to 9) excluding any attacks occurring on the shortest route and any attacks within a 15km radius of market; *Shortest route to 2nd growing region* counts incidents of conflict per month occurring 5 kilometres either side of the transportation route to the second closest maize growing area, excluding attacks within a 15km radius of market; *lean season* = 1 during months of lean season (January, February, March, April, August, September); all regressions control for rainfall (in mm) during previous growing season; Standard errors are clustered at the market level and in parentheses; Wild Cluster Bootstrap (Roodman et al., 2018) and Randomisation Inference (Hess, 2017) p-values for *Conflict en route* (1,000 replications) are reported in brackets. **Data sources:** ACLED, FAO, FEWS NET.

administrative unit. Given that retrospective questions cover different recollection periods, we adjust the period over which we measure incidents of conflict accordingly.

4.2 Baseline results

Table 2 reports our baseline results. One incidence of conflict along the transportation route ($conflict_{route_{itm}}$ in equation 2) increases the price of maize by 0.38 percent (column 1). For a one standard-deviation change in conflict this translates to a 1.4% effect, which is sizeable and amounts to 15% of the standardized effect of rainfall in the closest growing area, 20% of the standardized effect of maize production in the growing area, and 44% of the standardized effect of the Standardized Precipitation-Evapotranspiration Index (SPEI), a commonly used measure for the severity of drought conditions (see columns (8)-(10) in Appendix Table A.3). Given that our sample consists of eleven markets, we also estimate p-values using two alternative methodologies: the Wild Cluster Bootstrap (Roodman et al., 2018) and Randomisation Inference (Hess, 2017) methods. Our estimates remain statistically significant.[17]

Column (2) controls for local conflict ($conflict_{local_{itm}}$ in equation 2) measured as violent incidents occurring 15km around market i. The coefficient on conflict en route remains virtually unchanged.[18] Additional estimates in appendix table A.2 show that the effects are driven by battles (such as armed clashes) and violence against civilians (such as forced disappearances), which together make up for almost 75% of violent conflicts.

To substantiate that we have indeed identified the most relevant trade routes, the next columns of Table 2 report results for alternative route definitions. In column (3), we use shortest paths between growing areas and markets computed from mapping software based on the FAO road network depicted in Figure 1b, and taking into account different road speeds as in Jedwab and Storeygard, 2022—see section 3 for details. Using attacks on these shortest routes, we find similar, albeit slightly smaller effects compared to our baseline approach.

To investigate the importance of alternative routes supplying market i with maize, we apply a depth-first search algorithm (Black, 2008) to establish all simple (non-cyclical) paths between each market and its growing area. The very basic nature of the Somali road network only allows for a relatively limited number of alternative routes between each origin-destination pair, with our algorithm identifying up to nine alternatives per market, in total 41 routes for all 11 markets combined. See Appendix Figure A.4 for a map of these. This inclusion leaves our effects virtually unchanged, and the effect of conflict along the routes to other markets is small and not statistically significantly different from zero (see columns (4)

[17]We use a wild bootstrap with 999 replications at the market level using the command *boottest*. We also carry out a randomization inference with 1,000 replications using the command *ritest*.

[18]The likely reason for the very small and insignificant effect of local violence is that market areas in our context are made up of comparatively large cities and the effect of an incidence of violence within a large area on the price of maize is much more diffuse compared to a violent incidence along the exact transportation route for maize that is relevant to that market.

and (5)). In column (6), we further show that attacks on the shortest route to the second-closest growing area do not matter. Together these findings suggest that in our baseline approach we have identified the most relevant trade routes, and that alternative routes play little role. In section 5 we model endogenous road choice explicitly.

To substantiate that our baseline results do not pick up spurious effects, we exploit the fact that the production of maize and thus the amount transported along roads varies along the crop calendar with its two rainy seasons, the Deyr and the Gu (see section 2). We would expect violence along the route to have smaller price effects during lean season, when stocks are running low and less maize is transported along roads.[19] Indeed, in column (7) of table 2, we find that the effect of conflict occurring during high seasons is almost 1 percent per attack whilst the estimate for lean seasons is around 0.0026 (0.0097-0.0071).

As we show in Appendix B, our results are highly robust across a wide range of specifications, including variations in conflict type and measurement, sample composition, econometric specifications, lag structures, placebo outcomes, and the sequential exclusion of markets.

Moreover, in Appendix C we rule out a number of identification threats to our findings. For example, we address the possibility of combatants targeting particular areas based on time-varying, unobserved factors by exploiting the inherent randomness in success rates of attacks (Jones and Olken, 2009; Brodeur, 2018). We also provide evidence against the concern that our results are contaminated by highly correlated conflict shocks or by omitted variables at a supra-regional level by showing that our effect is precisely driven by attacks along the transportation network while attacks occurring in the same areas but away from transport roads have no effect. As an additional check, we use goods transported along other routes as placebos and estimate the effect of terrorist attacks in general and dropping any incidents aimed at the food transportation network. Appendix D investigates price reactions to well-defined events. We find that maize prices decreased as a result of the Galkayo Ceasefire and incapacitation of al-Shabaab by US airstrikes. By contrast, prices increased significantly during the Battle of Belet Weyne.

4.3 Mechanisms

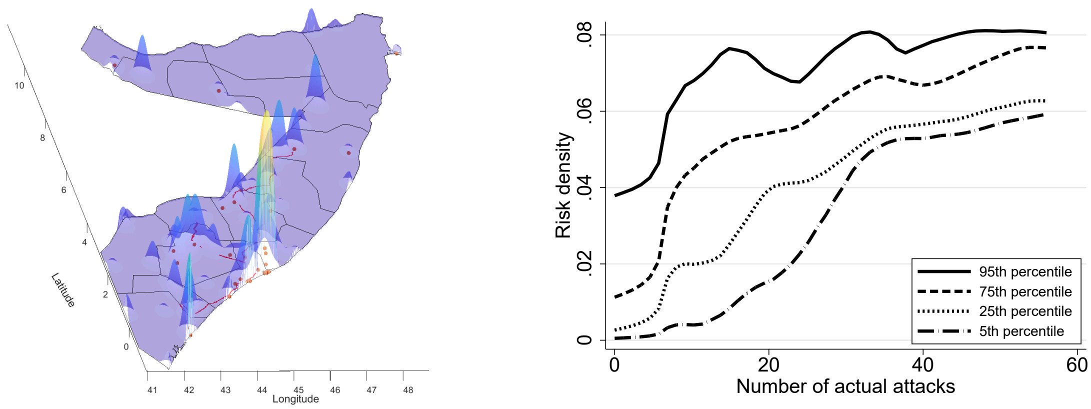
Having shown that conflict along transport routes raises maize prices in distant markets, we now explore the underlying mechanisms. Several channels may be at work. First, anticipated violence may heighten safety concerns, increasing transport cost through additional safety measures, changes to shipment schedules or routes, or risk compensation for transport crews (Besley et al., 2015). Second, conflict en route may increase prices via destruction of

[19] We define *lean seasons* as the three months before and including the first harvesting month (May to July and October to December).

Figure 4: Attack risk and actual attacks

(a) Density and attacks across space

(b) Density variation conditional on attacks



Notes: Panel a: The figure shows the density for the occurrence of attacks across longitude and latitude in Somalia for the 15th March 2007 as an example. It is derived from multivariate kernel density estimates across longitude, latitude and time following the method developed by Tapsoba (2023). Higher elevation levels represent a higher probability density for the occurrence of attacks. The red dots represent actual attacks that occurred in the same month. Panel b: The figure plots percentiles of the attack risk density aggregated along transportation routes as a function of the number of actual attacks along these routes at the market-month level, estimated using a local polynomial regression with an Epanechnikov kernel and a bandwidth of 3. Actual attacks are measured over the current and preceding six months, consistent with the period used to estimate attack risk (see Appendix E for details). To improve readability, the horizontal axis is trimmed at the 95th percentile of actual attacks. **Data sources:** ACLED.

transport infrastructure or maize supply. Finally, as a result of these mechanisms, traffic and shipment volumes might decline. Our findings point to safety concerns as a key driver of price increases, with some evidence of reduced transport volumes. In contrast, destruction of infrastructure or maize supply appear less important.

Attack risk and realized attacks. To isolate the role of safety concerns, we distinguish between realized attacks and perceived attack risk. Whilst attack risk and realized attacks both can generate safety concerns, only realized attacks can destroy infrastructure.

We derive a measure of attack risk from a kernel density estimation of the distribution of attack events across space and time as suggested by Tapsoba (2023)—see Appendix E for detail. Figure 4a) provides an example comparing actual attacks (denoted as dots) to attack risk (denoted as multicolored peaks) for March 2007. Whilst actual attacks often coincide with attack risk (such as in Mogadishu), some attacks occur in places with no elevated density, suggesting no recent violence. Moreover, some density peaks exist where no attacks happened, suggesting an elevated risk predicted from the occurrence of nearby attacks over recent months. Figure 4b) plots percentiles of the attack risk density aggregated along transportation routes against the number of actual attacks along these routes. It shows a positive correlation between attack risk and actual attacks, but also substantial variation in risk conditional on the number of attacks. Appendix Figure A.5 further confirms that attack risk and observed attacks exhibit similar temporal patterns.

After summing up the density estimates along transportation routes, we create a dummy variable indicating a high attack risk (density in the upper quartile) along the route. In column (1) of Table 3 we report results from including this dummy into our baseline specification and find that a high attack risk increases prices by around 6 percent. In column (2), the effect of attack risk remains very similar when we add actual violence along transport roads. The effect of realized violence along transit routes retains a strong independent effect, albeit slightly smaller than the effect from our baseline specification in Table 2. Because the density estimation for the attack risk takes into account violent incidents that occurred over the recent past, it could in principle pick up persistent effects of past attacks. In column (3), we therefore additionally control for dummies indicating the decile bins of the total number of attacks that occurred over the past 6 months. When controlling flexibly for past attacks in this way, the effect of the attack risk remains very stable.[20] We conclude from this exercise that prices react to the risk of attacks independently of actual attacks, suggesting that safety concerns triggered by heightened attack risk play an important part in increases maize prices.

Characteristics of attacks Next, we examine which types of attacks have the greatest impact, as this can offer further insight into the underlying mechanisms. Using detailed GTD data, we classify incidents by their target and damage profile. First, we identify terrorist attacks that damage property and find that these affect prices much less than attacks that do not (column 4 of table 3). Moreover, attacks classified as kidnappings and hijackings as well as armed and unarmed assaults show a much stronger effect on prices (column 5). Finally, in columns (3), (4), and (5) of Appendix Table A.3 we use the precise geographical coordinates of attacks to corroborate the importance of safety concerns. The results show that violent incidents occurring between 2.5km and 5km from roads increase maize prices. Since these attacks cannot damage infrastructure or injure drivers, an effect through perceptions of risk appears likely.

Destruction of maize supply Could conflict in growing areas reduce maize production and thereby raise prices? To test this, we construct a variable capturing violent incidents in

[20]In Appendix Table A.6 (columns 5 and 6) we further show that we find similar results when including the aggregated density along transport routes as a linear regressor rather than a high-risk dummy, and that the standardized effects of the attack risk and of the number of actual attacks over the past 6 months, are of a similar magnitude.

Table 3: Effect of conflict along route on maize price - Mechanisms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent variable: log of						
	Maize price	Maize price	Maize price	Maize price	Maize price	Maize price	Night lights
High conflict risk	0.0599	0.0561	0.0551				
	(0.0253)	(0.0260)	(0.0270)				
Conflict en route		0.0031	0.0030			0.0037	−0.0102
		(0.0014)	(0.0010)			(0.0014)	(0.0009)
Conflict en route (no prop. damage)				0.0290			
				(0.0077)			
Conflict en route (prop. damage)				0.0024			
				(0.0053)			
Kidnappings					0.0283		
					(0.0071)		
Conflict in agricultural areas						0.0029	
						(0.0016)	
Conflict dummies (last 6 months)			yes				
Observations	2,085	2,085	2,085	2,085	2,085	2,085	238
R^2	0.926	0.926	0.927	0.925	0.926	0.925	0.877

Notes: Table reports effect of conflict along maize transportation routes on the price of maize. Estimations are based on equation (2). Dependent variable is the log of the price of maize apart from column (7) 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 attacks carried out within a 15km radius of market and for season specific rainfall in growing region. *Conflict en route* counts terrorist attacks (based on GTD) or incidents of conflict (based on ACLED) per month occurring 5 kilometres either side of the transportation route supplying maize to each market, excluding attacks within a 15km radius of market; *High conflict risk* uses the method proporsed by Tapsoba (2023) to calculate the predicted number of attacks per month occurring 5 kilometres either side of the transportation route supplying maize to each market, excluding attacks within a 15km radius of market. *High conflict risk*=1 if conflict risk is above the 75th percentile. *Conflict en route (no prop. damage)* and *Conflict en route (prop damage)* denote terrorist attacks en route that do not and that do lead to property damage respectively, *Kidnappings* denotes terrorist attacks en route that are classified as kidnappings, hijackings, armed and unarmed assaults, *Conflict in agricultural areas* denotes terrorist attacks in area where maize is cultivated that supplies each market (excluding roads and cities within that area). Column (3) also controls for decile bin dummies for conflict along transportation roads in the last six months.
Data sources: ACLED, FAO, FSNAU, GTD, NASA.

rural parts of the growing area only, excluding cities and roads. Adding attacks in growing areas into the regression in column (6) of Table 3 shows that these attacks have their own effect on prices. Crucially, however, the coefficient on conflict en route remains virtually unchanged. Thus, destruction of produce in growing areas is not driving our main results. This is corroborated by our finding in column (10) of Appendix Table A.3, which shows that our results remain robust to controlling for maize production.

Road traffic. Finally, we provide suggestive evidence for conflict along transportation routes decreasing road traffic frequency. We use the Visible and Infrared Imaging Suite (VIIRS) Day Night Band (DNB) data, the increased precision of which has arguably made it possible to measure road traffic using nightlight emissions (see Chang et al., 2020; for instance). To this end, we calculate light emissions 1km either side of maize transit routes *excluding* any emissions from cities or towns along roads (see red lines in Appendix Figure A.1g) for an example). See Appendix I for details on data pre-processing. We focus on Somalia's major road connecting Lower Shebelle with Mudug, which encompasses the three markets of Galkayo, Qorioley, and Marka as well as the road connecting Hargeisa to its supplying region in the north, and where nightlight density on roads only is strong enough to detect.[21] The result in column (7) of Table 3 shows that conflict along roads decreases nightlights along these roads by around 1 percent. This tallies with anecdotal evidence that safety concerns disrupt road travel in Somalia[22], and that traveling in the hours of darkness is affected by security concerns.[23] This negative effect on road traffic suggests decreased maize supply in market areas as a possible pathway of impact. Alternatively, it could indicate higher transport costs, as drivers have to pause at nights, or as they use (potentially longer) alternative transport routes, a mechanism that we will explore more directly in section 5.

4.4 Reach of spillovers across space and time

Spatial spillovers of conflict have important implications for the targeting of policies. Accordingly, it is crucial to understand both the spatial and temporal range over which conflict affects outcomes. To investigate this, we estimate the effect of conflict on transport roads in growing areas only, distinguishing markets by their distance from these areas and considering different time lags.[24]

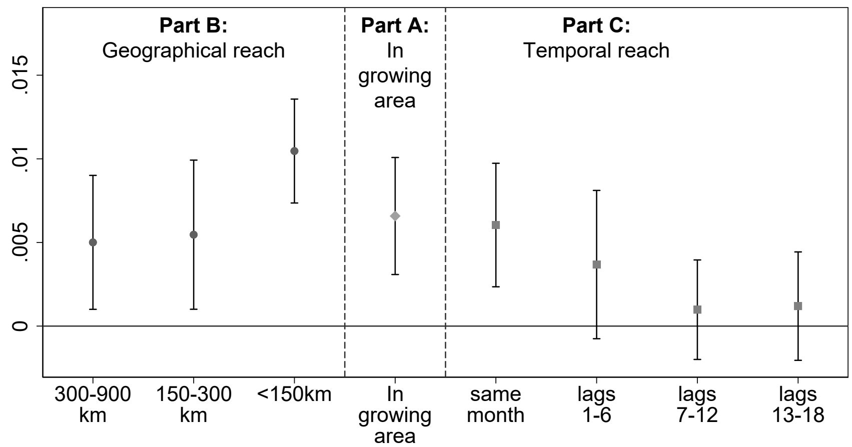
[21]This selection combined with the fact that nightlight data are only available from late 2012 onwards explains the smaller sample sizes.

[22]`https://landinfo.no/asset/3569/1/3569_1.pdf`. accessed January 2025.

[23]`https://reliefweb.int/report/somalia/road-tanzania-somalia` accessed January 2025.

[24]The 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

Figure 5: The long reach of conflict



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. Part A: reports parameter estimate for conflict occurring in the current month on transportation route in the growing area supplying each market with maize. Part B: groups markets into three bins for less than 150 kilometres (markets of Borama, Buale, Marka, Qorioley and Hargeisa), 150 to 300 kilometres (markets of Baidoa, Kismayo and Mogadishu) and 400 to 900 kilometres (markets of Belet Weyne, Hudur, and Galkayo). Part C: reports parameter regression for conflict in growing areas along with the sum of attacks occurring 1 to 6 months, 7 to 12 months, and 13 to 18 months before the current month. **Data sources:** ACLED, FAO.

Reach across space Part A of Figure 5 shows that each attack occurring on the road in growing regions increases the price of maize by 0.65 percent. This is slightly larger, although not statistically significantly different, from our baseline effect in column (1) of Table 2. Part B of Figure 5 shows the effect of conflict along roads in growing areas obtained from grouping markets into three bins: markets located less than 4 hours (markets of Borama, Marka, Qorioley and Hargeisa), 4 to 6 hours (markets of Baidoa and Mogadishu) and 7 to 14 hours (markets of Belet Weyne, Buale, Hudur, Galkayo, and Kismayo). For the nearest markets, the effect of violent incidents in growing regions is very strong, around 1 percent per attack. The strength of the effect decreases with distance, but we can still detect important and statistically significant effects of around 0.5 percent per attack for the markets that are up to 14 hours away from where the violence occurs (corresponding to 900km).

Reach across time To explore the temporal reach of conflict, we regress maize prices on $conflict_{growing_{itm}}$ along with its 18 month lags aggregated into 3 groups (1–6, 7–12, and 13–18 months). The estimates in Part C of Figure 5 show that the effect of contemporaneous

Kismayo. The growing region in Woqooyi Galbeed serves the market of Hargeisa. The growing region in Awdal serves the market of Borama.

attacks remains unchanged compared to the specification without lags in Part A. Violence occurring between 1 and 6 months earlier on roads in growing areas retains an effect on current maize prices, albeit of a slightly smaller magnitude. Earlier attacks, by contrast, do not appear to matter. In Appendix Table A.8 we show that the effect of violence occurring 1 to 6 months in the past is not driven by any particular months (column 1). Importantly, columns (2) and (3) in Appendix Table A.8 show a very similar degree of persistence when we use our main measure of attacks along routes rather than attacks occurring on routes in growing areas only. Finally, in column (4), when aggregating attacks of the current and the past 6 months together into average monthly attacks over the past half year, we find that one such additional average monthly attack increases maize prices by 2.1 percent.

4.5 Spatial spillovers of conflict on food security and human capital

Thus far, we have documented that conflict along transportation routes significantly increases maize prices in distant markets. In this section, we use SHFS data to explore whether these price effects translate into broader consequences for household well-being—specifically, food security, health, and education. Descriptives in Panel C of Table 1 highlight the very low socio-economic status of the Somali population. Food security is strongly linked to food prices as shown by several policy reports for Africa[25] in general and Somalia[26] 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).

Table 4 contains results from regressing household outcomes on conflict along transportation routes to the main market city in each household's administrative area, conditional on region effects, year effects, and household characteristics (see section 4.1 for details). In column (1) we find that conflict along transportation routes increases the probability that households state in the survey that they have experienced high food prices and have changed their eating patterns as a result. Columns (2) and (3) report the effects on the consumption of maize and of sorghum, the closest substitute to maize. The estimates suggest a reduction in the consumption of maize (though not statistically significant), accompanied by an increase in the consumption of sorghum. The relatively small sizes of these substitution effects tally with previous work documenting the slow changing nature of nutritional behavior (Atkin, 2013, 2016).

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

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

Table 4: Effects on hunger, spending patterns, health and education

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	High prices affecting food	Log quantity consumed		Household spent savings	Index of non-food spending	Child suffered from		Not enrolled in school (aged 6-14)
		Maize	Sorghum			Any illness	Infectuous illness	
Conflict en route (excl. same region)	0.008	-0.018	0.034	0.004	-0.259	0.004	0.005	0.0043
	(0.003)	(0.017)	(0.012)	(0.002)	(0.048)	(0.002)	(0.001)	(0.0018)
Observations	5354	8,137	8,113	2442	5759	8180	8180	8134
R^2	0.02	0.12	0.10	0.019	0.111	0.042	0.062	0.429
Mean	0.01	-	-	0.07	6.72	0.18	0.11	0.47

Notes: Regressions control for region and year effects, attacks in own area, household size, proportion literate in household, gender of household head, and household below poverty line, and child-level regressions in columns (6)-(8) additionally control for child age dummies. The outcomes in columns (1), (4) and (6)-(8) are dummy variables. The index in column (5) is the sum of eight dummies indicating any spending in eight non-food categories. Variable and sample definitions are explained in more detail in Appendix F. Robust standard errors clustered at the region level are in parentheses. **Data sources:** ACLED, SHFS.

Column (4) of Table 4 shows that 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 5).[27]

Next, we show that conflict along transportation routes affects child health and education in market areas. This could occur through several channels High food prices may generate an income effect that leads households to reduce spending on health and education.[28] Households may also respond by increasing labor supply, such as taking children out of school to work.[29] Food insecurity associated with high prices can further impair children's ability to learn.[30]

Columns (6) and (7) of Table 4 report effects of conflict occurring on far-away transportation routes on health outcomes of children aged below 10 years. We find no general effect on having suffered any illness over the past two months, but we find that an increase in conflict en route and at some distance from respondents indeed infectious illnesses by about

[27] This 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).

[28] A growing body of research by nutritionists and economists has also established a negative relation between nutrition and schooling (see Behrman et al., 2004; Glewwe and Miguel, 2007).

[29] A number of papers have established a link between food prices and education (Raihan, 2009; Grimm, 2011; Singh and Vatta, 2013; Baten et al., 2014).

[30] Policy makers also recognize hunger and malnutrition as important impediments to good health and schooling (see World Food Programme and the FAO, `https://www.wfp.org/news/fao-and-wfp-join-forces-boost-childrens-right-food-schools`, accessed August 2022, for a recent example).

half a percentage point (column 2), an effect of five percent relative to the mean. This is in line with well-known links between malnutrition and infectious diseases (Scrimshaw, 2003; Black et al., 2008; Calder, 2013). It suggests food insecurity to be a likely channel and makes alternative explanations less likely. For example, if medical drugs were transported on the same transport routes as maize, then conflict along the route could lead to drug shortages that adversely affect health. Yet, if this were the case, there would be no immediate reason why only infectious illnesses should be affected.[31]

Finally, 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. 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 (e.g. Bertoni et al., 2018; Alfano and Görlach, 2024).[32]

5 A trade cost model for maize

Our baseline results up to this point are based on a reduced-form approach that assumes traders follow fixed routes from growing areas to markets. However, traders may adjust their routes in response to conflict, opting for longer but safer alternatives. To capture this response, we extend the trade-cost framework in (1) to allow conflict to alter route choice, thereby affecting trade costs and maize prices. This more structural framework allows us to quantify the trade-off between travel time and conflict risk. Importantly, this enables us to simulate policy-relevant counterfactuals, offering insights into how improved safety or better road infrastructure could alleviate the adverse effects of conflict on trade and prices.

5.1 Estimation framework

Consider the trade-cost framework from equation (1), where trade costs are now indexed by a superscript r to reflect that, for a given origin–destination pair and time period, traders may choose among multiple alternative routes r.

$$\ln p_{dt} \quad = \quad \ln \tau^{r}_{odt} + \ln p_{ot} \tag{3}$$

[31]As column (1) in Panel B of Appendix Table A.10 shows, we find no effect on non-infectious illnesses, which are much less likely to be affected by malnutrition. The remaining columns of that panel contain a break-down of 'any infectious illness' into its specific components.

[32]To check to what extent conflict-induced migration may affect our results in this section, we run robustness checks where we exclude households that have migrated in the past. The results are in Table A.11 in the Appendix and show that our main conclusions carry through in the sample that excludes migrated households.

We assume that at every point in time, traders choose the lowest cost trade route r^* amongst the available routes between an origin and a destination. Trade costs on the realized route are

$$\tau_{odt}^{r^*} = \min\{\tau_{odt}^{r}\}. \tag{4}$$

We model trade costs, τ_{odt}^{r}, as a function of travel time (speed-weighted distance) between o and d on route r and the number of violent attacks along that route in the respective period as

$$\ln \tau_{odt}^{r} = \mu + \gamma \ln \left[traveltime_{od}^{r} (attacks_{odt}^{r} + 1)^{\alpha} \right]. \tag{5}$$

The parameters γ and α capture the effects of travel time and attacks along the road on trade costs. In absence of attacks, the term in brackets reduces simply to travel time. For a given positive number of attacks, travel time gets augmented by a proportionate factor greater than one. Combining equations (3) – (5) yields the regression model

$$\ln p_{dt} = \mu_{ot} + \mu_{od} + \gamma \ln \left[traveltime_{od}^{r^*} (attacks_{odt}^{r^*} + 1)^{\alpha} \right] + \eta_{rodt}, \tag{6}$$

in which the price at origin is absorbed by an origin-by-time fixed effect, μ_{ot}, and an origin-destination-market effect, μ_{od}, controls for time-constant characteristics of the origin-destination market pair.[33] The variables of interest, $traveltime_{od}^{r^*}$ and $attacks_{odt}^{r^*}$, are switching regressors that capture the travel time and the number of attacks on the lowest cost route between origin and destination in period t—and the determination of the most cost effective route depends itself on the parameters to be estimated. We estimate equation (6) by non-linear least squares. Although, in principle, $traveltime_{od}^{r^*}$ varies within markets as traders choose the optimal route r^* between origin and destination in response to attacks, we find this variation to be very limited.[34] We therefore identify γ in a first step from between-market variation.

To identify γ independently of conflict, we take advantage of our unique setting in which we have access to a conflict-free pre-period. We exploit the fact that the al-Shabaab insurgency started in the mid-2000s and regress log maize prices on travel time of the shortest route in the year 2001, in which attacks are close to zero, controlling for market size and

[33] Our estimation equation is similar to equation (12) in Donaldson (2018), which models higher-cost transport modes—rather than violent attacks—as proportionate increases in effective distance.

[34] As we discuss in detail below, the reason for the lack of within-market variation of $traveltime_{od}^{r^*}$ is the absence of alternative route use between given origin-destination pairs, due to alternative routes being considerably longer and equally affected by high levels of violence.

month effects. Keeping γ at its first-stage value, we then perform a grid search over α, determining travel time and attacks on the lowest-cost route at each iteration, and select the value of α for which equation (6) yields the lowest residual sum of squares. We bootstrap standard errors with both stages of the estimation included in the bootstrap loops.

To establish the lowest-cost route between origin-destination pairs at each iteration, we follow the methodology outlined in section 4.2 and apply a depth-first search algorithm (Black, 2008) to the road network depicted in Figure 1b yielding 41 routes for all 11 markets combined. While each route's travel time is fixed, the lowest-cost route between any origin-destination pair varies over time due to the occurrence of violent attacks on all routes, weighted by α. For any given route, we specify attacks along the route in equation (6) as the average monthly attacks over the past half year (i.e., average over the current and the past six months). We do so in order to have the persistent effects of lagged attacks shown in Figure 5 and in Appendix Table A.8 reflected in the model and the associated policy simulations.

The descriptive statistics on alternative routes in Appendix Table A.12 show a strong variation in road distance with the average shortest route across all markets having a travel time of 6.3 hours, rising to 9 hours for the three most distant markets, and with a maximum observed travel time on the shortest route of 13.9 hours (see panel A). Second and third alternatives to the shortest route are typically 40 percent longer, while higher-order alternatives are four times longer. Moreover, alternative routes on average experience 50 percent more violence which could be due to the fact that they are longer—see panel B. Interestingly, attacks on the shortest route and on alternative routes are highly correlated, with a correlation coefficient of violent attacks of 0.92 between the shortest and second shortest route.

5.2 Baseline results

Results from the estimation of equation 6 are in Panel A of Table 5. We find an effect of travel time of $\hat{\gamma} = 0.46$ (column 1), implying that an increase of travel time by 10 percent increases the iceberg trade costs and the maize price by 4.6%. As we discuss in Online Appendix G, this effect is slightly larger than comparable effects found in other contexts, which is plausibly due to the comparatively high share of transportation costs in the total price in the context of Sub-Saharan Africa (Christ and Ferrantino, 2011). Moreover, as we show in Appendix Table A.13, this estimate remains similar if we use the full 2001-2018 sample period and control for violence along the route and for local violence linearly (column 3) or flexibly (column 4). For α we estimate a value of 0.204 (column 2), implying a decreasing marginal effect of attacks on effective travel time.[35] The estimates for γ and α translate to a marginal effect at the mean per average monthly attack over the past six months on the price of maize of 3.8% (column 3). The marginal effect of 3.8% is not too far off the corresponding effect of 2.1% that we get in a reduced-form regression using average attacks over the past half year within our baseline specification of equation 2 (column(4) of Table A.8), or the 2.6% effect when—more similar to equation 6—we replace the market-by-year and market-by-month effects by a growing area-by-year-by-month and a market fixed effect (column (5)). Strikingly, the model predicts that alternative routes are never used (column 4 of Panel A, Table 5) despite frequent violent attacks, a finding most likely explained by the rudimentary nature of the Somali road network and the pervasiveness of violent conflict.

5.3 Counterfactual scenarios

Our finding that, under the status quo, alternative routes are virtually never used, raises the question which interventions might lead to alternative routes becoming more effective, and to what extent this would alleviate price pressures. A related policy question concerns the price effects of securing specific routes from attacks. To shed light on these questions, we use our estimates from the trade-cost model to perform policy counterfactuals. We simulate changes in the road network or in violence along routes, re-calculate lowest-cost paths under each scenario, and use $\hat{\gamma}$ and $\hat{\alpha}$ to predict maize price distributions, which we compare to the baseline.[36]

Counterfactual 1: Preventing attacks on all shortest routes. In the first row of Table 5, Panel B, we simulate the absence of all attacks from the shortest route, which amounts to the prevention of 1,557 attacks.[37] Unsurprisingly, as the first two columns show, the shortest route remains always optimal (zero percent use of alternative routes). The removal of attacks reduces the maize price on average across all locations and time periods

[35] It implies that one average attack over the past half year is equivalent to increasing travel time by 15% ($2^{0.204} = 1.15$), two such attacks are equivalent to increasing it by 25% ($3^{0.204} = 1.25$), and 5 such attacks increase it by 44% ($6^{0.204} = 1.44$).

[36] One caveat of our counterfactual analysis is that, when simulating scenarios in which routes are secured from attacks, we assume that such attacks are prevented rather than displaced to other locations. Modeling the spatial reallocation of violence lies beyond the scope of this paper; for recent work in this area, see Khanna et al. (2023); Couttenier et al. (2024). Importantly, this limitation does not affect our first counterfactual—securing the shortest routes—since once these routes are attack-free, any potential displacement of violence to alternative routes has no impact on prices.

[37] Also removing attacks from alternative routes would have no additional effect because once attacks on the shortest routes have been removed, alternative routes become irrelevant.

by 4.9% (column 3).[38] The average effect includes market-month observations in which no violence occurred and in which the policy scenario can therefore by definition have no effect. We, therefore, also report the price effect conditional on the market-month observation experiencing non-zero violence (which implies that attacks are prevented). This effect in column (4) amounts to a reduction of maize prices by 9.8%. This is a sizeable effect similar to the effect of a one-standard deviation increase in rainfall—which reduces prices by 9%—see column (8) in Appendix Table A.3. For a group of more distant markets that are more affected by violence we find an average reduction of the maize price of 9.2% (column 5), which rises to a 20.8% effect when additionally focusing on the period after 2016 in which violence was at its peak (column 6).

Counterfactuals 2 and 3: Preventing attacks on second shortest route. Next, we simulate absence of attacks only from the second-shortest route. This leads to a strong increase in the use of the second-shortest route with a frequency of 12.9% compared to 0% at baseline. However, compared to the first counterfactual, price reductions are relatively modest. The most likely reason for these small decreases in prices is the rudimentary nature of the Somali road network. Given that second shortest roads are significantly longer, moving to the attack-free second-shortest routes entails a counteracting price-increasing effect from the longer distance of these routes. In fact, in the next row, when simultaneously making the second route attack-free and also shorter (1.1 times the travel time of the first route, rather than 1.4 times at baseline), the frequency of second route use increases to 33.7%, and the price effects move much closer to the effects of making the first route free of attacks.

Counterfactual 4: Preventing attacks in key areas Policy makers with restricted resources may prefer to secure areas that are key for maize distribution, such as the Lower Shebelle area, which supplies seven of our eleven markets see map (c) in Appendix Figure A.1. The average price effect of securing the Lower Shebelle region is 1.7% (column 3), rising to 6.4% (column 4) when conditioning on those market-years with a non-zero effect. These effects respectively amount to one third and two thirds of the corresponding effects of removing all attacks on all shortest routes in counterfactual 1. Yet, the attacks that need to be prevented in this targeted area amount to only 274 attacks over the observation period, equivalent to about 18% of all attacks on shortest routes. Thus, if targeted strategically, a potentially much cheaper intervention can yield substantial parts of the effects of

[38] The effect size tallies with the corresponding reduced-form results in column (4) of Appendix Table A.8. There we find an effect size of 2.1% per average monthly attack over the past half year. The mean of these attacks is 2.09, implying that removing all attacks (reducing the mean to zero) has a price effect of $2.1\% \times 2.09 = 4.4\%$.

Table 5: Least-cost route choice model

	Panel A: Baseline estimates				
	(1)	(2)	(3)	(4)	(5)
	$\hat{\gamma}$	$\hat{\alpha}$	Marg. eff. (attack)	Alternative route use (2nd-9th)	Obs.
Baseline parameter estimates	0.464 (0.087)	0.204 (0.021)	0.038 (0.012)	0.0%	2,085

	Panel B: Price effects of counterfactual scenarios					
	(1)	(2)	(3)	(4)	(5)	(6)
	Alternative route use		Relative price effect of intervention			
	2nd route	3rd-9th route	Overall	Conditional on nonzero	Distant	After 2016, distant
1. Absence of attacks from shortest route	0.0%	0.0%	-4.9% (1.7%)	-9.8% (1.7%)	-9.2% (4.2%)	-20.7% (6.2%)
2. Absence of attacks from 2nd shortest route	12.9% (9.6%)	0.0%	-0.8% (0.6%)	-6.5% (2.8%)	-2.1% (1.6%)	-6.8% (4.2%)
3. Absence of attacks from 2nd shortest and shortening it	33.7% (14.1%)	0.0%	-3.1% (1.3%)	-9.2% (1.5%)	-6.4% (3.2%)	-16.3% (5.5%)
4. Securing main roads in Lower Shebelle growing area	0.0%	0.0%	-1.7% (0.2%)	-6.4% (1.2%)	-2.6% (0.8%)	-7.6% (2.6%)
5. Add missing 2nd routes (attack-free, 1.4 times longer than first route)	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
6. Add missing 2nd routes (attack-free, same length as first route)	13.2% (5.3%)	0.0%	-0.6% (0.4%)	-4.5% (1.2%)	-1.2% (0.7%)	-3.4% (1.6%)
7. Alternative routes are shorter	14.9% (8.4%)	0.8% (0.7%)	-0.5% (0.2%)	-3.4% (1.0%)	-0.4% (0.3%)	-0.4% (0.3%)
8. Alternative routes are shorter, attacks uncorrelated with shortest route	12.6% (3.1%)	9.7% (6.1%)	-2.1% (0.6%)	-9.3% (3.5%)	-5.0% (3.3%)	-9.2% (6.2%)

Notes: Panel A reports baseline results from the switching regime trade cost model in equation (6). γ is estimated from between-market variation by regressing the log maize price on log travel time on the shortest route, controlling for population size and month effects using the sample of 2001 in which attacks were close to zero. Keeping γ at its first-stage value, eq. (6) is estimated via a grid search on α minimizing the residual sum of squares. Column (3) reports the marginal effect per attack at means. Given the rudimentary Somali road network and the pattern of realized attacks, the baseline model predicts that alternative road use is virtually never optimal (0% in column 4). Panel B reports results for counterfactual scenarios. Keeping γ and α at baseline values, optimal route choice and predicted prices are recalculated under an altered attack pattern or road network shape. For each scenario, columns (1) and (2) report the frequency of alternative route use, and columns (3)-(6) report relative price differences compared to predicted prices at baseline. Column (3) reports the average effect, column (4) the average effect conditional on being non-zero, column (5) the average effect in distant markets, and column (6) the average effect in distant markets after 2016 (Belet Weyne, Hudur, Galkayo, and Baidoa). Bootstrapped standard errors with clustering at the market level are in parentheses. **Data sources:** ACLED, and own route computations.

substantially more expensive interventions.[39]

Counterfactuals 5-8: Changes in road network. A recent report by the United Nations Conference on Trade and Development (2023) emphasizes the importance of transport networks like roads, to drive economic growth and regional trade. The last three rows of Table 5 simulate changes to the Somali road network. First, for the five markets with only one route, we add an alternative route, which is attack free and 40 percent longer (corresponding to the average length ratio of the second shortest route in our sample). The frequency of use of additional roads remains at zero, leading to no reductions in prices.

In the next row, we simulate these additional attack-free second routes to have the same length as their respective shortest routes. This leads to a 13.2% frequency of second-route use, with an average price reduction by 0.6%, rising to 4.5% in those market-months with non-zero effects.

Counterfactual 7 of table 5 further corroborates the importance of a well-developed road network by simulating an alternative transport network in which all existing alternative routes would be considerably shorter than they currently are. Rather than 40% longer than the shortest route, we model the second route as the same length as the shortest route, and each further alternative route to be an additional 10% longer than the shortest route. This alternative road network yields an alternative route use frequency of 15%, and an average maize price reduction of 0.5%, which rises to 3.4% when conditioning on markets with non-zero effects. Thus, by itself, this intervention yields relatively moderate effects, most likely owing to the strong correlation between attacks on the shortest and the second-shortest alternative route. We investigate this possibility in counterfactual 8, where we randomly permute the attacks on the alternative routes across time such that they become uncorrelated with the attacks on other routes. In this scenario alternative route use in the last row of the table rises to 22% (sum of columns 1 and 2) and average price reductions amount to around half of the effect of the first counterfactual, preventing all attacks on shortest routes.

Key policy implications. The main policy implication from this exercise is that a diversified transport system offering alternative routes between origin-destination pairs can

[39] To evaluate whether securing this area indeed has the strongest effect relative to others, we divided the shortest-route network into ten sections and simulated the price effects of eliminating attacks in each. This exploratory analysis—abstracting from alternative route choices—revealed that securing the main transport corridor in the Lower Shebelle region produces the largest price impact, approximately 6.5 times greater than that of the next most influential section. This effect remains robust when normalizing for the size of the area to be secured (approximated by travel time), with the Lower Shebelle route still generating a threefold larger impact.

reduce price pressures from violent conflict along transit routes. However, this benefit is limited when alternative routes are significantly longer than primary ones or when attacks are highly correlated across routes over time. In such cases, alternative routes alone are insufficient without simultaneously tackling the occurence of violence. An effective approach is to target security interventions at areas that contain transport routes to a range of more distant markets, as this can yield relatively large effects at a fraction of the cost of making all areas attack-free. In our application, this would imply that policymakers might want to target limited resources towards the prevention of attacks along the key transport route in the Lower Shebelle area of Somalia.

6 Beyond the price of maize: a market access approach

Focusing on the maize market, as in our analysis so far, offers the advantage of clearly defined origins, destinations, and transport routes. However, it also raises the question of how far the spatial spillovers we document extend beyond maize. In the final part of our analysis, we show that the spatial spillovers observed for maize prices also impact two broader price indices—one for a basket of food items and another also including non-food goods. Additionally, we identify further spatial spillovers from attacks within cities that distribute or produce goods.

Considering broader price indices breaks the link of each destination market to a specific origin market because various goods will be produced in, or distributed through, different origin markets. Therefore, when explaining a general price index in a given destination market, all other markets now become relevant origin markets. For each market in our sample we now consider the fastest routes to all other markets and model the effect of violence along these routes. Because the importance of each of the other markets is likely to differ according to the size of the market and how well origin and destination market are connected, we implement a market access approach. The concept of market access was derived by Donaldson and Hornbeck (2016) based on an Eaton and Kortum (2002)-style trade model and captures how well a given location is connected via the transport system to other economically important locations.[40] Adopting this framework allows us to weight

[40]Market access approaches have recently been used to estimate the effects of shocks or changes to the transport system. Donaldson and Hornbeck (2016) estimate effects of market access on land value as motivated by their underlying theoretical model, exploiting changes in market access from the expansion of the US rail network in the late 19th century. Chiovelli et al. (2024) estimate effects of market access on economic activity proxied by nightlight luminosity, exploiting variation in market access from the reinstatement of previously blocked transport links due to landmine clearances in Mozambique. Jedwab and Storeygard (2022) estimate the effects of market access on the population of cities in Africa, exploiting variation in market access from the construction of major roads.

conflict along transportation routes between each origin-destination pair according to the level of 'market access' between these locations.

Set up. We define market access of a location d at time t as the weighted sum of the population size of the locations o that location d has access to through the transport system, inversely weighted by the trade cost to each location. That is,

$$MA_{dt} \quad = \quad \sum_{o \neq d} \frac{N_o}{\tau_{dot}^{\theta}}, \tag{7}$$

where N_o is location o's population size, τ_{dot} is the trade cost between locations o and d, and θ is a trade elasticity that governs how fast the value of trade declines when trade costs increase. As such, market access increases if a given location is connected to more markets, or if these markets are larger, or if the transport links are better.[41]

To compute the market access measure highlighted in equation (7), we find the shortest route between each market and the other ten. These connections are shown in Figure 1(d). In line with the literature, we use a baseline value of $\theta = 3.8$.[42] We incorporate conflict into this market access measure by operationalizing trade costs as

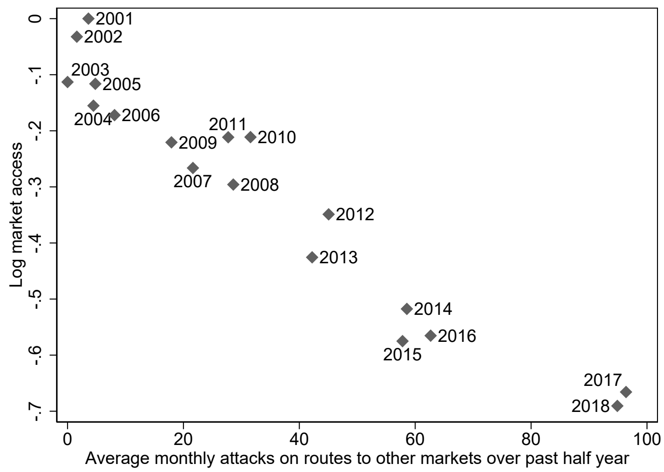
$$\tau_{dot} \quad = \quad traveltime_{do}(1 + attacks_{dot})^{\lambda}, \tag{8}$$

where $traveltime_{do}$ is the travel time (speed-weighted distance) between markets o and d, and $attacks_{dot}$ are the average monthly number of violent attacks along the route in the half year up to t. In absence of attacks, ($attacks_{dot} = 0$), τ_{dot} simply equals the travel time. In case of a positive number of attacks, and if $0 < \lambda < 1$, additional attacks increase the transport cost at a declining rate. We set $\lambda = 0.204$ which is equal to our estimate of $\hat{\alpha}$ from equation (6), where we estimated an equivalent functional form. This implies that one average monthly attack over the past six months is equivalent to an increase in distance by about 15% ($2^{0.204} = 1.15$), with decreasing marginal effects of every additional attack.

[41] Treating population size as time constant yields a market access measure in which the time variation is solely driven by changes in violent attacks affecting the transport system, avoiding endogenous changes of market access due to changes over time in the population size of markets. The Somali road network has hardly changed over our sample period (see section 3). This market access measure is similar to Chiovelli et al. (2024)'s 'Log MA Population (Initial)' measure, which also uses a time-constant population and transportation network to gain exogenous variation.

[42] Our choice of $\theta = 3.8$ follows Chiovelli et al. (2024) who identify $\theta = 3.8$ as a middle estimate in the literature. In the Appendix, we probe the sensitivity of our results with respect to alternative choices of θ across a wide range from from 1 to 8.22.

Figure 6: Market access and conflict along transportation routes



Notes: The figure plots the annual log of market access (as defined in equations 7 and 8) against annual conflict along transportation routes. Annual values are obtained as the year coefficients from regressing each respective variable (varying at the market-month level) on a set of year and market fixed effects, normalizing the year effect of the highest market access to zero.
Data sources: ACLED, own computations based on transportation maps.

Summary statistics. In Appendix Table A.14 we present descriptive statistics of the market access measure. The table shows strong cross-market variation in market access driven by geography, transport links, and population sizes. Market access is strongly driven by proximity to some of the largest markets. The three cities with the highest market access (Panel A) all benefit from closeness to either the largest city Mogadishu (in the case of Qorioley and Marka) or the second-largest city Hargeisa (in the case of Borama)—see Figure 1(c). The markets with the lowest market access are Kismayo, Buale, and Galkayo, due to their relatively peripheral locations at long distances from other big markets. Setting violent attacks to zero, which eliminates time variation in the market access measure, yields a between-market standard deviation of 3.09 (Panel B of Table A.14). Setting attacks at their observed values raises the between-market standard deviation to 3.30 (as some markets are more affected by attacks than others), and introduces time variation in the market access measure, with a within-market standard deviation of 0.29, driven by attacks.

Figure 6 plots log market access against average attacks on routes to the other ten markets, both aggregated at the yearly level, where market access is normalized to zero in the year with the highest market access (2001). It reveals a strong negative relationship between market access and attacks along transportation routes, and a clear time trend. Average monthly attacks have steadily increased from zero in the early 2000s to around 100 in 2018 and have reduced market access by close to 70%, corresponding to about 20% of its standard deviation in absence of attacks.

Table 6: General market access, and attacks in other cities

	(1)	(2)	(3)
	Panel A: General Market Access		
	Food price index		Total price index
Log market access	-0.165	-0.159	-0.095
	(0.051)	(0.070)	(0.038)
Attacks on routes to other cities		0.0001	
		(0.0007)	
Change to return to 2001 level	0.69	0.69	0.69
Price effect of change	-11.4%	-11.0%	-6.6%
Observations	1,039	1,039	1,050
	Panel B: Attacks in other cities		
	Food price index	Total price index	Non-food price index
Attacks in other cities (6 months)	0.0006	0.0008	0.0013
	(0.0006)	(0.0002)	(0.0003)
Change to return to 2001 level	-100	-100	-100
Price effect of change	-6.0%	-8.1%	-13.3%
Observations	1039	1050	1050

Notes: Standard errors clustered at the market level in parentheses. In Panel A, standard errors are bootstrapped, including the computation of market access in the bootstrap loop. **Data sources:** ACLED, and own route computations.

Results. In Table 6 we report results from regressing a wider food price index on log market access. The food price index is collected from the FSNAU, which publishes monthly Costs of Minimum Basket (CMB), and includes the prices of sorghum, wheat flour, sugar, vegetable oil, milk, meat, tea leaves, and cowpeas. We employ our reduced-form identification strategy from equation (2), exploiting within-market changes in market access driven by changes in attacks along transportation routes.

We find that a 10% increase in market access makes the Cost of Minimum Food Basket 1.65% cheaper (column (1), Panel A). This implies that if market access were increased from its 2018 level back to its 2001 level (an increase in market access by 69 log points), the cost of the food basket would decrease by 11.4%. In the next column, we add the attacks on routes to other cities (which drive the variation in market access) into the regression. We find that the market access effect strongly persists, while the measure of the number of attacks has a negligibly small coefficient. This finding suggests that the market access measure is better in predicting prices than the number of attacks suggesting that violence along transit routes affects prices by reducing market access and trade opportunities. In column (3), we use a wider price index, which expands the food price index by non-food items such as kerosene, laundry soap, firewood, water, human drugs, and clothes. We find that restoring market access from its 2018 level back to its 2001 level would reduce the combined price index by 6.6%.

Robustness. In Appendix Table A.15, we show that our conclusions remain stable across different values of θ. Considering a range from 1 to 8.22, we find that the effect of returning market access from its 2018 to its 2001 level decreases prices from 8% to 15%, with our baseline estimate of 11.4% occupying a middle ground (the higher θ, the larger the range of decrease of market access from 2001 to 2018, but the smaller the effect of market access on prices).

Attacks in other cities. As the market access measure in equation (7) makes clear, market access depends not only on the transport system and the trade costs (in the denominator), but also on the economic activity or economic importance of the markets that a given location is connected to (the numerator). Since the goods contained in the CMB are likely to be distributed through or even produced in other market cities, violent incidence in other cities can also be relevant for prices. In Appendix Figure A.6 we show the evolution over time in the average monthly attacks happening within our eleven market cities. These have risen from zero in early 2000 to around 100 per city and month in 2018.

In Panel B of Table 6, we regress the total price index on attacks in other cities and find that these do, in fact, raise prices. This effect is driven by non-food prices, with no statistically significant effect on food prices. This finding is intuitive, since food staples are likely to be transported from growing regions and not from cities. The results imply that reducing attacks in other cities from their 2018 level back to their 2001 level would reduce non-food prices by 13.3%.

Overall, we conclude from this section that the spatial spillovers highlighted in this paper—that violent attacks along transportation route increase prices in distant destination markets—are not confined to maize prices, and that there can be additional spatial spillovers from attacks within cities that distribute or produce goods.

7 Discussion and Conclusion

Our analysis has documented that conflict occurring in one part of Somalia can affect food prices, market access, food security, health and education in distant areas. 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. Humanitarian interventions, such as the Word Food Programme's nutrition assistance intervention (WFP, 2021), most commonly focus on where the conflict occurs, particularly in the areas around Mogadishu. By contrast, our results provide evidence that conflict in this area affects faraway individuals, for instance in the city of Gakayo, located 700km from Mogadishu.

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. If the effects of conflict in the treatment region spill over to the control region, it is likely that traditional research designs might in some cases have provided lower bound estimates, hence providing further reasons to invest in humanitarian interventions in conflict zones.

Echoing academic work on the economic value of transport networks (Donaldson and Hornbeck, 2016; Donaldson, 2018; Chiovelli et al., 2024; Jedwab and Storeygard, 2022), The World Bank (2023) highlights Africa's significant infrastructure deficit and notes the transformative potential of better road networks. Our analysis reveals that well-developed road networks can contribute to enhancing economic resilience, mitigating the adverse impacts of violent conflict, a prevalent challenge across Africa.

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Appendix for Online Publication

Spatial Spillovers of Conflict in Somalia

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Appendix A Additional tables and figures

Table A.1: Further summary statistics

	A: Terrorist attacks (GTD)				
Type of incidence	All	Aimed at Military	Aimed at transport	Aimed at other	Involving barricades
Nr of incidents	4,496	1,890	37	2,569	12
% of total		42.0%	0.8%	57.2%	0.3%
	B: Terrorist attacks along transportation routes (GTD)				
Type of incidence	All	Aimed at Military	Aimed at transport	Aimed at other	Involving barricades
Nr of incidents	180	114	4	62	0
% of total		63.3%	2.2%	34.4%	0%

Notes: Table reports summary statistics on conflict and characteristics of households in Somalia. Panel A: reports terrorist attacks in Somalia by target (based on GTD); Panel B: reports terrorist attacks within 5 kilometres either side of transportation routes by target (based on GTD); **Data sources:** GTD, The World Bank (2017).

Table A.2: Types of violence

	(1)	(2)	(3)	(4)	(5)
	Dependent variable: Log price of maize				
Type of conflict	Battle	Against Civilians	Remote	Strategic	Riots
	Panel A: number of conflict events				
Mean of conflict/month	1.29	0.34	0.33	0.16	0.02
Conflict en route (z-score)	0.0108	0.0166	−0.0008	−0.0003	−0.0019
	(0.0026)	(0.0039)	(0.0029)	(0.0059)	(0.0026)
	Panel B: = 1 if conflict lasts at least 4 months				
Mean of conflict/month	0.17	0.02	0.02	0.00	0.00
Conflict en route	0.0601	0.0607	0.0808	n.a	n.a
	(0.0185)	(0.0379)	(0.0300)		
Observations	2,085	2,085	2,085	2,085	2,085
R^2	0.925	0.926	0.925	0.925	0.925

Notes: Table shows effect of conflict along transit route by type of conflict. Panel A: *Battle* includes Armed clash, Non-state actor overtakes territory, Government regains territory; *Against civilians* includes Abduction/forced disappearance, Attack, Sexual violence; *Remote* includes Grenade, Remote explosive/landmine/IED, Shelling/artillery/missile attack, Suicide bomb, Air/drone strike, Chemical weapon; *Strategic* includes Agreement, Arrests, Change to group/activity, Disrupted weapons use, Headquarters or base established, Looting/property destruction, Non-violent transfer of territory; *Riots* includes Mob violence, Violent demonstration, Peaceful protest, Protest with intervention, Excessive force against protesters. All estimates are based on z-scores. Panel B: explanatory variables take value = 1 if respective type of conflict lasted at least 4 months. Incidents of strategic violence and riots in columns (4) and (5) are too low (0.003 and 0.000, respectively) for meaningful estimates. **Data sources:** ACLED, FAO.

Table A.3: Alternative measurements

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Dependent variable: Log price of maize													
Conflict en route 1km corridor	0.0043				0.0037									
	(0.0015)				(0.0016)									
Conflict en route 2.5km corridor		0.0031		0.0025										
		(0.0014)		(0.0015)										
Conflict en route 2.5-5km corridor			0.0062	0.0057	0.0057									
			(0.0032)	(0.0034)	(0.0033)									
Conflict en route						0.0038	0.0034	0.0139	0.0187	0.0145	0.0139	0.0095	0.0026	0.0004
						(0.0012)	(0.0009)	(0.0053)	(0.0057)	(0.0056)	(0.0053)	(0.0034)	(0.0058)	(0.0250)
Rainfall (z-score)								−0.0900						
								(0.0359)						
SPEI (z-score)									−0.0319					
									(0.0076)					
Log maize prod. (z-score)										−0.0710				
										(0.0194)				
Observations	2,085	2,085	2,085	2,085	2,085	2,085	2,085	2,085	2,085	2,085	2,085	2,085	2,085	2,085
R^2	0.925	0.925	0.925	0.925	0.925	0.925	0.925	0.925	0.923	0.923	0.925	0.925	0.925	0.925
Geogr precise						yes								
Not own admin							yes							
GTD												yes		
z-score								yes	yes	yes	yes	yes		
Destruction related													yes	
Tax related														yes

Notes: Table reports spillover effects of conflict on maize prices using different measurements. Dependent variable is log of maize price. *Conflict en route 1km corridor*, *Conflict en route 2.5km corridor*, *Conflict en route 2.5-5km corridor* counts number of violent incidents occurring within along the shortest route between maize growing area and market per month for a corridor of 1km, 2.5km, and between 2.5 and 5km, respectively. *Rainfall (z-score)* denotes the z-score of rainfall in the growing season prior to month m. *SPEI (z-score)* denotes the z-score of the Standardised Precipitation-Evapotranspiration Index in the growing season prior to month m. *Log maize prod (z-score)* denotes the z-score of the log production of maize (in metric tonnes) in the growing season prior to month m, which we obtained from the FSNAU and match to each market. Explanatory variable in column (6) excludes any conflict occurring in the same administrative region as m. Explanatory variable in column (7) only uses violent incidents classified as 'geographically precise' by ACLED. Columns (8) to (12) use the z-score of *Conflict en route*. Column (12) defines *Conflict en route* as terrorist attacks taken from the GTD. Column (13) uses description in ACLED data and selects only incidents described with words 'destroy', 'explode', 'roadblock', 'checkpoint', and 'barricade'. Column (14) uses description in ACLED data and selects only incidents described with word 'tax'. Standard errors clustered at market level are reported in parentheses. **Data sources:** ACLED, FAO, FSNAU.

Table A.4: Alternative specifications and samples

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent variable:									
	Log price of maize								Conflict en route	
Conflict en route	0.0039	0.0048	0.0050	0.0038	0.0034	0.0050	0.0046	0.0070		
	(0.0012)	(0.0019)	(0.0017)	(0.0014)	(0.0014)	(0.0017)	(0.0012)	(0.0036)		
Conflict en route	0.0019									
× log border dist	(0.011)									
Conflict en route		−0.0004								
× informal imports		(0.0015)								
Conflict en route			0.0050							
× formal imports			(0.0033)							
Battle of Bel. Weyn									3.6308	
									(0.8330)	
Galkayo ceasefire										−3.3406
										(0.2658)
Observations	2,085	1,182	2,085	1,708	1,733	1,671	1,312	250	238	393
R^2	0.925	0.924	0.926	0.916	0.935	0.922	0.923	0.958	0.497	0.564
Sample	All	2010-18	All	No Somali-land	Not next to Kenya	Not next to Ethiopia	2009-18	Feb 2016 to Dec 2017	Mar, Qor, BW, Gal 2006-10	All 2015-17
Market, Year, Month FE									yes	yes

Notes: Table reports effect of incidents of conflict along maize transportation route on the price of maize using different samples and specifications. Dependent variable is the log of the price of maize in columns (1) to (8) and conflict along transportation routes in columns (9) and (10). *Conflict en route* counts number of violent incidents occurring within a 5km radius either side of the shortest route between maize growing area and market per month, *log border dist* is the logarithm of the aerial distance between market i and the closest point on the Somali border (transformed to z-score), *informal imports* is the number of informal maize imports into Somalia as reported by FSNAU (transformed to z-score), *formal imports* is the number of formal maize imports into Somalia as reported by UNCTAD (transformed to z-score). Column (4) drops markets located in Somaliland (Borama and Hargeisa), column (5) drops markets located close to Kenya (Buale and Kismayo), column (6) drops markets located close to the Ethiopian border (Belet Weyne and Hudur), column (7) uses only years 2009 to 2018, column (8) uses only observations between February 2016 and December 2017 **Battle of Bel. Weyn** = 1 in column (9) for June and July 2008 for markets of Belet Weyne and Galkayo, sample consists of markets of Marka, Qorioley, Belet Weyne, and Galkayo from 2006 to 2010. **Galkayo ceasefire** = 1 in column (10) for December 2015 to September 2016 for Galkayo, sample consist of all markets from 2015 to 2016. **Data sources:** ACLED, FAO.

Table A.5: Robustness to exclusion of markets

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Dependent variable: Log price of maize										
Conflict en route	0.0041	0.0043	0.0037	0.0034	0.0038	0.0042	0.0036	0.0038	0.0033	0.0038	0.0028
	(0.0016)	(0.0015)	(0.0014)	(0.0014)	(0.0014)	(0.0016)	(0.0019)	(0.0015)	(0.0014)	(0.0016)	(0.0010)
Observations	1,880	1,876	1,906	1,892	1,887	1,880	1,883	1,926	1,877	1,965	1,878
R^2	0.930	0.924	0.923	0.932	0.921	0.923	0.916	0.928	0.926	0.926	0.927
Excluded market	Baidoa	BeletW	Borama	Buale	Hargeisa	Hudur	Galkayo	Kismayo	Marka	Mogadishu	Qorioley

Notes: Table reports effect of incidents of conflict along maize transportation route on the price of maize using different samples. *Conflict en route* counts number of violent incidents occurring within a 5km radius either side of the shortest route between maize growing area and market per month. Dependent variable is the log of the price of maize. Columns (1) to (11) sequentially drop the following markets respectively Baidoa, Belet Weyne, Borama, Buale, Hargeisa, Hudur, Galkayo, Kismayo, Marka, Mogadishu, and Qorioley. **Data sources:** ACLED, FAO.

Table A.6: Additional specifications

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: Log price of maize					
Conflict en route	0.0042	0.0037				
	(0.0021)	(0.0014)				
Main roads (J&S)			0.0030	0.0027		
			(0.0011)	(0.0010)		
Secondary roads (J&S)				0.0011		
				(0.0020)		
Attack risk (z-score)					0.0603	0.0417
					(0.0164)	(0.0172)
Conflict en route (0-6 lags, z-score)						0.0492
						(0.0264)
Observations	2,085	2,059	2,085	2,085	2,085	2,085
R^2	0.951	0.927	0.925	0.925	0.926	0.926
year-by-month FE	yes					
3 lags and leads		yes				

Notes: Dependent variable is the log of the price of maize. *Conflict en route* counts number of violent incidents occurring within a 5km radius either side of the shortest route between maize growing area and market per month. *Main roads (J&S)* and *Secondary roads (J&S)* counts number of violent incidents occurring within a 5km radius either side of main and secondary roads on the road network used by Jedwab and Storeygard (2022) per month. *Attack risk* uses the method proposed by Tapsoba (2023) to capture attack risk in a given month by aggregating the estimated density of the occurrence of attacks along a corridor 5 kilometres either side of the transportation route supplying maize to each market, excluding attacks within a 15km radius of market (transformed to z-score)—see Section 4.3 and Appendix E for detail, *Conflict en route (0-6 lags)* is the average of *Conflict en route* over the current and the past 6 months (transformed to z-score). Column (1) also controls for year-by-month fixed effects. Column (2) also controls for 3 months leads and lags of *Conflict en route*. **Data sources:** ACLED, FAO.

Table A.7: Effect of conflict along transportation route on price of maize —Identification

	(1)	(2)	(3)	(4)	(5)
Dependent variable	Log price of maize	Placebo price index	Log price of maize	Log price of maize	Log price of maize
Conflict en route	0.0035	−0.0010	0.0111	0.0158	0.0111
	(0.0015)	(0.0008)	(0.0039)	(0.0051)	(0.0039)
Conflict 15km around market	0.0004	0.0006	−0.0004	−0.0004	−0.0005
	(0.0010)	(0.0008)	(0.0013)	(0.0010)	(0.0013)
Conflict betw. growing area and market	0.0006				
	(0.0004)				
Observations	2,085	2,128	2,085	701	2,085
R^2	0.925	0.977	0.925	0.908	0.925
Conflict	ACLED	ACLED	GTD	GTD	GTD
Terrorist attacks			All	Successful	No food

Notes: Table includes identification checks for effect of conflict along transportation routes on price of maize. Estimation is based on equation (2). Dependent variable is log price of maize in columns (1), (3), (4), and (5) and average of log prices of charcoal, diesel, petrol, potable water, goats, sheep, and camels in column (2). *Conflict en route* counts incidents of conflict per month occurring 5 kilometres either side of the transportation route supplying maize to each market, excluding attacks within a 15km radius of market; *Conflict 15km around market* denotes incidents of conflict occurring within a 15km radius of each market; *Conflict betw. growing area and market* denotes incidents of conflict occurring in any administrative region located between each market and its growing area *excluding* any incidents within 5 kilometres of the transportation route to that market; all regressions control for rainfall (in mm) during previous growing season; Standard errors are clustered at the market level and reported in parentheses. **Data sources:** ACLED, FAO, FEWS NET.

Table A.8: Lagged conflict

	(1)	(2)	(3)	(4)	(5)
	Dependent variable: Log price of maize				
Conflict en route	0.0062	0.0038	0.0039		
	(0.0015)	(0.0014)	(0.0014)		
Conflict en route (lagged 1 month)	0.0038		0.0029		
	(0.0020)		(0.0018)		
Conflict en route (lagged 2 months)	0.0035		0.0027		
	(0.0024)		(0.0019)		
Conflict en route (lagged 3 months)	0.0037		0.0046		
	(0.0026)		(0.0022)		
Conflict en route (lagged 4 months)	0.0032		0.0030		
	(0.0025)		(0.0015)		
Conflict en route (lagged 5 months)	0.0031		0.0023		
	(0.0015)		(0.0008)		
Conflict en route (lagged 6 months)	0.0012		0.0020		
	(0.0023)		(0.0019)		
Conflict en route (1-6 lags)		0.0034			
		(0.0015)			
Conflict en route (7-12 lags)		0.0013			
		(0.0013)			
Conflict en route (13-18 lags)		0.0009			
		(0.0012)			
Average monthly conflict en route over past half year				0.0214	0.0260
				(0.0077)	(.0214)
Observations	2,079	2,085	2,079	2,085	2,085
R^2	0.926	0.926	0.926	0.926	0.931
In growing region	yes				
Growing region-by-year and-month fixed effects					yes

Notes: Dependent variable is the log of the price of maize. *Conflict en route* counts number of violent incidents occurring within a 5km radius either side of the shortest route between maize growing area and market per month. *Conflict en route (lagged x months)* refers to respective lags of *Conflict en route*. *Conflict en route 1-6 lags*, *Conflict en route 7-12 lags*, and *Conflict en route 13-18 lags* refer to the sums of *Conflict en route* for 1 to 6, 7 to 12, and 13 to 18 months, respectively. *Average monthly conflict en route over past half year*, refers to the average of monthly *Conflict en route* over the current and the past 6 months, as a way of aggregating up the persistent effects of past conflict. *Conflict en route* in column (1) relates to conflict on roads in growing areas only. Column (5) modifies the baseline specification by controlling for growing-region by year-and-month fixed effects and market fixed effects, instead of market-by-year and market-by-month fixed effects. **Data sources:** ACLED, FAO.

Table A.9: Placebo regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Imports				Exports	
Log price of	Diesel	Petrol	Water	Char-coal	Goats (for export)	Sheep (for export)	Camels
				Panel A: All markets			
Conflict along maize route	0.0012	−0.0011	−0.0009	−0.0004	0.0001	−0.0000	−0.0022
	(0.0009)	(0.0009)	(0.0010)	(0.0008)	(0.0011)	(0.0007)	(0.0016)
Observations	2,126	2,126	1,789	2,073	2,124	1,944	2,052
R^2	0.982	0.975	0.944	0.973	0.954	0.970	0.969
				Panel B: markets close to and far away from the coast			
Conflict along maize route	0.0007	−0.0003	−0.0012	−0.0015	−0.0021	−0.0006	0.0010
	(0.0013)	(0.0011)	(0.0006)	(0.0016)	(0.0017)	(0.0007)	(0.0018)
Sample		Far away from coast				Close to coast	
Observations	1,418	1,418	1,128	708	707	577	636
R^2	0.984	0.981	0.957	0.939	0.871	0.949	0.952

Notes: Table reports effect of incidents of conflict along maize transportation route on the price of *other* goods traded along different roads. *Conflict en route* counts number of violent incidents occurring within a 5km radius either side of the shortest route between maize growing area and market per month. Dependent variables are the log prices of three common imports into and four common exports out of Somalia: diesel (column 1), petrol (column 2), water (column 3), charcoal (column 4), goats of export quality (column 5), sheep of export quality (column 6), and camels (column 7). Sample in panel A consists of all 11 markets. Prices of export goods measured in markets located far away from the coast may not include the transport cost to the export port. Likewise, prices of import goods measured in markets located at the coast may not include the transport cost to the final destination market. In Panel B, we therefore use import prices in columns (1) to (3) only for markets located far away from the coast (Baidoa, Belet Weyne, Borama, Buale, Galkayo, Hargeisa, and Hudur), and export prices in columns (4) to (7) only for markets close to the coast (Kismayo, Marka, Mogadishu, and Kismayo). Data are drawn from FSNAU available under https://fsnau.org/ids/index.php, accessed September 2024. **Data sources:** ACLED, FSNAU.

Table A.10: Additional household outcomes

	(1)	(2)	(3)	(4)	(5)
	In the past 2 months child (aged $<$ 10) suffered from				
	Non-infectuous illness	Gastro-enteritis	Malaria	Typhoid fever	Chest infection
Conflict en route (excl. same region)	0.0007	0.002*	0.004***	0.0002***	0.0001*
	(0.0004)	(0.001)	(0.001)	(3.1E-05)	(3.4E-05)
Observations	8180	8180	8180	8180	8180
R2	0.00	0.05	0.03	0.004	0.003
Mean Dep. Variable:	0.02	0.08	0.04	0.002	0.003

Notes: Regressions control for region effects, attacks in own area, household size, proportion literate in household, gender of household head, household below poverty line, and child age dummies. The health outcomes were asked only in 2016 and exploit cross-sectional variation only. The time horizon of the definition of *Conflict en route* is adjusted to the time horizon of the respective survey questions—see Appendix F for more detail. Robust standard errors clustered at the region level are in parentheses.

Data sources: SHFS, ACLED.

Table A.11: Robustness against excluding migrant households

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	High prices affecting food	Log quantity consumed		Household spent savings	Index of non-food spending	Child suffered from		Not enrolled in school (aged 6-14)
		Maize	Sorghum			Any illness	Infectuous illness	
Conflict en route (excl. same region)	0.003	-0.019	0.04	0.006	-0.278	0.003	0.004	0.0053
	(0.002)	(0.027)	(0.023)	(0.002)	(0.07)	(0.002)	(0.001)	(0.0015)
Observations	3,644	5,562	5,534	1,889	3,880	7,452	7,452	6,172

Notes: The table replicates the effects of violent incidents along maize transportation routes on the outcomes from Table 4 using the same regression specifications but excluding migrant households. Migration household are defined by the household head living in a different region of Somalia than where they were born (information available in both the 2016 and 2017 waves), or by the number of years that any of the household members has lived in the current district being smaller than their age (available in the 2016 wave), or by the household falling 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. Robust standard errors clustered at the region level are in parentheses. **Data sources:** SHFS.

Table A.12: Descriptives - Alternative Routes

	(1) All markets	(2) Distant markets
	Panel A: Travel time	
Travel time (speed-weighted distance) of shortest route (hours)		
Mean	6.3	9.0
Standard deviation	3.7	3.0
Minimum	1.5	6.3
Maximum	13.9	13.9
Travel time on alternative routes relative to shortest route (ratio)		
2nd route	1.4	1.4
3rd route	1.4	1.4
4th route	4.1	4.1
5th - 9th route (average)	4.2	4.2
	Panel B: Attacks on routes	
Attacks on shortest route		
Whole sample period	1.5	3.1
After 2016	4.1	8.9
Attacks on alternative routes relative to shortest route (ratio)		
2nd route	1.5	1.6
3rd route	1.7	1.7
4th route	1.5	1.5
Correlation with attacks on shortest route		
2nd route	0.92	0.95
3rd route	0.93	0.93
4th route	0.86	0.86
Observations	2,085	821

Notes: Not all 11 markets have alternative routes; 5 have only one route, 2 have two routes, 1 has 4 routes and 3 have 9 routes. The 'distant markets' are Belet Weyne, Hudur, Galkayo, and Baidoa. **Data sources:** ACLED, FAO.

Table A.13: Estimation of γ

	(1)	(2)	(3)	(4)
Log travel time on least-cost route	0.464	0.427	0.404	0.503
	(0.098)	(0.153)	(0.066)	(0.077)
N	89	82	2,085	2,085
Sample years	2001	2001	2001-2018	2001-2018
Population size	Yes	Yes	Yes	Yes
Year-month effects	Yes		Yes	Yes
Growing region-year-month effects		Yes		
Attacks linear			Yes	
Attacks flexible				Yes

Notes: The table reports results from regressing the log maize price on log travel time on the least-cost route to get an estimate for γ in equation 6 using between-market variation. Columns (1) and (2) keep attacks along transportation routes constant by focusing on the period of 2001, a period before the onset of the al-Shabab insurgency in which attacks were close to zero. The remaining columns instead focus on the full sample period but control for attacks along transportation routes and local attacks linearly (column 3) or flexibly (column 4). For the flexible specification in column (4) we create dummies indicating the 10 decile bins of violence along the route and of local violence, and include interactions of these dummies with each other and with year dummies. Standard errors clustered at the market level in parentheses. **Data sources:** ACLED, FSNAU.

Table A.14: Descriptive statistics - market access

	Panel A: Market information	
	Population	Log market access at zero attacks
Kismayo	243,043	0.00
Buale	121,894	0.73
Galkayo	501,542	3.29
BeletWeyne	278,118	4.67
Mogadishu	2,330,708	6.23
Hudur	123,442	7.07
Baidoa	546,957	7.34
Hargeisa	1,346,651	7.67
Qorioley	286,402	8.30
Borama	597,842	8.48
Marka	199,872	8.61
	Panel B: Variation	
Log market access at zero attacks		
Between-market std. dev.		3.09
Within-market std. dev.		0.00
Log market access at observed attacks		
Between-market std. dev.		3.30
Within-market std. dev.		0.29

Notes: The table reports descriptive statistics for the market access measure computed according to equations (7) and (8) in the main text. Log market access at zero attacks is computed by setting the number of violent attacks to zero, which eliminates time variation in market access and reflects only the cross-market variation. The measure is normalized to 0 for the market with the lowest market access. Log market access at observed attacks includes time variation from the occurence of attacks and is the measure used for the analysis in Table 6 of the main text. **Data sources:** ACLED.

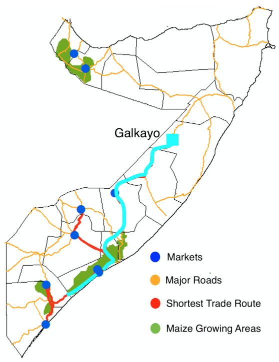
Table A.15: Robustness check of varying θ for market access computation

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Market access range	Effect of market access on food prices			Total effect	Effect of attacks when added to regression	
θ	(2001-2018)	b	se	t	(2)×(3)	b	se
1	-0.30	-0.50	0.17	-2.97	15.1%	-0.0003	0.0009
2.74	-0.57	-0.23	0.07	-3.18	13.3%	-0.0001	0.0008
3.8	-0.69	-0.17	0.05	-3.22	11.4%	0.0001	0.0007
5.4	-0.87	-0.11	0.03	-3.32	9.4%	0.0003	0.0007
8.22	-1.21	-0.07	0.02	-3.16	8.1%	0.0003	0.0007

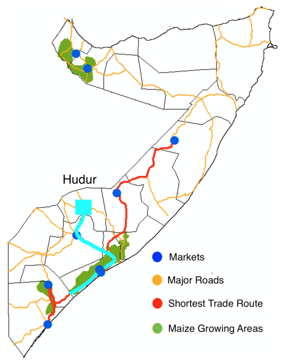
Notes: The table reports robustness checks for the effect of market access on the food price index. The baseline results using $\theta = 3.8$ are in column (1), Panel A, of Table . The present table shows how the results change when market access (see equations) is computed at varying levels of θ, ranging from 1 to 8.22. **Data sources:** ACLED, FSNAU.

Figure A.1: Additional maps

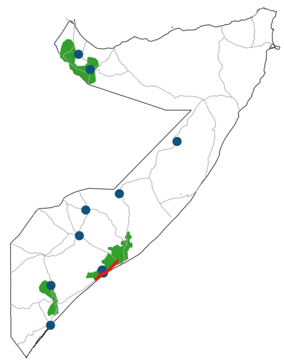
(a) Transport to Galkayo



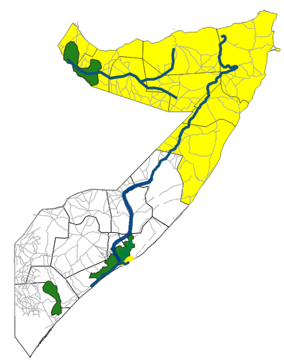
(b) Transport to Hudur



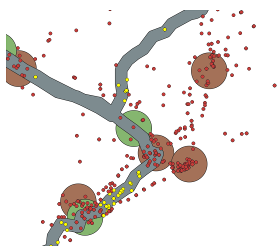
(c) Lower Shebelle Route



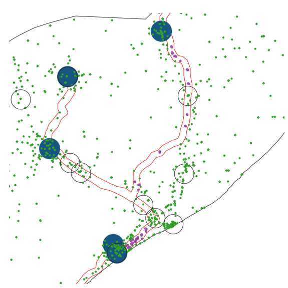
(d) SHFS routes



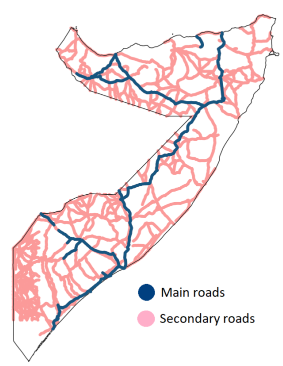
(e) Conflict in 5km corridor



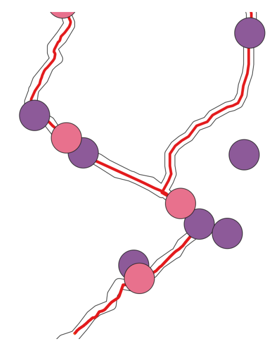
(f) Example for 'Confl betw. growing area and market' variable



(g) Roads used by Jedwab and Storeygard

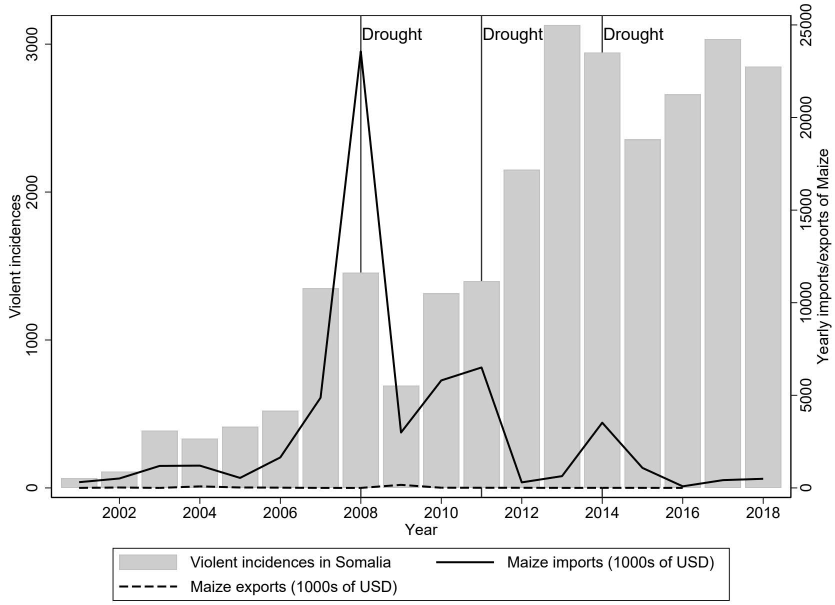


(h) Preprocessing for nightlight data



Notes: Map a: shows transportation route used to supply market of Galkayo with maize; Map b: shows transportation route used to supply market of Hudur with maize; Map c: shows main transportation road in Lower Shebelle in red; Map d: shows the shortest maize trading routes to areas covered by the SHFS implemented by the World Bank (Awdal, Banaadir, Bari, Mudug, Nugal, Sanaag, Sool, Togdheer, and Woqooyi Galbeed). Map e: shows geographical location of roads (grey), towns (maroon) and cities (green), incidents of conflict falling within 5 kilometres of transportation routes are denoted as yellow dots and incidents falling outside of the corridor as red dots; Map f: shows attacks captured by variable *Conflict en route* in purple and attacks captured by variable *Confl betw. growing area and market* in green, transportation routes are shown in red, market towns in blue and other towns in black; Map g: shows primary and secondary roads used by Jedwab and Storeygard (2022) Map h: shows the 1km corridor we use to extract nightlights in red (excluding any emissions 15km around cities and towns)

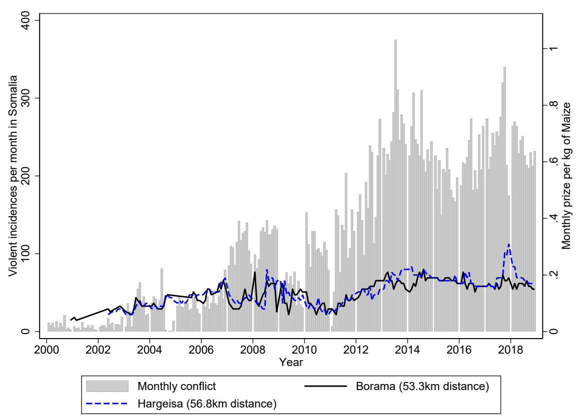
Figure A.2: Imports and exports of maize



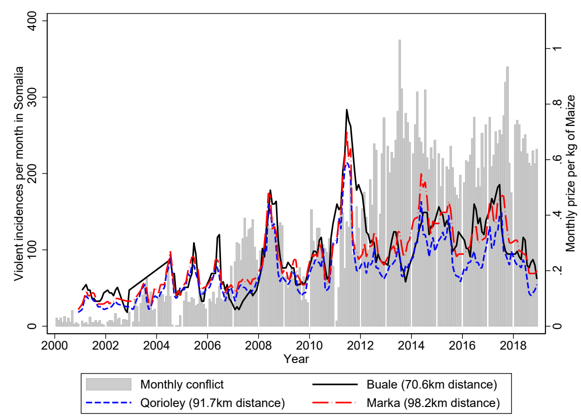
Notes: Figure reports conflict in Somalia along with imports and exports of maize. Bars indicate yearly incidents of violence drawn from ACLED; solid line refers to yearly imports of maize in 1000s USD drawn from United Nations Conference on Trade and Development (UNCTAD); dashed line refers to yearly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

Figure A.3: Prices over time for all 11 markets

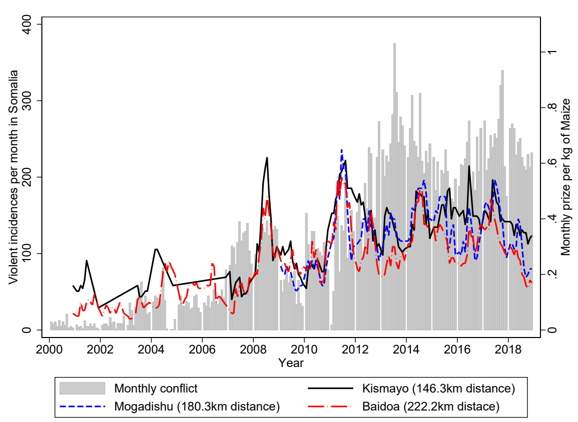
(a) 53km to 57km aerial distance



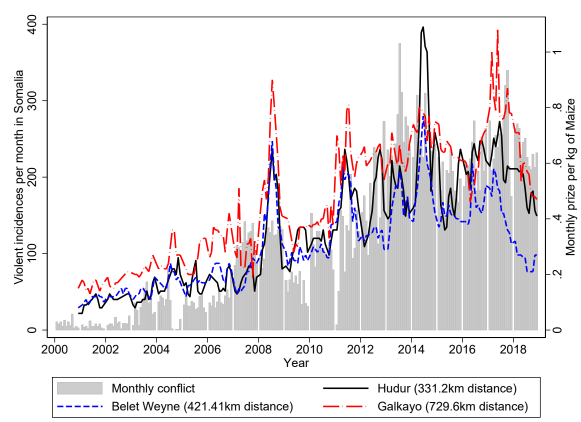
(b) 71km to 98km aerial distance



(c) 143km to 222km aerial distance

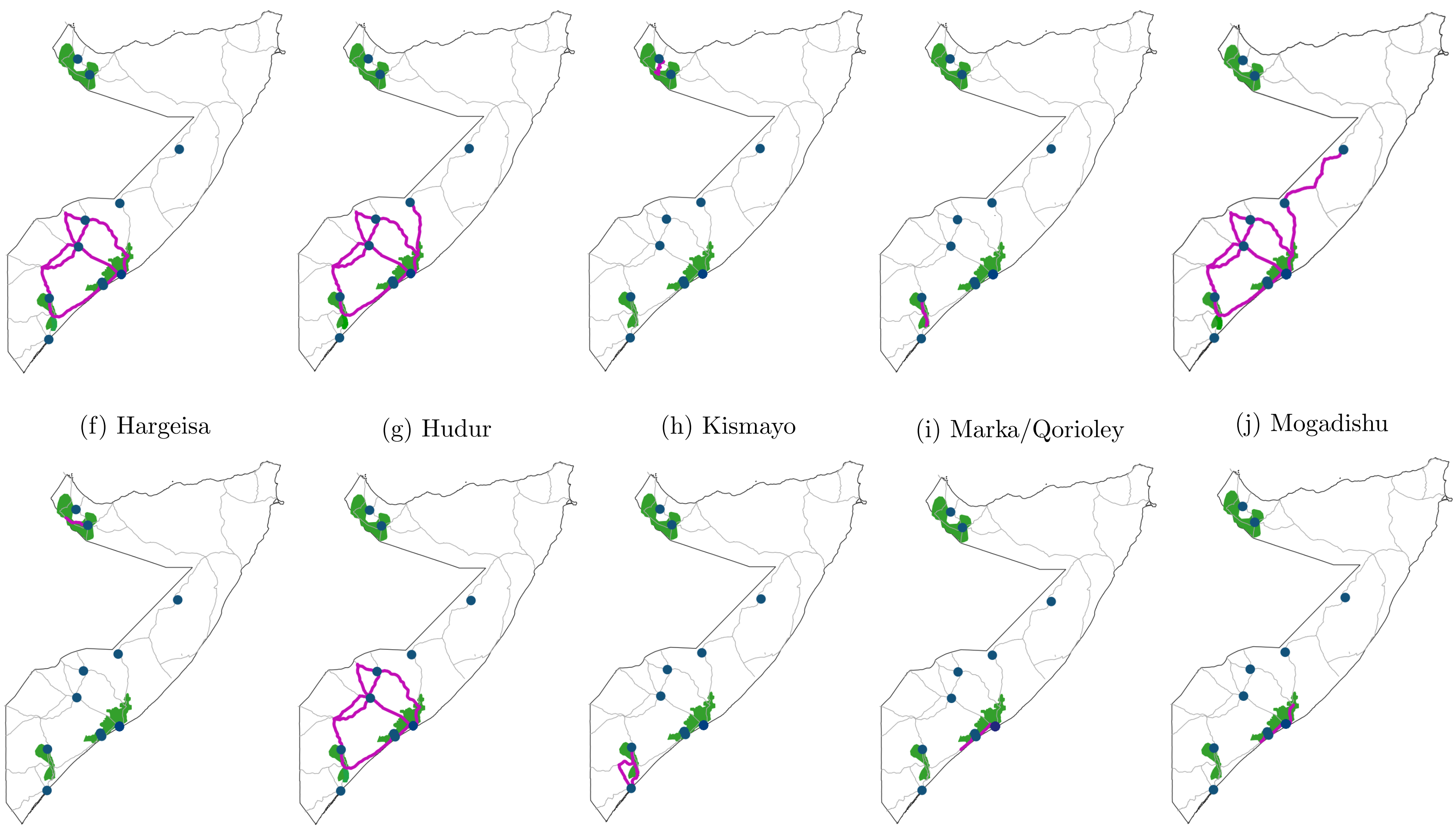


(d) 331 to 730km aerial distance



Notes: The figure reports conflict and maize prices over time and by market in Somalia. Lines denote monthly maize prices and bars monthly incidents of conflict. Distances are in kilometres and refer to aerial distances. **Data sources:** ACLED, FAO.

Figure A.4: Alternative transportation routes

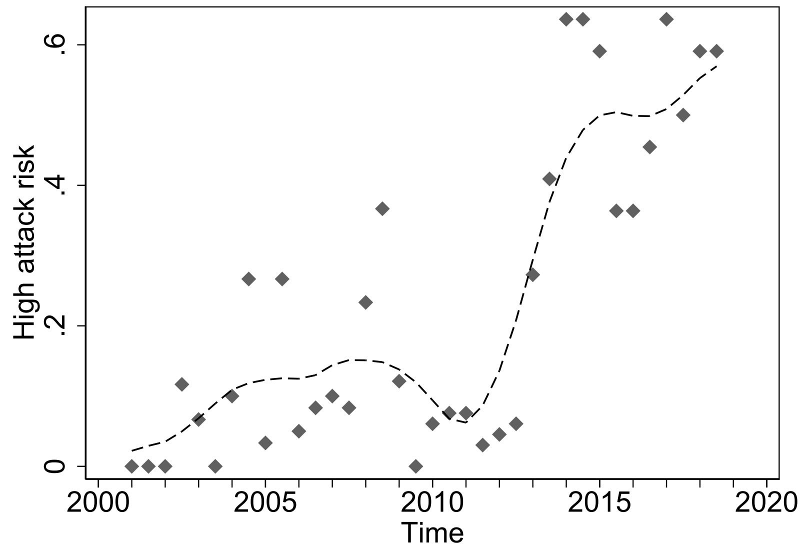


(a) Baidoa (b) Belet Weyne (c) Borama (d) Buale (e) Galkayo

(f) Hargeisa (g) Hudur (h) Kismayo (i) Marka/Qorioley (j) Mogadishu

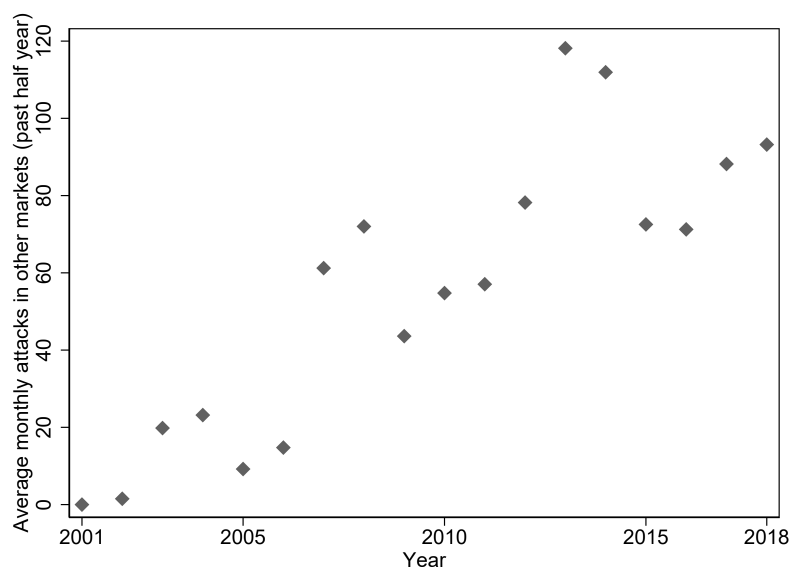
Notes: Figure shows the network of the shortest and of alternative routes from the closest growing area to each market. Shortest and alternative routes have been computed by applying a depth-first search algorithm (Black, 2008) to the road network depicted in Figure 1b to find all simple (non-cyclical) paths between each market and its growing area.

Figure A.5: Evolution of attacks risk and actual attacks over time



Notes: This figure shows the time evolution of the attack risk along transportation routes for maize. For this, the density estimates were aggregated along transportation routes for maize at a monthly level, and transformed into an indicator for the upper quartile of the density (high-attack risk). The figure shows semi-annual average of the high-attack risk indicator. **Data sources:** ACLED.

Figure A.6: Evolution of attacks located within markets



Notes: The figure plots annual averages of attacks located within the cities corresponding to the 11 markets of our analysis. Annual averages are obtained as the year coefficients from regressing average monthly attacks in other markets (varying at the market-month level) on a set of year and market fixed effects. **Data sources:** ACLED.

Appendix B Robustness

Alternative measurements. Our baseline results are robust against a wide battery of alternative specifications. Columns (1) and (2) of Appendix Table A.3 show that our results remain robust to using smaller corridor sizes of 1km and 2.5km to define attacks along roads. In column (3) we only use violent incidents occurring between 2.5km and 5km away from roads (and thus not on the roads themselves). We find a strong positive effect, which tallies with our analysis in section 4.3 suggesting that uncertainty is an important pathway of impact. In column (4) and (5) we control for two corridors contemporaneously: between 0 and 2.5km and between 2.5km and 5km and between 0 and 1km and 2.5km and 5km, respectively. The size of the point estimates remains comparable to our baseline specification and the two effects are not statistically different from each other. In column (6), we re-estimate equation (2) using only incidents of conflict classified as 'geographically precise' by ACLED and find virtually identical results. Column (7), in turn, uses an alternative measure of local conflict (defined as occurring within the same administrative region as market i) and finds very similar results. The next three columns control for productivity in growing regions in three ways: column (8) uses rainfall, column (9) uses the Standardised Precipitation-Evapotranspiration Index (SPEI),[43] a common drought measure, and column (10) the log of maize production in megatons (all as standardized z-scores).[44] As expected, both measures negatively affect prices and our results remain robust. In columns (11) and (12), we compare the effect of violent incidents drawn from the ACLED and GTD using z-scores and find very similar effect sizes. In column (13), we use the description of each ACLED data point to exclude any incidents related to road blocks, food, or barricades. Finally, in column (14), we use ACLED notes to select violent incidents related to 'tax' and find no effect.

Imports and specific markets. We investigate the importance of differential access to maize imports in columns (1) to (3) of Appendix Table A.4 where we interact violence along transit routes with the z-scores of log distance to the closest border, informal maize imports via Ethiopia, and official maize imports, respectively. The baseline effect of conflict en route remains stable. The interaction terms do not show a clear pattern and are not statistically significant. Moreover, columns (4) to (8) show that our results remain robust to excluding different markets and time periods. More generally, in Appendix Table A.5 we re-estimate equation (2) eleven times, dropping a different market at each iteration. The effects remain robust. Thus, our results are not driven by only a few specific markets.

Alternative specifications. To investigate whether our results remain robust to different specifications, we start by showing that our results do not change when we additionally control for year-by-month fixed effects in column (1) of Appendix Table A.6. Results also remain unchanged when controlling for three lags and leads of attacks along roads in column (2). Column (3) shows that we get very similar results if we compute the shortest route based on the road network used by Jedwab and Storeygard (2022). Column (4) further shows that

[43]The data are publicly available under `https://spei.csic.es/`.
[44]The data are publicly available under `https://crops.fsnau.org/`.

the secondary roads in the Jedwab and Storeygard (2022) road network do not matter for prices in our context.

Appendix C Identification checks

In this appendix we provide additional evidence to rule out a range of potential endogeneity concerns.

Supra-regional omitted variables and correlated conflict shocks. A possible identification concern relates to highly correlated waves of conflict or 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).

By controlling for local violence in market i's administrative area and for market-specific year and month effects, our specification in equation (2) allows already for changes in general levels of violence at the supra-regional level. To further address this concern, however, we augment equation (2) with an additional covariate including incidents of conflict occurring in any administrative region located between each market and its growing area, but excluding any incidents within 5 kilometres of the transportation route to that market, which are already included in $conflict_{route_{itm}}$. The map in Appendix Figure A.1f) shows these incidents in green whereas attacks captured by $conflict_{route_{itm}}$ are shown in purple. It acts as a further control for generalized conflict and helps us to establish whether the effect is driven by more general incidents of conflict, or specifically by those occurring along transportation routes. As the results in column (1) of Table A.7 show, the effect of violence along the transportation route remains robust, and violence between growing areas and markets away from transportation routes has no 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 generalized violence across different parts of the country.

Placebo outcomes. Using data provided by the Food Security and Nutrition Analysis Unit (FSNAU) for Somalia we focus on three imports: petrol, diesel, and drinking water. Moreover, we consider four exports: charcoal, goats of export quality, sheep of export quality, and camels. These imports and exports are transported along very different routes than maize, between the respective markets and the relevant entry points into (and exit points from) Somalia. Column (2) of table A.7 shows a very small and statistically insignificant effect of conflict along the transportation route for maize on the average placebo price index. In Appendix Table A.9 we find the same when looking at each price separately. As an additional check, in panel B, we also distinguish cities close to and far away from the coast and find the same patterns.

Alternative measure of attacks. Next we explore the question whether our results might be affected by ACLED not recording all violent incidents that may be relevant for the price of maize by using information drawn from the GTD and re-defining the variable $conflict_{route_{itm}}$

as *terrorist attacks* occurring 5 kilometres either side of the shortest transportation route. As column (3) in Table A.7 shows, each terrorist attack en route increases the price of maize by around 1.1 percent. Moreover, the standardized effects of attacks defined from the ACLED and GTD databases are very similar (columns 11 and 12 of Appendix Table A.3).

Endogenous targeting of transport routes. We provide two pieces of evidence addressing 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.

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 incidents. 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 A.7 confirm that each successful terrorist attack (conditional on attempted attacks) increases the price of maize by 1.58 percent, not too different from the 1.1 percent baseline effect in column (3) of the table. Second, we use detailed information contained in the GTD on characteristics of violent incidents and drop all incidents of conflict coded as aimed at food consumption and distribution. Column (5) shows that the results remain stable.

Appendix D Event-driven changes in conflict

To add transparency regarding the sources of variation in conflict and to shed light on the role of specific policies, we estimate the price reaction to sudden changes in conflict driven by three specific events. We exploit the sudden increase in conflict during the Battle of Belet Weyne (2008), the sudden decrease during the Galkay ceasefire (2015/16), and reduced terrorist activity resulting from US airstrikes aimed at al-Shabaab (2007-18).

The Battle of Belet Weyne. The Battle of Belet Weyne was a sudden increase in fighting from June to July 2008, which affected the two markets of Belet Weyne and Galkayo. In early June 2008, Islamist forces initiated the takeover of the area around Belet Weyne after the Ethiopian garrison withdrew from the area. Fighting drastically escalated in July when Somali opposition fighters ambushed a retreating Ethiopian Army. This fighting caused an estimated 200 casualties. In column (9) of table A.4 we regress conflict along transit routes on a dummy for the battle and find that this event decreased attacks along roads by around 3.6 attacks. Focusing on the years 2006 to 2010, we compare prices in these two affected markets to two other markets on the same transportation route closer to the growing area and thus unaffected by the Battle (Marka and Qorioley—see map in Figure 1). Interacting quarterly dummies with an indicator for the two affected markets, we find a drastic and statistically significant increase in prices in the second quarter of 2008—see Figure D.1a).[45]

The Galkayo ceasefire. Following a bout of conflict occurring in November 2015 between the markets of Galkayo and Belet Weyne (see map 1b) a peace agreement was brokered on December 2, 2015. Policy reports argue that the ceasefire led to a marked decrease in fighting (Puntland Development Center, 2021). This tallies with our own data, which show no terrorist attacks along routes to Galkayo from late 2015 until September 2016, with fighting resuming in October 2016. Column (10) of table A.4 shows that the Galkayo ceasefire decreased attacks along transportation routes by around 3.3 attacks. To evaluate the impact of this ceasefire on maize prices we select the years 2015 and 2016, interact a dummy for the market of Galkayo with month dummies and regress these on maize prices in USD whilst controlling for market, year, and month fixed effects, and using all other markets as the reference group. As figure D.1b) shows, maize prices in Galkayo decrease significantly relative to the comparison markets. After violence re-erupts towards the end of 2016, prices in Galkayo increase once more.

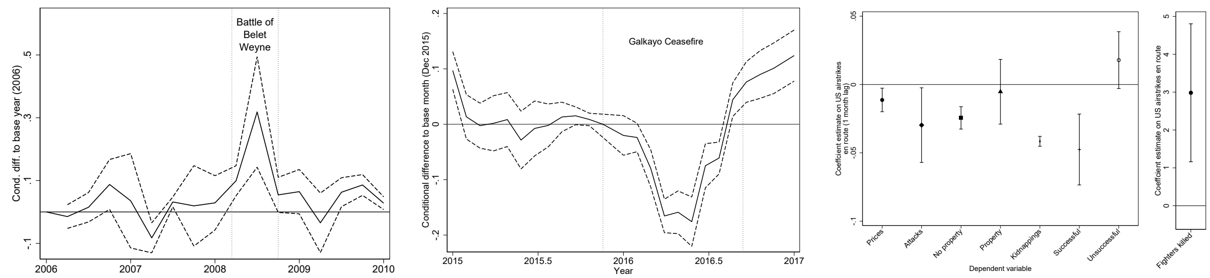
US air strikes. Since 2007, as part of the 'war on terror', the US has been targetting al-Shabaab fighters with airstrikes to decrease terrorist activity and the organization's capacity.[46] According to the Bureau of Investigative Journalism (BIJ), the US carried out 112 separate airstrikes (of which 44 used drones) in Somalia between 2007 and 2018, killing 850 individuals of which 11 were civilians. By decreasing al-Shabaab's capacity, we would expect US drone strikes to decrease conflict along transportation routes and thus decrease far-away maize prices.

[45] We also control for market, year, and month fixed effects and for market-specific rainfall.

[46] https://www.cfr.org/backgrounder/al-shabaab Accessed June 2023.

Figure D.1: Price reactions to event-driven changes in conflict

(a) Battle of Belet Weyne (b) Galkayo ceasefire (c) US airstrikes



Notes: Panel a: shows point estimates (solid lines) and 95% confidence intervals (dashed lines) for month dummies interacted with indicator variable for the markets of Belet Weye and Galkayo - the markets of Marka and Qorioley are the base category (base month is May 2008). The dependent variable is maize prices in USD. Regression controls for market, year, and month fixed effects and market, season-specific rainfall. Panel b: shows point estimates (solid lines) and 95% confidence intervals (dashed lines) for month dummies interacted with indicator variable for the market of Galkayo - the remaining 10 markets are the base category (base month is December 2015). Dependent variable is the log of maize prices in USD. Regression controls for market, year, and month fixed effects and market, season-specific rainfall. Panel c estimates equation (2) to show effect of US airstrikes (1 month lag) on the log maize price, the number of terrorist attacks en route, the number of terrorist attacks by whether they involve property damage or not, the number of terrorist attacks by whether they are successful or not, log of nightlight emissions along transit routes, and fighters killed between market and growing region. **Data sources:** ACLED, FAO, NASA, GTD.

Using data from The Bureau of Investigative Journalism (TBIJ), we define a variable measuring all incidents of US airstrikes occurring between market i and its supplying growing region in the month before m.[47] Figure D.1c) shows that lagged US airstrikes along transportation routes decrease maize prices. A one standard deviation increase in lagged airstrikes decreases prices by around 1 percent, which is similar in magnitude to the positive, standardized effect of conflict in columns (11) and (12) of table A.3. In line with an incapacitation or deterrence effect, we find that airstrikes between growing areas and markets cause around 3 al-Shabaab casualties per strike and also significantly decrease terrorist attacks along transportation routes one month later, particularly for attacks not causing property damage, successful terrorist attacks and kidnappings, which have a particularly strong effect on prices (see Table 3).

[47] Since there are no exact geo-coordinates of attacks, we exclude attacks in the same administrative region as market i.

Appendix E Computation of the risk of violence

We follow the method developed by Tapsoba (2023) to compute the risk of violence over space and time. We start by creating an evaluation grid of points in space and time at which to evaluate the risk of violence. For this we cover Somalia with a 2-dimensional grid of points spaced 0.018 degrees of longitude and latitude (correpsonding to an approximately 2 km spacing in each direction) and create a time grid comprising the 15th of each month from January 2001 to December 2018. We then iterate over these time points t, with the following steps at each iteration:

1. Load ACLED data including all battles and violent attacks against civilians in Somalia from one year before t up to the end of the month comprising t

2. Use this data to estimate the probability density of attacks evaluated at all spatial points of the grid and at time point t using multivariate normal kernel density estimation (using *mvksdensity* in Matlab)

This leaves us with an estimated probability density for the occurrence of an attack at each grid point in time and space. For every month t, and for each of the shortest transport routes to a given market, we then compute a measure of attack risk along the transportation route by adding up the density over all spatial grid points that are within a 2km corridor along the road. To do this, we overlay Somalia with 2km by 2km grid squares, retain those squares that are crossed by any of the shortest routes, and then aggregate the attack density over all grid points that fall into these squares.

Appendix F Detail on SHFS analysis

The regressions in Table 4 are based on the 2016 and 2017 panel waves of the Somali High-Frequency Survey survey (see Appendix H for the source), with the exception of the outcomes in columns (4) and (6)-(7), which were only asked in 2016 and exploit cross-sectional variation only.

Dependent variables: The index in column (5) 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. Infectious illness is an indicator for having suffered from gastroenteritis, malaria, typhoid fever, or chest infection. 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.

Conflict en route definition: For outcomes asked for the current month or week, conflict en route is based on violent incidents in the survey month of each respective wave (columns 2-4 in Table 4). For outcomes asked retrospectively over the past year, violent attacks are averaged over the year prior to the survey (columns 1 and 5 in Table 4). The health outcomes in columns 6-7 refer to the past two months, but to allow for a cumulative effect of past conflict, we define conflict en route over the year preceding the past two months (similarly in Table A.10). School enrollment is asked 'currently', and to allow for cumulative effects of past conflict we define conflict en route over the past year.

Sample sizes: Sample sizes vary across columns in Table 4 due to the following reasons. Columns (1)-(5) are at the household level, columns (6)-(7) at the child level covering children aged 0-10, and column (8) at the child level covering children aged 6-14. Outcomes in columns (4) and (6)-(7) were only asked in the 2016 survey wave. Moreover, according to the survey design, not all households have been asked all consumption items, and in 2016 the module on shocks that have affected households (including high food prices, column 1) has not been asked to all households.

Appendix G Context on distance and transport cost

In section 5, τ_{od} represents an iceberg trade cost, linking the price at destination p_d to the price at origin p_o through $p_d = p_o\tau_{od}$. We can think of τ_{od} defined as $\tau_{od} = 1 + t_{od}$, where t_{od} is a tax equivalent trade cost. As argued in Anderson and Van Wincoop (2004), it is reasonable to assume that distance $dist_{od}$ affects trade cost via the tax equivalent trade cost, i.e., t_{od} is a function of distance: $t_{od} = f(dist_{od})$. For the effect of distance on the price at destination, γ, this setup yields:

$$\begin{aligned}
\gamma = \frac{d\ln p_d}{d\ln dist_{od}} &= \frac{\partial \ln p_d}{\partial \ln t_{od}} \times \frac{d\ln t_{od}}{d\ln dist_{od}} = \frac{\partial \ln[p_o(1+t_{od})]}{\partial \ln t_{od}} \times \frac{d\ln t_{od}}{d\ln dist_{od}} \\
&= \frac{\partial \ln(1+t_{od})}{\partial \ln t_{od}} \times \frac{d\ln t_{od}}{d\ln dist_{od}} = \frac{\partial \ln(1+t_{od})}{\partial t_{od}} t_{od} \times \frac{d\ln t_{od}}{d\ln dist_{od}} \\
&= \frac{t_{od}}{1+t_{od}} \times \frac{d\ln t_{od}}{d\ln dist_{od}} \qquad \text{(G.1)}
\end{aligned}$$

The term $\frac{t_{od}}{1+t_{od}}$ is the share of tax equivalent trade costs relative to the total price at destination. Equation (G.1) has two key implications. First, the effect of distance on the price in a log-log model will be larger the higher the share of trade costs in the total price. Second, if we assume that $\frac{d\ln t_{od}}{d\ln dist_{od}} <= 1$, meaning that the trade cost does not over-proportionately react to changes in distance, then the share of trade costs in the total price provides an upper bound for the price effect of distance.

In our context of the maize market in Somalia in the 2000s, we find $\hat{\gamma} = 0.46$ (Appendix Table A.13). In comparison, Donaldson (2018) reports an effect of 0.169 for the salt market in India in the 1860-1930 period, and Limao and Venables (2001), albeit in the context of international container shipping costs, find elasticities of iceberg transport cost with respect to distance of around 0.25–0.38.

As equation (G.1) demonstrates, an explanation for the relatively larger effect in our context could be a higher share of transportation costs in the total price. Several pieces of evidence suggest this as a plausible explanation. First, the mode of transport in our context is exclusively by road. Notably, railway transport, which is present in Donaldson (2018)'s context (and estimated to be cheaper by a factor of around 2 per unit-distance costs) is absent in our context. Moreover, Somalia's road network and transport infrastructure are poor, a factor that has been shown by Limao and Venables (2001) as an important determinant of high transport costs.

In their literature survey, Anderson and Van Wincoop (2004) cite a tax-equivalent share of direct and indirect transport cost of 21% as their preferred estimate, but also make clear that transport costs can be higher in bulky agricultural products and that developing countries have significantly higher trade costs. Focusing on Sub-Saharan Africa, Christ and Ferrantino (2011) report a wide range of anecdotal evidence about the high costs and time of land-transport in the region, which is a result not only of poor infrastructure, but also of prolonged delays due to slow administrative procedures or frequent road blocks. In addition to monetary and time cost, they also highlight significant uncertainty in land transport caused by unpredictable and changing road and rail conditions, administrative obstacles, corruption, and informal payment demands. As Christ and Ferrantino (2011) state, 'This uncertainty leads to numerous costs such as scheduling costs, information costs, suboptimal inventory levels, supply chain redundancy, and reduced orders.' For selected commodities destined for export, these authors provide estimates of the total monetary and non-monetary costs for land transport in Sub-Saharan Africa, and find that in many cases these far exceed Anderson and Van Wincoop (2004)'s transport cost estimate of 21% for the US. Focusing specifically on the maize market in East Africa, The World Bank (2009) identify domestic transport cost as one of the most important item (averaging to up to 76%) of total marketing costs of maize, due to various factors, including poor infrastructure, delays and bribes, as well as cost and market structures in the trucking industry. A UNDP/SCALA Report (2024), for instance, interviewed a private company (ADCO) working with maize and sesame farmers in southern Somalia. ADCO reported transportation costs of around USD44 per truck. However, for insecure areas an additional fee of USD50-USD100 per lorry is typically imposed. Moreover, a policy report by the Rift Valley Institute documents the pervasiveness of road checkpoints and bribes in the Somali context, a practice already common before the onset of the al-Shabaab insurgency.[48] Al-Shabaab's activities have made this problem worse since the organisation frequently uses highways to ambush government forces and to disrupt trade[49] through, for instance, hijacking and kidnapping.[50] Given this background of high transport costs, a comparatively high estimate for the effect of distance on prices seems reasonable.

[48] https://riftvalley.net/wp-content/uploads/2023/10/Paying-the-Price_Final-Reduced3-reduced.pdf, accessed December 2024.

[49] https://landinfo.no/asset/3569/1/3569_1.pdf. accessed January 2025.

[50] https://insecurityinsight.org/wp-content/uploads/2023/02/Somalia-Conflict-Hunger-and-Aid-Security-February-2023.pdf?. accessed January 2025.

Appendix H Data sources

We use the following data sources in the paper

- Armed Conflict Location & Event Data Project (ACLED) are available at https://acleddata.com.
- Global Terrorism Database (GTD) data are available at https://www.start.umd.edu/gtd/about/.
- US airstrike data from the Bureau of Investigative Journalism (TBIJ) are available at https://www.thebureauinvestigates.com/stories/2017-01-01/drone-wars-the-full-data/.
- FAO maize price data are available at https://fpma.apps.fao.org/giews/food-prices/tool/public/#/home
- First round of Somali High Frequency Survey (SHFS) is available at https://microdata.worldbank.org/index.php/catalog/2738.
- Second round of Somali High Frequency Survey (SHFS) is available at https://microdata.worldbank.org/index.php/catalog/3181.
- Food Security and Nutrition Analysis Unit (FSNAU) data on prices for food and non-food Minimum Expenditure Basket (MEB) prices are available at https://fsnau.org/ids/index.php. The data are available only from 2011 to 2018.
- Visible and Infrared Imaging Suite (VIIRS) Day Night Band (DNB) data are available at https://eogdata.mines.edu/products/vnl/. The data are available only from April 2012 to December 2018.
- Maize trade maps by FEWS NET are available at https://fews.net/east-africa/somalia
- Somali road network as provided by the FAO, depicted on Figure 1b is available athttps://spatial.faoswalim.org/layers/geonode:SOM_Primary_Roads_UNOCHA
- SPEI data are available under https://spei.csic.es/
- Food Security and Nutrition Analysis Unit (FSNAU) maize production data are available under https://crops.fsnau.org/

Appendix I Detail on Nightlight data preparation

In line with the literature, we apply several preprocessing steps:

- We use monthly averaged NASA nightlight data, which reduces noise and atmospheric distortions through temporal averaging techniques (NASA Visualisation Studio, 2023; Earth Observation Group, n.d.; Li et al., 2020).
- To focus on traffic rather than economic activity or population movements, we exclude cities and towns along transit routes (Mellander et al., 2015).
- Following Sánchez de Miguel et al. (2020), who warn against oversaturation in the vicinity of cities, we create 15km buffer zones around these areas.
- QGIS requires a polygon-defined area to calculate average raster values. Based on this, use a tight band of 1km around roads, excluding towns and cities. The extracted areas are shown as red lines in Figure A.1(h).
- In separate steps, we also check our estimates for robustness by dropping particularly large emissions (Liu et al., 2020).

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