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Near-Real-Time Welfare and Livelihood Impacts of an Active Civil War

Evidence from Ethiopia

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Abstract

Ethiopia is currently embroiled in a large-scale civil war that has continued for more than a year. Using unique High-Frequency Phone Survey data, which spans several months before and after the outbreak of the war, this paper provides fresh evidence on the ex durante impacts of the conflict on the food security and livelihood activities of affected households. The analysis uses difference-in-differences estimation to compare trends in the outcomes of interest across affected and unaffected regions (households) and before and after the outbreak of the civil war. The findings show that seven months into the conflict, the outbreak of the civil war increased the probability of moderate to severe food insecurity by 38 percentage points. Using the Armed Conflict Location and Event Data on households' exposure to violent conflict, the analysis shows that exposure to one additional battle leads to a 1 percentage point increase in the probability of moderate to severe food insecurity. The conflict has reduced households' access to food through supply chain disruptions while also curtailing non-farm livelihood activities. Non-farm and wage-related activities have been the most affected by the conflict, while farming activities have been relatively more resilient. Similarly, economic activities in urban areas have been much more affected than those in rural areas. These substantial impact estimates, which are likely to be underestimates of the true average effects on the population, constitute novel evidence of the near-real-time impacts of an ongoing civil conflict, providing direct evidence of how violent conflict disrupts the functioning of market supply chains and livelihoods activities. The paper highlights the potential of phone surveys to monitor active and large-scale conflicts, especially in contexts where conventional data sources are not immediately available.

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Near-Real-Time Welfare and Livelihood Impacts of an Active Civil War: Evidence from Ethiopia

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1. Introduction

Political disagreements between the Ethiopian federal government and the Tigray regional state ensued into full-scale war on November 4, 2020, with the armed forces of the Tigray region on one side and the federal army and its allied forces from Amhara region and neighboring Eritrea on the other. The conflict played out in most parts of Tigray while also spilling over into parts of Amhara and Afar regions. As a direct consequence of the war, a deep humanitarian crisis continues to unfold, with widespread loss of life, displacement of people, property damages, and disruptions to economic livelihoods documented in the press.[1] In November 2021, the United Nations estimated that about 7 million people in Tigray, Amhara and Afar regions have been directly affected, with 2.4 million internally displaced persons in dire need of food assistance.[2] As the conflict continues, these figures are rising. A more recent assessment by the World Food Programme shows that across the three conflict-affected regions (Tigray, Amhara and Afar) more than 9 million people need humanitarian food assistance and 83 percent of people in Tigray are food insecure (WFP, 2022).[3]

Despite these high-level assessments and anecdotal accounts, to date there has not been any micro-level assessment of the welfare impacts of the armed conflict on affected households. Using a unique High-Frequency Phone Survey (HFPS) dataset, we provide the first empirical evidence of the (near real-time) impacts of the conflict on food security, access to food markets and disruptions to livelihood activities. We also evaluate the distributional patterns of these effects across economic sectors, geography and household characteristics.

Much of the earliest work on the adverse impacts of violent conflict is cross-country in nature, examining macro-level relationships between conflict and economic growth and development outcomes. Most of these cross-country studies find significant negative impacts of conflicts on macro-level economic outcomes (Barro, 1991; Gupta et al., 2004), some of which are transitory and are followed by quick recovery (Miguel and Roland, 2006; Justino and Verwimp,

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[1] https://www.wfp.org/news/severe-hunger-tightens-grip-northern-ethiopia#:~:text=The%20Tigray%20Emergency%20Food%20Security,extreme%20coping%20strategies%20to%20survive.

[2] https://news.un.org/en/story/2021/10/1102182

[3] The war has led to significant internal and cross-country displacements. Immediately after the outbreak of the war, around 63,000 refugees fled to Sudan (UNOCHA, 2021).

2006; Chen et al., 2008; Cerra and Saxena, 2008), while in other cases negative consequences are found to persist over longer periods (Blattman and Miguel, 2010).

The increase in the availability of household survey data in the last decade has generated some recent micro-level studies which examine the effects of violent conflict on welfare and economic outcomes of affected populations (e.g., Akresh and de Walque, 2008; Bundervoet et al., 2008; Akresh et al., 2011; Chamarbagwala and Moran, 2011; Merrouche, 2011; Shemyakina, 2011; Akresh et al., 2012; Leon, 2012; Mansour and Rees, 2012;Akbulut-Yuksel, 2014; Grimard and Laszlo, 2014; Valente, 2014; Pivovarova and Swee, 2015; Brück et al., 2019; Martin-Shields and Stojetz, 2019).

The micro studies that have focused on African conflicts have typically examined delayed outcomes observed many years following conflict. For example, Akresh (2008), and Kraehnert et al. (2019) examine the longer-term impacts of the Rwandan genocide on schooling and fertility outcomes.[4] Minoiu and Shemyakina (2012) find strong negative impacts of the 2002-2007 Côte d'Ivoire civil conflict on children's health status in subsequent years.[5] Similarly, studies of the impacts of the 1998-2000 Ethiopia-Eritrea border conflict find evidence of negative impacts on child health and schooling outcomes in subsequent years (Akresh et al., 2012; Weldeegzie, 2017). In northern Nigeria, Adelaja and George (2019) find that increased intensity of Boko Haram attacks reduced agricultural productivity.[6]

Most micro-level studies evaluating the impact of violent conflict suffer from two major data-related limitations. First, because the outbreak of violent conflict disrupts traditional data collection efforts, evaluating the immediate impacts of an active violent conflict proves difficult. Second, tracking the trajectory of outcomes associated with violent conflict may require high-frequency data that are not usually collected in conflict settings. This is particularly crucial for large-scale high-intensity violent conflicts that may evolve in ways that are difficult to foresee. In other words, these limitations lead to delays in reliable data collection, leaving most micro-level

[4] Similarly, Leon (2012) and Bertoni et al. (2017) find negative impacts of conflict on human capital accumulation and schooling outcomes, respectively, in Peru and Nigeria; while Odozi and Oyelere (2019) examine the impacts of a broader range of conflicts on poverty outcomes.
[5] Dabalen and Paul (2014) find evidence of reduced dietary diversity for the same period.
[6] Other studies in Africa have focused on identifying causes of violent conflicts as in the case of increases in food price levels and extreme climatic conditions leading to socio-political unrest (e.g., Hsiang, 2011; Hendrix et al., 2012; Smith, 2014; Maystadt and Ecker, 2014; van Weezel, 2019). For the case of Ethiopia, Akresh et al. (2012) and Weldeegzie (2017) use panel data to estimate impacts of the 1998-2000 Ethiopia-Eritrea border conflict on child health and schooling outcomes of children.

studies to rely on recall data, sometimes dating back several years, along with several aggregations, which are prone to recall bias (e.g., Gibson and Kim, 2007; Beegle et al., 2012) and aggregation bias (Sharma and Gibson, 2019; Rockmore, 2017; Rockmore et al., 2020) that may significantly affect statistical estimates of the impacts of violent conflicts. Besides limiting our understandings of the nature and consequences of violent conflicts, such data-related limitations are, among others, likely to hinder the speed and capacity of humanitarian organizations to target and deliver lifesaving humanitarian assistance to affected populations (Baker et al., 2020).

We make several key contributions to this literature, including to addressing some of the above data-related limitations. First, to our knowledge, we provide the first quantitative *ex durante* study of the microeconomic consequences of an active large-scale conflict, giving insights into the immediate effects of war. Second, in addition to examining food security – a natural focus of war's impacts on immediate welfare outcomes – we also document disruptions to household participation in livelihood pursuits and food markets, giving insights into sectoral and geographical patterns of resilience. We then discuss how such *ex durante* monitoring and analysis may inform post-conflict recovery efforts. Finally, we discuss how similar high-frequency phone surveys and related remote data collection efforts could best be mobilized for monitoring of similar conflict contexts in other settings in the future.

Our analysis is enabled by combining High-Frequency Phone Surveys (HFPS) with conflict events data to identify the impact of the conflict on welfare outcomes.[7] The HFPS are monthly phone surveys that cover all regions of Ethiopia and span April 2020-May 2021, with multiple waves before and after the outbreak of the civil war. The HFPS sample is drawn from a nationally representative face-to-face survey fielded in 2019 (the 4th round of the Ethiopian LSMS-ISA). These combined data offer several advantages and a unique opportunity to link households' welfare outcomes to exposure to conflict events. First, the spatiotemporal coverage of the HFPS data permits the construction of aggregate (affected versus unaffected regions) and disaggregated (household-level) measures of exposure to conflict. Importantly, because the HFPS surveys are georeferenced, we were able to merge the household data with granular conflict events data from the Armed Conflict Location and Event Data (ACLED) project. Second, the HFPS data also allow us to go beyond standard welfare measures that are typically assessed in conflict studies. In

[7] The HFPS data were collected by the World Bank in partnership with the Central Statistical Agency of Ethiopia and were designed to monitor the local impacts of the COVID-19 pandemic.

particular, we are able to investigate disruptions in economic activities and food market supply chains, mechanisms through which violent conflicts can affect food security and related welfare outcomes.

We focus on three sets of household outcomes: (1) food security, measured using the Food Insecurity Experience Scale (FIES); (2) access to food and food markets; and (3) household participation in major economic and livelihood activities (farming, non-farm business, and wage employment). To quantify the impact of violent conflict on these outcomes, we use a Difference-in-Differences (DID) approach, where the periods (months) before and after the outbreak of the war are collapsed into pre-war and post-war-onset periods for aggregate analysis, and a two-way panel fixed effects model is implemented for disaggregated analysis using (monthly) household-level exposure to conflict data. The first stage of the war (November 2020 to June 2021) was mostly confined to Tigray, spilling over to neighboring Afar and Amhara regions thereafter. Thus, our analysis focuses on the first period of the war, so that we can precisely define the spatial extent of the conflict. To account for potential intermittent conflicts elsewhere, we relax this treatment assignment in the analysis by using monthly household-level exposure to conflict from the ACLED database.

The high-frequency nature of the data facilitates our identification strategy in two useful ways. First, the monthly follow-up and hence comparison of outcomes across affected and unaffected regions allows us to minimize compounding trends. The existence of multiple pre-war and post-war-onset waves also allow us to indirectly test for parallel trends, the main identifying assumption for a DID estimation strategy. Second, the relatively large sample size due to high-frequency data allows us to probe the robustness of our results using alternative definitions of control groups. For example, in some of our estimations, we restrict our sample to the Highland regions of the country, with Amhara, Oromia and SNNP regions assigned as the controls.

We find that the outbreak of the civil war increased the probability of moderate or severe food insecurity by 38 percentage points. This is a substantial impact, but not surprising given the massive disruptions to livelihoods and services as well as the scale of the war. Our analysis of the granular conflict data in the ACLED database indicates that exposure to an additional battle leads to 1 percentage point increase in the probability of moderate to severe food insecurity. Some of the ultimate effects on food security are driven by disruptions in markets and supply chains, destruction of livelihoods and income losses while some may have simply been consequences of the suspension of public services (e.g., banking, telecommunication, electricity, and transport services). Specifically, we find that the outbreak of the civil war has dramatically reduced households' access and ability to buy food while also significantly disrupting livelihoods of households in conflict affected areas. Non-farm and wage related activities appear to be the most affected while farm activities were more resilient than other activities.[8] Similarly, economic activities in urban areas were much more affected than those in rural areas. This is partly because urban areas and main roads connecting towns continued to be heavily militarized even during periods of relative lull in high intensity active war. These suggest that the ultimate impacts of the violent conflict, in addition to curtailment of livelihoods, were likely mediated through disruptions in the functioning of markets and supply chains in urban areas. Tigray has continued to be disconnected from the rest of the country for several months after the last survey round, and it is likely that these impacts have deepened in subsequent months. Our findings support the urgent calls for large-scale humanitarian assistance that were made even at early stages of the conflict.

The rest of the paper is structured as follows. Section 2 describes the geographic and political context of this study and data used. Section 3 summarizes trends in welfare outcomes. Section 4 outlines the empirical strategy while Section 5 presents our results and discussion. In Section 6, we provide concluding remarks as well as general discussion of the value – and shortcomings – of high-frequency phone surveys for monitoring large-scale conflicts in other settings in the future, including the preparatory work that would be required to enable mobilization of such efforts.

2. Context and Data

2.1 Context

For over two decades, Ethiopia has been one of the world's fastest-growing economies and often nicknamed as the "hub of stability" in a volatile Horn of Africa region.[9] This changed drastically in early November 2020 when war broke out in Tigray, costing thousands of lives, inflicting massive humanitarian disasters and infrastructural damages. Initially, the war involved the Tigray regional forces, and an alliance of the federal army, regional forces from neighboring Amhara

[8] It is important to note that farmers in many instances continued to prepare their land when the rainy season approached in April to June 2021 often at a risk to their lives.

[9] Example, see the Atlantic Council, November 2021 (https://www.atlanticcouncil.org/content-series/fastthinking/fast-thinking-ethiopia-is-on-the-brink/).

(from the west) and Afar (from the east). The conflict escalated when neighboring Eritrean forces (from the north) joined the alliance led by the federal Ethiopian army. Banking, telephone, electricity, transport, and other basic services were suspended in most parts of the region immediately after the war broke out. Most of Tigray was directly affected by the war and quickly became inaccessible to humanitarian assistance. After weeks of intense fighting, the federal and allied forces took control of large swaths of Tigray, including the regional capital Mekelle at the end of November 2020, which continued until June 2021. After capturing the regional capital Mekelle, the federal government installed a provisional regional government in Tigray and some public services such as telecommunication and electricity services were restored, especially in those areas in full control of the federal army. Some humanitarian assistance resumed after the capture of the regional capital but most of these services discontinued after June 2021 when the federal army and the provisional regional government left the capital.

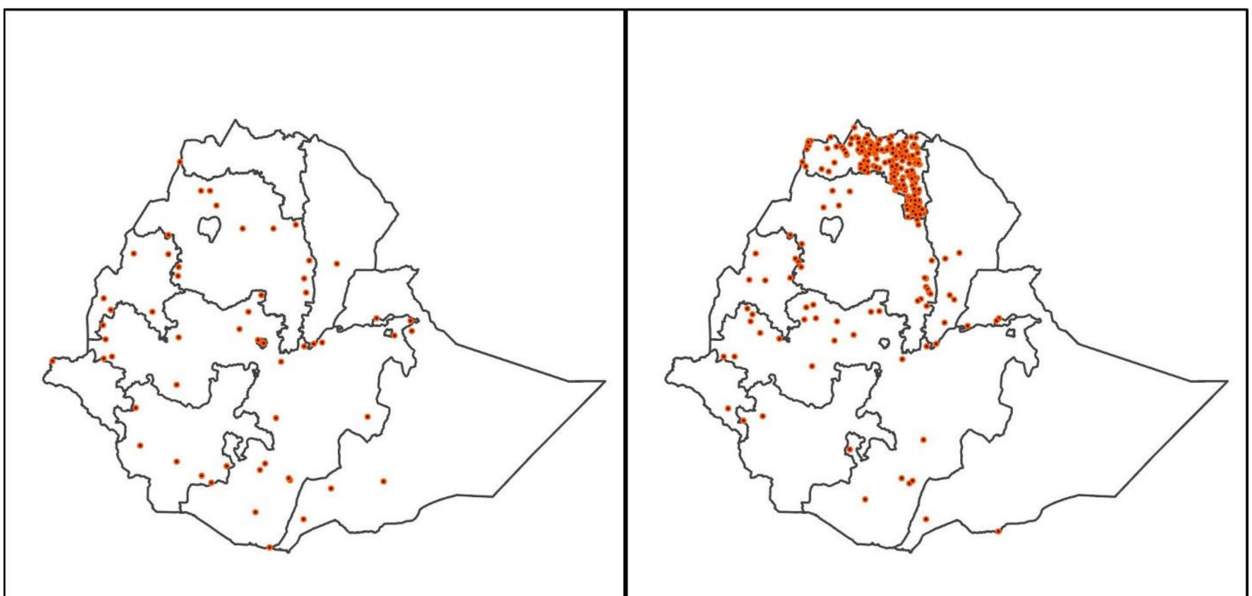
Internal displacements from several parts of Tigray swelled camps set up for internally displaced people (IDPs) in several towns, including the regional capital, Mekelle. While effects of the war remained largely unreported because of the restricted access to internet and telephone services, widespread disruptions, lootings, and civilian massacres were later confirmed, including by an investigation led by the Office of the United Nations High Commissioner for Human Rights (OHCHR).[10] The war has thus far, in addition to deaths and displacements, caused disruptions in livelihoods, loss of economic activity, and incomes to those exposed to it.

The conflict moved southwards into neighboring Amhara and Afar regions when the Ethiopian federal army and allied forces left Tigray in June 2021. As a result, the war subsided in some parts of Tigray but spilled over to neighboring Amhara and Afar regions.[11] The expansion of the war into neighboring Amhara and Afar regions have caused further economic and welfare damages in those regions. A recent assessment by the World Food Programme shows that “hunger has more than doubled” in the Amhara region during the immediate five months since the war expanded to the region (WFP, 2022). Thus far, the HFPS data cover the period until May 2021, forcing us to focus on impacts of the first phase of the civil conflict, which was confined to the Tigray region.

[10] https://www.ohchr.org/Documents/Countries/ET/OHCHR-EHRC-Tigray-Report.pdf
[11] However, Tigray remained without communication, electricity and banking services and a dire humanitarian crisis continues to unfold (WFP, 2022).

Figure 1 presents the distribution of violent conflicts, specifically battles, across all regions of Ethiopia before (August 2019-October 2020) and after the outbreak of the war (November 2020-May 2021). These figures are based on conflict event records in the Armed Conflict Location and Event Data (ACLED). Panel (a) shows that battles were sparsely and evenly distributed across regions before November 2020, except in Tigray where there were no major battles recorded during that time. Panel (b) confirms that during the November 2020 - May 2021 period, there was a dramatic spike in battle events, the vast majority of which were confined to Tigray, with little change in battle incidents elsewhere. This figure further highlights that these battles covered all parts of Tigray. This is not surprising given the number of actors in the war and battle fronts. In southern Tigray the armed conflict was between Tigray regional forces and the federal army and allied forces. In the north it was between Tigray regional forces and the Eritrean army. In western Tigray, the war involved the federal army (along with their allied Amhara regional forces and Eritrean army) and Tigray regional forces. Thus, most of Tigray was effectively an active war zone.

Figure 1: Spatial distribution of violent conflicts before and after the outbreak of the war



(a) Battles August 2019–October 2020

(b) Battles November 2020–May 2021

2.2 Data and Data Sources

We use the World Bank's HFPS data for Ethiopia, conducted between April 2020 and May 2021 to monitor the impacts of the COVID-19 pandemic (World Bank, 2020).[12] The phone survey sample is a subsample of households drawn from both urban and rural areas in all regions of Ethiopia surveyed face-to-face in the Living Standards Measurement Study - Integrated Survey on Agriculture (LSMS-ISA) in 2019. The 2019 LSMS-ISA Ethiopia data are nationally representative sample of 6,770 households. Of these, 5,374 (79.3 percent) reported phone ownership and were used as sampling frame for the phone survey in 2020. The actual sample size for the phone survey was set at 3,300 households of which 3,247 of them were successfully interviewed in the first phone survey in April 2020 (Wieser et al., 2020). These households were re-interviewed every 3-4 weeks, for eleven rounds, until May 2021, allowing high-frequency monitoring of changes in key outcomes of interest including labor market participation and food security. We combine the 2019 face-to-face survey data with these HFPS data.

The 2019 baseline data provide detailed characteristics of households, including GPS coordinates of household residence, which we used to merge these data with the ACLED database, which records conflict events at specific locations and which has been widely used to study the consequences of conflicts in different settings. The ACLED database provides event-based information for different types of conflicts, including battles, attacks against civilians, remote violence, and protests and riots. For our purpose, we focus on number of battles because the Ethiopian civil war that broke out on November 4, 2020, involved intensive battles. More than half of the incidents recorded by ACLED during our sample period (August 2019-May 2021) represent battles. We construct household-level measure of exposure to battles by counting the number of battles within a 10, 20, 30, 40 and 50 km radius around each survey household location. We compute cumulative number of battles in the previous months until the end of the survey month. Table A1 shows that the number of battles has tripled after November 2020.[13]

The HFPS sample continually declined in follow-up rounds due to non-response to calls and attrition. Further, the Tigray sample was especially affected by the war itself and disruptions in telecommunication services in the region, further reducing the sample to 1,982 households in

[12] World Bank. Ethiopia-COVID-19 High Frequency Phone Survey of Households 2020. Dataset downloaded from www.microdata.worldbank.org.
[13] Before November 2020, such events consisted of limited-scale armed conflicts between state police or armed forces and ethnic militias, typically reflecting localized political grievances.

May 2021 (Table A2). Our analysis is, therefore, based on the panel of households interviewed in the pre-war and post-war-onset phone surveys between April 2020 and May 2021 (Table A4). While the pre-pandemic (and pre-conflict) sample of the LSMS-ISA survey in Ethiopia is randomly selected from urban and rural households in each district, the follow-up phone surveys are subject to two levels of non-random selection issues. First, the phone sample may differ in systematic ways from the original 2019 sample, partly because of ownership of mobile phones may be correlated with wealth (see Table A4). Second, phone surveys in conflict hotspot areas are likely to suffer from pervasive non-response, partly because of inaccessibility and network problems. The likelihood of being contacted in the phone surveys is likely to be greater for those who are relatively better off economically, as well as those located in areas with better access to telecommunication services (due to better infrastructure or less destruction by the war). In line with this, Table A3 shows that sample attrition increases with the presence of armed conflicts because the response rate for all regions is higher than for Tigray. This can be explained by the disruption in telecommunication and electricity services in the region. As the war continued, telecommunication and electricity services were suspended or intermittent in areas under the control of the Tigray region government. In areas that came under the control of the federal government and provisional regional government in Tigray, telecommunication and electricity services were restored, which allowed access to some households by phone.

To account for these systematic non-responses in the phone surveys, we constructed inverse probability sampling weights which we used in our subsequent analysis. Our final sample consists of those households appearing (at least once) in the pre-war and post-war-onset phone survey rounds, implying that the weights need to be constructed considering attrition and non-responses in both phases.[14] We use a rich set of household and location characteristics collected in the 2019 survey to characterize and predict the (joint) probability of response in the pre-war and post-war-onset phone surveys using a logit model (see Table A3). We then construct sampling weights as the inverse of the predicted probability of responses in both pre-war and post-war-onset phone surveys. We note that applying the weights markedly reduces the differences between the unweighted and weighted mean differences in the observable characteristics sample (Table A4). In particular, Table A4 shows that applying the sampling weights makes observable characteristics

[14] Households appearing only either in the pre-war or post-war phone surveys were dropped from the analysis and assumed as nonresponses in constructing the sample weights.

of the phone survey sample comparable to the full sample. These weights were applied in all our analyses to address potential biases due to systematic sample attrition and non-response (Wooldridge, 2007; Korinek et al., 2007). Nonetheless, to the extent that our results fail to control for this bias, our results may be taken as lower bounds of the actual impacts of the conflict.

2.3 Measuring Key Outcomes

The paper focuses on three broad categories of outcomes that are observed both in the pre-war and post-war-onset phone surveys. These are: (i) the household food insecurity experience, (ii) Households' access to food markets, and (iii) participation in labor market and livelihood activities. The 2019 face-to-face survey collected a wealth of information on household food security, employment and labor market participation, consumption, and other socio-economic characteristics that serve as baseline for the phone surveys. The phone survey also covered these topics which are of interest in this study, particularly household food security and participation in various livelihood activities. Because phone surveys cover a few modules, the surveys implemented similar questionnaires across rounds but followed a modular approach – some modules were dropped, and others kept or added in different rounds. Thus, we observe food security and labor market outcome indicators across multiple pre-war and post-war-onset rounds but not necessarily across all twelve rounds.

Food Insecurity

Food insecurity is measured using the Food Insecurity Experience Scale (FIES), an experience-based food insecurity metric developed by the Food and Agriculture Organization (FAO) of the United Nations that is widely applied to measure prevalence of food insecurity (FAO, 2014a).[15] The FIES relies on respondent's direct responses to an eight-question survey module, referring to experiences of difficulties to access sufficient and nutritious food in the last 30 days. The FIES elicits responses based on whether the respondent or another household member (1) was *worried* about having enough food to eat, (2) ate only a *few kinds* of foods, (3) unable to eat *healthy* and nutritious foods, (4) *ate less* than should have eaten, (5) had *skipped* a meal, (6) *run out* of food, (7) was *hungry* but did not eat, and (8) went without eating for a *whole day*. A binary variable is coded for each question that takes the value of 1 if the answer is "yes" and zero if otherwise, and

[15] https://www.fao.org/in-action/voices-of-the-hungry/background/en/

these responses are used to construct various food insecurity indicators. An advantage of FIES is that it generates a direct composite estimate of food insecurity summarized from a set of easy-to-understand questions, convenient to include in high-frequency surveys. It, thus, allows comparability across time and space. This standard module was included in many of the high-frequency phone surveys, with reference period for the last 30 days preceding the survey date.

Based on the above FIES questions, we adopt two approaches to measure food insecurity. First, we use the raw values of the responses and associated "raw score" which we generate by summing the responses to the eight questions. The raw value of these responses assumes binary nature while the raw score assumes a value between zero and eight. By this definition, those households reporting experience of food insecurity across one or more of the eight dimensions are assumed to be facing food insecurity.

Second, data from this module is analyzed further, following procedures detailed by the FAO, to generate a food insecurity metric based on responses provided to each of the FIES questions (FAO, 2014b).[16] The analysis involves parameter estimation, statistical validation against global standards, and calculation of individual and population-level food insecurity prevalence rates.[17] For this purpose, we follow the following steps: First, we compile all binary responses for each of the eight FIES questions above (this requires specific ordering and naming of variables) along with appropriate weights. We retain this file and export it to .csv format. Second, we upload the .csv file to the FIES Shiny App: https://fies.shinyapps.io/ExtendedApp/, which is developed and managed by the FAO. Third, we follow the analyses, exclusion and inclusion steps described by FAO for generating respondent-level model-based food insecurity indicators. In particular, this analysis generates several important indicators of food insecurity, including: (i) raw score that is simply generated by adding the raw values of responses to the eight FIES questions, (ii) severity of food insecurity, an interval score ranging between zero and eight which is used to classify households' severity of food insecurity (into moderate or severe food insecurity) (FAO, 2014b).[18] (iii) probability of moderate or severe food insecurity, and (iv) probability of severe food insecurity. We finally downloaded and merged these indicators with our main sample.

[16] See detailed procedures and definitions at: https://www.fao.org/3/i7835e/i7835e.pdf
[17] See detailed procedures at: https://www.fao.org/3/ca9318en/ca9318en.pdf
[18] Details of the implementation procedures of this analysis are given in FAO, 2014a, 2014b and Josephson et al. (2020).

Based on these alternative approaches we end up with four sets of food insecurity indicators: (i) raw responses to each of the eight questions, (ii) raw score across the eight questions, (iii) a binary indicator of experience of moderate or severe food insecurity based on severity of food insecurity, and (iv) binary indicator of experience of food insecurity (assuming a value of 1 for those households with raw score above zero and 0 otherwise). Table 1 shows the weighted pooled summary statistics. Forty-five percent of households experienced moderate or severe food insecurity. These are comparable with other recent studies from Ethiopia and other African countries (e.g., Josephson et al., 2020). Sixty-four percent of households report experiencing at least one of the eight dimensions of food insecurity that constitute the FIES. Figure 2 (in Section 3) shows the temporal evolution of these outcomes across survey rounds as well as across conflict affected and unaffected regions.

Table 1: Summary of Food Insecurity Measures and Indicators

	Number of observations	Mean	Standard deviations
Moderate or severe food insecure	14,523	0.45	0.50
Food insecure	14,523	0.64	0.48
Raw FIES score	14,523	2.49	2.50
Worried	14,524	0.48	0.50
Healthy	14,524	0.51	0.50
Few Food	14,524	0.48	0.50
Skipped	14,524	0.29	0.45
AteLess	14,524	0.34	0.47
RunOut	17,196	0.21	0.41
Hungry	17,196	0.12	0.33
WhlDay	17,196	0.10	0.30

Notes: households' classification into moderate or severe insecurity follows the parametric analysis and procedure outlined by FAO and using the analytical tool: https://fies.shinyapps.io/ExtendedApp/. This tool categorizes households' food insecurity status based on severity of food insecurity experience. We construct the second binary indicator, which assumes a value of 1 for those households experiencing one or more form of food insecurity and 0 otherwise, based on the raw FIES score. The third indicator is constructed by adding raw responses to the eight FIES questions. Th remaining eight indicators come from responses to standard FIES questions on whether the respondent or household member (1) was *worried* about having enough food to eat, (2) ate only a *few kinds* of foods, (3) unable to eat *healthy* and nutritious foods, (4) *ate less* than should have eaten, (5) had *skipped* a meal, (6) *run out* of food, (7) was *hungry* but did not eat, and (8) went without eating for a *whole day*. Summary statistics are weighted using the sampling weight discussed above.

Households' Access to Food and Food Markets

Besides the ultimate food insecurity experience, the HFPS for Ethiopia elicited responses related to households' access to food and food markets. In particular, households were asked whether they were able to buy enough staple foods (e.g., *teff/injera*, wheat/bread, maize and cooking oil) in the previous week. These questions are important to capture households' physical access to and affordability of food, and allow us to investigate the ways through which the conflict may have impacted food systems and livelihoods. On the one hand, the outbreak of the war has directly affected access to food by impeding the functioning of markets, especially in conflict hotspot areas. On the other hand, the war curtailed livelihood activities, leading to reductions in income and hence rendering food unaffordable. Thus, the outbreak of the war is expected to directly impact the accessibility as well as affordability of food. Table A5 shows pooled summary statistics of these measures and proxies for accessibility and affordability of food and food markets.

Labor Market Participation

Both the 2019 face-to-face survey and the 2020–2021 phone surveys collected detailed household-level data on labor market participation in income-generating activities, including farming, non-farm family businesses, and wage employment. The labor market outcomes for the 2019 LSMS-ISA survey were mostly collected in August and hence we refer to the baseline data as August 2019 round. The data on households' participation in various livelihood activities are available for most rounds, but with slight differences across livelihood activities and rounds. First, the data on farming and non-farm activities are available for all rounds, but wage-related activities were dropped in some rounds (August 2020, February 2021, and May 2021) of the phone surveys. These wage-related data are available for two rounds after the outbreak of the war (December 2020 and January 2021), allowing us to assess labor market participation effects of the war in the immediate aftermath of the outbreak of the war. Second, there was a slight change in the reference period across rounds. In the August 2019 face-to-face survey collected the labor market participation information of household members in the last 7 days preceding the survey. But the reference period and framing of the questions were slightly changed during the phone surveys. Specifically, when the phone survey started in April 2020, respondents were asked to report on whether household members were able to perform farming and non-farm activities since the outbreak of the COVID-

19 pandemic (since March 2020).[19] In the follow-up phone surveys (starting from May 2020 to May 2021), the above labor market participation questions were asked referencing the time as since last call, which is approximately one month.[20] As far as these changes in reference period trigger similar implications across all regions, they will be captured by round dummies in our estimations.

We define three indicator variables for each of the major employment activities, taking a value of 1 if any member of the household participated in farming, non-farm own business, and wage employment, respectively, and 0 otherwise. We also generate an indicator variable for participation in any of these livelihood activities.[21] Figure 5 (in Section 3) provides temporally and spatially disaggregated trends in households' participation in these activities.

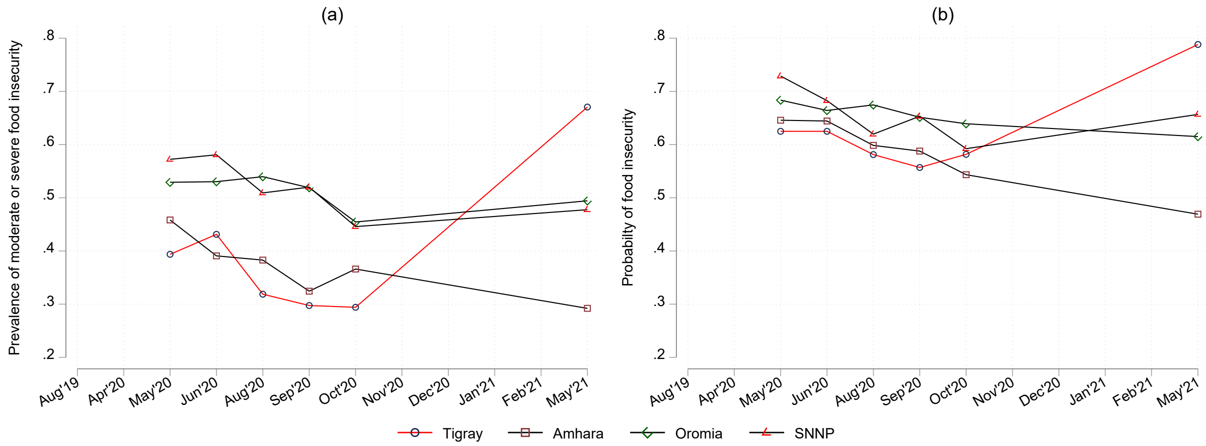
3. Descriptive Trends in Welfare Outcomes

3.1 Food Insecurity

We start by describing trends in household level aggregate food security outcomes. Figure 2 reports trends in overall prevalence of food insecurity across survey rounds and the four major highland regions in Ethiopia, Amhara, Oromia, SNNP and Tigray. The two measures of food insecurity, prevalence of moderate or severe food insecurity and probability of food insecurity, were constructed using the eight FIES questions as described in section 2.3. Panel (a) shows that prevalence of moderate or severe food insecurity (experienced during the previous month) more than doubled in Tigray after the outbreak of the civil war, jumping from about 30 percent during the immediate pre-war round to about 67 percent in May 2021. In comparison, food insecurity slightly declined in Amhara (from 37 percent to 29 percent) but slightly increased in Oromia and SNNP (from 45 percent to 49 percent, and from 45 percent to 48 percent, respectively).[22]

[19] For wage-related activities this continued to be one week (since last week).
[20] The specific labor market participation questions are: (i) since last call, did you or any member of your household work on a family farm growing crops or raising livestock? (ii) since last call, did you or any member of your household operate a non-farm family business?, and (iii) in the last week, were you able to do your wage/salary job as usual either from place of work or work from home?.
[21] It is thus important to note that our estimations on labor market participation aim to quantify the implications of the war at the extensive margins of the outcomes.
[22] Note that the war expanded to Amhara and Afar regions after late June 2021. This period is not covered by this study.

Figure 2: Trends in prevalence of food insecurity

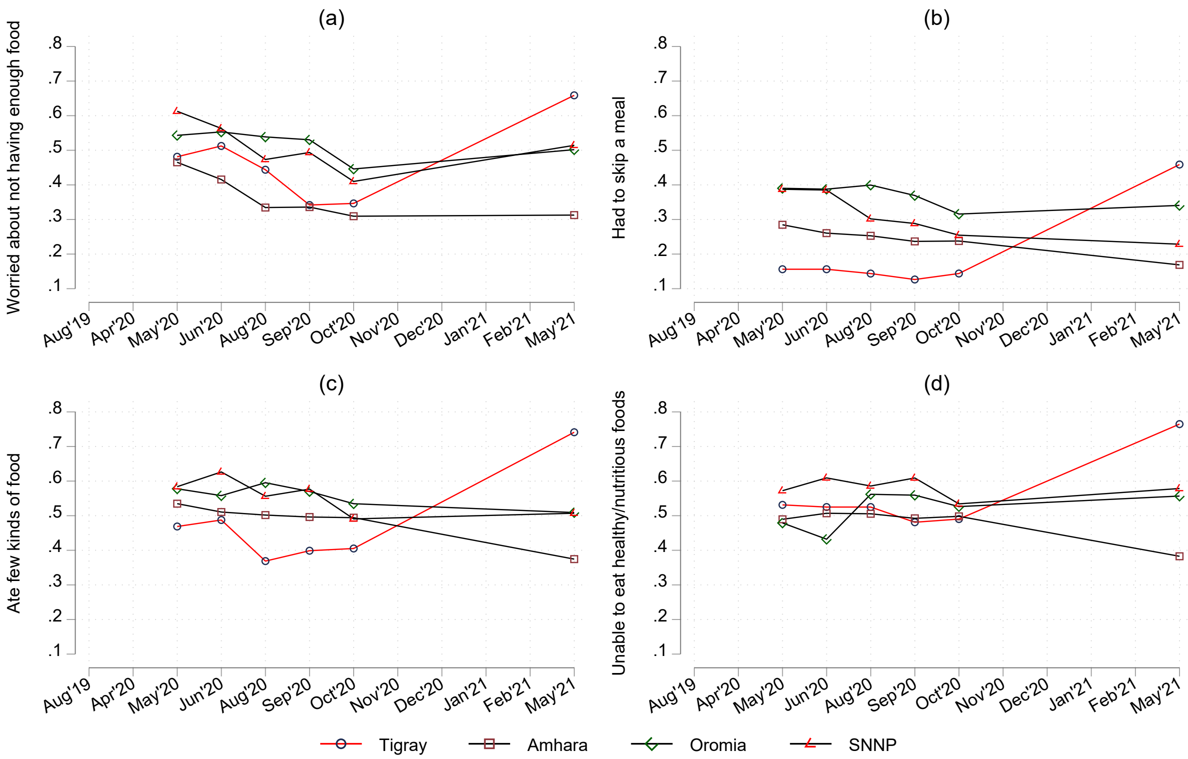


Similarly, panel (b) shows that the share of households experiencing food insecurity increased by 25 percentage points (from 55 percent to 80 percent). This is consistent with the recent assessment by the World Food Programme, which reports that 83 percent of people in Tigray are food insecure (WFP, 2022). On the other hand, trends in the other major regions remained relatively stable. To put these trends in context, immediately before the war, the trends in the overall prevalence of food insecurity were broadly comparable across regions (with similar trends in Tigray and Amhara), but by May 2021 the prevalence and probability of food insecurity sharply increased in Tigray while the corresponding trends for the other regions remained relatively stable.

Figure 3 further disaggregates the patterns of food insecurity experiences using some of the questions included in the FIES module. Panel (a) shows that the percentage of households who reported worrying about not having enough food during the previous 30 days. The figure remained reasonably stable between May 2020 and October 2020, after which the share increased from 41 percent to 65 percent in Tigray.[23] For the other regions, the corresponding trend remained stable.

[23] Compared to May 2020, there are 16 percent more households reporting being worried about having enough food.

Figure 3: Disaggregate Food Insecurity Experience



In panel (b), relative to the pre-war period, the share of households in Tigray who report having to skip a meal in the last 30 days has shown a sharp rise from 19 percent to 45 percent – an increase of 26 percentage points. Panel (c) shows the share of households who reported consuming fewer varieties of food. Compared to October 2020, the decline in food varieties consumed after the outbreak of the war is significantly higher in Tigray (increased from 44 percent to 73 percent) than in the other three regions. Panel (d) shows the percentage of households who reported not being able to consume healthy and nutritious foods. In Tigray, the figure jumped from 51 percent in October 2020 to 76 percent in May 2021. For the other regions, the corresponding figures changed little (51 percent in October 2020 and 50 percent in May 2021). Overall, the results shown in Figure 2 and 3, attest to the dramatic deterioration in food security in Tigray in the aftermath of the breakout of civil war in November 2020.

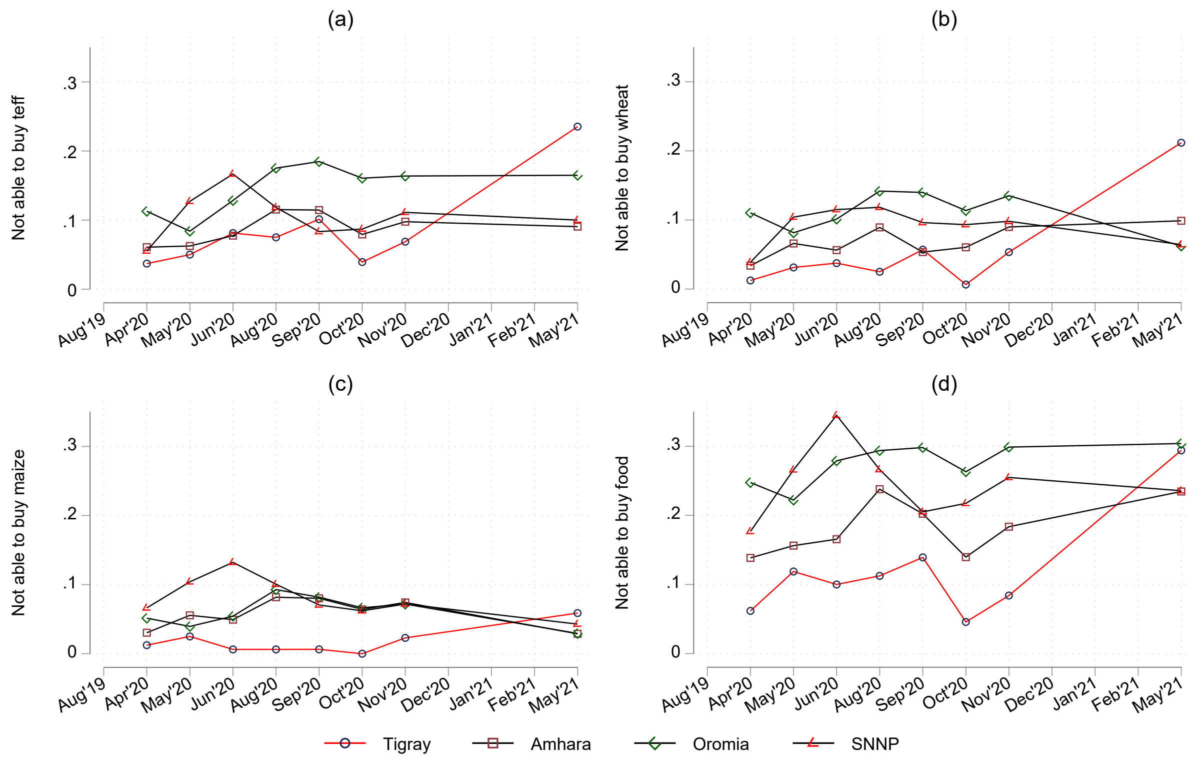
3.2 Access to Food and Food Markets

We next examine how food access and market functions have been affected by the conflict. Figure 4 presents the trends in households' ability to purchase staple food from the market. Panels (a)-(c) show temporal trends in households' ability to buy *teff*, wheat and maize in the four main highland regions of Ethiopia.[24] In all three panels, access to food markets remained stable for Amhara, Oromia and SNNP regions. The story is completely different for Tigray. Between October 2020 and May 2021, the share of households that reported not being able to purchase *teff* increased from 5 percent to 23 percent and the corresponding value for wheat increased from 2 percent to 21 percent while the change in ability to buy maize was much smaller. Households were asked to report major causes for their inability to buy these food items. The main reasons for households' inability to buy *teff* were increase in prices (61 percent) and decrease in incomes (37 percent). Likewise, among those who report not being able to buy wheat, increase in prices and decrease in incomes are the main reason for 51 percent and 44 percent of households, respectively.

Finally, panel (d) shows trends in broader access to food items. Prior to the start of the war, households in Tigray had slightly better access to food with the lowest share of households reporting inability to buy food among the major four regions. After the war broke out, this figure increased by 24 percentage points, from 5 percent in October 2020 to 29 percent in May 2021. The four panels in Figure 4 paint a grim picture of food access and affordability in Tigray following the outbreak of the war that also disrupted the overall value chains for these goods and services.

[24] *Teff* is the most grown and most important staple food in Ethiopia (Minten et al., 2018).

Figure 4: Access to food and food market

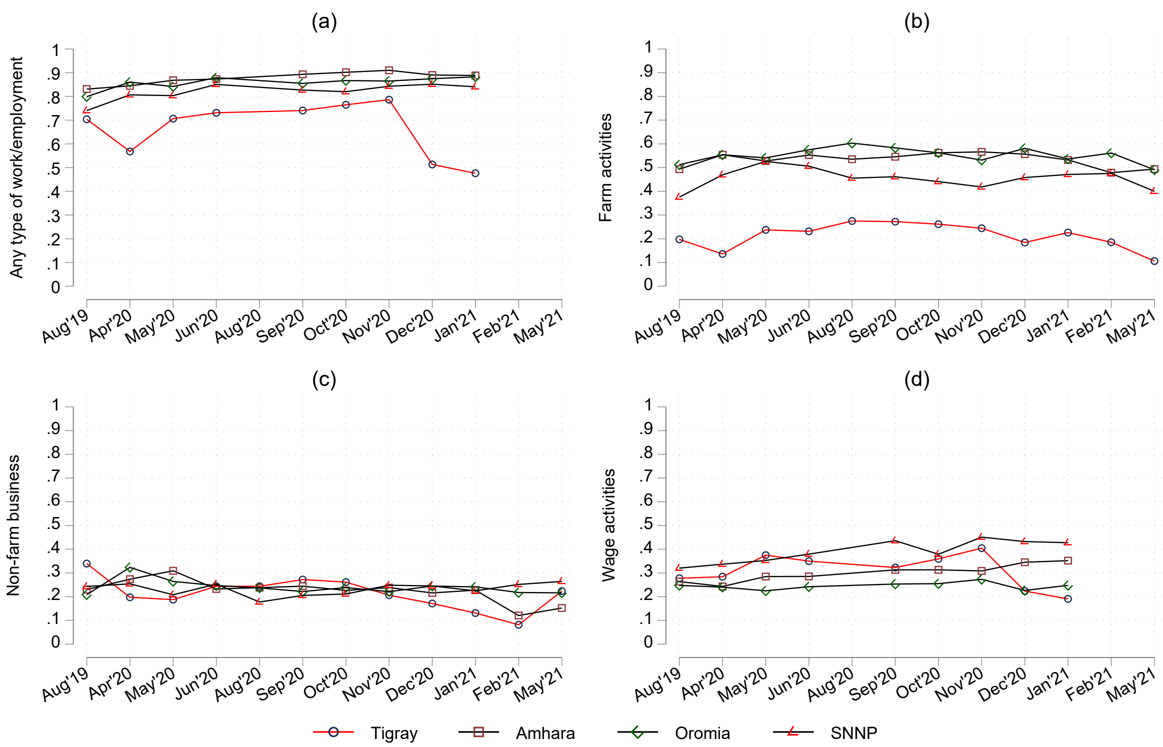


3.3 Labor Market Participation and Livelihoods

In this section, we discuss descriptive results on employment patterns of households between August 2019 and May 2021. Figure 5 presents temporal trends in overall employment and employment by activity type for the four weeks preceding survey interviews. Three important trends in these outcomes emerge. First, compared to the other regions, the proportion of households that participated in any economic activity was slightly lower in Tigray both before and after the war broke out. Second, the share of households who report engagement in non-farm and wage related activities in Tigray is comparable to the other three regions, while that of those who engage in farming is much less. Three, in the aftermath of the start of the war, there is a significant drop in participation in economic activities in Tigray compared to the other regions.

As shown in panel (a), the share of households that reported being engaged in any employment activity was stable in Amhara, Oromia and SNNP. In Tigray, on the other hand, the patterns of engagement in any activity dramatically changed at the start of the war in November 2020. 95 percent of the interviews for the November 2020 round were completed before the outbreak of the war (November 4). Thus, we do not expect uniformly dramatic declines in livelihood activities in the November 2020 round. However, the share of households participating in any activity in Tigray declined sharply from 78 percent in October 2020 to 48 percent in January 2021. Much of this decrease is associated with a concomitant decline in non-farm employment (panel (c)) and wage employment (panel (d)). The change in patterns of non-farm business activities appears slightly nuanced, however. After the war broke out, the share of households who report employment in non-farm business decreased from 29 in October 2020 to 8 percent in February 2021, before bouncing back to 23 percent in May 2021. In the other three regions, both non-farm employment and wage employment remained somewhat stable or increased. Farm activities are much more resilient. The share of households who engaged in farming activities in Tigray changed little immediately after the start of the war, though it decreased considerably in the May 2021 round (15 percentage points less than October 2020 levels).[25]

Figure 5: Trends in labor market participation



[25] When compared to the April/May 2020 levels, this drop is between 3 and 13 percentage points.

Much of the observed decline in labor market participation in Tigray was primarily driven by the sharp falls in employment in urban areas (see Figure A1 in the Appendix). The share of households who reported participation in any economic activity in urban areas of Tigray declined by 48 percentage points from 72 percent in October 2020 to 38 percent in January 2021. In rural areas, on the other hand, employment quickly recovered after a brief dip in November 2021 to their pre-war levels by January 2021. The latter is related to the return of farm families to cultivate their land albeit at a high security risk.

4. Empirical Strategy

The monthly nature of our data allows us to use alternative empirical strategies to identify the impact of the conflict on affected households. To evaluate the impact of conflict on food security and labor market outcomes, we employ three approaches. The first approach uses a standard Difference-in-Differences (DID) strategy to identify the aggregate impacts of the war by collapsing the months preceding and following the war into pre-war and post-war-onset periods. The second approach estimates disaggregated DID model where survey round dummies are interacted with region dummy variables. Third, we use the ACLED database to generate household-level and time-varying exposure to violent conflict and estimate two-way fixed effects model. We start with the following simple DID specification:

$$Y_{hrt} = \alpha_h + \alpha_1 Wartime_t + \alpha_2 Tigray_r \times Wartime_t + \alpha_3 X_{hrt} + \epsilon_{hrt} \quad (1)$$

where Y_{hrt} stands for a measure of food insecurity and labor market outcomes associated with household *h* living in region *r* observed in time *t* (pre- or post-war-onset). α_h stands for household-specific fixed effects. $Wartime_t$ stands for an indicator variable equal to 1 for the post-war-onset period, the period after November 2020, zero otherwise. We note that because the November 2020 round interviews were completed before the outbreak of the war, this round appears as pre-war. α_1 capture aggregate changes in labor market and food security outcomes including in the absence of the war. $Tigray_r$ represents an indicator variable for households living in Tigray region and hence those affected by the violent conflict. The first stage of the war, which lasted between November 2020 to June 2021 took place in Tigray and later expanded to neighboring regions of

Amhara and Afar in late June 2021.[26] Thus, Tigray is the region affected in the first phase of the war. The other regions in Ethiopia that were not affected by the first phase of the war serve as controls. We then relax this assumption using the granular data from ACLED and apply alternative definitions of control group to probe the robustness of our results. We also restrict this control sample to the three highland regions of Ethiopia (i.e., Amhara, Oromia, and SNNP) given their similarities to Tigray in both agroecological and livelihood contexts. As shown in Section 3, these regions share comparable trends in food security and participation in livelihood activities before the war. If the identifying parallel trends assumption holds in our context, the parameter associated with the interaction term, α_2, identifies the impact of the war on food security and labor market outcomes. ϵ_{hrt} is an error term and captures other unobservable factors that may affect food security and labor market outcomes.

Multiple pre- and post-war-onset round data allows us to estimate time-varying effects of the conflict and relax the assumption of homogenous and time-invariant treatment effects needed to identify the difference-in-difference parameters in equation (1) (de Chaisemartin and D'Haultfœuille, 2020; Goodman-Bacon, 2021). Moreover, multiple pre-war round data allow us to test the parallel trend assumption in the pre-war period. For these purposes, we also estimate an alternative DID specification with month-specific controls and outcomes:

$$Y_{hrm} = \alpha_h + \alpha_m + \sum_{m=1}^{M1} \delta_m \, Tigray_r \times \mathbb{1}(D = m) + \sum_{m=M1+1}^{M2} \gamma_m \, Tigray_r \times \mathbb{1}(D = m) + \varepsilon_{hrm} \qquad (2)$$

where Y_{hrm} is a measure of food insecurity and labor market outcomes associated with household h living in region r observed in month m, α_h represents household-specific fixed effects, and α_m is a vector of month or round dummies. Pre-war survey rounds range from 1 to *M1* while post-war-onset rounds range from *M+1* to *M2*. The third (interaction) term in equation (2) captures Tigray specific pre-war trends and hence the parameters associated with this term serve us to indirectly test the parallel trend assumption. The fourth (interaction) term in equation (2) captures Tigray specific trends immediately after the outbreak of the war in November 2020, and the parameters associated with this term identify the impacts of the war on labor market and food

[26] Because the conflict spilled over to other regions after June 2021 in ways that are difficult to relate to the administrative area codes observed in our data, we limit our study to the period in which the conflict was within Tigray.

security outcomes. The key parameters of interest are thus stacked in γ_m, the interaction effects of being from the affected region and the post-war-onset month dummies. As we are following households for several months, unobserved effects (error terms) can be correlated across time as well as across households living in the same district. Hence, we cluster standard errors at district (*woreda*) level. We also consider alternative definitions of conflict exposure and control group assignments as defined above. Thus, we estimate Equations (1) and (2) for the full sample as well as for a restricted sample consisting of households from the highland regions of Ethiopia.

As noted above, the first two approaches consider Tigray as the treatment region and the rest of the country as a comparison group. This assumes all survey households from Tigray have been affected by the war. Given the depth and breadth of the conflict, this is a reasonable working assumption. It is possible, however, that some survey households were completely immune from impacts of the war. With exposure to war so defined, our estimates measure intention to treat (ITT) impacts. If households who were not affected by the conflict were rather erroneously considered to have been impacted by it, these estimates would be smaller than the average treatment effect (ATE) of the war.

We generate more granular measures of exposure to violent conflict using ACLED's battle events recorded between August 2019 and May 2021, which coincides with our pre-war and post-war-onset HFPS data. Given the intensity of conflict, exposure is computed by counting the number of battles that took place within 20 and 30 km radius around the homestead of households. These allow us to identify the potential heterogeneities in impacts associated with the intensity of exposure to battles. It also serves to probe the robustness of our main results. We estimate the following specifications:

$$Y_{hrt} = \alpha_h + \alpha_m + \varphi_1 Battles_{hrt} + \omega_{hrt} \tag{3}$$

where $Battles_{hrt}$ stands for the cumulative number battles experienced within 20 km or 30 km radius from households' residence. All other terms are as defined before.

Unlike the coarse measure of exposure to conflict in the two DID approaches, which is based on region of residence at the time survey, the granular measures of exposure defined on the basis of distance between location of battle events and households' residence is less likely to suffer from misclassification of households into affected and comparison. More specifically, it is highly likely that battles that take place close to a household's residence would affect its food security and livelihoods. Given these are not exact measures of exposure at the household level, our estimates are still technically ITT. However, we argue that for the short distance buffers based on which exposure is defined, it is unlikely that these ITT estimates differ much from ATE.

Despite these alternative probing specifications our analysis is constrained by some remaining shortcomings, which merit discussion. First, while the pre-conflict (pre-pandemic) sample of the LSMS-ISA in Ethiopia is randomly selected from urban and rural households in each district, the follow-up phone surveys are prone to systematic non-response and attrition. To account for these systematic non-responses in the phone survey, we construct and employ sampling weights as discussed in Section 2. These sampling weights can help to recover appropriate and representative statistics if the observable characteristics we use to construct our weights sufficiently capture these systematic non-responses and attrition (Wooldridge, 2007; Korinek et al., 2007). To the extent that they fail to control for this bias, our results may be taken as a lower bound of the actual impacts of the conflict. A final issue is the potential uncertainty related to the impact of COVID-19 related economic restrictions, which may interact with the effects of the war. Most mobility restrictions and pandemic-related policies in Ethiopia had been relaxed long before the outbreak of the war. In the worst case, our maintained assumption is that these are additive effects which may be captured by the time dummies or household fixed effects. However, it is possible that violent conflict largely substitutes for economic restrictions. If this is the case, then we might worry that economic or mobility restrictions are only imposed (or enforced) in areas not affected by the war. In such a case, our estimates are also lower bound estimates of the actual effects of the conflict.

5. Results and Discussion

In this section, we present three sets of results based on the approaches outlined in Section 4: DID, disaggregated DID and ACLED-based results. In all our estimations, we apply the sampling weights constructed using the procedure described in Section 2.[27]

[27] We estimated both weighted and unweighted regressions for each outcome variable. However, there is little difference between the weighted and unweighted results, suggesting that our results are robust to applying sampling weights. Thus, we present results based on the weighted regressions and the unweighted results are available upon request.

5.1 DID Results

The first set of results focus on three aggregate food insecurity measures constructed from FIES questions – prevalence of moderate or severe food insecurity, probability of being food insecure and raw food insecurity score (Table 2). The coefficients in the first row of Table 2 show that there was no significant change in the overall food security of households outside of Tigray after the outbreak of the war. This is not surprising, given the war was confined to the Tigray region in the study period. Our key coefficient of interest is the interaction term of wartime dummy and the dummy variable for Tigray region. The results in column 1 show, in contrast to the trend in the other regions, the prevalence of moderate and severe food insecurity increased dramatically in Tigray in the post-war-onset period. The conflict led to 38 percentage points increase in moderate or severe food insecurity in Tigray. This amounts to 106 percent increase, relative to the prevalence rate in the pre-war period. Column 2 presents similar results for the probability of being food insecure. Compared to the pre-war period, the incidence of food insecurity in Tigray is 26 percentage points higher, which is a 47 percent increase from the pre-war level. In column 3, we show regression results for the raw food insecurity index calculated from FIES questions. The results are consistent with those obtained for the other two aggregate food insecurity measures. In Tigray, the war has led to 1.6 units increase in the number of dimensions of food insecurity reported by households. These large effects are plausible given the massive humanitarian crises the war has caused in the region (see WFP, 2022).

Table 2: The Impact of violent conflict on aggregate measures of food insecurity

	(1) Moderate or severe food insecurity	(2) Food insecure	(3) Raw score
Wartime dummy	-0.014	-0.025	-0.073
	(0.017)	(0.015)	(0.106)
Tigray × Wartime dummy	0.384***	0.261***	1.607***
	(0.052)	(0.033)	(0.236)
Household fixed effects	Yes	Yes	Yes
R-squared	0.008	0.004	0.007
Mean dep. var (pre-war)	0.361	0.557	2.054
No. observations	14523	14523	14523

Notes: The outcome variable in the first column stands for a binary indicator assuming a value of 1 for those households classified as moderate or severe food insecure based on the severity of food insecurity generated from the eight FIES questions. The dependent variable in the second column stands for binary indicator assuming a value 1 for those households experiencing one or more types of food insecurity and 0 otherwise. The outcome variable in the last column stands for raw sum of the responses to the eight FIES questions. All estimations use sampling weights to capture systematic non-response and attrition in phone surveys. Standard errors, clustered at district (woreda) level, are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Next, we study the impacts on the eight FIES variables that constitute the aggregate indices shown in Table 2. We find that the war increased households' experience of alternative forms of food insecurity (Table 3). For example, the conflict increased the share of households who skipped meals by 39 percentage points and those who reduced food consumption by 36 percentage points. It also increased the share of households who reported being worried about lack of food by 25 percentage points. The number of households who were unable to eat healthy/nutritious foods increased by 34 percentage points. We find no impact on the outcomes in columns 6-8, although some of these coefficients turn out to be statistically significant in our disaggregated DID estimations (see Section 5.2).

Table 3: The Impact of violent conflict on experience of food insecurity

	(1) Worried not enough food	(2) Unable to eat healthy foods	(3) Ate few kinds of food	(4) Skipped meal	(5) Ate less food	(6) Run out of food	(7) Hungry but did not eat	(8) Didn't eat all day
Wartime dummy	-0.004	0.001	0.003	-0.049***	-0.053***	-0.011	-0.015	0.005
	(0.015)	(0.018)	(0.021)	(0.015)	(0.019)	(0.022)	(0.019)	(0.020)
Tigray × Wartime dummy	0.251***	0.344***	0.343***	0.388***	0.364***	-0.025	0.046	-0.041
	(0.047)	(0.055)	(0.051)	(0.081)	(0.087)	(0.036)	(0.040)	(0.044)
Household fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.003	0.006	0.006	0.010	0.008	0.000	0.000	0.000
Mean dep. var (pre-war)	0.387	0.429	0.427	0.221	0.287	0.183	0.098	0.062
No. observations	14524	14524	14524	14524	14524	17196	17196	17196

Notes: the outcome variables in this table are raw responses to standard FIES questions on whether the respondent or household member (1) was *worried* about having enough food to eat, (2) ate only a *few kinds* of foods, (3) unable to eat *healthy* and nutritious foods, (4) *ate less* than should have eaten, (5) had *skipped* a meal, (6) *run out* of food, (7) was *hungry* but did not eat, (8) went without eating for a *whole day*. All estimations use sampling weights to capture systematic non-response and attrition in phone surveys. Standard errors, clustered at district (woreda) level, are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4 presents the impacts of the war on access to food as measured by households' ability to purchase a variety of foods. In columns 1-4, we show results for commonly consumed staples and oil followed by results for more broadly defined access to food in column 5. Columns 1-3 show that the war led to 30, 24 and 5 percentage points increase in households' inability to buy *teff*, wheat and maize, respectively. These are large impacts.[28] The dramatic deterioration in access to staples in a short amount of time reflects one of the key aspects of the war – the blockade of trade between Tigray and the rest of the country. Note that these are net impacts and combine the effects due to unavailability of these staples on the market as well as reduced purchasing power of households due to lost income and increase in the prices of these staples. In fact, as discussed in Section 3.2, most households report that increase in prices, due perhaps supply shortages, and reduction in incomes are the main reasons for their inability to purchase *teff* and wheat. We do not find statistically significant effect on households' ability to purchase oil – although the coefficient is relatively large, it is imprecisely estimated. In column 5, we find similar detrimental impacts of the war on broader access to food. In the aftermath of the war, the share of households who report being unable to buy food (either of the staples in columns 1-4) increased by 26 percentage points, approximately a 159 percent increase relative to pre-war national levels.

Table 4: The Impact of violent conflict on households' access to food and market

	(1) Unable to buy teff	(2) Unable to buy wheat	(3) Unable to buy maize	(4) Unable to buy oil	(5) Unable to buy food
Wartime dummy	-0.027	0.038^{**}	0.002	0.060^{***}	0.048^{**}
	(0.017)	(0.019)	(0.011)	(0.020)	(0.020)
Tigray × Wartime dummy	0.301^{***}	0.236^{**}	0.047^{*}	0.136	0.261^{***}
	(0.095)	(0.100)	(0.028)	(0.101)	(0.095)
Household fixed effect	Yes	Yes	Yes	Yes	Yes
R-squared	0.006	0.007	0.000	0.005	0.006
Mean dep. var (pre-war)	0.082	0.064	0.037	0.103	0.164
No. observations	19495	19495	19495	19495	19495

Notes: the outcome variables in this table come from a series of questions eliciting whether a household was not able to buy each of the above staple foods. All estimations use sampling weights to capture systematic non-response and attrition in phone surveys. Standard errors, clustered at district (woreda) level, are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5 reports the impacts of the violent conflict on livelihood activities, mainly overall labor market participation of households and participation in farm, non-farm business and wage employment. The war disrupted households' overall labor market participation in Tigray, with engagement in any activity down by 10 percentage points after the war broke out. Besides the overall impact on livelihoods, sectoral differences in the resilience of different sectors are evident.

[28] Compared to the pre-war period for the full sample, these amount to 367, 269 and 127 percent increase in inability to buy teff, wheat and maize, respectively.

As shown in columns 3 and 4, the war caused 10 and 15 percentage points decline in non-farm business activities and wage related activities, respectively. On the contrary, participation in farm employment increased by a modest 3 percentage points (10 percent). These findings appear to suggest that as the war led to wide-ranging economic decline in Tigray, and especially in urban centers where non-farm business and wage employment are concentrated, households have increasingly found economic refuge in farm activities. This might be because battles mainly took place in areas around the main highways in the region, where incidentally all larger urban centers are located. Thus, precipitating displacement of livelihood activities from non-farm to farm based modes. These developments may have lasting dire implications to the slowly evolving structural transformation that was taking shape. This potential undoing of achievements of the last two decades in gradually reducing the share of agriculture in GDP and employment is likely to set the region back decades.

Table 5: The Impact of violent conflict on labor market and livelihood activities

	(1) Any activity	(2) Farm activity	(3) Non-farm business	(4) Wage related activities
Wartime dummy	0.016	-0.031***	-0.013*	0.020***
	(0.010)	(0.007)	(0.008)	(0.008)
Tigray × Wartime dummy	-0.101*	0.032*	-0.097***	-0.151***
	(0.057)	(0.018)	(0.025)	(0.029)
Household fixed effect	Yes	Yes	Yes	Yes
R-squared	0.001	0.003	0.002	0.003
Mean dep. var (pre-war)	0.801	0.313	0.241	0.417
No. observations	21940	28558	28558	21940

Notes: The outcome variable in the first column is a dummy variable for participation in any economic activity. The variables in columns 2-4 are binary indicators assuming a value of 1 for those households participating in these activities. All estimations use sampling weights to capture systematic non-response and attrition in phone surveys. Standard errors, clustered at district (woreda) level, are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.2 Disaggregated DID Results

The availability of multiple pre- and post-war-onset survey rounds enables estimation of a more disaggregated DID model using round dummies instead of before and after dummies. This uncovers potential temporal heterogeneities in the impact of the conflict while also allowing testing pre-war trends in food security and labor market outcomes. Table 6 provides estimates of disaggregated impacts of the conflict on overall food insecurity. The full set of FIES questions were first introduced in the May 2020 round, dropped in rounds 8-11, and then reintroduced in round 12 (May 2021). Thus, in Table 6, the third round serves as a base period and round 12 as the post-war-onset period. The key measure of the impact of the war on food security outcomes is thus the interaction term of round 12 and the Tigray dummy.

Relative to the base period, food insecurity has been declining in most of Ethiopia. Prior to the outbreak of the war, the overall trends in food security outcomes had been similar across Tigray and the rest of Ethiopia, as shown by the statistically insignificant time trends in Table 6. More specifically, the coefficients associated with the interaction terms between the Tigray dummy and pre-war survey rounds confirm that the parallel trend assumption holds for almost all cases. However, after the outbreak of the war, Tigray experienced a statistically differential trend in food security. Compared to the May 2020 round, households in Tigray reported 37 percentage points higher probability of experiencing moderate or severe food insecurity in the May 2021 round. This is almost identical to the aggregate results discussed in Section 5.1, despite the different base (pre-war) outcome to which this is compared. Similarly, households from Tigray report 20-22 percentage points higher probability of experiencing food insecurity after the outbreak of the war.

Table 6: Impact of violent conflict on aggregate measures of food insecurity: disaggregated results

	(1) Moderate or severe food insecurity	(2) Food insecurity	(3) Raw score
Round 4	-0.017	-0.009	-0.217***
	(0.013)	(0.013)	(0.074)
Round 5	-0.038***	-0.036**	-0.258***
	(0.015)	(0.016)	(0.076)
Round 6	-0.068***	-0.028	-0.364***
	(0.018)	(0.018)	(0.102)
Round 7	-0.107***	-0.072***	-0.589***
	(0.020)	(0.020)	(0.115)
Round 12	-0.059***	-0.053***	-0.351***
	(0.020)	(0.019)	(0.124)
Round 4 × Tigray	0.039	-0.050	0.104
	(0.074)	(0.066)	(0.297)
Round 5 × Tigray	-0.082	-0.080	-0.390*
	(0.063)	(0.054)	(0.228)
Round 6 × Tigray	-0.072	-0.129**	-0.450**
	(0.057)	(0.058)	(0.192)
Round 7 × Tigray	0.026	-0.037	0.036
	(0.078)	(0.054)	(0.269)
Round 12 × Tigray	0.366***	0.202***	1.464***
	(0.070)	(0.043)	(0.312)
Household fixed effects	Yes	Yes	Yes
R-squared	0.023	0.011	0.025
Mean dep. var (pre-war)	0.361	0.557	2.054
No. observations	14523	14523	14523

Notes: The outcome variable in the first column stands for a binary indicator assuming a value of 1 for those households classified as moderate or severe food insecure based on the severity of food insecurity generated from the eight FIES questions. The dependent variable in the second and third columns stand for binary indicator assuming a value 1 for those households whose probability of facing food insecurity is above 0 and 0 otherwise. The outcomes variable in the last column stands for raw sum of the responses to the eight FIES questions. All estimations use sampling weights to capture systematic non-response and attrition in phone surveys. Standard errors, clustered at district (woreda) level, are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7 provides disaggregated results using responses to the eight FIES questions separately. Besides uncovering the statistically indistinguishable pre-war trends in food insecurity experience between Tigray and the rest of the country, the results in Table 7 confirm the main results in Table 3. The coefficients of the year dummies show the generally improving food security situation. The coefficients of the interaction terms between pre-war round dummies and Tigray establish the overall statistically similar trend between Tigray and the other regions of Ethiopia. A clear divergent trend emerges in Tigray in the post-war-onset period as evidenced by the coefficients of Round 12 × Tigray. In fact, despite the different pre-war comparison period, the impact sizes for these disaggregated estimates are almost identical to those based on aggregated time window (Table 3). The only exceptions are the results in columns 7 and 8 for which the aggregate impacts are statistically insignificant, but the disaggregated estimations result in positive effects.[29]

Table 7: Impact of violent conflict on experience of food insecurity: disaggregated results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Worried not enough food	Unable to eat healthy foods	Ate few kinds of food	Skipped meal	Ate less food	Ran out of food	Hungry but did not eat	Did not eat all day
Round 4	-0.014	-0.008	0.008	-0.009	-0.011	-0.018	-0.088***	-0.045***
	(0.010)	(0.012)	(0.011)	(0.011)	(0.010)	(0.012)	(0.012)	(0.011)
Round 5	-0.064***	0.045**	0.035**	-0.031***	-0.059***	0.001	-0.084***	-0.049***
	(0.011)	(0.017)	(0.017)	(0.010)	(0.011)	(0.012)	(0.012)	(0.010)
Round 6	-0.069***	0.049***	0.030*	-0.053***	-0.067***	-0.013	-0.073***	-0.047***
	(0.012)	(0.016)	(0.017)	(0.011)	(0.014)	(0.013)	(0.013)	(0.010)
Round 7	-0.114***	0.006	-0.016	-0.077***	-0.090***	-0.016	-0.079***	-0.053***
	(0.012)	(0.015)	(0.018)	(0.011)	(0.015)	(0.013)	(0.013)	(0.011)
Round 12	-0.039**	0.037**	-0.010	-0.074***	-0.088***	-0.019	-0.088***	-0.042***
	(0.016)	(0.017)	(0.022)	(0.012)	(0.017)	(0.015)	(0.013)	(0.011)
Round 4 × Tigray	0.045	0.002	0.010	0.008	0.010	0.043	0.045	0.070***
	(0.045)	(0.037)	(0.041)	(0.035)	(0.034)	(0.027)	(0.029)	(0.019)
Round 5 × Tigray	0.030	-0.047	-0.133**	0.018	0.002	-0.038	0.047	0.056***
	(0.050)	(0.048)	(0.052)	(0.038)	(0.031)	(0.029)	(0.031)	(0.017)
Round 6 × Tigray	-0.071	-0.101**	-0.101**	0.023	-0.014	-0.022	0.039	0.062***
	(0.050)	(0.048)	(0.051)	(0.043)	(0.036)	(0.020)	(0.025)	(0.018)
Round 7 × Tigray	-0.021	-0.044	-0.043	0.068**	0.016	0.017	0.048*	0.071***
	(0.055)	(0.056)	(0.044)	(0.029)	(0.030)	(0.023)	(0.027)	(0.015)
Round 12 × Tigray	0.223***	0.238***	0.318***	0.383***	0.304***	0.007	0.074**	0.064**
	(0.053)	(0.053)	(0.063)	(0.098)	(0.092)	(0.032)	(0.031)	(0.026)
Household fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.019	0.009	0.009	0.018	0.017	0.002	0.017	0.008
Mean dep. var (pre-war)	0.387	0.429	0.427	0.221	0.287	0.183	0.098	0.062
No. observations	14691	14691	14691	14691	14691	17396	17396	17396

Notes: the outcome variables in this table are raw responses to standard FIES questions on whether the respondent or household member (1) was *worried* about having enough food to eat, (2) ate only a *few kinds* of foods, (3) unable to

[29] These may be due to prevalent differences in trends between respondents from Tigray and the rest of the country. For some of these outcomes, the interaction terms between the pre-war round dummies and Tigray indicator dummy are significant, suggesting a potentially greater number of households reporting that they did not eat all day in Tigray before the start of the war.

eat *healthy* and nutritious foods, (4) *ate less* than should have eaten, (5) had *skipped* a meal, (6) *run out* of food, (7) was *hungry* but did not eat, (8) went without eating for a *whole day*. All estimations use sampling weights to capture systematic non-response and attrition in phone surveys. Standard errors, clustered at district (woreda) level, are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Finally, Table 8 presents the disaggregated DID estimates for labor market and livelihood outcomes. We use data from rounds 1-10 of the surveys for this analysis, where rounds 1-8 represent the pre-war and rounds 9-10 represent the post-war-onset periods. Again, these results confirm that pre-war trends of participation in various labor market and livelihood activities are generally statistically similar trends across households affected and unaffected by the armed conflict, as evidenced by the coefficients of the interaction between Round 2 – Round 8 dummies and the indicator for Tigray region. Furthermore, immediately after the outbreak of the war households from Tigray experienced a significant reduction in economic activities, with the war reducing participation in any economic activity by 20 - 21 percentage points.

However, the impacts vary by type of livelihood activity. Relative to the baseline, households from Tigray experienced 20 - 22 percentage point reduction in participation in non-farm business activities in the aftermath of outbreak of the armed conflict (December 2020 and January 2021). Similarly, war-affected households reported 19 - 20 percentage point reduction in participation in wage-related activities in the first two months after the outbreak of the conflict.[30] The sizes of these impacts are comparable to the aggregated results in Table 5. Consistent with the aggregated results in Table 5, farm activities, however, appear to be unaffected. These findings are intuitive because relative to smallholder farming, the war has led to massive destruction of business enterprises, infrastructure, and disruptions of major public services (electricity, telephone, banking and transport services), which are essential sources of these activities. This is consistent with evolving evidence that agriculture in general and smallholder farming activities can be resilient to covariate shocks such as armed conflict and pandemic. For example, some recent macro and micro-level studies show that farming activities are relatively resilient to the COVID-19 pandemic and associated mobility restrictions (e.g., Amare et al., 2021; Josephson et al., 2021; Khamis et al., 2021).

[30] We note that the parallel trends assumption does not appear to hold for non-farm activities, with pre-war trends in Tigray indicating an already deteriorating environment. This may have to do with an increasingly worsening security situation on highways leading to Tigray with vigilante groups reportedly confiscating goods being transported to Tigray through Amhara region prior to the start of the war in November 2020.

Table 8: The Impact of violent conflict on labor market and livelihood activities

	(1)	(2)	(3)	(4)
	Any activity	Farm activity	Non-farm business	Wage related activities
Round 2	0.049**	0.041**	0.057***	0.067***
	(0.021)	(0.019)	(0.020)	(0.023)
Round 3	0.053**	0.068***	0.033*	0.049**
	(0.025)	(0.018)	(0.019)	(0.023)
Round 4	0.087***	0.084***	0.022	0.045**
	(0.021)	(0.018)	(0.020)	(0.022)
Round 6	0.081***	0.062***	0.008	0.057***
	(0.020)	(0.017)	(0.017)	(0.019)
Round 7	0.086***	0.055***	0.016	0.063***
	(0.020)	(0.015)	(0.019)	(0.017)
Round 8	0.080***	0.041**	0.011	0.077***
	(0.021)	(0.017)	(0.018)	(0.022)
Round 9	0.071***	0.036**	0.022	0.070***
	(0.023)	(0.017)	(0.017)	(0.021)
Round 10	0.083***	0.034**	0.025	0.072***
	(0.021)	(0.017)	(0.017)	(0.021)
Round 2 × Tigray	-0.294***	-0.219***	-0.184***	-0.102
	(0.083)	(0.072)	(0.060)	(0.075)
Round 3 × Tigray	-0.094	-0.047	-0.170***	-0.031
	(0.058)	(0.030)	(0.062)	(0.082)
Round 4 × Tigray	-0.112*	-0.073**	-0.112	-0.038
	(0.062)	(0.034)	(0.079)	(0.080)
Round 6 × Tigray	-0.066	-0.005	-0.058	-0.066
	(0.047)	(0.028)	(0.080)	(0.080)
Round 7 × Tigray	-0.060	0.002	-0.115*	-0.053
	(0.047)	(0.028)	(0.059)	(0.074)
Round 8 × Tigray	-0.079	-0.020	-0.180***	-0.026
	(0.058)	(0.034)	(0.060)	(0.078)
Round 9 × Tigray	-0.197***	0.016	-0.200***	-0.193***
	(0.062)	(0.028)	(0.052)	(0.067)
Round 10 × Tigray	-0.210***	0.044	-0.219***	-0.202***
	(0.070)	(0.034)	(0.056)	(0.062)
Household fixed effect	Yes	Yes	Yes	Yes
R-squared	0.001	0.003	0.002	0.003
Mean dep. var (pre-war)	0.801	0.313	0.241	0.417
No. observations	21940	28558	28558	21940

Notes: The outcome variable in the first two columns is a dummy variable for participation in any economic activity. The variables in columns 3-8 are binary indicators assuming a value of 1 for those households participating in these activities. All estimations use sampling weights to capture systematic non-response and attrition in phone surveys. Standard errors, clustered at district (woreda) level, are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.3 Results Based on ACLED Data

We triangulate our results based on interaction between post-war-onset dummies and the war-affected region dummy by running the same set of outcome variables on exposure to battles that took place within 20 km and 30 km of the household's' residence. More specifically, we compute the cumulative number of battles that have taken place within 20 km and 30 km radius of the residence of households prior to each survey round.[31] We chose a buffer of 20 km and 30 km distance to ensure that battles are close enough to have impacts on our outcome variables. The coefficients on these variables measure the effect of exposure to an additional battle event on household food security and labor market outcomes.

Table 9 presents the impact of battles that occurred within 20 and 30 km distance from households' residence on food insecurity. For all three measures, exposure to battles leads to an increase in food insecurity. Exposure to an additional battle within 20 km of residence increases moderate or severe food insecurity and probability of food insecurity by 1 percentage point each. Likewise, battles within 30 km of residence have similar negative impact on food insecurity, though the impacts are slightly smaller. We experimented with varying battle distances from residence, including 10, 20, 30, 40 and 50 km radius. We find that the impact of exposure to battles increase the closer the battles get to the household residence.[32]

Table 9: Number of battles and food security

	(1)	(2)	(3)	(4)	(5)	(6)
	Moderate or severe food insecurity	Moderate or severe food insecurity	Food insecurity	Food insecurity	Raw score	Raw score
Battles within 20km	0.010^{***}		0.007^{***}		0.040^{***}	
	(0.001)		(0.001)		(0.007)	
Battles within 30km		0.008^{***}		0.005^{***}		0.031^{***}
		(0.001)		(0.001)		(0.005)
Household fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.020	0.021	0.009	0.010	0.021	0.022
Mean dep. var (pre-war)	0.361	0.361	0.557	0.557	2.054	2.054
No. observations	14374	14374	14374	14374	14374	14374

Notes: The outcome variable in the first two columns stands for a binary indicator assuming a value of 1 for those households classified as moderate or severe food insecure based on the severity of food insecurity constructed from

[31] We have also computed battle exposure at 10 km, 40 km, and 50 km distance radius. As expected, the effect of exposure to battles in close distances is greater than those further from the residence. Results based on these buffers are available upon request.

[32] These results are available upon request.

the eight FIES questions. The dependent variable in columns 3-4 stands for binary indicator assuming a value 1 for those households experiencing one or more types of food insecurity and 0 otherwise. The outcome variable in the last two columns stands for raw sum of the responses to the eight FIES questions. The measure of battle exposure is cumulative number of battles withing 20 km and 30 km of place of residence by the survey time. All estimations use sampling weights to capture systematic non-response and attrition in phone surveys. Standard errors, clustered at district (woreda) level, are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10 reports results for impacts of battle exposure on the eight FIES outcomes. For each outcome variable, experiences of battles within 20 and 30 km radius are associated with increased food insecurity as shown in Panel A and B, respectively. The share of households who report being worried about getting enough food, unable to eat healthy foods or ate few food varieties increased by approximately 1 percentage points with an additional battle event within 20 km of the residence of the household. The impact on the share of households who skip a meal or eat less food is similar – one more battle event is associated with about 1 percentage points increase in these coping strategies. Like the previous coarse measure of exposure to conflict in Tables 3 and 7, we do not find statistically significant effects for the more extreme outcomes – "ran out of food", "hungry but did not eat", and "did not eat at all".

Table 10: Number of battles and food security

	(1) Worried not enough food	(2) Unable to eat healthy foods	(3) Ate few kinds of food	(4) Skipped meal	(5) Ate less food	(6) Ran out of food	(7) Hungry but did not eat	(8) Didn't eat all day
Panel A: Using battles within 20 km								
Battles within 20 km	0.006^{***}	0.009^{***}	0.009^{***}	0.010^{***}	0.010^{***}	-0.001	0.000	-0.002
	(0.001)	(0.002)	(0.001)	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)
Household fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.020	0.009	0.008	0.030	0.038	0.007	0.038	0.021
Panel B: Using battles within 30 km								
Battles within 30km	0.005^{***}	0.007^{***}	0.007^{***}	0.007^{***}	0.007^{***}	-0.001	0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Household fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.021	0.010	0.009	0.030	0.039	0.007	0.038	0.021
Mean dep. var (pre-war)	0.387	0.429	0.427	0.221	0.287	0.183	0.098	0.062
No. observations	14375	14375	14375	14375	14375	17018	17018	17018

Notes: the outcome variables in this table are raw responses to standard FIES questions on whether the respondent or household member (1) was *worried* about having enough food to eat, (2) ate only a *few kinds* of foods, (3) unable to eat *healthy* and nutritious foods, (4) *ate less* than should have eaten, (5) had *skipped* a meal, (6) *run out* of food, (7) was *hungry* but did not eat, (8) went without eating for a *whole day*. Exposure to conflict is measured by counting the number of battles withing 20 km and 30 km of place of residence by the survey time. All estimations use sampling weights to capture systematic non-response and attrition in phone surveys. Standard errors, clustered at district (woreda) level, are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The labor market impacts of the war estimated using households' exposure to battles within 20 km and 30 km are consistent with the DID findings reported earlier. An additional battle leads to about 0.5 percentage points reduction in participation in any livelihood activity (Table 11). The fall in economic activity was primarily due to a decrease in non-farm business and wage-earning activities. An additional battle is associated with 0.2 percentage points decrease in non-farm business activities and wage employment. There was, however, no impact on farm activities, signifying the resilience of the agriculture sector to the stresses of armed conflict.

Table 11: Armed conflict and livelihood activities

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Any activity	Any activity	Farm activity	Farm activity	Non-farm business	Non-farm business	Wage related activities	Wage related activities
Battles within 20 km	-0.005***		0.000		-0.002**		-0.002**	
	(0.002)		(0.001)		(0.001)		(0.001)	
Battles within 30 km		-0.004***		0.001		-0.002***		-0.002***
		(0.001)		(0.000)		(0.001)		(0.001)
Household fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.012	0.012	0.013	0.013	0.004	0.005	0.004	0.005
Mean dep. var (pre-war)	0.801	0.801	0.313	0.313	0.241	0.241	0.417	0.417
No. observations	21704	21704	28247	28247	28247	28247	28247	28247

Notes: The outcome variable in the first two columns is a dummy variable for participation in any economic activity. The outcome variable in the third and fourth columns stands for a dummy variable capturing participation in non-farm business activities while the dependent variable in the last two columns represents an indicator variable for engagement in wage-related activities. All estimations use sampling weights to capture systematic non-response and attrition in phone surveys. Standard errors, clustered at district (woreda) level, are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.4 Robustness Tests and Heterogeneity Analyses

We run several empirical tests to prob the robustness of our results. Most importantly, our main estimations consider the rest of Ethiopia except Tigray as control group. However, households living in the highland regions (Amhara, Oromia, Tigray and SNNP) and lowland regions engage in slightly different livelihood activities.[33] Similarly, households living in some of the major urban centers (e.g., Addis Ababa) have markedly different economic conditions and sources of livelihood. To reduce potential differences in the impacts of the war due to differences in livelihood activities between Tigray and the control group, we restricted the sample to the four highland regions, with households from the three regions (Amhara, Oromia, and SNNP) serving as control group. We then run all our estimations on this restricted and significantly smaller sample. Despite the change in the sample size, the results in Tables A6-A8 show remarkably similar impacts to those reported using the full sample.

Table A6 shows the impact of the war on the share of households who are moderately or severely food insecure and the probability of food insecurity for the reduced four-region sample. The results associated with food insecurity prevalence are similar to the full sample (42 vs 38 percentage points). Similarly, the impacts on probability of food insecurity compare well with the full sample (31 vs 26 percentage points). The results for the disaggregate household level experiences of food insecurity presented in Table A7 are similarly consistent with the full sample. The conflict had comparable impact on the share of households who worry about food shortages; those that report having to eat fewer kinds of food, reduce food consumption or lower quality foods; households who skip meal. The estimates for the more extreme outcomes are either statistically insignificant or weekly significant (responses for “hungry but did not eat”). If anything, these estimates appear to indicate that effect of the violent conflict on food security is likely higher than that established in Tables 2-4.

We also run a range of heterogeneity analyses by splitting the sample by several observable characteristics: households living in rural and urban areas; poor and non-poor households. These results are reported in Tables A9-A11. The most striking difference we observe is in terms of impacts in economic activities across rural and urban areas (Table A10). Households engaged in non-farm business activities and wage related activities in urban areas appear to be more affected than those engaged in similar activities in rural areas.

[33] For example, households in Ethiopian highlands are likely to practice mixed farming while those in the lowlands (arid and semi-arid lands of Ethiopia) practice animal husbandry as dominant source of livelihood (e.g., Abay and Jensen, 2020).

6. Conclusions

An ongoing and large-scale civil war in Tigray has resulted in significant human suffering and economic disruptions, which are still being experienced at the time of writing. To make matters worse, besides the direct effects of the war on lives and livelihoods, what the UN calls a de facto blockade of the region has obstructed humanitarian assistance while also limiting our understanding of the breadth and consequences of the armed conflict.[34] One fortuitous aspect of this situation, however, has been the opportunity to repurpose a high frequency phone survey (HFPS), originally developed by the World Bank to monitor the COVID-19 situation and impacts in Ethiopia and continued to monitor household food security and economic activities amid an armed conflict. Using these survey data, in tandem with armed conflict location and events data (ACLED), we show evidence of significant disruptions to livelihoods, with negative impacts on household food security and access to food in the first few months of the war covered by the HFPS data. We find that, as a result of the conflict, moderate or severe food insecurity increased by 38 percentage points. Using the ACLED granular data on households' exposure to violent conflict, we show that exposure to an additional battle within 20 km radius leads to 1 percentage point increase in the probability of moderate to severe food insecurity. Similarly, affected households report a 10 percentage point reduction in non-farm activities and 15 percent reduction in wage employment within two months of the start of the war. Farming, on the other hand, was notably resilient to impacts of the war, with participation in farm activities remaining relatively steady.

The HFPS sample is a subsample of a nationally representative sample of households drawn for an in-person survey in 2019. It covers households who reported phone ownership in the in-person survey. Due to this non-random sample and additional complication of war related nonresponse and displacements of households during the survey period, the survey is likely to include those who are relatively less exposed and less vulnerable to the vicissitudes of the war. While we try to account for systematic non-response and attrition using sample weights constructed using a long list of observables, the actual negative impacts of the conflict are likely to be larger on average, and it is difficult to fully quantify the extent to which this is the case. Moreover, we note that these impacts refer to the first few months after the onset of the crisis but also in months relatively closer to the harvest season. We know that even in normal times food

[34] https://www.reuters.com/world/un-warns-catastrophe-looms-ethiopias-north-urges-government-end-de-facto-aid-2021-09-02/

insecurity worsens closer to the lean season (Berhane et al., 2010). Given the continued obstruction of humanitarian assistance, these simmering impacts are likely substantial in subsequent lean season-months not covered in our study.

To a certain extent, these results are not surprising – human suffering has been widely reported in contexts of war. In fact, the share of affected people who report continuing work is perhaps surprisingly high, given the circumstances, and even after allowing for selection bias. For example, despite the war, some households continued participation in various farm and non-farm activities. This reflects the exigencies of feeding one's family, even under conditions where the pursuit of livelihoods is fraught with danger. By the same token, our results may be taken as indicators of the resilience of some livelihood sectors and of ordinary people to persevere their livelihoods despite the complications of an active conflict.

Our insights into these outcomes are limited by the ways in which information was elicited in the surveys. For example, while we observe the extensive margin of economic activity (i.e., whether or not labor was allocated to a particular activity in the reference period), we are unable to directly observe the intensive margin (e.g., as the number of hours worked). It may be useful for further efforts to probe for other measures of economic disruption, including qualitative assessments by wage employees and business owners.

A final caveat is in our measures of conflict exposure. We have shown that our regional-dummy approach generates results which are consistent with those obtained from point location estimates of battle events derived from media reports (via the ACLED database). However, future rounds of the HFPS may also ask respondents to indicate their exposure to conflict via the survey instrument.

These caveats notwithstanding, our analysis indicates enormous potential for using high-frequency phone surveys and related remote data collection methods -ideally associated with a baseline sample of respondents -to monitor the impacts of active conflicts, and to quickly devise post-conflict responses that are tailored to geographical and household heterogeneity in impacts suffered. This corroborates recent efforts and innovations in remote data collection in fragile states (e.g., Dabalen et al., 2016; Hoogeveen and Pape, 2020). To facilitate effective use of remote data collection methods, it would be useful to maintain access to a much larger database of potential telephone survey respondents, designed for maximum geographical and socioeconomic representativeness, given the constraints of household-level phone access and regional ICT infrastructure.

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Appendix

Figure and Tables

Table A1: Number of battles and battle-related fatalities, pre-and post-war-onset

	Pre-war			Post-war-onset		
Spatial resolution	No. obs.	Mean	SD	No. obs.	Mean	SD
Number of battles 10km	20,006	0.46	0.96	8,250	1.42	3.61
Number of battles 20km	20,006	0.88	1.51	8,250	2.80	7.03
Number of battles 30km	20,006	1.14	1.69	8,250	3.65	8.91
Number of battles 40km	20,006	1.31	2.07	8,250	4.94	13.30
Number of battles 50km	20,006	1.55	2.43	8,250	6.25	16.88

Notes: this table provides pooled summary statistics associated with number of battles and associated fatalities. These data are based on ACLED.

Table A2: Sample of households interviewed across survey rounds

Round	Time/month	All regions	Outside Tigray region	Tigray region
Baseline	19-Aug	6770	6094	676
1	20-Apr	3,247	2,915	332
2	20-May	3,105	2,782	323
3	20-Jun	3,056	2,737	319
4	20-Aug	2,876	2,569	307
5	20-Sep	2,768	2,465	303
6	20-Oct	2,702	2,412	290
7	20-Nov	2,535	2,277	258
8	20-Dec	2,221	2,144	77
9	21-Jan	2,076	1,992	84
10	21-Feb	2,176	2,041	135
11	21-May	1,982	1,896	86

Table A3: Modeling the probability of response in both pre-and post-war-onset phone surveys

Explanatory variables	Coefficients
Household head age in years	0.004
	(0.002)
Household head is female	0.055
	(0.069)
Education of household head: Upper primary	0.026
	(0.089)
Education of household head: Secondary or higher	0.318^{***}
	(0.088)
Household size	-0.012
	(0.021)
Adult household members size	0.047
	(0.034)
Household head engaged in agriculture	-0.020
	(0.161)
Household head engaged in wage earning	0.020
	(0.148)
Household head engaged in non-farm business	-0.105
	(0.142)
Asset quintile: Second	0.187^{*}
	(0.104)
Asset quintile: Third	0.474^{***}
	(0.115)
Asset quintile: Fourth	0.833^{***}
	(0.127)
Asset quintile: Fifth	0.876^{***}
	(0.149)
Household located in rural area	-0.081
	(0.095)
Household participated in PSNP	0.012
	(0.108)
Log household consumption PAE per year	0.125^{**}
	(0.052)
Household owns a mobile phone	1.385^{***}
	(0.103)
Number of mobiles available in the household	0.132^{***}
	(0.046)
Household has access to electricity	0.062
	(0.104)
Log (distance to nearest market, in KM)	-0.112^{***}
	(0.041)
Log (distance to nearest town, in KM)	0.008
	(0.042)
Region dummy: Afar	0.777^{***}
	(0.149)
Region dummy: Amhara	1.253^{***}
	(0.138)
Region dummy: Oromia	1.840^{***}

	(0.138)
Region dummy: Somali	-0.024
	(0.165)
Region dummy: Benishangul Gumuz	1.443***
	(0.170)
Region dummy: SNNP	0.615***
	(0.146)
Gambela	0.429***
	(0.159)
Harar	0.719***
	(0.158)
Addis Ababa	0.581***
	(0.142)
Dire Dawa	0.417***
	(0.153)
Constant	-4.032***
	(0.600)
Number of observations	6664

Notes: this table reports coefficients from a logit regression. The base education is those below upper primary education. The base asset quintile is the first quintile, and the base region is Tigray. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Descriptive statistics of the sample, by sample weights

	Unweighted full sample (1)	Unweighted phone survey (2)	Weighted phone survey (3)
Household head age in years	42.19	40.99	42.34
Household head is female	0.32	0.30	0.32
Education of household head: Lower primary	0.56	0.39	0.56
Upper primary	0.16	0.18	0.16
Secondary or higher	0.28	0.42	0.29
Household size	4.36	4.09	4.37
Adult household members size	2.45	2.51	2.45
Household head engaged in agriculture	0.56	0.47	0.56
Household head engaged in wage earning	0.30	0.36	0.29
Household head engaged in non-farm business	0.18	0.22	0.19
Asset quintiles: First quintile	0.20	0.10	0.19
Second quintile	0.24	0.14	0.23
Third quintile	0.16	0.14	0.17
Fourth quintile	0.20	0.28	0.20
Fifth quintile	0.20	0.33	0.21
Household located in rural area	0.46	0.28	0.46
Household participated in PSNP	0.13	0.08	0.13
Household consumption PAE per year	21880.51	25982.92	22071.15
Log household consumption PAE per year	9.68	9.91	9.72
Household owns a mobile phone	0.67	0.90	0.67
Number of mobiles available in the household	1.14	1.66	1.16
Household has access to electricity	0.52	0.72	0.53
Distance to market in KM	54.98	37.66	52.69
Distance to nearest town in KM	26.75	18.59	25.78
Log (distance to market in KM)	3.23	2.75	3.21
Log (distance to nearest town in KM)	2.66	2.27	2.62
Tigray	0.10	0.06	0.09
Afar	0.08	0.06	0.07
Amhara	0.11	0.11	0.11
Oromia	0.11	0.15	0.12
Somali	0.09	0.04	0.13
Benishangul Gumuz	0.05	0.06	0.05
SNNP	0.10	0.06	0.09
Gambella	0.07	0.06	0.07
Harar	0.08	0.10	0.08
Addis Ababa	0.11	0.19	0.12
Dire Dawa	0.09	0.10	0.07
Other highland regions	0.32	0.32	0.32
Other regions	0.90	0.94	0.91
Number of observations	6770	2677	2677

Table A5: Summary of households' access to food

Access to food		Weighted values	
	No. observations	Mean	Standard deviations
Not able to buy teff/injera	19,495	0.11	0.32
Not able to buy wheat	19,495	0.10	0.30
Not able to buy maize	19,495	0.05	0.22
Not able to buy edible oil	19,495	0.15	0.36
Not able to buy food	19,495	0.24	0.43

Notes: These values come from a series of questions eliciting whether a household was not able to buy each of the above staple foods and essential goods.

Figure A1: Labor market participation of household head by rural and urban areas

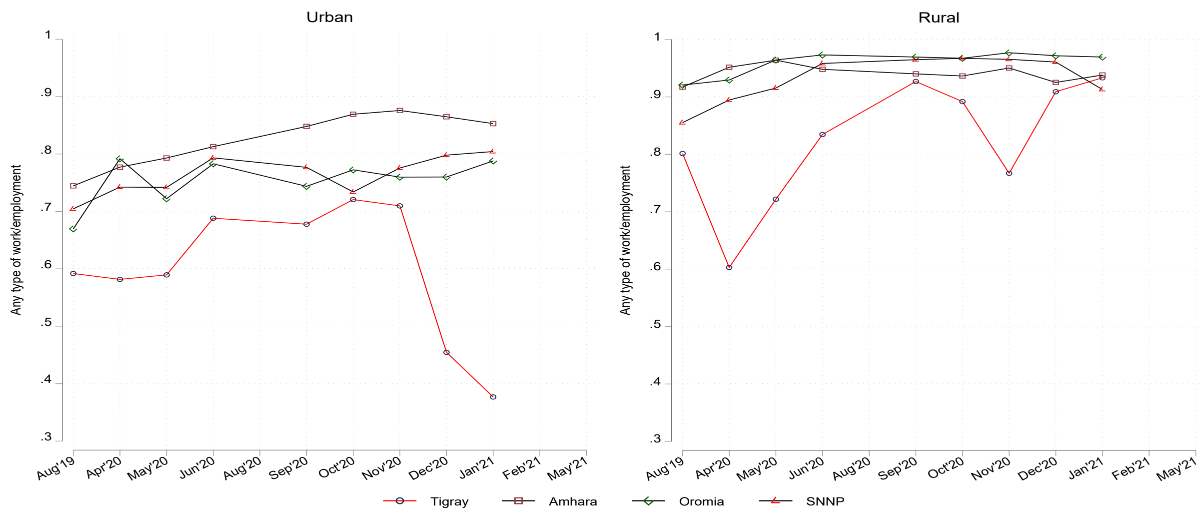

Table A6: The Impact of violent conflict on aggregate measures of food insecurity: sample restricted to highland regions

	(1) Moderate or severe	(2) Food insecure	(3) Raw score
Wartime dummy	-0.051*	-0.072***	-0.441**
	(0.028)	(0.023)	(0.178)
Tigray*Wartime dummy	0.421***	0.308***	1.975***
	(0.057)	(0.037)	(0.277)
Household fixed effects	Yes	Yes	Yes
R-squared	0.021	0.012	0.021
Mean dep. var (pre-war)	0.454	0.634	2.598
No. observations	5580	5580	5580

Notes: The outcome variable in the first column stands for a binary indicator assuming a value of 1 for those households classified as moderate or severe food insecure based on the severity of food insecurity generated from the eight FIES questions. The dependent variable in the second column stands for binary indicator assuming a value 1 for those households experiencing one or more types of food insecurity and 0 otherwise. The outcome variable in the last column stands for raw sum of the responses to the eight FIES questions. All estimations use sampling weights to capture systematic non-response and attrition in phone surveys. Standard errors, clustered at district (woreda) level, are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: The Impact of violent conflict on experience of food insecurity: sample restricted to highland regions

	(1) Worried not enough food	(2) Unable to eat healthy foods	(3) Ate few kinds of food	(4) Skipped meal	(5) Ate less food	(6) Run out of food	(7) Hungry but did not eat	(8) Didn't eat all day
Wartime dummy	-0.030	-0.040	-0.068**	-0.068**	-0.106***	-0.041	-0.055*	-0.033
	(0.024)	(0.026)	(0.029)	(0.030)	(0.029)	(0.037)	(0.033)	(0.029)
Tigray*Wartime dummy	0.276***	0.384***	0.414***	0.407***	0.417***	0.005	0.086*	-0.003
	(0.051)	(0.058)	(0.055)	(0.085)	(0.090)	(0.047)	(0.049)	(0.049)
Household fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sampling weights	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.008	0.016	0.019	0.020	0.022	0.002	0.003	0.002
Mean dep. var (pre-war)	0.465	0.518	0.527	0.295	0.383	0.193	0.138	0.083
No. observations	5580	5580	5580	5580	5580	6609	6609	6609

Notes: the outcome variables in this table are raw responses to standard FIES questions on whether the respondent or household member (1) was *worried* about having enough food to eat, (2) ate only a *few kinds* of foods, (3) unable to eat *healthy* and nutritious foods, (4) *ate less* than should have eaten, (5) had *skipped* a meal, (6) *run out* of food, (7) was *hungry* but did not eat, (8) went without eating for a *whole day*. All estimations use sampling weights to capture systematic non-response and attrition in phone surveys. Standard errors, clustered at district (woreda) level, are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: The Impact of violent conflict on labor market and livelihood activities: sample restricted to highland regions

	(1) Any activity	(2) Any activity	(3) Farm activity	(4) Farm activity	(5) Non-farm business	(6) Non-farm business	(7) Wage related activities	(8) Wage related activities
Wartime dummy	0.021**	0.013	-0.014*	-0.026**	-0.028**	-0.010	0.021**	0.022**
	(0.009)	(0.010)	(0.008)	(0.010)	(0.012)	(0.011)	(0.008)	(0.009)
Tigray*Wartime dummy	-0.194***	-0.099*	0.016	0.027	-0.076***	-0.099***	-0.180***	-0.153***
	(0.044)	(0.057)	(0.012)	(0.019)	(0.029)	(0.027)	(0.032)	(0.030)
Household fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sampling weights	No	Yes	No	Yes	No	Yes	No	Yes
R-squared	0.007	0.002	0.001	0.002	0.005	0.006	0.007	0.007
Mean dep. var (pre-war)	0.829	0.832	0.485	0.486	0.243	0.244	0.294	0.293
No. observations	8509	8372	11056	10874	11056	10874	8509	8372

Notes: The outcome variable in the first two columns stands for a binary indicator assuming a value of 1 for those participating in these activities in the last 7 days. Standard errors, clustered at district (woreda) level, are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A9: The Impact of violent conflict on aggregate measures of food insecurity: differences across rural and urban households

	(1) Moderate or severe (rural)	(2) Moderate or severe (urban)	(3) Probability of food insecurity (rural)	(4) Probability of food insecurity (urban)	(5) Raw score (rural)	(6) Raw score (urban)
Wartime dummy	0.012	-0.031	-0.031	-0.021	0.186	-0.242^{**}
	(0.029)	(0.020)	(0.025)	(0.019)	(0.206)	(0.103)
Tigray*Wartime dummy	0.516^{***}	0.358^{***}	0.389^{***}	0.224^{***}	1.958^{***}	1.609^{***}
	(0.089)	(0.058)	(0.094)	(0.028)	(0.555)	(0.244)
Household fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Sampling weights	No	Yes	No	Yes	No	Yes
R-squared	0.008	0.010	0.005	0.003	0.007	0.011
Mean dep. var (pre-war)	0.455	0.326	0.654	0.521	2.534	1.875
No. observations	3868	10655	3868	10655	3868	10655

Notes: This table models food insecurity outcomes for rural and urban households. Odd columns provide results for rural areas while even columns provide results for urban areas. All estimations use sampling weights to capture systematic non-response and attrition in phone surveys. Standard errors, clustered at district (woreda) level, are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A10: The Impact of violent conflict on labor market and livelihood activities: differences across rural and urban households

	(1) Any activity (rural)	(2) Any activity (urban)	(3) Farm activity (rural)	(4) Farm activity (urban)	(5) Non-farm business (rural)	(6) Non-farm business (urban)	(7) Wage related activities (rural)	(8) Wage related activities (urban)
Wartime dummy	-0.013	0.037^{***}	-0.046^{***}	-0.020^{***}	-0.018	-0.009	0.003	0.034^{***}
	(0.017)	(0.011)	(0.014)	(0.007)	(0.013)	(0.009)	(0.010)	(0.011)
Tigray*Wartime dummy	0.134^{***}	-0.275^{***}	0.054	0.017^{**}	-0.060^{*}	-0.123^{***}	-0.060^{***}	-0.219^{***}
	(0.041)	(0.035)	(0.043)	(0.008)	(0.032)	(0.036)	(0.021)	(0.035)
Household fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sampling weights	No	Yes	No	Yes	No	Yes	No	Yes
R-squared	0.003	0.007	0.006	0.002	0.002	0.003	0.001	0.005
Mean dep. var (pre-war)	0.920	0.756	0.836	0.116	0.151	0.274	0.156	0.516
No. observations	5969	15971	7634	20924	7634	20924	5969	15971

Notes: This table characterizes households' participation in various labor market outcomes for rural and urban households. Odd columns provide results for rural areas while even columns provide results for urban areas. All estimations use sampling weights to capture systematic non-response and attrition in phone surveys. Standard errors, clustered at district (woreda) level, are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A11: The Impact of violent conflict on aggregate measures of food insecurity: differences across poor and non-poor households

	(1) Moderate or severe (poor)	(2) Moderate or severe (non-poor)	(3) Food insecure (poor)	(4) Food insecure (non-poor)	(5) Raw score (poor)	(6) Raw score (non-poor)
Wartime dummy	-0.036^{*}	0.023	-0.057^{***}	0.031	-0.216	0.176
	(0.021)	(0.022)	(0.018)	(0.020)	(0.132)	(0.121)
Tigray*Wartime dummy	0.398^{***}	0.357^{***}	0.284^{***}	0.217^{***}	1.839^{***}	1.245^{***}
	(0.063)	(0.072)	(0.034)	(0.064)	(0.204)	(0.382)
Household fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Sampling weights	No	Yes	No	Yes	No	Yes
R-squared	0.008	0.012	0.006	0.005	0.008	0.010
Mean dep. var (pre-war)	0.420	0.278	0.622	0.465	2.403	1.559
No. observations	8500	6023	8500	6023	8500	6023

Notes: This table models food insecurity outcomes for poor and non-poor households. Odd columns provide results for poor households while even columns provide results for urban areas. All estimations use sampling weights to capture systematic non-response and attrition in phone surveys. Standard errors, clustered at district (woreda) level, are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.