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ARMED CONFLICT AND FOOD PRICE DYNAMICS IN ETHIOPIA: AN INTERRUPTED TIME SERIES ANALYSIS OF THE TIGRAY WAR

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Abstract

This study, through a quasi-experimental interrupted time series, examines how the Tigray armed conflict between November 2020 - November 2022 impacted food prices across Ethiopia's administrative regions. Using segmented regression technique, the empirical findings reveal that conflict produced an immediate level decrease followed by a 270% increase in inflation rate that persisted through the ceasefire period and beyond. The study goes on to reconcile these seemingly contradictory results through data censoring hypothesis. Policy implications emphasize that humanitarian organizations should treat statistical measurement gaps as evidence of crisis severity. Early warning systems require parallel monitoring streams activating alternative information sources including satellite imagery, mobile phone crowdsourcing, and humanitarian field reports when primary data fail.

Keywords: Armed conflict, food prices, interrupted time series analysis, Ethiopia, Tigray war, data censoring, humanitarian crisis, market disruption, food security

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These past thirty months have been a whirlwind of challenges. I leave now much larger than the person who arrived. I have traded my comfort for character, and my uncertainty for a voice that finally knows its own strength and for that, I am thankful.

"The world is yourz"- Nas

Dedication

I dedicate this work to the people of Tigray and all Ethiopians who have endured, and continue to endure, the devastating weight of armed conflict. To the women, children, and elders of Tigray: I am profoundly sorry for the collective failure to protect you; for allowing history to repeat its darkest chapters. I pray that we have finally learned the true price of peace and will commit ourselves to the arduous path of compromise and understanding. My heart remains with the farmers and the most vulnerable, whose stories often go untold, but whose resilience remains the bedrock of our hope.

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List of Abbreviations

ACLED	Armed Conflict Location & Event Data
CPI	Consumer Price Index
CSA	Central Statistics Agency
ENDF	Ethiopian National Defence Force
EPO	Ethiopia Peace Observatory
FEWS NET	Famine Early Warning Systems Network
GDP	Gross Domestic Product
GHA	Greater Horn of Africa
IDP	Internally Displaced Person
ITS	Interrupted Time Series
TPLF	Tigray People's Liberation Front
TWFE	Two-Way Fixed Effects
UNDP	United Nations Development Programme
VIF	Variance Inflation Factor
WFP	World Food Programme

CHAPTER I: INTRODUCTION

1.1. Overview of the Regional Context:

1.1.1. The Greater Horn of Africa – geographic scope and strategic importance

The Greater Horn of Africa is a geostrategic and ecological region spanning over 6 million km^2 and home to an estimated 500 million people. It is one of the world's most vulnerable geographical areas in relation to climate-related risks. The region represents a complex 'security-environment' nexus where extreme climatic variability and chronic armed conflict form a feedback loop of food insecurity.

All in all, the region consists of Burundi, Djibouti, Eritrea, Ethiopia, Kenya, Rwanda, Somalia, South Sudan, Sudan, Tanzania and Uganda. It is characterized by significant concentration of pastoralist communities heavily reliant upon rain-fed agriculture which itself is extremely sensitive to climate variability.

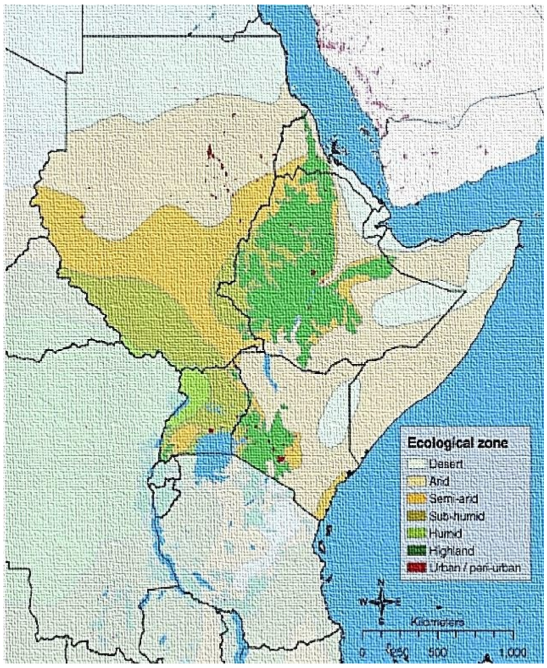
1.1.2. Agroecological diversity and livelihood systems

Although mostly arid or semi-arid, the region encompasses some temperate zones which cut across a wide range of agroecological zones, from expansive deserts to equatorial highlands. Local rainfall regimes in the region generally consist of unimodal rainfall during summer and bimodal, i.e., long rains during the spring, short rains during fall cycles, with annual rainfall being erratic.

Whilst in southern Ethiopia, southern Somalia, most of Kenya rainfall is delivered in the two-season model, the northern half of Ethiopia and countries further from the equator have a single wet season, sometimes with a mid-season break in precipitation. (Tierney et al, 2015)

Seasonal rainfall in the Horn of Africa drylands is a lifeline for agrarian communities who rely on water for crop growth, livestock rearing, and drinking water (Mati 2005; Palmer et al. 2023). Unconventional rainfall and droughts have been detected as the principal source of vulnerability to food insecurity within arid and semiarid areas (Amwata et al. 2016; Funk et al. 2019; Verdin et al. 2005).

By the same token, extreme flooding in key rainy seasons can have devastating impacts on rural communities living along major rivers (Matano et al. 2022)



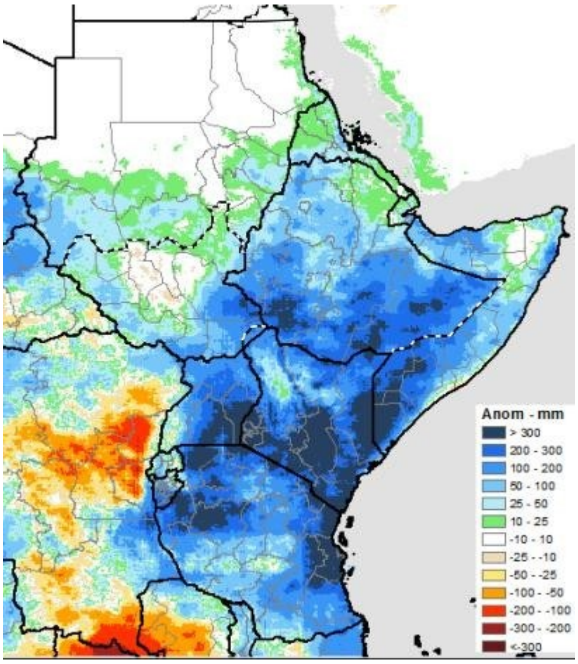


Figure 1 (on the left). Agroecological zones in the Horn of Africa.
Source: Knips, V. (2004). Review of the Livestock Sector in the Horn of Africa (IGAD countries). Rome: FAO

Figure 2 (on the right). East Africa seasonal precipitation anomaly (relative difference to long-term average, October – December 2019).
Source: FAO GIEWS (2020)

In the past 30 years, there have been at least six outbreaks and/or re-emergence of agricultural pests and diseases in the Eastern African region. The worst Desert Locust outbreak in 25 years, *Schistocerca 13 gregaria*, occurred in 2019-2020. It caused immense havoc on food production in Ethiopia, Kenya, Somalia, Sudan, Eritrea, Djibouti, Uganda, and South Sudan.

The locusts transformed into hopper bands and their very survival and profusion was sustained by the prolonged wet conditions, notably the 400% above-average autumn rain recorded in 2019.

The availability of moist sandy soils across most arid and semi-arid lands (ASALs) of IGAD and the Middle East adding to the abundance of lush vegetation cover and the south-ward monsoonal winds accelerated their transboundary advance.

In Ethiopia, the hopper bands were observed consuming at least 1,755,000 MT of green vegetation per day. In Amhara region, some farms registered nearly 100% loss of teff, a staple crop in the country. Oromia was the worst affected region with a total cereal loss of 122,835 MT on 41,051.4 hectares of cropland. Somali region experienced the second-largest cereal crop loss of 102,613 MT on 90,076 ha of cropland. Tigray region was third with 84,324 MT lost on 40,577 ha of land. (Relief Web, 2020)

In response, Kenya and Ethiopia sprayed millions of hectares of cropland and pastures with chemical pesticides which in Ethiopia alone, according to a new study estimate, led 76 billion honeybees to either perish or abandon their hives. As a result, honey production declined by nearly 80% between 2017-18 and 2021, translating into losses of 500 million USD. (Vyawahare, 2023)

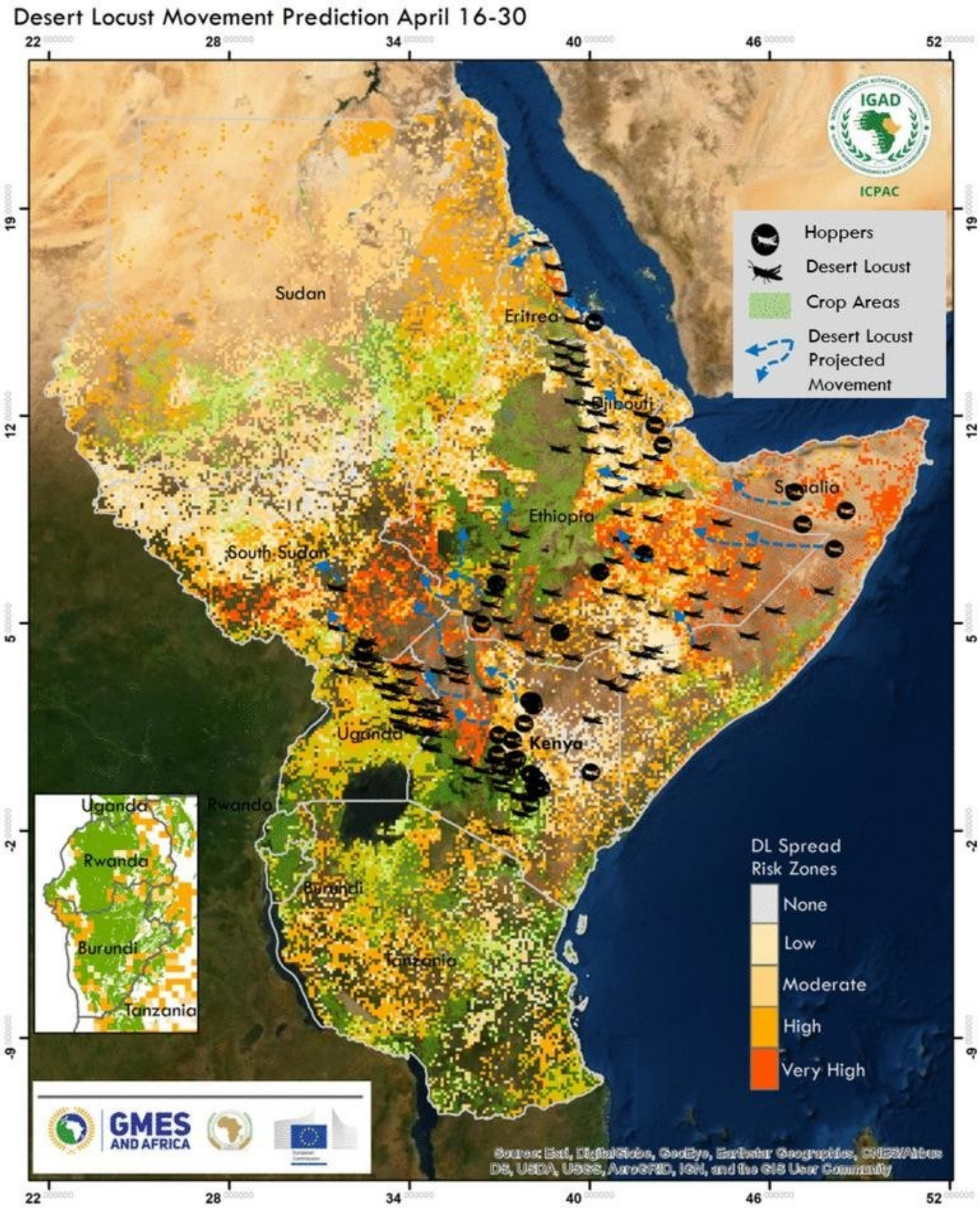


Figure 3. Desert Locust Movement Prediction, April 16-30, 2020
Source: ICPAC (2020). Base map: Esri, DigitalGlobe, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AeroGRID, IGN, and the GIS User Community.

1.2. Background of Study

1.2.1. Ethiopia: Country Context

Ethiopia situated in the northeastern part of the Horn of Africa, covers a total area of 1.1 million km^2. Frequently dubbed "the water tower of East Africa", the riparian country sources major rivers that sustain its population alongside neighbouring countries, contributing approximately 85% of the total flow of the Nile.

The country is landlocked, sharing strategic frontiers with Eritrea, Djibouti, Somalia, Kenya, South Sudan, and Sudan. (FAO, 2016) After the last cluster-based administrative restructuring which took place in August 2023, currently, there are 12 regional states and two chartered city administrations.

As of 2025, the country's total population is estimated to be 135.5 million (UNFPA, 2025). Its annual population growth is 2.6%. The life expectancy at birth is 67 years. The Human Capital Index is 0.38 as of 2020, 2% off the average for the Sub-Saharan Africa region (40%). The poverty headcount ratio at $3 a day (adjusted to 2021 PPP) is 38.6% of the total population. (World Bank, 2024)

The percentage of unemployed from the total labour force is estimated to be 3.4%, reflecting rather a high degree of informal labour and underemployment as most Ethiopians cannot afford to be "unemployed" to be able to survive, making them acutely vulnerable to market shocks. Inflation tagged by consumer prices stands at 21% with urban households being hit the hardest. Personal remittances received as a portion of GDP is 0.3%. Net Inflows of Foreign Direct Investment as a percentage of GDP is 2.7%.

Central government debt as a total percentage of GDP is 31.4%. (World Bank, 2024) Multilayered episodes of crises including COVID-19, the Tigray conflict, and droughts which worsened economic imbalances, led to a debt default in late 2023, taking a further toll on living standards amid structurally high inflation, high levels of internal displacement and humanitarian needs. (World Bank, 2024)

The country's GDP values at $149.74 billion with an annual growth rate of 7.6%. GDP per capita is $1,133.9. This pace of growth was supported by the hamper crop harvests during *meher* season in FY 2024/25, with production amounting to 506.8 million quintals despite the structural hurdles.

In addition, the adoption of the Four-Year Electricity Tariff Adjustment Plan in September 2024, a core requirement of the IMF-backed Homegrown Economic Reform Agenda 2.0, led to a surge in electricity and water tariffs. Mounting economic pressures also necessitated a transition to a floating currency regime, a non-negotiable binder to the IMF plan in mid-2024 (UNDP, April 2025). This has also created new barriers to food access and affordability as notably most rural families failed to benefit from higher food prices due to their limited market engagement.

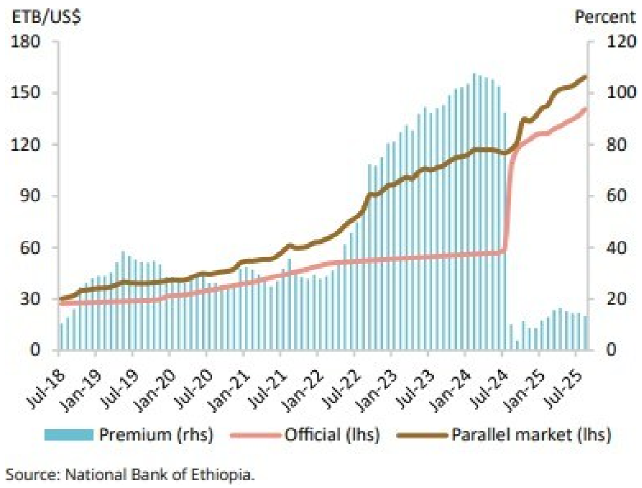


Figure 4. Nominal exchange rate of Ethiopian Birr (ETB), 2018-2024
Source: National Bank of Ethiopia (2024)

This transition also led to gold being "rerouted" into official exports as gold miners switched to the market-based rate, hence the surge in export performance of gold and even coffee, where the latter witnessed a 144% increase in export volumes, reaching 469,000 metric tons in FY 2024/25. (Ethiopian Monitor, 2025)

1.2.2. The Biophysical Context

a. Topography & Climate

Ethiopia's topographical diversity features a rugged and diverse topography, split by the Great East African Rift Valley, with altitudes ranging from 110m below mean sea level at Danakil Depression to a peak exceeding 4600m at Ras Dashen Mountain.

It is estimated that over 37 million ha is cultivated and approximately 23 million ha are permanent meadows and pastures. Water bodies cover around 744 400 ha (IUCN, 2010), forest area about 26.7 million ha (EFD, 2024), while 19.2 million ha terrestrial and inland waters are protected. (UNEP-WCMC,2025)

b. Ethiopian Agroclimatic Zones (Indigenous Classification Belts)

Table 1
Agroclimatic Zones Based on Water Balance and Altitude

Meters above MSL	*Annual Rainfall (mm)*		
	<900	900-1400	>1400
>3700			High *Wurch/Kur* (no crops)
3700-3200		Moist *Wurch* (barley)	Wet *Wurch* (barley)
3200-2300		Moist *Dega* (barley, wheat, pulses)	Wet *Dega* (barley, wheat, pulses, oilseeds)
2300-1500	Dry *Weyna Dega* (wheat, teff, maize)	Moist *Weyna Dega* (maize, sorghum, teff, wheat	Wet *Weyna Dega* (teff, maize, enset, oilseeds, barley)
1500-500	Dry *Kolla* (sorghum, teff)	Moist *Kolla* (sorghum, teff, pulses, oilseeds)	
<500	*Bereha* (only irrigated crops)		

Note: Bereha represents the hot lowlands. In the arid east, crop production is very limited; in the humid west, root crops and maize are largely grown. Kolla represents lowlands where sorghum, finger millet, sesame, cowpeas & groundnuts are grown. Woina Dega includes midlands and the major staples grown are wheat, teff, barley, maize, sorghum, chickpeas & haricot beans. Dega represents the highlands. Barley, wheat, highland oilseeds and highland pulses are cultivated. Wurch represents highlands and barley is the common staple, while Kur is the highest of the highlands and primarily used for grazing.

Source: Adapted from Hurni (1998)

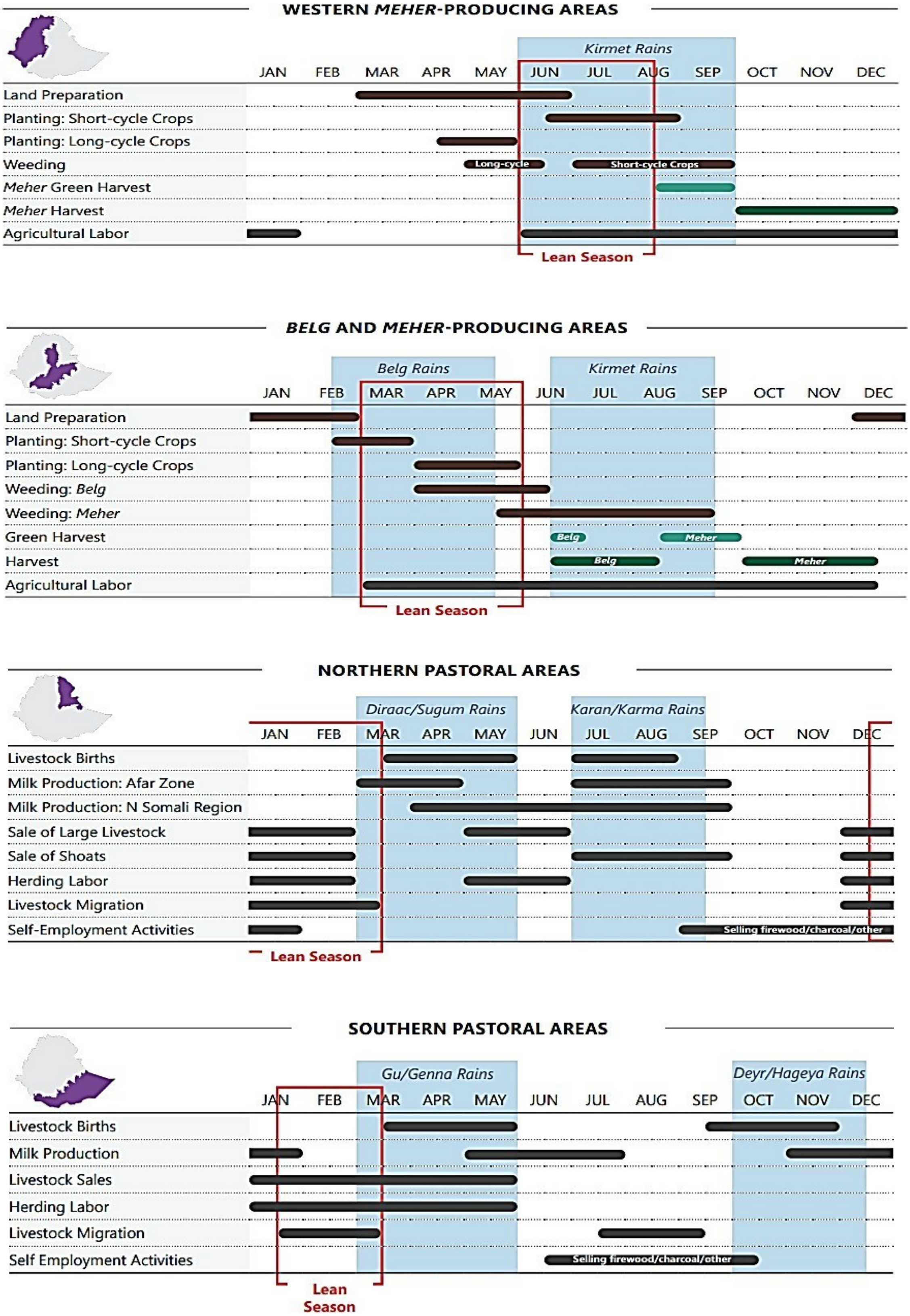
Rainfall in Ethiopia is highly erratic, resulting in a very high risk of intra-seasonal dry spells and annual droughts, of which the 1973-74, 1983-84, 1987-88, 1990-91, 1993-94 and 2015-16 are the major ones in the last decades. The drought in 2015-16 is even considered to be the worst drought for over 30 years.

The agroclimatic zones can also be divided in terms of water balance and the length of the growing period:

1. Arid or Semi-Arid Regime: These are areas without a significant growing period, with little or no rainfall (Eastern, Northeastern, Southeastern, Southern and Northern lowlands). Primary livelihood also includes nomadic or semi-nomadic pastoralism
2. Unimodal Regime (Mono-modal): Areas with a single growing period and one rainy season from February/March to October/November, covering the western half of the country, with the duration of the wet period decreasing from South to North.
3. Areas with a double growing period and two rainy seasons (Meher and Belg) which are of two types: i) in the east of the country: there are a small rainfall peak in April and a major one in August; ii) most of the lowlands of the south and southeast have two distinct wet periods, February-April and June-September, interrupted by two clear-cut dry periods. The peak rainfall months are April and September.

Table 2

Seasonal Calendar for a typical Ethiopian year.



Source: FEWS NET & USAID (2024)

1.2.3. The Socio-Economic Context

a. Agricultural Structure

The agricultural sector continues to play a dominant role, contributing 33-37% to the national GDP, though this represents a gradual decline from 42% in 2014 as the industrial and services sectors expand. (World Bank, 2024; NBE, 2023)

Despite this relative decline, agriculture remains the primary source of livelihood for many Ethiopians, employing approximately 66-70% of the active population, down from 83% in 2011 (ILO, 2023). The sector also generates roughly 70-75% of the country's export earnings, underscoring its critical importance to the national economy. (NBE, 2023)

Approximately 95% of cultivated land in Ethiopia is rain-fed (Belay et al., 2022). Staple crops include teff, wheat, maize, sorghum, barley and pulses. The country also has the largest livestock population in Africa. (CSA, 2022; FAO, 2023)

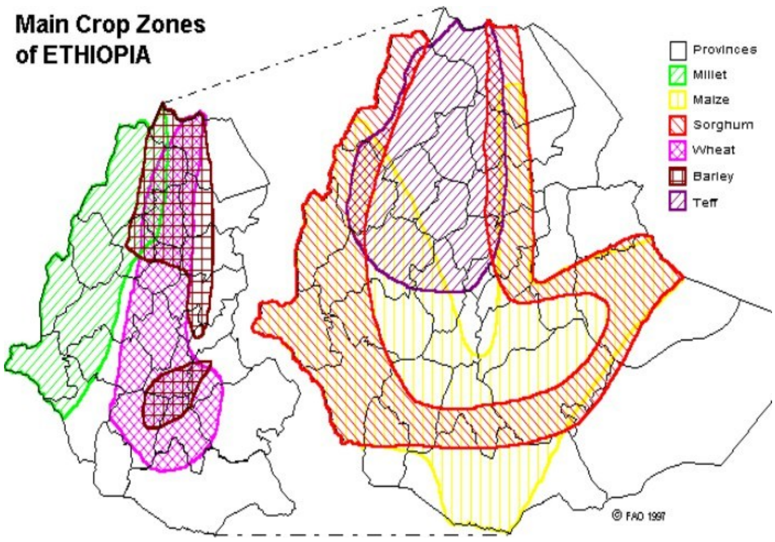


Figure 5: Main Crop Zones of Ethiopia.
Source: FAO, 1997

Socio-economic Vulnerability: Smallholder Farming Dominance and Land Fragmentation

Ethiopian agriculture is overwhelmingly dominated by smallholder farmers who cultivate over 95% of the total cropland (Bachewe et al., 2018). As of 2020, there were approximately 16.7 million agricultural households in the country, with the average farm size having declined to 0.89 hectares from 0.95 hectares in 2015, reflecting on ongoing land fragmentation (CSA, 2020).

The government has responded by scaling up Agricultural Commercialization Clusters (ACCs) whereby neighboring smallholders aggregate their small plots to grow the same crop variety using same inputs and planting windows.

Inheritance patterns have also accelerated the division to “micro-plots” that are no longer economically viable for subsistence. Recent 2024/25 data shows that farmers under 35 have even smaller plots (averaging 0.8 ha) compared to the national average. This has fueled a surge in the rural land rental market, where landless youth rent "in" parcels from older farmers to create a viable farming unit. (GIZ, 2025)

Many of these farmers are net food buyers. Because their small plots cannot grow enough food to last 12 months, they purchase grains from the market during “lean season”. When food prices rise, these farmers suffer as much as urban dwellers. (UNDP, 2025)

b. Agricultural Production Systems

(i) Highland mixed farming system integrates crop production with livestock rearing and practiced at elevations above 1500m. It’s the most productive and densely populated agricultural zone in Ethiopia. Cereals such as teff, wheat, barley and pulses form the foundation of cropping patterns. It is predominantly found in the central and northern highlands and most regions of the south and southwest with prolonged humid periods.

(ii) Lowland mixed system is practiced in low-lying plains, valleys and mountain foothills below 1500m. Crops such as maize, sorghum, and cotton are cultivated alongside livestock production. It covers the northern parts of the Awash River basin and the rift valley regions.

(iii) Pastoral and agro-pastoral production systems are characterized by extensive livestock rearing with seasonal migration between wet and dry season grazing areas serving as a key adaptation strategy to variable rainfall and forage availability. It is primarily practiced in the Afar and Somali regions and the Borena zone of Oromia. (Bachewe et al., 2018)

(iv) Shifting cultivation is practiced in the southern and western areas of the country with lower population density and abundant land availability, although increasing demographic pressure has shortened fallow periods.

(v) Commercial agriculture contributes immensely to agricultural output and export earnings, particularly in horticulture, floriculture, and large-scale cereal production (Berhane et al., 2020). The floriculture industry has been particularly successful, with Ethiopia becoming a major exporter of cut flowers to European markets, earning over $500 million annually by 2022. (EHPEA, 2023)

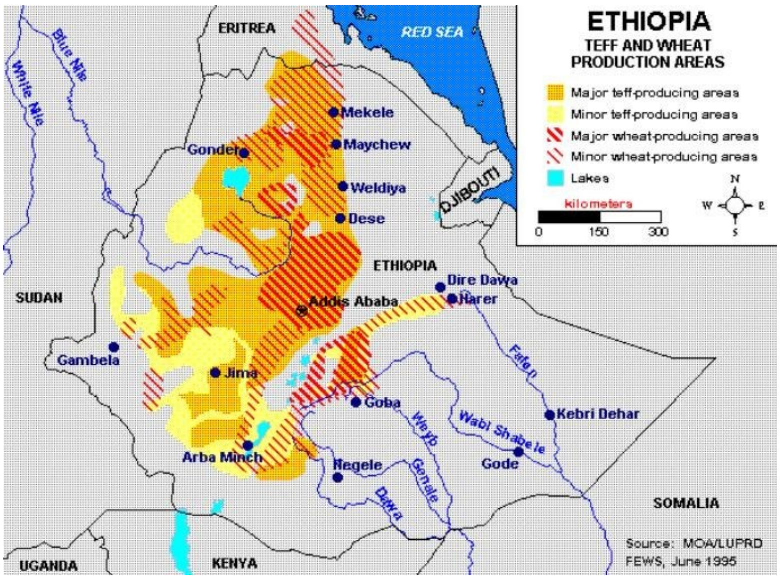


Figure 6: Major Teff and Wheat-Producing Area in Ethiopia.

Source: MOA/LUPRD & FEWS (1995)

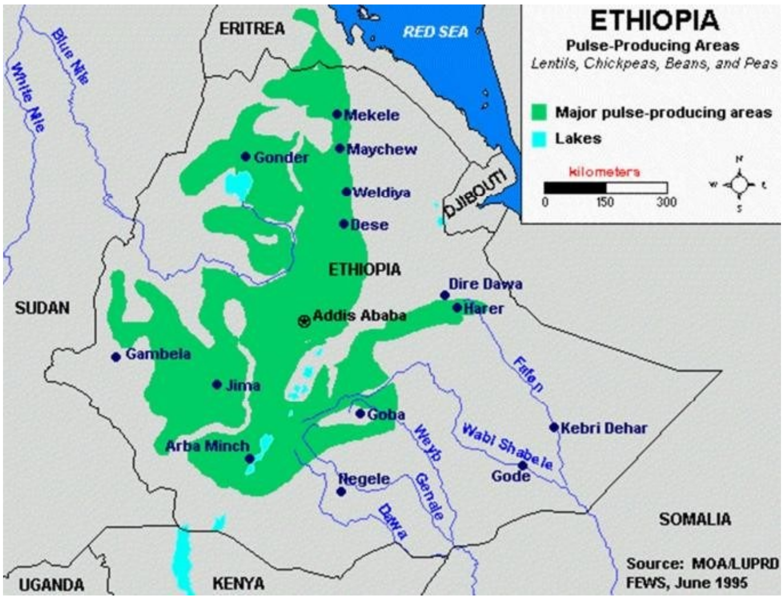


Figure 7: Major Pulse-Producing Areas in Ethiopia.

Source: MOA/LUPRD & FEWS (1995)

1.2.4. The Horn as a "Contested Corridor"

While this thesis focuses on Ethiopia's internal conflict dynamics, food prices, especially in border regions, cannot be understood without accounting for regional security externalities.

For half a century now, this corner of the continent has been a byword for conflict and poverty, two mutually reinforcing afflictions. It is home to scores of 'national liberation' movements fighting for power within their own states, striving to join another state, or to build a state of their own. Ruptures and regime changes often occur when the center of political hegemony is politically divided and weakened, thus being vulnerable to challenges from the periphery. By peripheries, in most instances, we mean to say the lowlands. (Markakis, 2011)

All state borders in the Horn are drawn through the lowlands. Ethiopia shares the biggest portion of its borders through this lowland pastoralist zone. Consequently, border (inter-state) conflicts are frequently fought in this arc. The fundamental difference between the high and low land in this region is the material foundation that determines the ways humankind makes a living. The escarpment is the boundary between 'the desert and the sown', the settled cultivation and mobile pastoralism. (Nelson 1973)

Conflicts here often refuse to observe cartographic lines. Borders are easily crossed. When war erupts, these transgressional movement patterns transform into refugee flows.

Building on Cliffe's (1989) pioneering quantification of conflict-induced agricultural collapse in Eritrea during the liberation struggle (1961-1991), the study demonstrates how annual food production shortfall of 65,000 – 95,000 tons; livestock losses of close to 44,000 animals and land mines which rendered 23,000 hectares permanently uncultivable led to cross-border spillover effects through refugee flows (mainly to Sudan and Ethiopia), trade route disruptions due to grain markets response to supply shocks and the proliferation of price shocks.

a. Eritrea-Ethiopia (1998-2000)

The Ethio-Eritrea war (1998-2000) exemplifies how borders fail to contain conflict. Over the course of the war, a total of 650,000 people were displaced. Border regions like Badme and Zalambessa saw massive disruption to agricultural production even being rendered uninhabitable during conflict. Border markets that sustained cross-border pastoral communities were destroyed. Refugee populations also strained already fragile food systems in host economies. Eritrean post-war economic isolation also created food import dependencies. (Riggan & Poole, 2018)

This eventually precipitated Ethiopia's loss of access to the Red Sea, forcing reliance on Djibouti and other alternative ports including signing controversial deals like the 2024 Ethiopia-Somaliland Memorandum of Understanding (MoU) on port access at Berbera. Egypt, already in a long-running dispute over the GERD on the Nile, sees this deal as an expansionist threat.

b. Somalia state collapse (1991-present)

The modern conflict architecture of the Horn began taking shape with Somalia's state collapse in 1991, which transformed the country into a patchwork of clan-based territories and warlord fiefdoms. The 2006 War in Somalia which saw the intervention of Ethiopia backed by the U.S. to oust the Islamic Courts Union paradoxically strengthened Al-Shabaab militancy, transforming what had been relatively effective local governance into radical militancy. (Hammond & Vaughan-Lee, 2012)

AMISOM, a multinational force under the auspices of the African Union, was formed to stabilize the regime change between the ICU and the newly installed Transitional Federal Government, thereby implementing a national security plan. It is by far the deadliest peacekeeping operation in the postwar era. (Maruf, 2023)

This fragmentation created a haven for smugglers, pirates and transnational crimes, even threatening global shipping lanes during its peak in 2008-2012. Foreign aid, often contested, diverted and taxed by armed groups, also became part of the conflict economy. The crisis wasn't merely a Somali problem. It has created one of the world's most protracted refugee situations, with camps in Dadaab, Kenya and Dollo Odo, Ethiopia housing generations born in exile. (Menkhaus, 2014)

c. Sudan civil wars (1983-2005, 2013-2018, 2023-present)

Dubbed 'Africa's longest war', the civil war in the Sudan erupted even before the country's independence in 1954 and went on with a brief intervention for five decades. The 2019 Sudanese revolution which briefly offered hope for civilian governance collapsed into a catastrophic civil war.

This war which erupted in April 2023 as a power struggle between General Burhan's Sudanese Armed Forces (SAF) and Hemedti's Rapid Support Forces (RSF) generated over 12 million displaced persons to date, creating the world's largest displacement crisis (IRC, 2025). Ethiopia in part has absorbed over 43,000 Sudanese refugees by late 2024 (UNHCR, 2024), straining resources in western border regions already affected by internal turmoil.

In 2008, a compromise was reached regarding Al Fashaga, a highly fertile agricultural area on the Ethiopian-Sudan border, allowing Ethiopian farmers to cultivate while Sudan retained administrative control of it. The compromise ended with the onset of the Tigray war in November 2020. The sesame trade here plays a central role in the conflict economy, its revenues funding SAF military operations. The Port Sudan route which, primarily through sesame exports, handled close to 2-5% of Ethiopian trade was halted.

d. South Sudan (2013-2018)

Meanwhile, Sudan's civil wars (1955–1972 and 1983–2005) followed ethnic and religious fault lines between the Arab-Muslim north and the predominantly Christian and Traditionalist south, ultimately leading to South Sudan's independence in 2011. Yet independence solved little: South Sudan's own civil war (2013-2018) between President Salva Kiir's Dinka-dominated government and Riek Machar's Nuer opposition forces displaced millions, many fleeing into northern Uganda and Ethiopia.

These conflicts were never purely internal. They involved Ugandan troops, Sudanese government interference, and competition over oil revenues that linked South Sudan's stability directly to global energy markets. (Johnson, 2016)

1.2.5. Previous Conflict-Induced Food Crises in the Horn

The Horn of Africa has experienced five major famines since the 1980s. Understanding these historical cases illuminates what is common across conflict food crises in the Horn, i.e., displacement, market disruption and aid restriction. A unique aspect to the Tigray war is the rapid urban price transmission, proliferation of social media information and the satellite documentation of agricultural destruction.

1983-85 Ethiopian famine

The 1983-1985 biblical famine in northern Ethiopia was man-made, killing approximately 400,000-500,000 people and leaving over 7.9 million people with acute food shortage. The Derg systemized scorched earth warfare through its counterinsurgency operations which led to the destruction of crops, livestock and food stores mainly in Tigray, Wollo and Eritrea.

Thereafter, Resettlement and Villagization was launched in 1984 as famine relief program. Criticized for its coercive nature and as a counter-insurgency strategy, it led to the relocation of close to 600,000 to 800,000 people from drought-stricken highlands of the north to the southwest. At the apex of the famine, Colonel Mengistu announced that 46% of the national budget would be spent on the military, while the health budget was slashed to roughly 3%.

1.3. Statement of the Problem

While the general relationship between armed conflict and deteriorating food security conditions is well-documented in academic literature, isolating the magnitude and mechanisms through which conflict intensity affects food prices requires more rigorous quantitative investigation

Existing research on Ethiopia has predominantly focused on aggregate national-level analyses or qualitative assessments of food insecurity, thereby overlooking important regional heterogeneity in both conflict exposure and market responses. Traditional regression models which treat conflict as a static, background variable fail to account for the sudden, non-linear "jumps" in market prices that occur during an outbreak of violence thereby offering little insight into the true temporal impact of violence on market functionality.

The research gaps this study addresses is threefold. First, there is limited quantitative evidence employing quasi-experimental designs to measure the causal impact of conflict on food prices in Ethiopia, particularly evidence that accounts for the staggered entry of different regions into conflict conditions. Second, previous studies have not systematically examined how conflict intensity, measured through fatality counts, correlates with the magnitude of price responses across regions experiencing different levels of violence. Third, the interaction between conflict and other concurrent shocks such as COVID-19 restrictions, rainfall deficits, and currency fluctuations has not been adequately controlled for in regional-level analyses thereby confounding the specific "threshold of violence".

This knowledge gap carries substantial policy implications. Humanitarian organizations require evidence-based projections of food price trajectories under different conflict scenarios to effectively target assistance programs and allocate resources. Government agencies need quantitative estimates of conflict impact to design appropriate food security interventions and early warning systems.

Without clear empirical evidence on the relationship between conflict intensity and food prices and a casual understanding of how fatality counts dictate price trajectories, policy responses risk being either insufficient in high-intensity conflict zones or unnecessarily resource-intensive in areas where conflict effects are more contained.

They may also end up being "blind" to structural breaks in the data, as in whether the November 2022 Peace Agreement restored market confidence or if supply chains remained permanently scarred. Understanding these dynamics is essential for developing effective humanitarian response strategies and informing peacebuilding priorities based on food security considerations.

The rest of this thesis is structured into four more chapters. Chapter II dives deep into numerous grey literatures, preprints and case studies on conflict and food security. This chapter also examines theoretical frameworks and empirical evidence on food security crises and price propagation mechanisms. Chapter III then demonstrates the data sources, explanatory variables and econometric methodology which includes the interrupted time series approach and diagnostic tests. Chapter IV presents empirical results like descriptive statistics, diagnostic test outcomes and regression results with interpretation. Chapter V concludes with a summary of findings, policy implications, recommendations, and suggestions for future research.

1.4. Research Questions

This study is guided by one overarching research question and four specific questions that operationalize the investigation into empirically testable components.

Main Research Question: How did the November 2020 conflict affect regional food prices in Ethiopia, specifically examining both immediate level shift and sustained trend change in the Food Consumer Price Index?

Specific Research Questions

1. What was the immediate level change in regional food CPI following the onset of the Tigray conflict in November 2020, after controlling for pre-existing price trends and seasonal patterns?
2. How did the conflict alter the monthly rate of food price inflation during the conflict period (November 2020-November 2022) compared to pre-conflict baseline trend, and did the November 2022 Pretoria Peace Agreement alter this inflation trajectory?
3. What is the relationship between conflict intensity, measured through monthly fatality counts, and regional food price levels, after controlling for rainfall variation, seasonal effects, and region-specific characteristics?
4. To what extent can the analysis isolate conflict-driven food price changes from climate-driven changes by controlling for rainfall variation, and what does rainfall's relationship with prices reveal about agricultural productivity effects?

1.5. Objectives of the Study

Against this background, the overarching aim of this thesis is to quantify the impact of the November 2020 Tigray Conflict on regional food prices in Ethiopia by estimating both immediate level shifts and sustained trend changes in regional food Consumer Price Index.

Specific Objectives include:

1. To estimate the immediate level change in food CPI following the onset of the Tigray conflict in November 2020.
2. To assess the change in the monthly inflation rate (slope) of food CPI during the conflict period compared to the pre-conflict baseline.
3. To evaluate whether the November 2022 Pretoria Peace Agreement arrested or attenuated food price inflation.
4. To quantify the relationship between conflict fatalities and food price inflation by controlling for precipitation data to prevent spurious attribution of drought-driven price increases and to explore potential conflict-rainfall interaction effects.
5. To provide evidence-based insights for humanitarian response and food security policy in conflict-affected regions.

1.6. Hypothesis

Based on the research questions above and theoretical expectations regarding conflict impacts on market systems, this study tests four hypotheses.

H1: Level Effect

The November 2020 conflict onset produced a significant immediate change in food CPI levels.

H2: Slope Effect

Food CPI exhibited a significant change in monthly inflation rate during the conflict period compared to the pre-conflict baseline trend.

H3: Peace Agreement Effect

The November 2022 Pretoria Peace Agreement significantly altered the post-conflict food price inflation trajectory.

H4: Conflict Intensity

There is a significant relationship between monthly conflict fatalities and food price levels, after controlling for other determinants.

1.7. Significance of Study

This study makes three primary contributions to the conflict-food security literature. First, it extends Interrupted Time Series methodology to conflict economics by providing rigorous quasi-experimental evidence on how armed conflict affects food prices through both immediate level shifts and sustained changes in inflation rates. The dual-intervention framework (war onset + peace agreement) allows assessment of whether peace agreements arrest conflict induced price trajectories or whether structural damage creates persistent inflation.

Second, the study addresses critical measurement challenges in conflict zones by documenting how data censoring can produce counterintuitive statistical relationships. The finding that conflict intensity correlates negatively with observed prices reveals that official statistics systematically understate food insecurity where conflict is most severe, with profound implications for humanitarian response targeting.

Third, the robustness analysis excluding Tigray demonstrates how credible causal inference can emerge despite imperfect data availability in fragile contexts. The strengthening of the negative conflict coefficient when frozen data are excluded provides transparency regarding inference limitations while validating core findings.

The findings inform humanitarian procurement timing, early warning system design, and resource allocation strategies by revealing that: (1) conflict accelerates food price inflation by 240% above baseline trends, (2) peace agreements do not automatically restore price stability due to ratchet effects from structural damage, and (3) measurement gaps should be interpreted as crisis severity indicators rather than data quality problems.

1.8. Scope & Limitations

This study examines food price changes across all eleven administrative regions of Ethiopia, including the nine regional states and two chartered cities, i.e., Addis Ababa and Dire Dawa. To maintain data consistency across the temporal scope, newer regions such as Sidama, South Ethiopia, Southwest Ethiopia and Central Ethiopia are integrated into their parent administrative units.

The study analyses monthly Food Consumer Price Index data spanning from January 2018 through December 2024. This temporal scope encompasses a 34-month pre-conflict baseline period of nearly three years, the November 2020 conflict onset, and approximately 50-month of conflict and post-acute-conflict observations, allowing for a robust Interrupted Time Series (ITS) evaluation, providing sufficient data points for interrupted time series analysis. The ITS analysis focuses specifically on food prices as measured by the regional Food Consumer Price Index, examining both the level and trend effects of conflict while controlling for rainfall patterns.

The study also relies on ACLED/EPO data, which likely underestimates conflict intensity due to several factors. First, the reliance on real-time reporting creates "information blackholes" in regions like Tigray (2020-2022), Oromia (Wellega, Guji, and Borena Zones), and Amhara (2023-2024). Areas such as the Metekel Zone in Benishangul Gumuz and the Siti Zone in Somali suffer from a geographical blackhole where the pastoralist and remote nature of the communities' further compounds data gaps.

Moreover, ACLED's methodology is event-based and focuses on direct political violence, primarily capturing deaths from battles, drone strikes and recorded massacres. It, however, does not account for indirect fatalities. Studies on the Tigray conflict suggest that direct violence accounts for only about 10% of total deaths, while the remaining 90% result from famine and the systematic collapse of healthcare services. (Annys et al., 2023)

The analysis is limited to economic indicators (CPI) and therefore misses biological data like malnutrition, stunting or morbidity rate. Furthermore, it overlooks household-level responses, thereby failing to capture coping mechanisms, i.e., how families liquidate their assets or migrate to survive the crisis.

Also, the official CPI does not capture informal markets or household production which are often the primary engines of survival and employment in Ethiopia and one which has also thrived on the conflict onset. Analyzing the data at the regional level may also mask significant intra-regional variations like specific “hotspot” kebeles which have faced total market disintegration.

The rainfall data consists of stations with missing meteorological values. Although this is addressed using regional monthly averages, it may potentially introduce a conservative bias through its linear imputation.

While ITS and Two-Way Fixed Effects (TWFE) strengthen causal inference, confounding variables may remain unmeasured. The assumption of a log-linear relationship between fatalities and prices may result in missing “threshold effects”.

It is also to be noted that the findings are specific to Ethiopian context and may not be directly extrapolatable to other conflict settings with different market structures or etiologies of violence.

CHAPTER II: LITERATURE REVIEW

2.1. Theoretical Frameworks for Analyzing Conflict-Induced Food Insecurity

2.1.1. Evolution of Food Security Thinking: From Malthus to Sen

The conceptual foundations of food security analysis have undergone significant transformation over the past century. As Sassi (2018) recounts, early approaches to food security were rooted in Malthusian concerns about the physical availability of food at the national level.

According to Malthus' natural law of population, "there is a natural tendency for population growth to surpass that of all possible means of production, mainly in land and, in turn, in food output". This standpoint dominated food security discourse from the 1940s through the 1970s, focusing policy interventions on increasing agricultural productivity and maintaining national food stocks.

The paradigm shift occurred in the 1980s when Amartya Sen's groundbreaking work questioned the adequacy of availability-focused frameworks. Sen (1981) demonstrated that "starvation is the characteristic of some people not having enough food to eat. It is not the characteristic of there being not enough food to eat".

Through his analysis of the 1943 Bengal famine and the 1972-74 Ethiopian famine, Sen exposed that food crises could occur even when aggregate food availability remained adequate or increased. His entitlement approach introduced a fundamental distinction between food availability and food access, arguing that hunger results from individuals' or households' inability to command food through legal means available in society.

Sen (1981) defined entitlements as "the set of alternative commodity bundles that a person can command in a society using the totality of rights and opportunities that he or she faces", distinguishing between

a. Trade-based entitlements, i.e., what can be bought with commodities or cash owned
b. Production-based entitlements which are rights to own what one produces
c. Labor entitlements include the sale of labor power and inheritance and
d. Transfer entitlements, ones which are willingly given by others.

This framework revolutionized food security analysis by shifting focus from national food balance sheets to household and individual access mechanisms. As Sassi (2018) notes, "By the mid-1980s... food emergencies were no longer regarded as a shortfall in food supply; they were instead acknowledged as a loss of access to food for poor people".

While Sen's entitlement approach represented a major theoretical advance, it suffers from a fundamental gender blindness by treating the household as a unitary decision-making unit, ignoring intra-household power dynamics and gendered access to resources.

As Haddad et al. (1997) document in their Ethiopian study, male household members receive priority in food allocation during scarcity and women eat last usually after adult men and children. Pregnant/lactating women also sacrifice their own intake despite being the ones with the highest nutritional needs.

Furthermore, Sen assumes equal access to "what one produces," but in Ethiopia, women perform 60-80% of agricultural labor but own only 20% of land (FAO 2011). Divorced/widowed women lose land access. During conflict settings, women cannot farm alone due to security risks and sexual violence threats suggesting women's production-based entitlements collapse faster than their men counterparts.

Sen overlooks how conflict differentially affects women's market access. Female-headed households had 40% lower market access during siege. (UN Women 2022)

A UN Women (2024) comprehensive survey estimates 120,000 - 150,000 cases of conflict-related sexual violence, with 75% experiencing social rejection. (Tigray Women's Association, 2025), 91% unable to access health services, 53% resulting in pregnancies, and 31% being forced into transactional sex for food survival.

Sen's framework would predict that if a household's aggregate entitlements remain above subsistence, members should not starve. But in conflict settings, intra-household gender dynamics mean women starve even in "food-secure" households, and gender-based violence destroys women's individual entitlements regardless of household status.

Doss et al. (2014) argue that gender analysis of conflict impacts must recognize that men and women participate in different market segments with different vulnerability profiles. Women's concentration in retail trade with minimal capital and rapid turnover makes their businesses easier to destroy and harder to reconstitute. Men's involvement in wholesale trade, transportation, and large-inventory storage provides more resilience: wholesalers can flee with capital, suspend operations temporarily, and resume from different locations more readily than small-scale retailers can.

This differential resilience implies that as conflict intensifies, the composition of surviving markets shifts toward male-dominated wholesale trade while female-dominated retail collapses, creating a systematic bias in any price data that can be collected. As a matter of fact, wholesale prices may remain observable while retail prices disappear, but households purchase at retail, not wholesale, so the observable prices increasingly fail to reflect actual food access conditions.

This gender critique necessitates moving beyond Sen to frameworks that explicitly incorporate power, violence, and gendered vulnerability, precisely what Devereux and De Waal provide.

2.1.2. Beyond Entitlement: Devereux's Critique and the Politics of Famine

Stephen Devereux, building on extensive field research in Africa, argues that Sen's framework "ignores the role of violence, power relations, and intentional policies that create or exacerbate famine". (Devereux, 2000)

Devereux (2000, 2009) distinguishes between "natural famines" resulting from environmental shocks and entitlement failures, and "political famines" where governments or armed groups deliberately create conditions of mass starvation.

He introduces the concept of "famine crimes" which are situations where starvation is used as a weapon of war against civilian populations; humanitarian access is deliberately blocked to maximize suffering; food aid is diverted to support military operations and markets are intentionally disrupted to undermine opposition control.

During the Mengistu regime in 1984/85, approximately one million people died in Tigray and Wollo provinces, not primarily from food shortage but from government policies that blocked aid delivery to opposition-controlled areas and to suppress TPLF insurgency. (De Waal 1997)

De Waal (2015) documents the concept of “new variant famine” which involves situations where “famine occurs not because food is unavailable, but because political actors deliberately create barriers to access, often in pursuit of military objectives. Unlike traditional famines driven by harvest failure, these crises are characterized by the systematic weaponization of food and humanitarian aid." (p. 178)

Devereux's framework has critical implications for interpreting price-conflict relationships. In a political famine scenario, intense violence may be associated with market annihilation thereby resulting in no price formation; siege economies where official prices become meaningless; controlled scarcity in government-held territories which result in artificial price suppression and data blackouts where measurement itself is weaponized.

This theoretical distinction provides a lens for interpreting Ethiopia's counterintuitive negative conflict intensity coefficient. Rather than indicating that violence reduces food insecurity, it may signal that extreme violence destroys the market mechanisms through which food insecurity would normally manifest as price increases.

The CPI values for Tigray which were "carried forward" from October 2020 CPI throughout the war period inadvertently document the completeness of market collapse. As Sassi (2018) notes in discussing complex emergencies, "official statistics systematically exclude worst-affected populations." (p. 124)

This interpretation aligns with Verme & Gigliarano's (2019) finding that in conflict zones, "the absence of price data often indicates not measurement failure but market failure of such magnitude that prices cease to have meaning." (p. 892)

2.2. Price Behavior in Extreme Conflict: Theoretical Foundations and Measurement Challenges

2.2.1. Market Collapse vs. Market Disruption: When Price Signals Fail

Alderman et al. (2018) distinguish between "market disruption" and "market destruction" in conflict settings, arguing that these represent qualitatively different states with distinct price implications.

Market disruption occurs when conflict increases transaction costs, reduces trader participation, and creates supply bottlenecks, but markets continue to function and prices remain observable. Market destruction, by contrast, occurs when violence eliminates the institutional infrastructure required for price formation itself. In such markets, the concept of "price" becomes ambiguous because the social mechanisms that generate prices through negotiation and exchange have ceased to exist.

Barrett (2008) provides theoretical foundations for understanding this distinction through the concept of "missing markets." In standard microeconomic theory, missing markets represent a more fundamental breakdown where exchange cannot occur at any price because the institutional prerequisites for market transactions are absent.

The analytical implication is that the relationship between conflict intensity and observed prices should be non-monotonic and threshold dependent. At low to moderate conflict intensity, increased violence should correlate positively with prices through standard disruption mechanisms. At extreme conflict intensity, however, the relationship may reverse, turn insignificant, or become unmeasurable as markets transition from disruption to destruction.

2.2.2. Empirical Evidence: Price Patterns in Siege Economies

Empirical studies from other extreme conflicts provide crucial precedents for interpreting anomalous price-conflict relationships. The Syrian civil war offers particularly relevant evidence because it combined conventional warfare, siege tactics, and prolonged market disruption across territories with varying levels of military control.

Verme and Ahmadiye (2020) analyze food prices across Syrian governorates during 2011-2018, finding systematic bifurcation between government-controlled and opposition-held areas. In Damascus and other regime-controlled cities, official Consumer Price Index data showed food price inflation averaging 180-220 percent over the period, reflecting severe economic stress but continued market functioning.

However, in besieged areas like Eastern Ghouta, Homs, and Aleppo's eastern neighborhoods, the researchers documented three distinct price regimes. First was hyperinflation, which reached 1,000- 4,000% in informal markets at a time when siege conditions permitted any trade at all. The second one was complete market absence where barter replaced monetary exchange and prices became undefined. The third one includes the “relief price” periods when humanitarian convoys temporarily entered and distributed food at nominal or zero prices.

Critically, official CPI data collection excluded besieged areas entirely after 2013, creating the appearance of moderate inflation in national statistics while populations in opposition territories experienced either hyperinflation or total market collapse.

Mundy (2017) examines the Yemeni civil war's impact on food markets, with particular attention to areas under Houthi siege by the Saudi-led coalition. His ethnographic research in Taizz, a city besieged for over two years, reveals that "price" as an analytical category becomes problematic under extreme siege conditions.

In Taizz's Old City district, surrounded by Houthi forces from 2015-2017, residents reported that food could occasionally be obtained through smuggling networks charging amounts 20-30 times pre-war prices, but these transactions occurred irregularly, involved barter and multiple currencies simultaneously, and were not observable to any systematic data collection.

Rockmore (2017) provides long-term perspective on market destruction through analysis of Rwanda's genocide and subsequent recovery. His research demonstrates that extreme violence creates persistent market failures that endure long after physical security is restored. In Rwandan communities that experienced high genocide intensity, market participation rates remained 40-50% below pre-conflict levels even fifteen years later, with households preferring subsistence production and informal sharing networks over market exchange.

The mechanism operates through destroyed social capital. Communities that experienced betrayal and mass killing developed lower interpersonal trust, making the repeated interactions and credit relationships that sustain market exchange more difficult to reestablish. This finding suggests that the Tigray conflict's market destruction may create long-lasting measurement challenges even after violence ends, as populations remain reluctant to engage in market activities that generate observable prices.

2.3. Spatial Economics and Geographic Determinants of Food Vulnerability

The systematic relationship between conflict intensity and data availability creates fundamental challenges for empirical analysis. Conventional missing data frameworks assume data is missing at random or missing completely at random. In conflict settings, data is systematically missing in the locations and for the populations experiencing the worst outcomes, creating what statisticians term a "non-ignorable non-response."

Summarizing work on data quality in fragile states, Verme and Gigliarano (2019) formalize the problem: let D_i indicate data availability for location i and C_i indicate conflict intensity. If $P\ (D_i = 1 \mid C_i)$ is decreasing in C_i, i.e., if higher conflict intensity reduces the probability of observing data, then standard regression analysis produces biased estimates of conflict's effects because the sample of locations with observed data systematically excludes high-conflict areas.

They demonstrate that this sample selection bias can produce spurious negative coefficients in price-conflict regressions even when the true relationship is positive, because the observed sample overrepresents low-conflict areas with normal price behavior while excluding high-conflict areas with price spikes or market collapse.

The implication for interpreting this study's negative conflict coefficient is critical. The coefficient may reflect genuine price reductions in measured locations (the standard causal interpretation), or it may reflect sample composition effects where high-conflict areas drop out of the data precisely when their prices would be highest, leaving only low-conflict areas with stable prices observable (the sample selection interpretation).

Distinguishing between these interpretations requires examining patterns of data availability: if data missingness correlates strongly with conflict intensity, sample selection becomes the more plausible explanation.

Miguel and Roland (2011) address this challenge in their study of Vietnam War bombing impacts, developing methods to handle systematic data missingness in conflict zones. They argue that researchers should treat data availability itself as an outcome of interest: areas where measurement becomes impossible likely experienced the most extreme impacts.

They propose using proxies for outcomes in unmeasured areas, such as satellite imagery of economic activity, mortality estimates from demographic modelling, or qualitative testimony from displaced populations. For food security analysis, this approach suggests using health outcomes like malnutrition prevalence and mortality rates as alternatives to price data when markets collapse and prices become unmeasurable.

2.3.1. Transportation Costs and Market Integration in Ethiopia

Fundamentally, spatial economics demonstrates that commodity prices should differ across locations by no more than the cost of transporting goods between them: when price differentials exceed transportation costs, arbitrage opportunities attract traders who equalize prices through spatial trade. However, when transportation costs are prohibitively high due to poor infrastructure or conflict-related barriers, markets become segmented with limited price transmission across regions.

Bachewe et al. (2018) found that between 2015-2017 period transportation costs from Addis Ababa to Mekelle averaged 18 to 28 percent of grain value on the improved federal highway, but the "last mile" problem remained severe with transportation from regional capitals like Mekelle rural district markets continuing to impose costs of 30 to 55 percent of grain value due to poor feeder road quality, limited truck availability in secondary markets, and small loads that make rural distribution economically inefficient.

Tamru et al. (2020), analysing Ethiopian grain trader networks for the 2016-2019 period, identify regulatory and institutional barriers as increasingly important constraints beyond physical infrastructure, with checkpoint delays proliferating during 2016-2019 as ethnic tensions escalated (traders reporting average delays of 4 to 8 hours at regional border crossings), truck shortages persisting despite economic growth (fleet expanding at only 3 to 5 percent annually while freight demand grew at 8 to 12 percent annually), and insurance costs spiking for northern routes with premiums for trucks traveling to Tigray increasing from 2 to 3 percent of cargo value in 2015 to 8 to 12 percent by 2019.

The COVID-19 pandemic further stressed these already fragile spatial market linkages, with Hirvonen et al. (2021) analysing food market prices during March-October 2020 and finding that pandemic-related restrictions on movement created severe disruptions where transportation costs spiked by 35 to 50 percent during lockdown periods and Tigray experienced price premiums over Addis Ababa reaching 60 to 80 percent by June 2020, levels not observed since the 2008 global food crisis.

These pre-conflict market conditions have critical implications for interpreting conflict impacts: Tigray entered the war period with food markets that were already fragmented, transportation costs that were already high, and price premiums over national averages that were already substantial due to COVID-19 disruptions, meaning the conflict's severance of trade corridors pushed already-strained spatial linkages past the breaking point into complete market collapse rather than disrupting well-integrated efficient markets.

FEWS NET's Ethiopia Price Bulletin for October 2020, the final month before conflict onset, shows teff prices in Mekelle averaged 18,450 Birr per quintal compared to 12,800 Birr in Addis Ababa (44 percent premium), with these prices already elevated by 18 to 25 percent above five-year October averages reflecting COVID-19 impacts while Addis prices were only 8 to 12 percent above averages, indicating Tigray markets were experiencing greater stress than central Ethiopian markets even before conflict.

The subsequent FEWS NET bulletins through 2021/2022 document the progression of market collapse. Recent assessments reveal persistent market damage extending well beyond conflict resolution. The World Bank's 2024 Infrastructure Assessment documents that only 35 to 40 percent of damaged road segments were restored by mid-2024, with 28 of 160 destroyed bridges rebuilt, keeping transportation costs at 2.5 to 3 times pre-war levels.

Minten et al. (2024) find that grain trader participation recovered to only 40 percent of pre-war levels by late 2023, with returning traders operating at substantially reduced scale due to capital losses and risk aversion.

Berhane et al. (2024) document that market purchases comprised only 38 percent of household food consumption in 2023 compared to 65 percent pre-war, with humanitarian aid substituting for dysfunctional commercial channels at 35 percent of consumption nearly a year after ceasefire.

2.3.2. Strategic Geography and Conflict Dynamics

The western lowlands that produce Tigray's agricultural surplus occupy territory that Amhara region claims historically belonged to Amhara before Tigray People's Liberation Front seized it during the 1991 Transition Period. The western lowlands' commercial agricultural potential, demonstrated through sesame export revenues exceeding 100 million USD annually before the conflict, makes territorial control economically significant beyond subsistence food production.

Since November 2020, the de facto administration of Western Tigray by Amhara regional forces has resulted in a structural shift in regional food security. The displacement of Tigrayan agrarian populations and the subsequent re-allocation of productive land has transformed a seasonal conflict disruption into a long-term loss of access to productive land, fundamentally altering Tigray's agricultural balance.

The road network geography further structured conflict impacts on food security. Tigray's connection to the rest of Ethiopia depends primarily on two arterial routes: the main highway south through Amhara region to Addis Ababa, and the eastern route through Afar region. Both routes traverse territories controlled by regional governments aligned with federal forces against TPLF, creating natural chokepoints where food flows could be interdicted.

Pinstrup-Andersen and Shimokawa (2008) analyze how geographic chokepoints affect food security in conflict, noting that regions dependent on narrow transportation corridors face vulnerability to blockades because alternative routes either do not exist or require prohibitively expensive detours.

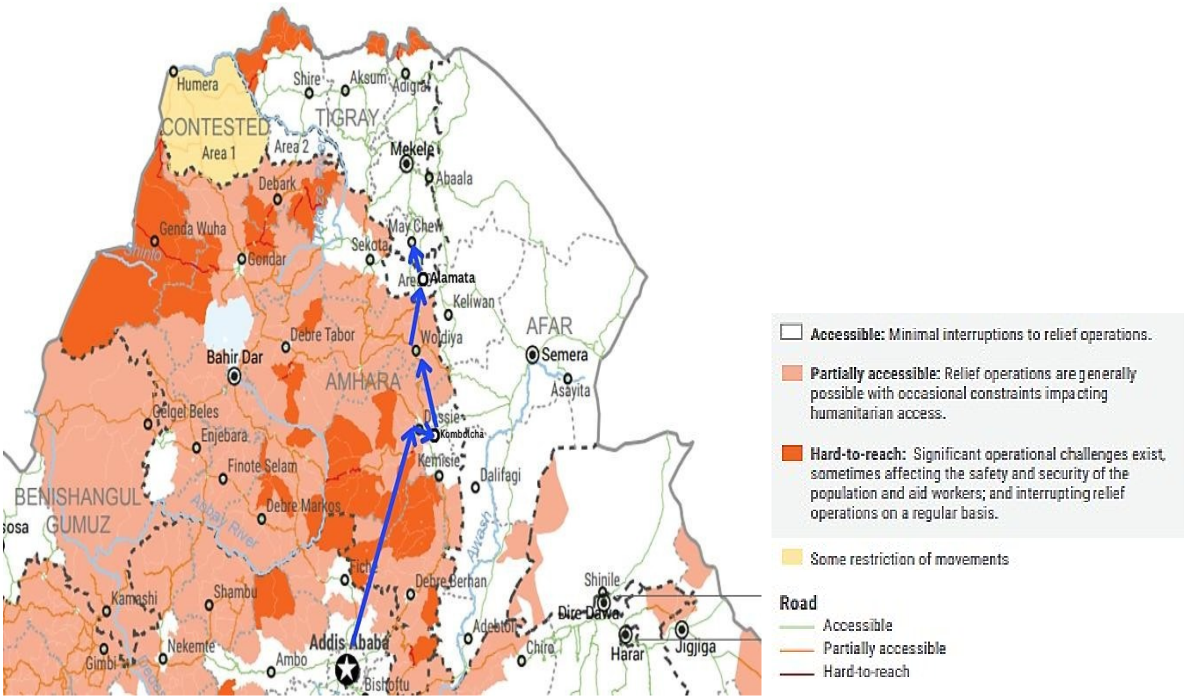


Figure 8. Strategic Corridor Map, Route 1: Addis Ababa-Dessie-Kombolcha-Weldiya- Alamata-Mekelle.

Source: OCHA (2025, October 31). Ethiopia Access Map.

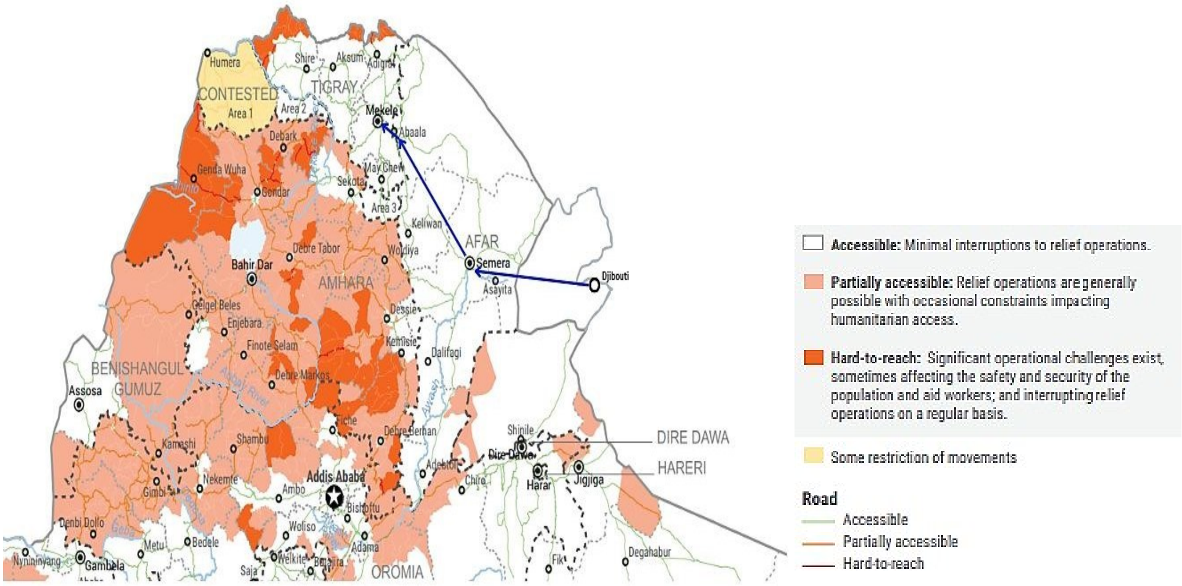


Figure 9. Strategic Corridor Map, Route 2: Djibouti Port-Afar Region (Semera)-Abala-Mekelle.

Source: OCHA (2025, October 31). Ethiopia Access Map.

The first route, also known as the South-North Corridor (A2 Highway) passes directly through the Amhara region. During the conflict, the frontline often sat near Weldiya and Kobo. When the Amhara regional forces or federal troops held these towns, they could physically halt all commercial and humanitarian trucks moving north.

The second route through Afar became the only lifeline for UN food aid. However, the town of Abaala, a border town between Afar and Tigray became a famous “bottleneck” where aid convoys were often stalled for months due to insecurity or administrative blocks.

The Tekeze River, which separates western Tigray from the central highlands, posed additional geographic constraints. Bridge destruction during conflict severed critical links between regions, with the economic effect of fragmentating markets within Tigray itself.

Markets in western Tigray that traditionally supplied grain to central markets became inaccessible even to remaining population of Tigray, while markets in central Tigray lost their supply source.

Dorosh et al. (2009) model the spatial economics of infrastructure destruction in conflict settings, demonstrating that bridge collapses create discontinuous market segmentation where nearby markets separated by a destroyed river crossing behave as if separated by hundreds of kilometers of distance, with price differentials exploding beyond any relationship to actual transport costs if bridges were functional.

2.4. Displacement Economics and Internal Refugee Markets

2.4.1. Economic Theory of Forced Migration and Household Displacement

Verwimp and Van Bavel (2014) examine the economics of asset abandonment during flight, using evidence from Rwanda's genocide to estimate that displaced households lose 60-90 percent of physical asset value through forced abandonment compared to 20-40 percent losses when households have time to sell assets before voluntary migration.

During the conflict's peak in mid-2022, the International Organization for Migration documented 2.1 million internally displaced persons. Such a speed and violence of displacement meant that stored grain that represented 6-12 months of food security was left in granaries. Agricultural tools and livestock were forfeited without compensation.

Jacobsen (2005) analyzes economic activity in refugee and IDP settlements, finding that despite common perception of camps as purely aid-dependent, residents engage in diverse livelihood strategies including informal labor, petty trade, and provision of services to other displaced people. The result, however, is an informal economy characterized by very small-scale activities, rapid turnover, intense competition for limited opportunities, and minimal capital accumulation.

The Tigray displacement followed a particular spatial pattern, with Mekelle receiving the largest influx of IDPs. The city's pre-war population of approximately 500,000 swelled to

800,000 - 900,000 during the conflict as rural populations sought safety in the regional capital. This 60-80% population increase created enormous pressure on urban food markets and informal housing.

Most often they operated through barter, small-scale vending, and social networks rather than formal monetary exchange. Bundervoet (2010) documents similar patterns in Burundi's civil war, where displaced populations developed complex informal economic systems including rotating credit associations, labor exchange networks, and commodity barter clubs that substituted for absent formal markets.

The displacement followed gendered pattern. UN Women (2022, 2023) documented that among IDP populations, female-headed households increased from approximately 18 percent to 67 percent by mid-2022.

Buvinic et al. (2013) synthesize evidence on female-headed household economics in post-conflict settings, challenging simplistic assumptions that these households are universally worse off. They find heterogeneity depending on why headship transitioned: widows who inherit property rights and maintain social networks may achieve relative stability, while separated or divorced women who lose property claims and face social stigma experience severe poverty.

In Tigray's context, female-headed households created through widowhood in a system where women lack independent land rights and where social safety nets collapsed faced particularly acute vulnerability.

2.4.2. Return Migration and Recovery Constraint

Return migration began gradually after the November 2022 ceasefire but proceeded slowly with approximately 35-40 percent of IDPs remaining displaced (IOM, 2025). In rural areas of central and eastern Tigray, landmine contamination makes farming dangerous, with UNMAS (2024) estimating 1.2 million hectares contaminated and requiring years of clearance.

These structural changes signify that even as conflict ends, the economic geography of food production, market access, and household livelihoods differs fundamentally from pre-war patterns, with implications for food security that will persist for years to come.

2.5. Household Economics of Maternal Nutrition and Infant Feeding

Pre-war Tigray showed relatively strong breastfeeding indicators compared to national averages. Exclusive breastfeeding rates for infants under six months stood at 64.2 percent. WHO assessments in 2022 found that 71 percent of lactating women in accessible areas of Tigray were acutely malnourished based on Mid-Upper Arm Circumference (MUAC) measurements below 23 centimetres, with 23 percent showing MUAC below 21 centimetres indicating severe acute malnutrition. 43 percent of lactating mothers reported “insufficient milk” as the reason for introducing other foods prematurely.

These figures represent deterioration of 154 percent from the pre-war anaemia baseline, and the assessments note that data collection occurred primarily in IDP camps and urban areas where humanitarian assistance was most accessible. Rural areas likely experienced worse conditions but remained unmeasurable.

By 2022, child wasting in Tigray had exploded to 22 percent based on assessments in accessible areas, representing a 168 percent increase from baseline and exceeding the WHO emergency threshold of 15 percent by a substantial margin. Child stunting reached 56 percent, indicating that not only were children experiencing acute crisis, but the prolonged food insecurity had created widespread permanent growth impairment.

CHAPTER III
METHODOLOGY

3.1. Introduction

This chapter delineates the methodological framework employed to investigate the causal impact of armed conflict on food price dynamics in Ethiopia. Given the sudden onset of hostilities in November 2020, this study adopts a **Quasi-Experimental Interrupted Time Series (ITS)** design with panel data.

This approach allows for the estimation of the longitudinal effect of both immediate "level shifts" and sustained "trend changes" in regional food Consumer Price Indices (CPI) while controlling for long-term price trajectories and seasonal fluctuations inherent in conflict-afflicted agricultural economies. By utilizing segmented regression analysis, the study quantifies how the conflict disrupted market integration and price stability across Ethiopia's regional states.

In addition, the chapter describes the research design, presents comprehensive data sources and the key variables including specifying the econometric model, estimation techniques and identification strategies. It proceeds to outline the diagnostic tests, and robustness checks along with the methodological limitations and ethical considerations.

3.2. Research Design Overview

The Quasi-Experimental Interrupted Time Series (ITS) design is employed by operationalizing segmented regression analysis of monthly panel data. As established in Section 2.4.2., ITS is the preferred quasi-experimental approach when: (1) a clearly defined intervention point exists, (2) sufficient pre- and post-intervention observations are available, and (3) randomized treatment assignment is infeasible due to the nature of the intervention (Shadish, Cook, & Campbell, 2002; Bernal et al., 2017).

The analytical unit in this study is the region-month, wherein each observation represents a specific administrative region in a given calendar month. The study period, which spans 84 months from January 2018 to December 2024, portioned into a 34-month pre-intervention period between January 2018 and October 2020 and a 50-month post-intervention period between November 2020 and December 2024, satisfies and exceeds the minimum ITS requirement with the prescribed threshold of 12 observations before and after intervention (Wagner et al, 2002).

The intervention point is November 2020 which marks the onset of large-scale armed conflict following the Ethiopian National Defence Force's (ENDF) military operations in Tigray region on November 4, 2020. The timeline represents an unambiguous temporal demarcation when total communication blackouts commenced in Tigray region and markets began experiencing acute disruptions.

While conflict is rarely exogenous, the precise timing of November 2020 approximates a natural experiment wherein treatment assignment (conflict exposure) is "as-if random" conditional on region fixed effects and pre-intervention trends, as the specific month of military belligerence was plausibly independent of food market dynamics.

Correspondingly, the segmented regression framework accommodates time-varying covariates, enabling simultaneous control for concurrent shocks, i.e., seasonal agricultural productivity shocks, harvest cycles and lean periods.

The overall dataset constitutes a balanced panel with 11 administrative regions and a time dimension of 84 months which collectively add up to 924 region-month observations.

The analytical framework recognizes two pivotal temporal junctures that structure the investigation. The baseline ITS specification treats November 2020 as the sole structural break. Secondary intervention occurred on November 2, 2022, when the Ethiopian government and TPLF signed the Pretoria Peace Agreement. This cessation may have potentially attenuated conflict-induced price trajectories.

The robustness analysis tests whether this secondary intervention flattened post-conflict price growth by estimating a two-interruption ITS model.

3.3. Data Sources and Collection

As of 2025, following consecutive successful referendums in prior years, there have been new administrative regions established including Sidama Regional State (2020), South Ethiopia Region (2023) and Central Ethiopian Regional State (2023). To preserve consistency with CPI data, the nine regional states and the two chartered cities, Addis Ababa and Dire Dawa, are the study area.

3.3.1. Dependent Variable: Food Consumer Price Index (CPI)

Food prices directly affect household purchasing power and food access, mediating conflict's impact on food security through the entitlement mechanism (Sen, 1981). The source for this data is the Central Statistics Agency (CSA) of Ethiopia. The food CPI is a Laspeyres-type price index aggregating weighted average prices of a standardized basket of food commodities consumed by Ethiopian households. It consists of 84 monthly observations from January 2018 to December 2024 of all 11 administrative regions.

The food CPI encompasses seven major categories with weights derived from the 2010/11 Ethiopian Fiscal Year Household Income, Consumption, and Expenditure Survey (HICES). Access for the data was made possible by integrating both CSA's public statistical database and a formal request to the price statistics CEO.

Table 3.

Seven major categories of Food CPI with their respective weights

Category	Weight(%)	Items
Cereals	45	Teff, wheat, maize, sorghum, barley
Pulses	8	Beans, lentils, chickpeas, peas
Vegetables & Fruits	12	Onions, tomatoes, cabbage, potatoes, bananas
Animal Products	15	Beef, chicken, eggs, milk, butter
Oils & Fats	10	Edible oil, ghee
Sugar & Sweets	5	Sugar, honey
Beverages & Condiments	5	Coffee, tea, salt, spices

Note: Weights derived from the 2010/11 Ethiopian Fiscal Year Household Income, Consumption, and Expenditure Survey (HICES).

Source: CSA (2011)

General CPI, Household CPI and Bread & Cereal CPI were obtained from the same source as well but later dropped during ITS analysis because of severe multicollinearity and endogeneity concerns.

$$CPI\_t = \Sigma (W\_i \times P\_it) / \Sigma (W\_i \times P\_i0) \times 100 \quad (1)$$

Where:

- W_i = Weight of item i in the basket
- P_it = Price of item i in period t
- P_i0 = Price of item i in base period

Σ = Sum over all items in basket

3.3.2. Key Independent Variables

i. Conflict fatalities

The data for conflict fatalities was obtained from the Ethiopia Peace Observatory (EPO), an Armed Conflict Location & Event Data (ACLED) specialized initiative. The data includes daily events geocoded to kebele (ward) level in real time obtained from local media outlets such as Addis Standard, Ethiopian Broadcasting Corporation, regional radio; civil society monitory like Ethiopian Human Rights Commission, Amnesty International and local NGOs; International news agencies like Reuters, AFP, BBC, Al Jazeera and social media reports verified through triangulation.

To align with CPI periodicity and geographic resolution, fatality data was aggregated to monthly conflict-related deaths per administrative regions irrespective of both the interaction parties involved and the nature of the conflict to avoid over-specification and reduce endogeneity concerns.

Since monthly fatality counts exhibit extreme right-skewness due to low median, higher mean and a much higher variance, the proxy has been logarithmically transformed to address skewness and stabilize variance. This is standard practice for count data with zeros. (Wooldridge, 2010)

ii. Rainfall (Agricultural Productivity Proxy)

Data was obtained after a Non-Disclosure Agreement (NDA) with the Ethiopian Meteorological Institute (EMI) permitting academic use for thesis purposes. The data consists of daily precipitation measurements from EMI's network of synoptic weather stations, aggregated to monthly totals (mm) for this study period.

The monthly rainfall data was chosen as a proxy for agricultural productivity. The justification behind this is that Ethiopia's agriculture is overwhelmingly rain-fed, with irrigation accounting for only 3-5% of cultivated area (World Bank, 2018). Consequently, rainfall variability is the primary determinant of crop yields. (Bewket & Conway, 2007; Verdin et al., 2005)

To ensure meteorological representativeness across Ethiopia's diverse climatic zones, 28 rain stations, then weighted to 11 regions, were selected based on the Köppen-Geiger classification to represent the agroclimatic zone of each region. For missing values, regional monthly averages where the average for each month across all years for that specific station was taken. Area-weighted averages or inverse-distance weighting would have required computational complexity without clear theoretical superiority.

$$Avg\_rainfall\_im = (1/n) \times \Sigma\ rainfall\_iy \quad (2)$$

Where:

- avg_rainfall_im = Imputed rainfall for month m in year i

- n = Number of available years for that month

(excluding the missing year)

- rainfall_iy = Observed rainfall for the same month m

in year y ($y \neq i$)

- Σ = Sum over all available years for that month

Table 4.

Administrative regions with their respective rain stations based on Köppen-Geiger Classification

Region	Station Names	Köppen Geiger Climate
Afar	Semera	Red BWh
	Dalifage	Orange BSh
Amhara	Dangla	Blue Aw/Green Cwb
	Kobbo	Green Cwb
	Cheffa	Orange BSh/Blue Aw
Benishangul Gumuz	Assossa	Blue Aw
Gambella	Abwobo	Blue Aw
Harari	Harari Indicative	Green Cwa
Oromia	Yabello	Orange BSh
	Bedele	Green Cwb
	Agra	Orange BSh
	Dembi Dolo	Green Cwb
SNNP	Welkite	Green Cwb
	Hosana	Green Cwb
	Hagere Selam	Green Cwb
	Walayta	Green Cwb
	Dilla	Green Cwb
	Turmi	Orange BSh
	Jinka	Orange BSh
	Mizan Aman	Blue Am, Blue Aw, Green Cwb
	Worka	Blue Aw, Green Cwb
Somali	Aisha	Red BWh
	Dollo Odo	Orange BSh
	Degahabur	Orange BSh
	Moyale	Orange BSh
Tigray	Adigrat	Orange Bsh, Orange BSk, Green Cwb
	Maisebre	Orange BSh, Blue Aw
	Maichew	Orange BSh, Blue Aw, Green Cwb
	Sinkata	Orange BSh, Blue Aw
Addis Ababa	Addis Ababa	Green Cwb
Dire Dawa	Dire Dawa	Orange BSh

Source: Ethiopian Meteorological Institute (EMI) & Beck et al. (2018)

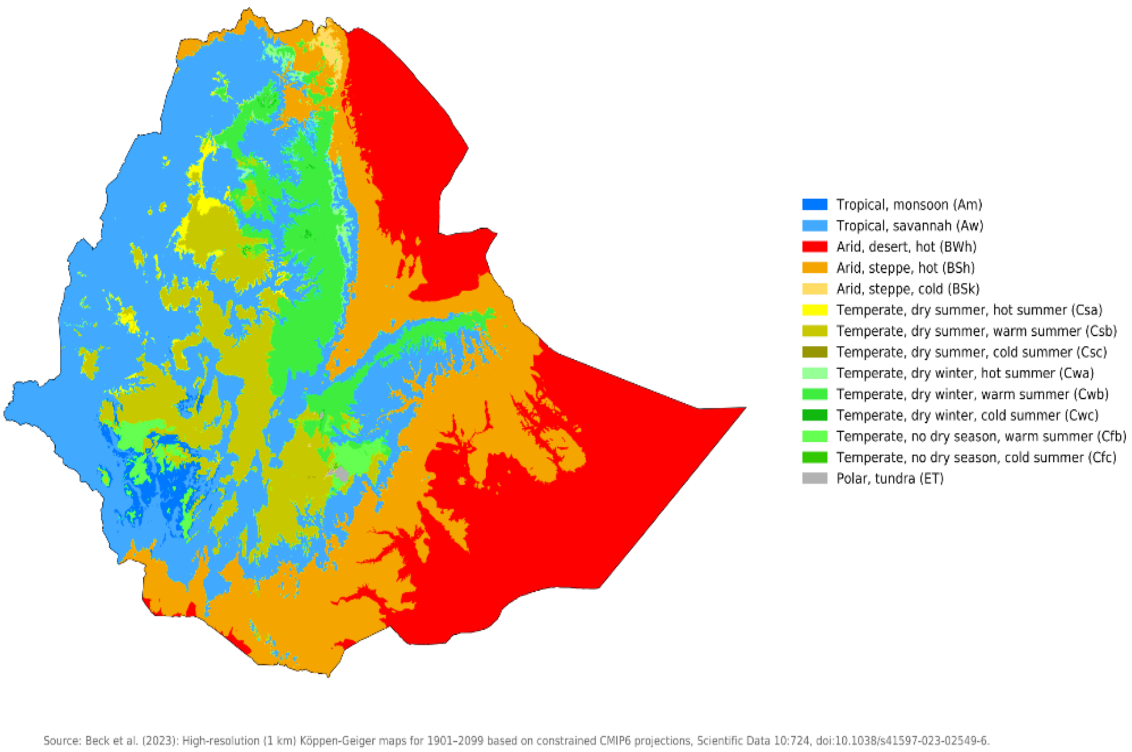


Figure 10. Koppen-Geiger climate classification map for Ethiopia (1991-2020)

Source: Beck, H.E., al. (2023).

iii. Control Variables

To account for unobserved heterogeneity across regions and predictable seasonal variation, two sets of fixed effects are included.

a. Region fixed effects (δ_i)

A set of 11 region-specific dummy variables capturing time-invariant characteristics unique to each Ethiopian administrative region.

$$\delta_i = \{\delta_1, \delta_2, \delta_3, ..., \delta_{11}\} \quad (3)$$

Where $\delta_i = 1$ if observation is from region i, 0 otherwise

Regions:

1. Tigray

2. Afar

3. Amhara

4. Oromia

5. Somali

6. Benishangul-Gumuz

7. SNNP (Southern Nations, Nationalities, and Peoples)

8. Gambella

9. Harari

10. Dire Dawa

11. Addis Ababa

b. Monthly fixed effects (seasonality) (θ_m)

A set of 12 month-specific dummy variables capturing predictable seasonal patterns in food prices.

$\theta_m = \{\theta_1, \theta_2, \theta_3, ..., \theta_{12}\}$ (4)

Where:

θ_1 = 1 if observation is from January, 0 otherwise

θ_2 = 1 if observation is from February, 0 otherwise

θ_3 = 1 if observation is from March, 0 otherwise

...

θ_{12} = 1 if observation is from December, 0 otherwise

iv. Intervention Variables

a. Baseline Time Trend (time_trend)

A continuous variable measuring time in months from the start of the observation period.

time_trend_t = t, where t = 1, 2, 3, ..., 84 (5)

b. War Onset Indicator (post)

A binary indicator variable marking the immediate level change (structural break) at the November 2020 conflict onset.

post_t = { (6)

0 if t < 35 (before November 2020)

1 if t ≥ 35 (November 2020 and after)

}

c. Post-War Slope Change (time_after)

A continuous variable counting months elapsed since the November 2020 conflict onset, capturing the change in the monthly inflation rate during the war period relative to the pre-war baseline.

time_after_t = { (7)

0 if t < 35

t - 34 if t ≥ 35

}

Equivalently: time_after_t = max(0, time_trend_t - 34)

d. Peace Onset Indicator (peace_post)

A binary indicator variable marking the immediate level change (structural break) at the November 2022 Cessation of Hostilities Agreement.

peace_post_t = { (8)

0 if t < 59 (before November 2022)

1 if t ≥ 59 (November 2022 and after)

}

e. Post-Peace Slope Change (time_after_peace)

A continuous variable counting months elapsed since the November 2022 peace agreement, capturing the change in monthly inflation rate during the post-peace period relative to the war-period slope.

time_after_peace_t = { (9)

0 if t < 59

t - 58 if t ≥ 59

}

Equivalently: time_after_peace_t = max(0, time_trend_t - 58)

3.4. Data Limitations

Data availability constraints necessitate a focused scope. Although initially this study foresaw integrating crop yields and livestock production data, infant and child mortality, maternal health care, child vaccination, trends in nutritional status of children, IDP condition from Data Tracking Matrix (DTM), total population figure classified under Integrated Food Security Phase Classification (IDP), these datasets were ultimately excluded due to incomplete temporal coverage for the required January 2018 – December 2024 monthly timeframe.

The Tigray region exhibits consecutive identical food CPI values throughout post-November 2020, likely reflecting data collection disruptions rather than actual price stability. This pattern is consistent with the severe communication blackout imposed across Tigray from November 2020 to July 2021. This study addresses this through sensitivity analyses excluding Tigray during the communication blackout periods.

Rainfall totals are imperfect proxies as effective water availability depends on rainfall timing (distribution within months), intensity as heavy storms cause runoff and soil properties, i.e., texture and organic matter.

In addition, fatality counts risk being underreported due to restricted media access and communication blackouts. The analysis does not disaggregate fatalities by victim type as civilian casualties have distinct economic impacts compared to combatant deaths.

3.5. Summary Table of Variables

Table 5.

Summary of Variables by Name, Definition, Source, Type, and Computation

Variable Name	***Definition***	***Source***	***Type***	***Computation***
A. Dependent Variable				
food_cpi	*Food Consumer Price Index (base year 2011 = 100)*	*CSA Ethiopia*	*Continuous*	*Direct from CSA.*
B. Temporal Variables				
Year	*Calendar year*	*Original dataset*	*Continuous*	*CSA Ethiopia (raw data)*
Month	*Calendar month*	*Original dataset*	*Categorical*	*CSA Ethiopia (raw data)*
Time	*Monthly time variable in Stata format*	*Computed from year and month*	*Continuous*	*gen time = ym(year, month)*
time_trend	*Sequential month counter (within each region)*	*Computed within each region*	*Continuous*	*by region_id: gen time_trend = _n*
month_num	*Month extracted from time variable*	*Extracted from time*	*Categorical*	*gen month_num = month(dofm(time))*
C. Intervention Variables				
Post	*Conflict onset indicator*	*Intervention date: November 4, 2020*	*Binary*	*gen post = (time >= tm(2020m11))*
time_after	*Additional monthly inflation during war*	*Computed from intervention date*	*Continuous*	*gen time_after = 0 replace time_after = (time – tm(2020m11) + 1) if time >= tm(2020m11)*
peace_post	*Immediate level change at peace (November 2022)*	*Pretoria Peace Agreement on November 2, 2022*	*Binary*	*gen peace_post = (time_trend >= 59)*
time_after_peace	*Additional monthly inflation during peace*	*Computed from peace agreement date*	*Continuous*	*gen time_after_peace = max(0, time_trend – 58) if time_trend >= 59 replace time_after_peace = 0 if time_trend < 59*
D. Conflict Intensity Variables				
Fatalities	*Monthly conflict-related deaths per region*	*Ethiopia Peace Observatory (EPO) / ACLED*	*Count*	*Ethiopia Peace Observatory (EPO)/ACLED*
ln_fatalities	*Natual log of fatalities*	*Computed from fatalities*	*Continuous*	*gen ln_fatalities = ln(fatalities + 1)*
fatal_post	*Interaction term: ln_fatalities x post*	*Computed interaction term*	*Continuous*	*gen fatal_post = ln_fatalities * post*
E. Agricultural Productivity Proxy				
avg_rainfall	*Average monthly precipitation across each region*	*Ethiopian Meteorological Institute (EMI)*	*Continuous*	*Ethiopian Meteorological Institute (EMI)*
F. Control Variables				
general_cpi	*General (non-food) Consumer Price Index*	*Central Statistics Agency (CSA) of Ethiopia*	*Continuous*	*CSA Ethiopia*

household_cpi	*Household goods CPI*	*Central Statistics Agency (CSA) of Ethiopia*	*Continuous*	*CSA Ethiopia (destrung from string)*
breadcereal_cpi	*Bread and cereals CPI (subset of food CPI)*	*Central Statistics Agency (CSA) of Ethiopia*	*Continuous*	*CSA Ethiopia (destrung from string)*
G. Seasonality Controls				
month_2 to month_12	*Month-of-year dummy variables (January omitted as reference category)*	*Generated from month_num*	*Binary*	*tab month_num, gen(month_)*
H. Panel Structures Identifiers				
Region	*Region name*	*Original dataset*	*Categorical*	*CSA Ethiopia (raw data)*
region_id	*Numeric region identifier*	*Encoded from region*	*Categorical*	*encode region, gen(region_id)*
I. Predicted Values				
food_cpi_hat	*Predicted food CPI from fixed effects model (without seasonality)*	*Generated after xtreg without month dummies*	*Continuous*	*predict food_cpi_hat, xb (after xtreg estimation)*
cpi_prediction	*Predicted food CPI from model with peace agreement intervention*	*Generated after model with peace agreement variables*	*Continuous*	*predict cpi_prediction, xb (after reghdfe with peace terms)*

3.6. Empirical Strategy

3.6.1. Interrupted Time Series (ITS) Design

The Interrupted Time Series design is well-suited to this research context on several grounds. First, the November 4, 2020 onset of the Tigray conflict constitutes a clearly defined, exogenous temporal break after which food price patterns may have altered from previously established trajectory. As Wagner et al. (2002, p.299) note, ITS represents 'the strongest quasi-experimental approach for evaluating longitudinal effects of interventions,' making it ideal for evaluating the food price consequences of a conflict that was not randomly assigned but occurred at a well-defined point in time.

Second, the outcome measure, i.e., monthly regional food CPI data constitutes the type of data ITS requires: ‘data on continuous or counted outcome measures, summarized at regular, evenly spaced intervals’ (Wagner et al., 2002, p.300).

Third, ITS explicitly controls for pre-existing trends in food prices. Thus war-induced price changes can be distinguished from secular trends that would have occurred regardless of the conflict. It does so by modeling baseline inflation trajectories before the conflict. This addresses the key threat to internal validity in non-randomized settings, namely, that observed changes may reflect pre-existing trends rather than conflict effects.

3.6.2. Model Specifications

Model 1: Basic ITS (Single Intervention)

$$food\_cpi\_it = \beta_0 + \beta_1(time\_trend) + \beta_2(post) + \beta_3(time\_after) + \beta_4(ln\_fatalities\_it) + \beta_5(avg\_rainfall\_it) + \delta\_i + \theta\_m + \varepsilon\_it \quad (10)$$

Where:

β_1: Pre-war baseline trend

β_2: Immediate level change at war onset

β_3: Change in slope after war onset

β_4: Effect of conflict related deaths on food CPI within regions over time

β_5: Effect of monthly average rainfall on food CPI

Model 2: Two-Intervention ITS (War + Peace)

This two-intervention ITS model extends the baseline specification to incorporate a second structural break corresponding to the November 2022 Cessation of Hostilities Agreement.

$$food\_cpi\_it = \beta_0 + \beta_1(time\_trend) + \beta_2(post) + \beta_3(time\_after) + \beta_4(peace\_post) + \beta_5(time\_after\_peace) + \beta_6(ln\_fatalities\_it) + \beta_7(avg\_rainfall\_it) + \delta\_i + \theta\_m + \varepsilon\_it \quad (11)$$

Where:

β_4: Immediate level change at peace onset

β_5: Change in slope after peace onset

i: region, t = time

δ_i: region fixed effects

θ_m: month fixed effects

ε_it: error term

3.6.3. Estimation Method

3.6.3.1. Fixed Effects Panel Regression

The panel dataset is composed of 11 Ethiopian regions observed over 84 monthly timeline which yields an unbalanced panel of 845 region-month observations. This structure necessitates panel data estimation methods that account for unobserved heterogeneity across regions.

A fixed effects (within) estimator is employed which controls for all time-invariant regional characteristics by demeaning observations within each region. This approach removes the influence of unobserved, time-invariant factors such as regional geography (spatial configuration), historical market development, infrastructure endowment, and cultural food consumption patterns which might be correlated with both conflict exposure and food prices.

By focusing exclusively on within-region variation over time, the fixed effects estimator provides more reliable estimates of the relationship between conflict and food prices than pooled OLS, which would conflate within-region and between-region variation.

The fixed effects model can be expressed as:

$$food\_cpi\_it - food\_cpi\_\bar{\imath} = \beta(X_{it} - \bar{X}_i) + (\varepsilon_{it} - \bar{\varepsilon}_i) \quad (12)$$

Where:

- $food\_cpi\_\bar{\imath}$ = time mean of food CPI for region i

- $\bar{X}_i$ = time mean of covariates for region i

- The within transformation removes all time-invariant regional heterogeneity (δ_i)

3.6.3.2. Standard Specification Test: F-test

The F-test is conducted to validate the fixed effects approach over pooled OLS.

A. F-test (Pooled OLS vs. Fixed Effects)

The F-test evaluates whether region-specific fixed effects are jointly significant, by testing the null hypothesis that all regional intercepts are equal. Rejection of this null hypothesis confirms significant heterogeneity in baseline food price levels across regions, validating the necessity of fixed effects over pooled OLS.

3.6.3.3. Cluster-Robust Standard Errors

Standard fixed effects estimation assumes that error terms are independently and identically distributed across observations. The panel data structure for this study violates this assumption due to heteroskedasticity and autocorrelation which necessitates the use of cluster-robust standard errors.

Heteroskedasticity is present because food price volatility differs systematically across Ethiopia's regions. It is driven primarily by differences in market integration, agro-ecology, infrastructure and exposure to shocks. Modified Wald test is implemented to test for groupwise heteroskedasticity, with a homoskedastic null hypothesis where all regions share a common error variance. The test rejects this null hypothesis conveying that the conventional standard errors are inconsistent and therefore leading to invalid inference.

Observations within the same region are also correlated over time, creating positive serial correlation in error terms. This within-region temporal dependence is a well-documented feature of price time series data (Wagner et al., 2002). Failing to account for autocorrelation leads to underestimated standard errors and overestimated statistical significance of estimated effects.

To address both concerns, cluster-robust standard errors are used at the regional level throughout the analysis. It allows for arbitrary correlation structures within each region over time, accommodating both heteroskedasticity and autocorrelation while maintaining consistency of the standard error estimates. The sandwich variance estimator takes the form:

$$V\_cluster = (X'X)^{-1} [\Sigma_i X_i'\varepsilon_i\varepsilon_i'X_i] (X'X)^{-1} \quad (13)$$

Where:

- The summation is over regions i = 1,...,11
- ε_i is the vector of residuals for region i
- This allows arbitrary within-region correlation patterns

Cameron and Miller (2015) note that cluster-robust standard errors may be less reliable when the number of clusters is small, typically below 30 to 50, and recommend wild cluster bootstrap procedures as a corrective in such settings. However, this concern applies specifically when clusters constitute a sample drawn from a larger population. That condition does not hold here. The 11 clusters in this study provide exhaustive coverage of Ethiopian administrative regions. Therefore, wild cluster bootstrap procedures are not required.

3.6.4. Robustness Checks

To assess the sensitivity of our main findings to alternative specifications and potential data quality concerns, three robustness checks are conducted. This section provides a brief overview of the rationale for each check.

3.6.4.1. Two-Way Fixed Effects (TWFE) Specification

Primary ITS specifications, although includes region and month fixed effects, may not fully control for common time shocks that affect all regions simultaneously, such as, national monetary policy changes, global commodity price fluctuations or nationwide supply chain disruptions.

To address this concern, the model is re-estimated by replacing the parametric time trend and seasonal controls with a full set of time fixed effects, i.e., one dummy for each of the 84 monthly time periods.

This two-way fixed effects (TWFE) specification:

$$food\_cpi\_it = \alpha + \beta(ln\_fatalities\_it) + \gamma(avg\_rainfall\_it) + \delta_i + \lambda_t + \varepsilon_{it} \quad (14)$$

Absorbs all common time shocks (λ_t) regardless of their source, providing a more conservative estimate of the conflict intensity effect.

This TWFE estimator identifies the conflict coefficient purely from cross-regional variation in fatality rates within each calendar month by comparing regions experiencing higher conflict to more peaceful regions in the same period.

Consistency between the ITS and TWFE estimates of the conflict intensity coefficient would strengthen confidence that the findings are not driven by inadequate control for common time trends.

3.6.4.2. Excluding Tigray Region

A specific data quality concern relates to Tigray region, where food CPI data was frozen at October 2020 levels following the communication blackout associated with the conflict. As documented in Section 3.4 (Data Limitations), this data freeze creates an artificial measurement pattern in Tigray's post-war price observations that differs fundamentally from the genuine market dynamics observed in other regions.

This data limitation raises two competing concerns about how frozen Tigray data may affect our estimates:

If frozen prices create a spurious negative relationship between conflict fatalities and food prices, excluding Tigray should weaken or eliminate the negative conflict coefficient.

If frozen prices attenuate the true negative relationship, excluding Tigray should strengthen the conflict coefficient.

TWFE specification is re-estimated excluding Tigray to distinguish between these possibilities, where N = 809 observations and 10 regions.

$$food\_cpi\_it = \alpha + \beta(ln\_fatalities\_it) + \gamma(avg\_rainfall\_it) + \delta_i + \lambda_t + \varepsilon_{it} \quad \text{for } i \neq \text{Tigray} \tag{15}$$

CHAPTER IV

RESULTS

4.1. Descriptive Statistics

4.1.1. Summary Statistics

Table 6.

Descriptive Statistics – Full Sample

Variable	Obs	Mean	Std. dev.	Min	Max
food_cpi	**924**	**282.9787**	**149.993**	**107.4**	**689.5**
general_cpi	**924**	**252.9461**	**124.3728**	**106.4**	**601.5**
household_cpi	**924**	**207.3824**	**96.6668**	**88.4**	**613.6**
breadcereal_cpi	**924**	**327.4219**	**188.6306**	**108.9**	**875.5**
Fatalities	**924**	**40.12338**	**132.0942**	**0**	**2408**
ln_fatalities	**924**	**1.4981**	**1.8849**	**0**	**7.7869**
avg_rainfall	**845**	**91.75185**	**89.89365**	**0**	**515.36**

Table 6 presents descriptive statistics for the full sample of 924 region-month observations. Mean food CPI was 282.98 (SD = 149.99), ranging from 107.4 to 689.5, reflecting substantial price variation over the study period. Conflict fatalities averaged 40.12 deaths per region-month but exhibited extreme variability (SD = 132.09), with a maximum of 2,408 fatalities in a single observation. The highly right-skewed distribution of fatalities - with 60% of observations at zero and a long tail extending to extreme values - motivated the log transformation, which produces a more symmetric distribution (mean = 1.49, SD = 1.88) suitable for linear regression. Average rainfall data were available for 845 observations (79 missing), averaging 91.75mm per region-month with high variability (SD = 89.89mm)

Table 7.

Descriptive Statistics by Pre-War vs. Post-War Period

Period	N	Mean	SD	Min	Q1	Median	Q3	Max	IQR
Pre-war (2018-2020)	**374**	**149.92**	**27.9**	**107.4**	**126.7**	**145.35**	**166.4**	**239.2**	**39.7**
Post-war (2020-2024)	**550**	**373.45**	**130.51**	**166.5**	**251.3**	**359**	**480.88**	**689.5**	**438.2**

Table 7 compares key variables across pre-war (January 2018 - October 2020) and post-war (November 2020 - December 2024) periods. Mean food CPI more than doubled, increasing from 149.92 to 373.45 (149% increase). The box plot (Figure 11) visually confirms this dramatic shift.

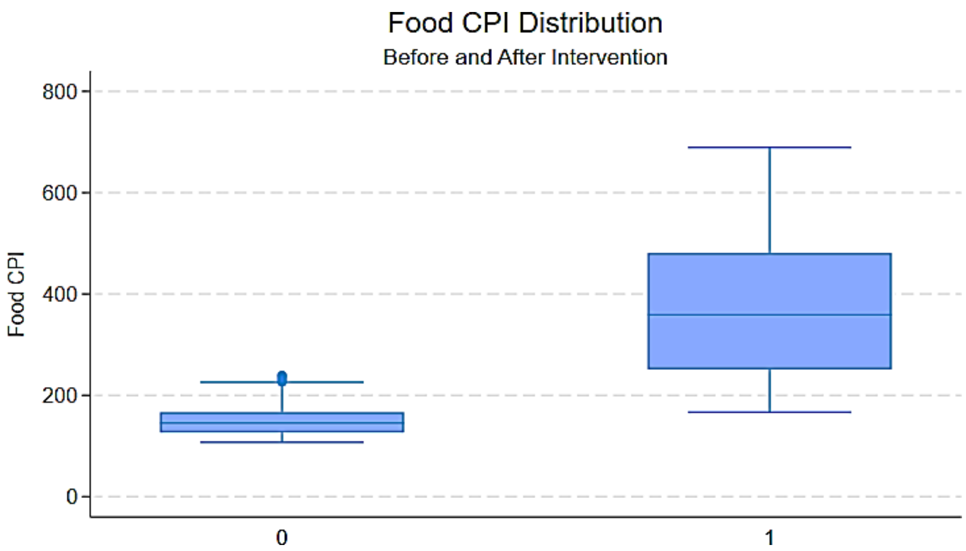


Figure 11. Box Plot comparing Pre-war and Post-war Food CPI Distributions

During the pre-war phase, median was at 145.35. The interquartile range is between 126.7 to 166.4. The range is between 107.4 to 239.2. The post-war phase has a median of 359. The interquartile range is between 251.3 to 480.8. It ranges from 166.5 to 689.5. This confirms that the median food CPI more than doubled after the conflict started.

There is also a massive increase in variability as the pre-war phase conveys a tighter box as opposed to the much wider box on the post-war period. This signifies that the war didn't just raise prices; it made them unpredictable and volatile. The pre-war outlier corresponds to Tigray region in October 2020[1].

4.1.2. Regional Variation

Table 8.

Food CPI by Region

region_id	Mean	SD	Min	Max
Addis Ababa	**288.67**	**155.73**	**112.10**	**610.10**
Afar	**290.47**	**161.27**	**111.40**	**620.90**
Amhara	**283.38**	**143.64**	**120.80**	**583.78**
Benishangul Gumuz	**324.91**	**184.68**	**118.80**	**689.50**
Dire Dawa	**310.63**	**172.14**	**110.60**	**688.10**
Gambella	**282.93**	**147.37**	**107.40**	**567.90**
Harari	**282.64**	**150.44**	**108.20**	**583.00**
Oromia	**283.01**	**147.97**	**115.10**	**589.60**
SNNP	**293.68**	**148.33**	**115.70**	**584.30**
Somali	**263.32**	**129.62**	**111.50**	**501.10**
Tigray	**209.12**	**42.82**	**114.70**	**239.20**
Total	**282.98**	**149.99**	**107.40**	**689.50**

This table breaks down Food CPI statistics by region. Dire Dawa has the highest mean for food CPI at 310.63. Benishangul Gumuz exhibits the widest price range (118.80-689.50), reflecting greater volatility. Tigray region shows the lowest price variation (SD = 42.82) and the lowest mean food CPI (209.12), likely reflecting data limitation rather than price stability. All four CPI indices (food, general, household, breadcereal) remained frozen at their October 2020 values throughout the remainder of the study period.

[1] This elevated price likely resulted from multiple simultaneous shocks: COVID-19 state of emergency (March 2020), desert locust infestation affecting regional agriculture, federal fund cuts following Tigray's unilateral September election, and currency reform announcement in September 2020 (AFP, 2020).]

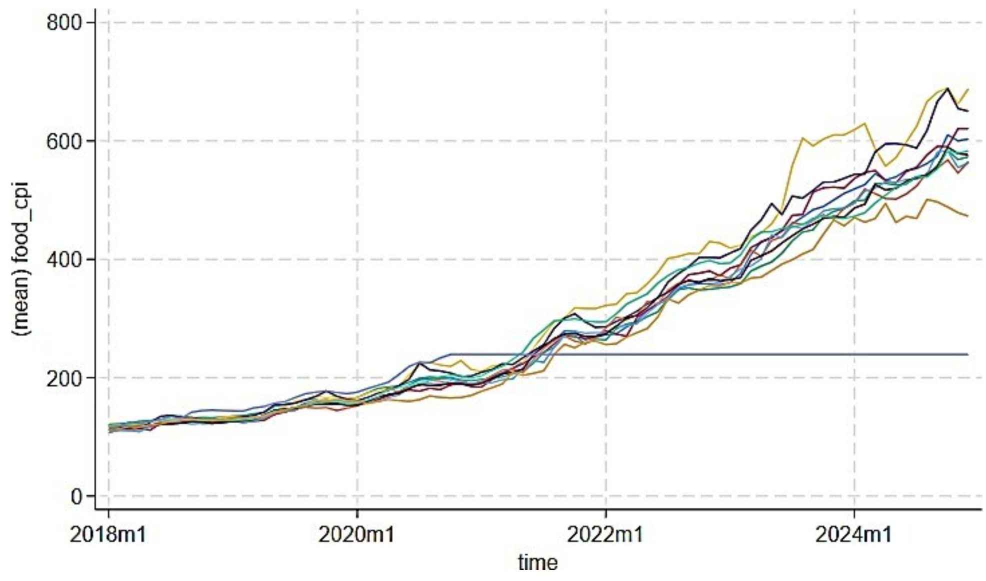


Figure 12. Food CPI Over Time by Region

All other regions exhibit clear upward trends with acceleration following conflict onset, except for the single sharp horizontal outlier post-intervention period which alludes to Tigray's "carried forward" data.

4.1.3. Visual Correlation Patterns

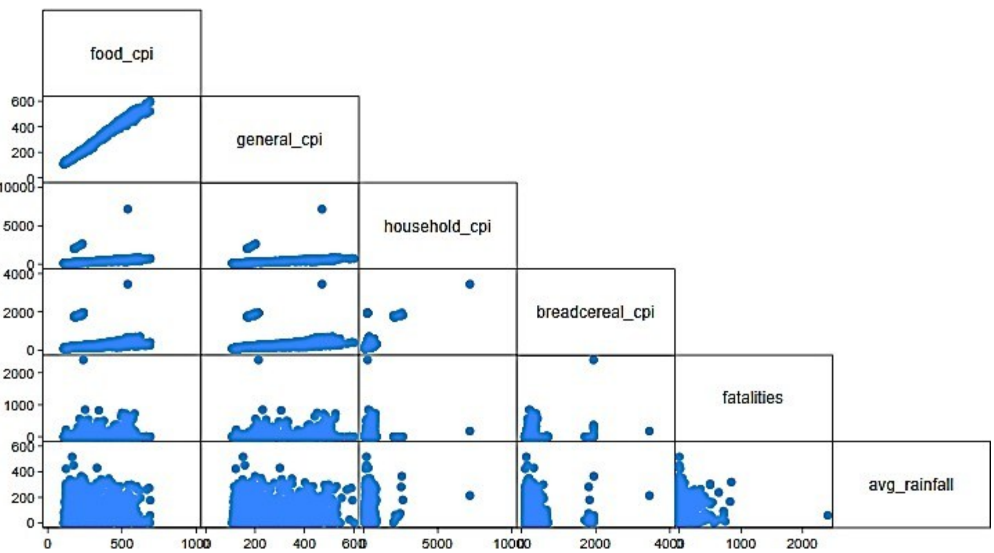


Figure 13. Scatterplot Matrix of Key Variables

Figure 13 reveals important patterns. Food CPI, general CPI, and household CPI exhibit very strong linear relationships ($r > 0.95$), confirming they track common inflationary pressures.

Breadcereal CPI shows greater volatility with several extreme outliers, suggesting staple grain prices are more sensitive to harvest shocks and conflict than overall food indices. The fatalities distribution shows extreme right-skew with most observations clustered near zero and a long tail extending to 2,400, validating the necessity of log transformation. Average rainfall shows no clear visual correlation with any CPI measure, consistent with subsequent regression findings

4.1.4. Bivariate Correlation Coefficients

Table 9.
Pairwise Correlations with Fatalities

	food_cpi	Fatalities	avg_rainfall	time_trend
food_cpi	**1.0000**			
fatalities	**0.1453** (0.0000)	**1.0000**		
avg_rainfall	**0.0672** (0.0509)	**0.0638** (0.0639)	**1.0000**	
time_trend	**0.9193** (0.0000)	**0.1551** (0.0000)	**0.0433** (0.2082)	**1.0000**

Table 10.
Pairwise Correlation with Fatalities (log transformed)

	food_cpi	ln_fatalities	avg_rainfall	time_trend
Food_cpi	**1.0000**			
ln_fatalities	**0.1182** (0.0003)	**1.0000**		
avg_rainfall	**0.0672** (0.0509)	**0.1199** (0.0005)	**1.0000**	
time_trend	**0.9193** (0.0000)	**0.1486** (0.0000)	**0.0433** (0.2082)	**1.0000**

Bivariate correlation (Table 9) reveals a very strong time trend in food CPI with an r = 0.919*** reflecting Ethiopia's persistent inflation problem. On the other hand, there is a statistically significant but weak positive correlation between fatalities & food CPI with r = 0.1453***. After log transformation (Table 10), this correlation weakens further with r = 0.118*** suggesting that extreme conflict events, i.e., high-fatality months were driving the bivariate relationship more than typical variation in conflict intensity.

The correlation between ln_fatalities and rainfall is positive with r = 0.120*** possibly reflecting seasonal patterns in conflict intensity as higher rainfall is shown to be associated with higher log fatalities. This pattern likely reflects the seasonal timing of major military operations: the June-July 2021 Tigrayan Defence Forces (TDF) counteroffensive to recapture Mekelle occurred during the *kiremt* rainy season, as did the August 2022 violence surge following the ceasefire collapse.[2]

[2] The timing of these operations may reflect strategic considerations around terrain accessibility (rainy season makes some areas impassable for mechanized forces), agricultural labour availability (farmers are tied to fields during planting season), and troop mobility. The August 2022 escalation occurred as roads became passable again after the rains

4.2. Specification and Diagnostic Tests

4.2.1. Model Specification Test: F-TEST (Pooled OLS vs. Fixed Effects)

F test that all $u_i = 0$: (F (**10, 818**) = **54.81**

Prob > F = **0.0000)**

The F-test strongly rejects the null hypothesis of equal regional intercepts (F (10, 818) = 54.81, $p < 0.001$), confirming significant heterogeneity in baseline food price levels across Ethiopia's 11 regions and validating the fixed effects approach.

4.2.2. Multicollinearity Assessment: Variance Inflation Factors (VIF)

Table 11.

Variance Inflation Factors

Variable	VIF	1/VIF
time_trend	**14.05**	**0.071189**
time_after	**8.78**	**0.113953**
Post	**4.06**	**0.246223**
ln_fatalities	**1.07**	**0.937888**
avg_rainfall	**1.04**	**0.965391**
Mean VIF	**5.80**	

Variance inflation factors in Table 11 indicate no problematic multicollinearity among substantive variables. The mean VIF is 5.80. Time trend variables exhibit high VIFs (time_trend = 14.05, time_after = 8.78), which is expected and structurally inherent to ITS designs given their correlation with time. Despite these elevated values, the intervention variables remain separately identifiable and capture conceptually distinct effects (baseline trend, level change, and slope change). Critically, substantive variables show no concerning multicollinearity: ln_fatalities (VIF = 1.07) and avg_rainfall (VIF = 1.04) are well below conventional thresholds, indicating these estimates are not distorted by collinearity with other regressors.

4.2.3. Heteroskedasticity Test

Modified Wald Test:

Ho: $\sigma_i^2 = \sigma^2$ *for all i*

χ 2 (11) = **968.46**

Prob > χ 2 = **0.0000**

The Modified Wald test for groupwise heteroskedasticity tests strongly rejects homoskedasticity (χ^2 (11) = 968.46, $p < 0.001$), confirming that different regions exhibit different levels of price volatility. This finding validates the use of region-clustered standard errors, which provide robust inference in the presence of heteroskedasticity, helping the model account for regional differences in variance of error.

4.2.4. Autocorrelation and Clustering Strategy

Wooldridge Test:

Ho: no first-order autocorrelation

F (1, 10) = **42.053**

Prob > F = **0.0001**

The Wooldridge Test has been employed to test for autocorrelation. The test strongly rejects the null hypothesis of no autocorrelation (F (1,10) = 42.053, $p < 0.001$), confirming the presence of first-order autocorrelation and validating the use of region-clustered standard errors.

4.2.5. Residual Analysis

To assess whether regression assumptions are satisfied, the distribution of model residuals is examined through visual and statistical diagnostics.

A. Normality Assessment

Table 12.

Shapiro-Wilk test

Variable	Obs	W	V	z	Prob>z
Resid	**845**	**0.88106**	**64.352**	**10.241**	**0.00000**

The Shapiro-Wilk test yields $W = 0.881$, $p < 0.001$. While the test formally rejects perfect normality, the W statistic near 1.0 indicates that residuals closely approximate a normal distribution. The significant p-value reflects the test's high power with large samples ($N = 845$) to detect even minor deviations rather than substantive violations of normality assumptions.

Visual inspection via the Q-Q plot below (Figure 14) confirms that departures are minor and concentrated in the tails. With the large sample size, the Central Limit Theorem ensures that coefficient estimates, and standard errors remain asymptotically valid despite these negligible deviations.

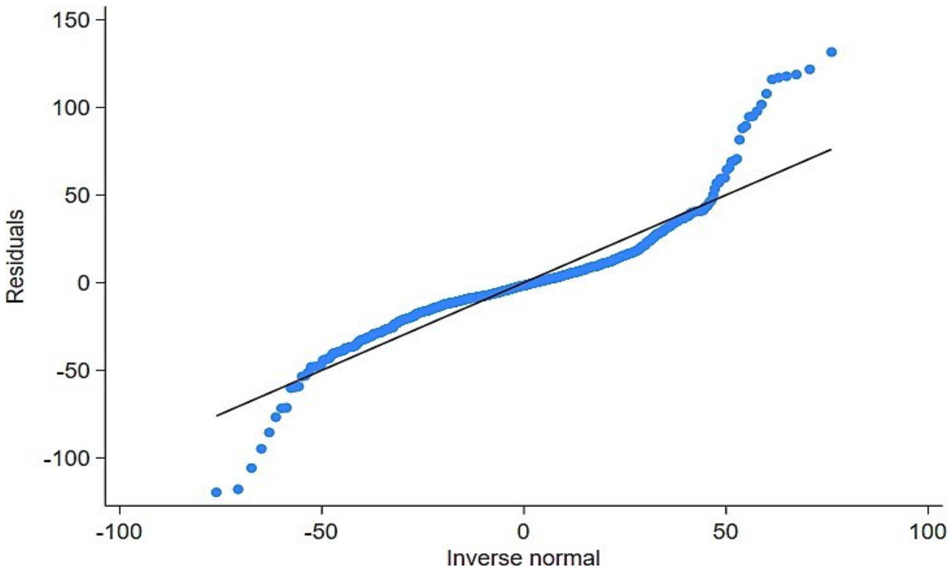


Figure 14. QQ plot comparing residuals against fitted values for normality

B. Homoskedasticity and Linearity Assessment

Figure 15 plots residuals against fitted values to assess homoskedasticity and detect potential non-linear patterns. As shown, the scatter exhibits no systematic funnel shape, confirming that variance does not systematically increase or decrease with the magnitude of fitted values. This validates the linear specification of ITS model.

Residuals are centred around zero across the full range of fitted values (100-600), confirming that the model is correctly specified. However, notable heterogeneity in residual variance is visible across different fitted value ranges. The lower fitted values corresponding to the pre-war period (100-250) show tighter clustering around zero, while the higher fitted values of the post-war period (400-600) exhibit greater dispersion. This pattern is consistent with the heteroskedasticity documented by the Modified Wald test (section 4.2.3), validating the use of region-clustered standard errors to ensure robust inference.

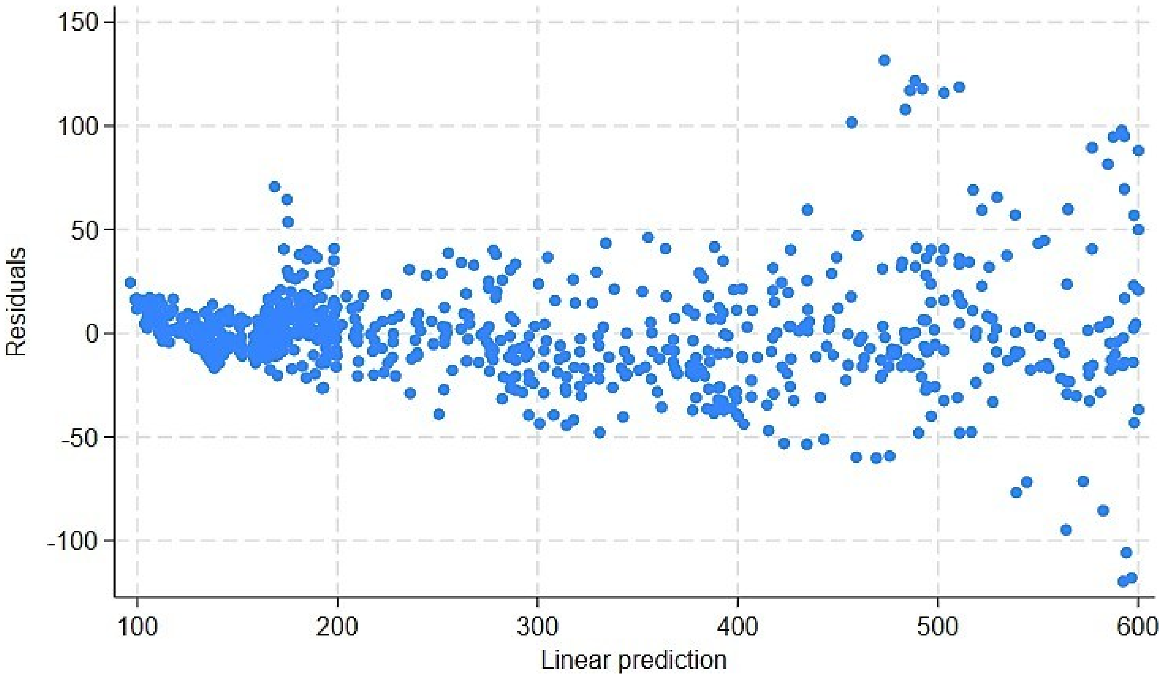


Figure 15. Residuals against Fitted Values plot

While several outliers are visible, particularly observations with residuals exceeding +/- 100 at higher fitted values, and they contribute to the non-normal residual distribution, they do not form systematic patterns suggesting model misspecification.

4.3. Main Regression Results

4.3.1. Single Intervention ITS Model

Table 13.

Single Intervention ITS Regression Results

Variable	(1) Basic	(2) Seasonality included
time_trend	**2.550*** **	**2.463*** **
	(0.125)	*(0.105)*
Post	**-22.918*** **	**-20.379*** **
	(4.336)	*(2.813)*
time_after	**6.132*** **	**6.182*** **
	(0.258)	*(0.122)*
ln_fatalities	**-1.536* **	**-1.891*** **
	(0.846)	*(0.897)*
avg_rainfall	**0.036*** **	**0.010**
	(0.005)	*(0.007)*
July		**8.033** **
		(3.771)
August		**10.741*** **
		(3.843)
September		**12.506*** **
		(3.643)
October		**11.692*** **
		(3.539)
November		**8.229** **
		(3.422)
Month FE	**No**	**Yes**
Region FE	**Yes**	**Yes**
R (within)	**0.982**	**0.983**
N	**845**	**845**
F-statistic	**575.36*** **	**3004.94*** **

Notes: Cluster-robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01. *All models include region fixed effects. Month coefficients for non-significant months (Feb-June, Dec) omitted for brevity; full results available upon request. January is the reference month.*

Intervention Effects

The baseline pre-war monthly inflation rate was 2.55 CPI points per month ($p<0.001$) representing Ethiopia's structural food price trajectory. At the November 2020 conflict onset, the model estimates an immediate level change (post coefficient) of -22.92 points.

This initial level change of -22.92 points at conflict onset likely captures a unique "liquidity-fragmentation" trap. As noted in Footnote [1], the Tigray region was already experiencing price volatility due to federal fund cuts and the September 2020 demonetization which already restricted cash liquidity and forced traders to move wealth into the formal banking sector (Chala, 2025). When hostilities commenced in November, the subsequent closure of regional banks and severance of major trade routes (e.g., the Addis-Mekelle corridor) prevented surplus-producing regions from exporting to northern deficit zones (Tadesse & Ghebru, 2021).

This created localized gluts in surplus areas, where prices collapsed as trapped traders, already cash-constrained by demonetization, engaged in distress sales to maintain liquidity. Consequently, the model captures an immediate, artificial price suppression driven by market paralysis rather than improved food security.

Adding monthly fixed effects (in Column 2) leaves core intervention coefficients substantively unchanged (time_trend = 2.46, post = -20.38, time_after = 6.18), confirming these estimates reflect genuine conflict effects rather than seasonal artifacts. The total war-period inflation rate remains 8.68 points per month, nearly identical to Column 1.

In column 1, the time_after coefficient of 6.13 ($p < 0.001$) indicates that monthly inflation accelerated dramatically during the war period. The total war-period inflation rate was 8.68 points per month (2.55 + 6.13), representing a 240% increase over the pre-war baseline. This acceleration captures the war's genuine impact on food price dynamics.

Conflict Intensity

The conflict intensity coefficient (ln_fatalities = -1.536) is only marginally significant (p=0.100). Intensity of violence acts as a shock to market access. High-fatality months likely correlate with total road blockages and the displacement of consumers which, as aforementioned, suppresses local prices through a "glut" of non-exportable surplus.

Consistent with this, the 95% confidence interval (-3.42,0.35) includes zero indicating the null hypothesis of no relationship cannot be rejected at 5% level. This suggests that within-region monthly variation in conflict intensity does not reliably predict food prices once the structural break caused by the war is controlled for.

However, with the addition of seasonal controls, the relationship becomes highly significant ($\beta = -1.891$, $p = 0.001$). While the coefficient strengthens and maintains its negative sign, a counterintuitive pattern addressed in Section 4.3.4., this likely reflects market dysfunction, measurement failure, or demand destruction in violent areas rather than genuine price suppression.

The rainfall coefficient appears positive and highly significant (0.036, $p < 0.001$), suggesting higher rainfall associates with higher food prices. However, Column 2 reveals this relationship is spurious, driven by seasonal confounding when Ethiopia's rainy season (June-August) overlaps with the lean season when food prices are naturally elevated.

Once seasonal cycles are absorbed by monthly fixed effects, rainfall variability has no independent effect on food prices. This finding provides policy-relevant dimension for drought and food response: the inter-annual rainfall variability does not substantially affect food prices in Ethiopia's context, where seasonal patterns dominate.

The basic ITS model demonstrates strong performance, with R^2 (within) = 0.982 explaining 98.2% of within-region price variation. The F-statistic of 575.36 ($p < 0.001$) confirms overall model significance. The panel is unbalanced (36-84 observations per region) due to Tigray's missing data, but the fixed effects estimator accommodates this structure without bias.

The monthly fixed effect coefficients reveal distinct seasonal price patterns. Food prices are significantly elevated during July-November relative to the January baseline, with September exhibiting the highest seasonal premium (+12.51 points, $p < 0.001$).

This corresponds to Ethiopia's hunger season when *Meher* harvest stocks are depleted. Particularly September exhibits the highest seasonal price premium and corresponds to what food security analysts call the “hunger gap”; the period of maximum vulnerability between planting and harvest when both food availability and household purchasing power are at their lowest.

February-June and December show no significant deviation, reflecting post-harvest abundance. This pattern validates the need for seasonal controls and explains the spurious rainfall effect in Column 1 because once monthly fixed effects absorb the predictable lean season price pattern, the remaining rainfall variation shows no significant relationship with prices.

The seasonality model fit remains strong (R^2 within = 0.983), with the F-statistic increasing to 3004.94 ($p < 0.001$) due to the additional significant monthly variables.

4.3.2. Two Intervention ITS Model (War + Peace)

Table 14.

Two-Intervention ITS Model (War + Peace)

Variable	**Coefficient**
time_trend	**2.449***** *(0.118)*
Post	**-8.645***** *(2.570)*
time_after	**5.217***** *(0.244)*

peace_post	**-7.593***
	(3.732)
time_after_peace	**1.387****
	(0.553)
ln_fatalities	**-1.997***
	(0.951)
avg_rainfall	**0.009**
	(0.007)
July	**9.193*****
	(2.437)
August	**12.097*****
	(2.052)
September	**13.988*****
	(2.055)
October	**13.313*****
	(2.718)
November	**7.090*****
	(1.420)
Month FE	**Yes**
Region FE	**Yes**
N	**845**

Comparison with ITS results

To interpret this result table, the coefficient of time structure variables (the intervention effects) can be categorized into three periods as follows.

Table 15.

Comparison with ITS results

Period 1: Pre-War (Jan 2018 – Oct 2020)	Period 2: Active War (Nov 2020 – Oct 2022)	Period 3: Relative Peace (Nov 2022 – Dec 2024)
Slope = time_trend = 2.45 points/month	Slope = time_trend + time_after = 7.67 points/month	Slope = time_trend + time_after + time_after_peace = 9.06 points/month

From this, it is learned that war tripled inflation rate, i.e., from pre-war 2.45/month to 7.67/month during war. The effect of the war led to a 213% acceleration in food CPI.

Critically, the coefficient of time_after_peace is 1.387 at 5% significance level. This indicates that the Pretoria Peace Agreement was associated with a further acceleration in food price inflation even after hostilities ceased, reflecting persistent economic damage from the conflict.

When looking at immediate level changes in food CPI (1) after the first intervention point, i.e., the Tigray war prices dropped by -8.645 points/month and (2) after the second intervention point when the Pretoria Peace Agreement took place, prices dropped again by 7.59 points at 10% significance level.

This also reflects that inflation pattern in Ethiopia exhibits a “ratchet effect”, when once the war pushed prices up, the structural damage including infrastructure loss, foreign exchange shortages and debt prevented it from coming back down, even when the guns were silenced.

Visualizing the Intervention Effect

This study also checks for predict fitted and draws the tsline for visual fit

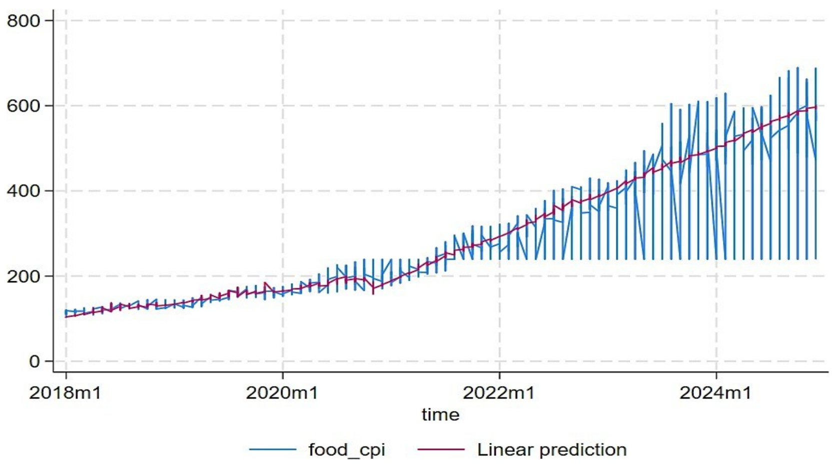


Figure 16. Plot showing actual food CPI observations against model predictions.

Note: The red line represents fitted values from the ITS specification. Visual inspection confirms good model fit (R^2 within = 0.98), with most observations clustering near predictions. The horizontal band of dots at approximately 230-240 represents Tigray's frozen data. The steeper post-intervention trajectory clearly demonstrates the war's acceleration of food price inflation.

4.4. Robustness Checks

4.4.1. Two-Way Fixed Effects Specification

Table 16.

TWFE Robustness Checks

Variable	Coefficient (Robust SE)	p-value
ln_fatalities	**-2.343**** *(1.045)*	**0.049**
avg_rainfall	**0.0043** *(0.008)*	**0.632**

Note: Absorbed degrees of freedom for region_id and time are 11 and 83-month dummies (January (1) left for reference) respectively leading to ITS variables being omitted since they are collinear

To assess the robustness of the findings to the most conservative specification, Table 16 presents a two-way fixed effects (TWFE) model that includes both region fixed effects and time (month-year) fixed effects. The within-R^2 of 0.026 is expectedly low because time fixed effects absorb 98%+ of price variation, leaving only 2.6% of within-region, within-month variation for conflict and rainfall to explain.

The conflict coefficient is -2.34 and statistically significant now, even at 5% level, confirming negative relationship persists even with strictest controls. This relationship reflects genuine dynamics rather than model-specific artifacts. The non-significance of the rainfall coefficient confirms it has no independent effect beyond seasonal patterns already captured by temporal controls.

4.4.2. Robustness Check: Excluding Tigray Region

To address concerns that frozen data from Tigray region may be driving results, the TWFE model is re-estimated excluding Tigray. This TWFE, therefore has 809 observations in total across 10 regions, the 36 observations equating Tigray's data.

Table 17.
TWFE excluding Tigray Region

Variable	Coefficient (Robust SE)	p-value
ln_fatalities	**-2.671**** *(0.993)*	**0.025**
avg_rainfall	**0.0046** *(0.009)*	**0.629**

The conflict effect becomes stronger and more statistically significant at 5% significance level (beta = -2.67, p = 0.025), indicating that the frozen Tigray data was in fact attenuating rather than creating a spurious negative relationship. This robustness check confirms that the findings reflect genuine market dynamics in conflict zones.

CHAPTER V

DISCUSSION, CONCLUSIONS, AND RECOMMENDATIONS

This final chapter synthesizes the empirical findings from the interrupted time series analysis of armed conflict's impact on food prices in Ethiopia during the 2020-2022 Tigray war period. The study employed a quasi-experimental design drawing on a panel of 11 Ethiopian administrative regions observed monthly from January 2018 through December 2024, yielding a balanced panel of 924 region-month observations for descriptive analysis. The regression sample is 845 region-month observations, reflecting the exclusion of 79 observations for which average monthly rainfall data were unavailable from the Ethiopian Meteorological Institute.

These missing rainfall observations are distributed across regions and time periods without systematic concentration in any particular conflict phase, and their exclusion is unlikely to introduce directional bias into the estimated conflict coefficients. The regression analysis therefore examines how conflict intensity affected food Consumer Price Index dynamics through both immediate level shifts and sustained trend changes.

The organization proceeds as follows. Section 5.1 summarizes the key empirical findings. Section 5.2 provides theoretical interpretation, reconciling the counterintuitive negative conflict intensity coefficient through the data censoring hypothesis. Section 5.3 discusses policy implications for humanitarian organizations, government agencies, and international donors. Section 5.4 acknowledges methodological limitations. Section 5.5 offers recommendations for future research. Section 5.6 provides concluding remarks.

5.1. Summary of Key Findings

The interrupted time series analysis yielded several empirical findings addressing the study's research questions regarding how the November 2020 conflict affected food security through food price dynamics. These findings emerge from segmented regression specifications controlling for region fixed effects, seasonal patterns, rainfall variation, and time trends, with robust standard errors clustered at the regional level.

5.1.1. Baseline Pre-War Inflation Trajectory

The pre-intervention period from January 2018 through October 2020 exhibited a baseline food CPI growth rate of 2.55 index points per month ($p < 0.001$), translating to approximately 30.6 index points annually. This persistent inflationary trend reflects Ethiopia's chronic macroeconomic challenges including foreign exchange shortages constraining food imports and COVID-19 pandemic disruptions during March-October 2020.

5.1.2. Immediate Level Effect of Conflict Onset

The November 2020 conflict onset produced an immediate level decrease in food CPI of 22.92 index points ($p < 0.001$), representing an abrupt downward shift precisely at the intervention point. Adding seasonality leaves core intervention coefficients substantively unchanged, which confirms that these estimates reflect genuine conflict effects rather than seasonal artifacts.

5.1.3. Post-Intervention Trend Acceleration

Following the initial level shift, the post-conflict period exhibited dramatically accelerated price growth of 6.13 index points per month ($p < 0.001$), representing the change in slope parameter from the single-intervention model (Table 13, Column 1). This indicates that after November 2020, the monthly rate of food price increase rose by 6.13 points above the pre-war baseline of 2.55 points, producing a total post- intervention growth rate of 8.68 index points monthly, equivalent to a 240% increase over the pre-war baseline.

This acceleration persisted throughout the 50-month post-intervention window. As further demonstrated by the two-intervention model (Table 14), despite the November 2022 Pretoria

Peace Agreement, the monthly inflation rate reached 9.06 index points, representing a 270% elevation above the pre-war baseline, confirming that conflict created permanent structural damage to market systems.

5.1.4. The Paradoxical Negative Conflict Intensity Coefficient

The most counterintuitive finding emerged from the conflict intensity variable: each one-unit increase in fatality variable (logarithmically transformed) is associated with a 1.536 index point decrease in food CPI ($p < 0.10$). This negative coefficient contradicts theoretical predictions from conflict economics literature, which uniformly predicts that violence intensity should raise food prices through supply chain disruption, market infrastructure destruction, and reduced agricultural production. Three potential interpretations merit consideration: (1) humanitarian aid substitution, (2) demand collapse, and (3) measurement failure, wherein the most violent regions became unmeasurable precisely because conflict destroyed the market and data infrastructure that generates observable prices.

5.2. Theoretical Interpretation and Reconciliation of Findings

5.2.1. The Data Censoring Hypothesis

The measurement failure interpretation provides the most theoretically coherent explanation for the negative conflict intensity coefficient. The data censoring hypothesis posits that extreme violence creates a threshold effect whereby beyond a critical intensity level, price data become unavailable not because prices fall, but because the institutional infrastructure for price observation collapses. This mechanism operates through telecommunications blackout preventing enumerator communication, physical insecurity making markets inaccessible to data collectors, displacement of retail vendors who serve as price informants, and destruction of market structures where price formation occurs.

This interpretation finds strong support in the Tigray case, where all four CPI indices remained frozen at October 2020 values throughout the 50-month conflict and post-conflict period despite overwhelming qualitative evidence of catastrophic food insecurity. Informal price reports documented by FEWS NET and UN agencies indicated teff prices in Mekelle informal markets reaching 60,000 to 80,000 Birr per quintal by mid-2021, more than triple the frozen official value of 18,450 Birr. The resumption of FEWS NET price monitoring in December 2022 revealed prices at 32,500 Birr per quintal, 76 percent above pre-war levels, confirming that frozen data massively understated true price inflation.

5.2.2. Alternative Explanations: Humanitarian Aid and Demand Collapse

While the data censoring hypothesis provides the primary explanation, the humanitarian aid substitution mechanism suggests that regions experiencing higher casualties attracted more intensive international food assistance, with in-kind commodity distributions suppressing market prices. However, several empirical patterns undermine this interpretation. First, Tigray faced a near-total aid blockade from November 2020 through July 2021, receiving minimal humanitarian assistance precisely when violence peaked. Second, the negative coefficient persists in robustness specifications excluding Tigray. Third, humanitarian food distributions typically operate through off-market channels targeting specific vulnerable populations rather than affecting CPI measurement.

The demand collapse mechanism posits that extreme violence so devastated household purchasing power that effective demand for food fell faster than supply contracted. However, economic theory predicts that when populations face starvation-level food insecurity, food assumes infinite marginal utility and households liquidate all assets to purchase sustenance at any price. The mechanism also contradicts informal price evidence showing hyperinflation in conflict zones.

5.2.3. Integration with Theoretical Frameworks

The empirical findings integrate with theoretical frameworks from Chapter 2. Sen's entitlement theory provides the foundational distinction between food availability and access but proves insufficient for explaining measurement dynamics in extreme conflict because it assumes functioning markets.

The gender-blind critique becomes empirically relevant when recognizing that women constituted 70 to 75 percent of retail food vendors in Tigray, meaning gender-based violence and displacement contributed directly to market infrastructure collapse and data unavailability. Devereux (2000, 2009) distinguishes between “natural famines” resulting from environmental shocks and entitlement failures, and “political famines where governments or armed groups deliberately create conditions of mass starvation. In siege economies, official prices become meaningless; controlled scarcity in government-held territories results in artificial price suppression and data blackouts where measurement itself is weaponized.

5.3. Policy Implications

5.3.1. Humanitarian Response and Resource Allocation

Humanitarian organizations must recognize that official food price data become unreliable precisely in zones requiring most urgent intervention. The finding that conflict intensity correlates negatively with reported prices while informal evidence shows hyperinflation implies that resource allocation models relying on official CPI data will systematically under-prioritize the most affected populations. Agencies should implement graduated evidentiary standards whereby absent or frozen official statistics trigger heightened alert rather than complacency.

The post-intervention trend acceleration demonstrates that conflict creates long-term structural damage requiring sustained humanitarian engagement beyond immediate emergency phase.

The finding that prices in December 2022 remained 76 percent above pre-war levels suggests even areas achieving nominal peace require multi-year support as trader networks, transportation infrastructure, and household purchasing power reconstruct. Resource mobilization frameworks should reflect extended timelines with multi-year funding commitments.

5.3.2. Early Warning System Design and Data Triangulation

The study's findings necessitate fundamental redesign of food security early warning systems to incorporate conflict-specific measurement challenges. Traditional systems like FEWS NET rely heavily on official price monitoring, making them vulnerable to the data gaps this study documents. Early warning architecture should implement parallel monitoring streams with explicit protocols for activating alternative information sources when primary data fail, including satellite-based agricultural monitoring, mobile phone-based crowdsourcing, humanitarian field reports, and statistical imputation models.

The negative conflict intensity coefficient provides a quantifiable threshold: when fatality counts exceed levels historically correlating with price data freezing (approximately 100 deaths monthly based on Tigray case), early warning systems should automatically flag affected regions for intensive alternative data collection and presume severe food insecurity. Systems should develop explicit uncertainty quantification around price estimates in conflict zones, communicating confidence intervals that widen proportionally to time since last verified observation.

5.3.3. Government Statistical Capacity and Crisis Protocols

National statistical agencies should establish explicit protocols for handling price data collection failures during conflict rather than defaulting to carrying forward historical values without annotation. The Tigray CPI remaining frozen for 50 months without public indication that values represented estimates created false impressions of price stability. Agencies should implement graduated response protocols: when enumerators cannot access markets for one month, label figures as estimated with collection constraints communicated; when gaps extend beyond three months, publish confidence intervals; when gaps exceed six months, discontinue publication and report data unavailability as substantive information.

Statistical agencies should invest in collection redundancy whereby multiple data streams monitor prices through different channels. Mobile phone-based price reporting, satellite imagery of market activity, and border crossing monitoring could supplement traditional enumerator-based collection, providing partial information when primary systems fail.

5.3.4. International Donor Programming and Financing

International donors should revise funding allocation criteria to account for data censoring in conflict zones. Current mechanisms often require demonstrable evidence through standard indicators, creating perverse incentives whereby the most affected populations receive inadequate resources because they cannot produce statistical documentation. Donors should implement inverse evidence requirements whereby inability to produce standard indicators due to access constraints constitutes sufficient justification for maximum funding allocations, provided conflict intensity and displacement metrics confirm crisis conditions.

Recovery financing requires longer timelines and larger resource commitments than typically provided. The finding that price inflation remained elevated 270% above baseline rates nearly two years after ceasefire indicates protracted recovery trajectories. Donor programming should structure post-conflict assistance as multi-year commitments tied to market recovery milestones rather than arbitrary timelines.

5.4. Limitations of the Study

5.4.1. Data Quality and Measurement Challenges

The study's central finding regarding data censoring paradoxically depends on the very data whose reliability it questions. The analysis relies on official CPI statistics which the study demonstrates systematically understate price inflation in high-conflict areas through data freezing. This creates inherent limitation: the most critical period and location, Tigray between November 2020-December 2024, contains no valid price observations, only carried-forward historical values. While the study interprets measurement failure as substantively meaningful evidence of market collapse, it cannot directly estimate true price levels in unmeasurable zones. Fatality data from Ethiopia Peace Observatory also faces accuracy challenges. Media-based event coding systematically undercounts deaths in areas where journalists cannot access or governments restrict reporting. If under-reporting varied systematically with violence intensity, the negative coefficient could partially reflect measurement error rather than purely data censoring. However, this limitation likely attenuates rather than creates the negative relationship.

5.4.2. Internal Validity and Causal Inference Constraints

The interrupted time series design, while representing the strongest quasi-experimental approach available absent randomization, cannot achieve internal validity of true experimental designs. The core identification assumption, i.e., during absent conflict, prices would have continued along pre-intervention trends, remains fundamentally untestable. While the study controls for observable confounders including seasonal patterns, rainfall variation, and general inflation, unobserved time-varying factors could potentially bias estimates.

The panel structure with only 11 regions, although reflecting Ethiopia's actual administrative structure, provides limited statistical power for detecting heterogeneous treatment effects due to the asymptotic properties of cluster-robust inference. The small number of clusters constrains ability to conduct granular subgroup analyses such as examining urban versus rural differences.

Region-clustered standard errors appropriately account for within-region correlation, but with only 11 clusters, asymptotic properties justifying cluster-robust inference are strained, suggesting treating the $p < 0.10$ threshold for conflict intensity coefficient with appropriate caution.

5.4.3. External Validity and Generalizability

The findings emerge from Ethiopia's specific institutional, economic, and conflict context, raising questions about generalizability. Ethiopia's federal structure, chronic macroeconomic vulnerabilities, and particular Tigray conflict dynamics including telecommunications blackout and comprehensive aid blockade create unique confluence of factors that may not replicate elsewhere. However, the theoretical mechanism linking extreme violence to data unavailability should operate across contexts where conflict intensity exceeds thresholds for normal market operations.

The study period 2018-2024 captures a particular historical moment including COVID-19 pandemic, elevated global food prices following Russia's invasion of Ukraine, and Ethiopia's currency regime transition. These concurrent shocks likely amplified conflict impacts, meaning estimated coefficients reflect conflict conditional on this global economic environment. Generalizing to other periods requires acknowledging that conflict-price relationships may vary with global commodity prices and exchange rate regimes.

5.4.4. Alternative Outcome Measures and Mechanisms

The study focuses exclusively on food Consumer Price Index as outcome measure, which captures market prices but does not directly measure food security outcomes including household consumption, nutritional status, or coping strategies. Price increases mechanically reduce purchasing power, but the relationship between prices and actual consumption depends on numerous mediating factors. The study cannot determine whether documented price impacts translated into proportional changes in food consumption or malnutrition without additional household-level data.

Additionally, the study examines aggregate food CPI rather than disaggregated commodity-specific prices, preventing analysis of how conflict differentially affects staple grains versus animal products versus perishable vegetables. Theoretical mechanisms suggest heterogeneous impacts, but the aggregate index masks these compositional dynamics.

5.5. Recommendations for Future Research

5.5.1. Methodological Innovations for Measuring Unmeasurable Prices

The central challenge this study documents, that prices become unmeasurable precisely when conflict is most severe, requires methodological innovation. Future research should develop alternative price measurement strategies specifically designed for extreme conflict environments. Promising approaches include satellite imagery analysis assessing market activity through vehicle counts, thermal signatures, and built environment changes; mobile phone-based crowdsourcing collecting informal price reports; and trader network analysis using social network methods to reconstruct price estimates based on reported differentials across connected markets.

5.5.2. Household-Level Impacts and Consumption Responses

Understanding welfare implications requires linking price changes to household consumption behaviour. Future research should conduct panel surveys of households in conflict-affected regions tracking how food consumption, dietary diversity, and coping strategies evolve in response to price shocks. Such analysis could estimate price elasticities under extreme conditions, examine which household types prove most vulnerable, and assess whether humanitarian assistance successfully offsets price impacts. The gendered dimensions suggest a particular value in examining female-headed versus male-headed household responses.

5.5.3. Comparative Analysis Across Conflict Types and Countries

Extending the interrupted time series framework to other conflict settings would test generalizability and identify which findings represent universal conflict-food price dynamics versus Ethiopia-specific phenomena. Particularly valuable comparison cases include Yemen's civil war, Syria's conflict, and South Sudan's violence, each featuring sustained high-intensity fighting and documented food crises. Comparative analysis could examine whether the negative conflict intensity coefficient emerges consistently across settings, strengthening the data censoring hypothesis as general mechanism.

5.5.4. Market Recovery Dynamics and Post-Conflict Reconstruction

The finding that price inflation remained elevated 270% above baseline nearly two years after ceasefire raises questions about market recovery trajectories. Future research should follow conflict-affected regions longitudinally through reconstruction periods, documenting how long various market functions require to normalize. Specific indicators include trader participation rates, transportation costs, spatial price correlation with national markets, credit availability recovery, and gender composition of market vendors. Survival analysis could estimate median recovery times for different market functions.

Research should examine which reconstruction interventions most effectively accelerate market recovery. Comparing regions receiving different combinations of cash assistance, in-kind food aid, infrastructure rehabilitation, and trader capital grants could identify highest-return investments for market system restoration. Randomized or quasi-experimental evaluations would provide policy-relevant evidence on optimal reconstruction strategies.

5.5.5. Theoretical Development of Measurement Failure in Crisis Economics

The study's findings call for theoretical development examining when and why economic measurements fail during crises and what implications measurement failure carries for economic theory. The conflict economics literature has extensively theorized about how violence affects production and exchange but devoted less attention to how violence affects observability of outcomes. Developing formal models incorporating endogenous measurement as function of crisis intensity would provide theoretical foundation for empirical patterns documented here.

Theoretical work could examine the political economy of statistical production during conflict, analysing governments' and armed groups' incentives regarding measurement and information control. The telecommunications blackout and statistical data freezing in Tigray were deliberate policy choices with strategic motivations. Theory could examine under what conditions governments prefer measurement suppression versus manipulation versus transparent data collection.

5.6. CONCLUDING REMARKS

This study employed interrupted time series analysis to examine how the November 2020 Tigray conflict affected food prices across Ethiopia's 11 administrative regions. The quasi-experimental design, controlling for region fixed effects, seasonal patterns, rainfall variation, and general inflation while employing region-clustered standard errors, provided rigorous estimates of conflict's causal impact on price dynamics.

The empirical findings revealed three primary patterns. First, conflict onset created an immediate level decrease of 22.92 index points ($p < 0.001$), representing apparent downward price shock. Second, the post-intervention period exhibited dramatically accelerated price inflation of 6.13 index points monthly ($p < 0.001$) above pre-war baseline of 2.55 points, representing 240% increase in monthly inflation rate that persisted through ceasefire and beyond. Third, conflict intensity correlated negatively with food CPI, with each unit increase in log fatalities associated with 1.536 index point price decrease ($p < 0.10$).

The theoretical interpretation reconciled these seemingly contradictory results through the data censoring hypothesis, arguing that extreme violence creates threshold effects whereby prices become unmeasurable precisely when conflict is most severe. The Tigray case provided definitive evidence: all four CPI indices froze at October 2020 values throughout 50 months as telecommunications blackout prevented data collection and market infrastructure collapsed, meaning the region experiencing highest absolute fatalities contributed systematically biased downward price observations.

Policy implications extend beyond Ethiopia to inform humanitarian response planning, early warning system design, and statistical agency protocols across conflict settings. The finding that violence correlates with data unavailability suggests humanitarian organizations should treat measurement gaps as evidence of crisis severity rather than data quality problems. Early warning systems should develop parallel monitoring streams activating alternative information sources when primary data fail. Statistical agencies should establish explicit protocols for handling collection failures during conflict.

As Ethiopia begins post-conflict recovery and reconstruction, the finding that price inflation remained elevated 270% above baseline rates nearly two years after ceasefire underscores that conflict creates lasting structural damage requiring sustained external support beyond immediate emergency response. Market systems, trader relationships, transportation infrastructure, and household asset bases destroyed during 24 months of fighting will require years if not decades to fully reconstruct.

Ultimately, this dissertation contributes to conflict economics literature by providing methodologically rigorous evidence on price dynamics in extreme conflict environments while simultaneously exposing fundamental measurement challenges affecting all quantitative research in such settings. The paradox of the negative conflict intensity coefficient resolves through recognizing that what researchers observe is not prices themselves but rather the data-generating process for prices, and this process systematically fails precisely where and when impacts are most severe. This insight should inform interpretation of this specific study and broader approaches to empirical research in conflict economics, encouraging healthy scepticism about official statistics from conflict zones and investment in alternative measurement strategies that can illuminate crises that conventional data obscure.

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