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Extreme Weather and Civil War in Somalia: Does Drought Fuel Conflict through Livestock Price Shocks?

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Extreme Weather and Civil War in Somalia: Does Drought Fuel Conflict through Livestock Price Shocks?

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Abstract

Climate change leads to more frequent and more intense droughts in Somalia. In a global context, weather shocks have been found to perpetuate poverty and fuel civil conflict. By relating regional and temporal variations in violent conflict outbreaks with drought incidence and severity, we show that this causality is valid also for Somalia at the local level. We find that livestock price shocks drive drought-induced conflicts through reducing the opportunity costs of conflict participation. Our estimation results indicate that a temperature rise of around 3.2 degrees Celsius—corresponding to the median Intergovernmental Panel on Climate Change scenario for eastern Africa by the end of the century—would lower cattle prices by about 4 percent and, in turn, increase the incidence of violent conflict by about 58 percent. Hence climate change will further aggravate Somalia's security challenges and calls for decisive action to strengthen both drought and conflict resilience, especially in pastoralist and agropastoralist livelihoods.

Keywords: drought, conflict, civil war, livestock, prices, Somalia, Horn of Africa

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1. Introduction

Extreme weather events have become more frequent and more intense since the middle of the 20th century worldwide and are likely to become even more pronounced throughout the 21st century due to climate change (IPCC 2012). Particularly, the number and length of warm weather spells and heat waves have increased globally. Strong evidence exists that such extreme temperature events will further augment at the global scale as well as in the Horn of Africa, giving rise to more and more severe droughts. After consecutive years of irregular or failing seasonal rainfall, in 2011 Somalia experienced the most destructive drought in the last 50 years (Maxwell and Fitzpatrick 2012). The resulting famine has pushed the number of Somalis in need of emergency assistance to about four million, with more than half a million at imminent risk of starvation in early 2012 (FSNAU and FEWSNET 2011). Although the 2011 drought was largely a result of the prevailing climatic phenomenon La Niña (leading to poor rainfall in the Horn of Africa), extreme temperatures and rainfall failures have become more common in recent years. At the same time, Somalia has been rattled by civil war, ongoing since 1991, and violent disputes have become more frequent recently, especially since 2002. The coexisting trends raise the fundamental question about a potential relationship between the occurrence of drought and the risk of civil conflict.

Historical data point to a strong relationship between warming and civil war on the African continent, with warmer years leading to increased likelihood of conflict. Burke et al. (2009) estimate that a rise in temperature of 1 degree Celsius increases the incidence of internal armed conflict in African countries south of the Sahara (SSA) by 4.5 percent in the same year and 0.9 percent in the next year. Combining these estimates with climate model projections of future temperature trends suggests a 54 percent increase in armed conflict incidence by 2030 (Burke et al. 2009). Hsiang, Meng, and Cane (2011) found that the probability of conflict outbreaks arising throughout the tropics doubles during El Niño years (leading to warmer and dryer weather in the continental tropics) relative to La Niña years. The authors estimate that El Niño–Southern Oscillation may have contributed globally to 21 percent of all civil conflicts since 1950. O'Loughlin et al. (2012) show that abnormally high temperatures and low rainfall increased the risk of violent conflict in East Africa (covering Burundi, Djibouti, Eritrea, Ethiopia, Kenya, Rwanda, Somalia, Tanzania, and Uganda) over the past two decades. Also, based on data from Ethiopia, Kenya, and Uganda, Raleigh and Kniveton (2012) found that the frequency of conflict events in East Africa increases in periods of extreme climate variation, with higher rates of rebel conflict exhibiting during anomalously dry conditions. Although these studies show that the stability of African societies relates strongly to the global climate (Hsiang, Meng, and Cane 2011) and emphasize the urgent need for reforming government (and development partner) policies to deal with rising temperatures (Burke et al. 2009), they reveal little about the channels and causal mechanisms through which climate extremes affect people's motivation to engage in civil conflict. Yet understanding the channels of transmission and the factors driving conflict is critical to the search for both effective climate change mitigation and conflict prevention strategies (Schreffan et al. 2012).

Following the seminal work by Collier and his coauthors on the causes of civil war (Collier and Hoeffler 1998, 2004; Collier and Sambanis 2002), economic behavior has been frequently used to explain people's incentives to participate in conflict. Probably the most robust finding throughout the conflict literature is that slow economic growth and low per capita income contribute to civil conflict (Blattman and Miguel 2010). Collier and Hoeffler (1998, 2004) found that economic opportunities, such as expected income from being a fighter relative to ordinary labor market rates, motivate people to participate in violent conflict rather than political and social grievances such as repression against particular social groups and societal inequality. Findings on the roles of ethnic or religious fractionalization (Easterly and Levine 1997; Fearon and Laitin 2003), natural resources dependency (Humphreys 2005; Brunnschweiler and Bulte 2009), and degree of democracy (Elbadawi and Sambanis 2002; Hegre et al. 2001) as drivers or preventers of civil conflict are quite inconsistent.

Introduced by Collier and Hoeffler (1998, 2004), the model explaining conflict participation as an outcome of changes in opportunity costs has been used and advanced to link the occurrence of conflict events to extreme weather conditions, assuming causal relationship between weather shocks and adverse economic conditions (Kurukalasuriya et al. 2006; Schlenker and Lobell 2010; Dell, Jones, and Olken 2012). Methodologically, this approach offers an appealing solution to address the endogeneity of economic variables to conflict in econometric estimations. Using rainfall variation as an instrument for gross domestic product (GDP) growth to minimize endogeneity biases and omitted variable problems, Miguel, Satyanath, and Sergenti (2004) estimate that a negative growth shock of five percentage points increases the likelihood of conflict in SSA by one-half in the following year.[1] Likewise Brückner (2010) uses rainfall-based variables as instruments in his estimation of the global conflict effects of population growth and GDP growth. In this paper, we adopt the basic estimation framework as proposed by Miguel, Satyanath, and Sergenti (2004) but modify it to focus our analysis rather on the effects of droughts on civil conflicts at the local level and livestock prices as channels of transmission.

We hypothesize that droughts fuel civil war in Somalia through lowering the opportunity costs of conflict participation. Given that the livestock sector is the mainstay of the country's economy, we further hypothesize that drought increases the risk of conflict through livestock price downturns that entail substantial income losses. The objective of our paper is to test these hypotheses, econometrically estimate the impact of drought and associated livestock price shocks

[1] The robustness of Miguel, Satyanath, and Sergenti's (2004) estimation results have been subject to an intense debate between Ciccone (2011) and Miguel and Satyanath (2011). For similar reasons Buhaug (2010) questions Burke et al.'s (2009) estimation results. Although reviewing the arguments related to these cross-country studies is beyond the scope of this paper, the debate has motivated our sensitivity analysis presented in Section 5. Klomp and Bulte (2012) provide a comprehensive review of the debate.

on the likelihood of conflict outbreaks, and derive policy-relevant conclusions from the estimation results.

Our paper makes several important contributions to the literature. It contributes to the microeconomic strand of the empirical literature that has been dominated by cross-country studies (for example, Blattman and Miguel 2010). The cross-country nature of previous studies, however, leaves regional (subnational) heterogeneity unobserved and thus limits the ability to derive context-specific recommendations for effective strategies and national policies of conflict prevention. In contrast, our analysis explores the heterogeneity at the administrative region level. While other studies on Somalia have dealt mainly with the economic and social consequences of the collapse of the central state in 1991 (for example, Little 2003; Mubarak 1997; Powell, Ford, and Nowrasteh 2008) or piracy in recent years (for example, Shortland 2011; Besley, Fetzer, and Mueller 2012), we provide evidence on people's incentives to participate in civil conflict. By looking at livestock price shocks, we shed light on the role of local market pricing in changing the incentives for conflict participation.

The rest of the paper is organized as follows: Section 2 provides contextual information on the links between drought, livestock prices, and conflict in Somalia and thus establishes the rationale underlying our empirical analysis. Section 3 explains our identification strategy and estimation framework applied to test our hypotheses. It also provides information on the underlying data and the constructed indicators used in the empirical model. Section 4 presents the estimation results of our preferred model specification, and Section 5 discusses the results of our robustness checks and validity of identifying assumptions. Section 6 concludes with policy implications.

2. Study Context and the Conflict–Drought Nexus

Since the collapse of the national government and the outbreak of civil war in 1991, Somalia has had no central government control over the entire territory. The country has been divided into at least three (semi)autonomous territories on a de facto basis, namely, Somaliland in the northwest, Puntland in the northeast, and the remainder of Somalia in the central and southern part with its capital, Mogadishu. While violent conflicts have occurred all over the country, most of them have taken place in the central-southern regions of the country, where the Islamist Al-Shabab militia has been most active.[2]

Despite the absence of effective national governance since 1991, Somalia has maintained a functioning informal economy dominated by livestock rearing and exports, remittances inflows and money transfers, and telecommunications (Powell, Ford, and Nowrasteh 2008; World Factbook 2011). Traditionally the livestock sector has been central to the economic and cultural life of Somalis. The livestock sector contributes to approximately 40 percent of gross domestic product (GDP) and accounts for almost 90 percent of total agricultural GDP and more than half of all exports earnings (Knips 2004; World Factbook 2011). It provides food and income to more than 60 percent of the total population (FSNAU and FEWSNET 2011). Given that about two-thirds of the population reside in rural areas (World Bank and UNDP 2003), pastoralism (nomadism) or semipastoralism is the source of livelihood for most rural Somalis, while a significant number of urban dwellers are also engaged in livestock-related activities including livestock trading and processing of livestock products. Purely pastoralist livelihoods are prevailing in northern and central Somalia, and agropastoral livelihoods are predominant in the southern part and some pockets in the northwestern and central parts (FSNAU 2011a). Countrywide goat and sheep herds are most common, while cattle herds are more numerous in the southern regions than in the northern regions. Somalia is highly vulnerable to weather shocks—especially droughts (but also floods)—because of its geographic location and fragile environments (FSNAU 2011a), so the occurrence of drought in Somalia is not unusual but is rather a recurring feature of the country's climate. Nonetheless, prolonged and consecutive droughts constitute a major constraint to development and threat to rural livelihoods in Somalia. Most of the regions typically affected by droughts are arid and semiarid areas that are low in resources and already under substantial ecological pressure under normal circumstances (Mutua and Balint 2009). Formal mechanisms to cope with shocks are unavailable because of lacking credit and insurance markets, and public safety nets are absent (Headey, Taffesse, and You 2012). Hence, drought mitigation strategies are often limited to recourse to clan-based support, migration, and selling of productive assets (Dercon and Hoddinott 2004; Lybbert et al. 2004; Mogues 2011). However, the capacity of the traditional support system is very limited when major droughts strike, because drought is a large-area disaster, and therefore a large share of the

[2] See Figure A.1 in the Appendix.

population faces the same fate at the same time.[3] Migration may involve costs related to transportation of people and assets, along with amplified competition over meager available resources, such as access to water and pasture.[4] Destocking of herds is therefore the dominant and often only remaining strategy to avoid extreme poverty and hunger, but all too frequently it is of limited effectiveness and ends in a poverty trap (Carter and Barrett 2006; Carter et al. 2007; McPeak and Barrett 2001).

Widespread poverty and lack of employment leave a breeding ground for recruitment of fighters into extremist groups like Al-Shabab (or other conflict parties), offering cash income and other benefits (Majid and McDowell 2012). Given these conditions, engaging in civil conflict to make one's own living at the expense of others (either directly as a fighter or indirectly as a supporter of either party) may appear opportunistic for some people. Such self-seeking behavior tends to be amplified in times of unusual hardship—when experiencing serious income loss from droughts—and facilitated by the political economy of the stateless order as in most of Somalia (Mubarak 1997; Powell, Ford, and Nowrasteh 2008; Leeson 2007). Anecdotal evidence from the 2011–2012 famine supports this notion. For example, a representative of the United Nations Refugee Agency in Somalia states that "this [famine] has been a boon for Al-Shabab's recruitment campaign because when you don't have purchasing power to buy the food, you will be encouraged to be recruited because then you will be saved, and you can use that salary or you could be given food" (Heilprin 2011). Moreover, interviews with Al-Shabab deserters reveal that the Islamist militia uses cash payments and promises regular salary for recruitment in combination with threats of force (Baldauf and Mohamed 2010).

Conflict and Drought Frequency

Both violent conflicts and droughts have drastically increased in Somalia in recent years. Data from the Armed Conflict Location and Event Dataset (ACLED 2011) show that violent conflicts have erupted more frequently since 2002. Between 1997 and 2009, violence outbreaks fall into two particular periods—from mid-2003 to mid-2004, and from 2007 onward—with several peaks of more than 80 events per month. These high-intensity conflict periods overlap with periods of major droughts.[5] Temperature data from the University of East Anglia Climate

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[3] Our drought data suggest that the spatial variation in the occurrence of droughts is low. Over the past 60 years (1950–2009) Somalia's 18 administrative regions experienced 6.3 drought months per year on average, with the least affected region at 6.2 drought months and the most affected region at 6.5 drought months on average. See Section 3, "Methodology and Data," for a detailed description of the underlying weather data and the calculation of the drought variables.

[4] Mutua and Balint (2009) note that during droughts local conflicts and fighting over water sources and grazing land surges, particularly when nomad communities move onto the lands of nonmobile communities and when different pastoral clans move to the same place and want to use the same scarce resources. Because of data limitations our empirical model cannot adequately account for increased competition over water and land resources due to drought-induced displacement as a driver of conflict. We therefore explore the robustness of our estimation results and discuss the underlying identifying assumptions in this regard.

[5] See Figure A.2 in the Appendix. See Section 3, "Methodology and Data," for a detailed description of the conflict data.

Research Unit (UEA-CRU 2011) suggest that Somalia's longest drought period since the beginning of the 19th century lasted 23 months from late 2002 to late 2004.[6] Also the second conflict period came along with a major drought. The resulting famine affected 3.3 million people in 2008 (EM-DAT 2012). Although Somalia was hit frequently by major droughts in the 1970s and 1980s too, the impact of the more recent droughts on humanity has been much more devastating, as the number of affected people indicates (EM-DAT 2012). Overall, our drought data indicate a clear trend toward more frequent, longer-lasting, and more intense droughts across Somalia: The number of drought months per year, the number of consecutive drought months, and the monthly temperature deviations from the long-term trend have significantly increased in all 18 administrative regions, particularly over the past 30 years.

The Livestock Market Channel

Droughts cause herders to sell more of their livestock than they would sell under normal conditions because of either livestock fodder and water shortages or insufficient household income to cope with rising staple food prices (Abebe et al. 2008; Morton and Barton 2002). The liquidation of herds can be expected to follow an empirical, egoistic rationale, considering a variety of interconnected factors such as available fodder and water capacities, livestock sale prices, herd restocking requirements, and capacities of smoothing household consumption (McPeak 2006). The fact that drought is a recurring feature in Somalia's climate and a slow-onset and large-area disaster has several important implications for herders' decisions on when to sell, how many animals to sell, and which ones to sell.

First, herders know well that fodder and water shortages may kill at least some of their animals, usually the weaker ones first. These animals may also be those that are less preferential genetically for restocking after the drought (such as those with lower milk and meat yields, fertility, and drought resistance) (Aklilu and Catley 2009; Aklilu and Wekesa 2002). Hence, selling these animals as early as possible might appear intuitive. Second, lean animals, however, reach lower prices than well-fatten ones, and only the well-fatten animals can be sold for export, while the local demand for livestock and meat might even collapse during times of widespread food shortage. Herding the animals to the market over long distances during drought reduces weights further—possibly below the minimum acceptable price (and may even kill some)—while transportation of herds by truck is often unaffordable. Third, given empty or thin local livestock markets after droughts and lacking cash liquidity because of missing credit and finance markets, herders may try to hold on to a large herd size as long as possible to maintain a sufficient number of animals for fast restocking after drought. Important to note in this context, herd size is critical and determines the herding system and hence the way of living (Devereux 2006; Lybbert et al. 2004). For the Somali region in neighboring Ethiopia, Lybbert et al. (2004) found a threshold level for cattle herds at an unstable equilibrium of 10–15 animals for a typical

[6] See Section 3, "Methodology and Data," for a detailed description of the underlying weather data and the calculation of the drought variables.

transhumant herder household of 6.0–6.5 members. Accordingly, 2-plus cattle per household member are necessary to sustain the opportunistic, spatially flexible herding associated with extensive pastoralism. When a household's herd size falls below this threshold level, it effectively switches to a sendentarized herding system that, however, is much more vulnerable to spatiotemporal variability in rainfall and provides lower returns. Hence, maintaining a herd of any size becomes then exceedingly difficult so that sedentarization with a small herd corresponds to dire poverty in pastoralist communities (Lybbert et al. 2004). Indeed, agropastoralists are particularly vulnerable to droughts mainly because of their inability to reach water sources and sufficient grazing land during droughts (Headey, Taffesse, and You 2012).

Finally, the slow onset of droughts may give herders time to choose their preferred coping strategy, but the large spatial spread of droughts not only limits herders' options but may also induce a similar, contemporaneous behavior that adversely affects the majority of herders.[7] For example, consider that herders' preferred strategy is to maintain their herd size as long as possible in the hope of a short drought period. When the drought becomes more severe, an increasing number of herders are forced to sell their livestock at the same time and to accept a lower price due to market oversupply of thin animals. The depression of livestock market prices in turn reduces herders' income and hence purchasing power, which is already diminished by high staple food prices. The deterioration of cattle body conditions during the 2010–2011 drought, for example, led to a drop in cattle prices in southern Somalia by 30–50 percent within four months (September–December 2010), while cereal prices spiked by 50–60 percent. As a result, the purchasing power in the southern regions plummeted by 40–60 percent at the end of 2010 from the previous year level (FSNAU 2011a).

[7] In contrast, floods occur much more rapidly, and the damage is much more localized. The effects on the livestock market can therefore be expected to fundamentally differ from the effects of drought and may be less pronounced overall. This, in addition to the scope of the disasters' impacts on humanity in the Somali context, induced us to limit our study to the analysis of droughts.

3. Methodology and Data

Identification Strategy

Our estimation of the effects of drought on civil conflicts through livestock price shocks follows a clear identification strategy. We begin by estimating the cross-sectional and intertemporal variation in the incidence of violent conflict events as a function of drought (hereafter referred to as *reduced-form* function) to detect a potential conflict–drought relationship and to quantify its strength implied by our data. Given that we find a statistically significant relationship, we then explore the possible channel through which droughts translate into conflict outbreaks, assuming that people's motivation to participate in violent conflicts is essentially driven by economic means. Along with Miguel, Satyanath, and Sergenti (2004), we adopt the opportunity costs approach according to which income losses—caused by an external shock, for example—lower the opportunity costs of the affected people for engaging in conflict activities. Hence the decisional factor of the individual's behavior is the current household income from ordinary activities relative to the expected income from conflict participation. Because of the large contribution of livestock husbandry to (rural) income earnings and lacking income (and consumption expenditure) data, we use changes in livestock prices as proxy for changes in household incomes. We use livestock prices for export quality instead of prices for local quality, because the former tend to be less influenced by the local meat demand.[8] Our hypothesis that producer prices of key exports matter for conflict is generally supported by Brückner and Ciccone (2010), who found that civil wars in Africa south of the Sahara (SSA) are more likely to erupt after downturns in the international price of the countries' main export commodities. At the subnational level, Dube and Vargas (2008) show for Colombia that the price of labor-intensive agricultural products affects conflict primarily through losses in opportunity costs. The authors found that the sharp fall in international coffee prices during the late 1990s led to increased violence in coffee-dependent municipalities.

To coherently estimate the effects of drought on conflicts transmitted through changes in livestock prices, we use a two-stage estimation framework. The challenge of our identification strategy is to isolate this livestock market channel from all other possible channels of transmission. Since we may not be able to fully exclude all other potential channels due to

[8] Livestock prices—especially for export quality—can be expected to be largely supply driven in Somalia. Domestic and foreign demand for livestock is fairly stable throughout the year except before Muslim Eid festivals. For example, export data from Bosaaso and Berbera ports—the main ports for export of live animals—show that the number of exported sheep and goats during the Hajj month in 2009 increased more than fivefold compared with the average of the previous three months, while the export of cattle increased less than twofold (FSNAU 2011a). Over the past two decades, two major demand-side shocks had important knock-on effects on the livestock sector in the Horn of Africa. Because of an outbreak of the Rift Valley Fever and concerns about inappropriate health screening, Saudi Arabia—the major importer of livestock from Somalia—imposed a ban on livestock imports from eastern Africa from February 1998 to April 1999, reestablished the ban in September 2000, and lifted it in November 2009, before the Hajj.

lacking data, we perform a comprehensive set of robustness checks to our preferred model specification and validity tests of our identifying assumptions.

Our empirical model requires dealing with endogeneity and potential problems of omitted variables and measurement errors. The causality between conflict and economic variables may run into both directions such that income shocks increase the likelihood of conflict (as outlined above), and conflict exposure can be a shock to income earnings. For example, conflicts may diminish or destroy productive assets such as livestock herds through theft and transportation infrastructure through sabotage, leading to higher producer prices (Blattman and Annan 2010; Bundervoet 2010; Verpoorten 2009). Devereux (2006) reports that looting of livestock is a common instrument of conflict in the Somali region of neighboring Ethiopia. A standard solution to address the endogeneity problem in econometric estimations is an instrumental variable approach. Weather-related variables such as changes in temperature or precipitation appear to be plausible instruments for changes in household income and prices of agricultural products in subsistence-based economies. Omitted variable biases may arise from unobserved factors that affect both our proxy for household incomes (livestock prices) and the conflict variable. Examples include historical grievances among and between pastoralist and agropastoralist communities, social or ethnic fragmentation of the population, population density, institutional conditions, transportation infrastructure, geography, and so on. Certainly, potential measurement errors in the data are a general concern of model specification and particularly so in Somalia.

We address the potential problem of omitted or unobserved variables in a general manner by controlling for region- and time-fixed effects in both the reduced-form estimation and the two-stage estimation. The region-fixed effects pick up time-constant, unobserved heterogeneity across regions, including region-specific factors of conflict and livestock market pricing such as colonial vestiges, ethnic composition of the population, and market structure. The time-fixed effects control for external shocks that affect all of Somalia similarly, such as Saudi Arabia's livestock import ban (imposed in 2000 and lifted in 2009).

Estimation Framework

The reduced-form regression has the following estimation equation:

$$conflict_{i,t} = c + \alpha_i + \phi_t + \eta\, drought_{i,t} + \varepsilon_{i,t} \,. \tag{1}$$

The dependent variable in Equation (1) is the number of violent conflict events in Somalia's administrative region i during the year–month time period t ($conflict_{i,t}$). The main deterministic variable ($drought_{i,t}$) identifies droughts, with high and positive value indicating severe droughts. Region-fixed effects are captured by a vector of region-identifying dichotomous variables (α_i). Time-fixed effects enter through a vector of dichotomous variables specific to each time period in the sample (ϕ_t). The term $\varepsilon_{i,t}$ is a disturbance term; the disturbances are allowed to be correlated across time periods for the same administrative region. The model works in differences and therefore explains variations within regions over time (that is, deviations from the regional means) rather than cross-sectional differences in levels. Hence it indicates what drives variations in conflicts rather than what causes conflicts.

The conflict–drought relationship implied by Equation (1) is decomposed into two stages, with livestock prices as a factor of transmission. Technically, we estimate an instrumental variable, two-stage least-squares, fixed-effects (IV-2SLS-FE) model with robust standard errors. The first-stage equation yields the effects of droughts on livestock prices and thereby provides statistical evidence on the strength of the weather variable as an instrument of livestock prices. The equation is as follows:

$$\ln price_{i,t} = c_1 + \alpha_{1i} + \phi_{1t} + \vartheta \, drought_{i,t} + \varepsilon_{1i,t} \, , \tag{2}$$

where $price_{i,t}$ denotes the time- and region-specific livestock price index. The second-stage equation, which yields the effects of livestock prices on the number of conflict events, is then

$$conflict_{i,t} = c_2 + \alpha_{2i} + \phi_{2t} + \psi \, \ln \widehat{price}_{i,t} + \varepsilon_{2i,t}. \tag{3}$$

Finally, we use the estimated coefficients to simulate changes in the number of conflict events and livestock prices, assuming two different scenarios of increasing drought.

Data and Indicators

Our estimations are based on monthly panel data by region compiled from three different sources. Somalia has 18 administrative regions, and the time frame of our analysis ranges from January 1997 to December 2009, yielding a total of 2,808 panel observations. The dependent variable is constructed as the sum of violent conflict events by administrative region per month, using the Armed Conflict Location and Event Dataset (ACLED 2011). A conflict event is defined as a single altercation where force is often used by one or more groups for a political end (Raleigh et al. 2010). For Somalia as a whole, ACLED reports 4,260 conflicts, of which 3,870 events were violent (including battles between groups and violence against civilians), between 1997 and 2009.

The drought variable—the deterministic exogenous variable in our model—is constructed from climatic data provided by the Climatic Research Unit at the University of East Anglia (UEA-CRU). The UEA-CRU (2011) time-series datasets (CRU-TS3.1) report month-by-month variations in temperature and precipitation available for the periods 1901–2009 and 1983–2009, respectively. They are calculated on high-resolution grids (0.5 × 0.5 degree or approximately 56km × 56km at the equator) based on measurements from weather stations distributed around the world (Harris et al. 2012; Mitchell and Jones 2005). We use temperature instead of precipitation in our preferred model specification, because temperature variations appear to better explain past spatial and temporal variation in agricultural yields and economic output on the African continent (for example, Dell, Jones, and Olken 2012; Lobell, Schlenker, and Costa-

Roberts 2011; Schlenker and Lobell 2010). Temperature data are available from the UEA-CRU for monthly averages of daily maximum and daily mean temperatures. We aggregate the gridded temperature data points to one (centered) data point by region using spatial interpolation (*kriging*, inbuilt in ESRI ArcGIS). Consistent with studies on extreme climates (for example, IPCC 2012), we use monthly averages of daily maximum temperatures in our preferred model specification (which give the highest temperatures in the daytime, causing the highest evaporation).

From these temperature data we construct a drought index that directly enters our estimations. In fact, no universal definition of *drought* is applicable; it is rather defined in a differential manner. Drought needs to be distinguished from high temperature or low rainfall as such; it is rather characterized by a deviation from normal weather conditions. Hence, drought differs from aridity. Drought is a temporary weather aberration, whereas aridity is a stable climatic condition. Accordingly, we define *drought months* as months with temperatures above the long-term maximum temperatures, while the reference period in our preferred model specification is 1950–2009. A valid drought index must account not only for the magnitude of deviation and the length of successive periods of abnormal temperatures but also for the cumulative effect that makes successive drought periods with temperature extremes a severe drought. In addition, to exclude any potential source of endogeneity from our model, we searched for a drought index that does not include components influenced by human activity and hence possibly conflict, such as soil characteristics, water availability, or vegetation.[9] Balint and Mutua (2011) developed such an index, tested its performance using data from Somalia and Kenya even under temperate continental climate conditions, and applied it for drought monitoring in Somalia. We use their Temperature Drought Index (TDI) in a slightly modified form.

For each administrative region, i, the TDI by time period, t, (year $[y]$ × month $[m]$) is calculated as follows:

$$drought_t = TDI^P_{y,m} = \sqrt{\frac{R^T_{y,m}}{\frac{1}{n}\sum_{k=1}^{n} R^T_{m,k}}} * \frac{\sum_{l=1}^{P} T_{y,(m-l+1)}}{\frac{1}{n}\sum_{k=1}^{n}\left(\sum_{l=1}^{P} T_{(m-l+1),k}\right)}. \tag{4}$$

In Equation (4), P denotes the reference period, comprising the current month, m, (of the current year, y) and preceding months. We chose a period length of three months in our preferred model specification (indicated as TDI3), because it is usually the maximum length of the two rainy seasons and approximately half of the main dry season in Somalia. The first term of the TDI measures the maximum number of successive months with temperatures, T, above the long-term average temperature during the current reference period ($R^T_{y,m}$) relative to the long-term average number of successive drought months considered normal for this time of the year ($\frac{1}{n}\sum_{k=1}^{n} R^T_{m,k}$).

[9] This condition leaves most common drought indexes, such as the Palmer Drought Severity Index (Palmer 1965), unsuitable.

The time frame for calculating the long-term averages is 1950–2009 ($n = 59$ years) in our preferred model specification. The second term of the TDI measures the deviation of the temperature averaged over the current reference period ($\sum_{l=1}^{P} T_{y,(m-l+1)}$) from the long-term average temperature considered normal for the period at this time of the year ($\frac{1}{n}\sum_{k=1}^{n}\left(\sum_{l=1}^{P} T_{(m-l+1),k}\right)$). Hence, the second term of the TDI captures the intensity of drought and is weighted by the first term, giving higher weights to successive drought months than to intermittent drought months.

Livestock price data for Somalia are available from the Food Security and Nutrition Analysis Unit database (FSNAU 2011b). In our preferred model specification, we use monthly market prices for living cattle of export quality by region for constructing the deterministic endogenous variable. We replaced missing price data by the price of the nearest region (from a maximum of the three closest regions) in the same month. About 36 percent of the maximum panel observations are imputed, while tests confirm that the imputation did not significantly alter our estimation results. We normalize livestock prices by dividing prices with local market prices of (imported) gasoline to control for regional price inflation and thus to obtain a better measure of local purchasing power. The normalization also makes prices reported in different currencies comparable, given that reported currency conversion rates appear to be flawed. Again, tests reveal no evidence that the normalization leads to biased estimates. The normalized livestock prices enter our estimations in logarithms, easing interpretation.[10]

[10] Descriptive statistics of the variables used in the preferred model specification are reported in Table A.1 in the Appendix. Given the relatively long time frame of our analysis (of 13 years), a matter of concern may be that the time series in the variables used are nonstationary, which can lead to spurious results in the sense that they indicate a relationship between variables where one does not exist. The statistics of the Fisher test for unit roots in panel data (proposed by Maddala and Wu 1999) reported in Table A.1 reject the null hypothesis of nonstationarity in all variables at any reasonable confidence level. We also note that, at the cost of removing relevant variations, all results of our preferred model specifications and the ones presented in the Appendix are robust to the addition of a region-specific time trend variable (with the exception of the district-level estimations).

4. Estimation Results

Our estimation results provide strong evidence that more droughts lead to more violent civil conflicts in Somalia and that drought-induced cattle price shocks drive conflict outbreaks. Tables 4.1 and 4.2 show the estimated coefficients of the reduced-form regression and two-stage regression, respectively, for our preferred model specifications. The coefficient of the Temperature Drought Index (TDI) in the reduced-form regression indicates that a one-point increase in the severity of a drought period gives rise to 1.4 additional conflict outbreaks on average. The coefficients of the two-stage regression suggest that this increase in drought severity brings down cattle prices by 12 percent, while a 100 percent price drop increases the number of conflicts by almost 12.

Table 4.1—Reduced-form regression results (preferred model specification)

Dependent variable	*Number of conflicts*
Drought (TDI3)	1.413 ***
	(0.372)
F-value	2.47 ***
R-squared	0.128
Number of regions	18
Observations	2,808

Source: Authors' estimation based on ACLED 2011 and UEA-CRU 2011.
Notes: *** Coefficient is statistically significant at the 1 percent level. Standard errors are reported in parentheses. Coefficient estimates for region-fixed and time-fixed effects are not reported. TDI3 = Temperature Drought Index, with 3-month reference period.

Table 4.2—Two-stage regression results (preferred model specification)

	Stage 1	***Stage 2***
Dependent variable	*Cattle price (log)*	*Number of conflicts*
Drought (TDI3)	–0.123 ***	
	(0.037)	
Cattle price (log)		–11.85 ***
		(4.187)
F-value	8.47 ***	
R-squared	0.302	
Number of regions	18	18
Observations	2,335	2,335
Underidentification test[1]	11.84 ***	
Weak identification test[2]	11.15	
Root mean square error		5.145

Source: Authors' estimation based on ACLED 2011, UEA-CRU 2011, and FSNAU 2011b.
Notes: *** Coefficient is statistically significant at the 1 percent level. Robust standard errors are reported in parentheses. Coefficient estimates for region-fixed and time-fixed effects are not reported. TDI3 = Temperature Drought Index, with 3-month reference period.
[1] Kleibergen-Paap rank LM statistic (Baum, Schaffer, and Stillman 2007; Kleibergen and Paap 2006. The test statistic strongly rejects the null hypothesis of underidenfication.

[2] Kleibergen-Paap rank Wald F statistic (Baum, Schaffer, and Stillman 2007; Kleibergen and Paap 2006). The test statistic rejects the null hypothesis of weak identification at least at the 15 percent level, based on the critical values provided by Stock and Yogo (2005).

Table 4.3 shows the changes in the number of conflict events and cattle prices under two scenarios. In the first scenario we arbitrarily assume that rising drought frequency and intensity lead to an increase of the TDI with 3-month reference period (TDI3) by one standard deviation (equivalent to 33 percent on average). The TDI3 increase translates into a 4 percent decline of cattle prices, which in turn, leads to an increase in the number of conflict events by 0.5 (equivalent to 37 percent at the sample mean). In the second scenario we simulate an increase of the TDI3 due to monthly temperature rises varying around 3.2 degrees Celsius (equivalent to an average TDI3 increase by 49 percent).[11] These changes in median temperatures are predictions by Christensen et al. (2007) that are likely to be present in eastern Africa by the end of the 21st century under the A1B scenario of the Intergovernmental Panel on Climate Change (IPCC). According to our model estimates, this TDI3 increase results in an increase of the number of conflict events by 0.8 (equivalent to 58 percent at the sample mean). Thus, temperature changes as predicted by the IPCC may increase the number of conflicts by more than half.

Table 4.3—Simulation of the effects of increasing drought on cattle prices and conflicts

Scenario	**TDI3 change**	**Cattle price change**	**Change in number of conflicts**	
	Percent	*Percent*	*Number*	*Percent*
Increase of TDI3 by one standard deviation	32.6	–4.3	0.52	37.4
Increase of TDI3 by temperature rise according to IPCC A1B scenario	49.0	–6.8	0.80	58.3

Source: Authors' estimation based on ACLED 2011, UEA-CRU 2011, and FSNAU 2011b data and Christensen et al. 2007.

Notes: IPCC = Intergovernmental Panel on Climate Change, TDI3 = Temperature Drought Index, with 3-month reference period. Changes in cattle prices are based on the estimated coefficient of the first stage of the two-stage regression, and changes in the number of conflict events are calculated based on the estimated coefficient of the second stage of the two-stage regression. Percent changes are reported at the sample mean for the time frame of our analysis (1997–2009).

[11] Precisely, the predicted temperature rises—which we use in our simulation—are 3.1 degrees Celsius for September throughout February, 3.2 degrees Celsius for March to May, and 3.4 degrees Celsius for June to August.

5. Robustness Checks and Identifying Assumptions

Robustness of Estimation Results

The results of our estimations may be sensitive to the specification of the empirical model. Therefore, we apply a comprehensive set of robustness checks to rule out potential disturbing effects systematically. We examined the robustness in terms of (1) the level of spatial aggregation, (2) alternative specifications of the dependent variable measuring conflict, (3) alternative specifications of the exogenous drought variable, (4) alternative specifications of the endogenous price variable, and (5) alternative specifications of the functional form. We pairwise compare our preferred model specification with these alternative modifications.[12]

First, the estimation results are not altered by the choice of the level of spatial aggregation. We ran the reduced-form regression and two-stage regression using the same raw data but aggregate them at the district level instead of the region level.[13] The estimated partial effects of a change in the Temperature Drought Index with 3-month reference period (TDI3) on the number of conflicts are quite similar to the ones from the region-level estimations, but the explanatory power of the district-level regressions is significantly lower.[14] Due to missing market price data, coverage of the district-level sample for the two-stage regression is only 69 percent of the maximum number of panel observations (even after applying the imputation method described above), compared with 83 percent in the region-level sample.[15] Moreover, estimations at lower spatial aggregation levels come along with a substantially increased probability of spatial dependency between neighboring districts. This becomes apparent when introducing spatial lags of the TDI3 in the district-level estimation. The same modification of the region-level estimation gives no indication for such spatial spillovers.[16] The smaller geographical and temporal coverage in combination with an increased spatial dependency may explain the lower explanatory power of the district-level regressions.

Second, the results are highly robust to the definition of *conflict* for both the reduced-form and the two-stage regressions.[17] Running the regressions with a dependent variable incorporating all types of conflict events as given in the Armed Conflict Location and Event Dataset, ACLED, (instead of violent conflicts only) changes neither the significance nor the coefficient estimates considerably. In addition, we ran the regressions with a dependent variable constructed from the database of the Uppsala Conflict Data Program (UCDP) at Uppsala University (UCDP 2011).

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[12] Descriptive statistics of the variables used in the alternative model specifications (at the region level) are reported in Table A.1 in the Appendix.

[13] Somalia has 74 districts.

[14] See Tables A.2 and A.3 in the Appendix.

[15] In the district-level sample about 53 percent of all price observations are imputed, compared to 36 percent in the region-level sample.

[16] District-level regression results augmented with the TDI3 spatially lagged are not reported. The region-level regression results augmented with the TDI spatially lagged are discussed below and presented in Table A.13 in the Appendix.

[17] See Tables A.4 and A.5 in the Appendix.

UCDP (2011) adopted a more restrictive definition of violent conflict events than ACLED (2011) and therefore reports fewer conflict events. According to UCDP definition, violent civil conflict events are those with at least one death as a direct consequence of an (armed) intrastate strife (Sundberg, Lindgren, and Padskocimaite 2011). Nonetheless, the estimated effects are almost identical (in relative terms). For example, an increase of the TDI3 by one standard deviation and the equivalent decline in cattle prices by 4 percent translates into an increase in the number of conflicts by 44 percent according to the UCDP data-based estimation, compared with 38 percent according to our preferred specification. However, the regressions based on UCDP data have lower explanatory power.

Third, the definition of *drought* does not compromise our results. We checked the robustness of the conflict–drought relationship using numerous modifications of the drought variable in the first-stage regression. We first modified the TDI in terms of the length of the reference period starting from 1 month up to 6 months as well as the length of the period for calculating long-term temperature averages, and we used monthly averages of mean daily temperatures instead of maximum daily temperatures and applied temperatures from an alternative data source.[18] The alternative temperature data are taken from the Prediction of Worldwide Energy Resource (POWER) project of the US National Aeronautics and Space Administration (NASA). They are computed based on solar radiation derived from satellite observations in combination with meteorological data from an assimilation model (NASA 2011). We also checked the robustness of the regression results with a temperature anomaly index instead of the TDI3. The main findings are that all these modifications do not alter the estimated conflict–drought relationship of our preferred model specification considerably and that the preferred TDI3 yields a relatively high model fit. Next, we tested whether temperature changes, precipitation changes, or both better explain changes in violent conflicts in Somalia and, in particular, in livestock prices.[19] We augmented the reduced-form and two-stage regressions with various modifications of Balint and Mutua's (2011) Precipitation Drought Index (PDI)—which is constructed similar to the TDI—and with a precipitation anomaly index.[20] The modifications of the precipitation-based indexes are consistent with the ones applied in the previous step.[21] The main findings here are that temperature-based indicators perform better than precipitation-based indicators—which confirms findings from previous studies (for example, Burke et al. 2009; Dell, Jones, and Olken 2009; Marchiori, Maystadt, and Schumacher 2012)—and anomaly indexes perform poorly. Although the coefficients of most PDI variations are statistically significant in the reduced-form

[18] See Tables A.6 and A.7 in the Appendix.

[19] See Tables A.8 and A.9 in the Appendix.

[20] We reverse the PDI to make the interpretation of the direction of PDI changes consistent with TDI changes. Abnormally *high* temperatures and abnormally *low* rainfall lead to droughts.

[21] The temperature/precipitation anomaly index is the ratio of the difference between the average temperature/precipitation in the current month and the long-term temperature/precipitation average of this month (enumerator) and the long-term average standard deviation of monthly temperature/precipitation (denominator). Unlike the TDI and PDI, temperature and precipitation anomalies do not account for the cumulative effect of droughts. For the regression results with modifications of the drought variable, see Tables A6, A7, A8, and A9 in the Appendix.

regression, their partial effects are small compared with those of the TDI3 effect. Moreover, the coefficients of most PDI variations are statistically insignificant in the two-stage regression, and the partial effects of the significant PDI coefficients are even much smaller. Thus, temperature shocks drive conflict incidence and deterioration in livestock prices, while the estimated effects are robust to the inclusion of precipitation-based drought variables. A stronger responsiveness of livestock prices to changes in temperatures compared with changes in precipitation is consistent with findings from previous studies (for example, Seo and Mendelsohn 2007), too.

Fourth, cattle prices are most responsive to drought; the normalization of prices does not compromise our estimation results. We performed robustness checks of the two-stage regressions using prices of cattle of different quality and prices of other common herd animals. Independent of the quality, cattle prices are responsive to changes in the TDI3, unlike prices of goat, sheep, and camel.[22] The statistical insignificance of goat, sheep, and camel prices points to cattle prices as the only identifiable livestock market channel. A possible explanation is that goats, sheep, and especially camels are more drought resistant than cattle, so that the price shock of droughts can be better smoothened over time. In addition, the absorption capacity of the local livestock markets may be quite limited, and the demand for some livestock may be met earlier than for others, particularly in periods of drought. During drought the markets for some livestock—notably camel—may even fully collapse. Our robustness checks also show that the normalization of cattle prices by petroleum prices or prices of other ordinary, (solely) imported goods such as sugar or rice does not compromise the estimation results, but only their efficiency.[23]

Fifth, modifications of the functional form of the two-stage regression reveal no evidence for the existence of time lags, spatial dependency, seasonality, and nonlinearity in our data or suggest that the resulting effects are unsystematic, small, and therefore negligible. Previous studies (for example, Miguel, Satyanath, and Sergenti 2004; Hendrix and Glaser 2007) point to delays in the response of prices and conflicts to weather shocks. To test for potential time lags in our data, we gradually augmented the two-stage regression equations of our preferred model specification with the TDI3 in lags of one to five months comprising one agricultural season (including one rainy and one dry season of approximately three months each).[24] We found some statistical evidence for a lagging effect of two to three months (comprising roughly one rainy/dry season) but not beyond three lags. Nonetheless, the second-stage coefficient estimates of all these modifications are quite similar to the estimate of our preferred specification, and the overall partial effect remains roughly constant, independent of the length of the lagging effect. Another point of concern is spatial dependency (Anselin 2002; Florax and Folmer 1992). Conceivably, drought in one part of the country may fuel conflicts in another part through an influx of herders and herds and the associated increased competition over scarce grazing land and water resources, for example. Ignoring such spatial dependencies can lead to underestimating the drought impact.

[22] See Table A.10 in the Appendix.
[23] See Table A.11 in the Appendix.
[24] See Table A.12 in the Appendix.

Augmenting the preferred specification with the spatially lagged TDI3 does not reveal spatial dependencies in our data. The spatially lagged TDI3 turns out to be statistically insignificant and to not affect the critical coefficients.[25] Yet it should be noted that the used Euclidean distance between the geographic centers of the regions is a crude proxy of the distance between origin and destination of cross-region migration. More accurate approximations were impossible, given lacking georeferenced data of the location of herders under normal conditions and of common destinations in times of drought. Next, the response to abnormally high temperatures may also be different during dry seasons compared with rainy seasons. Augmenting the preferred two-stage regression equations with a dichotomous variable for the season and an interaction term between this variable and the TDI3 shows no differentiated seasonal effect.[26] Finally, adding the TDI3 in squared terms to the preferred specification provides no evidence of nonlinearity in the drought–livestock price relationships, so that the specification of our model in linear terms remains our preferred one.[27]

Validity of Identifying Assumptions

Our strategy for identifying livestock price shocks as the driver of drought-induced conflicts rests on the validity of TDI3 variations as an instrument of livestock price changes. The test statistics in Table 4.2 give indeed strong confidence in the validity of this assumption. The F-value of the first-stage regression is high (in a just-identified two-stage regression), which provides a first indication of the strength of the instrument. In addition, the weak instrumental variable test (developed by Kleibergen and Paap 2006) rejects the hypothesis of weak instruments at least at the 15 percent level.

Next, our two-stage regression is built on the assumption that droughts—precisely, droughts as determined based on temperature measurements—increase conflicts only through changes in livestock prices. As shown above, the estimation results of the reduced-form and two-stage regressions are driven entirely by temperature variation and no other weather phenomena, notably precipitation. Even though the coefficients of some of the PDI modifications are statistically significant in the reduced-form regression, the coefficients of these PDI modifications in the two-stage regression are insignificant or the implied partial effects are quite small and therefore negligible.[28] Hence we can rule out that precipitation variation affects livestock price changes considerably, but there may be additional conflict–drought channels other than livestock prices that may be also subject to precipitation variation. As argued in Section 2, changes in livestock prices provide an accurate proxy for changes in household

[25] The spatially lagged TDI3s are constructed based on distance-based spatial matrices that weight the TDI3 of each region by the inverse of the Euclidean distance to the considered one. We test the TDI3 spatially lagged in order, one and two. For the regression results, see Table A.13 in the Appendix.
[26] See Table A.13 in the Appendix.
[27] See Table A.13 in the Appendix.
[28] See Tables A.8 and A.9 in the Appendix.

incomes in Somalia, but we cannot completely rule out the possibility of other channels of transmission. It is therefore critical to demonstrate—as much as the data allow—that the existence of other channels is unlikely to jeopardize our findings. Besides income from sales of herd animals, droughts may affect (nonherd) farm income and, in turn, influence the economic incentives to participate in conflict. In the absence of farm income data, we test the validity of our exclusion restriction by incorporating an additional instrumental variable in the equations of both stages of our preferred two-stage regression specification, which we expect to affect conflicts through no other channel than livestock price changes. Hence, we create an overidentified model.[29] The added price index determines the exposure of Somali herders to international livestock prices.[30] Following Angrist and Pischke (2009), we also test the robustness of the results under overidentifying restrictions using the Limited Information Maximum Likelihood (LIML) estimator, which is approximately median unbiased for overidentified models. Yet the estimation results of all augmented regressions do not reveal any channel of transmission other than livestock prices. That is, the test for overidentification fails to reject the null hypothesis of zero correlation between the two instrumental variables and the error term.

Participation in conflicts may also be motivated by changing economic factors other than livestock prices such as wage losses and spiking consumer prices of main staple foods. In addition, changes in these factors may be associated more with precipitation variation than with temperature variation. To test these channels, we augmented our preferred two-stage regression specification at both the first and the second stages with the PDI3 and variables such as wage rates of causal labor in agriculture and consumer prices of wheat flour, maize, red sorghum, and rice.[31] All these modifications do not alter the TDI3 coefficient estimates considerably, if the

[29] See Table A.14 in the Appendix.

[30] The exposure to international livestock prices is determined by the proximity from the considered region to the port for livestock exports combined with the importance of cattle exports relative to other livestock exports through that port. Precisely, we determine the proximity as the inverse of the Euclidian distance from the geographical center of the region to the nearest major livestock export port. The two major livestock ports are located in Berbera and Bosaaso in northern Somalia. The share of cattle exports on total ruminant exports serves as proxy of the degree of relative exposure of the cattle prices in this port (and hence in the dependent regions) to international cattle prices. The index measuring the exposure of the region, i, to international cattle prices is constructed for each month, m, and year, y, as follows:

$$P_{i,m,y} = w_{i,c}\, p_{c,m,y}\,, \qquad \text{with} \qquad w_{i,c} = \frac{1}{dist_{ih}} \frac{export_{h,c}}{\sum_{l=1}^{3} export_{h,l}}\,,$$

where $w_{i,c}$ is the region-specific weight for cattle, and $p_{c,m,y}$ is the international price for beef, as available from the Primary Commodity database of the International Monetary Fund (IMF 2011). Entering the weight, the variables $export_{h,c}$ and $export_{h,l}$ give the total number of head of cattle, c, and the livestock species, l, through port, h, between January 1994 and December 1996, as provided by the Food Security and Nutrition Analysis Unit—Somalia (FSNAU 2011a). The livestock species considered are goats (and sheep), cattle, and camels. We chose the time period of 1994–1996 because it is prior to the time frame of our analysis and therefore strictly exogenous. As a robustness check, we also estimated all model specifications with an extended reference period ranging from January 1994 to December 2010. The estimation results are very similar and therefore not reported.

[31] See Table A.15 in the Appendix. The wage and food price variables enter the regression as lags to avoid potential problems of simultaneity.

coefficients are statistically significant at all. The stability of the TDI3 coefficient estimates indicates a high level of confidence in the validity of the exclusion restriction of our instrumental variable approach.

Another possible violation of the exclusion restriction can emerge from humanitarian assistance delivered in response to drought-caused food shortages. Over the time frame of our analysis, humanitarian assistance in Somalia was provided mostly in the form of food aid, which can be expected to be targeted to the disaster areas. The distribution of (staple) foods may theoretically contribute to an increase in the demand for meat as a result of freeing up household resources destined for food purchases. However, the resulting income effect can be assumed to be minor, considering that most food aid recipients are suffering from severe acute malnutrition and do not hold enough purchasing power to afford meat consumption anyway. Food aid delivered prior to a drought—which seems to be quite rare, even in the case of famine early warnings (Hillbruner and Moloney 2012; Lautze et al. 2012)—may smoothen the liquidation of herds through reducing herders' immediate necessity to sell livestock for purchasing food, which may reflect slower declines of livestock prices. Yet to have a significant effect on livestock prices, food aid would have to be of multiple quantities as typically delivered and to be targeted perfectly in terms of time and space, and herders would have to be major beneficiaries (despite their relative asset wealth). Past experiences do not support these conditions in Somalia, and previous studies revealed rather weak links between volumes of food aid delivered and market price movements in general (for example, Dorosh, del Ninni, and Sahn 1995; Kirwan and McMillan 2007; Mabuza et al. 2009). Moreover, it can be ruled out realistically that people's expectation of receiving food aid in times of emergency affects consumer (and producer) behavior, given the well-known shortcomings of food aid delivery. Cushioning effects to livestock price declines through deferred liquidation of herds as a result of food aid diverted to livestock feed can be assumed to be insignificant, too, because (most) food aid recipients are in dire need to consume the food themselves and hold few or no livestock (anymore); handout quantities are barely sufficient to stave off hunger among humans, let alone livestock; and food handouts come often in inappropriate form for feeding livestock (for example, flour). Hence, distortions of livestock prices due to food aid can be expected to be rather minor (if measurable at all).

However, legitimate concerns exist—particularly in Somalia—that food aid has been misused to feed and compensate fighters, to attract new fighters, to buy loyalty among the impoverished population, or to exchange for military equipment and may contribute to an expansion and intensification of conflict (for example, Anderson 1999; Nunn and Qian 2012; Collier and Hoeffler 2007). On the contrary, humanitarian assistance has also been argued to reduce the likelihood of conflict participation for earning a living, which becomes particularly relevant under circumstances of lacking alternative sources of livelihood such as in times of hardship triggered by natural disasters or conflicts (Bas and Coe 2011; Gilligan and Hoddinott 2007). If the former, the fueling effect of food aid on conflict, dominates the latter, the opportunity income effect, our analysis provides lower-bound estimates of the true impact of livestock prices on conflict. Unfortunately, lacking data on food aid prevents us from testing the relationship between conflict and food aid in Somalia.

6. Conclusions

As a result of climate change, extreme weather events are predicted to become more frequent and more severe globally and in the Horn of Africa. Evidence suggests that climate change has contributed to the increasing occurrence of major droughts in the Horn of Africa and particularly Somalia, which are expected to further rise in frequency and intensity throughout this century. In addition to the human suffering from the immediate impacts of climate change, weather extremes—and therewith climate change—increase the risk of civil conflict, putting an additional burden to human well-being and economic development. Sparking some controversy, the causality between weather variations and increased risk of conflict has been demonstrated at the global and regional levels and for the long term by several previous studies (for example, Burke et al. 2009; Hsiang, Meng, and Cane 2011; O'Loughlin et al. 2012). In this paper, first we showed that this causality is valid also for a single country—Somalia—at the local level, and over a relatively short period of time (namely, 13 years).

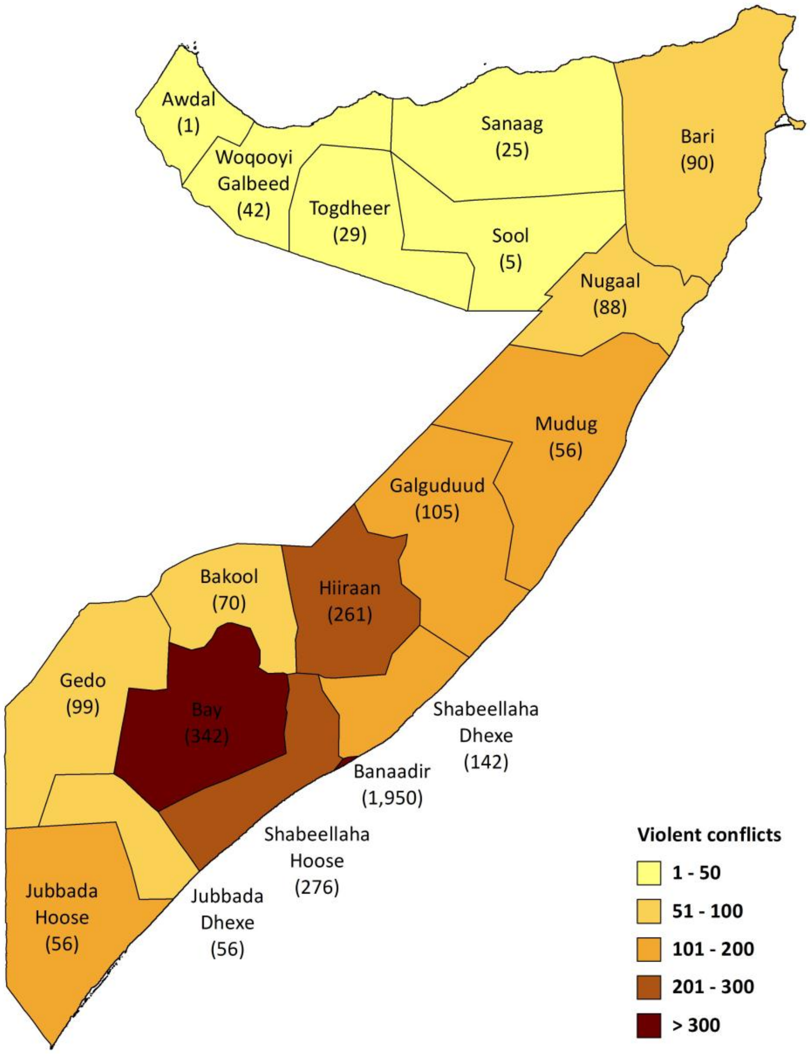
This finding has important policy implications. Recognizing the conflict–drought relationship implies that policies and investments for drought impact mitigation and resilience building are critical for both climate change adaptation and conflict prevention in Somalia. Such measures should be targeted primarily toward drought-prone areas that are at particular risk of civil conflict. The costs of inaction go beyond the immediate economic and environmental costs of climate change and may involve substantial costs from intensified conflict activities including civilian casualties, destruction of infrastructure, and loss of economic growth potential, which have been largely ignored in estimations of climate change costs.

The second main finding of our analysis is that factors of economic well-being are indeed key determinants of individuals' participation in conflict and, in consequence, that poverty alleviation is an effective strategy for conflict mitigation in Somalia. On the contrary, if no action is taken, the poverty–conflict trap is likely to deepen in the course of progressing climate change. Innovatively, our analysis shows that local livestock markets are an important channel through which droughts fuel conflict in Somalia and that plummeting livestock producer prices and hence losses in livestock income lower Somalis' resistance to engage in conflict activities. Therefore, increasing these opportunity costs among pastoralists and semipastoralists through fostering growth in the livestock sector, providing alternative income-earning opportunities, and establishing social safety nets, for example, reduces people's economic incentives for participating in conflicts. Similarly, investments in rural transportation infrastructure and in the livestock sector can help to smoothen the liquidation of herds and therewith to mitigate the rapid deterioration of livestock prices and household income losses. Other potentially effective measures include weather insurance and financial and technical support to adjust herds toward more drought-resistant and more fast-marketable animals.

However, this list of possible actions also reveals the limitations of our analysis in proposing specific policy recommendations. Critical knowledge gaps remain regarding the effectiveness of feasible policies and investments to strengthen resilience in pastoralist and semipastoralist livelihoods in Somalia and in other countries facing similar vulnerabilities. Quantitative research in this direction suffers from the absence of standard economic data. Another limitation of our analysis may be related to the external validity of the results. Certainly, Somalia may be considered an extreme case in terms of length and intensity of civil war and droughts, but Sahel countries such as Mali, Chad, Niger, and Sudan have seen increasing civil conflicts and droughts, too, and can serve as study sites for validating our findings. Nonetheless, this paper provides strong evidence of the relationship between civil conflict and climate change at the local level and the relevance of economic behavior in this context.

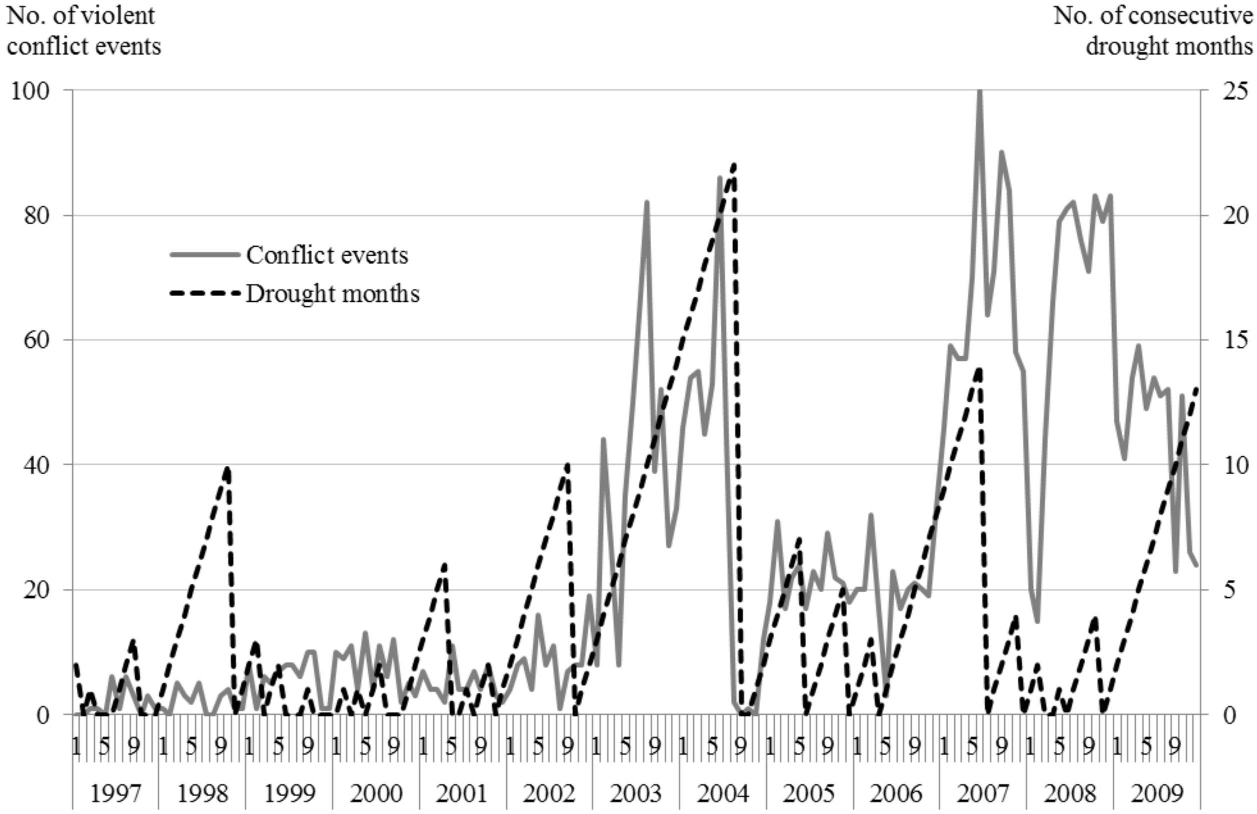
Appendix: Supplementary Figures and Tables

Figure A.1—Number of violent conflicts by administrative region, 1997–2009



Source: Authors' presentation based on ACLED 2011.

Figure A.2—Frequency of conflict and drought events by month, nationwide in Somalia



Source: Authors' presentation based on ACLED 2011 and UEA-CRU 2011.
Note: See Section 3, "Methodology and Data," for the identification of drought months.

Table A.1—Descriptive statistics and unit root test statistics

	Observations	Mean	Standard deviation	Minimum	Maximum	Fisher unit root test statistic	
Preferred model specification							
Number of violent conflicts (ACLED data; 1997–2009)	2,808	1.38	4.96	0.00	79.00	842.34	***
Price of cattle of export quality (in logs; normalized by gasoline price)	2,335	5.25	0.48	3.31	6.98	213.76	***
Temperature Drought Index with 3-month reference period (TDI3) (UEA-CRU data; daily maximum temperature; long-term average: 1950–2009)	2,808	1.13	0.35	0.00	1.58	715.59	***
Alternative model specifications (selected variables)							
Number of violent conflicts (UCDP data; 1997–2009)	2,808	0.39	1.84	0.00	28.00	828.78	***
Temperature Drought Index with 6-month reference period (TDI6) (UEA-CRU data; daily maximum temp.; long-term average: 1950–2009)	2,808	1.14	0.30	0.00	1.65	436.57	***
Temperature Drought Index with 3-month reference period (TDI3) (UEA-CRU data; daily mean temp.; long-term average: 1950–2009)	2,808	1.09	0.39	0.00	1.63	671.14	***
Temperature Drought Index with 3-month reference period (TDI3) (UEA-CRU data; daily maximum temp.; long-term average: 1901–2009)	2,808	1.15	0.38	0.00	1.71	691.71	***
Temperature Drought Index with 3-month reference period (TDI3) (NASA data; daily maximum temp.; long-term average: 1997–2007)	2,340	0.88	0.50	0.00	1.85	534.61	***
Precipitation Drought Index with 3-month reference period (PDI3) (EA-CRU data; long-term average: 1983–2009)[1]	2,808	–0.51	0.54	–2.18	0.00	462.95	***
Temperature anomaly (EA-CRU data; long-term average: 1950–2009)	2,808	0.40	0.82	–3.51	3.28	886.73	***
Rainfall anomaly (EA-CRU data; long-term average: 1983–2009)	2,808	–0.25	0.62	–3.92	1.96	912.61	***
Price of cattle of local quality (in logs; normalized by gasoline price)	2,417	4.86	0.50	2.91	6.74	146.24	***
Price of goat of export quality (in logs; normalized by gasoline price)	2,464	3.61	0.37	2.37	5.74	187.62	***
Price of cattle of export quality (in logs; no normalization)	2,531	14.29	0.69	11.70	16.47	24.55	
Price of cattle of export quality (in logs; normalized by sugar price)	2,511	5.44	0.45	3.28	7.11	245.06	***
Price of cattle of export quality (in logs; normalized by rice price)	2,524	5.48	0.45	3.31	6.94	236.70	***

Source: Authors' calculation based on ACLED 2011, FSNAU 2011b, NASA 2011, UCDP 2011, and UEA-CRU 2011.

Notes: *** Coefficient is statistically significant at the 1 percent level. TDI = Temperature Drought Index.

[1] The time frame is March 1997 to December 2007.

Table A.2—Reduced-from regression results of alternative model specification, district-level estimation

Level of aggregation	**Region**	**District**
Dependent variable	*Number of conflicts*	*Number of conflicts*
Drought (TDI3)	**1.413 *****	0.327 ***
	(0.372)	(0.089)
F-value	**2.47 *****	2.39 ***
R-squared	**0.128**	0.019
Number of regions/districts	**18**	74
Observations	**2,808**	11,544

Source: Authors' estimation based on ACLED 2011, and UEA-CRU 2011.

Note: *** Coefficient is statistically significant at the 1 percent level. Standard errors are reported in parentheses. Coefficient estimates for region-fixed and time-fixed effects are not reported. TDI = Temperature Drought Index.

Table A.3—Two-stage regression results of alternative model specification, district-level estimation

Level of aggregation	**Region**		**District**	
	Stage 1	***Stage 2***	***Stage 1***	***Stage 2***
Dependent variable	*Cattle price (log)*	*Number of conflicts*	*Cattle price (log)*	*Number of conflicts*
Drought (TDI3)	**–0.123 *****		–0.080 ***	
	(0.037)		(0.021)	
Cattle price (log)		**–11.85 *****		–4.79 ***
		(4.187)		(1.684)
F-value	**8.47 *****		21.57 ***	
R-squared	**0.302**		0.220	
Number of regions	**18**		74	
Observations	**2,335**		8,562	
Underidentification test[1]	**11.84 *****		14.83 ***	
Weak identification test[2]	**11.15**		14.53	
Root mean square error		**5.145**		2.725

Source: Authors' estimation based on ACLED 2011, FSNAU 2011b, and UEA-CRU 2011.

Note: *** Coefficient is statistically significant at the 1 percent level. Robust standard errors are reported in parentheses. Coefficient estimates for region-fixed and time-fixed are not reported. TDI = Temperature Drought Index.

[1] Kleibergen-Paap rank LM statistic (Baum, Schaffer, and Stillman 2007; Kleibergen and Paap 2006). The test statistic strongly rejects the null hypothesis of underidenfication.

[2] Kleibergen-Paap rank Wald F statistic (Baum, Schaffer, and Stillman 2007; Kleibergen and Paap 2006).

Table A.4—Reduced-form regression results of alternative model specification, conflict definition

Conflict data	**ACLED (violent conflicts)**		**ACLED (all conflicts)**		**UCDP (violent conflicts)**	
Dependent variable	*Number of conflicts*		*Number of conflicts*		*Number of conflicts*	
Drought (TDI3)	**1.413**	*******	1.588	***	0.255	***
	(0.372)		(0.378)		(0.138)	
F-value	**2.47**	*******	2.94	***	1.33	***
R-squared	**0.128**		0.148		0.073	

Source: Authors' estimation based on ACLED 2011, UCDP 2011, and UEA-CRU 2011.

Note: *** Coefficient is statistically significant at the 1 percent level. Standard errors are reported in parentheses. Coefficient estimates for region-fixed and time-fixed effects are not reported. TDI = Temperature Drought Index, ACLED = Armed Conflict Location and Event Dataset, UCDP = Uppsala Conflict Data Program.

Table A.5—Two-stage regression results of alternative model specification, conflict definition

Conflict data	**ACLED (violent conflicts)**		**ACLED (all conflicts)**		**UCDP (violent conflicts)**	
	Stage 1	***Stage 2***	***Stage 1***	***Stage 2***	***Stage 1***	***Stage 2***
Dependent variable	*Cattle price (log)*	*Number of conflicts*	*Cattle price (log)*	*Number of conflicts*	*Cattle price (log)*	*Number of conflicts*
Drought (TDI3)	**–0.123 *****		–0.123 ***		–0.123 ***	
	(0.037)		(0.037)		(0.037)	
Cattle price (log)		**–11.85 *****		–13.39 ***		–3.88 ***
		(4.187)		(4.567)		(1.594)
F-value	**8.47 *****		8.47 ***		8.47 ***	
R-squared	**0.302**		0.302		0.302	
Underidentification test[1]	**11.84 *****		11,836 ***		11,836 ***	
Weak identification test[2]	**11.15**		11.15		11.15	
Root mean square error		**5.145**		5,457		2,028

Source: Authors' estimation based on ACLED 2011, FSNAU 2011b, UCDP 2011, and UEA-CRU 2011.

Note: *** Coefficient is statistically significant at the 1 percent level. Robust standard errors are reported in parentheses. Coefficient estimates for region-fixed and time-fixed are not reported. TDI = Temperature Drought Index, ACLED = Armed Conflict Location and Event Dataset, UCDP = Uppsala Conflict Data Program.

[1] Kleibergen-Paap rank LM statistic (Baum, Schaffer, and Stillman 2007; Kleibergen and Paap 2006). The test statistic strongly rejects the null hypothesis of underidenfication.

[2] Kleibergen-Paap rank Wald F statistic (Baum, Schaffer, and Stillman 2007; Kleibergen and Paap 2006).

Table A.6—Reduced-form regression results of alternative model specifications, modifications of the temperature-based drought variable

Drought variable	TDI3	TDI1	TDI2	TDI4	TDI5	TDI6
Dependent variable			*Number of conflicts*			
TDI3, UEA-CRU, daily maximum, 1950–2009	**1.413 ***** **(0.372)**					
TDI1, UEA-CRU, daily maximum, 1950–2009		0.426 ** (0.199)				
TDI2, UEA-CRU, daily maximum, 1950–2009			0.978 *** (0.304)			
TDI4, UEA-CRU, daily maximum, 1950–2009				1.923 *** (0.444)		
TDI5, UEA-CRU, daily maximum, 1950–2009					1.995 *** (0.463)	
TDI6, UEA-CRU, daily maximum, 1950–2009						2.117 *** (0.476)
F-value	**2.47 *****	2.40 ***	2.44 ***	2.50 ***	2.50 ***	2.51 ***
R-squared	**0.128**	0.125	0.126	0.129	0.129	0.130

Table A.6 *(continued)*

Drought variable	TDI3	TDI3	TDI3	TDI3	TA
Dependent variable			*Number of conflicts*		
TDI3, UEA-CRU, daily maximum, 1901–2009	1.090 *** (0.337)				
TDI3, UEA-CRU, daily maximum, 1983–2009		0.923 *** (0.318)			
TDI3, UEA-CRU, daily mean, 1950–2009			1.170 *** (0.360)		
TDI3, NASA, daily mean, 1997–2007)				0.617 *** (0.238)	
TA, UEA-CRU, daily maximum, 1950–2009					0.230 (0.181)
F-value	2.44 ***	2.43 ***	2.45 ***	2.05 ***	2.38 ***
R-squared	0.126	0.126	0.126	0.108	0.124

Source: Authors' estimation based on ACLED 2011, NASA 2011, and UEA-CRU 2011.
Note: ***,** Coefficient is statistically significant at the 1 percent and 5 percent levels, respectively. Standard errors are reported in parentheses. Coefficient estimates for region-fixed and time-fixed effects are not reported. The terminology of the drought variables is as follows: [drought index][reference period], [data source], [temperature measurement], [period for calculating long-term average]; TDI = Temperature Drought Index, TA = temperature anomaly, UEA-CRU = University of East Anglia Climate Research Unit.

Table A.7—Two-stage regression results of alternative model specifications, modifications of the temperature-based drought variable

Drought variable	**TDI3**	**TDI1**	**TDI2**	**TDI4**	**TDI5**	**TDI6**
Stage 1						
Dependent variable	*Cattle price (log)*					
TDI3, UEA-CRU, daily maximum, 1950–2009	**–0.123 *****					
	(0.037)					
TDI1, UEA-CRU, daily maximum, 1950–2009		–0.065 ***				
		(0.019)				
TDI2, UEA-CRU, daily maximum, 1950–2009			–0.147 ***			
			(0.032)			
TDI4, UEA-CRU, daily maximum, 1950–2009				–0.140 ***		
				(0.042)		
TDI5, UEA-CRU, daily maximum, 1950–2009					–0.119 ***	
					(0.043)	
TDI6, UEA-CRU, daily maximum, 1950–2009						–0.138 ***
						(0.044)
F-value	**8.47 *****	8.38 ***	8.64 ***	8.34 ***	8.34 ***	8.42 ***
R-squared	**0.302**	0.302	0.308	0.302	0.302	0.300
Underidentification test[1]	**11.84 *****	12.62 ***	22.08 ***	11.48 ***	8.24 ***	10.32 ***
Weak identification test[2]	**11.15**	12.14	21.47	11.06	7.79	9.73
Stage 2						
Dependent variable	*Number of conflicts*					
Cattle price (log)	**–11.85 *****	–7.12 **	–7.05 ***	–14.09 ***	–16.94 **	–15.42 ***
	(4.187)	(3.226)	(2.206)	(4.662)	(6.696)	(5.626)
Root mean square error	**5.15**	4.46	4.45	5.57	6.17	5.84

Table A.7—Continued

Drought variable	**TDI3**	**TDI3**	**TDI3**	**TDI3**	**TA**
Stage 1					
Dependent variable			*Cattle price (log)*		
TDI3, UEA-CRU, daily mean, 1950–2009	–0.139 *** (0.034)				
TDI3, UEA-CRU, daily maximum, 1901–2009		–0.112 *** (0.032)			
TDI3, UEA-CRU, daily maximum, 1983–2009			–0.082 ** (0.035)		
TDI3, NASA, daily mean, 1997–2007				–0.132 *** (0.025)	
TA, UEA-CRU, daily maximum, 1950–2009					–0.029 * (0.017)
F-value	8.48 ***	8.45 ***	8.32 ***	9.10 ***	8.25 ***
R-squared	0.304	0.301	0.302	0.300	0.324
Underidentification test[1]	17.25 ***	12.64 ***	5.71 **	28.10 ***	3.24 *
Weak identification test[2]	16.99	12.01	5.39	27.25	3.04
Stage 2					
Dependent variable			*Number of conflicts*		
Cattle price (log)	–8.44 *** (4.643)	–10.82 ** (4.579)	–10.12 * (5.405)	–5.88 *** (2.237)	–7.58 (6.676)
Root mean square error	4.62	4.97	4.86	4.29	4.51

Source: Authors' estimation based on ACLED 2011, FSNAU 2011b, NASA 2011, and UEA-CRU 2011.
Note: ***,**,* Coefficient is statistically significant at the 1 percent, 5 percent, and 10 percent level, respectively. Robust standard errors are reported in parentheses. Coefficient estimates for region-fixed and time-fixed effects are not reported. The terminology of the drought variables is: [drought index][reference period], [data source], [temperature measurement], [period for calculating long-term average]; NASA = National Aeronautics and Space Administration, TDI = Temperature Drought Index, TA = temperature anomaly, UEA-CRU = University of East Anglia Climate Research Unit.
[1] Kleibergen-Paap rank LM statistic (Baum, Schaffer, and Stillman 2007; Kleibergen and Paap 2006). The test statistic strongly rejects the null hypothesis of underidenfication.
[2] Kleibergen-Paap rank Wald F statistic (Baum, Schaffer, and Stillman 2007; Kleibergen and Paap 2006).

Table A.8—Reduced-form regression results of alternative model specifications, temperature versus precipitation

Added precipitation variable		**PDI3**	**PDI1**	**PDI2**	**PDI4**	**PDI5**	**PDI6**	**PDI3**	**PA**
Dependent variable	*Number of conflicts*								
TDI3	**1.413 *****	1.394 ***	1.423 ***	1.411 ***	1.378 ***	1.375 ***	1.363 ***	1.225 ***	1.404 ***
	(0.372)	(0.372)	(0.372)	(0.372)	(0.372)	(0.372)	(0.372)	(0.398)	(0.372)
PDI3, UEA-CRU, 1983–2009		–0.398 **							
		(0.178)							
PDI1, UEA-CRU, 1983–2009			–0.254						
			(0.171)						
PDI2, UEA-CRU, 1983–2009				–0.419 **					
				(0.170)					
PDI4, UEA-CRU, 1983–2009					–0.421 **				
					(0.190)				
PDI5, UEA-CRU, 1983–2009						–0.510 **			
						(0.200)			
PDI6, UEA-CRU, 1983–2009							–0.623 ***		
							(0.212)		
PDI3, NASA, 1997–2007								0.437 *	
								(0.240)	
PA, UEA–CRU, 1950–2009									0.183
									(0.179)
F-value	**2.47 *****	2.47 ***	2.50 ***	2.50 ***	2.49 ***	2.50 ***	2.52 ***	2.08 ***	2.46 ***
R-squared	**0.128**	0.129	0.129	0.130	0.129	0.130	0.131	0.111	0.128

Source: Authors' estimation based on ACLED 2011, NASA 2011, and UEA-CRU 2011.

Note: ***,**,* Coefficient is statistically significant at the 1 percent, 5 percent, and 10 percent level, respectively. Standard errors are reported in parentheses. Coefficient estimates for region-fixed and time-fixed effects are not reported. The terminology of the added precipitation variables is as follows: [drought index][reference period], [data source], [period for calculating long-term average]; PDI = Precipitation Drought Index, PA = precipitation anomaly.

Table A.9—Two-stage regression results of alternative model specifications, temperature versus precipitation

Added precipitation variable		**PDI3**	**PDI1**	**PDI2**	**PDI4**	**PDI5**	**PDI6**	**PDI3**	**PA**
Stage 1									
Dependent variable	*Cattle price (log)*								
TDI3	**–0.123 *****	–0.123 ***	–0.125 ***	–0.124 ***	–0.124 ***	–0.124 ***	–0.124 ***	–0.124 ***	–0.136 ***
	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)	(0.044)
PDI3, UEA-CRU, 1983–2009		0.002							
		(0.017)							
PDI1, UEA-CRU, 1983–2009			0.033 **						
			(0.017)						
PDI2, UEA-CRU, 1983–2009				0.007					
				(0.016)					
PDI4, UEA-CRU, 1983–2009					0.007				
					(0.018)				
PDI5, UEA-CRU, 1983–2009						0.019			
						(0.018)			
PDI6, UEA-CRU, 1983–2009							0.015		
							(0.019)		
PDI3, NASA, 1997–2007								–0.065 ***	
								(0.021)	
PA, UEA-CRU, 1950–2009									0.007
									(0.018)
F-value	**8.47 *****	8.41 ***	8.45 ***	8.41 ***	8.40 ***	8.40 ***	8.43 ***	9.02 ***	8.42 ***
R-squared	**0.302**	0.302	0.304	0.302	0.303	0.302	0.302	0.320	0.302
Underidentification test[1]	**11.836 *****	12.013 ***	14.345 ***	11.862 ***	11.843 ***	12.184 ***	11.96 ***	20.698 ***	12.555 ***
Weak identification test[2]	**11.15**	5.673	6.761	5.585	5.574	5.748	5.638	9921.00	6.014
Stage 2									
Dependent variable	*Number of conflicts*								
Cattle price (log)	**–11.85 *****	–12.04 ***	–10.52 ***	–12.62 ***	–12.43 ***	–13.07 **	–13.23 ***	–8.47 ***	–11.58 ***
	(4.187)	(4.235)	(3.692)	(4.388)	(4.324)	(4.418)	(4.469)	(2.922)	(4.025)
Root mean square error	**5.15**	5.18	4.92	5.28	5.25	5.37	5.40	4.60	5.10

Source: Authors' estimation based on ACLED 2011, FSNAU 2011b, NASA 2011, and UEA-CRU 2011.

Note: ***,**,* Coefficient is statistically significant at the 1 percent, 5 percent, and 10 percent level, respectively. Robust standard errors are reported in parentheses. Coefficient estimates for region-fixed and time-fixed effects are not reported. The terminology of the added precipitation variables is as follows: [drought index][reference period], [data source], [period for calculating long-term average]; PDI = Precipitation Drought Index, PA = precipitation anomaly, UEA-CRU = University of East Anglia Climate Research Unit.[1] Kleibergen-Paap rank LM statistic (Baum, Schaffer, and Stillman 2007; Kleibergen and Paap 2006). The test statistic strongly rejects the null hypothesis of underidenfication. [2] Kleibergen-Paap rank Wald F statistic (Baum, Schaffer, and Stillman 2007; Kleibergen and Paap 2006).

Table A.10—Two-stage regression results of alternative model specifications, modifications of livestock price index

Stage 1					
Dependent variable	***Cattle, EQ***	*Cattle, LQ*	*Goat, EQ*	*Sheep, EQ*	*Camel, LQ*
Drought (TDI3)	**–0.123 *****	–0.128 ***	–0.008	0.039	–0.031
	(0.037)	(0.039)	(0.028)	(0.038)	(0.041)
Stage 2					
Dependent variable			*Number of conflicts*		
Cattle, EQ	**–11.85 *****				
	(4.187)				
Cattle, LQ		–11.59 ***			
		(4.245)			
Goat, EQ			–177.6		
			(588.1)		
Sheep, EQ				25.24	
				(28.39)	
Camel, LQ					–46.22
					(59.69)
Observations	**2,335**	2,417	2,464	1,787	2,517

Source: Authors' estimation based on ACLED 2011, FSNAU 2011b, and UEA-CRU 2011.
Note: *** Coefficient is statistically significant at the 1 percent level. Robust standard errors are reported in parentheses. Coefficient estimates for region-fixed and time-fixed effects are not reported. The terminology of the livestock price index is as follows: [livestock], [quality]; EQ = export quality, LQ = local quality. All livestock prices are in logarithms and normalized by gasoline prices. Camel prices are available for local quality only.

Table A.11—Two-stage regression results of alternative model specifications, modifications of cattle price normalization

Normalizing price	**Gasoline**	**Sugar**	**Rice**	**None**
Stage 1				
Dependent variable		*Cattle price (log)*		
Drought (TDI3)	**–0.123 *****	–0.053 *	–0.053 *	–0.038 *
	(0.037)	(0.032)	(0.031)	(0.028)
Stage 2				
Dependent variable		*Number of conflicts*		
Cattle price (log)	**–11.85 *****	–27.55 ***	–27.66 ***	–38.44
	(4.187)	(16.67)	(16.10)	(28.07)
Observations	**2,335**	2,510	2,524	2,531

Source: Authors' estimation based on ACLED 2011, FSNAU 2011b, and UEA-CRU 2011.
Note: ***,* Coefficient is statistically significant at the 1 percent and 10 percent level, respectively. Robust standard errors are reported in parentheses. Coefficient estimates for region-fixed and time-fixed effects are not reported. TDI = Temperature Drought Index.

Table A.12—Two-stage regression results of alternative model specifications, time lags

	No lags	*1-month lag*	*2-month lag*	*3-month lag*	*4-month lag*	*5-month lag*
Stage 1						
Dependent variable	*Cattle price (log)*					
TDI3						
t	**–0.123 *****	–0.092 **	–0.106 **	–0.104 **	–0.100 **	–0.101 **
	(0.037)	(0.044)	(0.045)	(0.045)	(0.045)	(0.045)
t-1		–0.059	–0.014	–0.039	–0.041	–0.039
		(0.039)	(0.047)	(0.048)	(0.048)	(0.048)
t-2			–0.071 *	0.013	0.003	0.001
			(0.041)	(0.049)	(0.049)	(0.05)
t-3				–0.134 ***	–0.096 **	–0.104 **
				('0.041)	(0.048)	(0.048)
t-4					–0.059	–0.029
					(0.039)	(0.048)
t-5						–0.049
						(0.042)
Stage 2						
Dependent variable	*Number of conflicts*					
Cattle price (log)	**–11.85 *****	–12.54 ***	–12.7 ***	–11.5 ***	–11.87 ***	–12.54 ***
	(4.187)	(3.796)	(3.612)	(2.709)	(2.665)	(2.718)

Source: Authors' estimation based on ACLED 2011, FSNAU 2011b, and UEA-CRU 2011.

Note: ***,**,* Coefficient is statistically significant at the 1 percent, 5 percent, and 10 percent level, respectively. Robust standard errors are reported in parentheses. Coefficient estimates for region-fixed and time-fixed effects are not reported.TDI = Temperature Drought Index.

Table A.13—Two-stage regression results of alternative model specifications; spatial dependency, seasonality, and nonlinearity

Modification	None	Spatial dependency of order 1	Spatial dependency of order 2	Seasonality	Nonlinearity
Stage 1					
Dependent variable			*Cattle price (log)*		
TDI3	**–0.123 *****	–0.124 ***	–0.127 ***	–0.149 ***	–0.229 ***
	(0.037)	(0.037)	(0.037)	(0.049)	(0.094)
TDI3, spatially lagged in order 1		0.054			
		(0.121)			
TDI3, spatially lagged in order 2			0.645		
			(0.599)		
Rainy season (1 = yes, 0 = no)				–0.106	
				(0.076)	
TDI3 * rainy season				0.034	
				(0.06)	
TDI3 squared					0.063
					(0.049)
Stage 2					
Dependent variable			*Number of conflicts*		
Cattle price (log)	**–11.85 *****	–11.38 ***	–10.23 ***	–11.99 ***	–9.97 ***
	(4.187)	(4.112)	(3.805)	(3.946)	(3.739)

Source: Authors' estimation based on ACLED 2011, FSNAU 2011b, and UEA-CRU 2011.

Note: *** Coefficient is statistically significant at the 1 percent. Robust standard errors are reported in parentheses. Coefficient estimates for region-fixed and time-fixed effects are not reported. The dichotomous variable for the season considers that the timing and length of the seasons are slightly different in Northern and Southern Somalia compared to Central Somalia. TDI = Temperature Drought Index.

Table A.14—Two-stage regression results, validity of the instrumental variable

IV estimation	Just identified		Overidentified		LIML estimator	
Stage 1						
Dependent variable			*Cattle price (log)*			
Drought (TDI3)	**–0.123**	*******	–0.108	***	–0.108	***
	(0.037)		(0.045)		(0.045)	
Exposure to international cattle prices			16,697	***	16,697	***
			(2,644)		(2,644)	
Stage 2						
Dependent variable			*Number of conflicts*			
Cattle price (log)	**–11.85**	*******	–6.71	**	–6.81	**
	(4.187)		(1.42)		(1.455)	
F-value	**8.47**	*******	9.45	***	9.45	***
R-squared	**0.302**		0.320		0.320	
Observations	**2,335**		1,905		1,905	
Underidentification test[1]	**11.84**	*******	48.23	***	48.23	***
Weak identification test[2]	**11.15**		24.21		24.21	
Overidentification test (p-value)[3]			0.225		0.227	
Root mean square error	**5.145**		4.375		4.375	

Source: Authors' estimation based on ACLED 2011, UEA-CRU 2011, IMF 2011, and FSNAU 2011b.
Note: ***,** Coefficient is statistically significant at the 1 percent and 5 percent level, respectively. Robust standard errors are reported in parentheses. Coefficient estimates for region-fixed and time-fixed effects are not reported. TDI = Temperature Drought Index, LIML = Limited Information Maximum Likelihood.
[1] Kleibergen-Paap rank LM statistic (Baum, Schaffer, and Stillman 2007; Kleibergen and Paap 2006). The test statistic of the augmented regression strongly rejects the null hypothesis of underidenfication.
[2] Kleibergen-Paap rank Wald F statistic (Baum, Schaffer, and Stillman 2007; Kleibergen and Paap 2006).
[3] Hansen J statistic (Baum, Schaffer, and Stillman 2007). The test statistic of the augmented regression does not reject the null hypothesis of zero correlation between the instrumental variables and the error term.

Table A.15—Two-stage regression results, additional channels of transmission

Additional channels	None	Precipitation	Agricultural wage	Wheat flour price	Maize price	Red sorghum price	Rice price
Stage 1							
Dependent variable				*Cattle price (log)*			
TDI3	**–0.123 *****	–0.123 ***	–0.127 ***	–0.141 ***	–0.143 ***	–0.144 ***	–0.129 ***
	(0.037)	(0.037)	(0.036)	(0.037)	(0.037)	(0.036)	(0.035)
PDI3		0.002	0.012	0.015	0.006	0.004	0.009
		(0.017)	(0.017)	(0.018)	(0.018)	(0.017)	(0.017)
Agricultural wage, (t-1)			–0.034 *				
			(0.020)				
Wheat flour price, (t-1)				–0.029			
				(0.023)			
Maize price, (t-1)					–0.081 *		
					(0.042)		
Red sorghum price, (t-1)						–0.015	
						(0.024)	
Rice price, (t-1)							–0.145 ***
							(0.046)

Table A.15 Continued

Additional channels	**None**	**Precipitation**	**Agricultural wage**	**Wheat flour price**	**Maize price**	**Red sorghum price**	**Rice price**
Stage 2							
Dependent variable				*Number of conflicts*			
Cattle price (log)	**–11.85 *****	–11.97 ***	–11.72 ***	–12.07 ***	–10.05 ***	–10.50 ***	–10.89 ***
	(4.187)	(4.203)	(4.152)	(4.056)	(3.534)	(3.501)	(3.952)
PDI3		–0.399	–0.359	–0.428	–0.581 **	–0.434	–0.370
		(0.271)	(0.287)	(0.306)	(0.281)	(0.276)	(0.276)
Agricultural wage, (t-1)			–0.286				
			(0.394)				
Wheat flour price, (t-1)				–0.530			
				(0.359)			
Maize price, (t-1)					2.394 ***		
					(0.659)		
Red sorghum price, (t-1)						–0.127	
						(0.358)	
Rice price, (t-1)							1.889 **
							(0.924)
Observations	**2,335**	2,335	2,066	1,888	1,958	1,980	2,081

Source: Authors' estimation based on ACLED 2011, UEA-CRU 2011, and FSNAU 2011b.

Note: ***,**,* Coefficient is statistically significant at the 1 percent, 5 percent, and 10 percent level, respectively. Robust standard errors are reported in parentheses. Coefficient estimates for region-fixed and time-fixed effects are not reported. Wage rates and all food prices are normalized by gasoline prices. They enter the regressions in logarithmic terms and lagged by one month. TDI = Temperature Drought Index, PDI = Precipitation Drought Index.

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